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Abstract

This paper focuses on the time-varying volatility of aggregate fluctuations in emerging markets. Both Latin American and Asian emerging economies experience volatility spikes during financial crises; however, only the latter group exhibits a long-run decline in volatility. Using business cycle data from South Korea, we estimate a small open economy real business cycle model with Markov-switching shock variances. We compare the model fit across alternative specifications of shock volatility structures and investigate the underlying drivers of volatility changes. The results indicate that the data favor the model in which all shock variances switch regimes synchronously. The estimated model captures both the declining trend in volatility over time and temporary volatility spikes during episodes of financial turmoil. It suggests that the long-run decline in volatility is not primarily driven by a reduction in the variance of the interest rate premium shock, though this shock contributes to temporary volatility spikes during crises. The model replicates key business cycle features of emerging markets and highlights that the drivers of aggregate fluctuations depend on the volatility regime.

JEL classification: E32, F41, C13

Keywords: Small open economy; real business cycles; regime switching.

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1 Introduction

Various studies have attempted to describe emerging market business cycles using real business cycle (RBC) models that incorporate shocks to the trend of productivity and/or shocks to the country interest rate premium, typically in combination with financial frictions. Notable contributions include Neumeyer and Perri (2005), Uribe and Yue (2006), Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010), Chang and Fernández (2013), and Miyamoto and Nguyen (2017), among others. Based on the literature, it appears that both types of shocks help explain aggregate fluctuations in emerging economies including its key features such as the excess volatility of consumption over GDP and the countercyclical behavior of external balances. While most of these studies focus on data from Latin American emerging economies, Hwang and Kim (2022) examine differences in aggregate fluctuations between Asian and Latin American emerging markets, and Naoussi and Tripier (2013) extend the analysis to include the least developed countries from Sub-Saharan Africa.

What much of the previous literature abstracts from is the heteroskedasticity of aggregate fluctuations in emerging economies. Figure 1 presents the median of 11-year moving standard deviations of HP-filtered GDP, consumption, and investment from 1965 to 2014 for a set of East Asian and Latin American emerging countries. The Asian sample includes South Korea, Indonesia, Taiwan, Thailand, Hong Kong, the Philippines, Malaysia, and Singapore, while the Latin American sample comprises Brazil, Mexico, Argentina, Colombia, Chile, Peru, and Venezuela.[1] All variables are expressed in per capita terms. The data are drawn from PWT 10.01 (Feenstra et al., 2015). In each country, the standard deviation is normalized to 1 in 1965, and the median is taken in each country group.

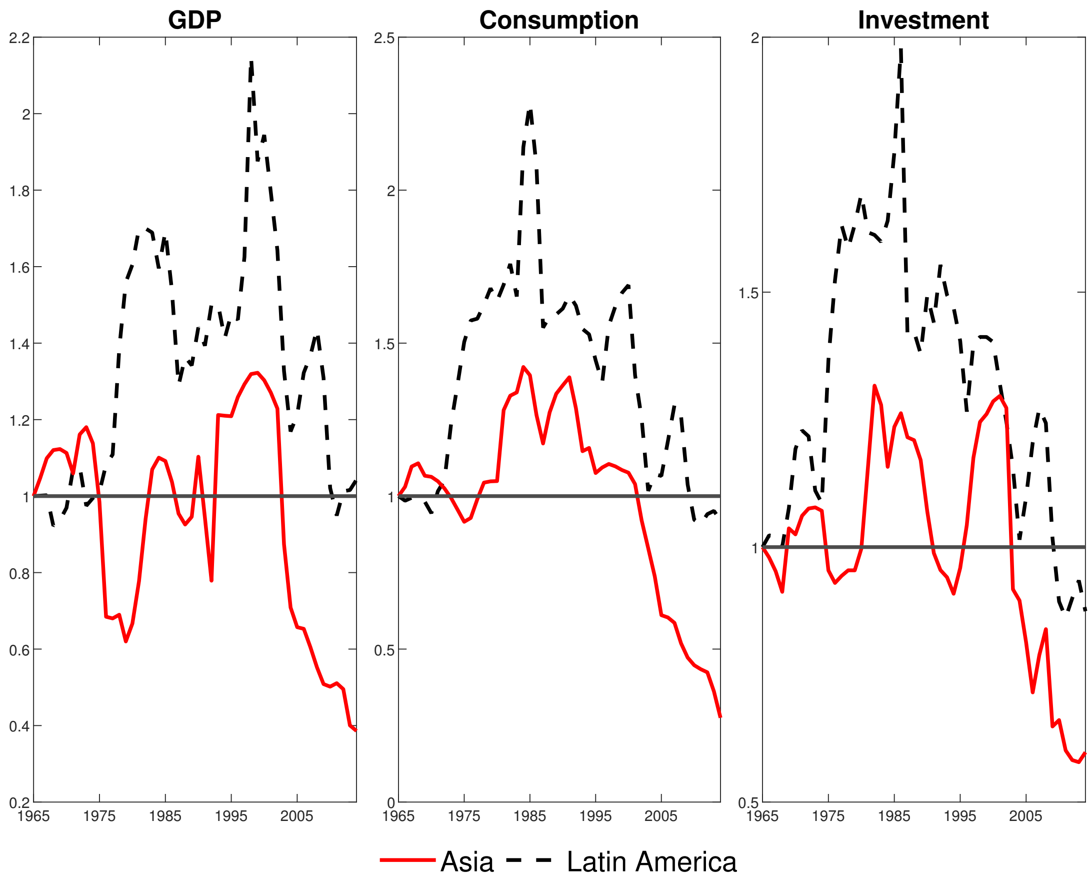
Two key patterns emerge. First, both regions exhibit spikes in macroeconomic volatility around periods of financial crisis. Second, Asian economies show a clear trend toward stabilization over time. Specifically, by 2014, the volatility of GDP, consumption, and investment in Asian countries had declined by approximately 60%, 70%, and 40%, respectively, relative to their 1965 levels. In contrast, the volatility of Latin American economies in 2014 remains largely unchanged from that of 1965.

These observations raise two questions not fully explored in the literature. First, how should the prototypical model be extended to account for both the transitory spikes in volatility during financial crises and the long-run decline in volatility which is particularly evident in Asian emerging markets? Second, what drives the changing volatility of aggregate fluctuations in emerging economies?

This paper addresses these questions by developing an extended small open economy RBC model with Markov-switching volatility. Specifically, we introduce heteroskedasticity into the model by allowing the variances of exogenous shocks to follow a Markov-switching process, and we estimate this Markov-switching DSGE model using business cycle data from South Korea. Incorporating time-varying volatility in DSGE models through a Markov-switching framework is a widely adopted

[1] The list of countries is based on Hwang and Kim (2022) and consists of those with relatively large GDP levels within each region.

Figure 1: Median Business Cycle Volatilities in Asia and Latin America



Note: This figure shows the median of 11-year moving standard deviations of HP-filtered GDP, consumption, and investment for Asian (solid line) and Latin American (dashed line) countries. For each country, the standard deviation in 1965 is normalized to 1, and the median is taken for each group. The figure looks similar when using growth rates.

approach in the literature (e.g., Liu et al., 2011, Bianchi, 2013, Lindé et al., 2016, and Bjørnland et al., 2018).[2] As in Garcia-Cicco et al. (2010), the model features five structural shocks as drivers of aggregate fluctuations: a temporary productivity shock, a permanent productivity shock, a preference shock, a domestic spending shock, and a country interest rate premium shock. We estimate several model specifications that differ in the structure of regime-switching in shock variances and compare their fit to the data. Based on the estimated model, we infer the time-varying state of macroeconomic volatility and examine the sources of volatility shifts and business cycle fluctuations.

[2]An alternative approach to modeling time-varying shock volatilities in DSGE models is to introduce stochastic volatility processes, as in Fernández-Villaverde and Rubio-Ramírez (2007) and Justiniano and Primiceri (2008), among others. While this approach is effective in capturing low-frequency changes in volatility, Cúrdia et al. (2014) point out that the inference about the low-frequency changes in volatility via stochastic volatility processes can vary depending on whether high-frequency changes in volatility driven by large transitory shocks are taken into account. Given that we observe both a long-run decline and short-lived spikes in volatility, we adopt a Markov-switching volatility framework. Lindé et al. (2016) demonstrate that the Markov-switching volatility captures both low and high frequency changes in volatility.

We find that the model with synchronized regime-switching of all shock variances achieves the best fit to the data among the specifications considered. Interestingly, allowing for multiple sources of volatility changes does not enhance the model's performance. In particular, allowing an independent regime-switch in the standard deviation of the interest rate premium shock while keeping the regime-switching synchronized for the other shocks does not improve model fit. Although our results are based on emerging market business cycles, they align with findings from Liu et al. (2011), who reach similar conclusions for U.S. aggregate fluctuations. Nonetheless, the data consistently favor models with regime-switching volatility over those with constant shock variances.

Our model identifies periods of high macroeconomic volatility during the earlier part of the sample up to the 1980s and during transitory periods associated with financial crises, such as the Asian financial crisis and the global financial crisis. In this way, the model captures both the long-run decline in macroeconomic volatility observed over the sample period and the temporary spikes in volatility during episodes of financial turmoil. When we allow for independent regime-switching in the standard deviation of the country interest rate premium shock, we do observe transitory increases in its volatility during financial crises. However, we find no evidence of a long-run declining trend in this shock's volatility. We therefore conclude that the long-run decline in macroeconomic volatility in Asian emerging economies is not driven by reduced volatility in the interest rate premium shock. In contrast, the transitory spikes in macroeconomic volatility during financial crises are partially attributed to heightened volatility in the country premium shock, which can be interpreted as reflecting increased risk in international financial markets (Fernandez-Villaverde et al., 2011).

The estimated model successfully replicates the relative volatility across regimes and key characteristics of the business cycle data, including the excess volatility of consumption over GDP and the countercyclical behavior of the trade balance. The shock decomposition reveals that the sources of aggregate fluctuations vary with the prevailing state of macroeconomic volatility. We find that, in the low-volatility regime, the shock to the nonstationary component of TFP are the primary driver of GDP growth. In contrast, during the high-volatility regime, GDP growth is predominantly driven by shocks to the stationary component of TFP. For consumption growth, the dominant source in the low-volatility regime is the stationary TFP shock, whereas in the high-volatility regime, both preference shocks and domestic spending shocks also play significant roles. These results suggest that distinguishing between different volatility regimes provides a new perspective on the sources of aggregate fluctuations that has not been fully explored since the "cycle is the trend" argument proposed by Aguiar and Gopinath (2007).

