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Analyzing Economic Fluctuations in East Asian Economies

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Abstract

Markov-switching (MS) regression of GDP growth is used to establish dates of high growth, low growth and crisis regimes. For each period t, the state of the economy with the highest probability of occurrence generated by the MS model is taken to be the state that prevailed during that period. A series representing the state of the economy, Y_t, is constructed from MS smoothed probabilities, to wit: $Y_t = s$ if $p_t(s) = \max\{p_t(1), p_t(2), p_t(3)\}$. This series is used in ordered probit regressions to model the probability of occurrence of regimes, conditional on changes in a set of macroeconomic variables. This is done for six East Asian economies using quarterly data from 1980 to 2006. In-sample and out-of-sample forecasts of the probabilities of occurrence of the state of the economy show satisfactory tracking ability of the models.

Keywords: Markov-switching, ordered probit, high growth state, low growth state, crisis state

JEL Classification: E32

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1 Introduction

It is important to analyze economic fluctuations in order to understand how an economy responds to shocks caused by both the external environment and local events (both political and economic). Knowing the causes and possible consequences of these shocks on the economy allows authorities to design policies that help dampen their adverse effects. Modern empirical business cycle analysis, as it is known in the Macroeconomics field, has been successfully employed in highly developed economies to examine economic fluctuations but this has not been the case in developing economies.

Unlike developed economies which go through the expansion and recession phases of a business cycle, the paths of developing economies especially those in East Asia were not easy routes to navigate. With the onset of globalization in the early 1990s, these countries had to cope with changes in the international environment. Given their inadequate institutional structures (inefficient banking systems for example), a number of them experienced economic crises emanating from the external sector. Researchers of aggregate economic fluctuations found this an interesting but complicated phenomenon to analyze because the resulting patterns of aggregate fluctuations do not lend themselves easily to standard statistical analysis that assume linearity (See Kaminsky and Reinhardt (2000) for example).

Developing East Asian economies experienced unprecedented high rates of growth before and after the crisis. For some of these economies however, periods of high and low but positive growth characterized their normal cycle. Without careful monitoring, economic fluctuations such as this could potentially jeopardize their development plans whose centerpiece is the sustainability of growth. The high-low growth cycle and the occurrence of crisis episodes make it difficult to model these cyclical fluctuations. For this reason, not much work has been done on

East Asian economic fluctuations. By focusing on this, the study hopes to contribute to the body of knowledge on the analysis of fluctuations in developing economies.

Recently developed macro-econometric techniques that try to deal with non-linear relationships have been applied successfully in empirical business cycle research in developed economies (See Hamilton and Raj, 2002, for a survey). This area of Macroeconomics has been one of the most dynamic fields of research because far richer insights as to how an economy operates have been obtained with these techniques. This study uses some of these methods to examine economic fluctuations in East Asian economies especially those which experienced crisis episodes. The six East Asian countries are Hong Kong, Indonesia, Korea, Malaysia, Philippines and Thailand. These economies are assumed to fall into any of the following three regimes each period: high growth state, low growth state and crisis state.

The objectives of the study are (1) to find an adequate statistical representation of the movements and direction of aggregate economic activity in selected East Asian economies using techniques in non-linear time series/business cycle analysis and (2) to make these results useful for policy analysis and forecasting the direction of economic activity. For each country in the study, univariate 3-state Markov-switching (MS) regression of GDP growth is used to identify the state of the economy per period. The novelty in this study is the use of MS regressions in dating the cycles in these economies. That is, for period *t*, the state of the economy with the highest probability of occurrence generated by the MS model is taken to be the state that prevailed during that period. This is a strong assumption that needs to be made because of the absence of agencies in the countries of this study that officially date recessions like the NBER business cycle dating committee of the U.S. The choice of the dating mechanism may be justified by the excellent record of the MS regression model's in-sample predictions of recessions in highly developed economies (See for example, Hamilton (1989) for the U.S.) With the regime dates determined from 3-state MS regressions, an attempt is made to predict the probability of occurrence of the state of the economy using ordered probit. These models permit the specification of a set of predictor variables. The next section of the study reviews the methods used in empirical business cycle research. Section 3 discusses the empirical strategy and the estimation results. The last section concludes.

2 Methods in empirical business cycle research

A huge literature on non-stationary business cycle analysis has been generated since the seminal article of Hamilton (1989). His article was among the first to recognize the inherent nonlinearities that are present in macroeconomic time series. His study showed that an econometric evaluation of GDP growth with regimes endogenously determined by Markov switches accurately describes the US business cycles and that the dates generated by his model in fact coincides with the NBER recession dates.

Hamilton's model was generalized by Lam (1990) to allow for a decomposition of the series into a trend and a cycle. Lam's model also replicated the NBER reference dates. Many other extensions of the univariate MS regressions have been proposed and several applications to a variety of problems in Macroeconomics and Finance can be found in the literature. Filardo (1994) extended the Hamilton model to allow for time varying transition probabilities. In his study, the duration of a state of the economy was made to vary with leading indicator variables. Kim (1994) improved on Hamilton's smoothing algorithm. Hamilton and Susmel (1994) studied ARCH effects with Markov-switching in the US stock market and Krolzig (1997) provided an implementation of Markov-switching VARs. A collection of more recent contributions can be found in a volume edited by Hamilton and Raj (2002).

The work by Burns and Mitchell emphasized two aspects of economic fluctuations: characterization of business cycle phases into expansions and recessions that led to the development of MS techniques discussed above and the analysis of co-movements of macroeconomic variables. The development of these ideas proceeded independently of each other. Modern models of co-movement began with the development of dynamic factor models of leading indicators by Stock and Watson (1988, 1992). More recent work by Diebold and Rudebusch (1996) and Kim and Murray (2002) allowed for regime switching in a dynamic factor model, thus allowing joint analysis of co-movements and business cycle phases.

The recent literature on recession forecasting using qualitative dependent variable modeling techniques pioneered by Estrella and Mishkin (1998) is related to the coincident and leading indicator studies by Stock and Watson through the use of exogenous variables in forecasting regime probabilities. Recession forecasting and regime probability modeling are also closely related to studies on nonstationary business cycle analysis reviewed above but were developed at a much later date. Both sets of studies use official dates of recessions determined by government agencies as prediction targets. The main difference is that the latter is a univariate time series technique while the former allows the utilization of other variables either as leading or coincident indicators that enter the right-hand side of the forecasting equation.

