MARKOV SWITCHING MODELS FOR THE EXCHANGE RATE AND THE STOCK RETURN BASED ON A CHARTIST-FUNDAMENTALIST EXPECTATION APPROACH

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แบบจำลองมาร์คอฟสวิตชิงสำหรับอัตราแลกเปลี่ยนและผลตอบแทนในตลาดหุ้น
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ธนพร เศรษฐอุดม : แบบจำลองมาร์คอฟสวิตชิงสำหรับอัตราแลกเปลี่ยนและผลตอบแทนในตลาดหุ้นบนพื้นฐานแนวทางการคาดการณ์ด้วยการวิเคราะห์ชาร์ตและปัจจัยพื้นฐาน (MARKOV SWITCHING MODELS FOR THE EXCHANGE RATE AND THE STOCK RETURN BASED ON A CHARTIST-FUNDAMENTALIST EXPECTATION APPROACH) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ดร.อนันต์ เจียรวงศ์, 174 หน้า.

วิทยานิพนธ์ฉบับนี้ประกอบไปด้วยสองบทความที่ทำการศึกษาพัฒนาแบบจำลองเชิงประจักษ์เพื่ออธิบายและคาดการณ์ความเคลื่อนไหวของอัตราแลกเปลี่ยนและผลตอบแทนในตลาดหุ้นรายวัน โดยใช้แบบจำลองมาร์คอฟสวิตชิงบนพื้นฐานแนวทางการคาดการณ์ด้วยการวิเคราะห์ชาร์ตและปัจจัยพื้นฐาน บทความแรกเรื่อง “แบบจำลองอัตราแลกเปลี่ยนมาร์คอฟสวิตชิงสำหรับอัตราแลกเปลี่ยนบนพื้นฐานแนวทางการวิเคราะห์ชาร์ตและปัจจัยพื้นฐาน” บทความนี้ได้พัฒนาแบบจำลองโดยอนุญาตให้นักลงทุนแต่ละกลุ่มสามารถใช้การคาดการณ์ทั้งการวิเคราะห์ชาร์ตและการวิเคราะห์ปัจจัยพื้นฐานในทั้ง 2 สถานะที่ไม่สามารถสังเกตได้ โดยได้นำ Hodrick-Prescott filter มาใช้ในการแบ่งกลุ่มนักลงทุนออกเป็น 2 กลุ่มใหญ่ ๆ ที่เป็นอิสระต่อกัน ได้แก่ กลุ่มนักเก็งกำไรระยะสั้น และกลุ่มผู้ลงทุนในระยะยาว โดยสมมติให้ผู้เล่นทั้งสองกลุ่มนี้มีการคาดการณ์และมีอิทธิพลต่อความเคลื่อนไหวของอัตราแลกเปลี่ยนรายวันในตลาดแตกต่างกัน อีกทั้งมีข้อสมมติว่า 2 สถานะที่ไม่สามารถสังเกตได้ซึ่งส่งผลกระทบต่อการคาดการณ์ของนักลงทุนทั้งสองกลุ่มนี้ไม่เหมือนกัน โดยศึกษาข้อมูลเชิงประจักษ์ของข้อมูลอัตราแลกเปลี่ยนรายวันที่มีมูลค่าการซื้อขายมากที่สุดห้าอันดับแรก บทความที่สองเรื่อง “การประยุกต์ใช้แนวทางการวิเคราะห์ชาร์ตและปัจจัยพื้นฐานสำหรับแบบจำลองพฤติกรรมการเก็งกำไรกับตลาดหุ้นของประเทศในเอเชีย” บทความนี้จัดทำแบบจำลองเพื่อศึกษาข้อมูลเชิงประจักษ์ของดัชนีราคาตลาดหุ้นในเอเชีย 4 ประเทศ เพื่อประโยชน์ในการเปรียบเทียบผลการศึกษา ได้แก่ ฮ่องกง อินเดีย เกาหลี และไทย โดยแบ่งกลุ่มผู้ซื้อขายหุ้นออกเป็น 2 กลุ่มใหญ่ ๆ คือ กลุ่มที่ใช้การคาดการณ์ด้วยการวิเคราะห์ชาร์ต และกลุ่มที่ใช้การคาดการณ์ด้วยการวิเคราะห์ปัจจัยพื้นฐาน ผลการศึกษาพบว่าแบบจำลองที่นำเสนอในงานศึกษานี้สามารถอธิบายความเคลื่อนไหวของอัตราแลกเปลี่ยนและอัตราผลตอบแทนในตลาดหุ้นรายวันได้อย่างมีเหตุมีผลและมีนัยสำคัญเชิงสถิติ

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THANAPORN SEDDHA-UDOM: MARKOV SWITCHING MODELS FOR THE EXCHANGE RATE AND THE STOCK RETURN BASED ON A CHARTIST-FUNDAMENTALIST EXPECTATION APPROACH. ADVISOR: ANANT CHIARAWONGSE, Ph.D., 174 pp.

This dissertation consists of two essays to develop empirical models to describe and to forecast daily exchange rate and stock return dynamics by using Markov switching (MS) models based on a chartist-fundamentalist expectation approach. The first essay is “a Markov switching model of the exchange rate based on a chartist-fundamentalist approach.” This study develops a Markov switching model by allowing each group of foreign exchange traders to use both chartist and fundamentalist expectations in the two unobservable states. This study makes use of the Hodrick-Prescott filter to separate the market participants into two independent groups: short-term speculators and longer-term investors. These two types of participants have different expectations and impacts on daily exchange rate movements. In addition, we assume that the two unobservable states affecting the expectations of these two groups are not the same. This study examines empirical evidences of the five most traded currency pairs. The second essay is “an application of the chartist-fundamentalist approach to a model of speculative behavior for Asian stock markets.” This study examines empirical evidences of the daily data of four stock indices in four Asian countries for comparison purpose, i.e., Hong Kong, India, Korea, and Thailand. The market participants are divided into two types: chartists and fundamentalists. The empirical results exhibit that the proposed models can reasonably and significantly explain the dynamics of daily exchange rates and stock returns.

Department:	Banking and Finance	Student's Signature	....
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Finally, I of course bear the sole responsibility for any shortcomings of this dissertation. I hereby proudly dedicate this piece of work to my mother and my father.

CONTENTS

Page

Page

Page

Page

Page

Page

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1
A MARKOV SWITCHING MODEL OF THE EXCHANGE RATE BASED ON A CHARTIST-FUNDAMENTALIST APPROACH

1.1 Introduction

1.1.1 Statement of the problem and its significance

Foreign exchange markets are by far the largest financial markets in the world. The average daily turnover in these markets was approximately $5.3 trillion in 2013.[1] In addition, the exchange rate is an essential variable in both macroeconomic and microeconomic management. While central banks often utilize exchange rates as the intermediate targets of monetary policy, agents in the business sector generally determine their trading and hedging strategies based on exchange rate expectations. Understanding both exchange rate determination and the dynamics thereof is therefore very useful to the public and private sectors.

According to the "exchange rate disconnect puzzle" documented in international finance research, it is an observable fact that the exchange rate cannot be explained by its fundamentals over the short-term. This is an issue that this study strives to illuminate. Although many studies have been conducted on this issue, a clear answer to the puzzle has not yet emerged. The results of the relevant empirical studies vary depending on the model and sample characteristics, such as selected currencies, data frequencies, and time periods. Thus, this study attempts to partially answer the exchange rate disconnect puzzle, which continues to be an interesting challenge for further research.

Figure 1 summarizes the development of exchange rate models. From the 1970s until the end of the 1980s, most of exchange rate models were based on fundamental theories, including purchasing power parity (PPP), uncovered interest

[1] Triennial Central Bank Survey (http://www.bis.org/publ/rpfx13fx.pdf), Bank for International Settlements, September 2013.

parity (UIP), monetary, and portfolio balance models.[2] However, these fundamental models do not sufficiently explain or forecast exchange rate dynamics over the short-term. Existing research on the exchange rate disconnect puzzle usually refers to the famous study conducted by Meese & Rogoff (1983), which demonstrates that a random walk model outperforms all of the fundamental exchange rate models in out-of-sample forecasting for periods of less than one year. This finding led to a dormant period in exchange rate modeling during the 1980s. Since the 1990s, new approaches to short-term exchange rate modeling have illuminated the issue and appear useful for further study in this area. The major interesting approaches are the microstructure approaches, hybrid models, behavioral finance frameworks, and nonlinear models.

[2] Among others, these models are described in Williamson (2008), Lam, Fung, & Yu (2008), and Chinn and Moore (2011).

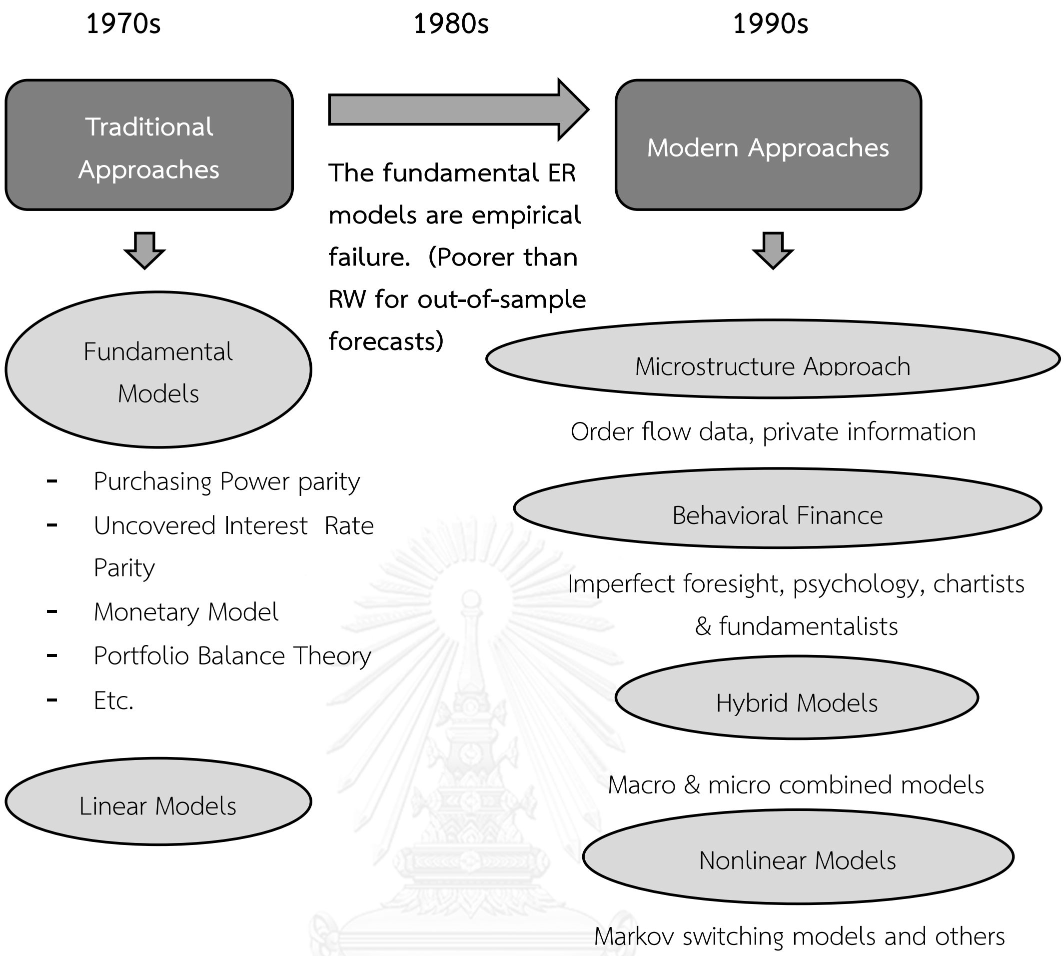

Figure 1 Development of exchange rate models

According to the microstructure literature[3], exchange rate models utilizing order flow data usually outperform a random walk model. Order flow data are measured by the number of buyer-initiated orders less the number of seller-initiated orders. The strong relationship between order flows and exchange rate dynamics is intuitively unsurprising. Because order flow data reflect time-varying foreign exchange demand and supply, these transactions should affect the market price directly. When buyer-initiated orders exceed seller-initiated orders, the commodity currency should

[3] See, for example, Evans & Lyons (2002), Bacchetta & Wincoop (2006), Rime, Sarno, & Sojli (2007), Berger, Chaboud, Chernenko, Howorka, & Wright (2008), Gyntelberg, Loretan, Subhanij, & Chan (2009a), Gyntelberg, Loretan, Subhanij, & Chan (2009b), Dunne, Hau, & Moore (2010), and Evans (2010).

logically appreciate and vice versa. However, to predict the exchange rate, order flows must first be forecast, which is itself not an easy task.

What is more interesting is that we understand the forces behind these order flows. How do investors form their expectations and decide to place buying or selling orders? In the behavioral finance framework, agents make decisions based on their bounded rationality. Agents do not have perfect foresight and may even be biased. Investors have the same public information, but their expectations can be different. DeGrauwe & Grimaldi (2006) develop exchange rate models utilizing a behavioral finance framework by assuming that market participants switch between chartist and fundamentalist trading rules, which can be categorized as a chartist-fundamentalist approach. These models assume that agent behavior does not conform to the rational expectation assumptions of fundamental models and that some limits to arbitrage exist. The results of these model simulations match the following observed characteristics of the data: non-normal distribution of exchange rate returns, booms and crashes in currency markets, volatility clustering, and nonlinear exchange rate dynamics. Most behavioral exchange rate models utilize simulation to explain exchange rate dynamics and need supports from empirical studies.

Research based on market participant surveys indicates that professionals typically consider both technical and fundamental analyses to determine their trading strategies.[4] Consequently, exchange rate models based on a chartist-fundamentalist approach have been developed. On the other hand, hybrid models that include both macro variables and order flow data can explain the exchange rate better than single-approach models. One early study of this type was conducted by Evans & Lyons (2002), which finds that hybrid models can explain exchange rate dynamics better than macro-only models, order flow-only models, or a random walk model. Another study, conducted by Rime et al. (2007), suggests that order flows reflect aggregate changes in agents' expectations of macroeconomic fundamentals and can

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[4] Menkhoff & Taylor (2007) provide an overview of relevant studies that survey or interview foreign exchange professionals about the use of technical and fundamental analyses in their decision making processes.

be utilized to predict future macroeconomic fundamentals. That study also confirms that exchange rates are not determined by a random walk but are determined by economic fundamentals directly and indirectly via order flows.

Another interesting development is the use of nonlinear models to explain exchange rate dynamics. Several studies propose the use of Markov switching (MS) models. For example, Engel & Hamilton (1990) indicate that a Markov switching model explains long swings in an exchange rate well. Frommel, MacDonald, & Menkhoff (2005) examine Markov switching regimes in a monetary exchange rate model, which supports the contention that fundamentals exert nonlinear effects on exchange rate movements. However, most of the studies on this subject report that Markov switching models outperform a random walk model (RW) for in-sample data but not for out-of-sample data, e.g., Engel (1994), Ahrens & Reitz (2005), Lee & Chen (2006), and Li (2008).

The exchange rate models have been developed continually. Although there has not been the best model that can explain the exchange rate dynamics in general, the new approaches of exchange rate models shed some lights for the studies in this area. Therefore, it is still interesting to develop an exchange rate model further from the existing literature to obtain a satisfactory model which can both explain and forecast the short-term exchange rate dynamics.

The existing literature indicates that fundamental theories cannot explain exchange rate movements and underperform a random walk model over the short run. However, new approaches to exchange rate modeling argue that exchange rate movements should not follow a random walk. This argument is reinforced by the evidences that technical strategies are widely operated among market participants [Allen & Taylor (1990)] while the fundamental theories still hold over the long run. Motivated by this fact, this study tries to develop a daily exchange rate model by seeking the synergy between the explanatory strength of a chartist-fundamentalist approach and the predictive strength of a nonlinear model.

In several extant MS models of exchange rate based on a chartist-fundamentalist approach such as Vigfusson (1997), Ahrens & Reitz (2005), and Li (2008), the two states of the world are defined as the chartist-expectation-only state and the fundamentalist-expectation-only state. The empirical results of these studies indicate that market volatility in the chartist-expectation-only state is lower than that in the fundamentalist-expectation-only state, which is a counter-intuitive finding in need of justification.

According to Levin (1997), when asset holders in the same group hold both chartist and fundamentalist expectations, the exchange rate can move along either a stable path or an unstable path and may converge to or diverge from its long-run equilibrium value.

Hommes (2005) surveys many works on heterogeneous agent models (HAMs) which is closely related to behavioral finance. In HAMs, there are more than one type of investors in the market, each type of investors may be not fully rational and do not take into account the existence of others. The expectation behaviors among various types of agents are not the same and should have different impacts on the market price dynamics.

To address this issue, this study proposes a Markov switching (MS) model based on a chartist-fundamentalist approach to capture difference in expectations between two major groups of market participants: the short-term speculators and the longer-term investors. These two groups should have different expectation behaviors because the former group aims at making daily profits from the short-run fluctuations in the market while the latter group has higher investment horizons and does not pay much attention on daily swings in an exchange rate. The short-term speculators tend to have expectation based on a chartist rule while the longer-term investors should consider both the fundamentalist rule and long-term trend of an exchange rate. In addition, expectations of these two groups of agents may depend on the current condition of the foreign exchange market as well. For example, when the market is quite volatile, this may be a good opportunity to bet for profits for short-term speculators. They would expect the change in exchange rate faster than when the market is calm. In contrast, the longer-term investors may not concern much about daily swings of an exchange rate but they consider whether an exchange rate is highly over- or under- valued or not. If it is, the longer-term investors expect an exchange rate to return to its fundamental value but sooner or later may depend on the limits to arbitrage in the market at that time. Therefore, the proposed MS models aim to capture the expectation behaviors of these two groups of investors which may vary in time depending on the market condition and environment. In each state of the markets perceived by each group of investors, we allow them to employ chartist or fundamentalist expectation or both in each state. We conjecture that the expectation behaviors of short-term speculators and longer-term investors should influence the daily exchange rate return in different ways.

1.1.2 Research question

The research question for this study is *"Can we develop an exchange rate return model to form the expectation behaviors of the two major groups of market agents, the short-term speculators and the longer-term investors, by using a Markov switching model based on a chartist-fundamentalist approach?"*

1.1.3 Objectives of the study

This study aims to develop a Markov switching (MS) model based on a chartist-fundamentalist approach to capture the expectation behavior of each group of market agents and to consider its impact on the daily exchange rate return which is complicated and cannot be explained by any pure fundamental model.

1.1.4 Scope of the study

This study develops a Markov switching model based on a chartist-fundamentalist approach to analyze the influence of expectation behaviors of two different types of agents, i.e., short-term speculators and longer-term investors on the daily exchange rate dynamics. *The proposed model examines the daily exchange rate movements* *of the five most traded currency pairs*[5] *in 2013: US dollar/euro, US dollar/yen, US dollar/Pound sterling, US dollar/Australian dollar, and US dollar/Canadian dollar.* The daily data used for empirical test in this study is during January 1999 to June 2013. The in-sample period ranges from January 1999 to June 2012 and the out-of-sample period ranges from July 2012 to June 2013. The proposed model also takes into account control variables such as the VIX index, MSCI returns, FX market intervention, and Quantitative Easing (QE) data.

1.1.5 Contributions

1. <u>Theoretical contribution</u>: This study adds to the literature on short-term exchange rate model developments based on a chartist-fundamentalist approach. The innovation in this study is to consider a Markov switching model as a tool to capture the expectation behavior of each group of market agents which may vary in time depending on the state of the market in their perceptions. This study separates the market participants into two groups: short-term speculators and longer-term investors. By this new aspect, we investigate the impacts of short-term speculator and longer-term investor expectations on the daily exchange rate dynamics.
2. <u>Contributions to private sector</u>: A short-term model of exchange rate which has both good explanatory and some predictive performances should help private sector, both banks and non-banks, to manage their trading strategies to increase profits or to reduce risks.

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[5] The model proposed in this study is appropriate for daily data because we want to separate the behavior of day traders who usually bet on daily FX market movements and are concerned only with very short-term profits from the behavior of longer-term investors who may consider more information and have longer-term expectations. The most traded pairs are considered because daily data for quantitative easing and FX market interventions in these developed markets are available.

3. <u>Contributions to policy makers</u>: It may be useful for monetary authorities to use this kind of model to manage their market interventions to maintain the exchange rate stability.

1.1.6 Organization of the study

Section 1.2 is the literature review on related studies focusing on new approaches of exchange rate modelling.

Section 1.3 describes the conceptual framework and the proposed model.

Section 1.4 the dataset and methodology are described.

Section 1.5 presents the empirical analysis and discussion of the results.

Section 1.6 is an application example using the proposed model.

Section 1.7 provides concluding remarks.

1.2 Literature review

Figure 2 illustrates the structure of related literature review for this essay. Literature in the dark-grey boxes lays the foundation to the conceptual framework of this study while literature in the light-grey boxes refers to other relevant literature. The white boxes indicate the key inputs or main ideas for each related literature.

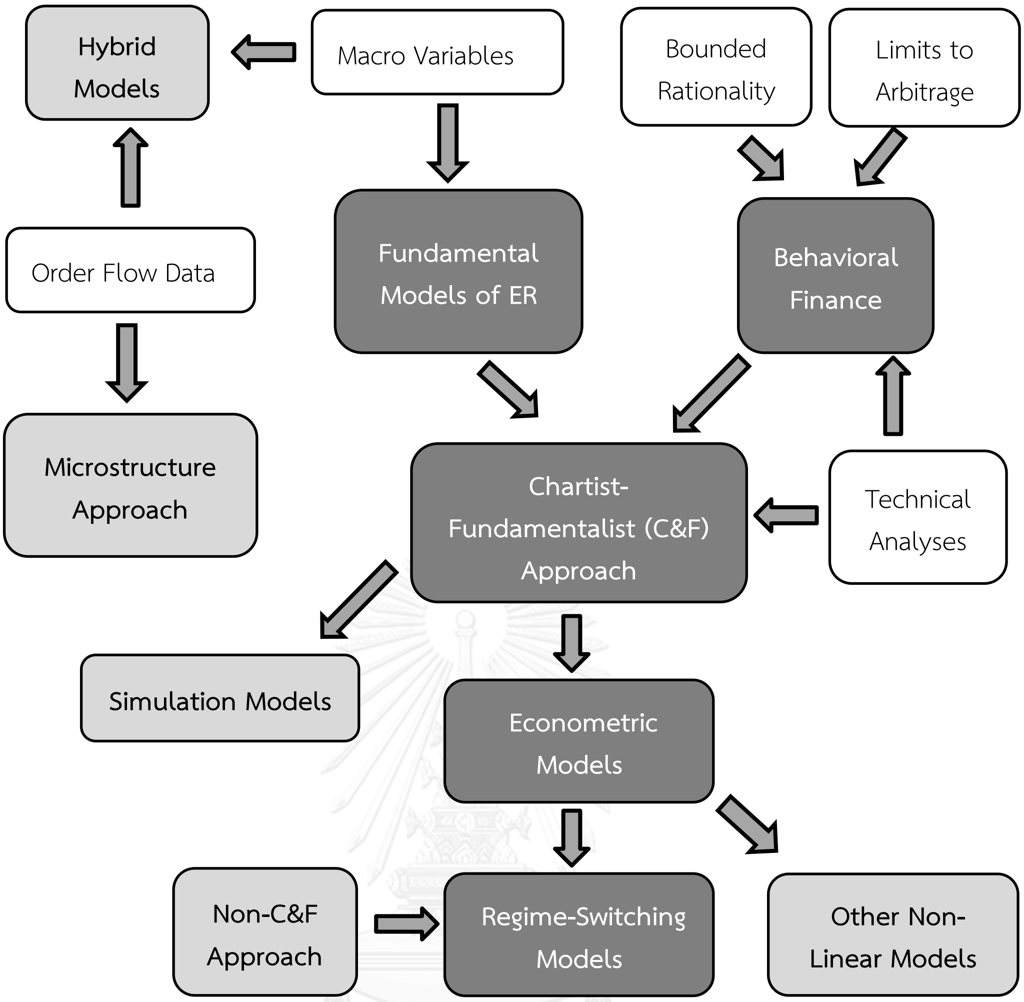

Figure 2 Literature review on related studies for a Markov switching model of the exchange rate based on a chartist-fundamentalist approach

In *the fundamental models* of exchange rate determination, the exchange rate is determined by the relative macroeconomic variables between the specified two countries. Prominent fundamental models are Purchasing Power Parity (PPP) model, Uncovered Interest Rate Parity (UIP) model, Sticky Price (SP) monetary model, and Uncovered Equity Parity (UEP) model. However, these fundamental models cannot explain the exchange rate dynamics in the short run well.

Since 1990s, there have been several new approaches of exchange rate modeling. The two outstanding approaches are the microstructure approach and the behavioral finance (BF) framework. For *the microstructure approach*, the literature utilizes the order flow data as the key explanatory variables on exchange rate determination. The main results of the literature on this approach find that order flows significantly determine exchange rate and most of microstructure models outperform a random walk model. On the other hand, literature of exchange rate models based on *the behavioral finance (BF) framework* believes that agents are not fully rational and the limits to arbitrage exist in the real world. The exchanged rate models on the BF framework can illustrate various stylized facts in the foreign exchange market such as non-normal distribution of exchange rate returns, booms and crashes in currency markets, volatility clustering, and nonlinear exchange rate dynamics. Nevertheless, applying the models in these two approaches to forecast exchange rate in the short-run still have some limitations. For the microstructure approach, it is difficult to forecast the order flow data since they are private information. For the behavioral finance framework, most of the models need many assumptions on the parameters of the models for simulation. Thus, the predictabilities of these models are rather limited.

Later on, there have been attempts to further develop the exchange rate models such as *the hybrid models* which utilize both macro variables and order flow data to explain the exchange rate. The hybrid models perform better than macro-only models, order flow-only models, or a random walk model. However, the limitation of using order flow data to forecast the exchange rate still persists. Besides, the prevalent of technical analyses by financial experts and traders in the market also motivate works on *the chartist-fundamentalist (C&F) approach*. The exchange rate models based on the C&F approach can be classified into two categories: *simulation models* and *econometric models*. Several related studies utilize the computational tools to simulate exchange rate models based on the C&F approach. Most of them can demonstrate many stylized facts in the foreign exchange market quite well but their forecasting abilities are still in difficulties. Therefore, the simulation models need more supports by empirical studies leading to the development of models based on the econometric approach.

Models based on *the econometric approach* can estimate parameters from actual empirical data. *This essay aims to further develop an empirical test for a Markov switching (MS) model based on a chartist-fundamentalist (C&F) approach to describe and forecast the daily exchange dynamics.* The extant literature of the MS models based on the C&F approach has counter-intuitive empirical results that market volatility in the chartist-expectation state is lower than that in the fundamentalist-expectation state. *The main differences* of the proposed model of this study from the previous studies are as follows. *Firstly, we divide market agents into two groups: short-term speculators and longer-term investors by using the Hodrick-Prescott (HP) filtering technique. Secondly, the two groups of agents are allowed to utilize chartist, fundamentalist, or both rules for their expectations in each unobservable state.* The change in market exchange rate is the collective results of these heterogeneous expectations among agents in the market.

1.2.1 Fundamental Models

This section summarizes some well-known fundamental models of exchange rate determination[6].

1 Purchasing Power Parity (PPP): Under the PPP model, an exchange rate between two currencies is the rate that equates prices of goods and services of the two specific countries. However, we may use the rate of change in prices of goods and services between the two countries for the relative version of the PPP model. Let e_t be a nominal exchange rate of domestic currencies per one unit of a foreign currency, p_t is the domestic price of goods and services, p_t^* is the foreign price of goods and services.

The absolute version of the PPP model:

$$e_t = \frac{p_t}{p_t^*} \tag{1}$$

The relative version of the PPP model:

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[6] The fundamental models presented here are summarized from the explanation of Hau & Rey (2006) and Lam et al. (2008)

$$ln\, e_t = ln\, p_t - ln\, p_t^* \tag{2}$$

2 Uncovered Interest Rate Parity (UIP): Under the UIP model, an exchange rate between two currencies is the rate that equates the expected returns of holding domestic and foreign assets. If the UIP holds, the expected percentage change in exchange rate will be equal to the difference in domestic and foreign interest rates.

$$E_t(ln\, e_{t+1} - ln\, e_t) = i_t - i_t^* \tag{3}$$

where $E_t(\cdot)$ is the expectation at time t,

e_t is a nominal exchange rate at time t,

i_t and i_t^* are domestic and foreign interest rates.

3 Sticky Price (SP) monetary model: In the monetary model, an exchange rate is determined by equilibria in three markets: the goods and services market, the money market, and the currency market. Because prices of goods and services are sticky in the short run, when a monetary shock occurs, an exchange rate will firstly overshoot its long-run equilibrium level and then will gradually adjust to its long-run equilibrium level after the prices of goods and services are fully adjusted. The sticky price monetary model is also known as the overshooting model explained in Dornbusch (1976) and Frankel (1979). In this model, change in exchange rate depends on relative changes of money supply, income, interest rates and expected inflation rates between the two specific countries. The model can be written as:

$$ln\, e_t = ln\, m_t - ln\, m_t^* - \emptyset(ln\, y_t - ln\, y_t^*) + \alpha\,(i_t - i_t^*) + \beta(\pi_t - \pi_t^*) \tag{4}$$

where e_t is a nominal exchange rate at time t,

m_t and m_t^* are domestic and foreign money supplies,

y_t and y_t^* are domestic and foreign income,

i_t and i_t^* are domestic and foreign interest rates,

π_t and π_t^* are expected domestic and foreign inflation rates,

$\emptyset, \alpha,$ and β are model parameters.

4 Uncovered Equity Parity (UEP): Intuition behind the UEP is the portfolio rebalance concept. When the return on foreign equity investment is higher than the return on domestic equity investment, domestic investors face with higher exposure of foreign exchange risk. So domestic investors reduce their exposure by selling some foreign currency and then the foreign currency depreciates. The UEP implies that percentage change in exchange rate (per one foreign currency unit) positively relates to the different of home equity return and foreign equity return in terms of their local currencies.

$$\ln(e_t) - \ln(e_{t-1}) = f\{(\ln s_t - \ln s_t^*)\} \tag{5}$$

where s_t and s_t^* are domestic and foreign equity prices.

1.2.2 Microstructure approach

The microstructure approach explains the exchange rate movements by using order flow data. The order flow is defined as a number of buyer-initiated orders minus a number of seller-initiated orders. Among others, related studies in this area are Evans & Lyons (2002), Bacchetta and Wincoop (2006), Rime et al. (2007), Berger et al. (2008), Gyntelberg et al. (2009b), Dunne et al. (2010), Evans (2010), etc. The literature on this approach believes that public information alone is not enough to explain exchange rate dynamics in short to medium term. The main rationale is that agents are heterogeneous and have their own private information. These heterogeneous agents signal their private information to the market via their trading actions which can be measured by order flow data. The microstructure studies find that the exchange rate models explained by order flow data usually outperform a random walk model. Some studies also test the long-run relationship between order flows and exchange rates. There are two views for the results, the strong-flow centric view and the weak-flow centric view. The strong-flow centric view supports the long-run relationship between order flows and exchange rates, for example, Gyntelberg et al. (2009b) finds that equity-related order flows have long-run relation with exchange rate movements. For the weak-flow centric view, order flows only have temporary effect on exchange rates such as the study results of Froot & Ramadorai (2005) which indicates that at long horizons, interest rate differentials matter while order flows do not. However, the empirical evidences are not conclusive because the results depend on time period, time horizon, and currencies used in each study. For the microstructure literature, more explanation about causes and consequences of exchange rate determination by order flows still need to be fulfilled. Other relevant studies such as Rime et al. (2007) and Evans (2010) examining the relation between macroeconomic information and order flows. They support that macroeconomic variables partially and indirectly affect order flows.

1.2.3 Behavioral finance (BF) framework

DeGrauwe & Grimaldi (2006) and DeGrauwe & Kaltwasser (2006) are examples of studies which develop exchange rate models based on a behavioral finance (BF) framework. Main idea of the BF framework is that not all agents behave perfectly rational. In addition, the foreign exchange market in reality is not perfectly complete because some limits to arbitrage exist. The exchange rate models in a BF framework can explain empirical fact of exchange rate dynamics better than fundamental models in several aspects. They can illustrate the stylized facts of non-normal distribution of exchange rate returns, booms and crashes in currency market, and volatility clustering. They also investigate the effectiveness of central bank's intervention in the foreign exchange market.

1.2.4 Hybrid models

Hybrid models combine macroeconomic and order flow data to explain exchange rate determination. One of the early studies on the hybrid models of exchange rate determination is Evans & Lyons (2002) which finds that a hybrid model can explain exchange rate dynamics better than a macro-only model, an order flow-only model, and a random walk model. Another related study, Rime et al. (2007) investigates the relation between order flow and macroeconomic information in the currency market. The study finds that order flow reflects aggregate change in agents' expectation on macroeconomic fundamentals and can be a predictor for the future macroeconomic fundamentals. The paper also concludes that current and future exchange rates do not follow a random walk but are determined by economic fundamentals directly and indirectly via order flow data.

1.2.5 Technical analyses

Neely & Weller (2011) explain that chartists believe in making profits from changes in the market psychology which is reflected in the market price and volume. In other words, the market information reflects attitudes and expectations of all market participants. Technical analysts try to capture various patterns from the past data to predict the future market movements. In the short-run, a currency trader usually uses technical analyses to some degree and tends to combine it with fundamental analysis for the longer-term expectations.

Schulmeister (2005) examines interaction between technical trading strategies and exchange rate dynamics. The study finds that technical trading signals have close relations with order flows and exchange rate dynamics. The paper concludes that the order flows are not only determined by fundamentals but also by technical trading. The study employs several technical trading rules and finds that most of these rules can generate profits both in- and out-of sample periods. There are several technical rules used in practice, both traditional and newer. Examples of some traditional rules are filter rules, moving average rules, and channel rules. For the newer rules, some examples are relative strength indicator (RSI), exponentially weighted moving average (EWMA), moving average convergence divergence (MACD), and rate of change (ROC).

Neely, Weller, & Ulrich (2009) and Neely & Weller (2011) analyze excess returns for some technical trading rules and consider changes in excess returns of these rules over time. The results indicate that technical trading rules actually give profits during 1970s to 1980s but the profits have disappeared since 1990s for simple technical rules such as filter and moving average rules while more complicated rules such as trading rules following to ARIMA and Markov switching models were still able to make some profits.

Neely & Weller (2011) try to find the reasons behind the profit takings of technical trading rules by reviewing various relevant studies. They conclude that data mining should not be the reason while central bank intervention should have a positive effect on technical rule profits. If the central bank uses the "leaning against the wind" policy, technical analysis can predict the exchange rate trend.

1.2.6 Chartist-fundamentalist (C&F) approach

Lam et al. (2008) compares the predictability of various exchange rate models which are the Purchasing Power Parity (PPP) model, the Uncovered Interest Rate Parity (UIP) model, the Sticky Price Monetary (SP) model, the Bayesian Model Averaging (BMA) method, and the combined forecast of the four models. The first three models are fundamental models while the fourth is a technical model. The results indicate that the combined model has the smallest root-mean-square-errors (RMSE) ratio and the highest percentage of correct prediction compared to any single model of the study. This implies that the combination of fundamental and technical analyses is better than using either fundamental-only or technical-only analysis.

Literature on exchange rates models based on chartist-fundamentalist approach are Hommes (2005), DeGrauwe & Grimaldi (2006), DeGrauwe & Kaltwasser (2006), Piccillo (2011), Vigfusson (1997), Ahrens & Reitz (2005), Li (2008), Levin (1997), etc. In these studies, the change in market exchange rate is a collective result of heterogeneous expectations of market agents by using chartist and fundamentalist rules.

1 Chartist rule: This rule is based on the past exchange rate movement. Chartists do not consider the fundamentals of exchange rate. They just forecast the future value of exchange rate from its past movement. The chartist expectation is sometimes called "a backward looking".

2 Fundamentalist rule: This rule bases on a fundamental analysis. Fundamental value of an exchange rate between two currencies should be determined by relative economic variables of the two countries in consideration as specified by fundamental theories. When an exchange rate deviates from its fundamental value, fundamentalists expect that it will return to the fundamental value sooner

or later. Thus, the expectation equation of fundamentalists is mean-reverting. Sometimes we call the fundamentalist expectation as “a forward looking”.

Exchange rate models based on the C&F approach can be grouped into two types: simulation models and econometric models.

1.2.6.1 Simulation models

Literature on simulation models of exchange rate based on the C&F approach are Hommes (2005), DeGrauwe & Grimaldi (2006), DeGrauwe & Kaltwasser (2006), etc. In this kind of models, agents often switch their trading rules between fundamentalist and chartist depending on their past profit performances. For the next period, an agent chooses a trading rule giving him the best risk-adjusted profit recently. These models can explain exchange rate dynamics as shown in stylized facts quite well but their predictive powers are rather limited. In general, simulation models need many assumptions on parameter values to simulate exchange rate paths.

1.2.6.2 Econometric models: the Markov switching model

One outstanding econometric models of exchange rate is the Markov switching (MS) model. In general, several studies find that Markov switching (MS) exchange rate models have better predictive power than a random walk model for in-sample periods, but not for the out-of-sample periods, e.g., Engel (1994), Ahrens & Reitz (2005), Lee & Chen (2006), and Li (2008).

Lo (2004) introduces the Adaptive Market Hypothesis (AMH) as an alternative to the traditional Efficient Market Hypothesis (EMH). Under the EMH, price movement should be unpredictable because all agents already incorporate all information in the market but the empirical facts usually do not support these models. Behavioral biases of agents in the real world such as overconfidence, overreaction, loss aversion, herding, etc.; may be the reasons making the efficient market models likely to be wrong.

Diebold, Lee, & Weinbach (1994) indicate that Markov switching models can capture occasional and recurrent regime shifts. Several studies; such as Engel & Hamilton (1990), Engel (1994), Frommel et al. (2005), Ahrens & Reitz (2005), Lee & Chen (2006), and Li (2008), etc.; find that Markov switching models outperform a random walk model (RW) at least for in-sample data. Therefore, a Markov switching model is one possible type of models which can be developed to investigate the behavior of investors in the real world.

There are both the econometric models based on chartist-fundamentalist (C&F) approach and those based on non C&F approach.

Non C&F approach

Engel & Hamilton (1990) examine the data-generating process of an exchange rate and find that it does not follow a random walk and can be explained by a Markov switching model with two regimes. They find that the mean values of exchange rates in the two regimes have opposite signs and the exchange rate volatilities in the two regimes are quite different.

Lovcha & Perez-Laborda (2010) examines a Markov Switching Model of exchange rate by using order flow data. They conclude that the regime changes are unobservable.

Lee & Chen (2006) investigate a Markov switching model of exchange rate under the dirty floating exchange rate regime. They develop a rational expectation model of exchange rate determination and solve for the equilibrium exchange rate under the dirty floating exchange rate system. The central bank intervention in the foreign exchange market affects the investors' expectation and then the market exchange rate and raises the discrepancy between exchange rate and its fundamentals. Thus, the exchange rate process is state-dependent and can be explained by a Markov switching model with two regimes of intervention and no intervention.

C&F approach

Vigfusson (1997) tests a Markov switching model based on a chartist-fundamentalist approach with the Canada-US daily exchange rate during Jan 1983 to Dec 1992. His model consists of two sets of equations: those for exchange rate forecasting and for the transition probabilities. For the exchange rate forecasting equations, the model assumes that there is either chartist or fundamentalist expectation in each state. The conditional probability of a regime given the last period's regime is calculated for the set of transition probability equations. The models are estimated by using an EM algorithm and the maximum likelihood method. The empirical results of the models with different fundamental theories are similar and also find that the chartist regime is more common and has lower variance compared to the fundamentalist regime.

