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DAILY EXCHANGE RATE DETERMINATION: SHORT-TERM SPECULATION AND LONGER-TERM EXPECTATION

Thanaporn Seddha-udom*

ABSTRACT: *This study develops an empirical model to forecast daily exchange rate dynamics by separating market participants into two groups: short-term speculators and longer-term investors. These two types of participants have different expectations and impacts on daily exchange rate movements. The proposed model is based on a chartist-fundamentalist approach, i.e., the expected daily exchange rate movement is influenced by its past movement as well as the extent to which the market rate deviates from its fundamental value.*

Additionally, data for some global risk factors, FX market intervention and Quantitative Easing (QE) are also incorporated into the model as control variables and to consider policy implications. The model is specified as a two-state Markov switching model due to its empirical support for in-sample prediction. This study examines the daily exchange rate movements of the five most traded currency pairs from 1999 until the first half of 2013. The proposed model logically and significantly explains daily exchange rate dynamics and outperforms a random walk model for both in-sample and out-of-sample periods. The model implies that monetary authorities can implement policies to potentially stabilize short-term exchange rate movements by influencing the expectations of short-term speculators. In contrast, the expectations of longer-term investors are quite stable and tend to converge to the trend and long-run equilibrium in the foreign exchange market without the need for short-run policy interventions.

JEL Classification:*F31, F37, G15*

Keywords*: Daily exchange rate determination; Chartist-fundamentalist approach; Markov switching model*

1. INTRODUCTION

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 April 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

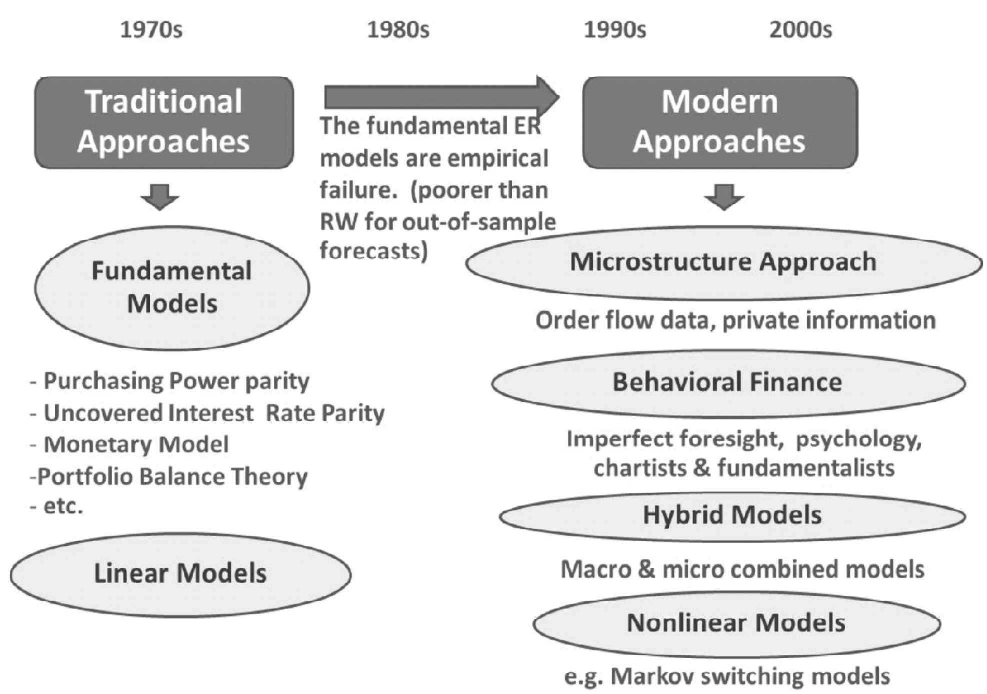
* Department of Banking and Finance, Faculty of Commerce and Accountancy, Chulalongkorn University, Bangkok, Thailand, *E-mail: thanaporn.se528@cbs.chula.ac.th*

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 well-known "exchange rate disconnect puzzle" documented in international finance research, it is an observable fact that the exchange rate cannot be explained by its fundamentals, especially 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 at least partially solve 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 rate parity (UIP), monetary, and portfolio balance models.[2] However, these fundamental models do not sufficiently explain or forecast exchange rate dynamics over the short- to medium-term. Existing research on the exchange rate disconnect puzzle usually refers to the famous study conducted by Meese and 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 exchange rate modeling have illuminated the issue and appear useful for further

Figure 1: The Development of Exchange Rate Models



study in this area. The major interesting approaches are the microstructure approaches, hybrid models, behavioral finance frameworks, and nonlinear 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 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. De Grauwe and 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 expectations 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, but their predictive powers remain rather limited.

Research based on market participant surveys indicates that professionals typically consider both technical and fundamental analyses to determine their trading strategies.[4] 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 and 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 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 and Hamilton (1990) indicate that a Markov switching model explains long swings in an exchange rate well. FrÖmmel *et al.* (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 periods but not for out-of-sample periods, e.g., Engle (1994), Ahrens and Reitz (2005), Lee & Chen (2006), and Li

(2008). Kilian and Taylor (2001) indicate that an exchange rate process near equilibrium is adequately described by a random walk process. Altavilla and De Grauwe (2010) suggest that an exchange rate can be explained by a linear model if the deviation from the long-run equilibrium is not too large but when an exchange rate departs from its fundamentals considerably, it tends to exhibit nonlinear mean-reverting behavior. Nevertheless, an adequate theoretical underpinning or a logical explanation for this nonlinearity must still be developed.

The literature review suggests 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 indicate that exchange rate movements should not follow a random walk. This assumption is reinforced by the facts that technical strategies can produce profits over the short-run while the fundamental theories hold over the long-run. Therefore, by combining the explanatory strength of a chartist-fundamentalist approach and the predictive strength of a Markov switching (MS) model, this study develops a daily exchange rate model characterized by both a logical explanation and satisfactory predictive power.

In several extant MS models of exchange rate, the two states of the world are the chartist-expectation-only and the fundamentalist-expectation-only states[5]. 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, whic his a counter-intuitive finding in need of justification. To address this issue, the proposed model in this study regards the two unobservable states as stable and unstable states. In addition, we classify investors into two groups: short-term speculators and long-term investors, where both types may employ both chartist and fundamentalist strategies. This is motivated by Levin (1997), who observes that 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. This study presumes that the expectation behavior on exchange rate return of short-term speculators and longer-term investors should induce the FX return's volatility 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 and letting the data say which types of expectation are statistically significant. The results indicate that short-term speculators use only chartist factor to form their expectation in both unobservable states while longer-term investors employ both chartist and fundamentalist factors to form their expectation in both unobservable states. Since the expected daily exchange rate volatilities of short-term speculators are more volatile than those of longer-term investors, it can be concluded that the daily exchange rate expectation of short-term speculators who use only a chartist strategy is more volatile than the daily exchange rate expectation of longer-term investors who use both chartist and fundamentalist strategies. So the proposed MS model does not produce counter-intuitive results of the previous models.