Qualitative dependent variable models are a natural choice in the recession forecasting literature because the problem being examined can be conveniently expressed as a choice of two regimes. Estrella and Mishkin (1998) attempt to forecast U.S. recessions with a binary logit model where financial variables are the indicators. They find that a parsimonious specification is necessary to generate reasonable predictions of recessions. Their study also finds that in-sample and out-of-sample forecast performance can differ significantly and that out-of-sample predictive performance can be very dependent on the forecast horizon.

Bernard and Gerlach (1998) conduct a similar study for several European countries, the US and Japan. Instead of using several financial and aggregate macroeconomic variables as in Estrella and Mishkin, the term structure is used as the sole predictor of a recession. The recession dates they used for the G7 countries are from Artis et al (1995). Birchenhall et al (1999) and

Birchenhall et al (2001) use logit analysis to predict business cycle regimes for the US and the UK. In the UK study, they find that real money (M4) is the best single leading indicator of a recession. In the case of the US however, Dueker (2002) points out that there seems to be some difficulties in predicting the 1990-91 recession even with a Markov switching probit model. Haltmaier (2008) using binary probit models in monthly panel and individual country data specifies both real and financial variables lagged up to six periods to examine economic cycles in eight developed countries.

In almost all developing country studies, the focus is on the prediction of the crisis and the formulation of early warning systems for use of policymakers (See for example, Kaminsky and Reinhardt (2000), Kamin et al (2007) and Lestano and Jacobs (2007)). A fairly recent application of nested logit in the prediction of currency crisis is by Lau and Yan (2005). To predict speculative attacks and determine successful defenses from attacks, they use data on interest differentials and monetary and fiscal variables from 16 countries as explanatory variables. Liquidity and financial fragility variables are found to be excellent predictors of a crisis. Except this last study, all of the studies reviewed above assume two states of the economy explicitly or implicitly and all of them use reference dates and turning points determined by government agencies of the respective countries or dates from previous studies that give details of regime histories.

3 Empirical strategy and estimation results

It is not a straightforward procedure to adopt developed country analysis of aggregate economic activity discussed in the previous section to the analysis of fluctuations in developing economies for two reasons: (1) the occurrence of deep crisis events that is indicative of a more complicated and possibly lengthy cycle of economic activity and (2) the absence in developing economies of business cycle dating committees like the NBER for the U.S. and hence the absence of established cycle reference dates.

The assumption that the state of the economy falls into two categories, while adequate for most highly developed economies, may not be appropriate for developing economies in East Asia because of crisis episodes. It can be observed further that the non-crisis periods themselves move through phases of high and low growth which became more volatile for some countries after the 1997 Asian crisis.

Because of this observation, the study considers three states in modeling East Asian economic fluctuations.[1] This study proposes a further categorization of the non-crisis periods into high growth and low growth states. The term 'recession,' usually defined as negative real economic growth for two or more successive quarters of a year, is avoided because negative growth is the defining characteristic of the third state (crisis state) in this study.[2] Unlike a recession, a crisis episode occurs infrequently and is not considered by this study as part of a normal phase of an economic cycle of a developing economy. Even if crisis episodes are infrequent relative to normal business cycle phases, they render 2-state models inadequate in providing a realistic description of aggregate economic fluctuations. As shown below, 2-state MS models trivially classify most of the East Asian economies as falling into either a crisis or a non-crisis state.

In this study, Markov-switching and ordered probit regressions are used in sequence to examine economic fluctuations in East Asian economies. This study hinges heavily on the assumption that Markov switching regressions correctly show the state of the economy that prevailed for each period. This choice of rule to establish the state of the economy is arguably the

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[1] There are a few developed country studies that consider three states. Sichel (1994) constructs a model with three business cycle phases for the US economy with the third phase being associated with a high-growth recovery phase. The notion of a third phase was also developed by Kim and Murray (2002) who, extending the Diebold and Rudebusch model, further decomposed recession into its permanent and transitory components that are governed by Markov switching. The model was constructed to examine peak reversion during the high-growth recovery phase.

[2] The term was invented to distinguish mild declines in economic activity from the depression of the 1930s where negative growth rates were very high. In this study, there is no range by which a particular growth figure can be associated with high or low growth. High or low growth of a country is relative its own

best given that one chooses from three states instead of two. Alternatively, in the absence of committee-established reference dates that record the history of cycles, one can adopt rules or dating mechanisms similar to those made in studies analyzing turning points of the economy (e.g., Birchenhall et al, 2001), but these procedures may not be viable when the choice of regimes exceeds two.

From the 3-state MS regressions of GDP growth, the state of the economy with the highest probability of occurrence in each period is chosen and is assumed to represent the state of the economy that prevailed in that period. For period t, the state with the highest smoothed probability of occurrence, denoted by Y_t, is taken to be the state of the economy in period t. That is, $Y_t = s$ if $p_t(s) = \max\{p_t(1), p_t(2), p_t(3)\}$; where $p_t(1) + p_t(2) + p_t(3) = 1$ and $t = 1, \ldots, T$. The latent variable, y_t^*, in the ordered probit models is based on this and the regression can be written as:

$$y_t^* = b_0 + b_1 x_{1t} + \ldots + b_K x_{Kt} + \varepsilon_t$$

ε_t is a disturbance term. The latent variable, y_t^*, is mapped onto the ordered categorical variable as follows:

$$\begin{aligned} Y_t &= 1 \quad \text{if} \quad a_0 < y_t^* \le a_1 \\ Y_t &= 2 \quad \text{if} \quad a_1 < y_t^* \le a_2 \\ Y_t &= 3 \quad \text{if} \quad a_2 < y_t^* \le a_3 \end{aligned}$$

where a_0, a_1, a_2 and a_3 are the thresholds used in assigning the value of Y_t to the latent variable. The x_{kt}s are the explanatory variables and the a_js and the b_ks are parameters that are estimated using maximum likelihood methods.[3]

historical record. In this regard cross country comparisons cannot be done using this terminology because a country's high growth figure could fall in the range of low growth in another.

[3] The Appendix further discusses Markov switching and ordered probit models.

3.1 Estimation results

The MS regressions are estimated using real GDP data from the earliest available period up to the last quarter of 1999 for Hong Kong, Indonesia, Korea and up to the last quarter of 2002 for Malaysia, Philippines and Thailand. The cutoff dates for the estimation are chosen to cover the 1997 Asian crisis and to ensure that there are enough data points for the estimation process. The remaining data up to the second quarter of 2006 are used for out-of-sample predictions of the state of the economy.