Ahrens & Reitz (2005) tests several regime-switching models by comparing the empirical results of four alternative specifications: RS-AR(0), RS-AR(1), RS-CF-AR(0), and RS-CF-AR(1) where RS denotes regime switching, CF denotes chartist-fundamentalist, and AR denotes autoregressive. The authors test the models by using the daily data of DM/USD from 1982 to 1998. In the mentioned study, the fundamentalist forecast depends on the Purchasing Power Parity (PPP) model while the chartist forecast uses the moving average method. The model parameters are estimated by using the quasi maximum likelihood method. The likelihood ratio statistics suggest that the RS-CF-AR (1) is the best model in consideration. It is also found that the exchange rate volatility in the fundamentalist regime is much higher than the volatility in the chartist regime, the same results as Vigfusson (1997). However, the authors note that the phenomenon of high volatility in the fundamentalist regime and low volatility in the chartist regime is not well understood.

Li (2008) investigates a Markov switching (MS) model of exchange rate based on fundamental and time-series analyses with time-varying loadings. He tests a model with three currencies of Korean Won (KOW), New Taiwan Dollar (NTD), and Singapore Dollar (SGD) during January 1980 to August 2000. The empirical results of his study show that investors increase the loading of fundamental factors in their expectations when the market price is highly volatile.

<u>Endogenous switching</u>

In general, studies of Markov switching models usually assume that the state variable follows a first order Markov chain while the transition probabilities are constant and determined exogenously. However, by economic intuition the state should have a close relation with the financial and economic conditions at that time. The transition probabilities from one to another regime may vary in time and be endogenously determined.

Kim, Piger, & Startz (2008) develops a Guassian model with endogenous Markov regime switching by using the probit specification of the transition probabilities. The model parameters are estimated by the maximum likelihood method. By the Monte Carlo experiments, the results show that the parameter estimation is quite accurate. The study also suggests that if the true process has endogenous switching but is treated as exogenous, the parameter estimation will be biased.

Kechim & Rezgui (2011) study the exchange rate dynamics by a Markov switching model with endogenous switching. In this model, the transition probabilities depend on some explanatory variables endogenously. The empirical study tests monthly exchange rate data of JPY/USD and NZD/USD from Jan 1994 to Dec 2008. The transition probabilities are determined by the recent past of exchange rates. The results show significant coefficients for the explanatory variables in the specified Markov switching model with endogenous switching.

1.3 Conceptual framework and the proposed model

1.3.1 Theoretical background

The catastrophe theory can describe the relationship between stock market behavior and two control factors: excess demand of fundamentalists and the chartists' participation in the market. This theory indicates that a stock market may have multiple equilibria under some conditions. The market can become unstable and reach a crash when the equilibrium path enters into the bifurcation set[7]. The cusp catastrophe can portray the dynamics of booms and busts in a financial market. The concept of this theory is consistent to a Markov-switching model in the sense that there may be more than one state of market condition such as stable and unstable states. The two control factors reflect the existence of fundamentalists and chartists in the market and their behaviors affect the stock price dynamics.

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[7] In a cusp-catastrophe model, a bifurcation set is the set of two control factors which can generate bimodal behaviors in a stock market.

Another related theoretical literature is literature on heterogeneous agent models (HAM). According to HAM, there are different types of agents in the market such as fundamentalists and chartists. Both fundamentalists and chartists are usually not fully rational because they do not take into account the existence of each other.

The co-evolution of market equilibrium dynamics as portrayed by catastrophe theory and the heterogeneous trading strategies among market participants in the HAM are relate to the concept of “Adaptive Rational Equilibrium Dynamics” (ARED).

Based on these theoretical concepts and models, this study proposes a two-state Markov switching (MS) model which allows different expectation behaviors among heterogeneous agents to induce the market price while the behaviors of market participants co-evolve with the unobservable state.

1.3.1.1 Catastrophe theory

Catastrophe theory was invented by René Thom in 1972 to describe all potential equilibrium points on smooth surfaces and to show that catastrophes can occur when the equilibrium breaks down. Thom’s classification theorem indicates that there are only seven elementary catastrophes for the processes which have no more than four control factors.

Zeeman (1976) applies one of the seven elementary catastrophes called “the cusp catastrophe” to portray the phenomena of bull and bear states in a stock market as shown in Figure 3. The stock market behavior is measured by the rate of change of price index as shown on the vertical axis. The stock market behavior is controlled by two factors: an excess demand for stock of fundamentalists and the proportion of chartists in the market. The horizontal plane is the control surface comprise of two control factors.

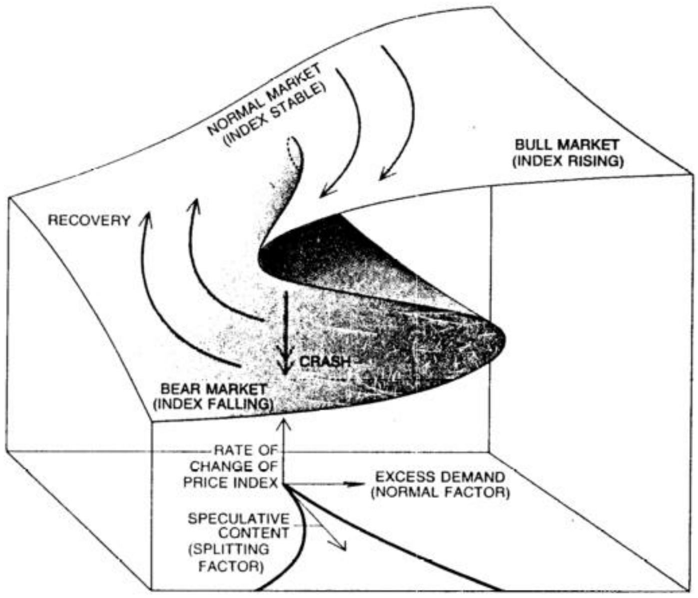

Figure 3 Behavior of the stock market

Source: Zeeman (1976), page 75.

The equilibrium surface shows all possible equilibria in the stock market which is shaped as the cusp catastrophe. The equilibrium surface has a 'pleat' in the middle where the top sheet folds over the bottom sheet. When this pleat is projected onto the control-surface plane, the edge of this pleat form a cusp-shaped curve called a bifurcation set. When a stock market moves to this bifurcation set of control factors, the market equilibrium is unstable and a sudden change can occur.

For illustration, let consider a starting point at normal market when the stock price index is stable or there is a zero rate of change in price index. After that, if excess demand for stock of fundamentalists in the market increases, the price index rises. This induces speculators to participate more in the market in search of their profits on the up-side market; the proportion of chartists in the market is then growing. In this situation, a stock market enters into "a bull market". Chartist proportion may increase and dominate the stock market leading the stock market to become unstable; a stock-price bubble is developing. Once fundamentalists perceive that the market is now over-priced, they reduce their excess demand, the movement of a bull stock market is shown as the direction of arrows on the top sheet until reaching the edge of the fold curve which is coincide with a bifurcation set of control factors, “a market crash” can happen. When a bubble is burst, the market equilibrium falls down to the bottom sheet abruptly or the catastrophe occurs. At that time, the stock price index falls sharply and the proportion of chartists in the market declines rapidly. Once fundamentalists recognized that the market is now under-priced, they return to the market again. The dynamics during a bear stock market or in a recovery period is shown as the direction of arrows on the bottom sheet. When the market becomes stable and returns to a normal situation again, all the process can repeat as boom and bust cycles. The concept of this theory should be able to apply with other financial markets as well.

Behavior of a stock market as illustrated by this theory reflects the relationship between the dynamics of market equilibrium and the two control variables: excess demand of fundamentalists and the chartists’ market participation. Although this explanation cannot be proved empirically because the two control variables are unobservable, we hypothesize that a financial market may enter into a stable or an unstable state related to the behaviors of heterogeneous market participants.

1.3.1.2 Heterogeneous Agents Models (HAM)

Hommes (2005) surveys many works on heterogeneous agent models (HAM) which are closely related to behavioral finance. According to “A Survey on Behavioral Finance” written by Barberis and Thaler in the Handbook of the economics and finance edited by Constantinides, Harris, & Stulz (2003), the two building blocks of behavioral finance are “limits to arbitrage” and “market psychology”. Sometimes investors may face with difficulty and risk to do arbitrages when the market price is influenced by non-rational traders. On the other hand, investors have bounded rationality and there are psychology effects on their decision makings such as social interactions. Heterogeneous agent models capture some of these features of behavioral finance framework.

1.3.1.3 Adaptive Rational Equilibrium Dynamics (ARED)

Brock & Hommes (1997) introduce "a model of endogenous, evolutionary selection of heterogeneous expectations rules". They present the concept of "Adaptive Rational Equilibrium Dynamics" (ARED) which describes the co-evolution of market equilibrium dynamics and selection among heterogeneous expectation rules. In their model, there are H different types of forecasting strategies, the proportion of traders using strategy *h* is determined by a performance measure such as past realized profits of strategy *h* compares to those of others which is changed over time. More successful strategies should be selected by agents more often than less successful strategies. The ARED model shows that equilibrium prices and the combination of heterogeneous agents' expectations co-evolve over time and the market can be either stable or unstable.

1.3.2 Conceptual framework

In accordance to the literature review and theoretical backgrounds, the conceptual framework of this study is illustrated in Figure 4.

Following the microstructure approach, agents have their private information and expectations. In line with HAM, *this study assumes that there are two types of agents in foreign exchange markets: the short-term speculators and longer-term investors.* These two types of agents have *heterogeneous expectations*. They may employ a fundamentalist rule, a chartist rule, or both to form their expectations on the future exchange rate movements. This concept is *a chartist-fundamentalist approach*. The market exchange rate is influenced by its past movement (the chartist rule) and the extent to which the market rate deviates from its fundamental value (the fundamentalist rule). According to the microstructure perspective, private expectation is converted into market data through trading. Then, the market price is readjusted in response to cumulative order flows. The new market price in turn influences agent expectations in the next period.

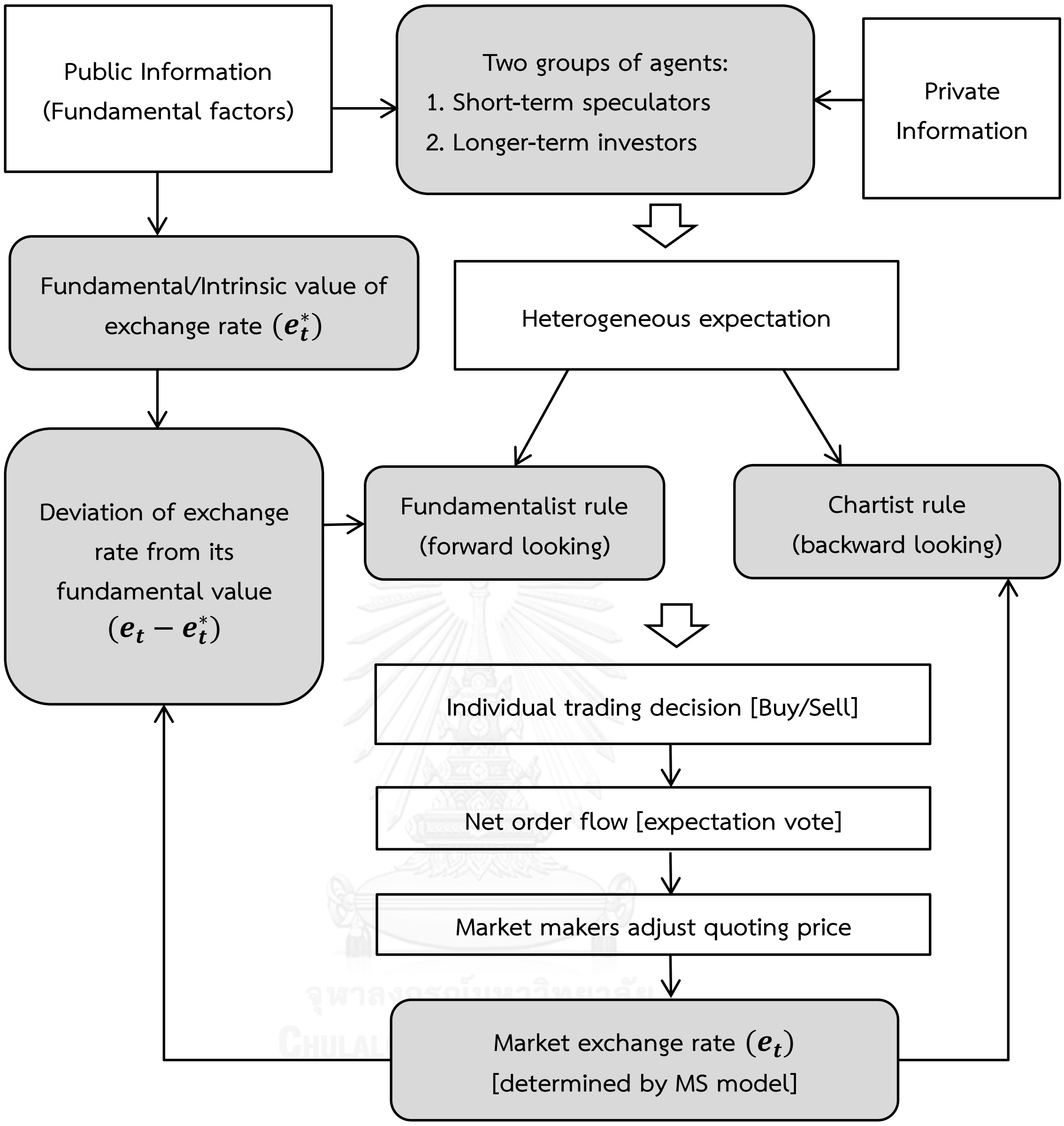

Figure 4 Conceptual framework of this study

According to DeGrauwe & Grimaldi (2006), a fundamental equilibrium occurs when both chartists and fundamentalists coexist in the market. In this equilibrium, the market exchange rate does not exhibit large deviations from its fundamental value. However, a non-fundamental equilibrium occurs when there are only chartists in the market. In this equilibrium, the market exchange rate may deviate considerably from its fundamental value. Therefore, exchange rate volatility should be low in the fundamental equilibrium case and high in the non-fundamental equilibrium case.

However, studies such as Vigfusson (1997), Ahrens & Reitz (2005), and Li (2008) observe conflicting empirical results of high volatility under the fundamentalist regime and low volatility under the chartist regime, which cannot be clarified. States of equilibrium are likely not defined by the use of chartist or fundamentalist expectations exclusively.

Since the two states of a Markov switching (MS) model are unobservable and arbitrary, this study allows both short-term speculators and longer-term investors to employ both chartist and fundamentalist expectations in both states. According to Levin (1997), when asset holders in the same group hold both chartist and fundamentalist expectations, the exchange rate can move along either a stable or an unstable path and may converge to or diverge from its long-run equilibrium value.

To address this issue, *the proposed model in this study is a Markov switching (MS) model based on a chartist-fundamentalist approach*. In line with HAM, we classify investors into two groups: short-term speculators and long-term investors. This study presumes that the expectation behaviour on exchange rate return of short-term speculators and longer-term investors should have impacts on the exchange rate differently. This presumption is to be confirmed by the estimation results.

For the estimation, we specify the MS model for each group of investors by allowing coexistence of both chartist and fundamentalist expectations in the same state.

1.3.3 The proposed model and hypotheses of this study

1.3.3.1 The proposed model

This study aims to develop a heterogeneous agent model based on a chartist-fundamentalist expectation approach for the daily exchange rate determination that yields intuitive interpretation on the expectation behaviors of the short-term speculators and the longer-term investors.

1.3.1.1.1 Short-term speculators and longer-term investor

One of the most important heterogeneity among individuals is the difference in their expectations. This study try to develop a Markov switching (MS) model based on *the chartist-fundamentalist expectation approach for the daily exchange rate in a new aspect by focusing on the different expectations between two groups of market agents, the short-term speculators and the longer-term investors. It is intuitive that the expectations and demand for foreign currency of these two groups should be quite different. If we estimate the MS model without separating these two groups, we may get confound results. In this study, we assume that the expectation behaviors of these two groups of agents are independent from each other. Actual movement of the daily exchange rate is the combined result of expectations by these two groups of market agents.*

We define the two groups of market participants as follows.

1) Short-term speculators: The short-term speculators here are defined as day traders who frequently buy and sell in search of their daily profits. Therefore, they focus and monitor closely on the up-and-down swings of the daily exchange rate movements to look for trading opportunity every day.

2) Longer-term investors. For the longer-term investors, they are defined as other market agents who are not day traders. They have longer-term expectations and investment horizons. We assume that these investors base their trades on estimates of fundamental value of an exchange rate and expect that the market exchange rate should return to its fundamental value. Besides, they may also use some chartist strategies to formulate their expectations in search of profits from the long-term movement of the daily exchange rate as well.

In this study, we aim to develop a model that describes the expectation behaviors of each group of agents but we do not have actual data. Since we know the nature that the short-term speculators only focus on the daily swings of exchange rate movement while the longer-term investors consider the longer term movement of an exchange rate, we need a tool to decompose the actual exchange rate data to be the results of the expectations by the short-term speculators and the longer-term investors. Since we assume that the expectations between these two groups are independent, this study adapts the *Hodrick-Prescott (HP) filter*[8] to decompose the series of an exchange rate into two components:

1) *The cyclical series as a representative of the exchange rate movement resulted by the short-term speculators' expectation, and*

2) *The smoothed series as a representative of the exchange rate movement expected by the longer-term investors.*

The HP filter, a smoothing method developed by Hodrick & Prescott (1997), is widely used among macroeconomists, especially for business-cycle studies. This filter produces a smoothed series (g_t) and cyclical series (c_t) for any time-series y_t by minimizing the following objective function:

$$\sum_{t=1}^{T} c_t{}^2 + \lambda \sum_{t=1}^{T} ((g_t - g_{t-1}) - (g_{t-1} - g_{t-2}))^2 \qquad (6)$$

where y_t is the original time-series data for the period of 1 to *T*,

g_t is the smoothed series from the HP filter,

c_t is the cyclical series from the HP filter, and

λ is the penalty parameter, which is a positive value controlling the smoothness of the series g_t. The larger the λ value, the smoother is the series g_t.[9]

Applying to this study, y_t, c_t,and g_t correspond to the actual market exchange rate, the exchange rate expected by short-term speculators, and the exchange rate expected by longer-term investors, respectively. Therefore, the cyclical series of exchange rate (*LN_FX_CY*) represents the exchange rate expectation by short-term

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[8] Other techniques such as a moving average method may be considered as alternatives for this decomposition purpose. This study uses of HP filter method because it assumes that the cyclical series and smoothed series are independent which is in line with an assumption in this study.

[9] If $\lambda \to 0$, there is only the first term of equation (6) left. The HP filter is to minimize $\sum_{t=1}^{T} c_t{}^2$ which is the same as Ordinary Least Square method (OLS) estimation of g_t. If $\lambda \to \infty$, only the second term of equation (6) is significant. The HP filter is to minimize the second term which means that the second term should be zero or g_t should be a straight line.

speculators and the smoothed series of exchange rate (*LN_FX_SM*) represents the exchange rate expectation by longer-term investors.

Since there is no common criterion to pre-determine the value of lambda (λ) used in the HP filtering for our purpose of separating the very short-term expectation and the longer-term expectation, we arbitrarily choose a small value of lambda (λ), such as 100. The decomposition indicates that the cycle series predominantly captures the standard deviation while the trend series mainly captures the mean value of percentage change in exchange rate of the original series, which are quite intuitive expectations for these two different types of agents. However, the appropriate value of lambda (λ) should be the value that reflects the daily movements of an exchange rate resulted by expectations of the short-term speculators and the longer-term investors. In a robustness check of this study, we vary values of the lambda (λ) and analyze impacts on the estimated MS models.

Short-term speculators

The short-term speculators are day traders who seek daily profits from up-and-down swings of the daily exchange rate dynamics. They may use either a momentum or a reversal rule to determine their trading strategies in every day. In this way, their expectations should mainly based on the chartist rules.

Furthermore, we conjecture that the exchange rate expectation behavior of the short-term speculators depends on the market situation and environment as well. For example, when the foreign exchange market has high-volatility, the short-term speculators may expect more aggressive exchange rate movements than those when the foreign exchange market has low-volatility. However, the actual state of the market that changes the short-term speculators expectation behaviors is assumed to be unobservable.

In this study, we assume that there are two different unobservable states of the market which can change the short-term speculator expectation behaviors. To setup a model with no constraint, we allow the short-term speculators to use a chartist or a fundamentalist rule or both rules to form their expectations in each state. Thus, the daily exchange rate movement at time t expected by the short-term speculators at time t-1 can be written as:

$$E_{t-1}^{CY}[dln(FX)_t^{CY}] = \delta_{0,j}^{CY} + \delta_{c,j}^{CY}(dln(FX)_{t-1}^{CY}) + \delta_{f,j}^{CY}(dev(FX)_{t-1}) + \varepsilon_{j,t}^{CY}, \text{ if } S_t^{CY} = j \quad (7)$$

where

$E_{t-1}^{CY}[.]$ denotes expectation at time t-1 by the short-term speculators;

$dln(FX)_t^{CY}$ is the daily exchange rate movement at time t expected by the short-term speculators;

$S_t^{CY} = j$ is the state of the market that affects short-term speculator expectation behaviors, $j = \{1, 2\}$;

$\delta_{0,j}^{CY}$ is a constant term;

$\delta_{c,j}^{CY}$ is the coefficient of expectation on the daily exchange rate movement of the short-term speculators based on their past expectations (a chartist rule) for the state $S_t^{CY} = j$, where $\delta_{c,j}^{CY} > 0$ for a momentum rule and $\delta_{c,j}^{CY} < 0$ for a reversal rule;

$dln(FX)_{t-1}^{CY}$ is the daily exchange rate movement at time t-1 expected by the short-term speculators;

$\delta_{f,j}^{CY}$ is the coefficient of expectation on the daily exchange rate movement of the short-term speculators based on the deviation of actual from fundamental value of an exchange rate (a fundamentalist rule) for the state $S_t^{CY} = j$, where $\delta_{f,j}^{CY} < 0$;

$dev(FX)_{t-1}$ is the deviation of actual from fundamental exchange rate at time t-1

$\varepsilon_{j,t}^{CY}$ is a stochastic error term of the expectation function of the short-term speculators which varies in time and depends on the state perceived by the short-term speculators, assuming that $\varepsilon_{j,t}^{CY} \sim N(0, \sigma_{CY,j}^2)$.

The excess demand for foreign currency of the short-term speculators is a function of their expectations on the daily exchange rate movement and can be written as follows.

$$D_t^{CY} = h_t^{CY}(E_{t-1}^{CY}[dln(FX)_t^{CY}]) \tag{8}$$

where

D_t^{CY} is the excess demand for foreign currency of the short-term speculators and is a function of their expectation on the change in exchange rate.

$h_t^{CY}(.)$ is a monotonic increasing function which disappears at zero.

Longer-term investors

The longer-term investors do not pay much attention to the daily fluctuation of an exchange rate. Assuming that the longer-term investors base their trades on estimates of fundamental value of an exchange rate, they expect for a reversion of a market exchange rate to its fundamental value. This means that if a foreign currency is now over-priced (under-priced), the longer-term investors expect that the foreign currency will depreciate (appreciate). In addition, the longer-term investors may use some chartist rules to form their expectations in search of profits from the long-term movement of the daily exchange rate as well.

Similar to that of the short-term speculators, we conjecture that the expectation behavior of the longer-term investors also depend on the market situation and environment. For example, when there is no limit to arbitrage, the longer-term investors should expect for the mean reversion to its fundamental value faster than when there are some limits to arbitrage in the market. However, the actual states that change the longer-term investor expectation behaviors may be complicated and are unobservable.

In this study, we assume that there are two different unobservable states of the market which can change the longer-term investor expectation behaviors. Hence, the daily exchange rate movement at time t expected by the longer-term investors at time t-1 can be written as:

$E_{t-1}^{SM}[dln(FX)_t^{SM}] = \delta_{0,l}^{SM} + \delta_{c,l}^{SM}\left(dln(FX)_{t-1}^{SM}\right) + \delta_{f,l}^{SM}(dev(FX)_{t-1}) + \varepsilon_{l,t}^{SM}$, if $S_t^{SM} = l$ (9)

where

$E_{t-1}^{SM}(.)$	denotes expectation at time t-1 by the longer-term investors;
$dln(FX)_t^{SM}$	is the daily exchange rate movement at time t expected by the longer-term investors;
$S_t^{SM} = l$	is the state of the market perceived by the longer-term investors that affects their expectation behaviors, $l = \{1, 2\}$;
$\delta_{0,l}^{SM}$	is a constant term;
$\delta_{c,l}^{SM}$	is the coefficient of expectation on the daily exchange rate movement of the longer-term investors based on their past expectations (a chartist rule) for the state $S_t^{SM} = l$, where $\delta_{c,l}^{SM} > 0$ for a momentum rule and $\delta_{c,l}^{SM} < 0$ for a reversal rule;
$dln(FX)_{t-1}^{SM}$	is the daily exchange rate movement at time t-1 expected by the longer-term investors;
$\delta_{f,l}^{SM}$	is the coefficient of expectation on the daily exchange rate movement of the longer-term investors based on the deviation of actual from fundamental value of an exchange rate (a fundamentalist rule) for the state $S_t^{SM} = l$, where $\delta_{f,l}^{SM} < 0$;
$dev(FX)_{t-1}$	is the deviation of actual from fundamental exchange rate at time t-1

$\varepsilon_{l,t}^{SM}$	is a stochastic error term of the expectation function for the longer-term investors which varies in time and depends on the state perceived by the longer-term investors, assuming that $\varepsilon_{l,t}^{SM} \sim N(0, \sigma_{SM,l}^2)$.

The excess demand for foreign currency of the longer-term investors is a function of their expectations on the daily exchange rate movement and can be written in an equation as follows.

$$D_t^{SM} = h_t^{SM}(E_{t-1}^{SM}[dln(FX)_t^{SM}]) \tag{10}$$

where

D_t^{SM}	is the excess demand for foreign currency of the longer-term investors and is a function of their expectation on the change in exchange rate.
$h_t^{SM}(.)$	is a monotonic increasing function which disappears at zero.

<u>Market exchange rate</u>

Beja & Goldman (1980) study on "the dynamic behavior of prices in disequilibrium" and explain that price changes are driven by excess demands of market participants. In the same spirit, we can write the market exchange rate equation as follows.

$$dln(FX)_t = H_t(D_t^{CY} + D_t^{SM}) \tag{11}$$

where

$dln(FX)_t$	is the daily market exchange rate movement at time t;
$H_t(.)$	is a monotonic increasing function which disappears at zero.

From equations (8), (10), (11), we have

$$dln(FX)_t = H_t(h_t^{CY}(E_{t-1}^{CY}[dln(FX)_t^{CY}]) + h_t^{SM}(E_{t-1}^{SM}[dln(FX)_t^{SM}])) \tag{12}$$

By using a first order approximation to equation (12), then we have

$$dln(FX)_t = a(E_{t-1}^{CY}[dln(FX)_t^{CY}]) + b(E_{t-1}^{SM}[dln(FX)_t^{SM}]) \quad (13)$$

where

a and b are non-negative constants which we are assumed to be time invariant.

Substitute equations (7) and (9) into (13), Then we have *the daily market exchange rate return at time t* as:

$$dln(FX)_t = a\{\delta_{0,j}^{CY} + \delta_{c,j}^{CY}(dln(FX)_{t-1}^{CY}) + \delta_{f,j}^{CY}(dev(FX)_{t-1}) + \varepsilon_{j,t}^{CY}\} + b\{\delta_{0,l}^{SM} + \delta_{c,l}^{SM}(dln(FX)_{t-1}^{SM}) + \delta_{f,l}^{SM}(dev(FX)_{t-1}) + \varepsilon_{l,t}^{SM}\}$$

if $S_t^{CY} = j$ and $S_t^{SM} = l$

or

$$dln(FX)_t = \{a\delta_{0,j}^{CY} + a\delta_{c,j}^{CY}(dln(FX)_{t-1}^{CY}) + a\delta_{f,j}^{CY}(dev(FX)_{t-1}) + a\varepsilon_{j,t}^{CY}\} + \{b\delta_{0,l}^{SM} + b\delta_{c,l}^{SM}(dln(FX)_{t-1}^{SM}) + b\delta_{f,l}^{SM}(dev(FX)_{t-1}) + b\varepsilon_{l,t}^{SM}\}$$

if $S_t^{CY} = j$ and $S_t^{SM} = l.$ (14)

Consequently, this model can be estimated by employing two independent Markov switching models: one is for the change in market exchange rate contributed by the short-term speculator expectations and the other one is for the change in market exchange rate contributed by the longer-term investor expectations, as illustrated in Figure 5.

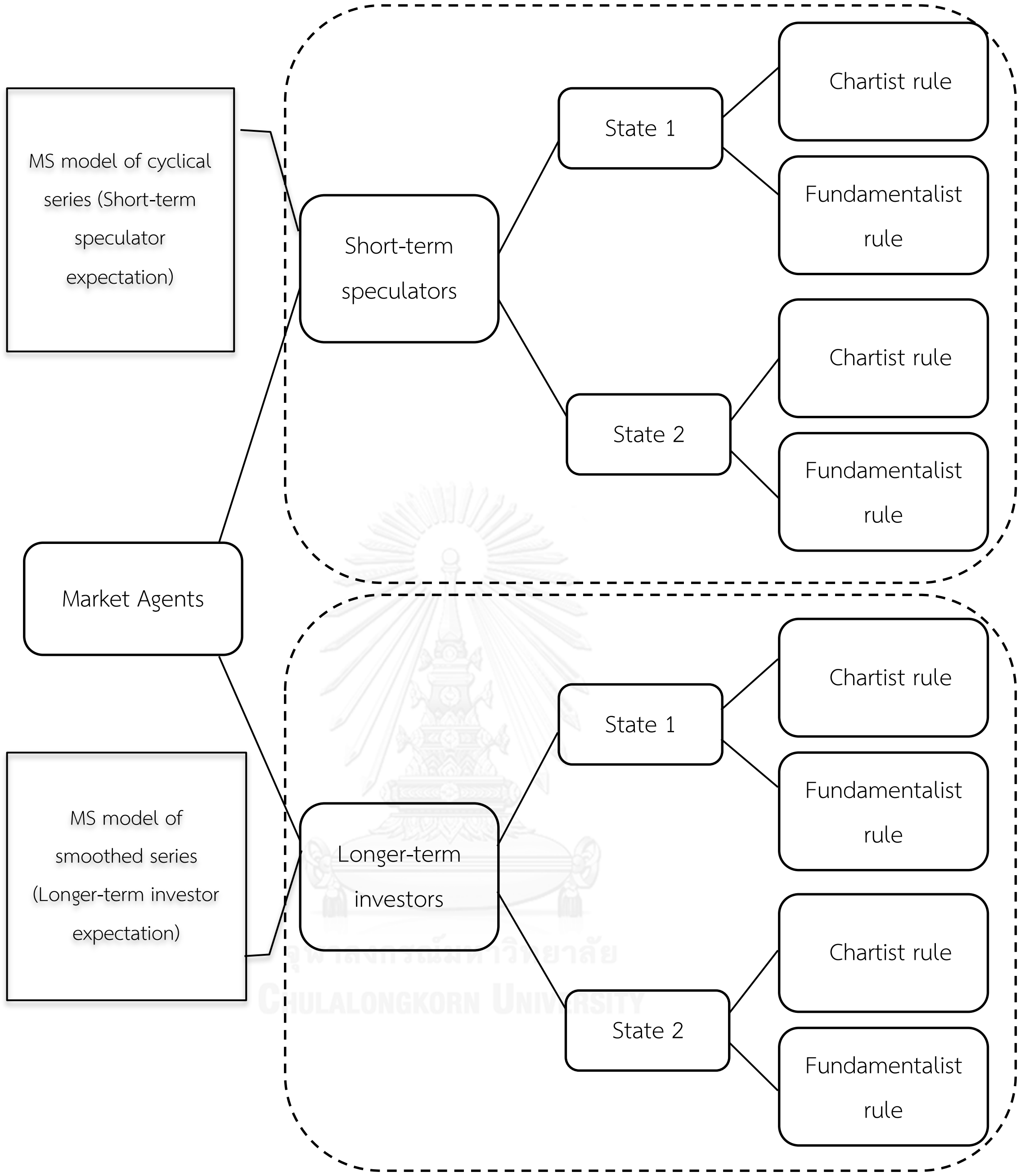

Figure 5 The structure of MS models for daily exchange rate return

1.3.3.1.2 The proposed Markov switching (MS) models

Let $dln(FX)_t^{CY}$ be the daily exchange rate return contributed by the short-term speculator expectations and $dln(FX)_t^{SM}$ be the daily exchange rate return contributed by the longer-term investor expectations for any currency pair. The proposed Markov switching (MS) models representing the daily exchange rate return contributed by the expectations of these two groups of agents can be written as follows.

1. **A Markov switching (MS) model for daily exchange rate return contributed by short-term speculator expectations:**

$$dln(FX)_t^{CY} = \alpha_{0j}^{CY} + \alpha_{cj}^{CY}[dln(FX)_{t-1}^{CY}] + \alpha_{fj}^{CY}[dev(FX)_{t-1}] + \epsilon_{jt}^{CY}\text{, if } S_t^{CY} = j \quad (15)$$

where

$dln(FX)_t^{CY}$ is daily exchange rate return at time t contributed by short-term speculator expectations;

$S_t^{CY} = j$ is the state of the market perceived by the short-term speculators that affects their expectation behaviors, $j = \{1,2\}$;

$\alpha_{0j}^{CY} = a\delta_{0,j}^{CY}$ is a constant term if $S_t^{CY} = j$;

$\alpha_{cj}^{CY} = a\delta_{c,j}^{CY}$ is a parameter reflecting the impact of chartist expectation on the daily exchange rate movement contributed by short-term speculator expectations if $S_t^{CY} = j$. The expected sign of this coefficient is either positive or negative $(\alpha_{cj}^{CY} > 0 \; or \; < 0)$ depending on the majority of short-term speculators employ a momentum or a reversal strategy;

$dln(FX)_{t-1}^{CY}$ is daily exchange rate return at time t-1 contributed by short-term speculator expectations;

$\alpha_{fj}^{CY} = a\delta_{f,j}^{CY}$ is a parameter reflecting the impact of fundamentalist expectation on the daily exchange rate return expected by the short-term speculators if $S_t^{CY} = j$. The expected sign of this coefficient is negative $(\alpha_{fj}^{CY} < 0)$ because fundamentalist expectation is the belief in a mean-reversion to the fundamental value;

$dev(FX)_{t-1}$ is the deviation of actual from fundamental value of the logarithm of the exchange rate on the previous day,

$\epsilon_{jt}^{CY} = a\varepsilon_{j,t}^{CY}$ denotes the stochastic error term in state j at time t; where $\epsilon_{jt}^{CY} \sim N\left(0, \sigma^{2}{}_{j}^{CY}\right)$ if $S_t^{CY} = j$;

$\sigma^{2}{}_{j}^{CY}$ is the variance of the residuals of this equation in state j.

2. **A Markov switching (MS) model for daily exchange rate return contributed by longer-term investor expectations:**

$$dln(FX)_t^{SM} = \alpha_{0l}^{SM} + \alpha_{cl}^{SM}[dln(FX)_{t-1}^{SM}] + \alpha_{fl}^{SM}[dev(FX)_{t-1}] + \epsilon_{lt}^{SM}\text{, if } S_t^{SM} = l \quad (16)$$

where

$dln(FX)_t^{SM}$ is daily exchange rate return at time t contributed by longer-term investor expectations;

$S_t^{SM} = l$ is the state of the market perceived by the longer-term investors that affects their expectation behaviors, $l = \{1, 2\}$;

$\alpha_{0l}^{SM} = b\delta_{0,l}^{SM}$ is a constant term if $S_t^{SM} = l$;

$\alpha_{cl}^{SM} = b\delta_{c,l}^{SM}$ is a parameter reflecting the impact of chartist expectation on the daily exchange rate return expected by the longer-term investors if $S_t^{SM} = l$. The expected sign of this coefficient is either positive or negative $(\alpha_{cl}^{SM} > 0 \; or \; < 0)$ depending on the majority of longer-term investors employ a trend following or a reversal strategy;

$dln(FX)_{t-1}^{SM}$ is daily exchange rate return at time t-1 contributed by longer-term investor expectations;

$\alpha_{fl}^{SM} = b\delta_{f,l}^{SM}$ is a parameter reflecting the impact of fundamentalist expectation on the daily exchange rate return expected by the longer-term investors if $S_t^{SM} = l$. The expected sign of this coefficient is negative $(\alpha_{fl}^{SM} < 0)$ because fundamentalist expectation is the belief in a mean-reversion to the fundamental value;

$dev(FX)_{t-1}$ is the deviation of actual from fundamental value of the logarithm of the exchange rate on the previous day,

$\epsilon_{lt}^{SM} = b \cdot \varepsilon_{l,t}^{SM}$ denotes the stochastic error term in state l at time t; where $\epsilon_{lt}^{SM} \sim N\left(0, {\sigma^2}_l^{SM}\right)$ if $S_t^{SM} = l$.

${\sigma^2}_l^{SM}$ is the variance of the residuals of this equation in state l,

1.3.3.1.3 Hypotheses of this study

According to the derivation of the proposed Markov switching (MS) models, we can set the four hypotheses of this study as follows.

For short-term speculators, they frequently buy and sell currencies in the market in search of daily profits. Their predominant trading rule should be a chartist rule.

<u>Hypothesis I</u>: For a parameter reflecting the impact of chartist expectation on the daily exchange rate return contributed by the short-term speculator expectations, the coefficient estimates are statistically significant in both states while the expected sign can be either positive or negative depending on the majority of short-term speculators employ a momentum or a reversal strategy. $(\alpha_{cj}^{CY} \neq 0)$

Since the short-term speculators take opportunities to make their profits from up and down swings of the daily exchange rate, their expectation behaviors should depend on whether the exchange rate volatility in the market is high or low. For example, in the state which has high-volatility of exchange rate, the short-term speculators should expect more aggressive changes in exchange rate than in the other state which has low-volatility of exchange rate. Therefore, the exchange rate volatilities in the two states which affect the expectation behavior of short-term speculators should be different.

<u>Hypothesis II</u>: The standard deviations of the residuals in the MS model of daily exchange rate contributed by short-term speculator expectations are not equal between the two states($\sigma_1^{CY} \neq \sigma_2^{CY}$).

For the other group of agents, longer-term investors, they should incorporate both long-term trends and fundamental factors into their decisions. Thus, it is expected that they employ both chartist and fundamentalist rules to form their expectations. When the market exchange rate moves away from its fundamentals, long-term investors expect to observe mean reversion.

<u>Hypothesis III</u>: For a parameter reflecting the impact of chartist expectation on the daily exchange rate return contributed by the longer-term investor expectations, the coefficient estimates are statistically significant in both states while the expected sign can be either positive or negative depending on the majority of short-term speculators employ a momentum or a reversal strategy. ($\alpha_{cl}^{SM} \neq 0$)

<u>Hypothesis IV</u>: For a parameter reflecting the fundamentalist expectation on the daily exchange rate return expected by the longer-term investors, the coefficient estimates are statistically significant in both states while the expected sign is negative because they believe in the mean-reversion to the fundamental value. ($\alpha_{fl}^{SM} < 0$)

Most of the time, there are both short-term speculators and longer-term investors in the market. Therefore, both types of expectations, chartist and fundamentalist rules, should always play their roles. The impact of chartist and fundamentalist factors on exchange rate dynamics can change over time depending on changing in market condition and environment. Along these lines, it is interesting to investigate the impact of chartist and fundamentalist expectations held by both short-term speculators and longer-term investors on the daily exchange rate dynamics.