The contribution of this study is to explain the different expectation behaviors of two different types of agents, i.e., short-term speculators and longer-term investors by allowing both chartist and fundamentalist expectations to coexist in each state of the Markov switching model. The results of this study are consistent with Levin (1997).[6] When agents in the same group employ both chartist expectation and fundamentalist expectation, the market can move to either a stable or an unstable path of exchange rate dynamics.

This study applies the proposed model to examine the daily exchange rate movements of the five most traded currency pairs[7]: US dollar/euro, US dollar/yen, US dollar/sterling, US dollar/Australian dollar, and US dollar/Canadian dollar during the period from 1999 to the first half of 2013. The results indicate that the proposed model logically and significantly explains daily exchange rate dynamics. Moreover, this model outperforms a random walk model for all five currency pairs and produces some policy implications.

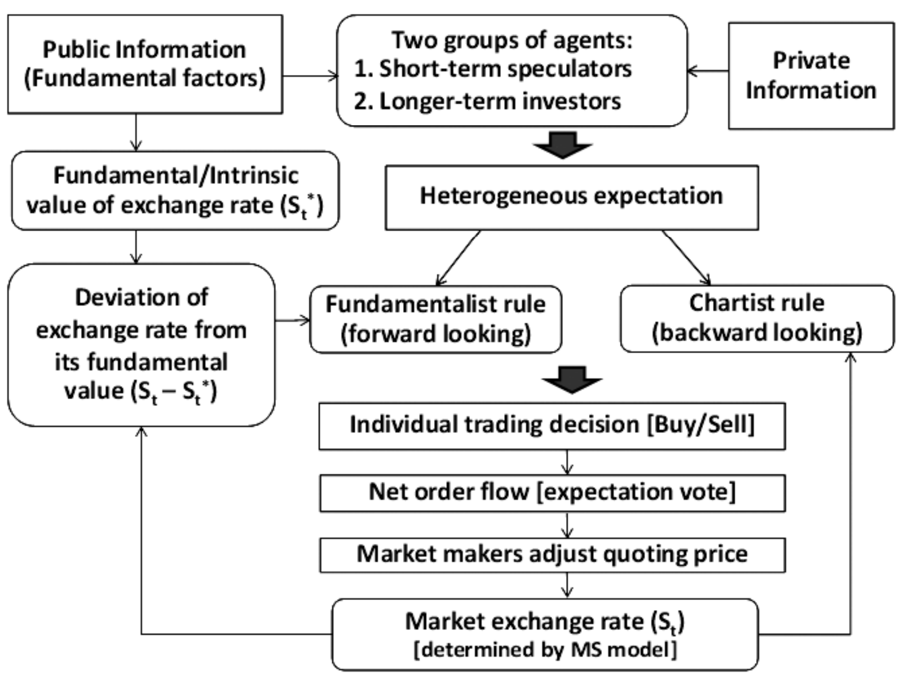
The remainder of the paper is organized as follows. Section 2 describes the conceptual framework and hypothetical story. Next, Section 3 presents the model. In Section 4, the dataset and methodology are described. Section 5 presents the empirical analysis and discussion of the results. Section 6 provides concluding remarks.

2. CONCEPTUAL FRAMEWORK

2.1. Conceptual Framework

The conceptual framework for model development in this study is summarized and presented in Figure 2. Following the microstructure approach, agents in the market possess not only public information on fundamentals but also their private information and expectations. Each group of agents may employ a fundamentalist (forward-looking) or a chartist (backward-looking) approach, or both to form their expectations for exchange rate movements. This study assumes that there are two types of agents in foreign exchange markets: short-term speculators and longer-term investors. The trading strategies of each group depend on the exchange rate

Figure 2: The Conceptual Framework of this Study



expectations formed by a fundamentalist-chartist approach, i.e., the expected daily exchange rate movement is influenced by its past movement as well as the extent to which the market rate deviates from its fundamental value. According to the microstructure perspective, private information is converted into market data, i.e., order flows, through trading. Then, the market price is readjusted in response to cumulative order flows. The new market price in turn affects agent expectations in the next period. The agents' trading rules may also vary over time with changing market conditions.

According to De Grauwe and Grimaldi (2006), the exchange rate model in a behavioral finance framework describes two possible types of equilibria in the foreign exchange market: fundamental and non-fundamental. 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. According to this study, 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 and Reitz (2005), and Li (2008) observe conflicting empirical results of high volatility in the fundamentalist regime and low volatility in the chartist regime, which cannot be clarified. Therefore, the states of equilibrium are likely not defined by the use of chartist or fundamentalist expectations exclusively. 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. It is possible that the two states of the world in a Markov switching model of the exchange rate are unobserved. Both chartists and fundamentalists may exist in each state but their roles and impacts on the exchange rate may differ between states and lead the market toward either a stable or an unstable path.

2.2. Hypothetical Story

The following hypothetical story describes the possible roles of chartist and fundamentalist expectations on exchange rate dynamics and their relationships to booms and busts.

Short-term speculators often buy and sell currencies in the market in search ofdaily profits. Their predominant trading rule should be a chartist rule. Another group of agents, longer-term investors, is expected to behave more rationally. They should incorporate long-term trends and fundamental factors into theirdecisions. Thus, the latter group of agents is expected to 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. Nevertheless, if fundamentalist expectations do not form quickly or trades are not large enough to pull the market exchange rate toward its long-run equilibrium, a market bubble can develop.

During a bubble, fundamentalist expectations may generate considerable losses for agents, which represent the limits to arbitrage identified in the behavioral finance literature. Under such circumstances, the foreign exchange market can become unstable. A bubble may grow until most market participants perceive that the exchange rate will eventually return to its fundamental value. If most traders switch their expectation rules abruptly, the market can crash.

Both short-term speculators and longer-term investors exist in the market. Therefore, it is possible that both types of expectations, under chartist and fundamentalist rules, occur in both stable and unstable states. The impact of chartist and fundamentalist factors on exchange rate dynamics can vary over time. 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 daily exchange rate dynamics.