Table 1 shows Hansen's (1992, 1996) likelihood ratio tests of the null of a one-state AR(k) model against the alternative of a 2-state Markov regime-switching model. As can be seen, for lag lengths of 3 and 4, the tests show a rejection of the null hypothesis in most cases. As a preliminary analysis, 2-state models are estimated.[4] These models do not adequately capture normal movements in economic activity when economic crises are deep. This can be observed in Figure 1 which shows the smoothed probability of a high growth state (left scale) along with actual GDP growth rates (right scale). For Indonesia, Malaysia, Philippines and Thailand, the state of the economy is classified trivially into crisis and non-crisis states.

The failure of 2-state models to produce a meaningful classification of the state of the economy provides a justification to estimate 3-state models. Lag lengths of up to four are specified. It is important to note that because of the highly non-linear nature of the problem, unrestricted maximum likelihood estimates of 3-state models are more difficult to obtain. Hence, to achieve convergence to a numerical solution, the values of some parameters that can reasonably be assumed to take on boundary values are determined. Specifically, some transition probabilities are set to zero to be able to estimate the other parameters of the 3-state models.

[4] Estimation results for 2-state models are not reported due to space constraint but are available upon request.

Restricting a parameter or a set of parameters to certain values is not an unusual procedure and has been employed by Hamilton (2005) in his study of U.S. unemployment.

Inspection of the time series reveals that in most cases, the movements in GDP growth around crisis periods show no abrupt decline from a position of high growth to negative growth. Rather, growth often decelerates before going into a crisis episode. This is also true when the economy is moving out of the crisis – the economy does not shift immediately to a high growth path but has to climb slowly out of the bottom. Hence, letting $s = 1$ as the state indicating high growth, $s = 2$ indicating low growth and $s = 3$ representing a crisis state, it is reasonable to assume that state 1 is never followed by state 3 and vice versa. More precisely, let p_{ij} represent the transition probabilities. The restriction amounts to an assumption that $p_{13} = p_{31} = 0$.

Table 2 reports the restricted maximum likelihood estimates of 3-state MS regression for each of the six countries using Hamilton's algorithm. Table 3 shows the corresponding transition probability matrix for each country. To get an idea of how the 3-state MS model tracks economic activity, Figure 2 plots the smoothed probabilities on the left scale and GDP growth on the right scale. It is clear from the diagrams that 3-state models perform better than the 2-state models in vividly characterizing the movements of the economy. It must be noted however that the high-low growth cycle is discernible for all countries except for Hong Kong. High growth episodes are identified during the beginning and the end of the sample period only and for the majority of the sample period, the Hong Kong cycle appears to shift between low growth and crisis states. This is also reflected in the fitted probabilities from the ordered probit model for Hong Kong.

As discussed in detail above, the next step is to construct a time series variable from the MS smoothed probabilities to indicate the state of the economy of each country in the study. This is used as the dependent variable in ordered probit regressions. Lagged values of four variables - the lending interest differential, exchange rate depreciation, money growth and stock price inflation, all in real terms - are used as the explanatory variables for all countries. Lags up to a maximum length of 4 are used. Insignificant lagged terms were excluded and only the equations with the remaining significant variables are reported.[5]

Table 4 reports the final ordered probit estimates. The sample used depends on the length of available observations of the explanatory variables in each country. The real interest differentials are statistically significant at the first lag only in Indonesia and Malaysia. The real depreciation rate and the real stock price inflation at various lags are significant in five out of the six countries. Real money growth is an important factor in Hong Kong, Korea, Malaysia and the Philippines. The predicted probabilities of occurrence of each state per quarter can be obtained from these estimates using both in-sample and out-of-sample data. Tools to evaluate predicted probabilities from ordered probit models are unavailable. Hence, the fitted probabilities are simply plotted with actual GDP growth to determine how well they track the movements of the economy.[6] Figure 3 shows the fitted probabilities using the left scale while annual GDP growth is plotted using the right scale. The shaded portion of the graphs shows the out-of-sample forecasts. Each column in Figure 3 represents the 3 states of an economy. The first, second and third row of each column show the high growth, low growth and crisis states, respectively.

One could see from the in-sample forecast results that the ordered probit models satisfactorily traced the movement of four out of six economies under study (Korea, Malaysia, Philippines and Thailand). The Asian crisis episode was correctly classified as a crisis period in all six countries. Other crisis episodes were also identified by the models like the power crisis in the Philippines in

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[5] Data were obtained mostly from the IMF's International Financial Statistics (July 2007 IFS CD-ROM). The IFS line numbers for the lending rate, end-of-period exchange rate, stock price index and CPI are 60p, ae, 62 and 64, respectively. The foreign lending rate is the U.S. lending rate, the foreign price level is the U.S. CPI and the exchange rate is expressed as the domestic currency value of the U.S. dollar. The CPI is used as the deflator. Hong Kong and Indonesian data were obtained from CEIC.

[6] The quadratic probability score (QPS), first employed by Diebold and Rudebusch (1989) to evaluate recession probability forecasts, is used in binary models. Jones and Hensher (2004) evaluate forecast performance of a mixed ordered logit and multinomial logit models of financial distress through an enumeration strategy that simply takes the proportion of occurrences of each predicted state to total and compares them with the actual.

the early 1990s. High and low growth states during normal periods were tracked satisfactorily with only a few misclassifications. The 2001 negative growth of Malaysia due to its poor export performance was identified as a low growth period though a spike could be seen in the corresponding diagram for the crisis state. The results for Hong Kong and Indonesia were however unremarkable. The in-sample (as well as the out-of-sample) results for both countries showed several misclassifications.

The shaded areas which show the out-of-sample forecasts reveal more interesting results for some countries. For most countries, the predicted probabilities closely tracked out-of-sample GDP growth movements up to 2 years. Beyond this, misclassifications understandably occurred. Korea's cycle was tracked reasonably with the probability of high growth preceding the peak of the GDP growth and the probability of low growth rising to its highest when the economy is about to hit the bottom. One can notice that the probability of being in the crisis state rose as the economy arrives at the bottom of the cycle but this is not enough for the period to be classified as a crisis. Thailand's cycle was also tracked reasonably well by the probabilities of high and low growth. Malaysian and Philippine economic activity were likewise tracked by the models satisfactorily. Hong Kong's negative growth in 2001 was classified by the model as a crisis period and its cycle, unlike in other countries, moves between low growth and crisis states – a result that follows from the MS model.

4 Concluding remarks

This study has demonstrated that econometric tools used to analyze fluctuations in advanced economies can feasibly be applied to developing economies. The results above show that the models constructed are able to track the movements of aggregate economic activity fairly well and have satisfactory out-of-sample performance in a majority of the countries in this study.