The present paper relates to a broad body of literature that seeks to explain the properties of business cycles in emerging economies. Boz et al. (2011) introduce information frictions in total factor productivity, Álvarez-Parra et al. (2013) explore the role of durable consumption, Boz et al. (2015) focus on the labor market frictions, and Seoane (2016) incorporate time-varying structural parameters. Guntin et al. (2023) provide micro-level support for the "cycle is the trend" argument using heterogeneous agent models and micro data. Na and Yoo (2025) incorporate diagnostic expectations. This paper contributes to the literature by emphasizing heteroskedasticity in emerging market business cycles and examining the underlying drivers of changing volatility.

This paper is also related to the literature that incorporates time-varying volatility in DSGE models through Markov-switching shock variances. The literature includes Liu and Mumtaz (2011), Liu et al. (2013), Baele et al. (2015), Binning and Maih (2016), Bianchi and Ilut (2017), Chang et al. (2021), and Maih et al. (2021), in addition to the studies mentioned earlier. Maih (2015), Foerster et al. (2016) and Barthélemy and Marx (2017) proposes the perturbation approach to solve the regime switching DSGE model. When the model is solved accurately up to the first order, the estimation can be carried out via likelihood-based methods using the filtering procedure introduced by Kim (1994) and Kim and Nelson (1999).

The remainder of the paper is organized as follows. Section 2 presents the small open economy model with Markov-switching volatility. Section 3 discusses the empirical implementation, including the solution and estimation methods, and reports the results from various exercises. Section 4 concludes the paper.

2 The Model

We augment the small open economy real business cycle model of Garcia-Cicco et al. (2010) by introducing regime switching in the standard deviation of exogenous shocks. The model features five structural shocks: temporary and permanent productivity shocks, a preference shock, a domestic spending shock, and a country interest rate premium shock. The standard deviation of each shock is allowed to switch between low and high volatility regimes, either synchronously or independently of the others.

The representative household maximizes expected lifetime utility,

$$E_0 \sum_{t=0}^{\infty} \nu_t \beta^t \frac{\left[C_t - \omega^{-1} X_{t-1} h_t^{\omega}\right]^{1-\gamma} - 1}{1-\gamma}, \tag{1}$$

where C_t and h_t denote consumption and hours worked in period t, respectively. The variable ν_t represents an exogenous intertemporal preference shock, and X_{t-1} denotes the exogenous shock to the nonstationary component of total factor productivity which determines the trend growth rate. The parameters $\beta \in (0,1)$, $\gamma > 0$ and $\omega > 1$ represent the subjective discount factor, the inverse of the intertemporal elasticity of substitution, and one plus the inverse of the Frisch elasticity of labor supply, respectively. Both the preference shock and the nonstationary productivity shock follow AR(1) processes

$$\ln \nu_t = \rho_\nu \ln \nu_{t-1} + \sigma_\nu \left(\mathcal{S}_t^m\right) \epsilon_t^\nu,$$

and

$$\ln\left(\frac{g_t}{g}\right) = \rho_g \ln\left(\frac{g_{t-1}}{g}\right) + \sigma_g\left(\mathcal{S}_t^m\right)\epsilon_t^g,$$

where $g_t = \frac{X_t}{X_{t-1}}$ denotes the gross growth rate of the economy and g is its steady state value. The innovations ϵ_t^ν and ϵ_t^g are normally distributed with mean zero and variance one. The parameters $\rho_i \in [0,1)$ for $i = \nu$, g govern the persistence of each shock, whereas $\sigma_i\left(\mathcal{S}_t^m\right)$ determine the regime-dependent standard deviation of each shock. We define a Markov chain $\mathcal{S}_t^m$ which has two states for the macroeconomic volatility as

$$\mathcal{S}_t^m \in \{\text{Low volatility, High volatility}\},$$

and assume the standard deviation of preference and nonstationary productivity shocks switches regimes following this chain.[3] The regime-switching process is governed by the transition matrix $\mathbb{Q}^m = \begin{bmatrix} 1-p_{\text{LH}}^m & p_{\text{LH}}^m \\ p_{\text{HL}}^m & 1-p_{\text{HL}}^m \end{bmatrix}$, where $p_{\text{LH}}^m \in [0,1]$ is the probability of switching from the low volatility state to the high volatility state, and $p_{\text{HL}}^m \in [0,1]$ is the probability of switching from the high volatility state to the low volatility state. These transition probabilities are assumed to be exogenous and are treated as parameters to be estimated.

The household maximizes the lifetime expected utility (1) subject to the period-by-period budget constraint,

$$D_t + C_t + I_t + S_t + \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t = Y_t + \frac{D_{t+1}}{1+r_t},$$

where D_{t+1}, I_t, K_{t+1}, and Y_t denote the household's borrowing from abroad, investment, capital stock, and output in period t, respectively. The variable r_t is taken as given by households and denotes the net interest rate at which households borrow from abroad. The parameter ϕ governs the size of capital adjustment cost. S_t denotes exogenous government spending, which follows

$$\ln\left(\frac{S_t/X_{t-1}}{s}\right) = \rho_s \ln\left(\frac{S_{t-1}/X_{t-2}}{s}\right) + \sigma_s\left(\mathcal{S}_t^m\right)\epsilon_t^s,$$

where s is the steady state level of detrended government spending, and ϵ_t^s is normally distributed with mean zero and variance one. The parameter $\rho_s \in [0,1)$ governs the persistence of the spending shock, while $\sigma_s\left(\mathcal{S}_t^m\right)$ denotes its standard deviation. As with the preference and nonstationary productivity shocks, the volatility of the government spending shock is assumed to switch between low and high volatility regimes according to the macroeconomic volatility chain $\mathcal{S}_t^m$.

The capital stock evolves according to the following law of motion,

$$K_{t+1} = (1-\delta)K_t + I_t,$$

[3] We normalize the first state of the macroeconomic volatility chain as the low-volatility state and the second state as the high-volatility state.

where $\delta \in [0,1)$ denotes the capital depreciation rate.

Output is produced with a Cobb-Douglas production function,

$$Y_t = a_t K_t^{\alpha} \left(X_t h_t\right)^{1-\alpha},$$

where a_t is the shock to the stationary component of total factor productivity, and the parameter $\alpha \in (0,1)$ represents the capital share in production. The stationary productivity shock follows an AR(1) process,

$$\ln a_t = \rho_a \ln a_{t-1} + \sigma_a \left(\mathcal{S}_t^m\right) \epsilon_t^a,$$

where $\rho_a \in [0,1)$ governs the persistence of the shock, and $\sigma_a \left(\mathcal{S}_t^m\right)$ is its regime-dependent standard deviation. As with the other exogenous shocks, the volatility of the stationary productivity shock is allowed to switch between two regimes following the macroeconomic volatility chain. The innovation ϵ_t^a is normally distributed with mean zero and variance one.

The interest rate faced by households is composed of the world interest rate and a country-specific interest rate premium, and is given by

$$r_t = r^* + \psi \left\{ \exp\left(\frac{\frac{\tilde{D_{t+1}}}{X_t} - d}{y} \right) - 1 \right\} + \exp\left(\mu_t - 1\right) - 1,$$

where the parameters r^* is the world interest rate, d denotes the steady-state level of detrended aggregate debt, and y is the steady-state level of detrended output. The interest rate premium is assumed to increase with the aggregate level of external debt, denoted by $\tilde{D_{t+1}}$. Since households are identical, individual and aggregate levels of debt are identical in equilibrium, thus $\tilde{D_{t+1}} = D_{t+1}$ holds. The parameter ψ governs the elasticity of the country-specific spread with respect to external borrowing. We employ the debt elastic interest rate premium to ensure stationarity in the small open economy setting following Schmitt-Grohé and Uribe (2003) and estimate ψ interpreting it as capturing financial frictions in the reduced-form manner as in Garcia-Cicco et al. (2010). In addition, we allow the interest rate premium to be affected by an exogenous shock, μ_t, which follows

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \sigma_\mu \left(\mathcal{S}_t^f\right) \epsilon_t^\mu,$$

where $\rho_\mu \in [0,1)$ captures the persistence of the shock, $\sigma_\mu \left(\mathcal{S}_t^f\right)$ is its standard deviation, and ϵ_t^μ is a normally distributed innovation with mean zero and unit variance. We allow the volatility profile of this financial shock to differ from that of other shocks.[4] Specifically, we define an independent Markov chain $\mathcal{S}_t^f$ which has the two states for the financial volatility as

$$\mathcal{S}_t^f \in \{\text{Low volatility, High volatility}\},$$

[4] Fernandez-Villaverde et al. (2011) provide evidence of time-varying volatility in the country interest rate premium faced by emerging economies.

and assume that the standard deviation of the interest rate premium shock switch between low and high volatility regimes according to the financial volatility chain $\mathcal{S}_t^f$.[5] The regime-switching process is governed by the transition matrix $\mathbb{Q}^f = \begin{bmatrix} 1-p_{\text{LH}}^f & p_{\text{LH}}^f \\ p_{\text{HL}}^f & 1-p_{\text{HL}}^f \end{bmatrix}$, where $p_{\text{LH}}^f \in [0,1]$ ($p_{\text{HL}}^f \in [0,1]$) denotes the probability of switching from the low (high) to the high (low) financial volatility state which are treated as parameters to be estimated.

The model features a stochastic trend, and we apply a stationarity-inducing transformation by dividing all trending variables by the nonstationary component of total factor productivity.

3 Empirical Implementation

3.1 Solution and Estimation Strategy

We solve the model accurately up to the first order using the perturbation technique developed by Maih (2015) and estimate it using Bayesian methods.[6] To numerically compute the likelihood, we employ the augmented Kalman filter proposed by Kim (1994) and Kim and Nelson (1999), which restricts the number of regimes carried forward at each iteration to avoid an explosive increase in the number of regime paths. We maximize the posterior kernel to obtain the posterior mode. The resulting mode is then used to initialize the random-walk Metropolis–Hastings algorithm, which is employed to construct the full posterior distributions. We run four parallel chains of Metropolis–Hastings, each with 1.1 million iterations, discarding the first $100,000$ draws of each chain as burn-in.[7] The scale parameter is adapted targeting an acceptance ratio of 23.4 percent. Convergence is monitored using multiple diagnostics, including cumulative mean plots (An and Schorfheide, 2007) and the Potential Scale Reduction Factor (PSRF) (Brooks and Gelman, 1998).[8]

We take the model to data from the South Korean economy spanning the period from 1960Q2 to 2019Q4. South Korea is chosen as a representative East Asian emerging economy for several reasons. First, its business cycles exhibit a long-run declining trend in volatility, as well as transitory spikes that primarily occur during periods of financial crisis. Appendix D presents the moving standard deviations of HP-filtered per capita GDP, consumption, and investment in South Korea. Second, the South Korean economy also displays key characteristics commonly observed in emerging markets, such as excess consumption volatility and a countercyclical trade balance. Third, quarterly national accounts data for South Korea are available for a span of 60 years, which is relatively long compared to other emerging economies. As emphasized by Garcia-Cicco et al. (2010) and Miyamoto and Nguyen (2017), using long-run data is helpful for identifying stationary and nonstationary productivity shocks. Seasonally adjusted quarterly national accounts data are obtained from the

[5] As with the macroeconomic volatility chain, we normalize the first state of the financial volatility chain as the low-volatility state and the second state as the high-volatility state.