3. THE PROPOSED MODEL

From the above conceptual framework, this study develops a daily exchange rate model that yields a more intuitive interpretation of heterogeneous agents' behavior in a Markov switching model and improves predictive power over a random walk model. To capture heterogeneous agents in the foreign exchange market, this study decomposes exchange rate determination into two components: short-term speculation and longer-term expectation. The underlying assumption is that both short-term speculators who buy and sell frequently to produce daily profits and longer-term investors who have forward-looking and reasonable expectations exist. Each group of agents may employ both chartist and fundamentalist strategies to form their expectations which behave as a Markov switching model.The proposed model is formulated as follows.

3.1. A Fundamental Exchange Rate Model: Purchasing Power Parity (PPP)

According to a review on an issue ofthe purchasing power parity (PPP) conducted by Taylor and Taylor (2004), although PPP does not hold over the short-run, exchange rates do revert to an equilibrium determined by relative prices between two countries over the long-run. Thus, the PPP model was selected to determine the fundamental value of an exchange rate. Under the PPP model, 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 to not equal one to allow for differences in the composition of tradable and non-tradable goods and transaction costs incurred during trade between two countries. In fact, there are three versions of the PPP model: absolute, relative, and empirical-study versions. Leter 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.

The absolute version of the PPP model:

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

The relative version of the PPP model:

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

The empirical-study version of the PPP model:

$$ln\ e_t = \beta_0 + \beta_1\ ln\, p_t - \beta_2\ ln\, p_t^* + \epsilon_t \tag{3}$$

3.2. Short-term Speculation and Longer-term Expectation

This study divides market participants into two groups: short-term speculators and longer-term investors. Short-term speculators include day traders who buy and sell to obtain daily profits in the FX market while longer-term investors are interested in long-term investment. To separate the exchange rate movements resulting from the expectations of these two groups of agents, the Hodrick-Prescott (HP) filter is adopted to decompose the natural logarithm of the exchange rate series *(LN_FX)* into two series: a cyclical series *(LN_FX_CY)* representing the short-term speculator expectations and a smoothed series *(LN_FX_SM)* representing the longer-term investor expectations.

The HP filter, a smoothing method developed by Hodrick and 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:

$$\Sigma_{t=1}^{T} c_t^2 + \lambda \Sigma_{t=1}^{T} ((g_t - g_{t-1}) - (g_{t-1} - g_{t-2}))^2 \tag{4}$$

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.

3.3. A Two-state Markov Switching Model based on a Chartist-fundamentalist Approach

For each group of agents, short-term speculators or longer-term investors, the roles of chartist and fundamentalist rules on their daily exchange rate expectations are specified by a two-state Markov switching model as follows:

- This model assumes that daily exchange rate expectation of each group of agents is the combined result from the selection of heterogeneous trading strategies. They may employ chartist, fundamentalist, or both trading rules.
- The chartist trading rule[8] depends on past changes in the market exchange rate, while the fundamentalist trading rule is determined by the deviation of the actual from the fundamental value of the exchange rate during the previous period.
- Therefore, the daily exchange rate expectation for each group of agents is a function of the change in the market exchange rate during the last period (the chartist rule) and the deviation of the actual exchange rate from its fundamental value during the last period (the fundamentalist rule).
- Let *LN_FX* be the natural logarithm of daily exchange rate index and *DLN_FX* be the daily exchange rate return expected by each group of agents for any currency. An equation representing the expectation on daily exchange rate return for each group of agents can be written as follows:

$$DLN\_FX = \alpha_1[DLN\_FX(-1)] + \alpha_2[DEV\_FX(-1)] + \epsilon_t \tag{5}$$

where *DLN_FX* is daily exchange rate return expected by each group of agents,

DLN_FX(–1) is daily exchange rate return expected by each group of agents on the previous day,

DEV_FX(–1) is deviation of actual from fundamental value of the logarithm of the exchange rate index on the previous day,

α_1 are α_2 parameters reflecting the impacts of chartist and fundamentalist factors on the daily exchange rate expectation for each group of agents, and

ϵ_t denotes a stochastic error term.

The model parametersand exchange rate volatilities in the two unobservable states are expected to be different. Then we specify a Markov switching model of daily exchange rate as follows:

$$DLN\_FX = \begin{cases} \alpha_{11}[DLN\_FX(-1)] + \alpha_{12}[DEV\_FX(-1)] + \epsilon_{1t}, \epsilon_{1t} \sim N(0, \sigma_1), if\ s_t = 1 \\ \alpha_{21}[DLN\_FX(-1)] + \alpha_{22}[DEV\_FX(-1)] + \epsilon_{2t}, \epsilon_{2t} \sim N(0, \sigma_2), if\ s_t = 2 \end{cases} \tag{6}$$

where α_{i1} is the parameter of the chartist factor in state *i*,

α_{i2} is the parameter of the fundamental factor in state *i*,

ϵ_{it} is the stochastic error term in state *i*,

σ_i is the standard deviation of the residuals in state *i*, and

s_t is the unobservable state at time t, which is either 1 or 2

when i = 1, 2.

Since s_t which represents the state at time *t* is unobservable, we can utilize the probability of being in each state given by the information available up to time *t* to calculate the expected change in the exchange rate as follows:

$$\begin{aligned} E[DLN\_FX] = P(s_t = 1 \mid I_t) * \{\alpha_{11}[DLN\_FX(-1)] + \alpha_{12}[DEV\_FX(-1)]\} \\ + P(s_t = 2 \mid I_t) * \{\alpha_{21}[DLN\_FX(-1)] + \alpha_{22}[DEV\_FX(-1)]\} \end{aligned} \tag{7}$$

where is the information set until time *t*.

The control variables for the proposed Markov switching model include global risk factors and monetary policy variables. This study considers two global risk indicators: changes in the Chicago Board Options Exchange'svolatility 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 Japanese central bank[9] (only for *JPY_USD*) and quantitative easing (QE) policies implemented by some central banks (for *EUR_USD, GBP_USD,* and *JPY_USD*).

Two alternative Markov Switching models are considered based on whether transition probabilities can be explained by the latest absolute deviation from the long-run market exchange rate equilibrium.

1. MS model with time-varying transition probabilities (TVTP): Intuitively, whether the exchange rate market is in a stable or an unstable stateshould be determined by the market conditions at that point of time. Here, the transition 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. The market has a high probability of switching states if the exchange rate is highly over-valued or under-valued.

$$\begin{aligned} P_t^{11} &= f\{|DEV\_FX(-1)|\} \\ P_t^{12} &= 1 - P_t^{11} \\ P_t^{22} &= f\{|DEV\_FX(-1)\}\} \\ P_t^{21} &= 1 - P_t^{22} \end{aligned} \tag{8}$$

where P_t^{ij} = transition probability from state i to state j

f = function that assumes value in the interval [0, 1].