1.3.3.1.4 Expected daily exchange rate return

Since S_t^{CY} and S_t^{SM} which represent the states at time *t* perceived by the short-term speculators and the longer-term investors are unobservable, we can utilize the probability of being in each state given by the information available up to time *t-1* to calculate the expected daily exchange rate return contributed by the short-term speculators and the longer-term investors as follows:

$$E_{t-1}[dln(FX)_t^{CY}] = P(S_t^{CY} = 1|I_{t-1}) * \{\alpha_{01}^{CY} + \alpha_{c1}^{CY}[dln(FX)_{t-1}^{CY}] + \alpha_{f1}^{CY}[dev(FX)_{t-1}]\} + P(S_t^{CY} = 2|I_{t-1}) * \{\alpha_{02}^{CY} + \alpha_{c2}^{CY}[dln(FX)_{t-1}^{CY}] + \alpha_{f2}^{CY}[dev(FX)_{t-1}]\} \quad (17)$$

$$E_{t-1}[dln(FX)_t^{SM}] = P(S_t^{SM} = 1|I_{t-1}) * \{\alpha_{01}^{SM} + \alpha_{c1}^{SM}[dln(FX)_{t-1}^{SM}] + \alpha_{f1}^{SM}[dev(FX)_{t-1}]\} + P(S_t^{SM} = 2|I_{t-1}) * \{\alpha_{02}^{SM} + \alpha_{c2}^{SM}[dln(FX)_{t-1}^{SM}] + \alpha_{f2}^{SM}[dev(FX)_{t-1}]\} \quad (18)$$

$$E_{t-1}[dln(FX)_t] = E_{t-1}[dln(FX)_t^{CY}] + E_{t-1}[dln(FX)_t^{SM}] \quad (19)$$

where $E_{t-1}[dln(FX)_t]$ is daily exchange rate return for time t expected at time t-1,

I_{t-1} is the information set until time *t-1*.

Besides the two key explanatory variables, chartist and fundamentalist rules, other control variables for the proposed Markov switching model are also taken into the consideration, i.e., global risk factors and monetary policy variables. This study considers two global risk indicators: changes in the Chicago Board Options Exchange's volatility index (*DVIX*) and the rates of return in the MSCI global equity index (*DLN_MSCI*). Monetary policy variables include foreign exchange market interventions by the ministry of finance (MOF) of Japan[10] (only for *JPY_USD*) and quantitative easing (QE) policies implemented by the central bank of each country (for *EUR_USD, GBP_USD,* and *JPY_USD*) and by the Federal Reserve of the United States.

1.3.3.1.5 Two alternative Markov Switching models

<u>MS model with time-varying transition probabilities (TVTP):</u>

Intuitively, whether the exchange rate market is stable or unstable should be determined by the market conditions at that point of time. Here, the transition

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[10] This variable is the value, measured in billions JPY, of the ministry of finance (MOF) of Japan interventions in the market by buying US dollars and selling Japanese yen to depreciate the yen. Thus, the expected relationship between this variable and the exchange rate movement is positive.

probabilities are assumed to vary over time and to be determined endogenously by the latest absolute deviation from the long-run equilibrium of the market exchange rate $(|dev(FX)_{t-1}|)$. The market should have a high probability of switching states if the exchange rate is highly over-valued or under-valued.

In this study, the transition probabilities are assumed to be logistic functions that assume value in the interval [0, 1]. Let $X'_{t-1} = (1, |dev(FX)_{t-1}|)$, the transition probabilities from state i to state j (P_t^{ij}) can be written as:

$$P_t^{ij} = \frac{exp(X'_{t-1}\beta_i)}{1+ exp(X'_{t-1}\beta_i)} \tag{20}$$

where β_i are the vector of parameters of the logistic function for switching from state i to state j.

We then estimate an MS Model with time-varying transition probabilities by adding the estimated parameters, β_1 and β_2.

<u>MS model with constant transition probabilities (CP):</u>

We also consider a simple MS model with constant transition probabilities (CP) with a transition probability matrix that can be written as follows:

$$\pi = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} \tag{21}$$

where P_{ij}= the transition probability from state *i* to state *j*, which is constant over time.

1.3.3.1.6 A fundamental exchange rate model: Purchasing Power Parity (PPP)

For the fundamental exchange rate determination, this study adopts the Purchasing Power Parity (PPP) model as a result of an intensive review on an issue of the PPP conducted by Taylor & Taylor (2004) concludes that exchange rates do revert to the PPP equilibrium over the long-run.

Under the PPP theory, the exchange rate between two currencies is the rate that equates the prices of goods and services in the two countries. In practice, we utilize price indices rather than the actual prices of goods and services. However, for this empirical study, we allow the price indices' coefficients may not equal to one. This may be possible as a result of differences in the composition of tradable and non-tradable goods and transaction costs incurred during trade between two countries. Let e_t be the nominal exchange rate of a domestic currency vis-à-vis one unit of a foreign currency, p_t be the domestic price of goods and services, p_t^* be the foreign price of goods and services, and ϵ_t be a stochastic error term. An empirical-study version of the PPP model in this study is:

$$ln\, e_t = \beta_0 + \beta_1 ln\, p_t - \beta_2 ln\, p_t^* + \epsilon_t \tag{22}$$

1.4 Data and methodology

1.4.1 Sample and data

This study utilizes daily data for the empirical study as it is common denominator for an application to both chartist and fundamentalist expectations of short-term speculators and longer-term investors in the proposed model. For the selected exchange rates, we investigate the five most traded currency pairs in 2013, i.e., US dollar/euro, US dollar/yen, US dollar/sterling, US dollar/Australian dollar, and US dollar/Canadian dollar. As shown in Table 1, these currency pairs represented 61.7% of the daily average turnover in the global foreign exchange market in April 2013. The period of study ranges from January 1999 to June 2013, which reflects the most recent exchange rate system, including the introduction of the euro and adoption of managed float regimes in several developing countries. This period also includes the recent global financial crisis, which is appropriate for examining the suggested MS model in both stable and unstable currency market states.

Table 1 Global foreign exchange market turnover by currency pair in 2013

Currency pair	Daily averages in April, in billions of USD	%
US dollar/euro	1,289	24.1
US dollar/yen	978	18.3
US dollar/sterling	472	8.8
US dollar/Australian dollar	364	6.8
US dollar/Canadian dollar	200	3.7
US dollar/Swiss franc	184	3.4
Euro/yen	147	2.8
US dollar/Mexican peso	128	2.4
US dollar/Chinese yuan	113	2.1
Euro/sterling	102	1.9
Other currency pairs	1,368	25.6
All currency pairs	**5,345**	**100.0**

Source: 2013 Triennial Central Bank Survey, Bank for International Settlements

The main source for the empirical investigation[11] is the CEIC[12], except the VIX which stands for the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange, foreign exchange market intervention data from the Ministry of Finance Japan, and Quantitative Easing (QE) data, which are the daily amounts of outright asset purchases released by the central banks of the specified countries.

The daily exchange rate data used in this study are retrieved from the CEIC, although the original data is provided by the Board of Governors of the Federal Reserve System. These data are the noon buying rates in New York for cable transfers payable in the listed currencies. All monthly economic and financial data for fundamental exchange rate determination of the selected countries are collected from several countries and provided by the CEIC.

[11] EViews 8 is the software package employed in this study for the unit root test, variance ratio test, ordinary least squares (OLS) regression, and Markov switching model estimation.

[12] The CEIC data are from the databases of the CEIC Data Company Ltd, which provides financial and economic data for many emerging and developed markets.

Each exchange rate was transformed into currency units per one US dollar and calculated as an index with a base year 2011 (2011=100). Therefore, a currency is depreciated against the US dollar when its exchange rate index increases and vice versa. For the empirical study, all of the exchange rate variables are in the natural logarithm of the exchange rate indices multiplied by 100, denoted by *LN_FX*. *"FX"* here represents an exchange rate for each of five currency pairs: *AUD/USD, CAD/USD, EUR/USD, GBP/USD,* and *JPY/USD*. The in-sample period of this study ranges from January 1999 to June 2012 and the out-of-sample period ranges from July 2012 to June 2013.

1.4.2 Research methodology

The research methodology of this study can be summarized in the following steps.

1. First, we estimate a fundamental exchange rate model based on the purchasing power parity (PPP) theory for each of the five selected exchange rates using monthly data for the exchange rates and relevant price indices. All dependent and explanatory variables are tested for their orders of integration. We then estimate the fundamental PPP exchange rates through ordinary least squares (OLS) regression. In addition, we also test for the residual stationarity to confirm the long-run relationship of the PPP model.
2. Next, the Hodrick-Prescott (HP) filter is utilized to decompose the natural logarithm of the exchange rate series (*LN_FX*) into two series: a cyclical component (*LN_FX_CY*) and a smoothed component (*LN_FX_SM*). The cyclical series represents the short-term speculator expectation while the smoothed series represents the longer-term investor expectation on the daily exchange rate dynamics.
3. For comparison purpose, we firstly estimate a linear model which has a chartist variable, *DLN_FX(-1)*, and a fundamentalist variable, *DEV_FX (-1)*, including some global risk indicators and monetary policy data as explanatory variables for cyclical and smoothed components of each daily exchange rate.

4. Lastly, a two-state Markov switching (MS) model is estimated for cyclical and smoothed components of each selected exchange rate. We estimate an MS model with both cases of time-varying transition probabilities (TVTP) and constant transition probabilities (CP). Then, we consider three selection criteria which are the Akaike information criterion, Hannan-Quinn criterion, and Schwarz criterion to compare the goodness of fit among various models. Additionally, we examine coefficient equalities between the two states of the proposed MS model by using the Wald test.

1.4.3 Estimating a Markov switching model

The Markov Switching (MS) model is estimated by the maximum likelihood method. As described by Diebold et al. (1994), define S_t = state 1 or state 2 at time t, let $\{S_t\}_{t=1}^{T}$ be the sample path of a 1st-order, two-state Markov chain with either constant or time-varying transition probabilities, and $\{e_t\}_{t=1}^{T}$ be the sample path of an exchange rate series depending on the state path, $\{S_t\}_{t=1}^{T}$.

Given the state, e_t is assumed to be identically distributed with normal distribution:

$$\left(e_t \middle| S_t = j;\ \alpha_j\right) \sim N(\mu_j, \sigma_j^2), \tag{23}$$

where $\alpha_j = \left(\mu_j, \sigma_j^2\right)'$, i = state 1 or 2.

In the case of time-varying transition probabilities, a set of explanatory variables, $X_{t-1}'\beta_i$, determines the probability of changing from state i to state j at time t.

Let $P(S_1 = 2) = \rho$, $\alpha = (\alpha_1', \alpha_2')'$, and $\beta = (\beta_1', \beta_2')'$

and let $\theta = (\alpha', \beta', \rho)'$ be a vector of all model parameters.

The complete-data likelihood in terms of *indicator functions* (I) can be written as

$$
\begin{aligned}
& f\left(e_{\_T}, S_{\_T} \middle| X_{\_T}; \theta\right) \\
& \quad = [I(S_1 = 2) f(e_1 | S_1 = 2; \alpha_2)\rho \\
& \quad + I(S_1 = 1) f(e_1 | S_1 = 1; \alpha_1)(1 - \rho)] \\
& \quad \times \prod_{t=2}^{T} \{I(S_t = 2, S_{t-1} \\
& \quad = 2) f(e_t | S_t = 2; \alpha_2) P_t^{22} \\
& \quad + \ I(S_t = 1, S_{t-1} \\
& \quad = 2) f(e_t | S_t = 1; \alpha_1)(1 - P_t^{22}) \\
& \quad + I(S_t = 2, S_{t-1} \\
& \quad = 1) f(e_t | S_t = 2; \alpha_2)(1 - P_t^{11}) \\
& \quad + I(S_t = 1, S_{t-1} = 1) f(e_t | S_t = 1; \alpha_1) P_t^{11}\}.
\end{aligned}
\tag{24}
$$

Note: The subscript _T denotes past history of the variable from t = 1 to t = T.

This equation can be written in the *logarithmic form* as follows:

$$
\begin{aligned}
& \log f\left(e_{\_T}, S_{\_T} \middle| X_{\_T}; \theta\right) \\
& \quad = I(S_1 = 2)[\log f(e_1 | S_1 = 2; \alpha_2) + \log \rho] \\
& \quad + I(S_1 = 1)[\log f(e_1 | S_1 = 1; \alpha_1) + \log(1 - \rho)] \\
& \quad + \sum_{t=2}^{T} \{I(S_t = 2) \log f(e_t | S_t = 2; \alpha_2) \\
& \quad + I(S_t = 1) \log f(e_t | S_t = 1; \alpha_1) \\
& \quad + I(S_t = 2, S_{t-1} = 2) \log P_t^{22} \\
& \quad + I(S_t = 1, S_{t-1} = 2) \log(1 - P_t^{22}) \\
& \quad + I(S_t = 2, S_{t-1} = 1) \log(1 - P_t^{11}) \\
& \quad + I(S_t = 1, S_{t-1} = 1) \log P_t^{11}\}.
\end{aligned}
\tag{25}
$$

Since the states are unobservable, the incomplete-data log likelihood can be used for the maximum likelihood method by summing over all possible state sequences:

$$
\log f\left(e_{\_T} \middle| X_{\_T}; \theta\right) = \log\left(\textstyle\sum_{S_1=1}^{2} \sum_{S_2=1}^{2} \dots \sum_{S_T=1}^{2} f(e_{\_T}, S_{\_T} | X_{\_T}; \theta)\right). \tag{26}
$$

This function will be maximized with respect to θ.

1.4.3 Forecasting an exchange rate by using a Markov switching model

For each of MS models for short-term speculators' expectation and for longer-term investors' expectation, we can forecast the expected change in exchange rate return by using the following forecasting procedure.

(1) The initial regime probabilities $(P(S_1 = j))$ which are the probabilities of falling into state 1 and state 2 in the first period are set to the ergodic (steady state) solutions by the EViews program.

(2) The conditional densities of an exchange rate (e_t) given state $S_t = j$ and the information set as of the previous period (I_0) in the first period denoted by $f(e_1|S_1 = 1, I_0;\ \theta)$ and $f(e_1|S_1 = 2, I_0;\ \theta)$ can be calculated from the following equations:

$f(e_1|S_1 = 1, I_0;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \cdot \exp\left\{\frac{-(e_1-\mu_1)^2}{2\sigma_1^2}\right\}$ and

$f(e_1|S_1 = 2, I_0;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \cdot \exp\left\{\frac{-(e_1-\mu_2)^2}{2\sigma_2^2}\right\}$.

Note: When there are explanatory variables in the information set I_{t-1} determining the expected value of an exchange rate given state, the value of μ_{1t} and μ_{2t} vary in time with its explanatory variables. In this study, $E_{t-1}[dln(FX)_t^{CY}]$ and $E_{t-1}[dln(FX)_t^{SM}]$ are functions of $dln(FX)_{t-1}^{CY}$ and $dln(FX)_{t-1}^{SM}$, respectively. Therefore, we need to update HP Filter every day before making a forecast on the next day.

(3) Then, we have $f(e_1|\ I_0;\ \theta)$ as:

$$\begin{aligned} f(e_1|\ I_0;\ \theta) & \\ &= f(e_1|S_1 = 1, I_0;\ \theta) \times P(S_1 = 1) \\ &+ f(e_1|S_1 = 2, I_0;\ \theta) \times P(S_1 = 2) \end{aligned}$$

where $P(S_1 = j)$ are the initial regime probabilities from step (1)

(4) The expected value of an exchange rate given state in the first period $E(e_1|S_1 = j, I_0;\ \theta)$ can be computed and denoted by μ_{11} and μ_{21}.

(5) Then, we have the expected value of an exchange rate in the first period of forecasting as:

$$E(e_1|\ I_0;\ \theta) = \mu_{11} \times P(S_1 = 1) + \mu_{21} \times P(S_1 = 2)$$

(6) The filtering probabilities of being in the state 1 and 2 in the first period can be updated as follows.

$$P(S_1 = 1|I_1;\ \theta) = \frac{f(e_1|S_1 = 1, I_0;\ \theta) \times\ P(S_1 = 1)}{f(e_1|\ I_0;\ \theta)}$$

$$P(S_1 = 2|I_1;\ \theta) = \frac{f(e_1|S_1 = 2, I_0;\ \theta)\ \times P(S_1 = 2)}{f(e_1|\ I_0;\ \theta)}$$

(7) Then, we can calculate the prediction probabilities for the next period as:

$$P(S_2 = j|I_1;\ \theta) = P(S_1 = 1, S_2 = j|I_1;\ \theta) + P(S_1 = 2, S_2 = j|I_1;\ \theta)$$
$$= P^{1j} \times P(S_1 = 1|I_1;\ \theta) + P^{2j} \times P(S_1 = 2|I_1;\ \theta)$$

where P^{1j} and P^{2j} are the transition probabilities from state 1 and 2 in this period to state j in the next period.

(8) The conditional densities of an exchange rate (e_t) given the state $S_t = j$ in the second period $(t = 2)$ denoted by $f(e_2|S_2 = 1, I_1;\ \theta)$ and $f(e_2|S_2 = 2, I_1;\ \theta)$ can be calculated similar to the step (2) from the following equations:

$$f(e_2|S_2 = 1, I_1;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \cdot \exp\left\{\frac{-(e_2-\mu_1)^2}{2\sigma_1^2}\right\} \text{ and}$$

$$f(e_2|S_2 = 2, I_1;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \cdot \exp\left\{\frac{-(e_2-\mu_2)^2}{2\sigma_2^2}\right\}.$$

(9) Instead of using the initial regime probabilities, now we calculate $f(e_2|\ I_1;\ \theta)$ by using the prediction probabilities from step (7) as:

$$f(e_2|\ I_1;\ \theta)$$
$$=\ f(e_2|S_2 = 1, I_1;\ \theta)\ \times P(S_2 = 1|I_1;\ \theta)$$
$$+\ f(e_2|S_2 = 2, I_1;\ \theta) \times\ P(S_2 = 2|I_1;\ \theta)$$

(10) Similar to the step (4), we compute the expected value of an exchange rate given the state in the second period $E(e_2|S_2 = j, I_1;\ \theta)$ and denoted by μ_{12} and μ_{22}.

(11) Then, we have the expected value of an exchange rate in the second period by using the prediction probabilities from step (7) as:

$$E(e_2|\ I_1;\ \theta) =\ \mu_{12} \times\ P(S_2 = 1|I_1;\ \theta) +\ \mu_{22} \times\ P(S_2 = 2|I_1;\ \theta)$$

(12) Next, the filtering probabilities of being in the state 1 and 2 in the second period can be updated as follows.

$$P(S_2 = 1|I_2;\ \theta) = \frac{f(e_2|S_2 = 1, I_1;\ \theta) \times\ P(S_2 = 1|I_1;\ \theta)}{f(e_2|\ I_1;\ \theta)}$$

$$P(S_2 = 2|I_2;\ \theta) = \frac{f(e_2|S_2 = 2, I_1;\ \theta)\ \times P(S_2 = 2|I_1;\ \theta)}{f(e_2|\ I_1;\ \theta)}$$

(13) All the steps from step (7) to (12) can be done recursively to forecast an exchange rate in the following periods until time T.

1.4.5 Forecasting performance tests

The standard statistical performance measures used in many studies and adopted in this study are the root-mean-squared error (RMSE), the mean-absolute error (MAE), and the percentage of correct sign predictions. The performance of the proposed model is compared to a random walk model.

1.5 Empirical results and discussion

1.5.1 Fundamental exchange rates

The fundamental exchange rates of the five major currency pairs, *AUD/USD, CAD/USD, EUR/USD, GBP/USD, JPY/USD,* are determined by the purchasing power parity (PPP) model[13]. Comparisons between the actual and fundamental exchange rates of the five selected currency pairs are displayed in Figure 6. The deviation of an exchange rate can be computed by subtracting the actual exchange rates from its PPP value. Although the PPP series of an exchange rate utilize monthly data, the actual daily exchange rate series minus monthly PPP exchange rate series provides the daily data of deviation of actual exchange rates from its fundamental value, assuming that the fundamental value of an exchange rate is the same each month.

[13] Results of PPP fundamental models for the selected exchange rates are in Appendix B.

Figure 6 Actual and fundamental values of the selected exchange rates

1.5.2 Descriptive statistics of daily exchange rate returns

Descriptive statistics

This study develops Markov switching models of daily exchange rates to describe the expectation behaviors of short-term speculators and of longer-term investors based on a chartist-fundamentalist approach. The main assumptions are that the behaviors of short-term speculators and longer-term investors are independent and investors who use a fundamentalist strategy know the fundamental value of an exchange rate. Descriptions of variables in this empirical study are presented in Appendix A.

<u>Variance ratio test</u>

For daily exchange rate data, *all of the LN_FX variables for the five selected exchange rates are integrated of order one and have non-normal distribution.* Furthermore, under the variance ratio tests, *we cannot reject the null hypothesis of a martingale*[14] *for all LN_FX variables*. When daily exchange rate series is a martingale, the expected value of an exchange rate tomorrow is the same as that of today. Thus, it is unsurprising that predicting daily exchange rate movement is a very difficult task. *So the random walk model should be used as a benchmark for the proposed model.* The first differences of all of the *LN_FX* variables or the *DLN_FX* variables are integrated of order zero. The descriptive statistics of the *DLN_FX* variables are presented in Table 2.

<u>Cyclical and smoothed series</u>

After decomposing the *LN_FX* variable for each daily exchange rate into two components - cyclical and smoothed components - we obtain the *LN_FX_CY* and *LN_FX_SM* series. We then calculate the daily changes in the cyclical and smoothed series to obtain *DLN_FX_CY* and *DLN_FX_SM,* which are described in Table 3 and Table 4.

It should be noted that the daily changes in the smoothed series, *DLN_FX_SM*, have higher mean values but lower standard deviations than the daily changes in the cyclical series, *DLN_FX_CY*. In other words, the cyclical series which represents the expectation of short-term speculators mainly capture the volatility of daily exchange rate movement while the smoothed series which represents the expectation of longer-term investors mainly capture the size and direction of daily exchange rate movement.

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[14] The results of the variance ratio tests are presented in Appendix C.

Table 2 Descriptive statistics of the daily changes in the original series

DLN_FX	AUD_USD	CAD_USD	EUR_USD	GBP_USD	JPY_USD
Mean	(0.0149)	(0.0119)	(0.0021)	0.0016	(0.0100)
Median	(0.0406)	(0.0088)	0.0000	(0.0050)	(0.0094)
Maximum	8.2120	3.8070	3.0031	4.9662	3.2361
Minimum	(7.7035)	(5.0716)	(4.6208)	(4.4349)	(4.4086)
Std. Dev.	0.8763	0.6006	0.6560	0.6050	0.6696
Skewness	0.6611	(0.0678)	(0.1220)	0.2456	(0.2580)
Kurtosis	14.6151	8.8507	5.0555	8.1750	6.1233
Observations	3389	3389	3389	3389	3389

This table presents the descriptive statistics of the daily changes in the original series of the natural logarithm of exchange rate indices for the selected currency pairs.

Table 3 Descriptive statistics of the daily changes in the cyclical series

DLN_FX_CY	AUD_USD	CAD_USD	EUR_USD	GBP_USD	JPY_USD
Mean	(0.0006)	(0.0004)	(0.0002)	(0.0001)	(0.0002)
Median	(0.0137)	0.0018	0.0168	(0.0062)	0.0060
Maximum	6.8656	3.4788	3.4516	4.3396	3.0711
Minimum	(8.7108)	(4.9626)	(4.0586)	(4.7557)	(4.3196)
Std. Dev.	0.8169	0.5571	0.6063	0.5612	0.6261
Skewness	0.0897	(0.2927)	(0.1758)	(0.0466)	(0.1782)
Kurtosis	14.8760	9.3834	4.9648	8.1239	6.0582
Observations	3389	3389	3389	3389	3389

This table presents the descriptive statistics of the daily changes in the cyclical series of the natural logarithms of the exchange rate indices of the selected currency pairs.

Table 4 Descriptive statistics of the daily changes in the smoothed series

DLN_FX_SM	AUD_USD	CAD_USD	EUR_USD	GBP_USD	JPY_USD
Mean	(0.0143)	(0.0116)	(0.0019)	0.0017	(0.0099)
Median	(0.0318)	(0.0197)	(0.0081)	(0.0030)	(0.0117)
Maximum	1.8520	1.2441	0.6790	0.8572	0.6701
Minimum	(0.7680)	(0.6564)	(0.9778)	(0.6010)	(0.5313)
Std. Dev.	0.2431	0.1679	0.1947	0.1717	0.1816
Skewness	1.1486	1.1298	(0.0335)	0.4221	(0.0179)
Kurtosis	8.4268	10.3655	3.9815	4.2213	3.0272
Observations	3389	3389	3389	3389	3389

This table presents the descriptive statistics of the daily changes in the smoothed series of the natural logarithms of the exchange rate indices of the selected currency pairs.

1.5.3 Empirical results of the proposed MS models

Comparison of information criteria to linear models

To compare the models, we first estimate linear models with the same explanatory variables[15]. The results of the linear models can be summarized as follows: a chartist rule determines the daily changes in the cyclical series while both chartist and fundamentalist rules determine the daily changes in the smoothed series. However, the model selection criteria indicate that the MS models are superior to the linear models based on a chartist-fundamentalist approach for all currency pairs as shown in Table 5.

15 The results of the linear models based on a chartist-fundamentalist approach are available in Appendix D.

Table 5 Comparison of model selection criteria between linear and MS models

DLN_AUD_USD	DLN_AUD_USD_CY		DLN_AUD_USD_SM	
	Linear model	MS model	Linear model	MS model
Akaike info criterion	2.3495	***2.1003***	(3.4154)	***(3.7924)***
Hannan-Quinn criter.	2.3534	***2.1106***	(3.4115)	***(3.7820)***
Schwarz criterion	2.3603	***2.1292***	(3.4045)	***(3.7634)***
DLN_CAD_USD	**DLN_CAD_USD_CY**		**DLN_CAD_USD_SM**	
	Linear model	MS model	Linear model	MS model
Akaike info criterion	1.6038	***1.3960***	(4.0384)	***(4.4597)***
Hannan-Quinn criter.	1.6077	***1.4064***	(4.0345)	***(4.4493)***
Schwarz criterion	1.6147	***1.4249***	(4.0275)	***(4.4307)***
DLN_EUR_USD	**DLN_EUR_USD_CY**		**DLN_EUR_USD_SM**	
	Linear model	MS model	Linear model	MS model
Akaike info criterion	1.8158	***1.7477***	(3.9119)	***(4.4160)***
Hannan-Quinn criter.	1.8203	***1.7593***	(3.9074)	***(4.4043)***
Schwarz criterion	1.8285	***1.7802***	(3.8992)	***(4.3834)***
DLN_GBP_USD	**DLN_GBP_USD_CY**		**DLN_GBP_USD_SM**	
	Linear model	MS model	Linear model	MS model
Akaike info criterion	1.6538	***1.4932***	(4.0850)	***(4.6334)***
Hannan-Quinn criter.	1.6583	***1.5048***	(4.0805)	***(4.6218)***
Schwarz criterion	1.6665	***1.5257***	(4.0724)	***(4.6009)***
DLN_JPY_USD	**DLN_JPY_USD_CY**		**DLN_JPY_USD_SM**	
	Linear model	MS model	Linear model	MS model
Akaike info criterion	1.8486	***1.7519***	(3.9866)	***(4.2426)***
Hannan-Quinn criter.	1.8537	***1.7649***	(3.9814)	***(4.2297)***
Schwarz criterion	1.8630	***1.7881***	(3.9721)	***(4.2064)***

This table presents three model-selection criteria: the Akaike Information Criterion, the Hannan-Quinn Criterion, and the Schwarz criterion to compare the goodness of fit between linear and Markov-switching (MS) models. A model with the lower information criteria value (shown in bold and italic font) is better fit than another model.

Estimation results of the proposed MS model

Table 6 and Table 7 present the empirical results of the proposed MS models of the daily return of the five exchange rates for the cyclical and smoothed series, respectively[16]. *The effects of chartist and fundamentalist variables on both cyclical and smoothed series support the four hypotheses of this study and are consistent for all selected currency pairs in terms of signs of coefficients and statistical significance.*

Short-term speculator expectations

In this study, the cyclical series of the exchange rate is assumed to represent short-term speculator expectations. Table 6 presents the results of MS models of the daily changes in the cyclical series (*DLN_FX_CY*) of the five selected exchange rates. Explanatory variables include a chartist variable (*DLN_FX_CY(-1)*), a fundamentalist variable (*DEV_FX(-1)*), and control variables. The results indicate that a chartist variable significantly determines the daily changes in the cyclical series while a fundamentalist variable rarely significant. This implies that *short-term speculators mainly use a chartist rule to form their exchange rate expectations*. *The negative sign of the chartist variable coefficient indicates that the technical expectation of short-term speculations is dominated by a reversal strategy.* This may be the results of day-to-day exchange rate betting behavior.

Longer-term investor expectations

For the smoothed series of exchange rate, we assume that it represents the longer-term investor expectations. Table 7 presents the results of MS models of the daily changes in the smoothed series (*DLN_FX_SM*) of the five selected exchange rates with a chartist variable (*DLN_FX_SM(-1)*), a fundamentalist variable (*DEV_FX(-1)*), and control variables. The results indicate that *longer-term investors consider both chartist and fundamentalist rules to forecast exchange rates*. The coefficient of the chartist variable is positive while the coefficient of the fundamentalist rule is

[16] The empirical results of the proposed MS models in details can be found in Appendix E.

negative. *The positive chartist coefficient implies that the majority of longer-term investors employ a trend following strategy while the negative fundamentalist coefficient suggests that longer-term investors expect a mean reversion of the exchange rate to its long-run equilibrium value.*

Control variables

The QE data do not significantly determine daily exchange rate movements while the FX intervention variable for *JPY_USD* is quite significant, especially in the cyclical series. The FX intervention here means the Japanese government buys the US dollar and sells the Japanese yen. Therefore, the sign of coefficient is positive as expected. The higher government intervention value is, the more the Japanese yen depreciates against US dollar.

Differences of coefficient estimates in the two states

According to the Wald test[17], the coefficient estimates are jointly differences in the two states for both cyclical series (short-term speculator expectations) and smoothed series (longer-term investor expectations) for all selected currency pairs. Most of the coefficient estimates of explanatory variables which are statistically significantly different between the two states, 11 out of 17 pairs, have higher absolute values in the high-volatility state than in the low-volatility state[18]. The results imply that expectations of market participants seem to be more sensitive to explanatory variables in the high-volatily state than in the low-lovatility state. These results are consistent to Lovcha & Perez-Laborda (2010) which find that the high sensitivity regime also has high volatility of exchange rate.

[17] The Wald test results are given in APPENDIX F.

Table 6 MS models for the cyclical series (short-term speculation)

DLN_FX_CY	AUD_USD	CAD_USD	EUR_USD	GBP_USD	JPY_USD
Unstable State (high volatility, high sensitivity)					
Constant $= \alpha_{01}^{CY}$	0.113495	-0.006237	0.006168	0.019711	-0.023773
Chartist-fundamentalist variables:					
DLN_FX_CY(-1) $= \alpha_{c1}^{CY}$	-0.471182***	-0.246403***	-0.136414***	-0.150163**	-0.135513***
DEV_FX(-1) $= \alpha_{f1}^{CY}$	-0.010853*	-0.006124*	-0.00472	-0.007459	-0.00342
Control variables:					
DVIX(-1)	0.057872	0.060226***	0.020231	0.00827	-0.065019***
DLN_MSCI(-1)	-23.73875***	-4.927965*	-2.342538	-7.40245**	-8.211482**
QE data (each country)			-0.000088	0.0000817	-0.000000478
Fed QE (US)	-0.00000262	-0.000000661	-0.000000239	-0.00000586	0.00000142
FX intervention					0.001392***
LOG(SIGMA) = $\log(\sigma_1^{CY})$	0.471136***	-0.242837***	-0.18097***	0.019308	-0.087077**
Expected duration (days)	16	62	34	57	20
Stable State (low volatility, low sensitivity)					
Constant $= \alpha_{02}^{CY}$	-0.005506	0.000494	-0.000819	-0.002722	-0.001253
Chartist-fundamentalist variables:					
DLN_FX_CY(-1) $= \alpha_{c2}^{CY}$	-0.171537***	-0.172398***	-0.17596***	-0.172952***	-0.185106***
DEV_FX(-1) $= \alpha_{f2}^{CY}$	-0.001521	-0.002385*	-0.001252	-0.001738	-0.000464
Control variables:					
DVIX(-1)	0.049775***	0.022938***	-0.005841	0.016303*	-0.022362***
DLN_MSCI(-1)	-4.267539**	-3.252408**	-1.628276	-1.55948	-1.288228
QE data (each country)			-0.0000358	0.0000156	-0.00000269
Fed QE (US)	0.000000567	-0.00000469	0.000000959	0.000000467	-0.0000012
FX intervention					0.000388***
LOG(SIGMA) = $\log(\sigma_2^{CY})$	-0.50713***	-0.978547***	-0.702001***	-0.778166***	-0.710122***
Expected duration (days)	136	136	102	464	74
Transition matrix parameters:					
P11-C	-2.721077***	-4.103932***	3.498107***	4.018147***	2.929997***
P22-C	- 4.902552***	4.903735***	-4.615179***	-6.137075***	-4.285774***
Observations	3388	3388	3388	3388	3388

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$$DLN\_FX\_CY = \alpha_{0j}^{CY} + \alpha_{cj}^{CY}[DLN\_FX\_CY(-1)] + \alpha_{fj}^{CY}[DEV\_FX] + \epsilon_{jt}^{CY}, \qquad \epsilon_{jt}^{CY} \sim N(0, \sigma_j^{CY}), \qquad if\ S_t = j$$

DLN_FX_CY is the change in a daily exchange rate return expected by short-term speculators. DLN_FX_CY (-1) denotes the coefficient of change in a daily exchange rate return expected by short-term speculators in the previous day. DEV_FX is the coefficient of deviation of an exchange rate from its PPP fundamental value while ABS_DEV_FX is its absolute value. The two global risk indicators are the Chicago Board Options Exchange's volatility index (DVIX) and the MSCI global equity index (DLN_MSCI). Monetary policy variables include foreign exchange market intervention by the Japanese central bank (for JPY_USD) and Quantitative Easing (QE) policies implemented by central banks (for EUR_USD, GBP_USD, JPY_USD) and by the US Federal Reserve (Fed QE). The estimated values of LOG (SIGMA) indicate the values of the natural logarithms of the volatilities in states 1 and 2. This table presents the estimation results of MS models with constant transition probabilities which have the values of information criteria better than MS models with TVTP.

Transition probabilities: $P_t^{ij} = \frac{exp(X'_{t-1}\beta_i)}{1+exp(X'_{t-1}\beta_i)}$ where P_t^{ij} = a transition probability from state i to state j

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

Table 7 MS models for the smoothed series (longer-term expectation)

DLN_FX_SM	AUD_USD	CAD_USD	EUR_USD	GBP_USD	JPY_USD
Unstable State (high volatility, high sensitivity)					
Constant $= \alpha_{01}^{SM}$	-0.004765**	-0.005487**	0.027436***	0.022215***	-0.003172**
Chartist-fundamentalist variables:					
DLN_FX_SM(-1) $= \alpha_{c1}^{SM}$	0.981216***	0.989225***	0.98226***	0.991303***	0.991832***
DEV_FX(-1) $= \alpha_{f1}^{SM}$	-0.000669***	-0.002441***	-0.000464***	-0.000706***	-0.001212***
Control variables:					
DVIX(-1)	0.001941*	0.001679**	-0.000313	0.000428	-0.001211*
DLN_MSCI(-1)	0.223972	0.252531*	-0.032961	0.093221	-0.218392**
QE data (each country)			-0.00000891	0.00000179	0.000000127
Fed QE (US)	0.000000111	0.000000143	-0.00000000388	0.0000000365	0.0000000035
FX intervention					0.00000217
LOG(SIGMA) = $\log(\sigma_1^{SM})$	-2.730904***	-2.973451***	-3.754104***	-3.833679***	-3.192845***
Expected duration (days)	12	13	11	14	13
Stable State (low volatility, low sensitivity)					
Constant $= \alpha_{02}^{SM}$	0.003942***	0.000951	-0.024575***	-0.02496***	0.003821***
Chartist-fundamentalist variables:					
DLN_FX_SM(-1) $= \alpha_{c2}^{SM}$	0.997731***	0.982181***	0.979047***	0.970818***	0.95806***
DEV_FX(-1) $= \alpha_{f2}^{SM}$	-0.000637***	-0.000274***	-0.000897***	-0.001663***	0.000309***
Control variables:					
DVIX(-1)	0.000696*	0.000151	0.000225	0.000686**	-0.000187
DLN_MSCI(-1)	-0.028866	-0.022391	0.084439	0.149236**	-0.212592***
QE data (each country)			0.0000106	0.00000225*	0.000000123
Fed QE (US)	0.000000175	0.000000194**	-0.0000000552	-0.000000122	-0.000000123
FX intervention					0.0000205***
LOG(SIGMA) = $\log(\sigma_2^{SM})$	-3.846535	-4.049342***	-3.833091***	-3.959392***	-4.15758***
Expected duration (days)	20	32	12	13	12
Transition matrix parameters:					
P11-C	-2.398225***	2.493072***	-2.26757***	2.533568***	2.487226***
P21-C	2.92942***	-3.421345***	2.435868***	-2.506589***	-2.421911***
Observations	3388	3388	3388	3388	3388

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$$DLN\_FX\_SM = \alpha_{0l}^{SM} + \alpha_{cl}^{SM}[DLN\_FX\_SM(-1)] + \alpha_{fl}^{SM}[DEV\_FX] + \epsilon_{lt}^{SM}, \quad \epsilon_{lt}^{SM} \sim N(0, \sigma_l^{SM}), \quad if\ S_t = l$$

DLN_FX_SM is the change in a daily exchange rate return expected by longer-term investors. DLN_FX_SM(-1) denotes the coefficient of change in a daily exchange rate return expected by longer-term investors in the previous day. DEV_FX is the coefficient of deviation of an exchange rate from its PPP fundamental value in the previous day while ABS_DEV_FX is its absolute value. The two global risk indicators are the Chicago Board Options Exchange's volatility index (DVIX) and the MSCI global equity index (DLN_MSCI). Monetary policy variables include foreign exchange market intervention by the Japanese central bank (for JPY_USD) and Quantitative Easing (QE) policies implemented by central banks (for EUR_USD, GBP_USD, JPY_USD) and by the US Federal Reserve (Fed QE). The estimated values of LOG (SIGMA) indicate the values of the natural logarithms of the volatilities in states 1 and 2. This table presents the estimation results of MS models with constant transition probabilities which have the values of information criteria better than MS models with TVTP.

Transition probabilities: $P_t^{kl} = \frac{exp(X_{t-1}'\beta_k)}{1+exp(X_{t-1}'\beta_k)}$ where P_t^{kl} = a transition probability from state k to state l

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

Table 8 Different coefficient estimates between the two unobservable states

	DLN_AUD_USD		DLN_CAD_USD		DLN_EUR_USD		DLN_GBP_USD		DLN_JPY_USD	
	SM	CY	SM	CY	SM	CY	SM	CY	SM	CY
High-Volatility State										
constant term	(0.0048)		(0.0055)		0.0274		0.0222		(0.0032)	
Chartist rule:										
DLN_FX(-1)		(0.4712)					0.9913		0.9918	
Fundamentalist rule:										
DEV_FX(-1)			(0.0024)		(0.0005)		(0.0007)		(0.0012)	
Global risk 1:										
DVIX(-1)				0.0602						
Global risk 2:										
DLN_MSCI(-1)		(23.7388)								
QE data (each country)					(0.000009)					
Fed QE (US)										
FX Intervention									0.000002	0.0014
SIGMA	0.0652	1.6018	0.0511	0.7844	0.0234	0.8345	0.0216	1.0195	0.0411	0.9166
Low-Volatility State										
constant term	0.0039		0.0010		(0.0246)		(0.0250)		0.0038	
Chartist rule:										
DLN_FX(-1)		(0.1715)					0.9708		0.9581	
Fundamentalist rule:										
DEV_FX(-1)			(0.0003)		(0.0009)		(0.0017)		0.0003	
Global risk 1:										
DVIX(-1)				0.0229						
Global risk 2:										
DLN_MSCI(-1)		(4.2675)								
QE data (each country)					0.000011					
Fed QE (US)										
FX Intervention									0.000021	0.0004
SIGMA	0.0214	0.6022	0.0174	0.3759	0.0216	0.4956	0.0191	0.4592	0.0156	0.4916

This table presents the coefficient estimates of the explanatory variables that the Wald test results show that they are different between in the two unobservable states. The upper panel shows the coefficient estimates in the state which has higher volatility while the lower panel shows the coefficient estimates in the state which has lower volatility. The grey-highlighted numbers are the coefficients which have bigger absolute values between the two states.