[6] All numerical analyses in this paper are conducted using the RISE toolbox (Maih, 2015).

[7] In each chain, every fourth draw is retained, resulting in $250,000$ draws per chain.

[8] Appendix C presents the cumulative mean plots, and PSRFs are reported alongside the prior and posterior distributions reported in Appendix A.

Table 1: Calibrated Parameters

	Parameter	Value
ω	Frisch labor elasticity	1.6
γ	Inverse of intertemporal elasticity of substitution	2
δ	Depreciation rate of capital	0.0338
α	Capital share	0.4783
β	Discount factor	0.98
g	Steady state growth rate	1.0145
s	Steady state government spending	5.2210
d	Steady state external debt	-16.1071

Organisation for Economic Co-operation and Development (OECD), and transformed into per capita terms using population data from the World Development Indicators (WDI).

A set of parameters is calibrated based on values commonly used in the literature or identified from long-run averages of time series data. The parameters related to the Frisch elasticity of labor supply and the intertemporal elasticity of substitution are set to $\omega = 1.6$ and $\gamma = 2$ as in Garcia-Cicco et al. (2010) and Miyamoto and Nguyen (2017). The depreciation rate δ is chosen to match the average investment-to-GDP ratio of 27.5 percent, while the capital share in production α is set to replicate the average labor income share of 52 percent.[9] The subjective discount factor is set to $\beta = 0.98$ in line with Aguiar and Gopinath (2007), which implies the steady state interest rate of 5.02 percent. The steady state level of the gross growth rate g is set to match the long-run average growth rate of per capita GDP, which is 1.0145. The steady state level of the government spending s is set to replicate the long-run average of government consumption-to-GDP ratio of 21.2 percent. Finally, the steady-state level of external debt d is chosen to match the average trade balance-to-GDP ratio of -2.22 percent. Table 1 summarizes the calibrated parameter values.

The remaining parameters, namely, the capital adjustment cost, the debt-elasticity of the country interest rate premium, the transition probabilities, and the persistence and standard deviation of each shock, are estimated using Bayesian methods. The dataset includes the log growth rate of real GDP per capita, the log growth rate of real private consumption per capita, the log growth rate of real investment per capita, and the first difference of the trade balance-to-GDP ratio, spanning the period from 1960Q2 to 2019Q4. The choice of observables follows Chang and Fernández (2013). We also estimate measurement errors corresponding to each observable variable. Following Garcia-Cicco et al. (2010), measurement errors are constrained to account for no more than 25 percent of the standard deviation of the respective observable variable. All estimated parameters are assigned uniform prior distributions. Appendix A reports the prior and posterior distributions of the estimated parameters.

[9]The data on the ratio of compensation to employees is obtained from the Economic Statistics System of Bank of Korea.

3.2 Model Fit

We estimate models with alternative specifications of regime-switching in shock volatilities and evaluate their relative performance in fitting the data. Specifically, we consider five model variants: 1) the M-mvfv model, in which the standard deviation of the interest rate premium shock follows an independent financial volatility chain, while all other shock variances follow a common macroeconomic volatility chain, 2) the M-cmv model, where all shock standard deviations follow the same macroeconomic volatility chain, 3) the M-mv model, where the variances of all shocks except that of the interest rate premium shock follow the macroeconomic volatility chain, while the variance of the interest rate premium shock is held constant, 4) the M-fv model, where only the variance of the interest rate premium shock is allowed to regime-switch, with other variances kept constant, and 5) the M-con model, which assumes constant variances for all shocks and contains no regime-switching.

Table 2 summarizes the log marginal data densities (MDD) for the alternative model specifications. Marginal data densities are computed using the modified harmonic mean approximation proposed by Geweke (1999).[10] According to the marginal data density, the model in which the standard deviations of all shocks follow a common macroeconomic volatility chain (M-cmv) provides the best fit to the data. Allowing for an independent regime-switching process for the volatility of the interest rate premium shock does not improve model fit. The log MDD for the M-mvfv, where the interest rate premium shock variance follows an independent financial volatility chain while the volatilities of other shocks follow the common macroeconomic volatility chain, is 2378, compared to 2385 for the M-cmv. When the regime-switching of the interest rate premium shock variance is prohibited, while other shocks still follow the macroeconomic volatility chain (M-mv), the model fits the data better than M-mvfv and achieves a similar degree of fit as M-cmv. When only the variance of the interest rate premium shock is allowed to regime-switch, while the volatilities of other shocks remain constant (M-fv), the log MDD is 2196, suggesting that improvements in model fit stem primarily from allowing volatility switching for macroeconomic shocks, rather than for the country spread shock alone. Nonetheless, any model that incorporates regime-switching in volatility, whether in the interest rate premium shock, the macroeconomic shocks, or both, outperforms the model with time-invariant shock variances (M-con), whose log MDD is 2185.

We find that data on emerging market business cycles favors models with time-varying shock volatilities. Among the alternatives considered, the data most strongly supports a relatively parsimonious specification in which all shock variances switch regimes synchronously following a single, common Markov process. This finding is consistent with Liu et al. (2011), who show that a model with synchronized regime-switching across all shocks provides the best fit to U.S. business cycle data among models with alternative volatility structures. Nonetheless, we acknowledge that more flexible volatility structures, such as those with a greater number of regimes or alternative groupings of synchronously switching shocks, may offer improved predictive performance. For instance, in contrast to Liu et al. (2011), Lindé et al. (2016) argue that U.S. data favors a more flexible specification with

[10] Using alternative methods to compute the marginal data density does not alter the ranking.

Table 2: Log Marginal Data Densities

Model	Log MDD
Macroeconomic and financial volatility (M-mvfv)	2378
Common Macroeconomic volatility (M-cmv)	2385
Macroeconomic volatility (M-mv)	2384
Financial volatility (M-fv)	2196
No switching (M-con)	2185

Note: Log marginal data densities are computed using the modified harmonic mean approximation proposed by Geweke (1999). Using alternative methods to compute the marginal data density does not alter the ranking.

multiple sources of volatility changes. However, in our framework, introducing additional regimes or alternative synchronization patterns would complicate the economic interpretation. Therefore, we restrict attention to relatively restrictive setups.

3.3 Parameter Estimates

We find that all shock variances are substantially larger in the high volatility regime than in the low volatility regime.[11] Compared to the model with synchronized regime-switching in all shock variances (M-cmv), allowing independent switching (M-mvfv) or prohibiting regime-switching (M-mv) for the volatility of the interest rate premium shock does not substantially affect the estimated parameter values. Both the low and high macroeconomic volatility regimes are estimated to be persistent. In the M-cmv, the posterior medians of the transition probabilities $p^m_{\mathrm{LH}} = 0.0366$ and $p^m_{\mathrm{HL}} = 0.0408$ imply that the average durations of the low and high volatility regimes are approximately 27 and 25 quarters, respectively. In the M-mvfv, the low financial volatility state is estimated to be highly persistent, with an average duration of 85 quarters at the posterior median. In contrast, the high financial volatility state is extremely short-lived, with an average duration of only one quarter.

The left panel of Figure 2 displays the median smoothed probability of being in the high macroeconomic volatility regime, as inferred from the model in which all shock variances follow a common macroeconomic volatility chain (M-cmv).[12] The high-volatility regime is estimated to prevail during the early part of the sample, from 1960 to 1981, suggesting that the variances of macroeconomic shocks were relatively higher in earlier decades than in more recent ones. In this way, the macroeconomic volatility chain captures the declining trend in volatility observed over the sample period. In addition to this long-run pattern, the macroeconomic volatility chain also captures transitory

[11] Appendix A presents the posterior estimates of shock variances for the alternative models.

[12] Allowing either independent regime-switching or prohibiting regime-switching for the variance of the interest rate premium shock does not alter the inference regarding the probability of being in the high macroeconomic volatility state. The left panel of Figure B.1 in Appendix B presents the smoothed probability of the high macroeconomic volatility state under the M-mvfv model, while the left panel of Figure B.2 in the same appendix shows the corresponding probability under the M-mv model.

changes in volatility. Specifically, we identify transitory periods of high macroeconomic volatility during 1997/1998 and 2008/2009, which coincide with the Asian financial crisis and the global financial crisis, respectively. The increase in volatility around the global financial crisis is also documented in regime-switching DSGE models estimated using data from other countries, including Bianchi (2013) and Bjørnland et al. (2018) for the United States, and Alstadheim et al. (2021) for developed small open economies. The model also detects a short-lived period of heightened volatility in 1988, which coincides with the aftermath of South Korea's democratization in 1987.

The right panel of Figure 2 displays the median smoothed probability of being in the high financial volatility state, as inferred from the model in which the variance of the interest rate premium shock follows an independent financial volatility chain, while the variances of all other shocks follow the common macroeconomic volatility chain (M-mvfv).[13] The figure indicates that high financial volatility states are rare and transitory. We observe temporary spikes in the probability of being in the high financial volatility state during the two aforementioned periods of financial turmoil, the Asian financial crisis and the global financial crisis.[14] However, when we allow for independent regime-switching in the variance of the interest rate premium shock, we do not find evidence of a declining trend in its volatility over time. As a result, we conclude that the declining volatility of macroeconomic variables observed throughout the sample is not driven by a reduction in the volatility of the interest rate premium shock, but rather by the declining volatility of other macroeconomic shocks.