This model building exercise makes use of data from six selected East Asian economies. The procedure outlined in this paper can be implemented in other developing economies as well. The models above can be utilized conveniently for policy analysis because it uses easy to obtain macroeconomic data to track and predict the state of the economy. The results show to some extent the usefulness of selected macroeconomic variables in predicting slowdowns. Simulations can also be done to determine under what combination of values of these variables can lead to crisis situations similar to early warning systems. The specification and expansion of the set of explanatory variables can be made to improve forecast accuracy. These are not done in this study but are areas for further work.

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Table 1: Hansen's likelihood ratio test

	Indonesia		Korea		Hong Kong	
k Lags =	3	4	3	4	3	4
LR stat =	3.299	3.638	9.626	3.758	4.003	3.593
Bandwidth:	p-values					
0	0.021	0.009	0.000	0.005	0.001	0.005
1	0.032	0.008	0.000	0.004	0.002	0.005
2	0.027	0.009	0.000	0.005	0.003	0.010
3	0.024	0.009	0.000	0.004	0.006	0.009
4	0.029	0.012	0.000	0.007	0.008	0.007
5	0.022	0.007	0.000	0.010	0.008	0.009

	Malaysia		Philippines		Thailand	
k Lags =	3	4	3	4	3	4
LR stat =	2.568	3.585	5.611	1.460	2.954	2.131
Bandwidth:	p-values					
0	0.056	0.009	0.000	0.565	0.022	0.225
1	0.073	0.009	0.000	0.577	0.030	0.218
2	0.094	0.013	0.000	0.572	0.033	0.247
3	0.092	0.012	0.000	0.569	0.028	0.255
4	0.110	0.011	0.000	0.573	0.034	0.259
5	0.113	0.010	0.000	0.571	0.041	0.269

H_0: one-state AR(k) model; H_1: 2-state Markov-switching model

Table 2
Three-state Markov Switching Estimates*

	Indonesia		Korea		Hong Kong		Malaysia		Philippines		Thailand	
	Coef	std.error	Coef	std.error	Coef	std.error	Coef	std.error	Coef	std.error	Coef	std.error
μ_1	1.907	0.134	2.683	0.108	3.307	0.114	2.679	0.124	1.493	0.052	2.189	0.214
μ_2	0.563	0.368	1.488	0.093	1.440	0.057	1.184	0.146	0.554	0.064	0.722	0.191
μ_3	-6.202	0.451	-3.519	0.223	-2.245	0.159	-3.856	0.224	-1.316	0.199	-3.203	0.270
ϕ_1	-0.602	0.152	-0.996	0.012	-0.579	0.123	-0.961	0.054	-0.702	0.253	-0.513	0.138
ϕ_2	-0.257	0.179	-0.975	0.015	-0.604	0.119	-0.995	0.034	-0.967	0.162	-0.869	0.068
ϕ_3	-0.100	0.150	-0.958	0.012	-0.266	0.116	-0.894	0.054	-0.627	0.212	-0.629	0.139
ϕ_4					0.610	0.108			-0.386	0.117		
σ	1.491	0.330	1.202	0.235	0.813	0.171	1.103	0.265	0.172	0.048	2.198	0.603
p_{11}	0.917	0.068	0.752	0.096	0.057	0.033	0.704	0.111	0.678	0.117	0.854	0.117
p_{12}	0.330	0.207	0.206	0.085	0.706	0.143	0.366	0.125	0.420	0.139	0.175	0.110
p_{23}	0.342	0.269	0.342	0.269	0.141	0.050	0.508	0.246	0.691	0.194	0.217	0.179
p_{32}	0.067	0.071	0.025	0.024	0.000	0.194	0.081	0.056	0.201	0.081	0.052	0.051
LogLik	-69.52		-70.31		-59.51		-61.02		-19.36		-46.04	
Sample	1980:1-1999:4		1981:1-1999:4		1981:1-1999:4		1988:1-2002:4		1986:4-2002:4		1993:1-2002:4	

* The univariate MS regression model is of the form: $y_t = \mu_{s_t} + \phi_1\left(y_{t-1} - \mu_{s_{t-1}}\right) + \ldots + \phi_k\left(y_{t-k} - \mu_{s_{t-k}}\right) + \varepsilon_t$ where $\varepsilon_t \sim N\left(0, \sigma^2\right)$

Table 3
Transition Probability Matrices

	Indonesia			Malaysia		
	State 1	State 2	State 3	State 1	State 2	State 3
State 1	0.917	0.330	0.000	0.704	0.366	0.000
State 2	0.083	0.603	0.342	0.296	0.553	0.508
State 3	0.000	0.067	0.658	0.000	0.081	0.492
	Korea			Philippines		
	State 1	State 2	State 3	State 1	State 2	State 3
State 1	0.752	0.206	0.000	0.678	0.420	0.000
State 2	0.248	0.770	0.342	0.322	0.379	0.691
State 3	0.000	0.025	0.658	0.000	0.201	0.309
	Hong Kong			Thailand		
	State 1	State 2	State 3	State 1	State 2	State 3
State 1	0.813	0.057	0.000	0.854	0.175	0.000
State 2	0.187	0.802	0.706	0.146	0.773	0.217
State 3	0.000	0.141	0.295	0.000	0.052	0.783

Table 4
Ordered Probit Estimates*

	Hong Kong		Indonesia		Korea		Malaysia		Philippines		Thailand	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
interest differential(t–1)			0.165	0.071			0.604	0.033				
depreciation(t – 1)			0.036	0.001	0.048	0.052			0.084	0.004	0.123	0.000
depreciation(t – 2)	-0.159	0.058	0.039	0.002	0.062	0.001					0.316	0.013
depreciation(t – 3)	-0.178	0.007									0.259	0.004
stock inflation(t – 1)					-0.027	0.043	-0.040	0.025			-0.092	0.006
stock inflation(t – 2)	-0.018	0.060					-0.032	0.049			-0.074	0.002
stock inflation(t – 3)	-0.032	0.006					-0.042	0.024			-0.034	0.054
stock inflation(t – 4)							0.033	0.094				
money growth(t – 1)	-0.258	0.000			-0.028	0.042	-0.098	0.004	-0.086	0.003		
money growth(t – 2)									-0.088	0.002		
money growth(t – 3)									-0.105	0.000		
money growth(t – 4)									-0.108	0.000		
γ_2	-2.331	0.000	1.181	0.000	-0.244	0.155	-0.099	0.655	-0.291	0.214	0.313	0.358
γ_3	0.288	0.248	2.894	0.000	2.330	0.000	2.294	0.000	1.212	0.000	6.210	0.001
Pseudo-R^2	0.236		0.238		0.209		0.287		0.193		0.644	
Sample	1983:1-1999:4		1981:1-1999:4		1982:1-1999:4		1989:2-2002:4		1988:1-2002:4		1994:1-2002:4	

*The dependent variable is the state of the economy: high growth state = 1, low growth state = 2, crisis state = 3.
The independent variables are in real terms and are computed as 100 times the first difference of the logarithm of their level values except for the interest differential which is computed as $100\ x \left[\frac{cpi_{t-1}}{cpi_t} \left(1 + r_t\right)^{1/4} - \frac{cpi^*_{t-1}}{cpi^*_t} \left(1 + r^*_t\right)^{1/4} \right]$.