Let $X'_{t-1} = [1, |DEV\_FX(-1)|]$. The transition probabilities are assumed to be logistic functions of $X'_{t-1}\beta_i, i = 1, 2$.

$$P_t^{11} = \frac{\exp\left(X'_{t-1}\beta_1\right)}{1 + \exp\left(X'_{t-1}\beta_1\right)}$$

$$P_t^{22} = \frac{\exp\left(X'_{t-1}\beta_2\right)}{1 + \exp\left(X'_{t-1}\beta_2\right)} \tag{9}$$

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

2. MS model with constant transition probabilities (CP): If the latest absolute deviation from the long-run equilibrium of the market exchange rate is insignificant to explaining time-varying transition probabilities, we may consider a simple MS model with constant transition probabilities (CP) with a transition probability matrix that can be written as follows:

$$\pi = \begin{bmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{bmatrix} \tag{10}$$

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

4. DATA AND METHODOLOGY

4.1. Sample and Data

This study utilizes daily data for the empirical test as it is common denominator for the 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 April 2013, i.e., US dollar/euro, US dollar/yen, US dollar/sterling, US dollar/Australian dollar, and US dollar/Canadian dollar. 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. The in-sample period ranges from January 1999 to June 2012 and the out-of-same period ranges from July 2012 to June 2013.

The main source for the empirical investigation[10] is the CEIC[11], except the SPX volatility index (VIX) from the Chicago Board Options Exchange, foreign exchange market intervention data from the Ministry of Finance Japan, and 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. Thesedata 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.

Each exchange rate was transformed into currency units per 1 US dollar and calculated as an index with a base year 2011 (2011=100). Therefore, a currency depreciates 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 the exchange rates for all five currency pairs: *AUD_USD, CAD_USD, EUR_USD, GBP_USD, and JPY*_USD.

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. We lastly test for the residual stationarity to confirm the long-run relationship of the PPP model.
2. To test whether the daily exchange rate follows a martingale, we employ the variance ratio test by allowing for heteroskedasticity through which the daily exchange rates of all currency pairs can be tested.
3. 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 trend or smoothed component (*LN_FX_SM*). The cyclical series represents short-run speculation, while the smoothed series represents longer-term expectation for daily exchange rate dynamics.

4. To compare the proposed Markov switching (MS) model, we first estimate a linear model which has a chartist factor, *DLN_FX(-1)*, and a fundamentalistfactor, *DEV_FX(-1)*, including some global risk indicators and monetary policy data as explanatory variables for both cyclical and smoothed components of each daily exchange rate.
5. Lastly, a two-state MS model with time-varying transition probabilities (TVTP) is estimated for cyclical and smoothed components of each selected exchange rate. In this study, the state with low volatility is called as"a stable state" and the state with high volatility is called as"an unstable state". We also estimate an MS model with constant transition probabilities (CP).
6. To compare the various model specifications for each currency pair, we adopt model selection criteria such as the Akaike information criterion, Hannan-Quinn criterion, and Schwarz criterion. In addition, we examine coefficient equality between the two states of the MS model for each currency pair using the Wald test.

4.3. Estimating a Markov Switching Model

The 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 $\{y_t\}_{t=1}^{T}$ be the sample path of an exchange rate series depending on the state path, $\{s_t\}_{t=1}^{T}$.

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

$$(y_t \mid s_t = i;\, \alpha_i) \sim N(\mu_i, \sigma_i^2), \tag{11}$$

where $\alpha_i = \left(\mu_i, \sigma_i^2\right)', i$ = 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 one to another state at time t.

Let $P(s_1 = 2) = \rho, \alpha = \left(\alpha_1', \alpha_2'\right)'$, and $\beta = \left(\beta_1', \beta_2'\right)'$

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

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

$$\begin{aligned} f(y_T, s_T \mid x_T; \theta) & \\ &= [I(s_1 = 2) f(y_1 \mid s_1 = 2; \alpha_2)\rho + I(s_1 = 1) f(y_1 \mid s_1 = 1;\, \alpha_1)(1-\rho)] \\ &\times \prod_{t=2}^{T} \{I(s_t = 2, s_{t-1} = 2)\, f(y_2 \mid s_t = 2; \alpha_2)\, p_t^{22} \\ &+ I(s_t = 1, s_{t-1} = 2)\, f(y_t \mid s_t = 1; \alpha_1)(1 - p_t^{22}) \\ &+ I(s_t = 2, s_{t-1} = 1)\, f(y_t \mid s_t = 2;\, \alpha_2)(1 - p_t^{11}) \\ &+ I(s_t = 1, s_{t-1} = 1)\, f(y_t \mid s_t = 1;\, \alpha_1)\, p_t^{11}\}. \end{aligned} \tag{12}$$

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

$$\begin{aligned}\log f(y_T, s_T \mid x_T;\theta) = I(s_1 = 2)&[\log f(y_1 \mid s_1 = 2;\alpha_2) + \log\rho]\\
&+ I(s_1 = 1)[\log f(y_1 \mid s_1 = 1;\alpha_1) + \log(1-\rho)]\\
&+ \sum_{t=2}^{T}\{I(s_t = 2)\log f(y_t \mid s_t = 2;\ \alpha_2)\\
&+ I(s_t = 1)\log f(y_t \mid s_t = 1;\ \alpha_1)\\
&+ I(s_t = 2, s_{t-1} = 2)\log p_t^{22}\\
&+ I(s_t = 1, s_{t-1} = 2)\log(1 - p_t^{22})\\
&+ I(s_t = 2, s_{t-1} = 1)\log(1 - p_t^{11})\\
&+ I(s_t = 1, s_{t-1} = 1)\log p_t^{11}\}.\end{aligned} \tag{13}$$

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:

$$\log f(y_T \mid x_T;\theta) = \log(\Sigma_{S_1=1}^{2}\Sigma_{S_2=1}^{2}\cdots\Sigma_{S_T=1}^{2} f(y_T, s_T \mid x_T;\theta)). \tag{14}$$

This function will be maximized with respect to θ.

4.4. 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.

5. EMPIRICAL RESULTS[12]

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. Comparisons between the actual and fundamental exchange rates of the five selected currency pairs are displayed in Figure 3. 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.

For the daily exchange rate data, all of the *LN_FX* variables for the five 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 for each *LN_FX* variable. If a daily exchange rate series is a martingale, then the expected value of an exchange rate tomorrow is the same as that of today. Therefore, it is unsurprising that predicting daily exchange rate movements is a difficult task. 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 1.