Predictive accuracies

In the proposed MS model, the daily changes of the cyclical series primarily determine the standard deviation while the daily changes of the smoothed series mostly influence the size and direction of the changes of the daily exchange rate dynamics. *The expected daily change from the MS model of the cyclical series and that of the smoothed series can be summed to forecast expected daily changes in the exchange rate in the original series. We thereby obtain the expected exchange rate returns with slightly improvements in predictive power compared to those of a random walk model for both in-sample and out-of-sample periods* as summarized in Table 10. On average, the percentage of correct-sign predictions of the proposed model improves upon that of the random walk model by 12.83% for in-sample data and 5.84% for out-of-sample data. Similarly, the mean absolute error (MAE) is reduced by 8.12% and 2.19% for in-sample and out-of-sample data, respectively. Lastly, the root mean squared error (RMSE) declines by 9.50% for the in-sample period and by 3.17% for the out-of-sample period.

In summary, the proposed model meets the main objective of this study to develop a daily exchange rate model that provides both a logical explanation and has a predictive power improvement over a random walk model. The conclusion of this study is robust to varying the lambda (λ) for HP filtering values of 50, 100, and 200 as well as when the sample is divided into two subsamples: pre-crisis (1999 to 2007) and crisis periods (2008 to H1/2012).

Naturally, the volatilities of daily exchange rate should be contributed by the short-term speculators and the longer-term investors following their proportions in daily trading volume in the global FX market. Unfortunately, there is no actual data of such proportions. For any given value of lambda (λ), after we decompose the exchange rate series into the cyclical and smoothed series as if the exchange rate expectations by the short-term speculators and the longer-term investors, we can compare the standard deviation of exchange rate return of the cyclical series and the smoothed series. The calculation of the standard deviation of the cyclical series or the smoothed series divided by the sum of the two series implies the initial investigation on the role of each group of agents to the daily exchange rate volatility as shown in Table 9.

Table 9 Comparison of the contribution to the daily FX return volatilities by the cyclical and the smoothed series for various values of lambda (λ)

	Contribution to the daily FX return volatilities by the cyclical and the smoothed series									
	AUD_USD		CAD_USD		EUR_USD		GBP_USD		JPY_USD	
lambda	by CY	by SM	by CY	by SM	by CY	by SM	by CY	by SM	by CY	by SM
50	75.19%	24.81%	74.69%	25.31%	73.81%	26.19%	74.58%	25.42%	75.68%	24.32%
100	77.07%	22.93%	76.84%	23.16%	75.69%	24.31%	76.57%	23.43%	77.51%	22.49%
200	78.79%	21.21%	78.86%	21.14%	77.39%	22.61%	78.32%	21.68%	79.18%	20.82%
400	80.40%	19.60%	80.76%	19.24%	78.91%	21.09%	79.88%	20.12%	80.75%	19.25%
1,600	83.17%	16.83%	84.11%	15.89%	81.56%	18.44%	82.69%	17.31%	83.65%	16.35%
6,400	85.39%	14.61%	86.60%	13.40%	84.07%	15.93%	85.21%	14.79%	86.11%	13.89%
25,600	87.39%	12.61%	88.57%	11.43%	86.41%	13.59%	87.29%	12.71%	88.03%	11.97%
1,000,000	91.09%	8.91%	91.93%	8.07%	90.99%	9.01%	90.70%	9.30%	92.40%	7.60%

This table presents the initial investigation on the roles of cyclical and smoothed series on volatility of the daily exchange rate return by calculating the proportion of standard deviation of the daily return of each series divided by the sum of standard deviations of the two series.

The lambda (λ) = 100 used in this study implies that we assume the volatility of daily exchange rate return is contributed by the short-term speculators about 75-78% and by the longer-term investors 22-25% for the empirical investigation in this study. However, if we increase the value of lambda (λ) for HP filtering to 6,400 or to as high as 1,000,000, the cyclical series will become more volatile while the smoothed series will be very smooth. Consequently, the coefficient estimates in the MS model for a cyclical series will be less statistically significant and are insignificant for some exchange rates while the coefficient estimates in the MS model for the smoothed series of all exchange rates will be more statistically significant. For the forecasting performance, the percent of correct direction declines while the mean absolute errors (MAE) and the root mean absolute errors (RMSE) improve.

Table 10 Predictabilities of the proposed MS model and a random walk model

Currency	Forecast period	The proposed MS model		
		% correct direction	MAE	RMSE
AUD_USD (TVTP)	In Sample	62.78%	0.5576	0.7817
	Out-of-Sample	53.60%	0.4427	0.5921
CAD_USD (CP)	In Sample	62.49%	0.3908	0.5402
	Out-of-Sample	55.60%	0.2491	0.3466
EUR_USD (CP)	In Sample	63.19%	0.4522	0.5985
	Out-of-Sample	56.80%	0.3944	0.5156
GBP_USD (CP)	In Sample	63.25%	0.4077	0.5511
	Out-of-Sample	55.80%	0.3250	0.4196
JPY_USD (CP)	In Sample	62.43%	0.4544	0.6096
	Out-of-Sample	55.60%	0.4743	0.6845
Avg. of 5 exchange rates	*In Sample*	*62.83%*	*0.4525*	*0.6162*
	Out-of-Sample	*55.48%*	*0.3771*	*0.5117*
Currency	**Forecast period**	**RW model**		
		% correct direction	MAE	RMSE
AUD_USD (TVTP)	In Sample	50.00%	0.6097	0.8764
	Out-of-Sample	50.00%	0.4259	0.5790
CAD_USD (CP)	In Sample	50.00%	0.4275	0.6007
	Out-of-Sample	50.00%	0.2581	0.3634
EUR_USD (CP)	In Sample	50.00%	0.4904	0.6559
	Out-of-Sample	50.00%	0.4096	0.5395
GBP_USD (CP)	In Sample	50.00%	0.4443	0.6050
	Out-of-Sample	50.00%	0.3376	0.4415
JPY_USD (CP)	In Sample	50.00%	0.4911	0.6695
	Out-of-Sample	50.00%	0.4936	0.7140
Avg. of 5 exchange rates	*In Sample*	*50.00%*	*0.4926*	*0.6815*
	Out-of-Sample	*50.00%*	*0.3850*	*0.5275*
Currency	**Forecast period**	**% Improvement from RW model**		
		% correct direction	MAE	RMSE
AUD_USD (TVTP)	In Sample	12.78%	8.54%	10.81%
	Out-of-Sample	3.60%	-3.93%	-2.27%
CAD_USD (CP)	In Sample	12.49%	8.58%	10.07%
	Out-of-Sample	5.60%	3.49%	4.61%
EUR_USD (CP)	In Sample	13.19%	7.77%	8.75%
	Out-of-Sample	6.80%	3.72%	4.44%
GBP_USD (CP)	In Sample	13.25%	8.25%	8.91%
	Out-of-Sample	5.80%	3.75%	4.95%
JPY_USD (CP)	In Sample	12.43%	7.46%	8.96%
	Out-of-Sample	5.60%	3.92%	4.13%
Avg. of 5 exchange rates	*In Sample*	*12.83%*	*8.12%*	*9.50%*
	Out-of-Sample	*5.48%*	*2.19%*	*3.17%*

This table presents the predictabilities of the proposed Markov switching (MS) models based on a chartist-fundamentalist approach compared to those of a random walk model for daily changes in the exchange rates of the selected currency pairs. MAE denotes the mean absolute error and RMSE denotes the root mean square error. The in-sample period ranges from January 1999 to the first half of 2012 while the out-of-sample period occurs from July 2012 to June 2013.

1.5.4 Discussion about policy implications

For policy implications, let us consider the case of JPY_USD due to active FX intervention in this currency pair and the availability of daily FX intervention data. By using the proposed model in this study, we can get the expected daily return plus and minus two standard deviations (S.D.) compared to the actual daily return of JPY_USD as shown in Figure 7. The daily expected return and volatility vary in time depending on the probabilities of being in the two states in each day.

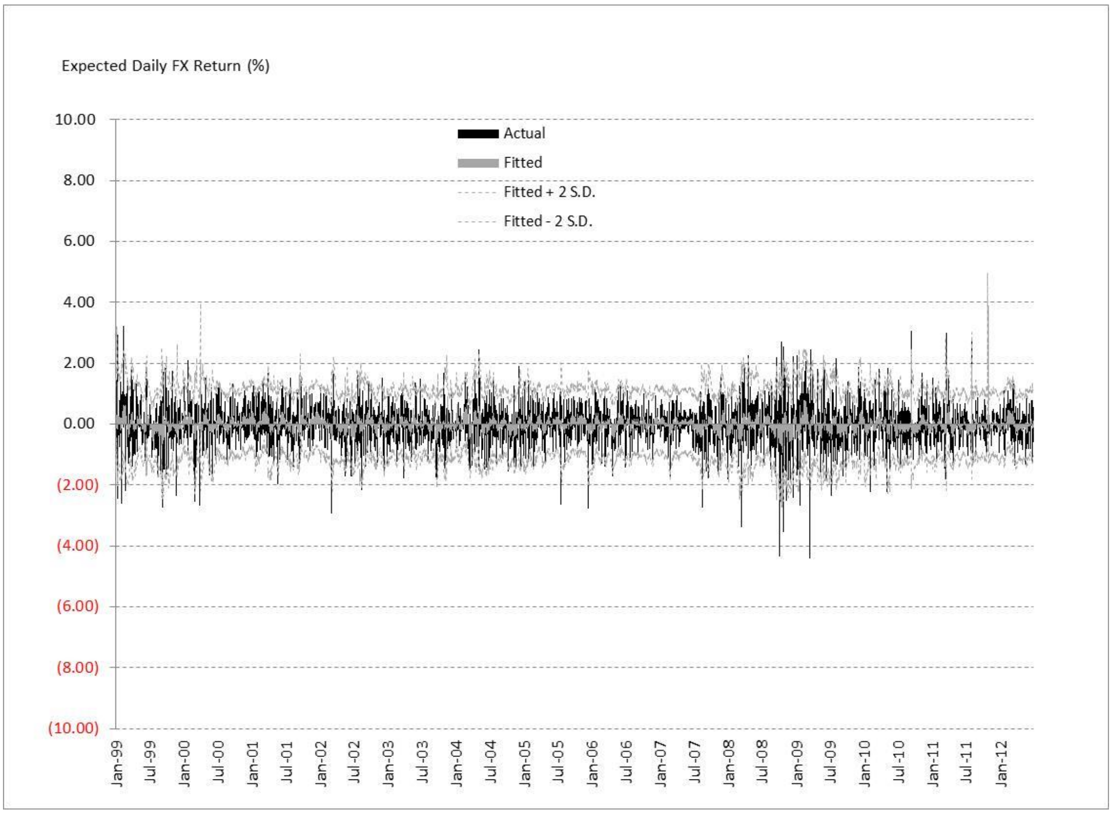

Figure 7 Actual and fitted daily exchange rate return of JPY_USD

According to the proposed model, we can decompose the expected daily exchange rate return into two components, i.e., those generated by short-term speculators and by longer-term investors. For each type of traders, we can estimate the one-step-ahead probabilities of being in state 1 and 2 and then calculate the expected daily return and the expected volatility. From Figure 8, the expected daily exchange rate return of short-term speculators, shown as the dark line of fitted DLN_FX_CY on the right-hand-side (RHS) scale, is roughly in the range of -0.50 to +3.50 per cent. It is more volatile than that of longer-term investors, shown as the gray line of fitted DLN_FX_SM on the left-hand-side (LHS) scale which varies in a narrow range of -0.50 to +0.50 per cent. Figure 9 shows that most of the expected exchange rate volatility, 96.41 per cent of total on average, is contributed by short-term speculators.

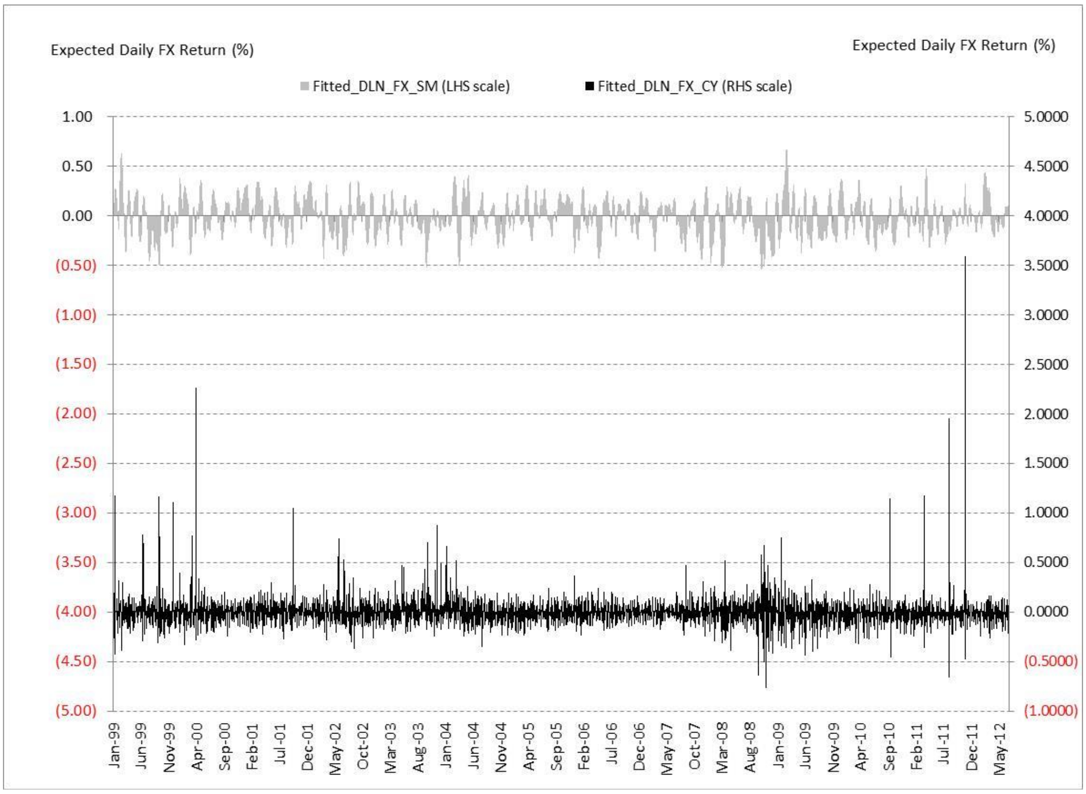

Figure 8 The expected daily exchange rate return of JPY_USD by short-term speculators (Fitted_DLN_FX_CY) and longer-term investors (Fitted_DLN_FX_SM)

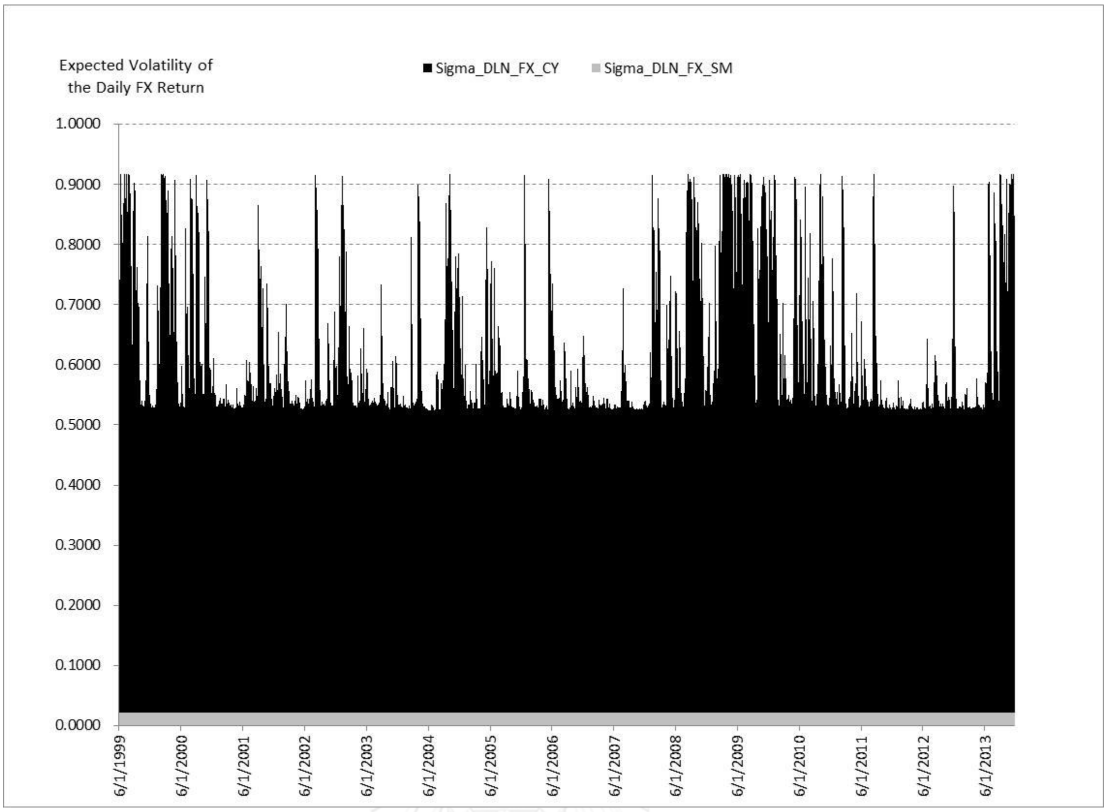

Figure 9 Expected volatility of JPY_USD contributed by short-term speculators (Sigma_DLN_FX_CY) and longer-term investors (Sigma_DLN_FX_SM)

The empirical study indicates that FX intervention significantly influences short-term speculator expectations, especially in the high-volatility state. For that reason, the government can intervene to potentially stabilize the foreign exchange market when the expected volatility is high. According to the empirical results in Table 6, one billion JPY in value of government's FX intervention by buying (selling) US dollars and selling (buying) Japanese yen lead to the expectation of short-term speculators for a depreciation (an appreciation) of the Japanese yen against US dollar on the day of intervention by 0.1392 basis point in the high-volatility state and by 0.0388 basis point in the low-volatility state.

In conclusion, the proposed model provides some policy implications by illustrating the expectations of two types of investors, i.e., short-term speculators and longer-term investors, on the daily exchange rate movement. Short-term expectations depend on chartist factors, global risk factors, and some monetary policy variables. They predominantly determine daily exchange rate volatility. An interesting policy implication is that the monetary authorities can intervene to potentially stabilize the foreign exchange market by guiding short-term speculators' expectation. For longer-term investors, the government's intervention in the foreign exchange market is inefficient as the intervention does not much induce their expectations.

1.6 An application example using the proposed model

This section considers an example of applying the proposed model to foreign currency portfolio management. The results show that trading strategies determined by the proposed model forecasting can give more profits than no strategy (a random walk expectation). The assumptions of a portfolio management example are:

1. There are five selected major currency pairs for portfolio investment in this example.
2. An investor considers profit or loss in US dollar terms. In other words, this is an example for a USD-based investor.
3. The investment horizon in this application example is one day which is consistent to the daily forecast of the proposed model and the information set should be updated every day for the best prediction.
4. An investor is allowed for taking either long or short position in any currency but the total amount of long and short positions in each day must not exceed 100 USD equivalence.
5. For simplicity, we assume that there is no transaction cost and borrowing cost. However, the qualitative conclusion should still remain when these costs exist because the comparison of relative profits would not change.
6. We consider two six-month investment periods: 1) an in-sample period which covers the first half of 2012 and 2) an out-of-sample period which covers the second half of 2012.
7. We consider three cases of risk aversion coefficients (μ): μ=0.5, μ=1.0, and μ=1.5. The risk-adjusted return in this study is the same as that of DeGrauwe & Grimaldi (2006) which is defined as $\pi' = \pi - \mu * \sigma^2$ where π' is the

expected risk-adjusted return, π is the expected return, μ is the coefficient of risk aversion, and σ^2 is the expected variance of return. We assume that an investor considers these expected risk-adjusted returns and variances of the five selected major currencies on the next day to determine his strategy to invest in his currency portfolio today.

We will compare the average daily returns, the portfolio daily return's standard deviations, and the Sharpe ratios for the in-sample period (the first half of 2012) and the out-of-sample period (the second half of 2012) among the following strategies.

1. **A Random-Walk (RW) Strategy:**
   a. On each day, buy 5 currencies in equal amount (20 USD equivalence for each currency);
   b. On the next day, sell all of 5 currencies bought on the previous day.
2. **Strategy A (Long best - Short Worst):**
   a. On each day, buy the currency which has positive and maximum tomorrow's expected risk adjusted return = 50 USD and sell the currency which has negative and minimum tomorrow's expected risk adjusted return = -50 USD;
   b. On the next day, liquidate or close all positions opened on the previous day.
3. **Strategy B (Long best only):**
   a. On each day, buy the currency which has positive and maximum tomorrow's expected risk adjusted return = 100 USD;
   b. On the next day, liquidate or close all positions opened on the previous day.
4. **Strategy C (Short worst only):**
   a. On each day, sell the currency which has negative and minimum tomorrow's expected risk adjusted return = -100 USD;

b. On the next day, liquidate or close all positions opened on the previous day.

5. **Strategy D (Long positive – Short negative):**

   a. buy the currency which has positive tomorrow's expected risk adjusted return = 20 USD equivalence per currency and sell the currency which has negative tomorrow's expected risk adjusted return = -20 USD equivalence per currency;

   b. On the next day, liquidate or close all positions opened on the previous day.

The results of portfolio performances of the five investment strategies can be summarized as Table 9 to Table 11. We can see that the Sharpe ratios of the investment strategies using the proposed MS model for prediction are better than the Sharpe ratio of a random-walk strategy in most of the cases for both in-sample and out-of-sample periods. Therefore, the proposed MS model is beneficial for the daily exchange rate forecasting for investor's portfolio management.

Table 11 Comparison of the portfolio performances among various strategies: coefficient of risk aversion (μ) =0.5

Period	Portfolio Performance	Portfolio_RW	Portfolio_A	Portfolio_B	Portfolio_C	Portfolio_D
2012H1	avg. return (% p.d.)	(0.02)	0.23	0.13	0.22	0.11
(In-Sample)	S.D. of daily return	0.36	0.46	0.39	0.54	0.31
	Sharpe Ratio	(0.06)	0.51	0.34	0.40	0.36
2012H2	avg. return (% p.d.)	0.01	0.21	0.12	0.18	0.09
(Out-of-Sample)	S.D. of daily return	0.31	0.38	0.35	0.49	0.24
	Sharpe Ratio	0.02	0.57	0.33	0.36	0.36

Table 12 Comparison of the portfolio performances among various strategies: coefficient of risk aversion (μ) =1.0

Period	Portfolio Performance	Portfolio_RW	Portfolio_A	Portfolio_B	Portfolio_C	Portfolio_D
2012H1	avg. return (% p.d.)	(0.02)	0.23	0.03	0.22	0.04
(In-Sample)	S.D. of daily return	0.36	0.55	0.11	0.56	0.35
	Sharpe Ratio	(0.06)	0.43	0.24	0.38	0.10
2012H2	avg. return (% p.d.)	0.01	0.17	0.03	0.15	0.01
(Out-of-Sample)	S.D. of daily return	0.31	0.46	0.18	0.50	0.28
	Sharpe Ratio	0.02	0.36	0.17	0.30	0.05

Table 13 Comparison of the portfolio performances among various strategies: coefficient of risk aversion (μ) =1.5

Period	Portfolio Performance	Portfolio_RW	Portfolio_A	Portfolio_B	Portfolio_C	Portfolio_D
2012H1	avg. return (% p.d.)	(0.02)	0.20	0.00	0.20	0.02
(In-Sample)	S.D. of daily return	0.36	0.56	0.00	0.56	0.36
	Sharpe Ratio	(0.06)	0.35	0.00	0.35	0.06
2012H2	avg. return (% p.d.)	0.01	0.13	0.01	0.12	(0.00)
(Out-of-Sample)	S.D. of daily return	0.31	0.51	0.10	0.55	0.30
	Sharpe Ratio	0.02	0.26	0.12	0.21	(0.00)

1.7 Conclusion

Although, the daily exchange rate movement usually appears to be a random walk, these are still subject to explanation by the fact that technical strategies are widely used among financial experts and traders over the short run while the fundamental theories still hold in the long-run. This study develops a daily exchange rate model by decomposing exchange rate determination into two components, the short-term speculation and the longer-term expectation. Simultaneously, we also allow investors to use both chartist and fundamentalist expectations within each of the two unobservable states in the Markov switching (MS) models. The proposed model is employed to examine the daily exchange rate movements of the five most traded currency pairs in the global market: US dollar/euro, US dollar/yen, US dollar/sterling, US dollar/Australian dollar, and US dollar/Canadian dollars. The in-sample period of this study ranges from January 1999 to June 2012 while the out-of-sample period ranges from July 2012 to June 2013.

A Hodrick-Prescott (HP) filter is adopted to decompose daily exchange rate movements into two components: the cyclical and smoothed components. The cyclical component represents the short-term speculator expectations while the smoothed component captures the longer-term investor expectations on the daily exchange rate dynamics.

1.7.1 Findings

The empirical results of the proposed MS model suggest that short-term speculators mainly utilize a reverse chartist rule to shape their expectations while longer-term investors make use of an extrapolative chartist rule and a mean-reversion to long-run equilibrium to form their expectations. The cyclical series predominantly affects the standard deviation while the smoothed series mainly influences the mean value of the daily exchange rate in the original series. When we combine the forecast results of the cyclical and smoothed series, we produce expected exchange rate returns with improved predictive power over a random walk model for both in-sample and out-of-sample periods. In an example of application using the proposed model, the Sharpe ratios of the investment strategies using the proposed MS model for prediction are better than that of a random-walk strategy in most of the cases for both in-sample and out-of-sample periods. Therefore, the proposed MS model explains daily changes logically with some predictive powers and is also useful for a portfolio strategy determination.

1.7.2 Policy implications

Under a floating exchange rate regime, monetary authorities can intervene to potentially stabilize short-term exchange rate in the short run by influencing short-term speculator expectations. However, the longer-term investor expectations are less affected by short-run policy interventions.

1.7.3 Limitations of the study

The proposed model was motivated by some theoretical papers which explain that heterogeneous agents' expectations affect the market price dynamics and can make the market falling into a stable or an unstable state. The unobservable state of the market can change over time. Therefore, the proposed MS model in this study is based on some theoretical concepts and an empirical test rather than based on a pure theoretical framework. It is possible to examine the Markov switching (MS) models with more than two states but the improvement may not added much. According to the extant literature, two-state MS models are usually well enough for explanation and understanding.

1.7.4 Suggestions for further study

The proposed model may be applied to test other financial markets beyond the currency market to consider whether there are differences or similarities among different types of financial market. In addition, other techniques beyond the HP filtering can be adopted to decompose the investors' expectations into different groups. Further studies may also include other fundamentalist and chartist rules as well.

CHAPTER 2
AN APPLICATION OF THE CHARTIST-FUNDAMENTALIST APPROACH TO A MODEL OF SPECULATIVE BEHAVIOR FOR ASIAN STOCK MARKETS

2.1 Introduction

2.1.1 Statement of the problem and its significance

Jensen (1978) defines that *"A market is efficient with respect to information set at time t* (I_t) *if it is impossible to make economic profits by trading on the basis of this information set."* There are three common forms of market efficiency: weak form, semi-strong form, and strong form[19]. In weak-form efficiency, future stock prices cannot be predicted by analyzing historical prices. In semi-strong-form efficiency, stock prices adjust abruptly to new public information in an unbiased manner. In strong-form efficiency, stock prices reflect all public and private information. The efficient market hypothesis (EMH) requires that agents in the market have rational expectations, i.e., the average expectation of all agents is correct. The EMH could not be rejected and was widely accepted by economists in 1970s. *However, many anomalies in the stock price dynamics and remarkable breaks which have actually occurred in stock markets cannot be explained solely by the EMH.* Since late-1980s, there have been several studies looking for new models and approaches to describe the stock price dynamics in a more convincing way than the rational expectations and EMH.

"One of the things that microeconomics teaches you is that individuals are not alike. There is heterogeneity, and probably the most important heterogeneity here is heterogeneity of expectations. If we didn't have heterogeneity, there would be no trade. But developing on analytic model with heterogeneous agents is difficult" [Ken Arrow, In: D. Colander, R.P.F. Holt and J. Barkley Rosser (eds.), *The Changing*

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[19] Among others, Dimson & Mussavian (2000) and Zunino, Barivierac, Guercioc, Martinezc, & Rossod (2012) recap the three common forms of market efficiency.

Face of Economics. Conversations with Cutting Edge Economists. The University of Michigan Press, Ann Arbor, 2004, p 301.]

Hommes (2005) quotes the above statements given by Arrow in 2004 to substantiate the role of heterogeneous agents and its challenge in economic and financial modelling. Nowadays, a behavioral and agent-based approach has become popular in economic and financial modelling as an alternative to a representative rational agent approach.

A Heterogeneous Agents Model (HAM) takes into account differences among agents in many aspects such as preferences and beliefs. The HAM closely relates to the literature based on the behavioral finance and the noise trader approach which believe that investors are bounded rational and some limits to arbitrage exist. The literature based on the HAM, behavioral finance, and the noise trader approach have developed models to describe several anomalies and stylized facts in the stock markets, for examples, high trading volume, excess equity premium, volatility clustering, excess volatility, speculative bubbles and sudden crashes in stock markets, etc.

The HAM can be categorized into two approaches, simulation and econometrics. Several studies on the HAM often employ computational and numerical tools to obtain the results. These simulation models are analytically tractable but need many assumptions on parameters to simulate the models of artificial stock markets. On the other hand, the econometric approach of HAM estimates parameters of a model from actual data. According to this advantage of the econometric approach, *this study employs an econometric model based on a HAM to describe and forecast stock markets in the real world.*

One interesting kind of the HAM-based econometric models is *the regime-switching models* which assume that the state of the market can change over time and investors' behavior depends on the state. Although several studies have utilized the regime-switching models to examine the stock price dynamics but *a handful of* *studies adopt the chartist-fundamentalist approach to explain the dynamics of stock returns by using the regime-switching models.*

As we know that investment experts and analysts in the stock markets generally use both technical and fundamental analyses to determine their trading strategies in practice. The facts reflect that agents apply the chartist rules to forecast stock prices at least in the short run while the fundamental analysis is still essential in the long run. However, investor expectations may vary in time with changing economic situation and market environment. Investors may switch their trading strategies from time to time. *These behaviors might be captured by a regime-switching model based on a chartist-fundamentalist approach.*

This study aims to improve previous works by Chiarella, He, Huang, & Zheng (2012) and Norden & Schaller (1996). The former work estimates a two-state Markov switching (MS) model that stock price change is the combination of expectations among various market participants, i.e., fundamentalists, chartists, noise traders, and market makers to explain monthly data of the S&P 500 index. The latter work develops a regime-switching model of speculative behavior that a stock price comprises two components, i.e., the fundamental component and the speculative component. This speculative component depends on the two states of the market; the bubble survives in one state and collapses in the other state.

These two research works show that the estimated regime-switching models provide the empirical results which outperform some models in the previous literature. However, *the coefficient estimates of fundamentalist and chartist variables which are the key explanatory variables of the models in these two papers are not statistically significant.* The empirical evidences just confirm differences in means and variances between the two states of regime-switching models. Consequently, *further model developments may possibly help us to prove that the impacts of fundamentalist and chartist expectations on the stock price dynamics are logical and statistically significant.*

For additional improvement, *this study develops a two-state Markov-switching (MS) model to explain the speculative component of a stock price by using the chartist-fundamentalist approach.* The proposed MS model in this study is different from Chiarella et al. (2012) that we allows the coefficient estimates on both chartist and fundamentalist variables to be different between the two unobservable states of the MS model. Comparing to the study of Norden & Schaller (1996), we add a chartist expectation as one more explanatory variable for the speculative component of the return on stocks. Another distinction from both studies, we include a global risk factor which is the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) as an explanatory variable on the stock return movements. Finally, we believe that the model based on this approach should be more appropriate for daily data than monthly data. Consequently, the empirical test in this study employs daily data instead of monthly data in the two reference works.

Many existing studies that based on regime-switching models have focused the major stock exchanges, especially the US market. There have been not many studies on the Asian stock markets. Since the stock markets in Asia are important destinations for global investment as well, *this study will develop a model of speculative behavior based on the chartist-fundamentalist approach to describe the daily stock return dynamics for countries in Asia.*

The *main results of this study* indicate that *fundamentalist and chartist expectations are statistically significant to explain net stock returns*. The empirical study confirm that the MS models based on the chartist-fundamentalist approach is *appropriate for daily data*. In addition, *a global risk factor is important* in determining the net return on stocks of Asian countries. The results comparison among four selected countries implies that *stock markets in Hong Kong and Korea seem to be more efficient than those in India and Thailand.* The empirical results are robust for the MS models with constant and time-varying transition probabilities and with the fundamental stock prices calculated from both static and dynamic Gordon growth models.

Table 14 Comparison of this study to the two reference works

Item	Norden & Schaller (1996)	Chiarella et al. (2012)	This study
Model specification	Two-state standard-switching model	Two-state MS model	Two-state MS model
Dependent variable	Gross stock return	Change in stock price	***Net stock return***
Explanatory variables	1) The ratio of deviation of actual from fundamental stock price relative to the actual stock price	1) The deviation of actual from fundamental stock price 2) The difference between actual stock price and short-term market value of stock price expected by chartists	1) The ratio of deviation of actual from fundamental stock price relative to the actual stock price ***2) The ratio of stock price change in last period relative to the actual stock price*** 3) ***Global risk factor***
Fundamental stock price determination	$P^* = \rho D_t$ where P^* = fundamental stock price ρ = the mean price-dividend ratio D_t = dividend yield	Static & dynamic Gordon growth model	Static & dynamic Gordon growth model
Coefficients of explanatory variables in the two states	Different	Same (different only for short-term market value of stock price expected by chartists)	***Allow to be different***

Item	**Norden & Schaller (1996)**	**Chiarella et al. (2012)**	**This study**
Volatilities in the two states	Different	Different	Different
Data	Monthly data, US (Jan 1926 - Dec 1989)	Monthly data, US (Jan 2000 – Jun 2010)	***Daily data, 4 Asian countries*** (Jan 2000 – Dec 2014)
The estimates on constant terms in the two states	Statistically significant	Statistically significant	Mixed results
The coefficient estimates of explanatory variables	Have expected sign but statistically insignificant	Have expected signs but statistically insignificant	Have expected signs and statistically ***significant***
The coefficient estimates of a global risk factor	N.A.	N.A.	Statistically ***significant***
The estimates on volatilities in the two states	Statistically significant and different between the two states	Statistically significant and different between the two states	Statistically significant and different between the two states

This table compares the specification and estimation results of the proposed model in this study to those of Norden & Schaller (1996) and Chiarella et al. (2012). Bold and italic fonts highlight the major differences of this study from the two previous works.

2.1.2 Research question

The research question for this study is *"Can we develop a Markov switching (MS) model by applying the chartist-fundamentalist approach to a model of speculative behavior in the stock markets to explain the dynamics of daily stock returns in Asian countries?"*

2.1.3 Objective of the study

To develop a Markov switching (MS) model to describe the dynamics of daily net stock returns for the selected countries in Asia. The proposed model applies the chartist-fundamentalist approach to explain a speculative component in a model of speculative behavior in the extant literature. In the proposed model, the adjustment of a stock price deviation from its fundamental value is explained by fundamentalist and chartist expectations. The change in market stock price is the collective results of these two types of expectation. From the estimation results, *we can analyse and compare the impacts of different expectations on the dynamics of daily stock returns of selected Asian countries in the two unobservable states.* Additionally, analyses on the probability of falling into each unobservable state should be beneficial for understanding the current stock market situation.

2.1.4 Scope of the study

This study develops a two-state Markov switching (MS) model based on a chartist-fundamentalist approach to analyze the influences of the fundamentalist and the chartist expectations on the daily stock returns. The proposed model examines the daily net stock returns of *four selected Asian countries*[20]*: Hong Kong, India, Korea, and Thailand.* The daily data of a stock market in each selected country from 2000 to 2013 is used an in-sample estimation while the 2014 data is reserved for an out-of-sample examination. After we have the estimated models, we analyze the expectation behaviors of market participants, the probabilities of being in the two states, and the expected durations of the two states for selected stock markets in Asia. Finally, we compare the forecasting accuracy of the proposed MS model to a random walk model.

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[20] The countries and stock indices are mainly selected based on the availability of data for the proposed model estimation. We select two developed countries and two developing countries for a comparison purpose.

2.1.5 Contributions

1. Theoretical contribution: This study tries to extend the model of speculative behaviour by applying a chartist-fundamentalist approach to explain the speculative component of the model. By this extended model, we can investigate the impacts of fundamentalist and chartist expectations on the dynamics of daily net stock returns of the selected Asian countries in the two unobservable states.
2. Contributions to policy makers: It could be useful for regulatory bodies to use this kind of model to develop an early warning system for the stock market since we can estimate the probabilities and the durations of being in high-volatility and low-volatility states of the stock market.

2.1.6 Organization of the study

Section 2.2 is the literature review on the stock market studies based on the heterogeneous agent models (HAMs), the chartist-fundamentalist approach, and the regime-switching models.

Section 2.3 describes the conceptual framework and the proposed model.

Section 2.4, the dataset and methodology are described.

Section 2.5 presents the empirical analysis and discussion of the results.

Section 2.6 provides concluding remarks.

2.2 Literature review

Figure 10 illustrates the structure of related literature review for this essay. Literature in the grey boxes lays the foundation to the conceptual framework of this study while literature in the white boxes refers to other relevant literature.