3.4 Business Cycle Moments

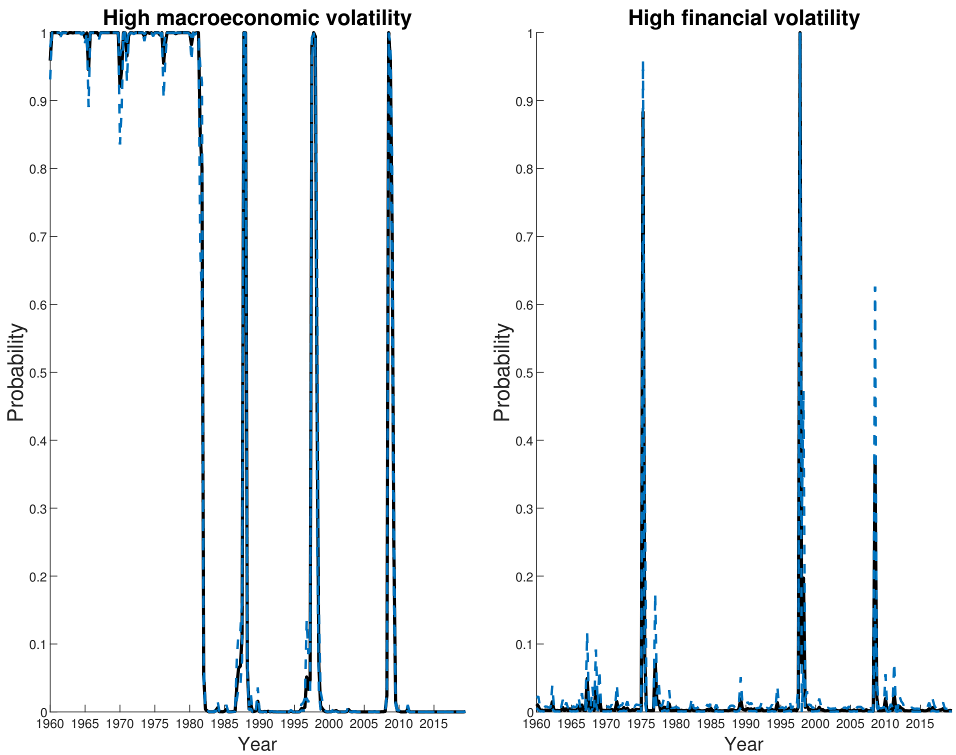
Table 3 summarizes the business cycle moments implied by the estimated model in which all shock variances follow a common macroeconomic volatility chain (M-cmv). These moments are calculated using simulated data of one million periods, generated after discarding the first $100,000$ periods from a simulation of 1.1 million periods. The table also reports the business cycle moments predicted by the actual data. Overall, the model successfully replicates key business cycle features, including the excess volatility of consumption over GDP and the countercyclical trade balance. However, in absolute terms, the model predicts a larger excess volatility of consumption growth and a milder countercyclicality of the trade balance compared to the data.

We also compute regime-specific moments. To calculate the regime-specific empirical moments, we separate the whole sample into high and low volatility periods. Specifically, high-volatility periods are identified as those in which the smoothed probability of being in the high-volatility regime based on the posterior medians of the M-cmv exceeds 50 percent. The following periods are classified as high-volatility episodes: 1960Q2:1982Q1, 1988Q1:1988Q2, 1997Q4:1998Q2, and

[13]The inference regarding the financial volatility state is not substantially affected when regime-switching in the variances of other shocks is prohibited. The right panel of Figure B.2 in Appendix B displays the smoothed probability of the high financial volatility regime predicted by the M-fv model.

[14]The hikes in the volatility of the interest rate premium during recessions are consistent with the findings of Fernandez-Villaverde et al. (2011).

Figure 2: Smoothed Probabilities of High Macroeconomic and Financial Volatility States



Note: The left panel plots the smoothed probability of the high macroeconomic volatility regime predicted by the M-cmv model. The right panel shows the smoothed probability of the high financial volatility state predicted by the M-mvfv model. The solid lines represent the median probabilities, while the dashed lines indicate the 68% probability bands.

2008Q4:2009Q2. The remaining periods are classified as belonging to the low-volatility regime.

We find that each variable is approximately two to three times more volatile in the high volatility regime than in the low volatility regime, and the model replicates the relative volatility of each variable across regimes reasonably well. In both regimes, the model replicates the volatility of macroeconomic variables fairly accurately in absolute terms, with the exception of consumption growth, for which the model predicts higher volatility than observed in the data. As a result, in the low-volatility regime, the model predicts excess volatility of consumption over GDP, whereas the data do not. In the high-volatility regime, the model's predictions are qualitatively consistent with the data, although consumption growth remains more volatile, and the trade balance is less countercyclical than in the data.

Both the model and the data exhibit a positive correlation between GDP and the trade balance in the low-volatility regime. Given that most periods after the 1980s in our sample fall into the low-volatility regime, we conclude that South Korea's trade balance no longer exhibits the stylized countercyclical behavior typically associated with emerging economies in recent decades.[15]

[15]This pattern is also observed in Mexico, a country frequently studied as a representative emerging economy. While Aguiar and Gopinath (2007) highlight the strong countercyclicality of Mexico's trade balance, Benigno et al.

Table 3: Business Cycle Moments

	Overall				Low volatility regime				High volatility regime			
	gy	*gc*	*gi*	*gtby*	*gy*	*gc*	*gi*	*gtby*	*gy*	*gc*	*gi*	*gtby*
Model												
Std	2.26	4.16	6.05	1.17	1.23	1.43	2.62	0.71	3.03	5.86	8.34	1.52
Corr with *gy*		0.68	0.44	−0.06		0.82	0.51	0.16		0.67	0.43	−0.11
Corr with *gtby*		−0.14	−0.15			−0.08	−0.49			−0.15	−0.10	
Data												
Std	1.95	2.01	6.93	0.94	1.13	1.06	2.73	0.70	2.76	2.91	10.36	1.21
Corr with *gy*		0.37	0.36	−0.24		0.65	0.52	0.01		0.31	0.34	−0.33
Corr with *gtby*		−0.41	−0.35			−0.18	−0.26			−0.49	−0.40	

Note: The table summarizes the standard deviations and correlations between key variables predicted by the estimated model (M-cmv) and those observed in the data. The variables include GDP growth (gy), consumption growth (gc), investment growth (gi), and the first difference of the trade balance-to-GDP ratio ($gtby$). Both overall and regime-specific moments are calculated.

3.5 Variance Decompositions

Table 4 reports the unconditional variance decompositions for key macroeconomic variables based on the estimated model in which all shock variances follow a common macroeconomic volatility chain (M-cmv). A central finding is that the relative contribution of each shock to business cycle fluctuations is regime-dependent. Although TFP shocks collectively account for the majority of fluctuations in GDP growth, their relative importance varies across regimes. The nonstationary TFP shock plays a dominant role in the low-volatility regime, whereas the stationary TFP shock becomes the primary driver in the high-volatility regime. Consumption growth is mainly driven by the stationary productivity shock in both regimes. However, in the high-volatility regime, the preference shock and the government spending shock together account for a share comparable to that of the stationary TFP shock. The movements of investment growth is largely attributed to the interest rate premium shock and the nonstationary TFP shock in the low-volatility regime, while in the high-volatility regime, the preference and spending shocks explain the majority of the variance. The trade balance-to-GDP ratio is mostly explained by the interest rate premium shock, consistent with findings from previous studies. These results highlight that the sources of aggregate fluctuations in emerging economies are conditional on the states of macroeconomic volatility.

(2025) report a mildly procyclical trade balance when using an extended sample period through 2016.

Table 4: Variance Decompositions

	Overall				Low volatility regime				High volatility regime			
Shock	gy	gc	gi	$gtby$	gy	gc	gi	$gtby$	gy	gc	gi	$gtby$
Stationary tech	56.42	49.95	12.00	7.09	28.22	62.68	5.68	1.86	63.17	46.66	13.19	10.66
Nonstationary tech	30.83	2.35	10.03	16.87	68.77	13.18	21.17	19.72	20.09	1.28	6.42	14.75
Preference	10.10	25.73	23.88	1.79	1.44	9.21	3.23	0.13	13.67	29.04	31.73	3.25
Spending	2.20	21.76	23.20	7.30	0.56	13.79	5.55	0.97	2.77	22.91	28.75	12.36
Country premium	0.46	0.21	30.89	66.95	1.01	1.14	64.38	77.32	0.30	0.11	19.91	58.98

Note: The table shows the unconditional variance decompositions for GDP growth (gy), consumption growth (gc), investment growth (gi), and the first difference of trade balance to GDP ratio ($gtby$) predicted by the M-cmv. Both overall and regime-specific variance decompositions are reported.

4 Conclusion

Motivated by the observed changes in the volatility of emerging market business cycles, we incorporate Markov-switching shock variances into a small open economy real business cycle model. The data favor a relatively simple specification in which the regime-switching of all shock variances is synchronized. The estimated model captures both the long-run decline in macroeconomic volatility and the transitory spikes in volatility associated with historical episodes of financial turmoil. We find that the declining trend in volatility is not driven by a reduction in the volatility of the interest rate premium shock. Nonetheless, elevated volatility in the country premium shock contributes to the temporary spikes in macroeconomic volatility during financial crises. The drivers of aggregate fluctuations vary depending on the prevailing macroeconomic volatility regime.

While our approach focuses on describing the characteristics of emerging market business cycles by modeling heteroskedastic exogenous shocks in a model with relatively limited frictions, an important direction for future research is to incorporate frictions that give rise to nonlinear business cycle dynamics. Examples include financial frictions with occasionally binding collateral constraints (Mendoza, 2010) and downward nominal wage rigidity (Schmitt-Grohé and Uribe, 2016). These types of nonlinearities can also be modeled using the regime-switching framework employed in this paper, as demonstrated by Binning and Maih (2017) and Benigno et al. (2025). We leave the exploration of these extensions to future research.