Figure 1: Two-state Markov switching smoothed probabilities

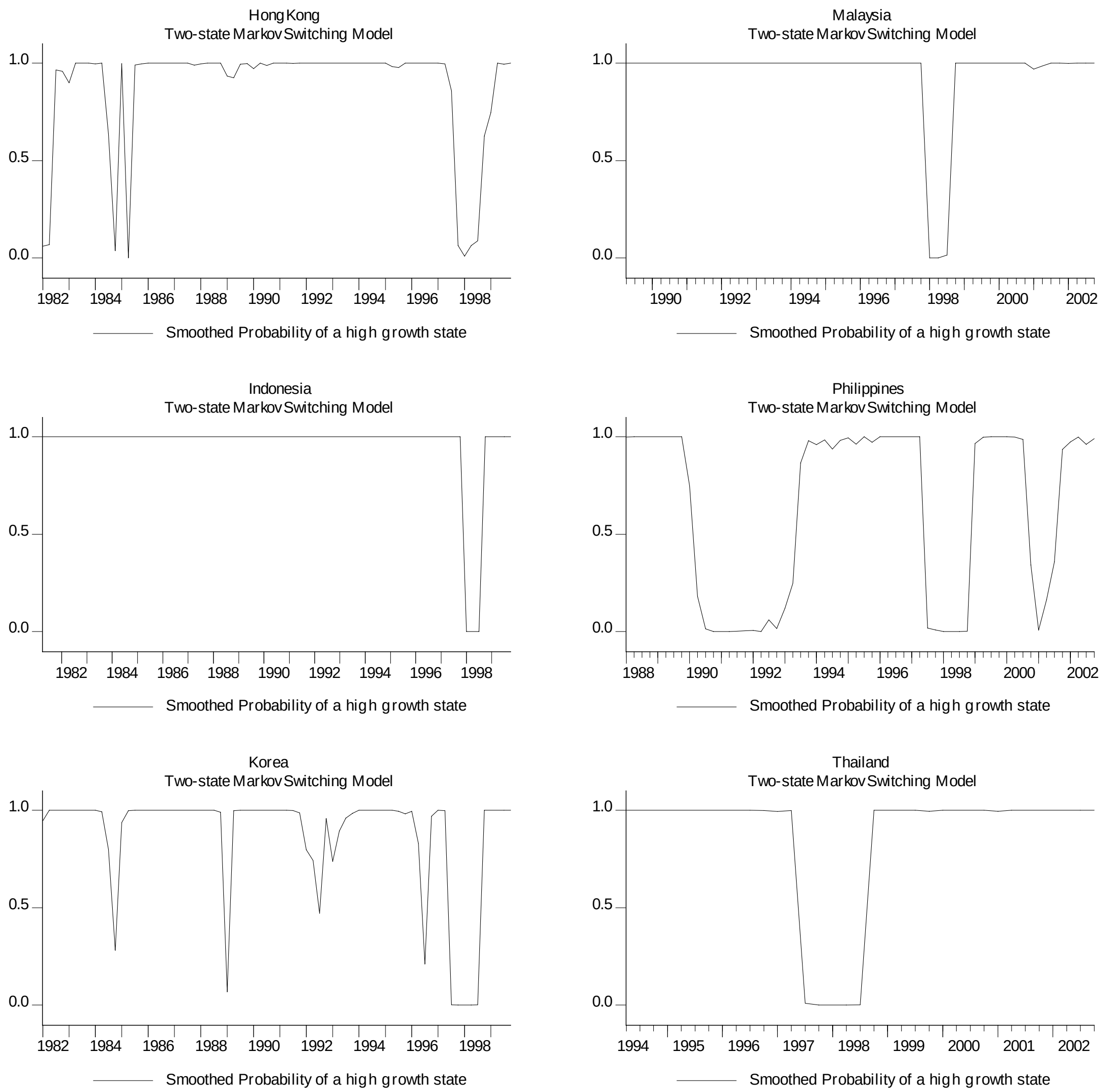


Figure 2:
Three-state Markov switching smoothed