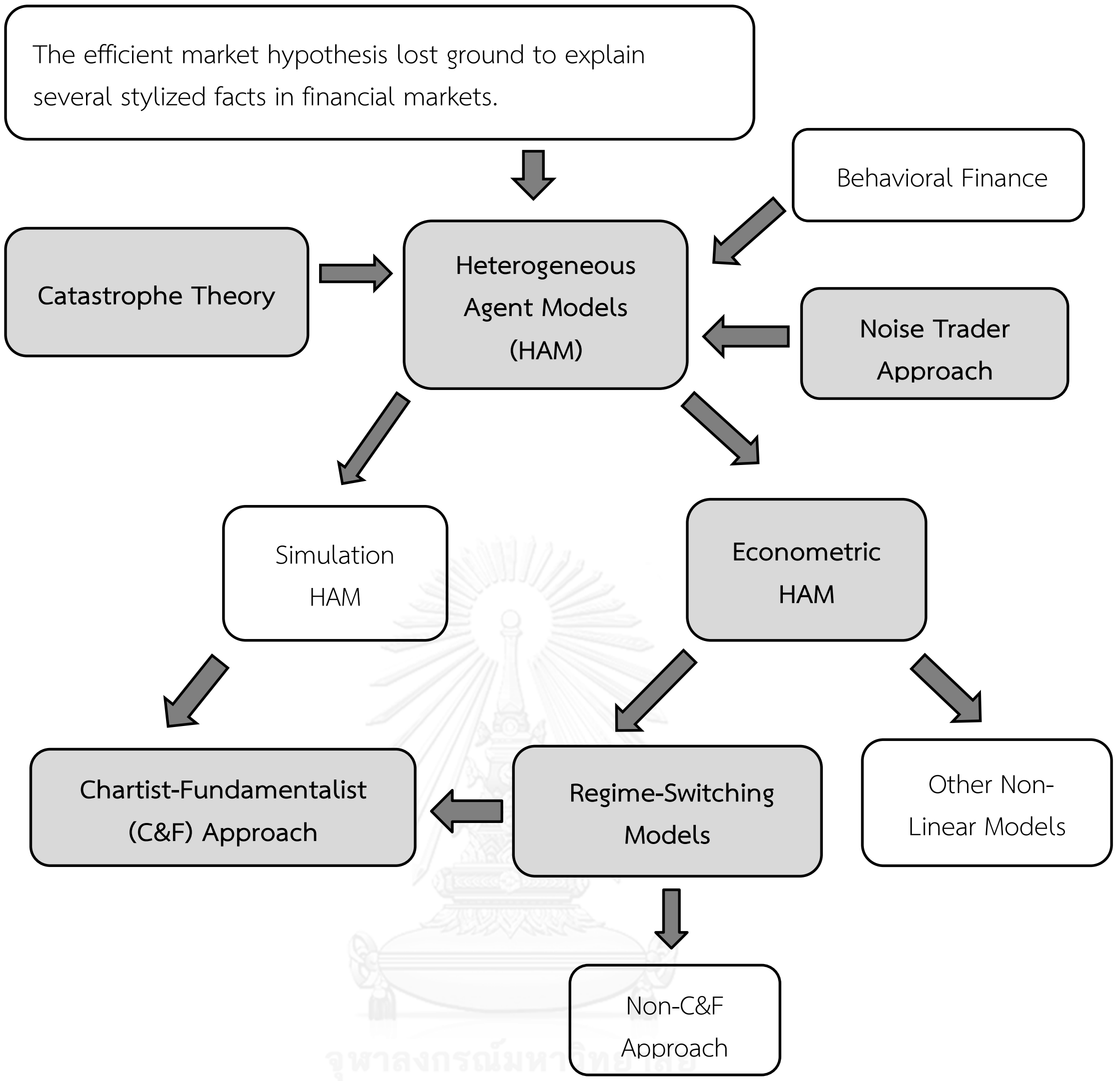

Figure 10 Literature review on related studies for an application of the chartist-fundamentalist approach to a model of speculative behavior for a stock market

Since the models based on *rational expectations and market efficiency* do not well explain several stylized facts such as high risk premium of stock returns, excess volatility, high trading volume, bubbles and crashes, clustered volatility, fat tails in return distribution, etc., there has been a shift to the *heterogeneous agent models (HAM)* paradigm since 1990s. The literature based on the HAM have become prevalent such as Brock & Hommes (1998), Hommes (2005), Boswijk, Hommes, & Manzan (2007), Bhamra & Uppal (2014), and so on. Readers who are interested in a survey on the literature about HAMs can see Hommes (2005). The HAM takes into account differences among investors in some aspects such as information, knowledge, preferences, expectations or beliefs. The conceptual framework of HAM is in line with those of catastrophe theory and the noise trader approach. According to *catastrophe theory*, Zeeman (1976) portrays the bull and bear stock market phenomenon by "the cusp catastrophe" to demonstrate possible equilibrium stock prices depending on two control variables: excess demand of fundamentalists and chartists' market participation. In addition, the HAM is also supported by literature based on *the noise trader approach* which assumes that some investors are not fully rational while arbitrage is risky and limited which is quite related to the concept of *behavioral finance*. Shleifer & Summers (1990) argue that the noise trader approach to financial markets is superior to the efficient market paradigm.

"It is absolutely not true that introducing a degree of irrationality of some investors into models eliminates all discipline and can explain anything." [Andrei Shleifer and Lawrence H. Summers, The noise trader approach to finance. Journal of economic perspectives, Vol. 4 No. 2 Spring 1990, p 20.]

Literature review based on the HAM in this study is categorized into two approaches, the simulation approach and the econometric approach.

The simulation approach constructs a HAM by generating an artificial asset market. A HAM assumes different trading expectation behaviors among heterogeneous agents and considers the impacts of these behaviors on the market price dynamics. A model in this approach operates a computational and numerical tool for analysis. In general, simulation models are analytically tractable but need the assumptions on many parameters. Therefore, the simulation models can be supported by empirical studies leading to the development of models based on the econometric approach.

The econometric approach can estimate parameters for a HAM from actual empirical data. One prevalent class of econometric model employed for estimating a HAM is a regime-switching model because of its nature and intuition. In *a regime-switching model*, trading rules of heterogeneous agents may vary in time depending on the state of the market. A Markov switching models is usually adopted by assuming that the unobservable state follows the Markov-chain stochastic process. However, there are also other types of non-linear econometric models to estimate HAM such as a smooth transition autoregressive model (STAR), a non-linear least squares model, etc.

For a HAM, the two common types of agents often assumed in a model are chartists and fundamentalists. Chartists utilize the patterns of historical stock price data to form their expectations on the future stock price while fundamentalists believe in a mean-reversion to the fundamental value of stock price. We may call a model which includes these two typical types of agents as a model based on *the chartist-fundamentalist (C&F) approach*. Most of simulation heterogeneous agent models are based on the C&F approach.

For the regime-switching models, there are both C&F and Non-C&F approaches. In the non-C&F regime switching models, there are no chartist and fundamentalist expectations as explanatory variables. The two states may have differences in mean values and volatilities, survival or collapse of bubbles, bull or bear markets, etc. In this study, we focus on the regime-switching model based on the C&F approach to analyze the impacts of heterogeneous expectation behaviors of agents on the daily stock price dynamics of selected Asian countries.

2.2.1 Catastrophe theory

This theory is already reviewed in the first essay (Section 1.3.1.1) of this dissertation.

2.2.2 The noise trader approach to finance

Shleifer & Summers (1990) and Delong, Shleifer, Summers, & Waldmann (1990) suggest that the unpredictable noise traders' beliefs and behaviors affect the asset price. Consequently, arbitragers face with both fundamental risk and resale price risk. When the investment horizons of arbitragers are finite, arbitrage to bet against noise traders is risky and limited. Therefore, the asset price can deviate far from its fundamental value. In the short run, noise traders may be more aggressive in trading than rational arbitragers and can earn higher expected returns resulting in limits to arbitrage. As a consequence, noise traders' behavior can influence the dynamics of market price and volatility. The noise trader approach to finance sheds light on a number of anomalies in financial markets such as equity premium puzzle, excess volatility of equity prices, the underpricing of closed-end mutual funds, etc.

2.2.3 Heterogeneous agent models (HAM)

Since a representative agent in the rational expectation models cannot well explain the real phenomena in financial markets, the literature based on the heterogeneous agent models (HAM) have become prevalent such as Brock & Hommes (1998), Hommes (2005), Boswijk et al. (2007), Bhamra & Uppal (2014), and so on. In this study, we consider the literature on HAM in two aspects: simulation HAM and econometric HAM.

2.2.3.1 Simulation HAM

Developments in computational and numerical methods motivate the simulation HAM. There have been quite a number of studies on simulation HAM to describe the evolutionary system of a stock market which are usually highly nonlinear and adaptive system, for examples, Day & Huang (1990), Grannan & Swindle (1994), Lux (1995), Brock & Hommes (1997), Brock & Hommes (1998), Lux (2000), etc. The simulation models of these studies generate artificial markets which explain many anomalies and stylized facts in financial markets. However, Boswijk et al. (2007) [p. 1962] state that "An important topic for future research is to investigate the robustness of behavioral heterogeneity in financial market data." Accordingly, the econometric HAM is an alternative for examining the role of heterogeneous agent behaviors in the stock price dynamics determination.

Some literature on simulation HAM for a stock market can be mentioned here for examples. Day & Huang (1990) present a simulation model of excess demand and stock price adjustment by assuming that there are three types of agents in the stock market: α-investors, β-investors, and market makers. For the first type of agents, α-investors employ their trading strategies based on sophisticated estimation on the long-run fundamental value of stock price. They incorporate the most recent information into their consideration at high cost. For the second type of agents, β-investors use relatively simple adaptive rules by comparing between the current stock price and the current fundamental value at low cost. These unsophisticated investors chase stock price up and down, generating bull and bear markets. The last type of agents is the group of market makers who adjust their prices to balance their asset holdings over time. Day & Huang (1990) conclude that their simulation model generates data in the same manners of the real stock market including excess volatility, switching between bull and bear markets, and high trading volumes at the tops of the bull-market regime and at the bottoms of the bear-market regime.

Another example, Lux (2000) presents a possible explanation of cluster volatility in financial data by using a multi-agent framework of speculative activity. Agents in the model comprise of fundamentalists, optimistic chartists, and pessimistic chartists. These traders are interacting. The model considers two types of switching: 1) chartists switching between optimistic and pessimistic opinion and 2) switching between chartist and fundamentalist strategy. A chartist has pressure to re-evaluate his behaviour between optimistic and pessimistic when the actual market price changes in the direction contradicting to his own expectation. For the switching between chartist and fundamentalist strategy, agents compare the past profit performances of these two strategies and choose the more successful strategy for the next period. The simulation results consistent with some stylized facts. First, returns are stationary and distributed around zero. Second, there are occasionally sudden, strong deviations which seem as clusters. When there is any outbreak of instability, the market will return to the usual tranquil mode sooner or later.

2.2.3.2 Econometric HAM

One of the most popular models for econometric HAM is the regime-switching model. Among studies on the regime-switching model of stock returns, there are both chartist-fundamentalist (C&F) approach and non-C&F approach. Although there are several studies utilize the regime-switching model to estimate the stock returns but most of them are non-C&F such as Granger (1992), Hardy (2002) Henkel, Martin, & Nardari (2011), Ang & Timmermann (2011), Liu, Margaritis, & Wang (2012), etc. The results of these works point out that the regime-switching models outperform linear models and most of other non-linear models in explaining the stock returns.

In this study, we are interested to develop a regime-switching model based on the chartist-fundamentalist (C&F) approach to consider the impacts of heterogeneous expectation on the stock return dynamics. However, the two nearest works to this study based on both non-C&F and C&F approaches. The first paper is Norden & Schaller (1996) which is non-C&F. That paper utilizes regime-switching models to study stock market crashes in the US in two different explanations: a speculative behavior model and a fundamental switching model. The conclusion is that both models are complements rather than substitutes in explaining the stock market crashes. According to a model of speculative behavior of that paper, a stock price comprises two components, i.e., the fundamental and speculative components. The speculative component depends on the two states of the market; the state of survival bubble and the state of collapsed bubble. The second reference paper is Chiarella et al. (2012) which bases on the C&F approach. The study proposes a two-state Markov switching model with various types of market participants, i.e., fundamentalists, chartists, noise traders, and market makers to explain monthly data of the S&P 500 index. The estimation results match well the tranquil and turbulent periods in the US stock market. The model shows an evidence of time-varying behavioral heterogeneity of investors and has satisfactory forecasting performance.

These two research works show that the estimated regime-switching models provide good empirical evidences. However, the coefficient estimates for fundamentalist and chartist expectations, the key explanatory variables, turn out to be not statistically significant. The empirical results just confirm the differences in means and variances between the two states of the proposed regime-switching models.

As a result, this study proposes a two-state Markov switching model of stock returns which is further developed from these two reference papers to prove that the impacts of fundamentalist and chartist expectations on the stock price dynamics should be both logical and statistically significant. In addition we examine the proposed model with four stock markets in Asia. Two markets are located in advanced economies, Hong Kong and Korea, while the other two markets are located in developing economies, India and Thailand. Accordingly, we then compare the results of the proposed model among these different markets.

2.3 Conceptual framework and the proposed model

2.3.1 Conceptual framework

Based on the model of speculative in the extant literature, a stock market price deviates from its fundamental value and we call this deviation the speculative component of a stock price. In this study, *we hypothesize that the dynamics of a speculative component or the deviation of actual stock price from fundamental value is the collective results of the chartist and fundamentalist expectations.* The behavior of investors expectation are presumed to depend on the unobservable states of a stock market which may be falling into *a "high-volatility state" or a "low-volatility state"* at a particular point of time. We allow the expectation behaviors of investors to be different between the two unobservable states. *The fundamental stock prices in this study are calculated by using the static Gordon growth* model as described in Chiarella et al. (2012). All growth rates of variables for fundamental stock prices calculation are in real terms, deflated by inflation rates, in the same concept as Boswijk et al. (2007).

2.3.2 The proposed model and hypotheses of this study

To construct the proposed model for empirical estimation, we begin with the assumption that there are two components of stock market price: fundamental and speculative components. The fundamental component in this study is determined by the future dividend expectation following the static Gordon growth model. We assume that the dividend process is a Gaussian random walk with drift. For the speculative component, we assume that the deviation of market price from fundamental price is the net result of chartist and fundamentalist expectations among heterogeneous agents in the market. These expectations also depend on the unobservable state which can change from time to time. Putting the fundamental and speculative components together, we obtain the proposed Markov switching (MS) model. Besides, we also include a global risk factor as one more explanatory variable of net stock return in the proposed model. The derivation of the proposed model and some rationales give us the expected signs of explanatory variables' coefficients to set the hypotheses of this study. For the transition probabilities in the proposed MS model, we examine both constant and time-varying transition probabilities (TVTP) cases. For the TVTP case, we assume that the probabilities to switch from one to another state depending on the size of latest deviation of actual stock price form its fundamental value.

2.3.2.1 Fundamental and speculative components of a stock price

The stock market return can be divided into two parts: 1) the capital gain and 2) the cash-flow yield. In this study, we consider the dividend yield as the cash-flow yield since it is the actual payment that investors receive and does not fluctuate as much as the earnings data. Assuming that a stock price can deviate from its fundamental value, we can write the expected gross return on a stock at time t+1 as follows.

$$E_t[R_{t+1}] = \frac{E_t[P_{t+1}^* + D_{t+1}]}{P_t} + \frac{E_t[B_{t+1}]}{P_t} \tag{27}$$

where $E_t[R_{t+1}]$ is the expectation on the gross return on a stock in period t+1 given the information at time t ,

P_{t+1}^* is the fundamental stock price at time t+1,

P_t is the actual stock price at time t.

D_{t+1} is the dividend payment at time t+1,

$B_{t+1} = P_{t+1} - P_{t+1}^*$ is the deviation of the actual stock price from its fundamental price at time t+1,

On the right-hand side of equation (1), the first term is called "the fundamental component" and the second term is called "the speculative component".

2.3.2.2 Fundamental component

Following the static Gordon growth model, the fundamental stock price is the summation of discounted future dividends from the next period to infinity. By assuming a constant growth rate of dividends and a constant required rate of stock return in the steady state, the fundamental stock price at time t (P_t^*) can be written as a function of dividend payment at time t (D_t), the average growth rate of dividends (g), and the average required rate of return on stock (r).

$$\begin{aligned} P_t^* &= \sum_{i=1}^{\infty} D_t \times \frac{(1+g)^{t+i}}{(1+r)^{t+i}} \\ &= D_t \times \frac{(1+g)}{(r-g)} \end{aligned} \tag{28}$$

where m denotes the fundamental price-dividend ratio.

Assume that the log dividend process is a Gaussian random walk with drift, we have

$$\log D_{t+1} = \mu + \log D_t + \vartheta_{t+1}, \qquad \vartheta_{t+1} \sim i.i.d.N(0, \sigma_\vartheta^2).$$

Then, the expectation of dividend payment at time t+1 can be written as:

$$\mathrm{E}_t[D_{t+1}] = \left(e^{\mu + \frac{\sigma_\vartheta^2}{2}}\right) \cdot D_t \tag{29}$$

From equations (28) and (29), we get the fundamental component of equation (24) as follows.

$$\begin{aligned} \frac{E_t[P_{t+1}^* + D_{t+1}]}{P_t} &= \frac{1}{P_t}\left[E_t(D_{t+1})\frac{(1+g)}{(r-g)} + E_t(D_{t+1})\right] \\ &= \frac{E_t(D_{t+1})}{P_t}\left[\frac{(1+g)}{(r-g)} + 1\right] \\ &= \frac{D_t}{P_t} \cdot \left(e^{\mu + \frac{\sigma_\vartheta^2}{2}}\right)\left[\frac{(1+g)}{(r-g)} + 1\right] \end{aligned} \tag{30}$$

2.3.2.3 Speculative component

For the speculative component, let $b_t = \frac{B_t}{P_t} = \frac{P_t - P_t^*}{P_t}$ and according to the static Gordon growth model, we have the fundamental price-dividend ratio $m = \frac{P_t^*}{D_t} = \frac{(1+g)}{(r-g)}$. Then, we get

$$\begin{aligned} b_t &= 1 - m \cdot \frac{D_t}{P_t} \\ \frac{D_t}{P_t} &= \frac{(1-b_t)}{m} \end{aligned} \tag{31}$$

In this study, we assume that the expectation on the speculative component depends on the two unobservable states of the stock market. We do not know exactly which state the stock market is falling into. The Markov-switching (MS) model can estimate the probabilities of falling into each of the two unobservable states. Subsequently, we have the expected value of the speculative component as:

$$E_t[B_{t+1}] = q_{t+1} \cdot E_t[B_{t+1}|S_{t+1} = 1] + (1 - q_{t+1}) \cdot E_t[B_{t+1}|S_{t+1} = 2]$$

Where q_{t+1} is the probability that the market will be in the state 1 at time t+1 $(S_{t+1} = 1)$,

$(1 - q_{t+1})$ is the probability that the market will be in the state 2 at time t $(S_{t+1} = 2)$.

In addition, we also assume that the speculative component is the results of a combination of chartist and fundamentalist expectations by investors in the market as follows. Given the state, the collective result of investor expectations based on the chartist and fundamentalist approach can be written as:

$$E_t[B_{t+1}|S_{t+1} = 1] = f_1 \cdot \alpha_{f1} \cdot B_t + (1 - f_1) \cdot \alpha_{c1} \cdot (P_t - P_{t-1})$$

$$E_t[B_{t+1}|S_{t+1} = 2] = f_2 \cdot \alpha_{f2} \cdot B_t + (1 - f_2) \cdot \alpha_{c2} \cdot (P_t - P_{t-1}) \qquad (32)$$

where f_j is the fraction of the fundamentalists in the state j $(S_{t+1} = j)$, where $j = \{1,2\}$,

$B_{t+1} = P_{t+1} - P^*_{t+1}$ is the deviation of the actual stock price from its fundamental price at time t+1,

$(P_t - P_{t-1})$ is the actual change of stock price from the previous period at time t,

$\alpha_{fj} < 0$ is the mean-reversion coefficient of fundamentalist expectation in the state j $(S_{t+1} = j)$.

α_{cj} is the coefficient of chartist expectation in the state j $(S_{t+1} = j)$. When the momentum traders dominate the market, $\alpha_{cj} > 0$, but if the reversal traders dominate the market, $\alpha_{cj} < 0$.

In practice, there are many chartist techniques used in the stock markets and these techniques were developed from time to time as adaptive learning. Thus, it is quite difficult to find explanatory variables which can well explain the chartist expectation and give consistent results for several stock markets in the time-series model analyses. Many studies based on a chartist-fundamentalist approach usually employ the latest change of a stock market price as a proxy for the chartist expectation because it is easy for understanding and works well in all simulation models and some empirical studies. Testing the model by using other chartist techniques is left for further studies. In this study, we just aim at considering the possibility to develop an MS model of daily net stock return by applying the chartist-fundamentalist approach to a model of speculative behavior by using this simple proxy for the chartist expectation.

2.3.2.4 Unobservable states

The unobservable state $S_{t+1} = j$ is assumed to be a stochastic process of Markov chain with the transition probabilities given by

$$P(S_{t+1} = j | S_t = i, S_{t-1} = k, \dots) = P(S_{t+1} = j | S_t = i) = P_{ij}$$

2.3.2.5 Volatilities

Volatilities of the stock returns in the two unobservable states are expected to be different as in the existing literature.

2.3.2.6 The Markov switching (MS) model and hypotheses of this study

From equations (27), (30), (31), and (32), we can specify a Markov switching model for the gross return of stock allowing for different means and variances between the two states as follows.

$$E_t[R_{t+1} | S_{t+1} = 1] = \theta_{01} + \frac{(1 - b_t)}{m} \cdot \left(e^{\mu + \frac{\sigma_\vartheta^2}{2}}\right)[m+1] + f_1 \cdot \alpha_{f1} \cdot \frac{B_t}{P_t}$$
$$+ (1 - f_1) \cdot \alpha_{c1} \cdot \frac{(P_t - P_{t-1})}{P_t} + E_t[\epsilon_{t+1}^1],$$

where $\epsilon_{t+1}^1 \sim N(0, \sigma_1) \quad if \quad S_{t+1} = 1$

$$E_t[R_{t+1}|S_{t+1}=2]=\theta_{02}+\frac{(1-\mathrm{b_t})}{\mathrm{m}}\cdot\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1]+f_2\cdot\alpha_{f2}\cdot\frac{B_t}{P_t}$$
$$+(1-f_2)\cdot\alpha_{c2}\cdot\frac{(P_t-P_{t-1})}{P_t}+E_t[\epsilon_{t+1}^2]\,,$$

where $\epsilon_{t+1}^2 \sim N(0,\sigma_2)$ if $S_{t+1}=2$

θ_{0j} is a shift term of expectation in state j and

Subtracting both sides by $\frac{P_t}{P_t}=1$ to get the net return on stocks and let $\frac{B_t}{P_t}=b_t$ and $\frac{(P_t-P_{t-1})}{P_t}=dp_t$, then we have the expected net return of stock (r_{t+1}) as:

$$E_t[r_{t+1}|S_t=j]=\theta_{0j}+\underbrace{\left\{\frac{1}{\mathrm{m}}\cdot\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1]-1\right\}}_{>0}$$
$$+\underbrace{\left\{\frac{-1}{\mathrm{m}}\cdot\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1]+f_j\cdot\alpha_{fj}\right\}}_{<0}\cdot b_t$$
$$+\underbrace{(1-f_j)\cdot\alpha_{cj}}_{>0\text{ or }<0}\cdot dp_t+E_t[\epsilon_{t+1}^j] \qquad (33)$$

The constant term $\left\{\frac{1}{\mathrm{m}}\cdot\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1]-1\right\}$ has a positive value because $m>0$ and $\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)>1$ in both states. The coefficient of b_t is expected to be negative since $\frac{-1}{\mathrm{m}}\cdot\left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1]<0$ and $f_j\cdot\alpha_{fj}<0$ as a results of f_j is the fraction of the fundamentalists in the state $S_{t+1}=j$ and α_{fj} is the mean-reversion coefficient of fundamentalist expectation in the state $S_{t+1}=j$ which has a negative value. Consequently, we have a hypothesis on the coefficient values of b_t to be statistically different from zero and have a negative sign.

<u>Hypothesis I</u>: When the stock return is over- or under- valued, fundamentalists expect the reversion to the fundamental value. So the coefficient estimate of the deviation of actual from fundamental price relative to the actual price ($\boldsymbol{b_t}$) in the proposed MS model is different from zero and has a negative sign in each unobservable state.

The coefficient of dp_t can be either positive or negative. The term $(1 - f_j)$ is the fraction of the chartists in the state $S_{t+1} = j$ which is always positive. However, α_{cj} which is the coefficient of chartist expectation in the state $S_{t+1} = j$ may be positive or negative. When the momentum traders dominate the market, it is positive. When the reversal traders dominate the market, it is negative. Therefore, we do not pre-specify the sign of the dp_t coefficient. However, the empirical results will tell us whether the chartist expectations in the two states have the same impacts on the stock returns and whether the results are different among various countries in Asia which should be useful for further analyses.

***Hypothesis II*: Since chartists can use either momentum or reversal strategy, the coefficient estimate of the ratio of price change to the actual price $(\boldsymbol{dp_t})$ in the proposed MS model is different from zero but may have a positive or a negative sign.**

For the error terms (ϵ_{t+1}^{j}) of the proposed MS model which reflect the uncertainty in investor expectations and stock price movements in both states, it is expected to be low in one state which we call "a low-volatility state" and to be high in another state which we call "a high-volatility state" in this study.

***Hypothesis III*: Volatilities of the net return on stocks of the proposed MS model are different between the two unobservable states.**

When we add a global risk factor into the proposed MS model, the coefficient of this explanatory variable is expected to be negative. According to Veronesi (1999) and Bansal, Kiku, Shaliastovich, & Yaron (2014), when the risk becomes higher, investors require more expected rate of stock return in the future and need for an additional discount price for buying a stock now as shown in Figure 11. Therefore, when the global risk is higher, the current stock price and net return on stock should decline. In Bollerslev, Litvinova, & Tauchen (2006), the negative impact of an expected increase in volatility on stock returns is called "a volatility feedback effect".

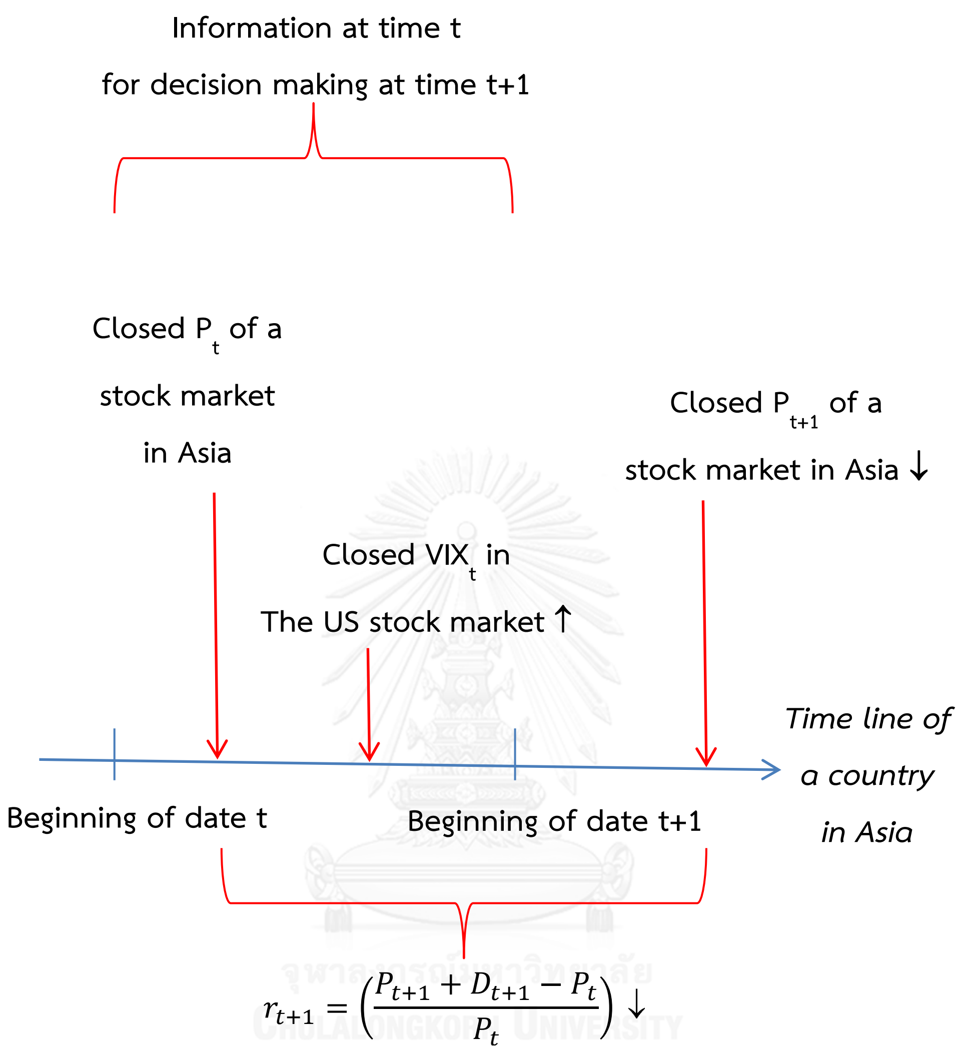

Figure 11 The effect of a global risk factor on net stock return in Asia

<u>*Hypothesis IV*</u>*: When the global risk increases, investors required a discount on the stock price for the higher expected return. So the coefficient estimate of a global risk factor* $(dVIX_t)$ *in the proposed MS model is different from zero and has a negative sign.*

2.3.2.7 Short form of the proposed MS model for empirical test

Let $\beta_{0j} = \theta_{0j} + \left\{\frac{1}{\mathrm{m}} \cdot \left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1] - 1\right\}$, $\beta_{fj} = \left\{\frac{-1}{\mathrm{m}} \cdot \left(e^{\mu+\frac{\sigma_\vartheta^2}{2}}\right)[m+1] + f_j \cdot \alpha_{fj}\right\}$, and $\beta_{cj} = \left(1 - f_j\right) \cdot \alpha_{cj}$, we can rewrite the proposed MS model in equation (33) plus a global risk factor in short notations for the empirical estimation in this study as follows.

$$E_t[r_{t+1}|S_{t+1} = 1] = \beta_{01} + \beta_{f1}b_t + \beta_{c1}dp_t + \beta_{g1}dVIX_t + E_t[\in_{t+1}^1],$$

where $\in_{t+1}^1 \sim N(0, \sigma_1)$ if $S_{t+1} = 1$,

$$E_t[r_{t+1}|S_{t+1} = 2] = \beta_{02} + \beta_{f2}b_t + \beta_{c2}dp_t + \beta_{g2}dVIX_t + E_t[\in_{t+1}^2],$$

where $\in_{t+1}^2 \sim N(0, \sigma_2)$ if $S_{t+1} = 2$,

The expected signs of coefficients are as follows:

$$\beta_{f1}, \beta_{f2} < 0, \beta_{c1}, \beta_{c2} > 0 \text{ or } < 0, \beta_{g1}, \beta_{g2} < 0, \text{and } \sigma_1 \neq \sigma_2. \tag{34}$$

2.3.2.8 Transition probabilities

For the case of constant transition probabilities, the transition probabilities matrix is

$$\pi = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} \tag{35}$$

Where P_{ij} = transition probability from state i to state j ($S_t = j$).

For the case of time-varying transition probabilities (TVTP), the stock market is expected to have a high probability of switching states if the market price is highly over-valued or under-valued. Thus, we assume that the transition probabilities depend on the ratio of the deviation of actual stock price form its fundamental value $(|\mathrm{b_t}|)$ in the form of a logistic function. Let $X_t' = (1, |\mathrm{b_t}|)$. The transition probabilities can be written as:

$$P_{t+1}^{ij} = \frac{exp(X_t'\gamma_i)}{1 + exp(X_t'\gamma_i)} \tag{36}$$

Where P_{t+1}^{ij} = transition probability from state i to state j.

γ_i = estimated parameters for a logistic function.

2.4 Data and methodology

2.4.1 Sample and data

The main data source for the empirical investigation in this study is the CEIC[21], only the volatility index of the SPX (S&P 500 Index) is retrieved from the Chicago Board Options Exchange. For comparison intention, we select two advanced economies and two developing economies in Asia which have available daily data for the proposed model estimation. We utilize monthly data of consumer price indices (CPI), stock prices, and dividend yields to calculate the constant price-dividend ratio for the daily fundamental stock price calculation. We use the inflation rates from CPI to calculate real growth rates of dividend yields and real required rates of stock returns in the selected stock markets.

According to the daily data availability, we obtain four stock indices of four countries in Asia for the proposed MS model estimation and for comparison. The selected indices are the Hang Seng Index from the Hong Kong Exchanges and Clearing Limited (HKEx), the Sensex Index from the Bombay Stock Exchange Limited, the KOSPI Index from the Korea Exchange, and the SET Index from the Stock Exchange of Thailand.

Two selected stock markets are located in advanced economies.

- Hong Kong Exchanges and Clearing Limited (HKEx) is a leading global operator of exchanges and clearing houses based in Hong Kong, Asia's premier international financial centre, and one of the world's largest exchange groups by market capitalisation. HKEx operates the securities and derivatives markets and their related clearing houses and is the frontline regulator of listed companies in Hong Kong.[22] As of 31 January 2015, the HKEx was ranked by the World Federation of Exchanges as the sixth largest exchange in the world with the market capitalization of 3,225 billion USD. This study investigates the net stock returns of the Hang Seng index of this exchange market.

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[21] The CEIC data are from the databases of the CEIC Data Company Ltd, which provides financial and economic data for many emerging and developed markets.
[22] http://www.hkex.com.hk/eng/exchange/exchange.htm

- Korea Exchange (KRX) is the sole securities exchange operator in South Korea. It was created through the integration of Korea Stock Exchange, Korea Futures Exchange and KOSDAQ Stock Market under the Korea Stock & Futures Exchange Act.[23] As of 31 January 2015, the KRX was ranked by the World Federation of Exchanges as the fifteenth largest exchange in the world with the market capitalization of 1,251 billion USD. This study investigates the net stock returns of the KOSPI Index of this exchange market.

The other two selected stock markets are located in developing countries.

- The Bombay Stock Exchange (BSE) is an Indian stock exchange established in 1875. It is the oldest exchange in Asia and now it is one of Asia's fastest stock exchanges, with a speed of 200 microseconds[24]. As of 31 January 2015, the BSE was ranked by the World Federation of Exchanges as the eleventh largest exchange in the world with the market capitalization of 1,682 billion USD. This study investigates the net stock returns of the Sensitive 30 (Sensex) Index of this exchange market.

- "The Securities Exchange of Thailand" officially started trading on 30 April 1975 and its name was formally changed to "The Stock Exchange of Thailand" (SET) on 1 January 1991.[25] The SET is not a major stock exchange in the global market but it is the second largest stock exchange by market capitalization in ASEAN, after the Singapore Exchange (SGX). According to the World Federation of Exchanges report, the SET market capitalization was around 461 billion USD as of 31 January 2015. This study investigates the net stock returns of the SET Index of this exchange market.

This study employs the daily data of Hong Kong, India, Korea, and Thailand during 2000 to 2013 as an in-sample data for the proposed MS model estimation and reserves the data in 2014 for testing the model in an out-of-sample period.

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[23] http://en.wikipedia.org/wiki/Korea_Exchange
[24] http://en.wikipedia.org/wiki/Bombay_Stock_Exchange
[25] http://www.set.or.th/en/about/overview/history_p1.html

2.4.2 Research methodology

The research methodology of this study can be summarized in the following steps.

1. First of all, we calculate the fundamental price-dividend ratio following the static Gordon growth model from monthly data by using the formula as same as Chiarella et al. (2012). The net return on stocks is calculated from the capital gain and dividend yield in each period. The dividend payment (D_t) is calculated from the dividend yield multiplied by the stock index and divided by 12 to obtain monthly data. The inflation rate is calculated as the rate of change in the consumer price index (CPI). The real growth rate of dividends (g_t) is the nominal growth rate of dividends minus the inflation rate. The real required rate of stock returns (r_t) is the dividend yield plus the real growth rate of dividends[26]. All growth rates are calculated in terms of per cent per annum. The constant price-dividend ratio (m) following the static Gordon growth model is calculated by $= \frac{(1+g)}{(r-g)}$, where g is the average real growth rate of dividend and r is the average real required rate of stock return. Then, we can calculate the daily fundamental stock prices (P_t^*) by multiplying the constant price-dividend ratio (m) with daily data of dividend payment (D_t).
2. Next, we collect daily data of the net stock return (r_t), the ratio of stock price deviation from its fundamental value (b_t) , the ratio of change in stock price (dp_t) which are key variables specified in the proposed Markov switching (MS) model of this study.
3. Before estimating the proposed MS model as presented in equation (34), we firstly estimate the linear model with the same explanatory variables as the proposed MS model of the net stock return for all countries for comparison.

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[26] According to the static Gordon growth model, the average rate of return from capital gains is equal to average growth rate of dividends.

4. Subsequently, we estimate the proposed model as a two-state Markov switching (MS) model with constant and time-varying transition probabilities (CP & TVTP), respectively, for all countries. In this study, the state with low volatility is called as "the low-volatility state" and the state with high volatility is called as "the high-volatility state".
5. We compare the three estimated models, i.e., the linear model, the MS model with constant transition probabilities (CP), the MS model with time-varying transition probabilities (TVTP) by comparing the Akaike information criterion, Hannan-Quinn criterion, and Schwarz criterion. The better model gives the lower value of an information criterion. Furthermore, we use the likelihood ratio test to evaluate whether a more complicated model has a statistically improvement from the simpler model.
6. We examine coefficient inequalities between the two states of the proposed MS model for each stock market by using the Wald test.
7. Finally, we forecast the daily net return on stocks of the four selected Asian countries by using the proposed MS model for both in-sample and out-of-sample periods. Then we compare the predictive accuracies of the proposed MS model to a random walk model.

2.4.3 Estimating a Markov switching model

The Markov Switching (MS) model is estimated by the maximum likelihood method. As described by Diebold et al. (1994), define S_t = state 1 or state 2 at time t, let $\{S_t\}_{t=1}^{T}$ be the sample path of a 1^{st}-order, two-state Markov chain with either constant or time-varying transition probabilities, and $\{r_t\}_{t=1}^{T}$ be the sample path of net stock returns depending on the state path, $\{S_t\}_{t=1}^{T}$.

Given the state, r_t is assumed to be identically distributed with normal distribution:

$$(r_t|S_t = j;\ \alpha_i) \sim N(\mu_j, \sigma_j^2), \tag{37}$$

where $\alpha_j = (\mu_j, \sigma_j^2)'$, i = state 1 or 2.

In the case of time-varying transition probabilities, a set of explanatory variables, $X'_{t-1}\gamma_i$, determines the probability of changing from one to another state at time t.

Let $P(S_1 = 2) = \rho$, $\alpha = (\alpha'_1, \alpha'_2)'$, and $\gamma = (\gamma'_1, \gamma'_2)'$

and let $\theta = (\alpha', \gamma', \rho)'$ be a vector of all model parameters.

The complete-data likelihood in terms of indicator functions can be written as

$$\begin{aligned}
&f(r_{_T}, S_{_T} | X_{_T}; \theta) \\
&\qquad = [I(S_1 = 2) f(r_1 | S_1 = 2; \alpha_2)\rho \\
&\qquad + I(S_1 = 1) f(r_1 | S_1 = 1; \alpha_1)(1-\rho)] \\
&\qquad \times \prod_{t=2}^{T} \{I(S_t = 2, S_{t-1} = 2) f(r_t | S_t = 2; \alpha_2) P_t^{22} \\
&\qquad + I(S_t = 1, S_{t-1} = 2) f(r_t | S_t = 1; \alpha_1)(1 - P_t^{22}) \\
&\qquad + I(S_t = 2, S_{t-1} = 1) f(r_t | S_t = 2; \alpha_2)(1 - P_t^{11}) \\
&\qquad + I(S_t = 1, S_{t-1} = 1) f(r_t | S_t = 1; \alpha_1) P_t^{11}\}.
\end{aligned} \tag{38}$$

Note: The subscript _T denotes past history of the variable from t = 1 to t = T.

This equation can be written in the logarithmic from as follows:

$$\begin{aligned}
&log\, f(r_{_T}, S_{_T} | X_{_T}; \theta) \\
&\qquad = I(S_1 = 2)[log\, f(r_1 | S_1 = 2; \alpha_2) + log\, \rho] \\
&\qquad + I(S_1 = 1)[log\, f(r_1 | S_1 = 1; \alpha_1) + log(1-\rho)] \\
&\qquad\quad + \sum_{t=2}^{T} \{I(S_t = 2)\, log\, f(r_t | S_t = 2; \alpha_2) \\
&\qquad\quad + I(S_t = 1)\, log\, f(r_t | S_t = 1; \alpha_1) \\
&\qquad\quad + I(S_t = 2, S_{t-1} = 2)\, log\, P_t^{22} \\
&\qquad\quad + I(S_t = 1, S_{t-1} = 2)\, log(1 - P_t^{22}) \\
&\qquad\quad + I(S_t = 2, S_{t-1} = 1)\, log(1 - P_t^{11}) \\
&\qquad\quad + I(S_t = 1, S_{t-1} = 1)\, log\, P_t^{11}\}.
\end{aligned} \tag{39}$$

Since the states are unobservable, the incomplete-data log likelihood can be used for the maximum likelihood method by summing over all possible state sequences:

$$\log f(r_{\_T} | X_{\_T}; \theta) = \log\left(\textstyle\sum_{S_1=1}^{2} \sum_{S_2=1}^{2} \cdots \sum_{S_T=1}^{2} f(r_{\_T}, S_{\_T} | X_{\_T}; \theta)\right). \tag{40}$$

This function will be maximized with respect to θ.