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Appendix

A Parameter Estimates

Table A.1: Priors and Posteriors for M-cmv

	Prior			Posterior				PSRF
	Distribution	Min	Max	Median	Mode	5%	95%	
ϕ	Uniform	0	32	6.3273	5.8074	3.7360	9.9270	1.0008
ψ	Uniform	0	10	0.0915	0.0855	0.0566	0.1545	1.0002
ρ_g	Uniform	0	0.9999	0.8172	0.8132	0.7216	0.8888	1.0004
ρ_a	Uniform	0	0.9999	0.9994	0.9999	0.9951	0.9999	1.0022
ρ_ν	Uniform	0	0.9999	0.9979	0.9974	0.9961	0.9986	1.0012
ρ_s	Uniform	0	0.9999	0.9455	0.9484	0.9168	0.9664	1.0004
ρ_μ	Uniform	0	0.9999	0.9903	0.9942	0.9636	0.9999	1.0004
$\sigma_g\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0083	0.0082	0.0068	0.0099	1.0006
$\sigma_g\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0156	0.0157	0.0096	0.0225	1.0010
$\sigma_a\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0031	0.0031	0.0024	0.0038	1.0004
$\sigma_a\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0164	0.0162	0.0134	0.0197	1.0000
$\sigma_\nu\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.2911	0.3104	0.0000	0.6387	1.0009
$\sigma_\nu\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	4	3.1299	2.6050	1.7386	4.0000	1.0006
$\sigma_s\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0194	0.0210	0.0014	0.0281	1.0000
$\sigma_s\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.1514	0.1506	0.1315	0.1757	1.0005
$\sigma_\mu\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0025	0.0022	0.0017	0.0037	1.0005
$\sigma_\mu\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0047	0.0042	0.0031	0.0071	1.0009
p^m_{LH}	Uniform	0	1	0.0366	0.0307	0.0146	0.0728	1.0010
p^m_{HL}	Uniform	0	1	0.0408	0.0339	0.0106	0.0997	1.0002
σ^{me}_{gy}	Uniform	0	0.0048	0.0048	0.0048	0.0044	0.0048	1.0001
σ^{me}_{gc}	Uniform	0	0.0051	0.0024	0.0000	0.0000	0.0051	1.0005
σ^{me}_{gi}	Uniform	0	0.0169	0.0165	0.0169	0.0149	0.0169	1.0010
σ^{me}_{gtby}	Uniform	0	0.0024	0.0024	0.0024	0.0022	0.0024	1.0000

Note: σ^{me}_{gy}, σ^{me}_{gc}, σ^{me}_{gi} and σ^{me}_{gtby} represent the measurement errors associated with the observables: log GDP growth, log consumption growth, log investment growth, and the first difference of trade balance to GDP ratio, respectively. The 5% and 95% values indicate the bounds of the 90% posterior probability intervals. PSRF refers to the Potential Scale Reduction Factor (Brooks and Gelman, 1998) for four chains with $250,000$ draws each.

Table A.2: Priors and Posteriors for M-mvfv

	Prior			Posterior				PSRF
	Distribution	Min	Max	Median	Mode	5%	95%	
ϕ	Uniform	0	32	5.5192	4.5936	3.0259	8.5307	1.0010
ψ	Uniform	0	10	0.1341	0.1190	0.0832	0.2595	1.0020
ρ_g	Uniform	0	0.9999	0.8168	0.8005	0.7180	0.8933	1.0010
ρ_a	Uniform	0	0.9999	0.9991	0.9999	0.9935	0.9999	1.0094
ρ_ν	Uniform	0	0.9999	0.9977	0.9973	0.9958	0.9984	1.0066
ρ_s	Uniform	0	0.9999	0.9503	0.9492	0.9227	0.9691	1.0048
ρ_μ	Uniform	0	0.9999	0.9902	0.9951	0.9607	0.9999	1.0011
$\sigma_g\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0082	0.0082	0.0066	0.0098	1.0011
$\sigma_g\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0143	0.0158	0.0100	0.0193	1.0001
$\sigma_a\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0032	0.0031	0.0025	0.0039	1.0014
$\sigma_a\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0167	0.0160	0.0140	0.0198	1.0005
$\sigma_\nu\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.2782	0.3112	0.0000	0.5888	1.0015
$\sigma_\nu\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	4	3.1068	2.5492	1.7353	4.0000	1.0072
$\sigma_s\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0188	0.0206	0.0021	0.0275	1.0019
$\sigma_s\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.1523	0.1517	0.1322	0.1771	1.0009
$\sigma_\mu\left(\mathcal{S}_t^f = \text{low}\right)$	Uniform	0	2	0.0032	0.0026	0.0021	0.0048	1.0027
$\sigma_\mu\left(\mathcal{S}_t^f = \text{high}\right)$	Uniform	0	2	0.0270	0.0157	0.0076	0.1332	1.0046
p^m_{LH}	Uniform	0	1	0.0395	0.0327	0.0161	0.0768	1.0003
p^m_{HL}	Uniform	0	1	0.0325	0.0297	0.0082	0.0855	1.0024
p^f_{LH}	Uniform	0	1	0.0117	0.0090	0.0022	0.0340	1.0014
p^f_{HL}	Uniform	0	1	0.9963	1.0000	0.9176	1.0000	1.0253
σ^{me}_{gy}	Uniform	0	0.0048	0.0048	0.0048	0.0044	0.0048	1.0013
σ^{me}_{gc}	Uniform	0	0.0051	0.0022	0.0000	0.0000	0.0051	1.0105
σ^{me}_{gi}	Uniform	0	0.0169	0.0166	0.0169	0.0151	0.0169	1.0056
σ^{me}_{gtby}	Uniform	0	0.0024	0.0024	0.0024	0.0022	0.0024	1.0001

Note: σ^{me}_{gy}, σ^{me}_{gc}, σ^{me}_{gi} and σ^{me}_{gtby} represent the measurement errors associated with the observables: log GDP growth, log consumption growth, log investment growth, and the first difference of trade balance to GDP ratio, respectively. The 5% and 95% values indicate the bounds of the 90% posterior probability intervals. PSRF refers to the Potential Scale Reduction Factor (Brooks and Gelman, 1998) for four chains with $250,000$ draws each.

Table A.3: Priors and Posteriors for M-mv

	Prior			Posterior				PSRF
	Distribution	Min	Max	Median	Mode	5%	95%	
ϕ	Uniform	0	32	3.2173	2.9914	1.9297	5.1960	1.0003
ψ	Uniform	0	10	0.1223	0.1118	0.0766	0.2066	1.0002
ρ_g	Uniform	0	0.9999	0.7758	0.7673	0.6735	0.8583	1.0005
ρ_a	Uniform	0	0.9999	0.9989	0.9999	0.9920	0.9999	1.0005
ρ_ν	Uniform	0	0.9999	0.9979	0.9979	0.9960	0.9986	1.0004
ρ_s	Uniform	0	0.9999	0.9390	0.9413	0.9103	0.9603	1.0002
ρ_μ	Uniform	0	0.9999	0.9864	0.9987	0.9336	0.9999	1.0008
$\sigma_g\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0084	0.0084	0.0069	0.0101	1.0002
$\sigma_g\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0184	0.0189	0.0140	0.0233	1.0003
$\sigma_a\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0032	0.0031	0.0024	0.0039	1.0005
$\sigma_a\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.0164	0.0160	0.0136	0.0197	1.0000
$\sigma_\nu\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.3199	0.4188	0.0000	0.6604	1.0002
$\sigma_\nu\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	4	3.1154	3.1217	1.7024	4.0000	1.0003
$\sigma_s\,(\mathcal{S}_t^m = \text{low})$	Uniform	0	2	0.0198	0.0215	0.0012	0.0285	1.0008
$\sigma_s\,(\mathcal{S}_t^m = \text{high})$	Uniform	0	2	0.1541	0.1536	0.1338	0.1787	1.0002
σ_μ	Uniform	0	2	0.0024	0.0021	0.0016	0.0036	1.0000
p^m_{LH}	Uniform	0	1	0.0402	0.0322	0.0166	0.0772	1.0003
p^m_{HL}	Uniform	0	1	0.0334	0.0306	0.0084	0.0898	1.0001
σ^{me}_{gy}	Uniform	0	0.0048	0.0048	0.0048	0.0043	0.0048	1.0002
σ^{me}_{gc}	Uniform	0	0.0051	0.0025	0.0006	0.0000	0.0051	1.0012
σ^{me}_{gi}	Uniform	0	0.0169	0.0165	0.0169	0.0149	0.0169	1.0008
σ^{me}_{gtby}	Uniform	0	0.0024	0.0024	0.0024	0.0023	0.0024	1.0000

Note: σ^{me}_{gy}, σ^{me}_{gc}, σ^{me}_{gi} and σ^{me}_{gtby} represent the measurement errors associated with the observables: log GDP growth, log consumption growth, log investment growth, and the first difference of trade balance to GDP ratio, respectively. The 5% and 95% values indicate the bounds of the 90% posterior probability intervals. PSRF refers to the Potential Scale Reduction Factor (Brooks and Gelman, 1998) for four chains with $250,000$ draws each.

Table A.4: Priors and Posteriors for M-fv

	Prior			Posterior				PSRF
	Distribution	Min	Max	Median	Mode	5%	95%	
ϕ	Uniform	0	32	0.1930	0.2137	0.0000	1.0854	1.0024
ψ	Uniform	0	10	4.9806	0.9317	0.7234	10.0000	1.0039
ρ_g	Uniform	0	0.9999	0.8775	0.8684	0.8236	0.9200	1.0001
ρ_a	Uniform	0	0.9999	0.8765	0.9035	0.7955	0.9331	1.0009
ρ_ν	Uniform	0	0.9999	0.9965	0.9981	0.9922	0.9982	1.0247
ρ_s	Uniform	0	0.9999	0.9234	0.9219	0.9017	0.9404	1.0002
ρ_μ	Uniform	0	0.9999	0.9533	0.9896	0.7537	0.9999	1.0008
σ_g	Uniform	0	2	0.0097	0.0104	0.0081	0.0116	1.0002
σ_a	Uniform	0	2	0.0123	0.0119	0.0110	0.0136	1.0004
σ_ν	Uniform	0	2	1.0310	1.8322	0.5020	1.8711	1.0202
σ_s	Uniform	0	2	0.1004	0.1003	0.0909	0.1114	1.0009
$\sigma_\mu\left(\mathcal{S}_t^f = \text{low}\right)$	Uniform	0	2	0.0085	0.0016	0.0000	0.0391	1.0016
$\sigma_\mu\left(\mathcal{S}_t^f = \text{high}\right)$	Uniform	0	2	0.0627	0.0115	0.0088	0.2304	1.0020
p_{LH}^f	Uniform	0	1	0.0301	0.0283	0.0053	0.0749	1.0013
p_{HL}^f	Uniform	0	1	0.2333	0.1707	0.0652	0.6428	1.0007
σ_{gy}^{me}	Uniform	0	0.0048	0.0047	0.0048	0.0038	0.0048	1.0015
σ_{gc}^{me}	Uniform	0	0.0051	0.0049	0.0051	0.0038	0.0051	1.0008
σ_{gi}^{me}	Uniform	0	0.0169	0.0167	0.0169	0.0159	0.0169	1.0003
σ_{gtby}^{me}	Uniform	0	0.0024	0.0024	0.0024	0.0022	0.0024	1.0001

Note: σ_{gy}^{me}, σ_{gc}^{me}, σ_{gi}^{me} and σ_{gtby}^{me} represent the measurement errors associated with the observables: log GDP growth, log consumption growth, log investment growth, and the first difference of trade balance to GDP ratio, respectively. The 5% and 95% values indicate the bounds of the 90% posterior probability intervals. PSRF refers to the Potential Scale Reduction Factor (Brooks and Gelman, 1998) for four chains with $250,000$ draws each.