Table 1
Descriptive Statistics of the Daily Changes in the Original Series

DLN_FX	*AUD_USD*	*CAD_USD*	*EUR_USD*	*GBP_USD*	*JPY_USD*
Mean	-0.014880	-0.011931	-0.002064	0.001637	-0.010038
Median	-0.040600	-0.008800	0.000000	-0.005000	-0.009400
Maximum	8.212000	3.807000	3.003100	4.966200	3.236100
Minimum	-7.703500	-5.071600	-4.620800	-4.434900	-4.408600
Std. Dev.	0.876345	0.600635	0.655953	0.605015	0.669635
Skewness	0.661067	-0.067845	-0.121985	0.245635	-0.257984
Kurtosis	14.615100	8.850730	5.055501	8.174966	6.123299
Observations	3389	3389	3389	3389	3389

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

After decomposing the *LN_FX* variable for each daily exchange rate[13] 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 2 and Table 3. 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*.

Table 2
Descriptive Statistics of the Daily Changes in the Cyclical Series

DLN_FX_CY	*AUD_USD*	*CAD_USD*	*EUR_USD*	*GBP_USD*	*JPY_USD*
Mean	-0.000611	-0.000368	-0.000151	-0.000080	-0.000182
Median	-0.013746	0.001770	0.016832	-0.006198	0.006010
Maximum	6.865559	3.478808	3.451588	4.339564	3.071094
Minimum	-8.710752	-4.962618	-4.058574	-4.755743	-4.319609
Std. Dev.	0.816852	0.557084	0.606345	0.561241	0.626054
Skewness	0.089654	-0.292666	-0.175784	-0.046558	-0.178198
Kurtosis	14.876020	9.383377	4.964820	8.123890	6.058190
Observations	3389	3389	3389	3389	3389

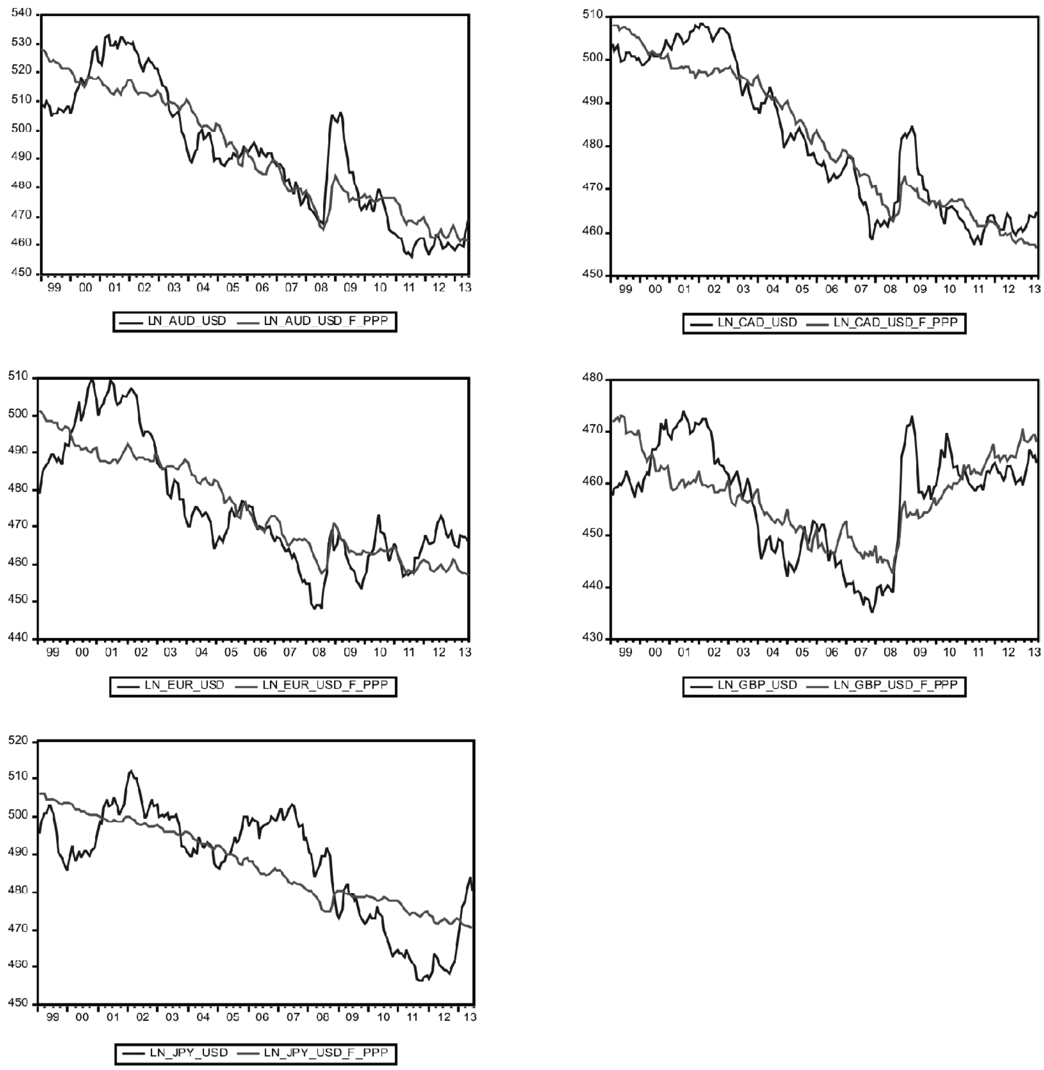
Notes: This table presents the descriptive statistics of the daily changes in the cyclical series of the natural logarithms of the exchange rate indices of the selected currency pairs.

Table 3
Descriptive Statistics of the Daily Changes in the Smoothed Series

DLN_FX_SM	*AUD_USD*	*CAD_USD*	*EUR_USD*	*GBP_USD*	*JPY_USD*
Mean	-0.014269	-0.011563	-0.001913	0.001718	-0.009856
Median	-0.031791	-0.019705	-0.008124	-0.002978	-0.011747
Maximum	1.851975	1.244080	0.679016	0.857237	0.670141
Minimum	-0.768019	-0.656434	-0.977821	-0.600967	-0.531307
Std. Dev.	0.243068	0.167877	0.194726	0.171708	0.181623
Skewness	1.148646	1.129811	-0.033525	0.422102	-0.017945
Kurtosis	8.426843	10.365500	3.981535	4.221263	3.027196
Observations	3389	3389	3389	3389	3389

Notes: 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.

Figure 3: Actual and Fundamental Values of the Selected Exchange Rates



To compare the models, we first estimate linear models with the same explanatory variables. 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.

Table 4 and Table 5 present the empirical results of the MS models of the daily changes in the five exchange rates for the cyclical and smoothed series, respectively. The effects of chartist and fundamentalist variables on both cyclical and smoothed series are consistent for all selected currency pairs in terms of signs of coefficients and statistical significance.