2.4.4 Forecasting net stock returns by using a Markov switching model

The forecasting procedure can be summarized as following steps.

(1) The initial regime probabilities $(P(S_1 = j))$ which are the probabilities of falling into state 1 and state 2 in the first period are set to the ergodic solutions by the EViews program.

(2) The conditional densities of net stock return (r_t) given state $S_t = j$ and the information set as of the previous period (I_0) in the first period denoted by $f(r_1|S_1 = 1, I_0;\ \theta)$ and $f(r_1|S_1 = 2, I_0;\ \theta)$ can be calculated from the following equations:

$$f(r_1|S_1 = 1, I_0;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \cdot \exp\left\{\frac{-(r_1-\mu_1)^2}{2\sigma_1^2}\right\} \text{ and}$$

$$f(r_1|S_1 = 2, I_0;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \cdot \exp\left\{\frac{-(r_1-\mu_2)^2}{2\sigma_2^2}\right\}.$$

Note: When there are explanatory variables in the information set I_{t-1} determining the expected value of net stock return given state, the values of μ_{1t} and μ_{2t} vary in time with its explanatory variables.

(3) Then, we have $f(r_1|\ I_0;\ \theta)$ as:

$$\begin{aligned} f(r_1|\ I_0;\ \theta) & \\ &= f(r_1|S_1 = 1, I_0;\ \theta) \times P(S_1 = 1) \\ &+ f(r_1|S_1 = 2, I_0;\ \theta) \times P(S_1 = 2) \end{aligned}$$

where $P(S_1 = j)$ are the initial regime probabilities from step (1)

(4) The expected value of net stock return given state in the first period $E(r_1|S_1 = j, I_0;\ \theta)$ can be computed and denoted by μ_{11} and μ_{21}.

(5) Then, we have the expected value of net stock return in the first period of forecasting as:

$$E(r_1|\ I_0;\ \theta) = \mu_{11} \times P(S_1 = 1) + \mu_{21} \times P(S_1 = 2)$$

(6) The filtering probabilities of being in the state 1 and 2 in the first period can be updated as follows.

$$P(S_1 = 1|I_1;\ \theta) = \frac{f(r_1|S_1 = 1, I_0;\ \theta) \times\ P(S_1 = 1)}{f(r_1|\ I_0;\ \theta)}$$

$$P(S_1 = 2|I_1;\ \theta) = \frac{f(r_1|S_1 = 2, I_0;\ \theta)\ \times P(S_1 = 2)}{f(r_1|\ I_0;\ \theta)}$$

(7) Then, we can calculate the prediction probabilities for the next period as:

$$\begin{aligned} P(S_2 = j|I_1;\ \theta) &= P(S_1 = 1, S_2 = j|I_1;\ \theta) + P(S_1 = 2, S_2 = j|I_1;\ \theta) \\ &= P^{1j} \times P(S_1 = 1|I_1;\ \theta) + P^{2j} \times P(S_1 = 2|I_1;\ \theta) \end{aligned}$$

where P^{1j} and P^{2j} are the transition probabilities from state 1 and 2 in this period to state j in the next period.

(8) The conditional densities of net stock return (r_t) given the state $S_t = j$ in the second period $(t = 2)$ denoted by $f(r_2|S_2 = 1, I_1;\ \theta)$ and $f(r_2|S_2 = 2, I_1;\ \theta)$ can be calculated similar to the step (2) from the following equations:

$$f(r_2|S_2 = 1, I_1;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \cdot \exp\left\{\frac{-(r_2-\mu_1)^2}{2\sigma_1^2}\right\} \text{ and}$$

$$f(r_2|S_2 = 2, I_1;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \cdot \exp\left\{\frac{-(r_2-\mu_2)^2}{2\sigma_2^2}\right\}.$$

(9) Instead of using the initial regime probabilities, now we calculate $f(r_2|\ I_1;\ \theta)$ by using the prediction probabilities from step (7) as:

$$\begin{aligned} f(r_2|\ I_1;\ \theta) & \\ &= f(r_2|S_2 = 1, I_1;\ \theta) \times\ P(S_2 = 1|I_1;\ \theta) \\ &+ f(r_2|S_2 = 2, I_1;\ \theta)\ \times P(S_2 = 2|I_1;\ \theta) \end{aligned}$$

(10) Similar to the step (4), we compute the expected value of an exchange rate given the state in the second period $\mathrm{E}(\mathrm{r}_2|\mathrm{S}_2 = \mathrm{j}, \mathrm{I}_1;\ \theta)$ and denoted by μ_{12} and μ_{22}.

(11) Then, we have the expected value of net stock return in the second period by using the prediction probabilities from step (7) as:

$$E(r_2|\ I_1;\ \theta) =\ \mu_{12} \times\ P(S_2 = 1|I_1;\ \theta) +\ \mu_{22} \times\ P(S_2 = 2|I_1;\ \theta)$$

(12) Next, the filtering probabilities of being in the state 1 and 2 in the second period can be updated as follows.

$$P(S_2 = 1|I_2;\ \theta) = \frac{f(r_2|S_2 = 1, I_1;\ \theta) \times\ P(S_2 = 1|I_1;\ \theta)}{f(r_2|\ I_1;\ \theta)}$$
$$P(S_2 = 2|I_2;\ \theta) = \frac{f(r_2|S_2 = 2, I_1;\ \theta) \times\ P(S_2 = 2|I_1;\ \theta)}{f(r_2|\ I_1;\ \theta)}$$

(13) All the steps from step (7) to (12) can be done recursively to forecast net stock return in the following periods until time T.

2.4.5 Forecasting performance tests

The standard statistical performance measures used in many studies and adopted in this study are the root-mean-squared error (RMSE), the mean-absolute error (MAE), and the percentage of correct sign predictions. The forecasting performance of the proposed model is compared to a random walk model.

2.5 Empirical results and discussion

2.5.1 Fundamental stock indices

The daily fundamental stock indices of the four selected countries: Hong Kong (HK), India (ID), Korea (KR), and Thailand (TH) are calculated by using a concept of the static Gordon growth model. Comparisons between the actual and fundamental stock indices of the four selected stock indices are displayed in Figure 12 to Figure 15.

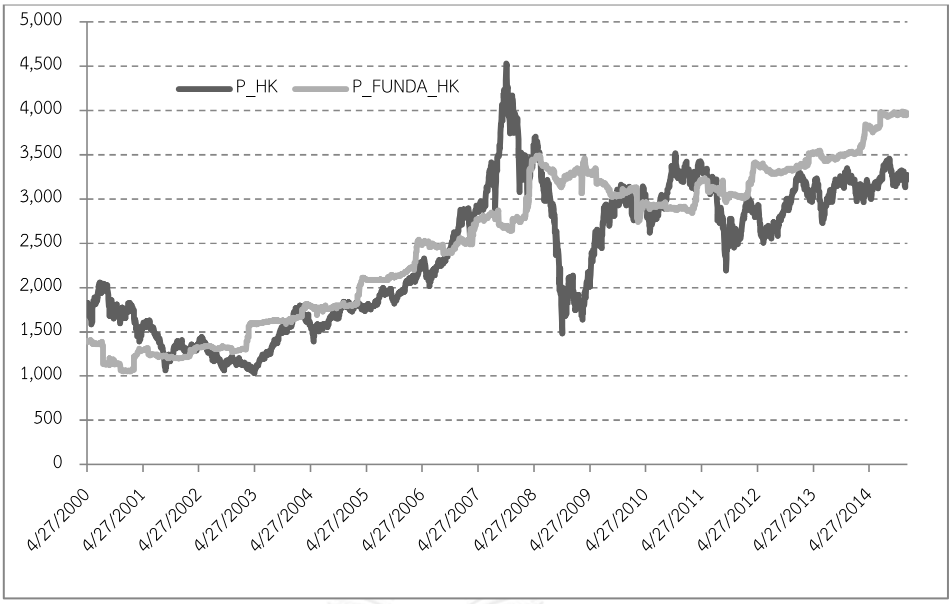

Figure 12 Actual and fundamental stock prices of Hong Kong

Figure 13 Actual and fundamental stock prices of India

Figure 14 Actual and fundamental stock prices of Korea

Figure 15 Actual and fundamental stock prices of Thailand

2.5.2 Descriptive statistics of the net stock returns

This study develops a two-state Markov switching models of the net stock returns to describe the expectation behaviors of the investors in the stock market based on the chartist-fundamentalist approach. Descriptions of variables in this empirical study are presented in Appendix A.

For the daily data of net return on stocks, all of the *net stock returns* for the four selected Asian countries are integrated of order zero and have non-normal distribution. The descriptive statistics of the *net stock returns* are presented in Table 15. The Unit Root Test gives the results that the daily net stock returns of all countries are stationary. For the variance ratio tests, we cannot reject the null hypothesis of an exponential martingale[27] for the daily stock prices of Hong Kong and Korea. The exponential martingale hypothesis implies that the best expected stock price for tomorrow is the stock price today or the daily stock price is a random walk process. So after we estimate the proposed MS model, we should compare the predictive accuracy of the proposed model to a random walk model.

Table 15 Descriptive statistics of the net return on stocks

	NET_RETURN_HK	NET_RETURN_ID	NET_RETURN_KR	NET_RETURN_TH
Mean	0.0004	0.0005	0.0004	0.0005
Median	0.0010	0.0010	0.0010	0.0010
Maximum	0.1250	0.1730	0.1220	0.1120
Minimum	(0.1150)	(0.1110)	(0.1200)	(0.1480)
Std. Dev.	0.0155	0.0163	0.0175	0.0145
Skewness	0.1285	0.1025	(0.2747)	(0.4560)
Kurtosis	9.9297	10.1464	7.5006	10.5074
Jarque-Bera	6,762.2940	7,189.9160	2,966.2030	7,904.4170
Probability	0.0000	0.0000	0.0000	0.0000
Sum	1.3110	1.8140	1.3770	1.5940
Sum Sq. Dev.	0.8112	0.8937	1.0570	0.6954
In-sample period	4/27/2000 to 12/31/2013	1/3/2000 to 12/31/2013	1/4/2000 to 12/30/2013	1/4/2000 to 12/27/2013
Observations	3,375	3,376	3,463	3,317

This table presents descriptive statistics of the daily data of net stock returns of four stock indices for four selected countries: Hong Kong, India, Korea, and Thailand.

[27] The results of the variance ratio tests are presented in Appendix B.

2.5.3 Empirical results of the proposed MS models

Before estimating the proposed MS models, we firstly estimate the linear models with the same explanatory variables[28]. The results show that in the linear models, the coefficient estimates of fundamental expectation are statistically significant in the net stock returns estimation for all countries except Thailand and the estimated coefficients are negative as expected. This means that if there is only one state, the fundamentalist rule determine the net stock returns in Hong Kong, India, and Korea but not for Thailand. On the other hand, the coefficient estimate of a chartist rule is statistically significant in the net return on stocks determination for all countries except India and Thailand. So it is notice that if we assume there is only one state, both fundamentalist and chartist rules are statistically insignificant in the net stock return determination for Thailand. The coefficients of the global risk factor are negative for all countries as expected and are statistically significant.

The three model-selection criteria, i.e., the Akaike Information Criterion, the Hannan-Quinn Criterion, and the Schwarz criterion, shown in Table 16 indicate that the proposed MS models both with constant and with time-varying transition probabilities are better fit than the linear models for all countries.

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[28] The results of the linear models based on a chartist-fundamentalist approach are available in Appendix C.

Table 16 Comparison of model selection criteria among various types of models

	NET_RETURN_HK		
	Linear model	**MS model with CP**	**MS model with TVTP**
Akaike info criterion	-5.6301	-5.9355	***-5.9389***
Hannan-Quinn criterion	-5.6274	-5.9275	***-5.9296***
Schwarz criterion	-5.6227	***-5.9132***	-5.9129
	NET_RETURN_ID		
	Linear model	**MS model with CP**	**MS model with TVTP**
Akaike info criterion	-5.4299	***-5.7314***	-5.7304
Hannan-Quinn criterion	-5.4273	***-5.7236***	-5.7213
Schwarz criterion	-5.4227	***-5.7096***	-5.7050
	NET_RETURN_KR		
	Linear model	**MS model with CP**	**MS model with TVTP**
Akaike info criterion	-5.3492	***-5.6242***	-5.6235
Hannan-Quinn criterion	-5.3466	***-5.6164***	-5.6144
Schwarz criterion	-5.3419	***-5.6023***	-5.5980
	NET_RETURN_TH		
	Linear model	**MS model with CP**	**MS model with TVTP**
Akaike info criterion	-5.6673	-5.8771	***-5.8781***
Hannan-Quinn criterion	-5.6647	***-5.8692***	-5.8689
Schwarz criterion	-5.6599	***-5.8550***	-5.8523

This table presents three model-selection criteria: the Akaike Information Criterion, the Hannan-Quinn Criterion, and the Schwarz criterion to compare the goodness of fit among linear model, the proposed MS models both with constant transition probabilities (CP) and with time-varying transition probabilities (TVTP). The most negative value or the best value of information criteria is highlighted in grey cell in each row.

The likelihood ratio test results are also presented in Table 17. We firstly compare the linear model to the MS models with constant and time-varying transition probabilities. The results indicate that the MS models with constant and time-varying transition probabilities are statistically better fit than the linear model for all countries. Then, we compare the MS model with constant transition probabilities to the MS model with time-varying transition probabilities. The likelihood ratio test results imply that there are statistically improvements of using time-varying transition probabilities in the MS model estimation for Hong Kong only but not for India, Korea, and Thailand. The estimation results in details of the MS models with both constant and time-varying transition probabilities for all four selected Asian countries are available in Appendix D.

Table 17 The likelihood ratio (LR) test results

		Linear model	MS model with CP vs. Linear model	MS model with TVTP vs. Linear model	MS model with TVTP vs. MS model with CP
Hong Kong	Log likelihood	9,248.59	9,758.03	9,765.61	9,765.61
	LR statistic		1,018.88	1,034.05	15.17
	p-Value		***< 0.01***	***< 0.01***	***< 0.05***
India	Log likelihood	9,169.70	9,686.54	9,686.96	9,686.96
	LR statistic		1,033.67	1,034.51	0.84
	p-Value		***< 0.01***	***< 0.01***	> 0.10
Korea	Log likelihood	8,971.98	9,441.02	9,441.81	9,441.81
	LR statistic		938.08	939.66	1.57
	p-Value		***< 0.01***	***< 0.01***	> 0.10
Thailand	Log likelihood	9,403.22	9,759.18	9,762.79	9,762.79
	LR statistic		711.91	719.14	7.23
	p-Value		***< 0.01***	***< 0.01***	> 0.10

This table show the likelihood ratio (LR) test results to compare
1) the MS model with constant transition probabilities (CP) to the linear model,
2) the MS model with time-varying transition probabilities (TVTP) to the linear model, and
3) the MS model with TVTP to the MS model with CP.
According to Garcia (1998), asymptotic distribution critical values for non-standard distribution of the likelihood ratio in a two-state Markov switching model (switching in both means and variances) at 5% and 1% significance levels are 13.68 and 17.52 respectively.
By considering the p-Value, if the null hypothesis is rejected, the more complicated model (more free parameters) is significantly better than the simpler models (less free parameters).

Table 18 presents the empirical results of the proposed MS models with constant transition probabilities based on the chartist-fundamentalist approach to estimate the daily net return on stocks of the four selected Asian countries.

Table 18 Estimation of the proposed MS models with constant transition probabilities for the net return on stocks of four Asian countries

Net stock return (r_{t+1})	Hong Kong	India	Korea	Thailand
High-Volatility State				
Constant = β_{01}	-0.0008	-0.0012	-0.0013	-0.0008**
Explanatory variables:				
DEV_RATIO (-1) = β_{f1}	-0.0044**	-0.0084***	-0.0073**	-0.000066***
DP_RATIO (-1) = β_{c1}	-0.1513***	-0.0166**	-0.0482*	-0.0577
DVIX (-1) = β_{g1}	-0.0032***	-0.0019***	-0.0025***	-0.0019***
Volatility:				
LOG(SIGMA) = $\log(\sigma_1)$	-3.6959***	-3.6514***	-3.7029***	-3.8596***
Expected Duration (days)	41	29	51	21
Low-Volatility State				
Constant = β_{02}	0.0004**	0.0011***	0.0012***	0.0006**
Explanatory variables:				
DEV_RATIO (-1) = β_{f2}	-0.002***	-0.0004*	-0.0026**	-0.0019**
DP_RATIO (-1) = β_{c2}	-0.0004***	0.0812***	-0.034	0.0371**
DVIX (-1) = β_{g2}	-0.0033***	-0.0012***	-0.0032***	-0.0012***
Volatility:				
LOG(SIGMA) = $\log(\sigma_2)$	-4.612***	-4.5623***	-4.6185***	-4.6604***
Expected Duration (days)	150	83	102	47
Transition matrix parameters:				
P11-C = γ_{01}	3.6926***	3.3337***	3.9042***	3.0165***
P22-C = γ_{02}	-5.0023***	-4.408***	-4.6185***	-3.8245***
No. of observations (after Adj.)	3,284	3,376	3,353	3,317

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$$E_t[r_{t+1}|S_{t+1} = j] = \beta_{0j} + \beta_{fj}b_t + \beta_{cj}dp_t + \beta_{gj}dVIX_t + E_t[\epsilon^j_{t+1}],$$

where $\epsilon^j_{t+1} \sim N(0, \sigma_j)$ if $S_{t+1} = j.$

DEV_RATIO (-1) is the coefficient of deviation of actual stock price from its fundamental price divided by the actual stock price in the previous day. DP_RATIO (-1) denotes the coefficient of change in stock price index relative to the price index in the previous day. DVIX (-1) is the coefficient of the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) in the previous day. The estimated values of LOG (SIGMA) indicate the natural logarithms of the volatilities in state 1 (high volatility) and state 2 (low volatility).

Constant transition probabilities: $$P^{ij} = \begin{bmatrix} P^{11} = \frac{exp(\gamma_{01})}{1+ exp(\gamma_{01})} & P^{12} = 1 - \frac{exp(\gamma_{01})}{1+ exp(\gamma_{01})} \\ P^{21} = \frac{exp(\gamma_{02})}{1+ exp(\gamma_{02})} & P^{21} = 1 - \frac{exp(\gamma_{02})}{1+ exp(\gamma_{02})} \end{bmatrix}$$

where P^{ij} = a constant transition probability from state i to state j

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

As presented in Table 18, the estimated coefficients of explanatory variables in the high-volatility states are in the state 1 and those in the low-volatility states are in the state 2. The Wald test[29] suggests that the Markov switching (MS) model parameters are statistically different between the two states, especially the volatility parameters.

For the coefficient estimates of DEV_RATIO (-1) which reflect the fundamentalist expectations, they are all statistically significant and have negative sign as expected in both states for most countries except for Thailand in the high-volatility state and for Korea in the low-volatility state. A negative sign of DEV_RATIO (-1) coefficient reflects the mean-reverting expectation of fundamentalists. The sizes of coefficient estimates for DEV_RATIO (-1) of Hong Kong and Korea are bigger than those of India and Thailand in the low-volatility state. This indicates that the speed of adjustment of the fundamentalist expectation in Hong Kong and Korea are faster than those in India and Thailand. The limits to arbitrage in Hong Kong and Korea may be less than in India and Thailand. However, in the high-volatility state, the speed of adjustment in the Indian stock market has the highest value compared to the others. This reflects that agents' expectation in the Indian stock market has a rapid adjustment for the return to fundamental value in the high volatility state.

On the other hand, the coefficient estimates of DP_RATIO (-1) which reflect the chartist expectation have positive signs in both states for India and Thailand but have negative signs in both states for Hong Kong and Korea in the low-volatility state. A positive sign of DP_RATIO (-1) coefficient represents the trend-following expectation of chartists while a negative sign of this coefficient indicate the reversal expectation of chartists. These results imply that in the low-volatility state, the chartist expectation of traders in Hong Kong and Korea are dominated by the reversal strategies reflecting the stabilizing speculation while the chartist expectation of traders in India and Thailand are dominated by the trend-following strategies reflecting the de-stabilizing speculation. These implications are consistent with the

[29] The Wald test results are given in APPENDIX E.

longer expected durations of the two states in Hong Kong and Korea than those in India and Thailand.

Since Hong Kong and Korea are advanced economies while India and Thailand are developing economies, stock markets in Hong Kong and Korea are supposed to be more efficient than those of India and Thailand. This conjecture is supported by the empirical results which indicate that daily stock prices of Hong Kong and Korea deviate from fundamentals less than those of India and Thailand[30]. The result of the test that we cannot reject the null hypothesis of an exponential martingale for the daily stock prices of Hong Kong and Korea also support the market efficiency in Hong Kong and Korea. The results are in accordance with Zunino et al. (2012) which find that informational efficiency is related to market size and the state of the economy.

For a global risk factor, DVIX (-1), the coefficient estimates are statistically significant and have negative signs for all countries. The results suggest that the higher risk in the global market gives the lower daily returns on stocks at present in all countries. The results are consistent to Veronesi (1999), Bansal et al. (2014), and Bollerslev et al. (2006) which find that when the risk becomes higher, investors will require higher expected rate of return and desire an additional discount price to buy a stock now.

These empirical results support our 4 hypotheses:

<u>Hypothesis I</u>: If fundamentalists perceive that stock return is over-valued, they will expect market return to decline to the fundamental value. If they perceive that stock return is under-valued, they will expect market return to increase to the fundamental value. Therefore, coefficient estimates of the deviation of actual from fundamental price relative to the actual price ($\boldsymbol{b_t}$) in the proposed MS model are statistically different from zero and have a negative sign in both of the two unobservable states.

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[30] Following the in-sample data of this study, absolute deviation ratios of actual price from the fundamental price relative to the actual price of Hong Kong, Korea, India, and Thailand are equal to 0.158940, 0.221119, 0.232792, and 0.326254 respectively.

<u>Hypothesis II</u>: Since chartists can use either momentum or reversal strategy, the coefficient estimate of the ratio of price change to the actual price $(\boldsymbol{dp_t})$ in the proposed MS model is different from zero but may have a positive or a negative sign.

<u>Hypothesis III</u>: Volatilities of the net return on stocks of the proposed MS model are statistically different between the two unobservable states.

<u>Hypothesis IV</u>: When the global risk increases, investors required a discount on the stock price for the higher expected return. So the coefficient estimate of a global risk factor $(dVIX_t)$ in the proposed MS model is different from zero and has a negative sign.

The empirical results of the models with time-varying transition probabilities as presented in Table 19 can be considered a robustness check of the proposed MS model. The qualitative conclusions are almost the same as those of the proposed models with constant transition probabilities. The only difference is the estimated coefficient of DP_RATIO (-1) in the low-volatility state for Hong Kong which is negative in the MS model with constant transition probabilities but is positive in the MS model with time-varying transition probabilities. The quantitative values of coefficient estimates are slightly different between the two approaches. We may conclude that the estimated results of the proposed MS models in this study are quite robust for both constant transition probabilities and time-varying transition probabilities.

Table 19 Estimation of the proposed MS models with time-varying transition probabilities for the net return on stocks of four Asian countries

Net stock return (r_{t+1})	Hong Kong	India	Korea	Thailand
High-Volatility State				
Constant = β_{01}	-0.0008	-0.0012**	-0.0013**	-0.0009
Explanatory variables:				
DEV_RATIO (-1) = β_{f1}	-0.0045*	-0.0083***	-0.0074***	-0.000212*
DP_RATIO (-1) = β_{c1}	-0.1528***	-0.0168	-0.0484**	-0.0605
DVIX (-1) = β_{g1}	-0.0032***	-0.0019***	-0.0025***	-0.0019***
Volatility:				
LOG(SIGMA) = $\log(\sigma_1)$	-3.6934***	-3.6506***	-3.6993***	-3.8502***
Expected Duration (days)	66	30	50	19
Low-Volatility State				
Constant = β_{02}	0.0004**	0.0011***	0.0012***	0.0006**
Explanatory variables:				
DEV_RATIO (-1) = β_{f2}	-0.0018*	-0.0004**	-0.0026**	-0.0019*
DP_RATIO (-1) = β_{c2}	0.0015***	0.081***	-0.0341	0.0411*
DVIX (-1) = β_{g2}	-0.0033***	-0.0012***	-0.0032***	-0.0012***
Volatility:				
LOG(SIGMA) = $\log(\sigma_2)$	-4.6151***	-4.5619***	-4.541***	-4.6585***
Expected Duration (days)	137	83	101	43
Transition matrix parameters:				
P11-C = γ_{01}	5.3815***	3.6776***	3.4409***	2.4081***
P22-C = γ_{02}	-2.3657***	-1.5109	-4.3404***	1.2571*
P11-ABS_DEV_RATIO (-1) = γ_{11}	-5.6791**	-4.4064***	1.8376*	-3.9829***
P22-ABS_DEV_RATIO (-1) = γ_{12}	-3.6749	-0.0208***	-1.118	0.8144
No. of observations (after Adj.)	3,284	3,376	3,353	3,317

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$$E_t[r_{t+1}|S_{t+1}=j] = \beta_{01} + \beta_{fj}b_t + \beta_{cj}dp_t + \beta_{gj}dVIX_t + E_t\left[\epsilon_{t+1}^{j}\right],$$

$$\text{where } \epsilon_{t+1}^{j} \sim N(0,\sigma_j) \text{ if } S_{t+1}=j.$$

DEV_RATIO (-1) is the coefficient of deviation of actual stock price from its fundamental price divided by the actual stock price in the previous day while ABS_DEV_RATIO (-1) is the coefficient of its absolute value$(|b_t|)$. DP_RATIO (-1) denotes the coefficient of change in stock price index relative to the price index in the previous day. DVIX (-1) is the coefficient of the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) in the previous day. The estimated values of LOG (SIGMA) indicate the natural logarithms of the volatilities in state 1 (high volatility) and state 2 (low volatility).

Time-varying transition probabilities: $P_{t+1}^{ij} = \begin{bmatrix} P_{t+1}^{11} = \frac{exp(\gamma_{01}+\gamma_{11}|b_t|)}{1+exp(\gamma_{01}+\gamma_{11}|b_t|)} & P_{t+1}^{12} = 1-\frac{exp(\gamma_{01}+\gamma_{11}|b_t|)}{1+exp(\gamma_{01}+\gamma_{11}|b_t|)} \\ P_{t+1}^{21} = \frac{exp(\gamma_{02}+\gamma_{12}|b_t|)}{1+exp(\gamma_{02}+\gamma_{12}|b_t|)} & P_{t+1}^{22} = 1-\frac{exp(\gamma_{02}+\gamma_{12}|b_t|)}{1+exp(\gamma_{02}+\gamma_{12}|b_t|)} \end{bmatrix}$

where P_{t+1}^{ij} = a time-varying transition probability from state i to state j

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

Table 20 compares the predictive accuracies of the estimated MS model with both constant and time-varying transition probabilities to those of the random walk model for both in-sample and out-of-sample periods. On average, the percentage of correct-sign predictions of the proposed model improves from a random walk model by 8.81% for in-sample data and 11.86% for out-of-sample data. However, the mean absolute error (MAE) and the root mean squared error (RMSE) of the proposed model slightly improve from those of a random walk model. The MAE declines by 3.59% for the in-sample period and by 3.77% for the out-of-sample period while the RMSE reduces by 3.66% for the in-sample period and by 4.14% for the out-of-sample period. Therefore, the proposed model may be more appropriate for explanation than forecasting. If we use the proposed MS model for forecasting, predicting the direction of changes seems to be more accurate than predicting the magnitude of changes.

Table 20 Predictabilities of the proposed MS model and a random walk model

Net Return	Forecast period	MS model			RW model			% improvement of MS model compared to RW model		
		% correct direction	MAE	RMSE	% correct direction	MAE	RMSE	% correct direction	MAE	RMSE
Hong Kong (CP)	In Sample	61.48%	0.0100	0.0144	50.00%	0.0107	0.0155	11.48%	6.74%	6.92%
	Out-of-Sample	65.15%	0.0062	0.0080	50.00%	0.0067	0.0086	15.15%	6.75%	6.10%
Hong Kong (TVTP)	In Sample	61.60%	0.0100	0.0144	50.00%	0.0107	0.0155	11.60%	6.69%	6.88%
	Out-of-Sample	65.15%	0.0062	0.0080	50.00%	0.0067	0.0086	15.15%	6.69%	6.11%
India (CP)	In Sample	56.78%	0.0112	0.0160	50.00%	0.0115	0.0163	6.78%	2.03%	1.82%
	Out-of-Sample	61.02%	0.0058	0.0076	50.00%	0.0061	0.0081	11.02%	4.68%	5.48%
India (TVTP)	In Sample	56.78%	0.0112	0.0160	50.00%	0.0115	0.0163	6.78%	2.03%	1.82%
	Out-of-Sample	61.02%	0.0058	0.0076	50.00%	0.0061	0.0081	11.02%	4.69%	5.48%
Korea (CP)	In Sample	59.86%	0.0118	0.0167	50.00%	0.0123	0.0174	9.86%	3.84%	4.13%
	Out-of-Sample	60.92%	0.0054	0.0070	50.00%	0.0055	0.0072	10.92%	0.87%	2.81%
Korea (TVTP)	In Sample	59.89%	0.0118	0.0167	50.00%	0.0123	0.0174	9.89%	3.84%	4.13%
	Out-of-Sample	61.34%	0.0054	0.0070	50.00%	0.0055	0.0072	11.34%	0.85%	2.79%
Thailand (CP)	In Sample	57.10%	0.0102	0.0142	50.00%	0.0104	0.0145	7.10%	1.78%	2.22%
	Out-of-Sample	60.34%	0.0055	0.0080	50.00%	0.0057	0.0082	10.34%	2.40%	2.15%
Thailand (TVTP)	In Sample	57.01%	0.0102	0.0142	50.00%	0.0104	0.0145	7.01%	1.76%	2.21%
	Out-of-Sample	59.92%	0.0055	0.0080	50.00%	0.0057	0.0082	9.92%	2.36%	2.21%
Avg. of 8 MS models in 4 countries	In Sample	**58.81%**	**0.0108**	**0.0153**	**50.00%**	**0.0112**	**0.0159**	**8.81%**	**3.59%**	**3.77%**
	Out-of-Sample	**61.86%**	**0.0058**	**0.0077**	**50.00%**	**0.0060**	**0.0080**	**11.86%**	**3.66%**	**4.14%**

This table presents the predictabilities of the proposed Markov switching (MS) models based on a chartist-fundamentalist approach compared to those of a random walk model for daily net returns on stocks of the selected Asian countries: Hong Kong, India, Korea, and Thailand. MAE denotes the mean absolute error and RMSE denotes the root mean square error. For the in-sample period, we use the empirical data from 2000 to 2013 for the proposed MS model estimation. We reserve the data in 2014 for an out-of-sample examination.

2.5.4 Further discussion on the results

One advantage of the MS models is that we can estimate the probabilities that the stock markets are falling into the high-volatility or low-volatility state at each point of time. Figure 16 to Figure 19 illustrate time series of the smoothed probabilities of falling into the high-volatility state for each stock market during the in-sample period which seem to be high during the periods of economic and financial crises in the global market and some critical domestic events in each stock market.

The smoothed probabilities indicate that Hong Kong and Korea are less frequently switching than India and Thailand. This coincides with the durations in both states of Hong Kong and Korea being longer than those of India and Thailand as presented in Table 18 and Table 19. The empirical results indicate that the fundamentalists in Hong Kong and Korea adjust to the deviation from fundamental stock returns more actively than in India and Thailand, especially in the low-volatility state. Moreover, the net chartist expectations in Hong Kong and Korea are reversal while those in India and Thailand are trend following in the low-volatility state. This means that in the normal state with low-volatility, stock markets in Hong Kong and Korea have stabilizing forces by both fundamentalist and chartist expectations while there are some destabilizing speculations in Indian and Thai stock markets. Therefore, the switching between the two states are more pronounced in Thailand and India compared to Hong Kong and Korea.

For all countries, as illustrated in Figure 16 to Figure 19, there are several periods that the daily returns on all selected stock markets had very high probabilities of falling into the high-volatility state. These periods coincide with the Dot-Com bust and Enron's problem in 2001-02, the global financial crisis during 2007-09, and the European debt crisis in 2011. For Thailand, the prolonged political uncertainty has also affected the Thai stock market.

According to the estimated MS model, the expected durations of being in the high-volatility and low-volatility states of the Hang Seng index in Hong Kong are 66 and 137 days (TVTP), of the Sensex index in India are 29 and 83 days (CP), of the KOSPI index in Korea are 51 and 102 days (CP), and of the SET index in Thailand are 21 and 47 days respectively (CP).

The average probabilities of remaining in the high-volatility and low-volatility states are persistent for all countries at 0.95 and 0.99 for Hong Kong, at 0.97 and 0.99 for India, at 0.98 and 0.99 for Korea, and at 0.94 and 0.98 for Thailand.

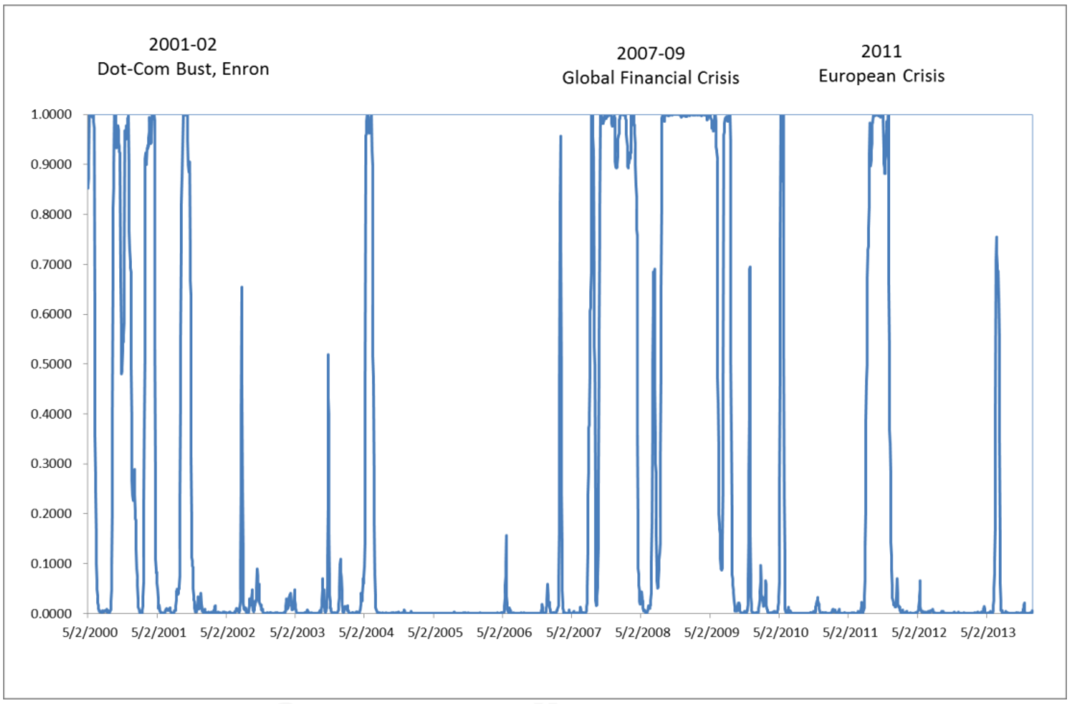

Figure 16 Smoothed probabilities of being in the high-volatility state from the estimated MS model with time-varying transition probabilities for Hong Kong

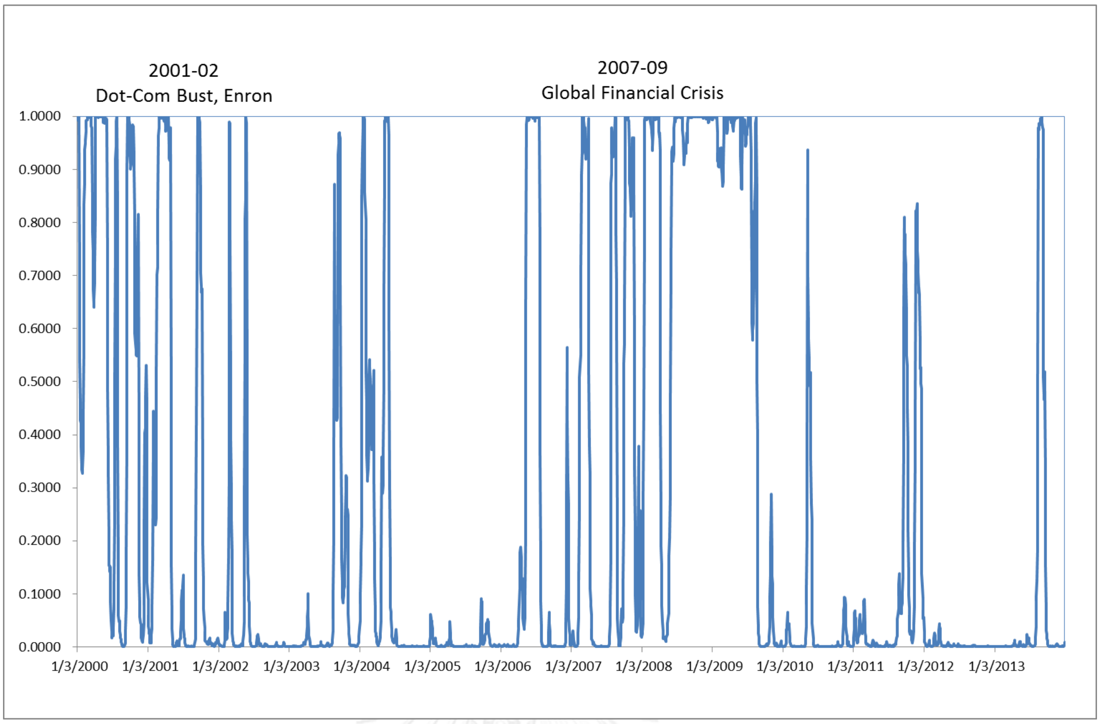

Figure 17 Smoothed probabilities of being in the high-volatility state from the estimated MS model with constant transition probabilities for India

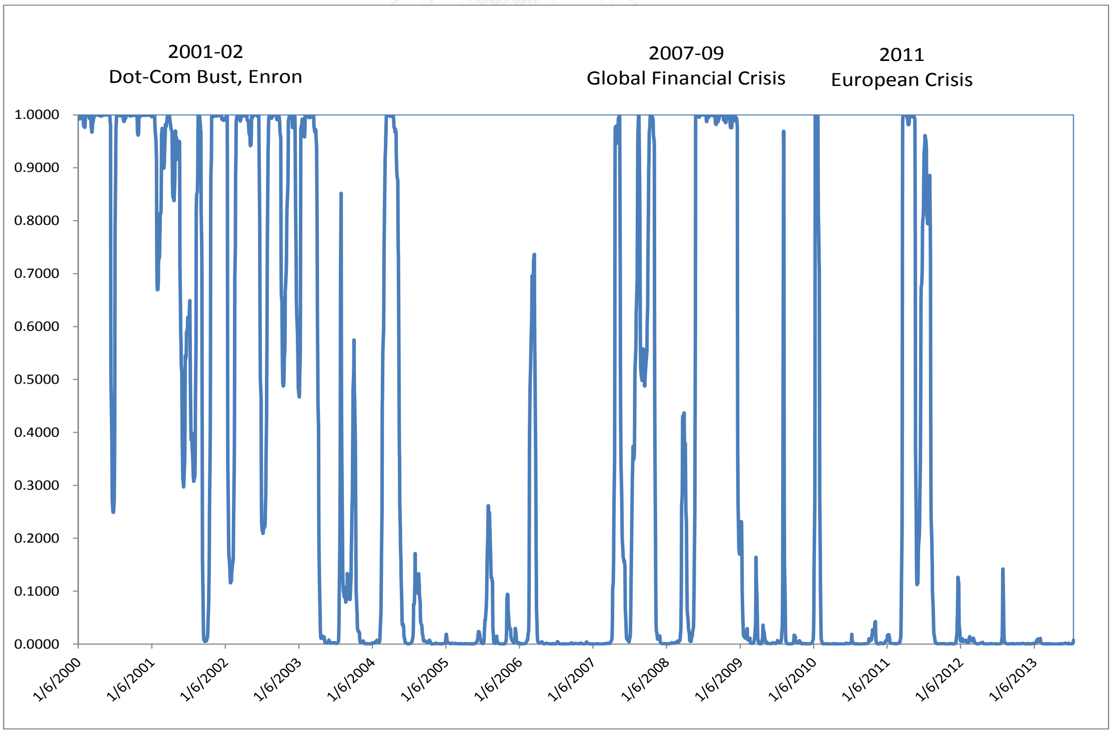

Figure 18 Smoothed probabilities of being in the high-volatility state from the estimated MS model with constant transition probabilities for Korea

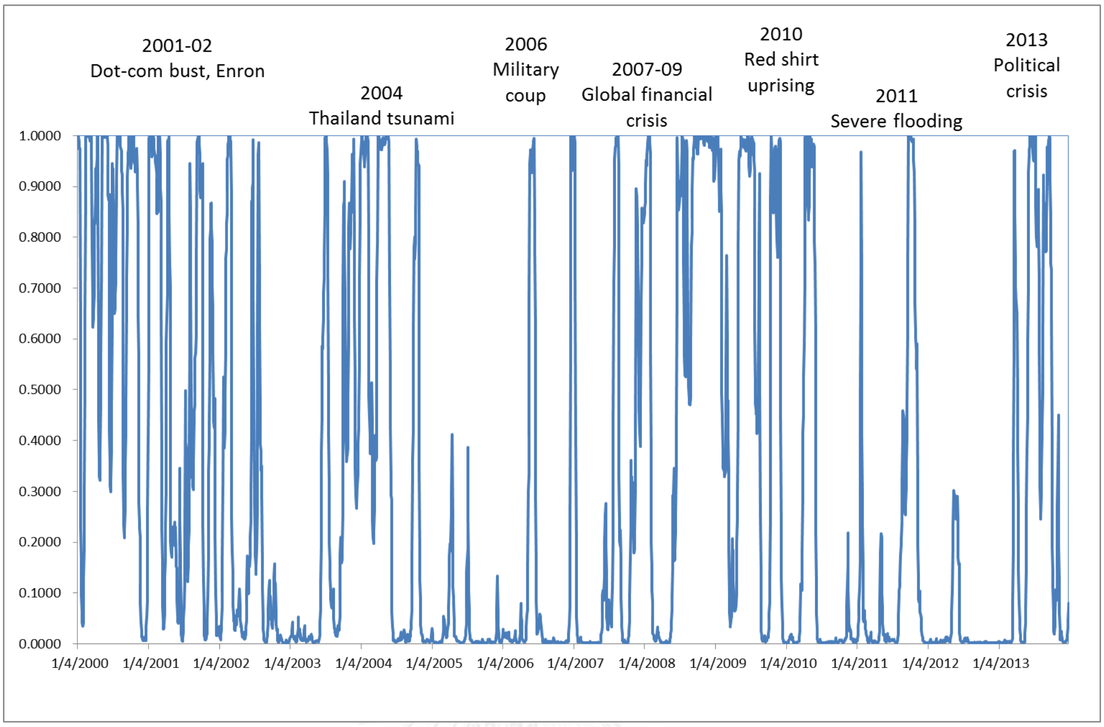

Figure 19 Smoothed probabilities of being in the high-volatility state from the estimated MS model with constant transition probabilities for Thailand

2.5.5 Robustness Check

In the estimation of the proposed MS models in this study, we use the fundamental values of stock indices of the four selected Asian countries following the static Gordon growth model. For the robustness check, we also estimate the proposed models by using the fundamental values of the selected stock indices using the dynamic Gordon growth model. This dynamic model relaxes the assumption of constant growth rates of dividends and required rate of stock returns in the static model. Boswijk et al. (2007) show the derivation of this model by using a first-order Taylor expansion around the mean values of the required rate of a stock return and the dividend growth rate. The fundamental stock price following the dynamic Gordon growth model $(P2_t^*)$ can be written as:

$$P2_t^* = m_t D_t$$

where m_t is the time-varying multiplier calculated by the following formula:

$$m_t = \left\{ \frac{(1+g)}{(r-g)} - \frac{\rho(1+g)}{(r-g)\big(1+r-\rho(1+g)\big)}(r_t - r) + \frac{\varphi(1+r)}{(r-g)(1+r-\varphi(1+g)}(g_t - g) \right\}$$

Where $P2_t^*$ is the fundamental stock price following the dynamic Gordon growth model,

D_t is the dividend paid at time t,

g is the average growth rate of dividends,

r is the average required rate of return on stock,

g_t is the growth rate of dividend at time t,

r_t is the required rate of return on stock at time t,

ρ is the coefficient of the AR(1) process: $E_t(r_{t+1} - r) = \rho(r_t - r)$,

φ is the coefficient of the AR(1) process: $E_t(g_{t+1} - g) = \varphi(g_t - g)$.