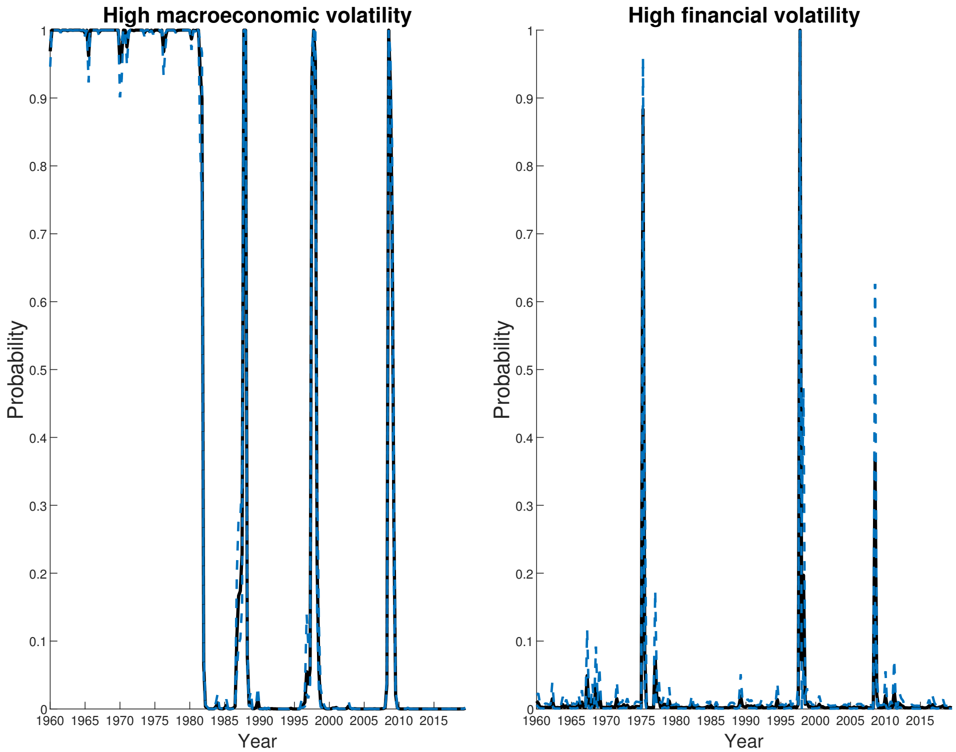
Table A.5: Priors and Posteriors for M-con

	Prior			Posterior				PSRF
	Distribution	Min	Max	Median	Mode	5%	95%	
ϕ	Uniform	0	32	0.6262	0.5204	0.0000	2.2952	1.0017
ψ	Uniform	0	10	0.5001	0.4477	0.1993	1.8578	1.0007
ρ_g	Uniform	0	0.9999	0.8646	0.8664	0.7949	0.9164	1.0005
ρ_a	Uniform	0	0.9999	0.9070	0.9161	0.8205	0.9597	1.0004
ρ_ν	Uniform	0	0.9999	0.9964	0.9977	0.9912	0.9983	1.0158
ρ_s	Uniform	0	0.9999	0.9170	0.9178	0.8919	0.9355	1.0002
ρ_μ	Uniform	0	0.9999	0.9088	0.9999	0.3402	0.9999	1.0004
σ_g	Uniform	0	2	0.0116	0.0116	0.0095	0.0138	1.0005
σ_a	Uniform	0	2	0.0121	0.0119	0.0106	0.0138	1.0003
σ_ν	Uniform	0	2	0.9441	1.4063	0.4248	1.8558	1.0175
σ_s	Uniform	0	2	0.0998	0.0999	0.0901	0.1108	1.0019
σ_μ	Uniform	0	2	0.0030	0.0026	0.0016	0.0060	1.0012
σ_{gy}^{me}	Uniform	0	0.0048	0.0047	0.0048	0.0037	0.0048	1.0005
σ_{gc}^{me}	Uniform	0	0.0051	0.0049	0.0051	0.0038	0.0051	1.0009
σ_{gi}^{me}	Uniform	0	0.0169	0.0167	0.0169	0.0157	0.0169	1.0003
σ_{gtby}^{me}	Uniform	0	0.0024	0.0024	0.0024	0.0022	0.0024	1.0001

Note: σ_{gy}^{me}, σ_{gc}^{me}, σ_{gi}^{me} and σ_{gtby}^{me} represent the measurement errors associated with the observables: log GDP growth, log consumption growth, log investment growth, and the first difference of trade balance to GDP ratio, respectively. The 5% and 95% values indicate the bounds of the 90% posterior probability intervals. PSRF refers to the Potential Scale Reduction Factor (Brooks and Gelman, 1998) for four chains with $250,000$ draws each.

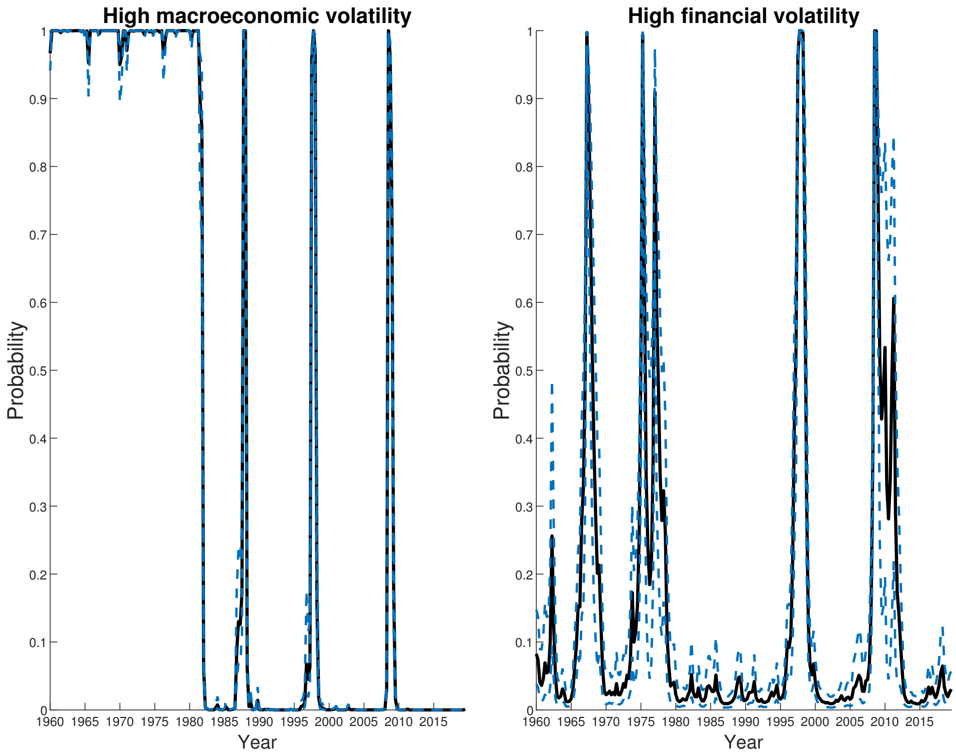
B Smoothed Probabilities with Alternative Model Specifications

Figure B.1: Smoothed Probabilities with M-mvfv



Note: The left panel plots the smoothed probability of the high macroeconomic volatility state, while the right panel shows the smoothed probability of the high financial volatility state. Both are predicted by the M-mvfv, in which the standard deviation of the interest rate premium shock follows an independent financial volatility chain, while all other shock standard deviations follow a common macroeconomic volatility chain. The solid lines represent median probabilities, and the dashed lines indicate the 68% probability bands.

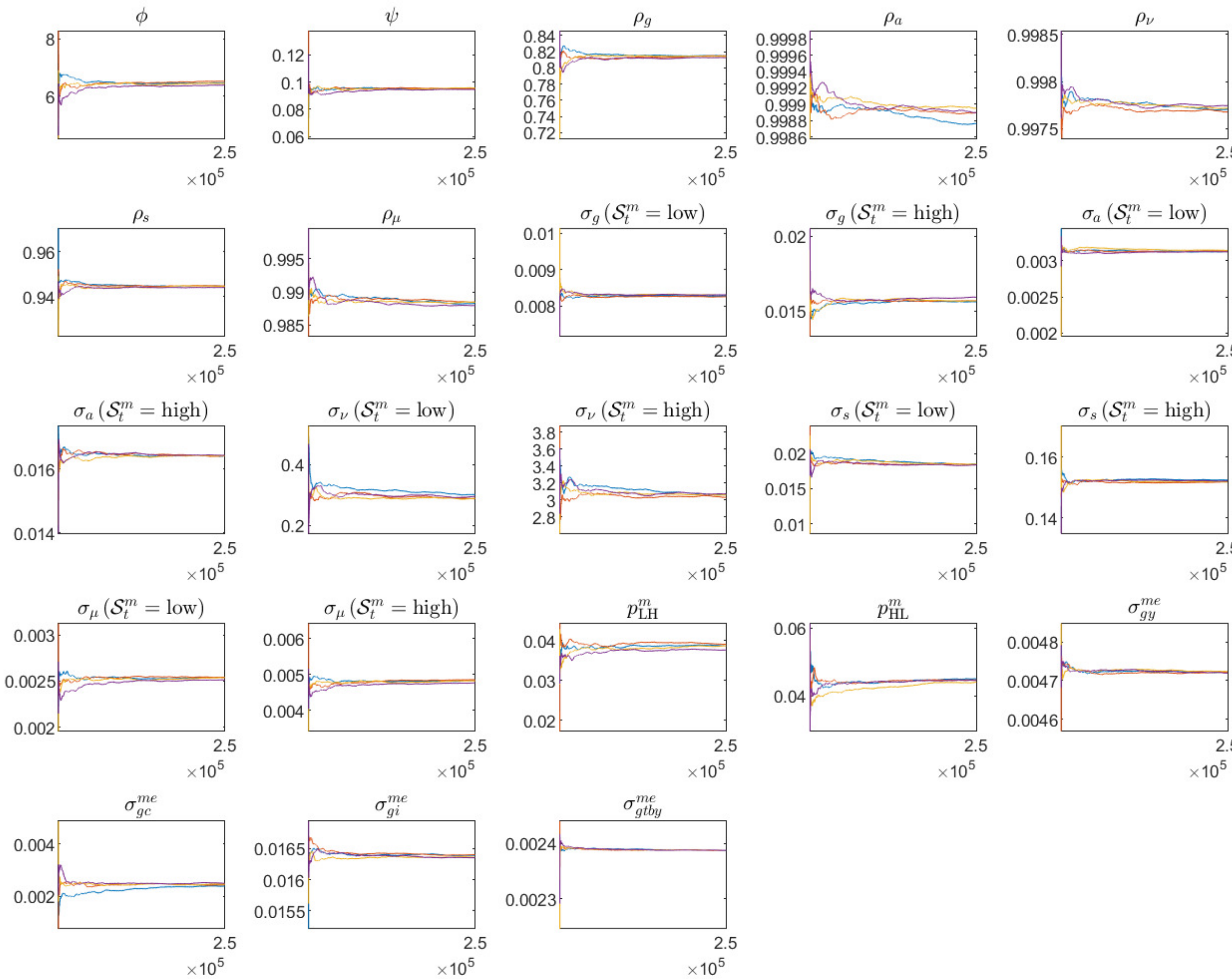
Figure B.2: Smoothed Probabilities with M-mv and M-fv