probabilities and GDP growth

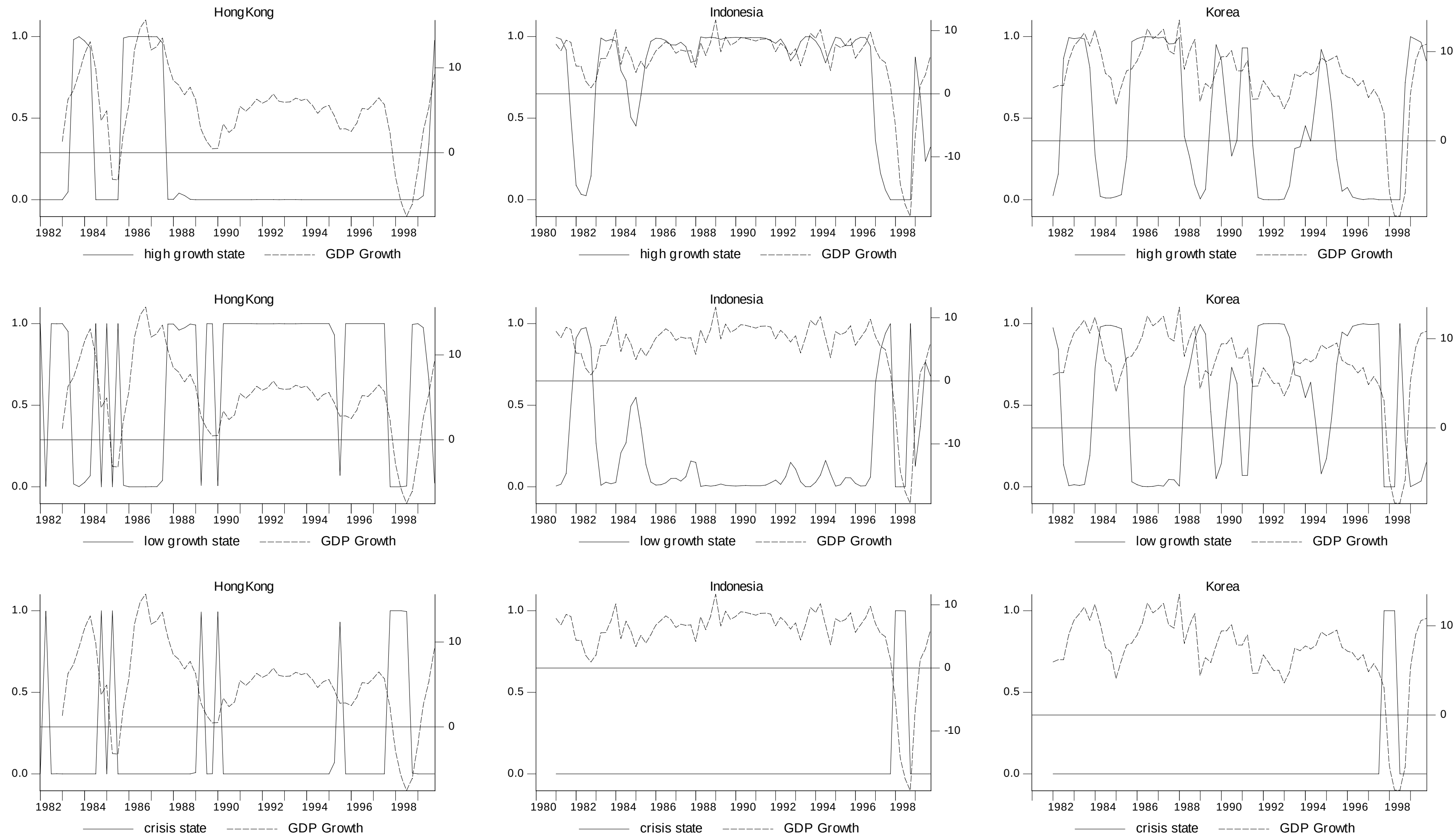


Figure 2
Continued

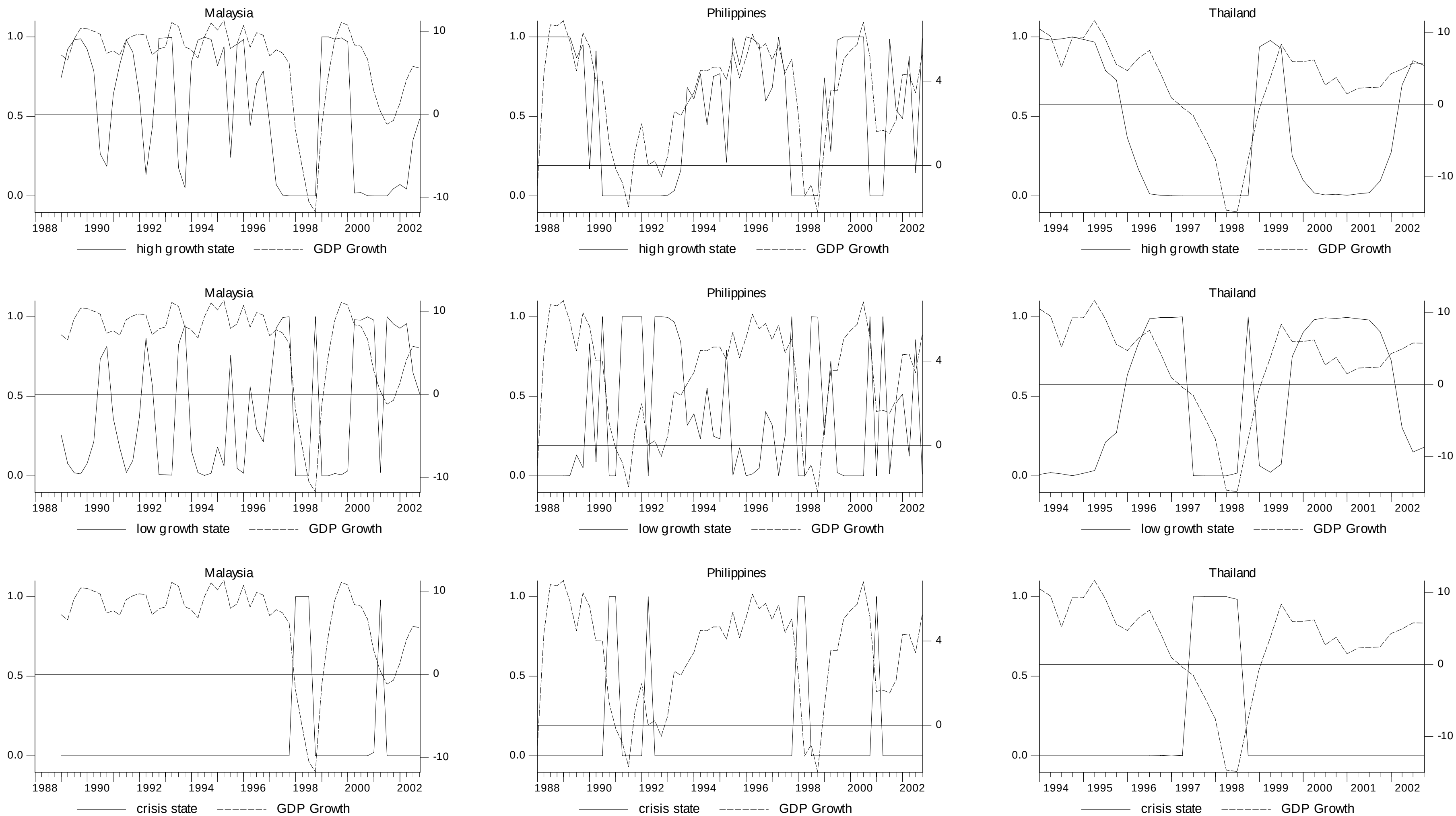


Figure 3:
In-sample and out-of-sample fitted probit probabilities, GDP Growth

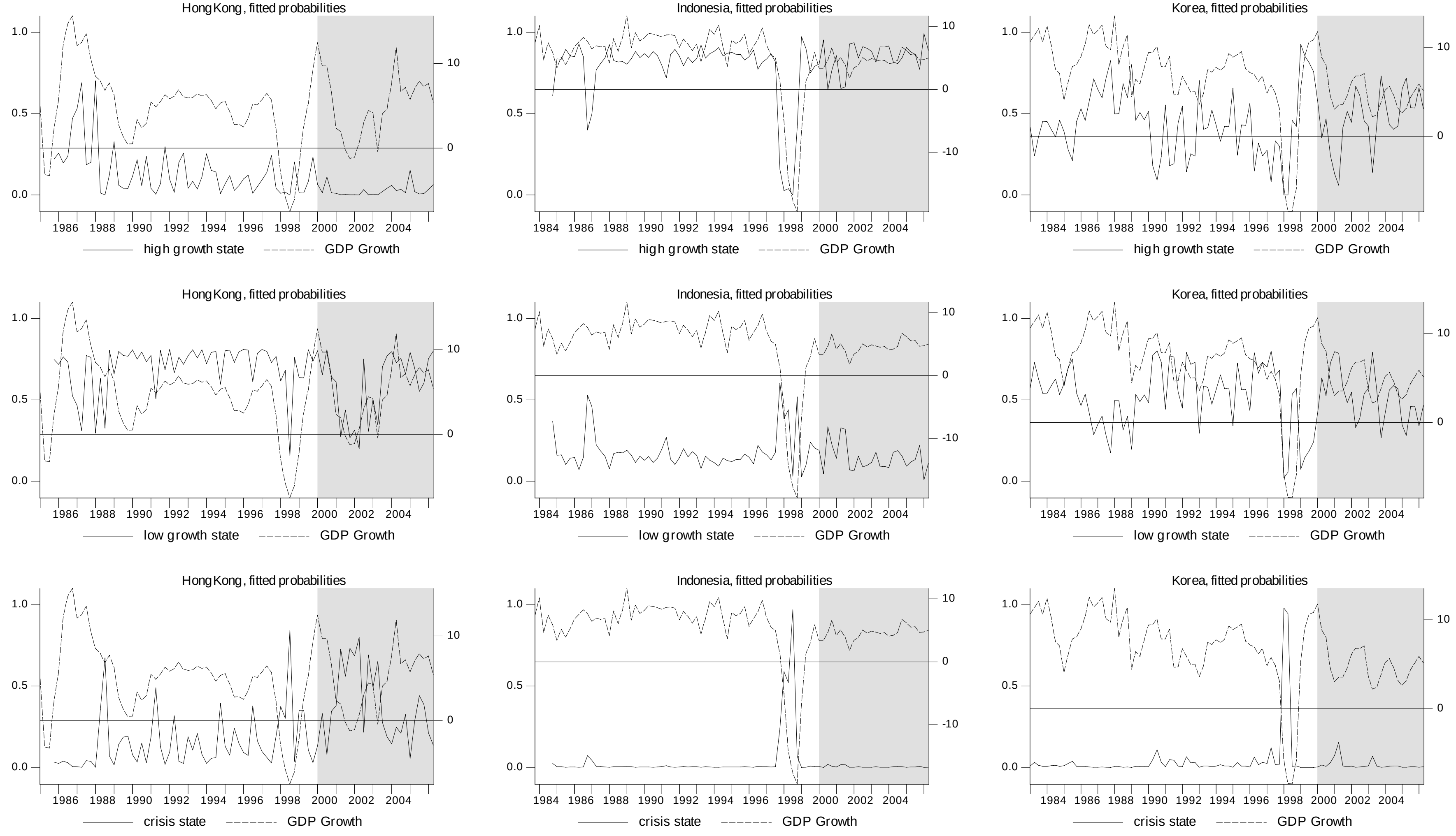
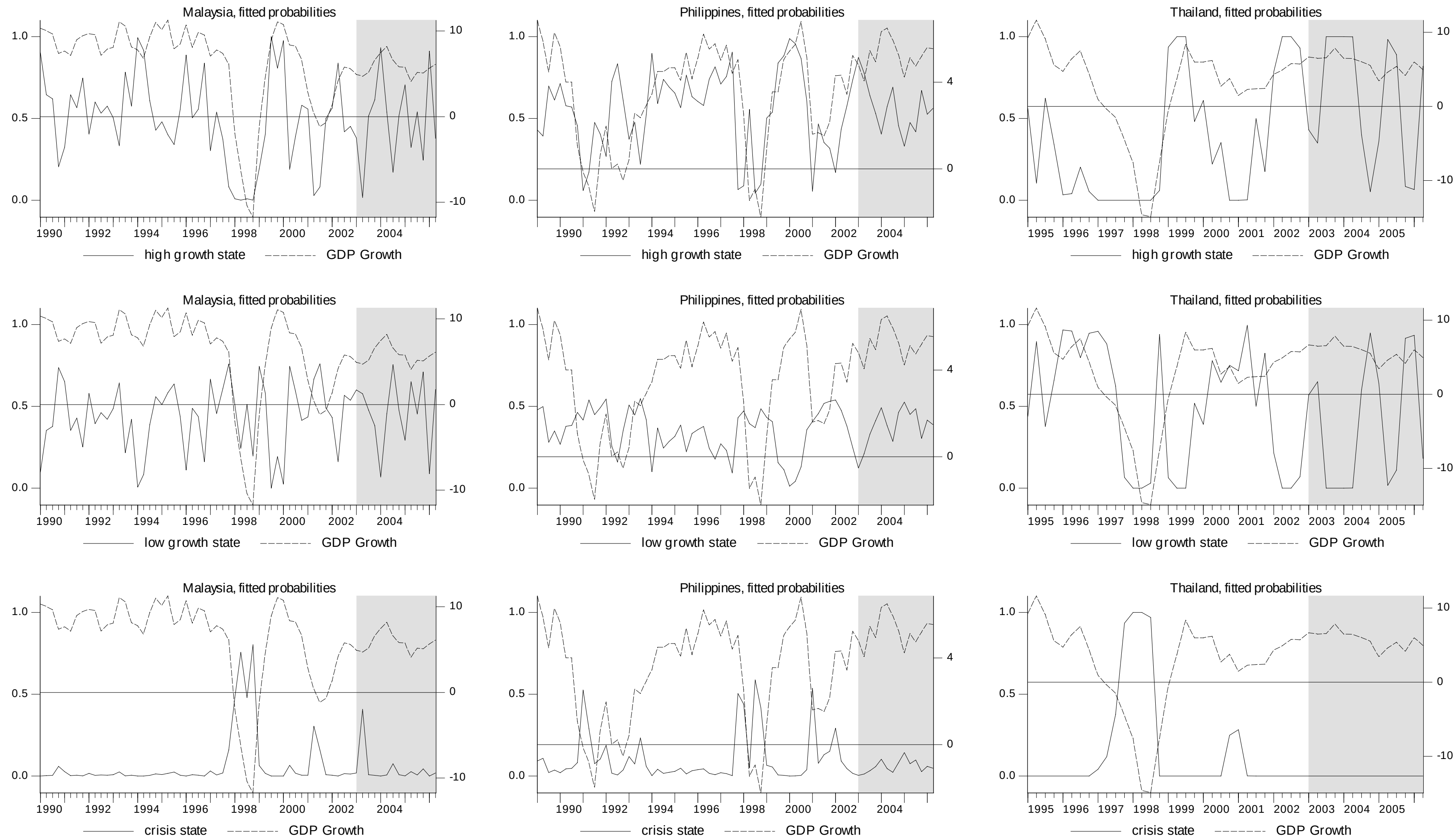