Table 4
The Markov Switching Models for the Cyclical Series based on a Chartist-fundamentalist Approach

DLN_FX_CY	*AUD_USD*	*CAD_USD*	*EUR_USD*	*GBP_USD*	*JPY_USD*
			State 1		
Constant	0.131021	-0.000141	-0.004625	0.034134	0.000828
Chartist-fundamentalist variables:					
DLN_FX_CY(-1)	-0.483881***	-0.172224***	-0.13662***	-0.141864**	-0.134247***
DEV_FX_PPP(-1)	-0.008481	-0.0000923	-0.000786	0.000176	0.002535
Control variables:					
DVIX(-1)	0.056683	0.024057***	0.020571	0.018121	-0.06601***
DLN_MSCI(-1)	-23.92187***	-3.082127**	-2.177028	-5.468225	-8.305406**
QE data			0.000118	-0.000119**	-0.0000213
FX intervention					0.001445***
LOG(SIGMA)	0.541981***	-0.978668***	-0.17998***	0.020147	-0.087354**
			State 2		
Constant	-0.006568	-0.0009	0.004122	-0.002394	0.001608
Chartist-fundamentalist variables:					
DLN_FX_CY(-1)	-0.175066***	-0.248813***	-0.177097***	-0.174096***	-0.18667***
DEV_FX_PPP(-1)	0.000361	-0.000302	-0.000077	-0.0000384	0.000546
Control variables:					
DVIX(-1)	0.05541***	0.061839***	-0.005307	0.016023**	-0.022161**
DLN_MSCI(-1)	-4.052244**	-4.674803	-1.510453	-1.56042	-1.252404
QE data			-0.000178	0.0000399*	-0.00000699*
FX intervention					0.000392***
LOG(SIGMA)	-0.500115***	-0.245043***	-0.702425***	-0.776996***	-0.709928***
Transition matrix parameters:					
P11-C	0.806525	4.949986***	3.499822***	4.11658***	2.941094***
P11-ABS_DEV_FX_PPP(-1)	0.11831***				
P21-C	-4.783348***	-4.166497***	-4.615582***	-6.239939***	-4.300678***
P21-ABS_DEV_FX_PPP(-1)	0.02238				
Log likelihood	-3,537.502	-2,352.186	-2,943.329	-2,512.285	-2,946.063
Akaike info criterion	2.097699	1.396804	1.746948	1.492494	1.749742
Hannan-Quinn criterion	2.108044	1.405856	1.757293	1.502840	1.761380
Schwarz criterion	2.126639	1.422126	1.775887	1.521434	1.782299
Observations	3388	3388	3388	3388	3388

Notes: This table presents coefficient estimates for the Markov switching (MS) models based on a chartist-fundamentalist approach. DLN_FX_CY denotes the change in the daily exchange rate of the cyclical series, which represents short-term speculator expectations. DEV_FX_PPP is the deviation of the smoothed LN_FX from the fundamentals while ABS_DEV_FX_PPP 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 some central banks (for EUR_USD, GBP_USD, and JPY_USD). The estimated values of LOG (SIGMA) indicate the values of the natural logarithms of the volatilities in states 1 and 2.Only for model AUD_USD does the MS model with time-varying transition probabilities (TVTP) produce better values for model selection criteria than those of the MS model with constant transition probabilities. Significance is depicted as ***, **, * for 1%, 5%, and 10% level, respectively.

Table 5
The Markov Switching Models for the Smoothed Series based on a Chartist-fundamentalist Approach

DLN_FX_SM	*AUD_USD*	*CAD_USD*	*EUR_USD*	*GBP_USD*	*JPY_USD*
			State 1		
Constant	-0.004957**	0.00017	0.026852***	0.021935***	0.024948***
Chartist-fundamentalist variables:					
DLN_FX_SM(-1)	0.98068***	0.977134***	0.983628***	0.990153***	0.975224***
DEV_FX_PPP(-1)	-0.00041**	0.000194	-0.000276***	-0.00044***	-0.000584***
Control variables:					
DVIX(-1)	0.002126*	0.000217	-0.000192	0.000526	-0.001401***
DLN_MSCI(-1)	0.267696	-0.008839	-0.007276	0.111206*	-0.260908***
QE data			-0.00000823	0.00000162	-0.0000000679
FX intervention					0.0000113**
LOG(SIGMA)	-2.717758***	-4.001859***	-3.750748***	-3.834038***	-3.843087***
			State 2		
Constant	0.003826***	-0.002718	-0.025229***	-0.025128***	-0.025751***
Chartist-fundamentalist variables:					
DLN_FX_SM(-1)	0.996687***	0.991683***	0.980171***	0.968425***	0.98025***
DEV_FX_PPP(-1)	-0.000518***	-0.002783***	-0.000724***	-0.001438***	-0.000471***
Control variables:					
DVIX(-1)	0.000779**	0.002142**	0.000344	0.000799*	-0.000279
DLN_MSCI(-1)	-0.01579	0.35829**	0.121732	0.169467**	-0.068085
QE data			0.00000846	0.000000585	0.000000141
FX intervention					0.00000384*
LOG(SIGMA)	-3.830004***	-2.947526***	-3.827966***	-3.934707***	-3.840925***
Transition matrix parameters:					
P11-C	2.190255***	3.527242***	2.289505***	2.514618***	2.419545***
P11-ABS_DEV_FX_PPP(-1)	0.021231				
P21-C	-3.097007***	-2.456482***	-2.396522***	-2.451906***	-2.33358***
P21-ABS_DEV_FX_PPP(-1)	0.01905				
Log likelihood	6,419.455	7,543.069	7,473.657	7,818.838	7,643.188
Akaike info criterion	-3.780080	-4.444551	-4.402395	-4.606162	-4.501292
Hannan-Quinn criterion	-3.769735	-4.435498	-4.392049	-4.595817	-4.489653
Schwarz criterion	-3.751140	-4.419228	-4.373455	-4.577222	-4.468734
Observations	3388	3388	3388	3388	3388

Notes: The this presents coefficient estimates for the Markov switching (MS) models based on a chartist-fundamentalist approach. DLN_FX_SM denotes the change in the daily exchange rate for the smoothed series, which represents longer-term investor expectations. DEV_FX_PPP is the deviation of the smoothed LN_FX from the fundamentals while ABS_DEV_FX_PPP 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 (only for JPY_USD) and Quantitative Easing (QE) policies implemented by some central banks (for EUR_USD, GBP_USD, and JPY_USD). The estimated values of LOG (SIGMA) indicate the values of natural logarithms of the volatilities in states 1 and 2.For the model for AUD_USD only, the MS model with time-varying transition probabilities (TVTP) produces better values for model selection criteria than those of the MS model with constant transition probabilities. Significance is depicted as ***, **, * for the 1%, 5%, and 10% levels, respectively.