Note: The left panel plots the smoothed probability of the high macroeconomic volatility regime predicted by the M-mv, in which all shock variances except that of the interest rate premium shock are allowed to regime-switch following a common macroeconomic volatility chain. The right panel shows the smoothed probability of the high financial volatility regime predicted by the M-fv, where only the standard deviation of the interest rate premium shock is allowed to regime-switch. The solid lines represent median probabilities, and the dashed lines indicate the 68% probability bands.

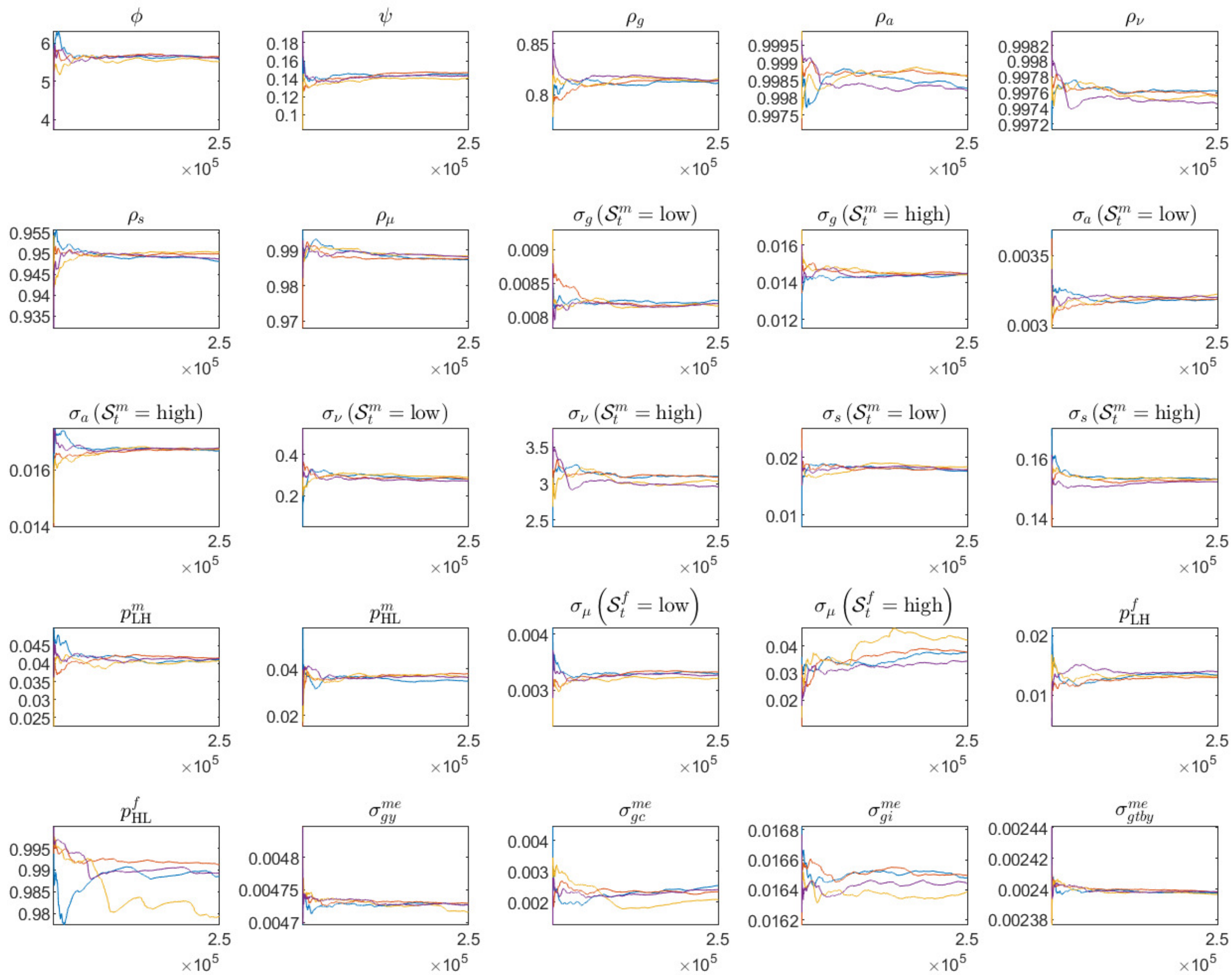
C Convergence

Figure C.1: Recursive Means for M-cmv



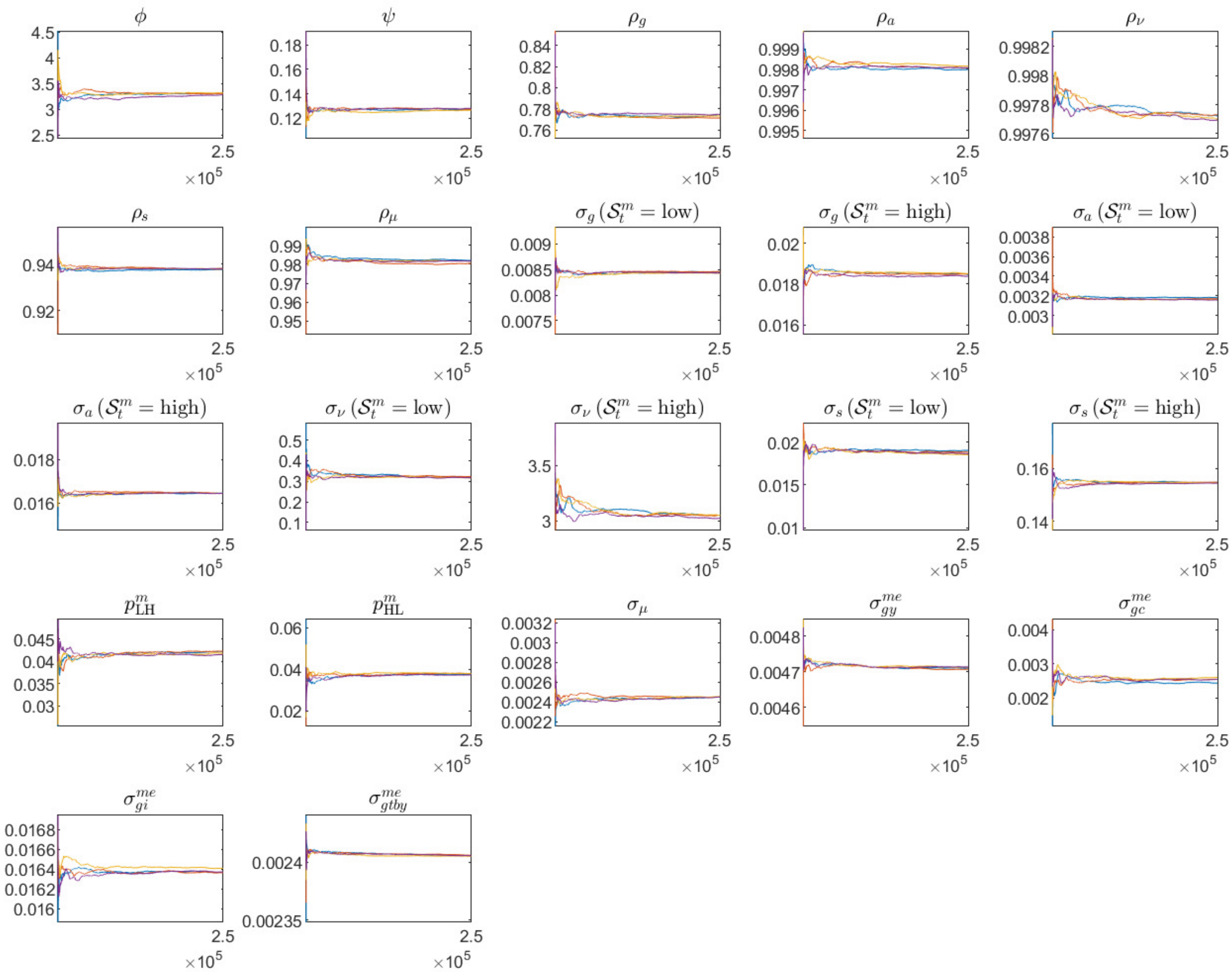
Note: Each line represents the recursive mean of a parameter of the M-cmv, calculated from one of four Markov chains, each containing 250,000 draws.