The estimation results of the proposed MS model with constant and time-varying transition probabilities by using the fundamental stock prices following the dynamic Gordon growth model are presented in Table 21 and Table 22 respectively. The coefficient estimates are similar to those of the proposed MS model using the fundamental stock prices following the static Gordon growth model. The qualitative conclusions are almost the same. Therefore, the proposed MS model is quite robust for the two methodologies of fundamental stock price calculation.

Table 21 Estimation of the proposed MS models with constant transition probabilities for the net return on stocks of four Asian countries (dynamic Gordon growth model)

Net stock return (r_{t+1})	Hong Kong	India	Korea	Thailand
High-Volatility State				
Constant = β'_{01}	-0.0008***	-0.0012***	-0.0014	-0.0008**
Explanatory variables:				
DEV_RATIO2 (-1) = β'_{f1}	-0.0045*	-0.0087***	-0.008**	-0.00019***
DP_RATIO (-1) = β'_{c1}	-0.1513***	-0.0164***	-0.0473**	-0.0576*
DVIX (-1) = β'_{g1}	-0.0032***	-0.0019***	-0.0025***	-0.0019***
Volatility:				
LOG(SIGMA) = $\log(\sigma'_1)$	-3.696***	-3.6514***	-3.7028***	-3.8555***
Expected Duration (days)	41	29	50	21
Low-Volatility State				
Constant = β'_{02}	0.0004*	0.0011***	0.0012***	0.0006**
Explanatory variables:				
DEV_RATIO2 (-1) = β'_{f2}	-0.0021*	-0.0004***	-0.0028**	-0.0023**
DP_RATIO (-1) = β'_{c2}	0.0003***	0.0812***	-0.0339	0.0373**
DVIX (-1) = β'_{g2}	-0.0033***	-0.0012***	-0.0032***	-0.0012***
Volatility:				
LOG(SIGMA) = $\log(\sigma'_2)$	-4.612***	-4.5623***	-4.6149***	-4.6584***
Expected Duration (days)	150	83	102	47
Transition matrix parameters:				
P11-C = γ'_{01}	3.6921***	3.3338***	3.8999***	3.0014***
P22-C = γ'_{02}	-5.003***	-4.4081***	-4.6149***	-3.8247***
No. of observations (after Adj.)	3,284	3,376	3,353	3,317

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$E_t[r_{t+1}|S_{t+1}=j] = \beta'_{0j} + \beta'_{fj}b2_t + \beta'_{cj}dp_t + \beta'_{gj}dVIX_t + E_t[\epsilon^j_{t+1}]$, where $\epsilon^j_{t+1} \sim N(0,\sigma'_j)$ if $S_{t+1}=j$.

DEV_RATIO2 (-1) is the coefficient of deviation of actual stock price from the dynamic Gordon fundamental price divided by the actual stock price in the previous day. DP_RATIO (-1) denotes the coefficient of change in stock price index relative to the price index in the previous day. DVIX (-1) is the coefficient of the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) in the previous day. The estimated values of LOG (SIGMA) indicate the natural logarithms of the volatilities in state 1 (high volatility) and state 2 (low volatility).

Constant transition probabilities: $$P^{ij} = \begin{bmatrix} P^{11} = \frac{exp(\gamma_{01})}{1+exp(\gamma_{01})} & P^{12} = 1 - \frac{exp(\gamma_{01})}{1+exp(\gamma_{01})} \\ P^{21} = \frac{exp(\gamma_{02})}{1+exp(\gamma_{02})} & P^{21} = 1 - \frac{exp(\gamma_{02})}{1+exp(\gamma_{02})} \end{bmatrix}$$

where P^{ij} = a constant transition probability from state i to state j

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

Table 22 Estimation of the proposed MS models with time-varying transition probabilities for the net return on stocks of four Asian countries (dynamic Gordon growth model)

Net stock return (r_{t+1})	Hong Kong	India	Korea	Thailand
High-Volatility State				
Constant = β'_{01}	-0.0008***	-0.0012**	-0.0014*	-0.0009
Explanatory variables:				
DEV_RATIO2 (-1) = β'_{f1}	-0.0046*	-0.0086***	-0.0082***	-0.000404*
DP_RATIO (-1) = β'_{c1}	-0.1527***	-0.0164***	-0.0475*	-0.0599
DVIX (-1) = β'_{g1}	-0.0032***	-0.0019***	-0.0025***	-0.0019***
Volatility:				
LOG(SIGMA) = $\log(\sigma'_1)$	-3.6934***	-3.6505***	-3.6985***	-3.8492***
Expected Duration (days)	64	30	51	21
Low-Volatility State				
Constant = β'_{02}	0.0004**	0.0011***	0.0012***	0.0006*
Explanatory variables:				
DEV_RATIO2 (-1) = β'_{f2}	-0.0019	-0.0004***	-0.0027**	-0.0022*
DP_RATIO (-1) = β'_{c2}	0.0016***	0.081***	-0.0338	0.0408*
DVIX (-1) = β'_{g2}	-0.0033***	-0.0012***	-0.0032***	-0.0012***
Volatility:				
LOG(SIGMA) = $\log(\sigma'_2)$	-4.6151***	-4.5618***	-4.5401***	-4.6558***
Expected Duration (days)	138	83	102	45
Transition matrix parameters:				
P11-C = γ'_{01}	2.3667***	3.6755***	3.428***	2.2287***
P22-C = γ'_{02}	-5.3895***	-1.5336**	-4.2956***	2.2717**
P11-ABS_DEV_RATIO2 (-1) = γ'_{11}	3.7866	-4.424***	2.1011*	-3.6888***
P22-ABS_DEV_RATIO2 (-1) = γ'_{12}	5.772	0.0645***	-1.4672***	-0.3167
No. of observations (after Adj.)	3,284	3,376	3,353	3,317

This table presents coefficient estimates for the MS models based on a chartist-fundamentalist approach.

$E_t[r_{t+1}|S_{t+1}=j] = \beta'_{01} + \beta'_{fj}b2_t + \beta'_{cj}dp_t + \beta'_{gj}dVIX_t + E_t[\epsilon^j_{t+1}]$, where $\epsilon^j_{t+1} \sim N(0,\sigma'_j)$ if $S_{t+1}=j$.

DEV_RATIO2 (-1) is the coefficient of deviation of actual stock price from the dynamic Gordon fundamental price divided by the actual stock price in the previous day while ABS_DEV_RATIO2 (-1) is the coefficient of its absolute value($|b2_t|$). DP_RATIO (-1) denotes the coefficient of change in stock price index relative to the price index in the previous day. DVIX (-1) is the coefficient of the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) in the previous day. The estimated values of LOG (SIGMA) indicate the natural logarithms of the volatilities in state 1 and state 2.

Time-varying transition probabilities:
$$P^{ij}_{t+1} = \begin{bmatrix} P^{11}_{t+1} = \frac{exp(\gamma_{01}+\gamma_{11}|b_t|)}{1+exp(\gamma_{01}+\gamma_{11}|b_t|)} & P^{12}_{t+1} = 1-\frac{exp(\gamma_{01}+\gamma_{11}|b_t|)}{1+exp(\gamma_{01}+\gamma_{11}|b_t|)} \\ P^{21}_{t+1} = \frac{exp(\gamma_{02}+\gamma_{12}|b_t|)}{1+exp(\gamma_{02}+\gamma_{12}|b_t|)} & P^{22}_{t+1} = 1-\frac{exp(\gamma_{02}+\gamma_{12}|b_t|)}{1+exp(\gamma_{02}+\gamma_{12}|b_t|)} \end{bmatrix}$$

where P^{ij}_{t+1} = a time-varying transition probability from state i to state j

Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

2.6 Conclusion

This study develops a two-state Markov switching (MS) model to explain the speculative component of a stock price by using the chartist-fundamentalist approach. We allow investors to use both chartist and fundamentalist expectations within each of the two unobservable states in the proposed MS model. A global risk factor which is the volatility index of the SPX (S&P 500 Index) from the Chicago Board Options Exchange (VIX) is also added as an explanatory variable on the stock returns. The proposed model is employed to examine the daily net returns on stock indices of the four Asian countries: Hong Kong, India, Korea, and Thailand. The daily data for the in-sample period for all countries are from 2000 to 2013. The daily data in 2014 are used for an out-of-sample examination.

2.6.1 Findings

The results indicate that the MS models with constant and time-varying transition probabilities are statistically better than the linear models for all countries. The likelihood ratio test results imply that there are statistical improvements of using time-varying transition probabilities in the MS model estimation for Hong Kong only but not for India, Korea, and Thailand. The empirical results of the proposed MS model support the four hypotheses of this study:

Hypothesis I: If fundamentalists perceive that stock return is over-valued, they will expect market return to decline to the fundamental value. If they perceive that stock return is under-valued, they will expect market return to increase to the fundamental value. Therefore, coefficient estimates of the deviation of actual from fundamental price relative to the actual price in the proposed MS model are statistically different from zero and have a negative sign in both of the two unobservable states.

Hypothesis II: Since chartists can use either momentum or reversal strategy, the coefficient estimate of the ratio of price change to the actual price in the proposed MS model is different from zero but may have a positive or a negative sign.

Hypothesis III: Volatilities of the net return on stocks of the proposed MS model are statistically different between the two unobservable states.

Hypothesis IV: When the global risk increases, investors required a discount on the stock price for the higher expected return. So the coefficient estimate of a global risk factor in the proposed MS model is different from zero and has a negative sign.

Most of the coefficient estimates of fundamentalist and chartist expectations are statistically significant and have expected signs. These results confirm that MS models based on the chartist-fundamentalist approach are appropriate for daily data. The results imply that the fundamentalist expectations in Hong Kong and Korea response to the deviation from fundamental stock returns more actively than in India and Thailand, especially in the low-volatility state. In addition, in the low-volatility state, the chartist expectations in Hong Kong and Korea are dominated by the reversal strategies while the chartist expectations in India and Thailand are dominated by the trend-following strategies. The stock markets in Hong Kong and Korea seem to be more efficient than those of India and Thailand because of the advanced state of market development. In addition, a global risk factor is important in determining the net return on stocks of Asian countries and it reflects the common risk among various countries. The empirical results are robust for both the proposed models with constant and time-varying transition probabilities and by using both fundamental stock prices calculated by static and dynamic Gordon growth models.

2.6.2 Discussion on the results

According to the estimated MS models, we can estimate the probabilities that the stock markets are falling into the high-volatility and low-volatility states. The results show that the periods which have high probabilities of falling into the high-volatility state coincide with the financial or economic crises in the past such as the Dot-com bust and Enron’s problem in 2001-02, the Global financial crisis in 2007-2009, and the European debt crisis in 2011, including some critical domestic events. Related parties may use these probabilities analyses to improve their understanding about the market situation to further make their decisions more appropriately.

2.6.3 Limitations of the study

Similar to the proposed model for daily exchange rates in Chapter 1, the model of the net stock returns in this study is based on some theoretical rationale and empirical facts. The model is used to examine the daily net stock returns expectation by assuming some behaviors of investors rather than based on a pure theoretical framework. It is possible to examine the Markov switching (MS) models with more than two states but the improvement may not added much. According to the extant literature, two-state MS models are usually well enough for explanation and understanding.

2.6.4 Suggestions for further study

The proposed model may be applied to test other financial markets beyond the stock market as well. It is interesting to consider that whether there are some differences or similarities among different types of financial market. In addition, other techniques for chartist expectation which can explain the trader behavior better than the stock price change in the previous period may be explored.

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Appendix to Chapter 1

Appendix A: Descriptions of variables

Variables	Description	Unit	Frequency	Source of data
XXX_USD	Index of the exchange rate of the local currency of country XXX against one US dollar	2011 = 100	daily, monthly	CEIC data
LN_XXX_USD	Natural Logarithm of an exchange rate index * 100	none	daily, monthly	calculation
DLN_XXX_USD	Difference of ln_XXX_USD from period t-1 to t	%	daily, monthly	calculation
CPI_XXX	Index of the consumer price index in country XXX	2011 = 100	monthly	CEIC data
LN_CPI_XXX	Natural logarithm of the consumer price index in country XXX	none	monthly	calculation
CPI_US	Index of the consumer price index in the United States	2011 = 100	monthly	CEIC data
LN_CPI_US	Natural logarithm of the consumer price index in the United States	none	monthly	calculation
PPP_ln_XXX_USD	Fundamental value of LN_XXX_USD following the Purchasing Power Parity (PPP) Model	none	monthly	calculation

Variables	Description	Unit	Frequency	Source of data
DEV_XXX	Deviation of actual LN_XXX_USD from fundamental LN_XXX_USD in the Purchasing Power Parity (PPP) Model	none	daily	calculation
ABS_DEV_XXX	Absolute value of DEV_XXX_PPP	none	daily	calculation
VIX	Implied volatility of S&P 500 index options for the next 30 days	percentage points (annualized rate)	daily	Chicago Board Options Exchange
DVIX	Daily change in the implied volatility of the S&P 500 index options for the next 30 days	percentage points (annualized rate)	daily	calculation
MSCI	Free float-adjusted market capitalization weighted equity index to measure the performance of equities in the developed and emerging markets of 45 countries	31Dec87=100	daily	MSCI Inc.
LN_MSCI	Natural logarithm of the MSCI index	none	daily	calculation
DLN_MSCI	Difference of LN_MSCI from period t-1 to t	none	daily	calculation
ECB_QE	Covered bond purchases by the European Central Bank (ECB)	million EUR	daily	European Central Bank (ECB)
BOE_QE	Outright asset purchases by the Bank of England (BOE)	million GBP	daily	Bank of England (BOE)

Variables	Description	Unit	Frequency	Source of data
BOJ_QE	Outright asset purchases by the Bank of Japan (BOJ)	100 million JPY	daily	Bank of Japan (BOJ)
FED_QE	Quantitative Easing (QE) Program 1 to 3	million USD	daily	Federal Reserve Bank of St. Louis
BOJ_FX Intervention	Intervention in the FX market by the Ministry of Finance Japan: the US dollar (bought) the Japanese yen (sold)	billion JPY	daily	Ministry of Finance Japan
DLN_FX_CY	Change in the natural logarithm of the cyclical series of each LN_XXX_USD series	%	daily	Hodrick-Prescott (HP) filter
DLN_FX_SM	Change in the natural logarithm of the smoothed series of each LN_XXX_USD series	%	daily	Hodrick-Prescott (HP) filter
LOG_SIGMA	Natural logarithm of the standard deviation of D_LN_FX_CY or D_LN_FX_SM in each state	none	daily	MS model estimation

Note: The five currencies selected for this study are EUR (the euro), JPY (the Japanese yen), GBP (the Pound sterling), AUD (the Australian dollar), and CAD (the Canadian dollar).

Appendix B: PPP models for fundamental value determination

PPP model for fundamental value determination: LN_AUD_USD

Dependent Variable: LN_AUD_USD
Method: Least Squares
Sample: 1999M01 2013M06
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1487.897	57.56395	25.84772	0.0000
LN_CPI_AUD	1.722327	0.581079	2.964015	0.0035
LN_CPI_US	-3.933458	0.685804	-5.735546	0.0000

R-squared	0.795582	Mean dependent var	492.2182
Adjusted R-squared	0.793191	S.D. dependent var	22.47087
S.E. of regression	10.21890	Akaike info criterion	7.503446
Sum squared resid	17856.83	Schwarz criterion	7.557912
Log likelihood	-649.7998	Hannan-Quinn criter.	7.525541
F-statistic	332.7612	Durbin-Watson stat	0.094881
Prob(F-statistic)	0.000000		

PPP model for fundamental value determination: LN_CAD_USD

Dependent Variable: LN_CAD_USD
Method: Least Squares
Sample: 1999M01 2013M06
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	983.7572	54.16762	18.16135	0.0000
LN_CPI_CAD	2.168742	0.600935	3.608946	0.0004
LN_CPI_US	-3.299685	0.492202	-6.703918	0.0000

R-squared	0.884697	Mean dependent var	481.4733
Adjusted R-squared	0.883349	S.D. dependent var	17.01608
S.E. of regression	5.811715	Akaike info criterion	6.374720
Sum squared resid	5775.702	Schwarz criterion	6.429186
Log likelihood	-551.6006	Hannan-Quinn criter.	6.396815
F-statistic	656.0259	Durbin-Watson stat	0.107740
Prob(F-statistic)	0.000000		

PPP model for fundamental value determination: LN_EUR_USD

Dependent Variable: LN_EUR_USD
Method: Least Squares
Sample: 1999M01 2013M06
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	827.9131	84.69112	9.775677	0.0000
LN_CPI_EUR	2.884192	1.062986	2.713293	0.0073
LN_CPI_US	-3.683671	0.894009	-4.120395	0.0001

R-squared	0.670345	Mean dependent var	475.3659
Adjusted R-squared	0.666489	S.D. dependent var	16.25670
S.E. of regression	9.388309	Akaike info criterion	7.333898
Sum squared resid	15072.00	Schwarz criterion	7.388365
Log likelihood	-635.0492	Hannan-Quinn criter.	7.355993
F-statistic	173.8620	Durbin-Watson stat	0.076083
Prob(F-statistic)	0.000000		

PPP model for fundamental value determination: LN_GBP_USD

Dependent Variable: LN_GBP_USD
Method: Least Squares
Sample: 1999M01 2013M06
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	425.7340	26.34410	16.16051	0.0000
LN_CPI_UK	2.670807	0.223127	11.96990	0.0000
LN_CPI_US	-2.592306	0.208152	-12.45394	0.0000

R-squared	0.475672	Mean dependent var	457.2637
Adjusted R-squared	0.469540	S.D. dependent var	10.27934
S.E. of regression	7.486724	Akaike info criterion	6.881231
Sum squared resid	9584.727	Schwarz criterion	6.935697
Log likelihood	-595.6671	Hannan-Quinn criter.	6.903326
F-statistic	77.56596	Durbin-Watson stat	0.091416
Prob(F-statistic)	0.000000		

PPP model for fundamental value determination: LN_JPY_USD

Dependent Variable: LN_JPY_USD
Method: Least Squares
Sample: 1999M01 2013M06
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1245.906	478.8402	2.601925	0.0101
LN_CPI_JPY	-0.580720	0.963804	-0.602529	0.5476
LN_CPI_US	-1.094851	0.103318	-10.59688	0.0000

R-squared	0.547153	Mean dependent var	487.3336
Adjusted R-squared	0.541856	S.D. dependent var	14.80122
S.E. of regression	10.01840	Akaike info criterion	7.463815
Sum squared resid	17162.99	Schwarz criterion	7.518282
Log likelihood	-646.3519	Hannan-Quinn criter.	7.485910
F-statistic	103.3053	Durbin-Watson stat	0.063788
Prob(F-statistic)	0.000000		

Note: The sign of LN_CPI_JPY's coefficient is incorrect but it is statistically insignificant.

Appendix C: Results of the variance ratio test

Variance ratio test: daily data of LN_AUD_USD

Null Hypothesis: LN_AUD_USD is a martingale
Sample: 1 3390
Included observations: 3389 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	1.107536	3389	0.7130

Variance ratio test: daily data of LN_CAD_USD

Null Hypothesis: LN_CAD_USD is a martingale
Sample: 1 3390
Included observations: 3389 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.919899	3389	0.8297

Variance ratio test: daily data of LN_EUR_USD

Null Hypothesis: LN_EUR_USD is a martingale
Sample: 1 3390
Included observations: 3389 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.843908	3389	0.8693

Variance ratio test: daily data of LN_GBP_USD

Null Hypothesis: LN_GBP_USD is a martingale
Sample: 1 3390
Included observations: 3389 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	0.647626	3389	0.9457

Variance ratio test: daily data of LN_JPY_USD

Null Hypothesis: LN_JPY_USD is a martingale
Sample: 1 3390
Included observations: 3389 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.770757	3389	0.2730

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Appendix D: Linear models of daily exchange rates based on a chartist-fundamentalist approach

Linear model: daily data of DLN_AUD_USD_CY and DLN_AUD_USD_SM

Method: Least Squares
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Dependent Variable: DLN_AUD_USD_CY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002601	0.013587	0.191434	0.8482
DLN_AUD_USD_CY(-1)	-0.265997	0.018707	-14.21878	0.0000
DEV_AUD_PPP(-1)	-0.002812	0.001288	-2.183378	0.0291
DVIX(-1)	0.065555	0.011683	5.611111	0.0000
DLN_MSCI(-1)	-7.625839	1.989338	-3.833354	0.0001
FED_QE(-1)	-1.38E-06	2.41E-06	-0.570806	0.5682

R-squared	0.083603	Mean dependent var	-0.000543
Adjusted R-squared	0.082249	S.D. dependent var	0.816962
S.E. of regression	0.782645	Akaike info criterion	2.349494
Sum squared resid	2071.586	Schwarz criterion	2.360346
Log likelihood	-3974.042	Hannan-Quinn criter.	2.353373
F-statistic	61.70833	Durbin-Watson stat	2.051956
Prob(F-statistic)	0.000000		

Dependent Variable: DLN_AUD_USD_SM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000257	0.000762	0.337483	0.7358
DLN_AUD_USD_SM(-1)	0.985152	0.003227	305.2737	0.0000
DEV_AUD_PPP(-1)	-0.000681	7.22E-05	-9.434349	0.0000
DVIX(-1)	0.001360	0.000647	2.103221	0.0355
DLN_MSCI(-1)	0.109889	0.103859	1.058059	0.2901
FED_QE(-1)	1.19E-07	1.35E-07	0.882310	0.3777

R-squared	0.967531	Mean dependent var	-0.014175
Adjusted R-squared	0.967483	S.D. dependent var	0.243042
S.E. of regression	0.043827	Akaike info criterion	-3.415379
Sum squared resid	6.496065	Schwarz criterion	-3.404527
Log likelihood	5791.653	Hannan-Quinn criter.	-3.411500
F-statistic	20155.54	Durbin-Watson stat	0.103951
Prob(F-statistic)	0.000000		

Linear model: daily data of DLN_CAD_USD_CY and DLN_CAD_USD_SM

Method: Least Squares

Sample (adjusted): 3 3390

Included observations: 3388 after adjustments

Dependent Variable: DLN_CAD_USD_CY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001925	0.009420	-0.204325	0.8381
DLN_CAD_USD_CY(-1)	-0.209666	0.018405	-11.39162	0.0000
DEV_CAD_PPP(-1)	-0.003810	0.001572	-2.422703	0.0155
DVIX(-1)	0.046648	0.008031	5.808415	0.0000
DLN_MSCI(-1)	-3.515825	1.343230	-2.617442	0.0089
FED_QE(-1)	-1.62E-06	1.66E-06	-0.973809	0.3302

R-squared	0.065200	Mean dependent var	-0.000265
Adjusted R-squared	0.063818	S.D. dependent var	0.557134
S.E. of regression	0.539064	Akaike info criterion	1.603803
Sum squared resid	982.7739	Schwarz criterion	1.614655
Log likelihood	-2710.842	Hannan-Quinn criter.	1.607682
F-statistic	47.17703	Durbin-Watson stat	2.052550
Prob(F-statistic)	0.000000		

Dependent Variable: DLN_CAD_USD_SM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001054	0.000562	-1.876663	0.0607
DLN_CAD_USD_SM(-1)	0.984604	0.003412	288.5546	0.0000
DEV_CAD_PPP(-1)	-0.001057	9.39E-05	-11.25790	0.0000
DVIX(-1)	0.000880	0.000474	1.857966	0.0633
DLN_MSCI(-1)	0.092876	0.075833	1.224732	0.2208
FED_QE(-1)	9.31E-08	9.91E-08	0.939025	0.3478

R-squared	0.963511	Mean dependent var	-0.011563
Adjusted R-squared	0.963457	S.D. dependent var	0.167902
S.E. of regression	0.032096	Akaike info criterion	-4.038386
Sum squared resid	3.484033	Schwarz criterion	-4.027533
Log likelihood	6847.025	Hannan-Quinn criter.	-4.034506
F-statistic	17860.90	Durbin-Watson stat	0.100510
Prob(F-statistic)	0.000000		

Linear model: daily data of DLN_EUR_USD_CY and DLN_EUR_USD_SM

Method: Least Squares
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Dependent Variable: DLN_EUR_USD_CY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000549	0.010653	-0.051575	0.9589
DLN_EUR_USD_CY(-1)	-0.155033	0.017792	-8.713383	0.0000
DEV_EUR_PPP(-1)	-0.002022	0.001104	-1.831398	0.0671
DVIX(-1)	0.008429	0.008921	0.944803	0.3448
DLN_MSCI(-1)	-2.159944	1.436784	-1.503318	0.1329
ECB_CBP(-1)	-3.93E-05	0.000124	-0.317538	0.7509
FED_QE(-1)	4.36E-07	1.86E-06	0.234697	0.8145

R-squared	0.025223	Mean dependent var	-0.000224
Adjusted R-squared	0.023493	S.D. dependent var	0.606420
S.E. of regression	0.599254	Akaike info criterion	1.815802
Sum squared resid	1214.136	Schwarz criterion	1.828463
Log likelihood	-3068.968	Hannan-Quinn criter.	1.820328
F-statistic	14.58080	Durbin-Watson stat	2.046085
Prob(F-statistic)	0.000000		

Dependent Variable: DLN_EUR_USD_SM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000253	0.000608	-0.416427	0.6771
DLN_EUR_USD_SM(-1)	0.985421	0.003057	322.3658	0.0000
DEV_EUR_PPP(-1)	-0.000529	6.30E-05	-8.394664	0.0000
DVIX(-1)	0.000187	0.000504	0.372248	0.7097
DLN_MSCI(-1)	0.100183	0.079449	1.260966	0.2074
ECB_CBP(-1)	-3.03E-07	7.07E-06	-0.042821	0.9658
FED_QE(-1)	-6.99E-08	1.06E-07	-0.660011	0.5093

R-squared	0.969231	Mean dependent var	-0.001972
Adjusted R-squared	0.969177	S.D. dependent var	0.194725
S.E. of regression	0.034187	Akaike info criterion	-3.911885
Sum squared resid	3.951522	Schwarz criterion	-3.899224
Log likelihood	6633.733	Hannan-Quinn criter.	-3.907359
F-statistic	17750.66	Durbin-Watson stat	0.100552
Prob(F-statistic)	0.000000		

Linear model: daily data of DLN_GBP_USD_CY and DLN_GBP_USD_SM

Method: Least Squares
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Dependent Variable: DLN_GBP_USD_CY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001759	0.009771	-0.180024	0.8571
DLN_GBP_USD_CY(-1)	-0.156733	0.017922	-8.745507	0.0000
DEV_GBP_PPP(-1)	-0.002520	0.001250	-2.016079	0.0439
DVIX(-1)	0.016987	0.008227	2.064804	0.0390
DLN_MSCI(-1)	-3.186510	1.335815	-2.385442	0.0171
BOE_QE(-1)	4.08E-05	2.18E-05	1.874887	0.0609
FED_QE(-1)	-3.54E-06	1.72E-06	-2.058637	0.0396

R-squared	0.032452	Mean dependent var	-7.99E-05
Adjusted R-squared	0.030735	S.D. dependent var	0.561323
S.E. of regression	0.552630	Akaike info criterion	1.653808
Sum squared resid	1032.557	Schwarz criterion	1.666469
Log likelihood	-2794.551	Hannan-Quinn criter.	1.658334
F-statistic	18.89996	Durbin-Watson stat	2.037147
Prob(F-statistic)	0.000000		

Dependent Variable: DLN_GBP_USD_SM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000105	0.000555	-0.189251	0.8499
DLN_GBP_USD_SM(-1)	0.983909	0.003192	308.2596	0.0000
DEV_GBP_SM_PPP(-1)	-0.000457	7.12E-05	-6.421632	0.0000
DVIX(-1)	0.000333	0.000463	0.719727	0.4717
DLN_MSCI(-1)	0.048744	0.072936	0.668307	0.5040
BOE_QE(-1)	8.03E-07	1.24E-06	0.648051	0.5170
FED_QE(-1)	-5.44E-08	9.77E-08	-0.556919	0.5776

R-squared	0.966728	Mean dependent var	0.001691
Adjusted R-squared	0.966669	S.D. dependent var	0.171726
S.E. of regression	0.031351	Akaike info criterion	-4.085046
Sum squared resid	3.323240	Schwarz criterion	-4.072385
Log likelihood	6927.067	Hannan-Quinn criter.	-4.080520
F-statistic	16372.82	Durbin-Watson stat	0.107511
Prob(F-statistic)	0.000000		

Linear model: daily data of DLN_JPY_USD_CY and DLN_JPY_USD_SM

Method: Least Squares
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Dependent Variable: DLN_JPY_USD_CY

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003904	0.012457	-0.313397	0.7540
DLN_JPY_USD_CY(-1)	-0.173510	0.017079	-10.15903	0.0000
DEV_JPY_PPP(-1)	-0.000982	0.001055	-0.930334	0.3523
DVIX(-1)	-0.039214	0.009012	-4.351131	0.0000
DLN_MSCI(-1)	-3.552442	1.397547	-2.541913	0.0111
INTV_JPY_SOLD	0.000464	5.49E-05	8.445761	0.0000
BOJ_QE(-1)	-2.66E-06	4.58E-06	-0.579637	0.5622
FED_QE(-1)	-5.94E-09	1.89E-06	-0.003146	0.9975

R-squared	0.055072	Mean dependent var	0.000112
Adjusted R-squared	0.053115	S.D. dependent var	0.625913
S.E. of regression	0.609063	Akaike info criterion	1.848569
Sum squared resid	1253.838	Schwarz criterion	1.863039
Log likelihood	-3123.476	Hannan-Quinn criter.	1.853741
F-statistic	28.14194	Durbin-Watson stat	2.055644
Prob(F-statistic)	0.000000		

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000452	0.000674	0.670335	0.5027
DLN_JPY_USD_SM(-1)	0.983258	0.003122	314.9223	0.0000
DEV_JPY_PPP(-1)	-0.000440	5.70E-05	-7.722275	0.0000
DVIX(-1)	-0.000761	0.000484	-1.572813	0.1159
DLN_MSCI(-1)	-0.199464	0.075561	-2.639764	0.0083
INTV_JPY_SOLD	6.86E-06	2.96E-06	2.314165	0.0207
BOJ_QE(-1)	5.99E-08	2.48E-07	0.241820	0.8089
FED_QE(-1)	-5.51E-08	1.02E-07	-0.539796	0.5894

R-squared	0.967203	Mean dependent var	-0.009888
Adjusted R-squared	0.967135	S.D. dependent var	0.181640
S.E. of regression	0.032929	Akaike info criterion	-3.986570
Sum squared resid	3.664988	Schwarz criterion	-3.972100
Log likelihood	6761.250	Hannan-Quinn criter.	-3.981398
F-statistic	14239.75	Durbin-Watson stat	0.107568
Prob(F-statistic)	0.000000		

Appendix E: Empirical results of the proposed MS models

MS model: daily data of DLN_AUD_USD_CY (Constant transition probabilities)

Dependent Variable: DLN_AUD_USD_CY
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 35 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.005506	0.007489	-0.735248	0.4622
DLN_AUD_USD_CY(-1)	-0.171537	0.019654	-8.727804	0.0000
DEV_AUD_PPP(-1)	-0.001521	0.001001	-1.520654	0.1283
DVIX(-1)	0.049775	0.012262	4.059266	0.0000
DLN_MSCI(-1)	-4.267539	1.828766	-2.333562	0.0196
FED_QE(-1)	5.67E-07	9.66E-07	0.587095	0.5571
LOG(SIGMA)	-0.507130	0.016120	-31.46005	0.0000
		Regime 2		
C	0.113495	0.087275	1.300438	0.1935
DLN_AUD_USD_CY(-1)	-0.471182	0.067137	-7.018231	0.0000
DEV_AUD_PPP(-1)	-0.010853	0.006065	-1.789605	0.0735
DVIX(-1)	0.057872	0.036590	1.581618	0.1137
DLN_MSCI(-1)	-23.73875	7.705479	-3.080763	0.0021
FED_QE(-1)	-2.62E-06	3.79E-06	-0.692390	0.4887
LOG(SIGMA)	0.471136	0.057139	8.245511	0.0000
		Transition Matrix Parameters		
P11-C	4.902552	0.300578	16.31041	0.0000
P21-C	-2.721077	0.346315	-7.857234	0.0000

Mean dependent var	-0.000543	S.D. dependent var	0.816962
S.E. of regression	0.778028	Sum squared resid	2042.373
Durbin-Watson stat	2.035005	Log likelihood	-3541.875
Akaike info criterion	2.100280	Schwarz criterion	2.129220
Hannan-Quinn criter.	2.110626		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.992627	0.007373
2	0.061741	0.938259

MS model: daily data of DLN_AUD_USD_SM (Constant transition probabilities)

Dependent Variable: DLN_AUD_USD_SM
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.003942	0.000946	4.168801	0.0000
DLN_AUD_USD_SM(-1)	0.997731	0.004804	207.7077	0.0000
DEV_AUD_PPP(-1)	-0.000637	8.59E-05	-7.412278	0.0000
DVIX(-1)	0.000696	0.000382	1.821253	0.0686
DLN_MSCI(-1)	-0.028866	0.024294	-1.188189	0.2348
FED_QE(-1)	1.75E-07	1.18E-07	1.476808	0.1397
LOG(SIGMA)	-3.846535	0.027321	-140.7926	0.0000
		Regime 2		
C	-0.004765	0.002131	-2.235600	0.0254
DLN_AUD_USD_SM(-1)	0.981216	0.006932	141.5450	0.0000
DEV_AUD_PPP(-1)	-0.000669	0.000171	-3.909899	0.0001
DVIX(-1)	0.001941	0.001028	1.888212	0.0590
DLN_MSCI(-1)	0.223972	0.173752	1.289031	0.1974
FED_QE(-1)	1.11E-07	1.59E-07	0.698523	0.4849
LOG(SIGMA)	-2.730904	0.026202	-104.2262	0.0000
		Transition Matrix Parameters		
P11-C	2.929420	0.129681	22.58940	0.0000
P21-C	-2.398225	0.128609	-18.64748	0.0000

Mean dependent var	-0.014175	S.D. dependent var	0.243042
S.E. of regression	0.043906	Sum squared resid	6.504315
Durbin-Watson stat	0.104424	Log likelihood	6440.263
Akaike info criterion	-3.792363	Schwarz criterion	-3.763423
Hannan-Quinn criter.	-3.782018		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.949282	0.050718
2	0.083308	0.916692

MS model: daily data of DLN_CAD_USD_CY (Constant transition probabilities)