In this study, the cyclical series of the exchange rate is assumed to represent short-term speculatorexpectations. Table 4 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_PPP(-1)*), and control variables. The results indicate that a chartist variable significantly determines the daily changes in the cyclical series while a fundamentalist variable does not. This likely means that short-term speculators mainly use chartist rules to formtheir exchange rate expectations.The negative sign of the chartist variable coefficient indicates that the technical strategy is a reversal. This may be the results of day-to-day exchange rate betting behavior.

For the smoothed series of exchange rate, we assume that it represents the longer-term investor expectations. Table 5 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_PPP(-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 negative. The positive chartist coefficient implies that longer-term investors use an extrapolative chartist rule to follow the long-term trend. Meanwhile, the negative fundamentalist coefficient suggests that longer-term investors expect mean reversion of the exchange rate to its long-run equilibrium value.

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 USD and sells the JPY. Therefore, the sign of coefficient is positive as expected. The more the government intervenes the market, the more the Japanese yen depreciates against the US dollar.

In the proposed MS model, the daily changes of the cyclical series mainly determine the standard deviation while the daily changes of the smoothed series influence the size and direction of the changes ofthe 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 greater predictive power than those of the random walk model for both in-sample and out-of-sample periods as summarized in Table 6. On average, the percentage of correct-sign predictions of the proposed model improves upon that of a random walk model by 16.67% for in-sample data and 15.48% for out-of-sample data. Similarly, the mean absolute error (MAE) is reduced by 25.72% and 15.08% for in-sample and out-of-sample data, respectively. Lastly, the root mean squared error (RMSE) declines by 26.61% for the in-sample period and by 15.04% 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 satisfactory predictive power. The conclusion of this study is robust to varying the lambda 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).

Table 6
Comparison of Prediction for the Proposed Markov Switching Model and a Random Walk Model

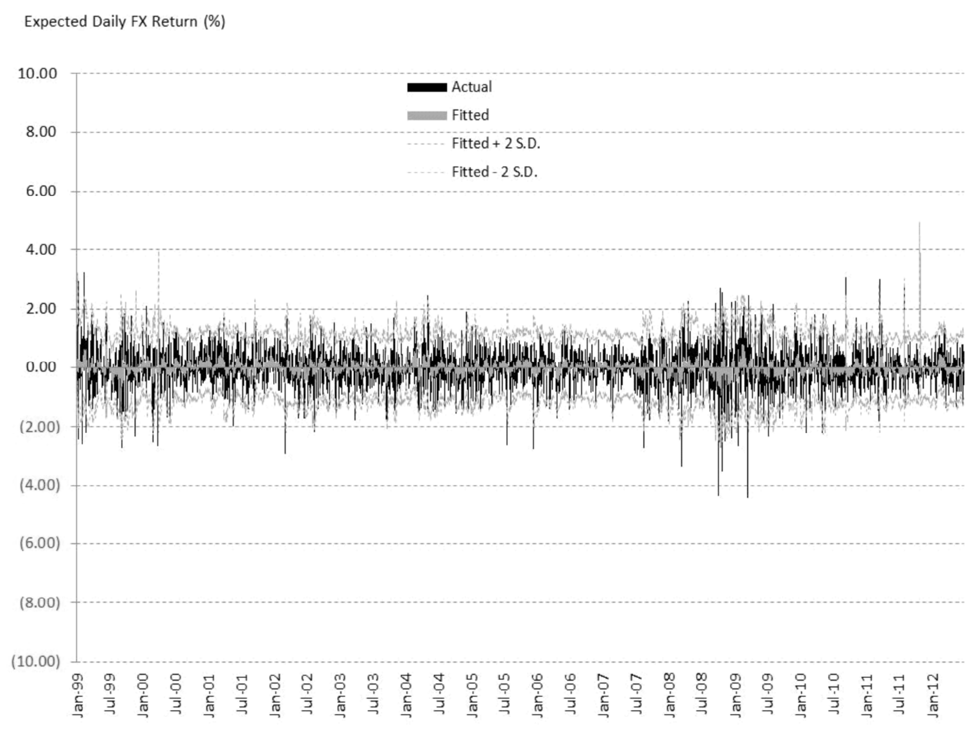
		The proposed MS model		
Currency	*Forecast period*	*% correct direction*	*MAE*	*RMSE*
AUD_USD (TVTP)	In Sample	62.78%	0.5576	0.7817
	Out-of-Sample	62.00%	0.4031	0.5390
CAD_USD (CP)	In Sample	62.49%	0.3909	0.5411
	Out-of-Sample	63.20%	0.2393	0.3224
EUR_USD (CP)	In Sample	54.99%	0.4303	0.5919
	Out-of-Sample	56.40%	0.2706	0.3688
GBP_USD (CP)	In Sample	55.11%	0.4264	0.5852
	Out-of-Sample	59.60%	0.2491	0.3395
JPY_USD (CP	In Sample	50.06%	0.4623	0.6456
	Out-of-Sample	50.40%	0.3226	0.4265
Avg. of 5 exchange rates	*In Sample*	*58.33%*	*0.3582*	*0.4915*
	Out-of-Sample	57.74%	0.3778	0.5167
		RW model		
Currency	*Forecast period*	*% correct direction*	*MAE*	*RMSE*
AUD_USD (TVTP)	In Sample	50.00%	0.5707	0.8168
	Out-of-Sample	50.00%	0.4009	0.5444
CAD_USD (CP)	In Sample	50.00%	0.5707	0.8168
	Out-of-Sample	50.00%	0.4009	0.5444
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%*	*0.4765*	*0.6657*
	Out-of-Sample	50.00%	0.4427	0.6058
		% Improvement from RW model		
Currency	*Forecast period*	*% correct direction*	*MAE*	*RMSE*
AUD_USD (TVTP)	In Sample	25.56%	2.30%	4.31%
	Out-of-Sample	24.00%	-0.55%	0.99%
CAD_USD (CP)	In Sample	24.97%	31.52%	33.76%
	Out-of-Sample	26.40%	40.32%	40.78%
EUR_USD (CP)	In Sample	9.98%	12.24%	9.76%
	Out-of-Sample	12.80%	33.94%	31.64%
GBP_USD (CP)	In Sample	10.21%	4.03%	3.27%
	Out-of-Sample	19.20%	26.21%	23.09%
JPY_USD (CP)	In Sample	0.12%	5.87%	3.58%
	Out-of-Sample	0.80%	34.64%	40.26%
Avg. of 5 exchange rates	*In Sample*	*16.67%*	*25.72%*	*26.61%*
	Out-of-Sample	15.48%	15.08%	15.04%

Notes: 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.