Figure C.2: Recursive Means for M-mvfv



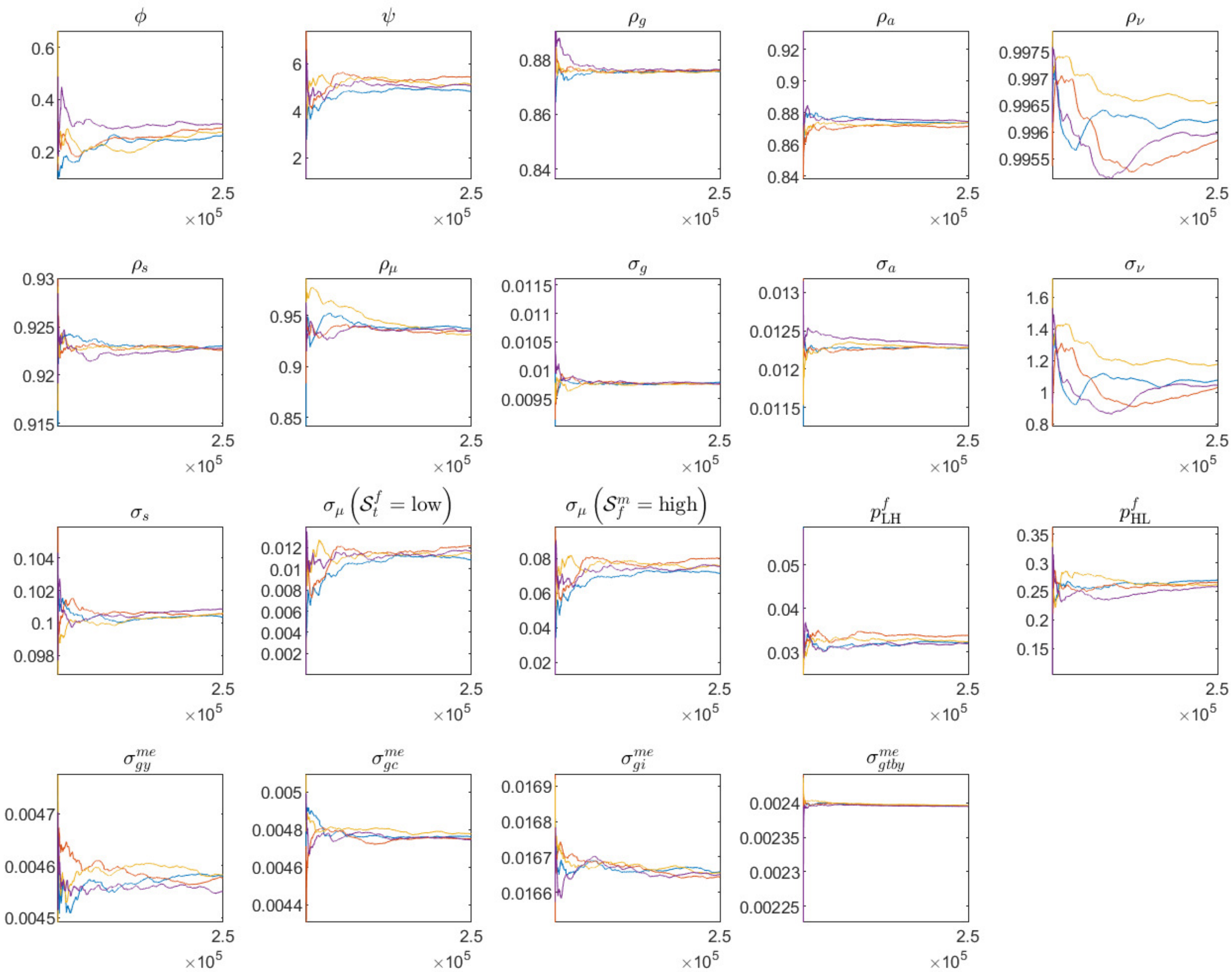
Note: Each line represents the recursive mean of a parameter of the M-mvfv, calculated from one of four Markov chains, each containing 250,000 draws.

Figure C.3: Recursive Means for M-mv



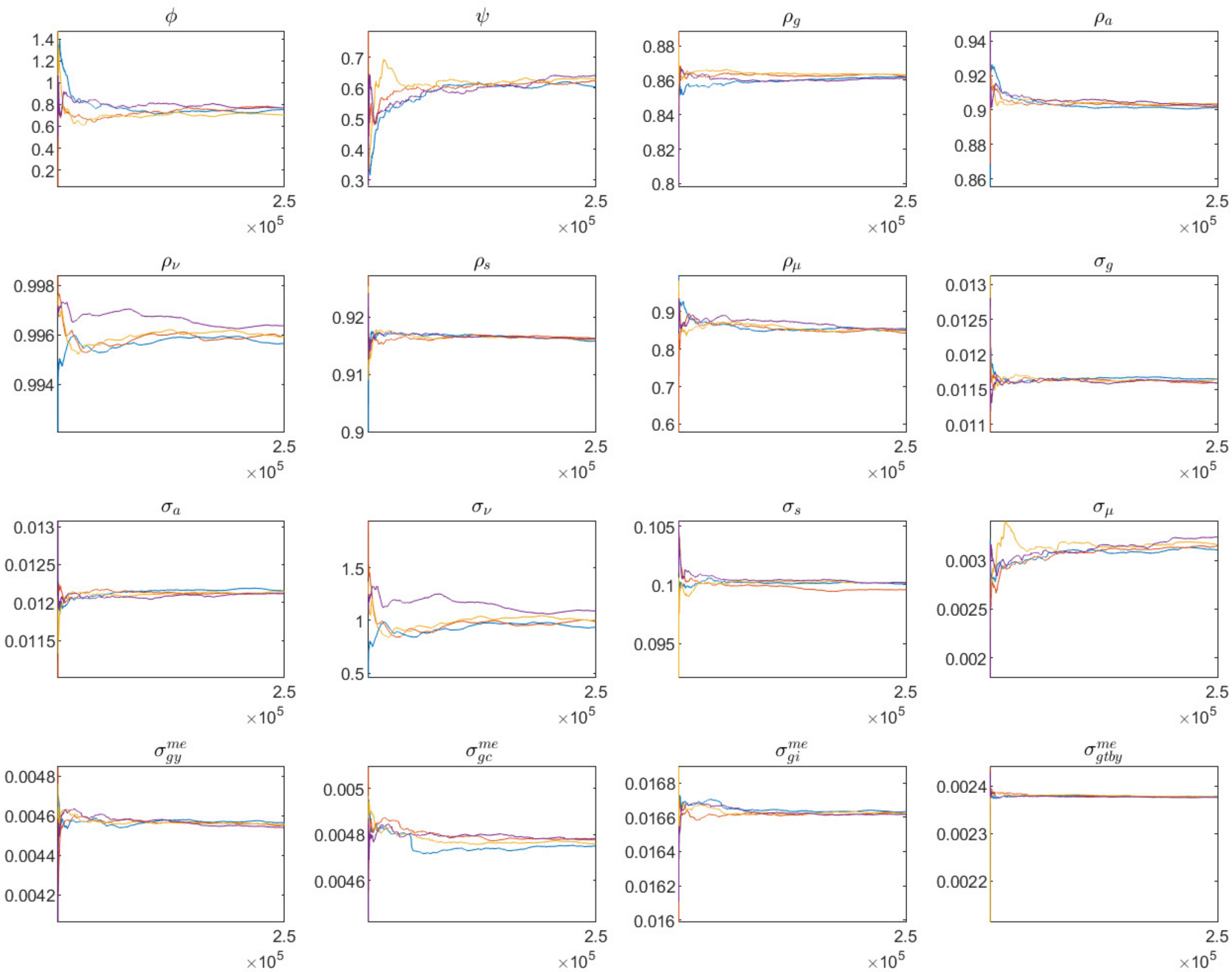
Note: Each line represents the recursive mean of a parameter of the M-mv, calculated from one of four Markov chains, each containing 250, 000 draws.

Figure C.4: Recursive Means for M-fv



Note: Each line represents the recursive mean of a parameter of the M-fv, calculated from one of four Markov chains, each containing 250,000 draws.

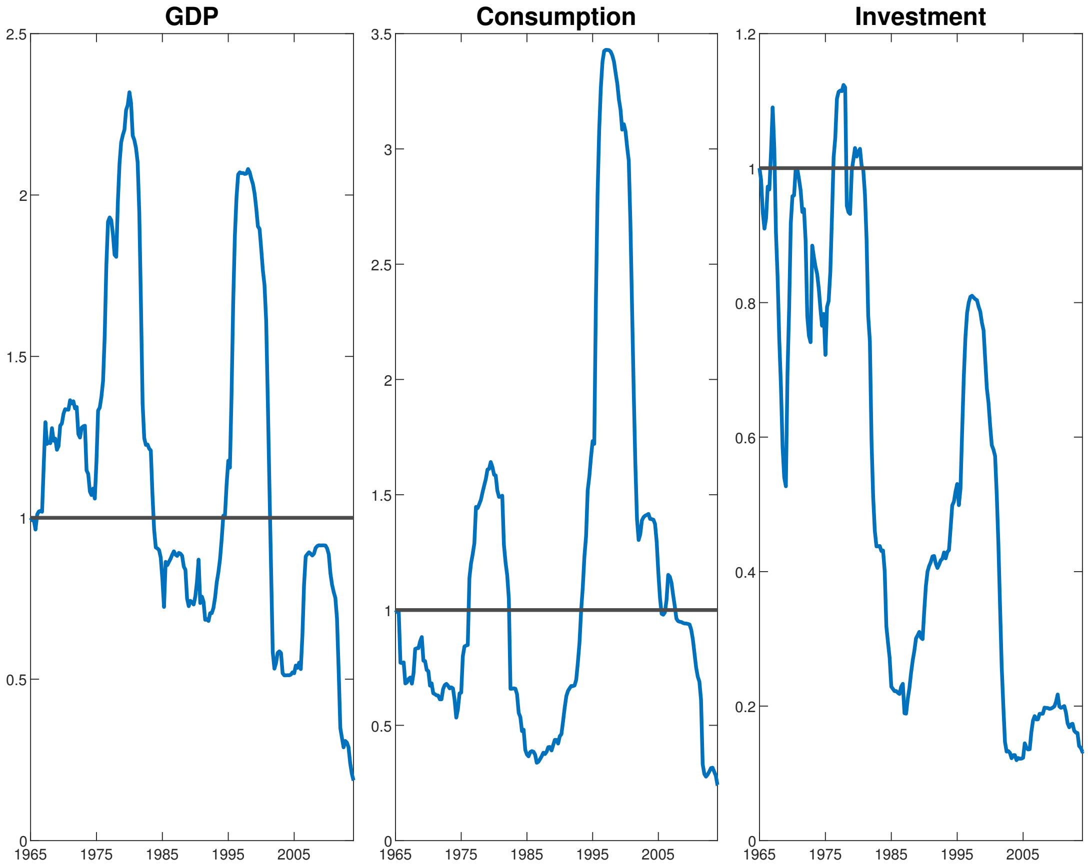
Figure C.5: Recursive Means for M-con



Note: Each line represents the recursive mean of a parameter of the M-con, calculated from one of four Markov chains, each containing 250,000 draws.

D Business Cycle Volatility in South Korea

Figure D.1: Business Cycle Volatility in South Korea



Note: The figure shows the 41-quarter moving standard deviations of HP-filtered per capita GDP, consumption, and investment for South Korea. The standard deviations are normalized to 1 in 1965. Similar patterns are observed when using growth rates or annual data.