Dependent Variable: DLN_CAD_USD_CY
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 11 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.000494	0.000712	0.693690	0.4879
DLN_CAD_USD_CY(-1)	-0.172398	0.023086	-7.467663	0.0000
DEV_CAD_PPP(-1)	-0.002385	0.001387	-1.719979	0.0854
DVIX(-1)	0.022938	0.008571	2.676084	0.0074
DLN_MSCI(-1)	-3.252408	1.309494	-2.483713	0.0130
FED_QE(-1)	-4.69E-06	3.57E-06	-1.312973	0.1892
LOG(SIGMA)	-0.978547	0.021016	-46.56277	0.0000
		Regime 2		
C	-0.006237	0.008784	-0.709949	0.4777
DLN_CAD_USD_CY(-1)	-0.246403	0.035625	-6.916569	0.0000
DEV_CAD_PPP(-1)	-0.006124	0.003351	-1.827521	0.0676
DVIX(-1)	0.060226	0.015709	3.833769	0.0001
DLN_MSCI(-1)	-4.927965	2.771535	-1.778063	0.0754
FED_QE(-1)	-6.61E-07	1.66E-06	-0.398174	0.6905
LOG(SIGMA)	-0.242837	0.031340	-7.748379	0.0000
		Transition Matrix Parameters		
P11-C	4.903735	0.322224	15.21842	0.0000
P21-C	-4.103932	0.342847	-11.97016	0.0000

Mean dependent var	-0.000265	S.D. dependent var	0.557134
S.E. of regression	0.538420	Sum squared resid	978.1093
Durbin-Watson stat	2.049079	Log likelihood	-2348.839
Akaike info criterion	1.396009	Schwarz criterion	1.424949
Hannan-Quinn criter.	1.406354		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.992636	0.007364
2	0.016240	0.983760

MS model: daily data of DLN_CAD_USD_SM (Constant transition probabilities)

Dependent Variable: DLN_CAD_USD_SM
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 11 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.005487	0.002211	-2.481603	0.0131
DLN_CAD_USD_SM(-1)	0.989225	0.007795	126.8991	0.0000
DEV_CAD_PPP(-1)	-0.002441	0.000323	-7.567836	0.0000
DVIX(-1)	0.001679	0.000849	1.977146	0.0480
DLN_MSCI(-1)	0.252531	0.138165	1.827748	0.0676
FED_QE(-1)	1.43E-07	1.16E-07	1.230858	0.2184
LOG(SIGMA)	-2.973451	0.030947	-96.08347	0.0000
		Regime 2		
C	0.000951	0.000645	1.475408	0.1401
DLN_CAD_USD_SM(-1)	0.982181	0.004715	208.3301	0.0000
DEV_CAD_PPP(-1)	-0.000274	0.000101	-2.722037	0.0065
DVIX(-1)	0.000151	0.000123	1.222912	0.2214
DLN_MSCI(-1)	-0.022391	0.028750	-0.778847	0.4361
FED_QE(-1)	1.94E-07	9.19E-08	2.108182	0.0350
LOG(SIGMA)	-4.049342	0.032554	-124.3880	0.0000
		Transition Matrix Parameters		
P11-C	2.493072	0.164304	15.17352	0.0000
P21-C	-3.421345	0.197464	-17.32644	0.0000

Mean dependent var	-0.011563	S.D. dependent var	0.167902
S.E. of regression	0.031421	Sum squared resid	3.330978
Durbin-Watson stat	0.105072	Log likelihood	7570.697
Akaike info criterion	-4.459679	Schwarz criterion	-4.430740
Hannan-Quinn criter.	-4.449334		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.923655	0.076345
2	0.031635	0.968365

MS model: daily data of DLN_EUR_USD_CY (Constant transition probabilities)

Dependent Variable: DLN_EUR_USD_CY
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 36 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.006168	0.008291	0.743956	0.4569
DLN_EUR_USD_CY(-1)	-0.136414	0.038067	-3.583515	0.0003
DEV_EUR_PPP(-1)	-0.004720	0.003109	-1.518334	0.1289
DVIX(-1)	0.020231	0.014751	1.371542	0.1702
DLN_MSCI(-1)	-2.342538	2.401165	-0.975584	0.3293
ECB_CBP(-1)	-8.80E-05	0.000125	-0.701886	0.4827
FED_QE(-1)	-2.39E-07	3.69E-07	-0.647605	0.5172
LOG(SIGMA)	-0.180970	0.043834	-4.128564	0.0000
		Regime 2		
C	-0.000819	0.002225	-0.368099	0.7128
DLN_EUR_USD_CY(-1)	-0.175960	0.021959	-8.013291	0.0000
DEV_EUR_PPP(-1)	-0.001252	0.000926	-1.351046	0.1767
DVIX(-1)	-0.005841	0.007628	-0.765756	0.4438
DLN_MSCI(-1)	-1.628276	1.347306	-1.208542	0.2268
ECB_CBP(-1)	-3.58E-05	5.17E-05	-0.692570	0.4886
FED_QE(-1)	9.59E-07	1.08E-06	0.886656	0.3753
LOG(SIGMA)	-0.702001	0.022387	-31.35785	0.0000
		Transition Matrix Parameters		
P11-C	3.498107	0.370254	9.447855	0.0000
P21-C	-4.615179	0.348568	-13.24039	0.0000

Mean dependent var	-0.000224	S.D. dependent var	0.606420
S.E. of regression	0.599948	Sum squared resid	1213.710
Durbin-Watson stat	2.042459	Log likelihood	-2942.532
Akaike info criterion	1.747658	Schwarz criterion	1.780215
Hannan-Quinn criter.	1.759296		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.970634	0.029366
2	0.009803	0.990197

MS model: daily data of DLN_EUR_USD_SM (Constant transition probabilities)

Dependent Variable: DLN_EUR_USD_SM
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 16 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.024575	0.000988	-24.86884	0.0000
DLN_EUR_USD_SM(-1)	0.979047	0.004029	243.0159	0.0000
DEV_EUR_PPP(-1)	-0.000897	7.81E-05	-11.48320	0.0000
DVIX(-1)	0.000225	0.000279	0.806748	0.4198
DLN_MSCI(-1)	0.084439	0.056155	1.503680	0.1327
ECB_CBP(-1)	1.06E-05	7.08E-06	1.490762	0.1360
FED_QE(-1)	-5.52E-08	6.24E-08	-0.883716	0.3768
LOG(SIGMA)	-3.833091	0.019456	-197.0083	0.0000
		Regime 2		
C	0.027436	0.001168	23.48214	0.0000
DLN_EUR_USD_SM(-1)	0.982260	0.004554	215.7060	0.0000
DEV_EUR_PPP(-1)	-0.000464	8.68E-05	-5.345775	0.0000
DVIX(-1)	-0.000313	0.000460	-0.680195	0.4964
DLN_MSCI(-1)	-0.032961	0.035368	-0.931959	0.3514
ECB_CBP(-1)	-8.91E-06	8.64E-06	-1.031069	0.3025
FED_QE(-1)	-3.88E-09	7.81E-09	-0.496647	0.6194
LOG(SIGMA)	-3.754104	0.019721	-190.3625	0.0000
		Transition Matrix Parameters		
P11-C	2.435868	0.099339	24.52084	0.0000
P21-C	-2.267570	0.098822	-22.94603	0.0000

Mean dependent var	-0.001972	S.D. dependent var	0.194725
S.E. of regression	0.024541	Sum squared resid	2.030777
Durbin-Watson stat	0.165715	Log likelihood	7498.633
Akaike info criterion	-4.415958	Schwarz criterion	-4.383401
Hannan-Quinn criter.	-4.404320		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.919522	0.080478
2	0.093845	0.906155

MS model: daily data of DLN_GBP_USD_CY (Constant transition probabilities)

Dependent Variable: DLN_GBP_USD_CY
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 20 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.019711	0.033400	0.590156	0.5551
DLN_GBP_USD_CY(-1)	-0.150163	0.058352	-2.573399	0.0101
DEV_GBP_PPP(-1)	-0.007459	0.005486	-1.359548	0.1740
DVIX(-1)	0.008270	0.010709	0.772222	0.4400
DLN_MSCI(-1)	-7.402450	3.321150	-2.228882	0.0258
BOE_QE(-1)	8.17E-05	5.64E-05	1.446767	0.1480
FED_QE(-1)	-5.86E-06	4.13E-06	-1.420688	0.1554
LOG(SIGMA)	0.019308	0.033036	0.584456	0.5589
		Regime 2		
C	-0.002722	0.006222	-0.437555	0.6617
DLN_GBP_USD_CY(-1)	-0.172952	0.018810	-9.194726	0.0000
DEV_GBP_PPP(-1)	-0.001738	0.001164	-1.493470	0.1353
DVIX(-1)	0.016303	0.008536	1.909952	0.0561
DLN_MSCI(-1)	-1.559480	1.257985	-1.239665	0.2151
BOE_QE(-1)	1.56E-05	2.75E-05	0.567587	0.5703
FED_QE(-1)	4.67E-07	1.15E-06	0.407211	0.6839
LOG(SIGMA)	-0.778166	0.014880	-52.29605	0.0000
		Transition Matrix Parameters		
P11-C	4.018147	0.516475	7.779953	0.0000
P21-C	-6.137075	0.527226	-11.64030	0.0000

Mean dependent var	-7.99E-05	S.D. dependent var	0.561323
S.E. of regression	0.552079	Sum squared resid	1027.755
Durbin-Watson stat	2.036272	Log likelihood	-2511.409
Akaike info criterion	1.493157	Schwarz criterion	1.525715
Hannan-Quinn criter.	1.504796		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.982332	0.017668
2	0.002157	0.997843

MS model: daily data of DLN_GBP_USD_SM (Constant transition probabilities)

Dependent Variable: DLN_GBP_USD_SM
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 27 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.022215	0.000728	30.52005	0.0000
DLN_GBP_USD_SM(-1)	0.991303	0.003666	270.4390	0.0000
DEV_GBP_PPP(-1)	-0.000706	8.97E-05	-7.863328	0.0000
DVIX(-1)	0.000428	0.000383	1.117635	0.2637
DLN_MSCI(-1)	0.093221	0.058732	1.587216	0.1125
BOE_QE(-1)	1.79E-06	1.27E-06	1.413581	0.1575
FED_QE(-1)	3.65E-08	1.72E-07	0.212049	0.8321
LOG(SIGMA)	-3.833679	0.018518	-207.0229	0.0000
		Regime 2		
C	-0.024960	0.000693	-36.03297	0.0000
DLN_GBP_USD_SM(-1)	0.970818	0.003805	255.1687	0.0000
DEV_GBP_PPP(-1)	-0.001663	8.74E-05	-19.03142	0.0000
DVIX(-1)	0.000686	0.000340	2.016693	0.0437
DLN_MSCI(-1)	0.149236	0.058868	2.535079	0.0112
BOE_QE(-1)	2.25E-06	1.24E-06	1.813827	0.0697
FED_QE(-1)	-1.22E-07	8.68E-08	-1.400233	0.1614
LOG(SIGMA)	-3.959392	0.019161	-206.6414	0.0000
		Transition Matrix Parameters		
P11-C	2.533568	0.098931	25.60943	0.0000
P21-C	-2.506589	0.100107	-25.03920	0.0000

Mean dependent var	0.001691	S.D. dependent var	0.171726
S.E. of regression	0.022305	Sum squared resid	1.677636
Durbin-Watson stat	0.179278	Log likelihood	7867.040
Akaike info criterion	-4.633436	Schwarz criterion	-4.600879
Hannan-Quinn criter.	-4.621797		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.926462	0.073538
2	0.075398	0.924602

MS model: daily data of DLN_JPY_USD_CY (Constant transition probabilities)

Dependent Variable: DLN_JPY_USD_CY
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 25 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.023773	0.027376	-0.868417	0.3852
DLN_JPY_USD_CY(-1)	-0.135513	0.041150	-3.293181	0.0010
DEV_JPY_PPP(-1)	-0.003420	0.003120	-1.096192	0.2730
DVIX(-1)	-0.065019	0.021542	-3.018238	0.0025
INTV_JPY_SOLD	0.001392	0.000315	4.412880	0.0000
DLN_MSCI(-1)	-8.211482	3.449400	-2.380554	0.0173
BOJ_QE(-1)	-4.78E-07	7.27E-07	-0.656737	0.5114
FED_QE(-1)	1.42E-06	2.81E-06	0.506638	0.6124
LOG(SIGMA)	-0.087077	0.042413	-2.053060	0.0401
		Regime 2		
C	-0.001253	0.002183	-0.574043	0.5659
DLN_JPY_USD_CY(-1)	-0.185106	0.020417	-9.066306	0.0000
DEV_JPY_PPP(-1)	-0.000464	0.000613	-0.756641	0.4493
DVIX(-1)	-0.022362	0.008497	-2.631680	0.0085
INTV_JPY_SOLD	0.000388	4.83E-05	8.026406	0.0000
DLN_MSCI(-1)	-1.288228	1.131461	-1.138553	0.2549
BOJ_QE(-1)	-2.69E-06	2.85E-06	-0.944394	0.3450
FED_QE(-1)	-1.20E-06	2.02E-06	-0.593154	0.5531
LOG(SIGMA)	-0.710122	0.020667	-34.35985	0.0000
		Transition Matrix Parameters		
P11-C	2.929997	0.317958	9.215030	0.0000
P21-C	-4.285774	0.301579	-14.21111	0.0000
Mean dependent var	0.000112	S.D. dependent var		0.625913
S.E. of regression	0.608368	Sum squared resid		1247.277
Durbin-Watson stat	2.055588	Log likelihood		-2947.778
Akaike info criterion	1.751935	Schwarz criterion		1.788110
Hannan-Quinn criter.	1.764867			

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.949310	0.050690
2	0.013576	0.986424

MS model: daily data of DLN_JPY_USD_SM (Constant transition probabilities)

Dependent Variable: DLN_JPY_USD_SM
Method: Switching Regression (Markov Switching)
Sample (adjusted): 3 3390
Included observations: 3388 after adjustments
Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.003172	0.001370	-2.315964	0.0206
DLN_JPY_USD_SM(-1)	0.991832	0.005818	170.4848	0.0000
DEV_JPY_PPP(-1)	-0.001212	0.000124	-9.797824	0.0000
DVIX(-1)	-0.001211	0.000679	-1.782931	0.0746
INTV_JPY_SOLD	2.17E-06	4.04E-06	0.535908	0.5920
DLN_MSCI(-1)	-0.218392	0.107228	-2.036703	0.0417
BOJ_QE(-1)	1.27E-07	1.56E-07	0.814449	0.4154
FED_QE(-1)	3.50E-09	3.40E-09	1.029671	0.3032
LOG(SIGMA)	-3.192845	0.023517	-135.7702	0.0000
		Regime 2		
C	0.003821	0.001037	3.684915	0.0002
DLN_JPY_USD_SM(-1)	0.958060	0.005301	180.7191	0.0000
DEV_JPY_PPP(-1)	0.000309	7.83E-05	3.951388	0.0001
DVIX(-1)	-0.000187	0.000181	-1.037372	0.2996
INTV_JPY_SOLD	2.05E-05	4.69E-06	4.380786	0.0000
DLN_MSCI(-1)	-0.212592	0.049104	-4.329454	0.0000
BOJ_QE(-1)	1.23E-07	1.10E-07	1.114021	0.2653
FED_QE(-1)	-1.23E-07	8.08E-08	-1.521549	0.1281
LOG(SIGMA)	-4.157580	0.033013	-125.9376	0.0000
		Transition Matrix Parameters		
P11-C	2.487226	0.120264	20.68131	0.0000
P21-C	-2.421911	0.120565	-20.08798	0.0000
Mean dependent var	-0.009888	S.D. dependent var		0.181640
S.E. of regression	0.031503	Sum squared resid		3.344536
Durbin-Watson stat	0.117800	Log likelihood		7206.937
Akaike info criterion	-4.242584	Schwarz criterion		-4.206409
Hannan-Quinn criter.	-4.229652			

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.923241	0.076759
2	0.081517	0.918483

Appendix F: The Wald test results

MS model: daily data of DLN_AUD_USD_CY (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	51.0755	(7, 3372)	0.0000
Chi-square	357.5281	7.0000	0.0000

MS model: daily data of DLN_AUD_USD_SM (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	238.0457	(7, 3372)	0.0000
Chi-square	1,666.3200	7.0000	0.0000

MS model: daily data of DLN_CAD_USD_CY (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	92.7641	(7, 3372)	0.0000
Chi-square	649.3484	7.0000	0.0000

MS model: daily data of DLN_CAD_USD_SM (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	206.5207	(7, 3372)	0.0000
Chi-square	1,445.6450	7.0000	0.0000

MS model: daily data of DLN_EUR_USD_CY (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	24.6589	(8, 3370)	0.0000
Chi-square	197.2708	8.0000	0.0000

MS model: daily data of DLN_EUR_USD_SM (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	507.8660	(8, 3370)	0.0000
Chi-square	4,062.9280	8.0000	0.0000

MS model: daily data of DLN_GBP_USD_CY (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	70.4740	(8, 3370)	0.0000
Chi-square	563.7917	8.0000	0.0000

MS model: daily data of DLN_GBP_USD_SM (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	528.5137	(8, 3370)	0.0000
Chi-square	4,228.1090	8.0000	0.0000

MS model: daily data of DLN_JPY_USD_CY (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	30.6329	(9, 3368)	0.0000
Chi-square	275.6957	9.0000	0.0000

MS model: daily data of DLN_JPY_USD_SM (Constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	144.9195	(9, 3368)	0.0000
Chi-square	1,304.2760	9.0000	0.0000

Appendix to Chapter 2

Appendix A: Descriptions of variables

Variables	Description	Unit	Frequency	Source of data
NET_RETURN_HK (Hong Kong)	The net return on stocks of the Hang Seng Index from the Hong Kong Exchanges and Clearing Limited (HKEx)	none $r_t = \left(\frac{P_t - P_{t-1} + D_t}{P_t}\right)$	daily	CEIC data and calculation
NET_RETURN_ID (India)	The net return on stocks of the Sensitive 30 (Sensex) Index from the Bombay Stock Exchange Limited	none $r_t = \left(\frac{P_t - P_{t-1} + D_t}{P_t}\right)$	daily	CEIC data and calculation
NET_RETURN_KR (Korea)	The net return on stocks of the KOSPI Index from the Korea Exchange	none $r_t = \left(\frac{P_t - P_{t-1} + D_t}{P_t}\right)$	daily	CEIC data and calculation
NET_RETURN_TH (Thailand)	The net return on stocks of the SET Index from the Stock Exchange of Thailand	none $r_t = \left(\frac{P_t - P_{t-1} + D_t}{P_t}\right)$	daily	CEIC data and calculation
DP_RATIO (-1)	the change in stock price index relative to the price index in the previous month	none $dp_t = \left(\frac{P_t - P_{t-1}}{P_t}\right)$	daily	CEIC data and calculation

Variables	Description	Unit	Frequency	Source of data
DEV_RATIO (-1)	The deviation of actual stock price from its fundamental price divided by the actual stock price in the previous month	none $b_t = \left(\frac{P_t - P_t^*}{P_t}\right)$	daily	CEIC data and calculation
ABS_DEV_RATIO (-1)	The absolute value of DEV_RATIO (-1)	none	daily	calculation
DVIX(-1)	Change in the volatility index of the SPX (S&P 500 Index)	Percentage points (annualized rate)	daily	The Chicago Board Options Exchange and calculation

Appendix B: Results of the variance ratio test

Variance ratio test: daily data of Hong Kong's stock price

Null Hypothesis: Log P_HK is a martingale
Sample: 1 3286
Included observations: 3285 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	0.345692	3285	0.9947

Variance ratio test: daily data of India's stock price

Null Hypothesis: NET_RETURN_ID is a martingale
Date: 07/09/15 Time: 21:35
Sample: 1979 5354
Included observations: 3376 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	13.44332	3376	0.0000

Variance ratio test: daily data of Korea's stock price

Null Hypothesis: Log P_KR is a martingale
Sample: 1 3355
Included observations: 3354 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	1.335086	3354	0.5519

Variance ratio test: daily data of Thailand's stock price

Null Hypothesis: NET_RETURN_TH is a martingale
Date: 07/09/15 Time: 21:39
Sample: 556 3872
Included observations: 3317 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	11.03893	3317	0.0000

Appendix C: Linear models of daily stock market returns based on a chartist-fundamentalist approach

Linear model: daily data of NET_RETURN_HK

Dependent Variable: NET_RETURN_HK
Method: Least Squares
Sample (adjusted): 3 3286
Included observations: 3284 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000207	0.000261	0.795037	0.4266
DEV_RATIO_HK(-1)	-0.003145	0.001158	-2.716072	0.0066
DP_RATIO_HK(-1)	-0.091451	0.016724	-5.468186	0.0000
DVIX(-1)	-0.003161	0.000146	-21.67984	0.0000

R-squared	0.128113	Mean dependent var	0.000368
Adjusted R-squared	0.127315	S.D. dependent var	0.015506
S.E. of regression	0.014486	Akaike info criterion	-5.630079
Sum squared resid	0.688269	Schwarz criterion	-5.622653
Log likelihood	9248.590	Hannan-Quinn criter.	-5.627421
F-statistic	160.6517	Durbin-Watson stat	2.047312
Prob(F-statistic)	0.000000		

Linear model: daily data of NET_RETURN_ID

Dependent Variable: NET_RETURN_ID
Method: Least Squares
Date: 07/09/15 Time: 10:50
Sample: 1979 5354
Included observations: 3376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000380	0.000281	1.355423	0.1754
DEV_RATIO_ID(-1)	-0.002633	0.000982	-2.681239	0.0074
DP_RATIO_ID(-1)	0.025245	0.017375	1.452957	0.1463
DVIX(-1)	-0.001534	0.000159	-9.644453	0.0000

R-squared	0.032832	Mean dependent var	0.000537
Adjusted R-squared	0.031972	S.D. dependent var	0.016273
S.E. of regression	0.016011	Akaike info criterion	-5.429918
Sum squared resid	0.864402	Schwarz criterion	-5.422661
Log likelihood	9169.701	Hannan-Quinn criter.	-5.427323
F-statistic	38.15624	Durbin-Watson stat	2.006824
Prob(F-statistic)	0.000000		

Linear model: daily data of NET_RETURN_KR

Dependent Variable: NET_RETURN_KR
Method: Least Squares
Date: 03/18/15 Time: 11:20
Sample (adjusted): 3 3355
Included observations: 3353 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000521	0.000289	1.800741	0.0718
DEV_RATIO_KR(-1)	-0.003920	0.001095	-3.581766	0.0003
DP_RATIO_KR(-1)	-0.041464	0.016808	-2.466845	0.0137
DVIX(-1)	-0.002733	0.000164	-16.63926	0.0000

R-squared	0.079973	Mean dependent var	0.000416
Adjusted R-squared	0.079149	S.D. dependent var	0.017372
S.E. of regression	0.016670	Akaike info criterion	-5.349227
Sum squared resid	0.930643	Schwarz criterion	-5.341929
Log likelihood	8971.979	Hannan-Quinn criter.	-5.346617
F-statistic	97.03650	Durbin-Watson stat	2.041674
Prob(F-statistic)	0.000000		

Linear model: daily data of NET_RETURN_TH

Dependent Variable: NET_RETURN_TH
Method: Least Squares
Date: 07/09/15 Time: 11:21
Sample: 556 3872
Included observations: 3317

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000318	0.000272	1.166786	0.2434
DEV_RATIO_TH(-1)	-0.000913	0.000633	-1.440762	0.1497
DP_RATIO_TH(-1)	-0.018775	0.017371	-1.080812	0.2799
DVIX(-1)	-0.001575	0.000142	-11.09666	0.0000

R-squared	0.036860	Mean dependent var	0.000481
Adjusted R-squared	0.035988	S.D. dependent var	0.014482
S.E. of regression	0.014219	Akaike info criterion	-5.667303
Sum squared resid	0.669800	Schwarz criterion	-5.659938
Log likelihood	9403.221	Hannan-Quinn criter.	-5.664667
F-statistic	42.26326	Durbin-Watson stat	2.032013
Prob(F-statistic)	0.000000		

Appendix D: Empirical results of the proposed MS models for daily data

MS model: NET_REURN_HK (constant transition probabilities)

Dependent Variable: NET_RETURN_HK
Method: Switching Regression (Markov Switching)
Included observations: 3284 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard deviation
Convergence achieved after 11 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.000754	0.001026	-0.734635	0.4626
DEV_RATIO_HK(-1)	-0.004357	0.001962	-2.220931	0.0264
DP_RATIO_HK(-1)	-0.151345	0.047396	-3.193224	0.0014
DVIX(-1)	-0.003155	0.000429	-7.347669	0.0000
LOG(SIGMA)	-3.695872	0.060851	-60.73594	0.0000
		Regime 2		
C	0.000416	0.000179	2.325750	0.0200
DEV_RATIO_HK(-1)	-0.001993	0.000719	-2.773543	0.0055
DP_RATIO_HK(-1)	-0.000354	4.39E-06	-80.58112	0.0000
DVIX(-1)	-0.003304	0.000305	-10.83472	0.0000
LOG(SIGMA)	-4.611983	0.023486	-196.3719	0.0000
		Transition Matrix Parameters		
P11-C	3.692565	0.427595	8.635653	0.0000
P21-C	-5.002270	0.371832	-13.45304	0.0000

Mean dependent var	0.000368	S.D. dependent var	0.015506
S.E. of regression	0.014455	Sum squared resid	0.684134
Durbin-Watson stat	2.040586	Log likelihood	9758.029
Akaike info criterion	-5.935462	Schwarz criterion	-5.913184
Hannan-Quinn criter.	-5.927486		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.975697	0.024303
2	0.006678	0.993322

MS model: NET_RETURN_HK (time-varying transition probabilities)

Dependent Variable: NET_RETURN_HK
Method: Switching Regression (Markov Switching)
Included observations: 3284 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard deviation
Convergence achieved after 31 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.000418	0.000174	2.396588	0.0165
DEV_RATIO_HK(-1)	-0.001807	0.000937	-1.928043	0.0538
DP_RATIO_HK(-1)	0.001536	7.75E-05	19.81030	0.0000
DVIX(-1)	-0.003314	0.000310	-10.70351	0.0000
LOG(SIGMA)	-4.615068	0.022073	-209.0813	0.0000
		Regime 2		
C	-0.000751	0.000604	-1.242807	0.2139
DEV_RATIO_HK(-1)	-0.004466	0.002558	-1.746108	0.0808
DP_RATIO_HK(-1)	-0.152810	0.050632	-3.018064	0.0025
DVIX(-1)	-0.003151	0.000440	-7.162963	0.0000
LOG(SIGMA)	-3.693365	0.058865	-62.74334	0.0000
		Transition Matrix Parameters		
P11-C	5.381460	0.542180	9.925594	0.0000
P11-ABS_DEV_RATIO_HK(-1)	-3.674929	2.520437	-1.458052	0.1448
P21-C	-2.365734	0.556537	-4.250812	0.0000
P21-ABS_DEV_RATIO_HK(-1)	-5.679086	2.804513	-2.024981	0.0429
Mean dependent var	0.000368	S.D. dependent var		0.015506
S.E. of regression	0.014461	Sum squared resid		0.684662
Durbin-Watson stat	2.039508	Log likelihood		9765.613
Akaike info criterion	-5.938863	Schwarz criterion		-5.912872
Hannan-Quinn criter.	-5.929557			

Time-varying transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

		1	2
Mean	1	0.989321	0.010679
	2	0.045817	0.954183
Std. Dev.	1	0.014506	0.014506
	2	0.022352	0.022352

MS model: NET_REURN_ID (constant transition probabilities)

Dependent Variable: NET_RETURN_ID
Method: Switching Regression (Markov Switching)
Included observations: 3376
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard
deviation (rng=kn, seed=1932789022)
Convergence achieved after 15 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.001170	0.000778	-1.504579	0.1324
DEV_RATIO_ID(-1)	-0.008431	0.003144	-2.681513	0.0073
DP_RATIO_ID(-1)	-0.016611	0.006866	-2.419191	0.0156
DVIX(-1)	-0.001855	0.000401	-4.627965	0.0000
LOG(SIGMA)	-3.651368	0.065633	-55.63311	0.0000
		Regime 2		
C	0.001053	0.000245	4.304102	0.0000
DEV_RATIO_ID(-1)	-0.000388	0.000200	-1.939950	0.0524
DP_RATIO_ID(-1)	0.081170	0.019062	4.258239	0.0000
DVIX(-1)	-0.001229	0.000185	-6.653182	0.0000
LOG(SIGMA)	-4.562347	0.032036	-142.4128	0.0000
		Transition Matrix Parameters		
P11-C	3.333722	0.314309	10.60652	0.0000
P21-C	-4.407988	0.309623	-14.23662	0.0000

Mean dependent var	0.000537	S.D. dependent var	0.016273
S.E. of regression	0.016006	Sum squared resid	0.862353
Durbin-Watson stat	1.999233	Log likelihood	9686.536
Akaike info criterion	-5.731360	Schwarz criterion	-5.709591
Hannan-Quinn criter.	-5.723577		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.965568	0.034432
2	0.012033	0.987967

MS model: NET_REURN_ID (time-varying transition probabilities)

Dependent Variable: NET_RETURN_ID
Method: Switching Regression (Markov Switching)
Included observations: 3376
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard
deviation (rng=kn, seed=1022579852)
Convergence achieved after 15 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.001173	0.000510	-2.299479	0.0215
DEV_RATIO_ID(-1)	-0.008344	0.002989	-2.791892	0.0052
DP_RATIO_ID(-1)	-0.016838	0.010703	-1.573246	0.1157
DVIX(-1)	-0.001856	0.000392	-4.730931	0.0000
LOG(SIGMA)	-3.650634	0.066116	-55.21572	0.0000
		Regime 2		
C	0.001052	0.000245	4.289296	0.0000
DEV_RATIO_ID(-1)	-0.000420	0.000198	-2.123497	0.0337
DP_RATIO_ID(-1)	0.080993	0.021281	3.805870	0.0001
DVIX(-1)	-0.001232	0.000190	-6.473295	0.0000
LOG(SIGMA)	-4.561942	0.033040	-138.0739	0.0000
		Transition Matrix Parameters		
P11-C	3.677634	0.437375	8.408415	0.0000
P11-ABS_DEV_RATIO_ID(-1)	-1.510879	1.224842	-1.233530	0.2174
P21-C	-4.406368	0.320875	-13.73236	0.0000
P21-ABS_DEV_RATIO_ID(-1)	-0.020750	0.000404	-51.41665	0.0000

Mean dependent var	0.000537	S.D. dependent var	0.016273
S.E. of regression	0.016007	Sum squared resid	0.862403
Durbin-Watson stat	1.999377	Log likelihood	9686.958
Akaike info criterion	-5.730425	Schwarz criterion	-5.705028
Hannan-Quinn criter.	-5.721344		

Time-varying transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

		1	2
Mean	1	0.964266	0.035734
	2	0.011995	0.988005
Std. Dev.	1	0.009469	0.009469
	2	4.06E-05	4.06E-05

MS model: NET_REURN_KR (constant transition probabilities)

Dependent Variable: NET_RETURN_KR
Method: Switching Regression (Markov Switching)
Included observations: 3353 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard deviation
Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Regime 1			
C	-0.001289	0.001834	-0.702806	0.4822
DEV_RATIO_KR(-1)	-0.007329	0.003133	-2.339501	0.0193
DP_RATIO_KR(-1)	-0.048171	0.027062	-1.780022	0.0751
DVIX(-1)	-0.002521	0.000403	-6.254734	0.0000
LOG(SIGMA)	-3.702914	0.074287	-49.84584	0.0000
	Regime 2			
C	0.001248	0.000411	3.033295	0.0024
DEV_RATIO_KR(-1)	-0.002609	0.001249	-2.089319	0.0367
DP_RATIO_KR(-1)	-0.033981	0.020799	-1.633775	0.1023
DVIX(-1)	-0.003179	0.000295	-10.76750	0.0000
LOG(SIGMA)	-4.541285	0.052176	-87.03782	0.0000
	Transition Matrix Parameters			
P11-C	3.904177	0.475456	8.211430	0.0000
P21-C	-4.618515	0.390342	-11.83198	0.0000

Mean dependent var	0.000416	S.D. dependent var	0.017372
S.E. of regression	0.016683	Sum squared resid	0.930450
Durbin-Watson stat	2.033452	Log likelihood	9441.020
Akaike info criterion	-5.624229	Schwarz criterion	-5.602335
Hannan-Quinn criter.	-5.616398		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.980241	0.019759
2	0.009771	0.990229

MS model: NET_REURN_KR (time-varying transition probabilities)

Dependent Variable: NET_RETURN_KR
Method: Switching Regression (Markov Switching)
Included observations: 3353 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard deviation
Convergence achieved after 11 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.001329	0.000611	-2.175810	0.0296
DEV_RATIO_KR(-1)	-0.007417	0.002634	-2.816257	0.0049
DP_RATIO_KR(-1)	-0.048425	0.020742	-2.334615	0.0196
DVIX(-1)	-0.002518	0.000389	-6.476076	0.0000
LOG(SIGMA)	-3.699257	0.072722	-50.86879	0.0000
		Regime 2		
C	0.001249	0.000384	3.256222	0.0011
DEV_RATIO_KR(-1)	-0.002588	0.001065	-2.430778	0.0151
DP_RATIO_KR(-1)	-0.034083	0.030882	-1.103628	0.2698
DVIX(-1)	-0.003178	0.000295	-10.75984	0.0000
LOG(SIGMA)	-4.540977	0.051504	-88.16826	0.0000
		Transition Matrix Parameters		
P11-C	3.440947	0.478544	7.190446	0.0000
P11-ABS_DEV_RATIO_KR(-1)	1.837587	0.939030	1.956898	0.0504
P21-C	-4.340358	0.714819	-6.071967	0.0000
P21-ABS_DEV_RATIO_KR(-1)	-1.117951	2.550307	-0.438360	0.6611

Mean dependent var	0.000416	S.D. dependent var	0.017372
S.E. of regression	0.016683	Sum squared resid	0.930453
Durbin-Watson stat	2.032969	Log likelihood	9441.807
Akaike info criterion	-5.623506	Schwarz criterion	-5.597963
Hannan-Quinn criter.	-5.614370		

Time-varying transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

		1	2
Mean	1	0.978445	0.021555
	2	0.010200	0.989800
Std. Dev.	1	0.005170	0.005170
	2	0.001549	0.001549

MS model: NET_REURN_TH (constant transition probabilities)

Dependent Variable: NET_RETURN_TH
Method: Switching Regression (Markov Switching)
Included observations: 3317
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=430815551)
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.000825	0.000334	-2.471125	0.0135
DEV_RATIO_TH(-1)	-6.61E-05	8.87E-06	-7.452168	0.0000
DP_RATIO_TH(-1)	-0.057721	0.038223	-1.510109	0.1310
DVIX(-1)	-0.001899	0.000424	-4.481984	0.0000
LOG(SIGMA)	-3.858644	0.093691	-41.18481	0.0000
		Regime 2		
C	0.000646	0.000281	2.300534	0.0214
DEV_RATIO_TH(-1)	-0.001880	0.000952	-1.973401	0.0484
DP_RATIO_TH(-1)	0.037111	0.015471	2.398724	0.0165
DVIX(-1)	-0.001199	0.000180	-6.647606	0.0000
LOG(SIGMA)	-4.660449	0.045829	-101.6922	0.0000
		Transition Matrix Parameters		
P11-C	3.016467	0.485350	6.215035	0.0000
P21-C	-3.824494	0.252370	-15.15431	0.0000

Mean dependent var	0.000481	S.D. dependent var	0.014482
S.E. of regression	0.014187	Sum squared resid	0.665598
Durbin-Watson stat	2.030198	Log likelihood	9759.178
Akaike info criterion	-5.877104	Schwarz criterion	-5.855012
Hannan-Quinn criter.	-5.869198		

Constant transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

	1	2
1	0.953313	0.046687
2	0.021363	0.978637

MS model: NET_REURN_TH (time-varying transition probabilities)

Dependent Variable: NET_RETURN_TH
Method: Switching Regression (Markov Switching)
Included observations: 3317
Number of states: 2
Initial probabilities obtained from ergodic solution
Huber-White robust standard errors & covariance
Random search: 50 starting values with 10 iterations using 1 standard
deviation (rng=kn, seed=432162041)
Convergence achieved after 30 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.000861	0.000968	-0.889801	0.3736
DEV_RATIO_TH(-1)	-0.000212	0.000127	-1.664771	0.0960
DP_RATIO_TH(-1)	-0.060492	0.056446	-1.071682	0.2839
DVIX(-1)	-0.001895	0.000438	-4.324882	0.0000
LOG(SIGMA)	-3.850236	0.098640	-39.03320	0.0000
		Regime 2		
C	0.000639	0.000297	2.149103	0.0316
DEV_RATIO_TH(-1)	-0.001881	0.001073	-1.753145	0.0796
DP_RATIO_TH(-1)	0.041141	0.022368	1.839300	0.0659
DVIX(-1)	-0.001209	0.000181	-6.662707	0.0000
LOG(SIGMA)	-4.658522	0.048992	-95.08646	0.0000
		Transition Matrix Parameters		
P11-C	2.408101	0.512992	4.694229	0.0000
P11-ABS_DEV_RATIO_TH(-1)	1.257077	0.733287	1.714305	0.0865
P21-C	-3.982896	0.287948	-13.83201	0.0000
P21-ABS_DEV_RATIO_TH(-1)	0.814407	0.686365	1.186549	0.2354

Mean dependent var	0.000481	S.D. dependent var	0.014482
S.E. of regression	0.014188	Sum squared resid	0.665732
Durbin-Watson stat	2.029951	Log likelihood	9762.793
Akaike info criterion	-5.878078	Schwarz criterion	-5.852303
Hannan-Quinn criter.	-5.868854		

Time-varying transition probabilities: P(i, k) = P(s(t) = k | s(t-1) = i), (row = i / column = j)

		1	2
Mean	1	0.941181	0.058819
	2	0.024398	0.975602
Std. Dev.	1	0.015248	0.015248
	2	0.007008	0.007008

Appendix E: The Wald test results

MS model: NET_REURN_HK (constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	67.14242	(5, 3272)	0.0000
Chi-square	335.7121	5	0.0000

MS model: NET_REURN_HK (time-varying transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	70.61325	(5, 3270)	0.0000
Chi-square	353.0663	5	0.0000

MS model: NET_REURN_ID (constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	91.63179	(5, 3364)	0.0000
Chi-square	458.1590	5	0.0000

MS model: NET_REURN_ID (time-varying transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	95.45204	(5, 3362)	0.0000
Chi-square	477.2602	5	0.0000

MS model: NET_REURN_KR (constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	91.81250	(5, 3341)	0.0000
Chi-square	459.0625	5	0.0000

MS model: NET_REURN_KR (time-varying transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	99.02309	(5, 3339)	0.0000
Chi-square	495.1154	5	0.0000

MS model: NET_REURN_TH (constant transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	48.08294	(5, 3305)	0.0000
Chi-square	240.4147	5	0.0000

MS model: NET_REURN_TH (time-varying transition probabilities)

Wald Test:

Test Statistic	Value	df	Probability
F-statistic	43.29791	(5, 3303)	0.0000
Chi-square	216.4896	5	0.0000

VITA

My name is Thanaporn Seddha-udom. I was born on October 13, 1969 at Bangkok, Thailand. I earned a Bachelor's Degree in Economics (1st class honors) from Thammasat University, in 1990, with a major in Economics and a minor in Finance. Later in 1993, I graduated with a Master's Degree in Economics, English Language Program, at Thammasat University funded by the Bank of Thailand's scholarship. In 1993, I started working with the Stock Exchange of Thailand as a research officer in the Research and Development Department. After that, I gained further experiences working in the field of research as a researcher in the Research and Planning Department at the Asia Credit PLC., senior researcher in the Capital Market Division, research manager in the Macroeconomic Department, and Senior Vice President at the SCB Research Institute. I was also an assistant manager in the Research Department of the ASEC Finance and Securities Co., Ltd. Now, I am holding a position of an assistant director at the Fiscal Policy Research Institute (FPRI). The FPRI was established under the auspices of the Ministry of Finance (MOF), and operates under the policy guidance of a Board of Trustees, chaired by the Permanent Secretary for Finance since May 2001. Functioning as a research-based policy consultancy, many studies emerging out of the FPRI have been applied to use for actual policy implementation, not only by the MOF but also the other government agencies and listed companies.