Figure 3
Continued



Appendix

Markov-Switching Regression

The univariate MS regression model used in this study is of the form:

1) $$y_t = \mu_{s_t} + \phi_1\left(y_{t-1} - \mu_{s_{t-1}}\right) + \ldots + \phi_k\left(y_{t-k} - \mu_{s_{t-k}}\right) + \varepsilon_t \quad ; \qquad \varepsilon_t \sim N\left(0, \sigma^2\right)$$

where y_t is the variable of interest; in this study, this variable is output growth; the ϕ_ks are the k autoregression parameters and ε_t is a white noise process. μ_{s_t} is the mean of y_t when the economy is in state s_t. In this study, the state of the economy is assumed to be the outcome of an unobserved first-order 3-state Markov process (i.e., s_t = 1, 2, 3). Its evolution can be described by transition probabilities, $\Pr\left(s_t = j \middle| s_{t-1} = i\right) = p_{ij}$, that can be written in matrix form:

2) $$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{33} \\ p_{13} & p_{23} & p_{33} \end{bmatrix}$$

where $\sum_{j=1}^{3} p_{ij} = 1$. Each element shows the probability that state i is followed by state j. The process is assumed to depend on past values of y_t and s_t only through s_{t-1}. Note that since only y_t is observed but not the state of the economy, a way must be found to form optimal inferences about the current state based on the observed values of y_t. Given the number of states, Hamilton (1989) shows how to estimate the parameters of the model and the transition probabilities governing the motion of the variable of interest. He provides a recursive method for drawing probabilistic inferences about what state the economy is in (the value of s_t) given the history of y_t. This is the basic MS regression that is going to be utilized in the proposed study to establish regime dates. As mentioned in the review above, several extensions of the basic model have been done since then (see also Kim and Nelson (1999).)

Ordered Response Model

In ordered response models, one can specify a latent variable, y_t^*, that are assumed to be influenced by a set of exogenous variables. Suppose there are K exogenous variables denoted by x_{kt}, where k = 1, …, K. Then one can write:

3) $$y_t^* = b_0 + b_1 x_{1t} + \ldots + b_K x_{Kt} + \varepsilon_t = z_t + \varepsilon_t$$

ε_t is a disturbance term. The latent variable, y_t^*, can be mapped onto an ordered categorical variable:

4) $$\begin{aligned} Y_t &= 1 \quad \text{if} \quad a_0 < y_t^* \le a_1 \\ Y_t &= 2 \quad \text{if} \quad a_1 < y_t^* \le a_2 \\ Y_t &= 3 \quad \text{if} \quad a_2 < y_t^* \le a_3 \end{aligned}$$

where a_0, a_1, a_2 and a_3 are thresholds that serve to assign the value of Y_t associated with the latent variable. To preserve the ordering, these thresholds that are to be estimated econometrically along with the coefficients of equation (4) must satisfy: $a_0 > a_1 > a_2 > a_3$. The latent variable's boundary values are unknown. Hence, one can simply set the beginning and ending thresholds to minus and plus infinity respectively (in this case, $a_0 = -\infty$ and $a_3 = +\infty$) and need not be estimated. From the above expressions, one can write the ordered regression model as:

5)

$$\begin{aligned}
\Pr(Y_t = 1 \mid x_{1t}, \ldots, x_{Kt}) &= \Pr(\varepsilon_t \le a_1 - z_t) \\
&= F(a_1 - z_t) \\[1em]
\Pr(Y_t = 2 \mid x_{1t}, \ldots, x_{Kt}) &= \Pr(a_1 - z_t < \varepsilon_t \le a_2 - z_t) \\
&= F(a_2 - z_t) - F(a_1 - z_t) \\[1em]
\Pr(Y_t = 3 \mid x_{1t}, \ldots, x_{Kt}) &= \Pr(\varepsilon_t \ge a_2 - z_t) \\
&= 1 - F(a_2 - z_t)
\end{aligned}$$

where F denotes the cumulative distribution function of ε. Let there be a total of T sample periods, ($t = 1, \ldots, T$), each of which can be treated as a single draw from a multinomial distribution. Suppose T_1, T_2 and T_3 are the number of periods belonging to states 1, 2 and 3 respectively, with $T_1 + T_2 + T_3 = T$. Then the likelihood of observing the sample is given by:

6)

$$L = F(a_1 - z_t)^{T_1} \left[F(a_2 - z_t) - F(a_1 - z_t)\right]^{T_2} \left[1 - F(a_2 - z_t)\right]^{T_3}$$

The parameters of the model, the a_h's and the b_k's, can be estimated by maximizing the (log of the) likelihood function given by equation (6). $\hat{z}_t$ can be computed once the b coefficients are estimated. With estimates of the limit coefficients, $\hat{a}_h s$, and $\hat{z}_t$, the probability of being at a particular state can be predicted for each period t in the sample:

7)

$$\begin{aligned}
\hat{p}_{1t} &= F(\hat{a}_1 - \hat{z}_t) \\[0.5em]
\hat{p}_{2t} &= F(\hat{a}_2 - \hat{z}_t) - F(\hat{a}_1 - \hat{z}_t) \\[0.5em]
\hat{p}_{3t} &= 1 - F(\hat{a}_2 - \hat{z}_t)
\end{aligned}$$

where $\hat{p}_{1t} + \hat{p}_{2t} + \hat{p}_{3t} = 1$. The disturbance term, ε_t, can be assumed to follow a normal or a logistic distribution to produce either the ordered probit or the ordered logit model, respectively. A good reference on qualitative and limited dependent variables regression like the above is Davidson and MacKinnon (1993). Ordered probit and logit models are known to be well-behaved and are easily implemented using commercially available econometric programs.