For the discussion on the policy implications for government intervention to stabilize the FX market, 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 4. The daily expected return and volatility vary in time depending on the probabilities of being in the two states in each day.

Figure 4: 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 5, 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 6 shows that most of the expected exchange rate volatility, 96.34 per cent of total on average, is contributed by short-term speculators.

Figure 5: The Expected Daily Exchange Rate Return of JPY_USD by Short-term Speculators (DLN_FX_CY) and Longer-term Investors (DLN_FX_SM)

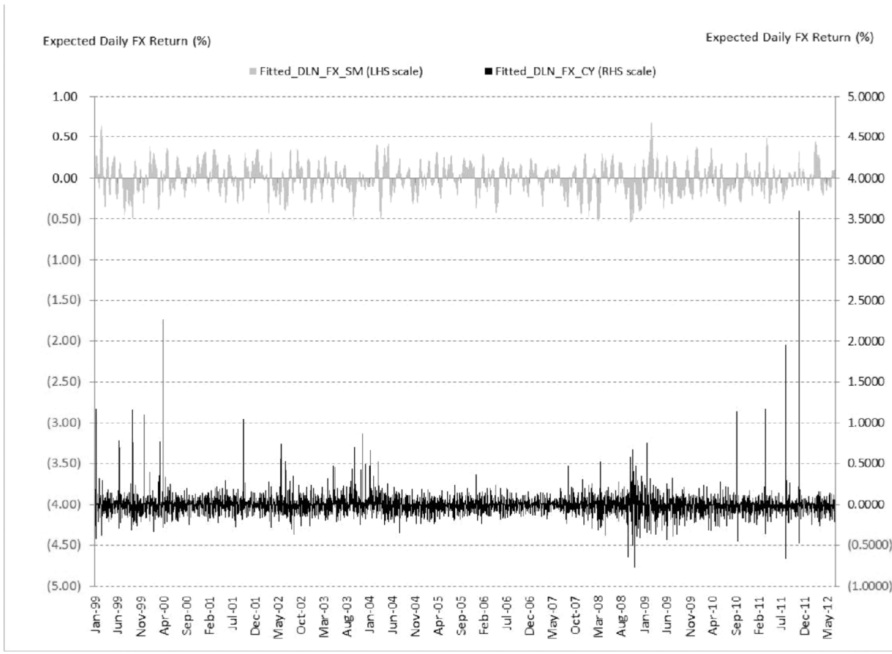
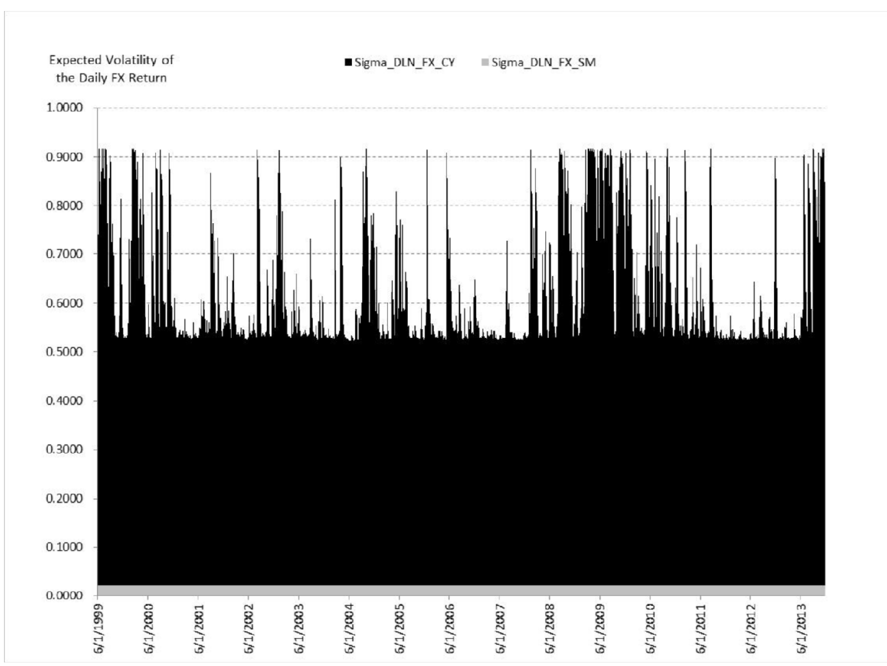


Figure 6: Expected Volatility of JPY_USD Contributed by Short-term Speculators (Sigma_DLN_FX_CY) and Longer-term Investors (Sigma_DLN_FX_SM)



The empirical study indicates that FX intervention significantly influences short-term speculator expectations, especially in the high volatility state. Therefore, the government can intervene to potentially stabilize the foreign exchange market when the expected volatility is high. According to the empirical results, one billion JPY in value of FX intervention by buying (selling) US dollars and selling (buying) Japanese yen lead to short-term speculator expectations for adepreciation (an appreciation) of the Japanese yen against the US dollar on the day of intervention by 0.1445 basis point in the high-volatility state and by 0.0392 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 speculators mainly determine daily exchange rate volatility. Their expectations depend on chartist factors, global risk factors, and some monetary policy variables. 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 expectation of this group is rather stable and converges toward the long-term trend and long-run equilibrium of the foreign exchange market. Thus, it is not necessary to implement policies to influence the expectations of these investors.

6. CONCLUSION

Although daily exchange rate movements appear to be random walks, these are still subject to explanation by the fact that some technical strategies can produce profits over the short-run while fundamental theories still hold over the long-run. This study develops a daily exchange rate model by decomposing exchange rate determination into two components, those by short-term speculators and by longer-terminvestors, and simultaneously allows for both chartist and fundamentalist expectations within each of the two 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 in April 2013: 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: a cyclical component and a smoothed component. The cyclical component is assumed to represent the exchange rate expectation by short-term speculators while the trend component captures the exchange rate expectation of longer-term investors. The empirical results of the proposed MS modelsuggest that short-term speculators mainly utilize a reversechartist rule to shape their expectations while longer-term investors utilize an extrapolative chartist rule and mean-reversion to long-run equilibrium in their expectations.

The cyclical series predominantly affects the standard deviation while the smoothed series mainly influences the mean daily exchange rate return 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 overa random walk model for both in-sample and out-of-sample periods. Therefore, the proposed model explains daily changes logically and withsatisfactory predictive power.

Under a floating exchange rate regime, monetary authorities can intervene to attempt to stabilize short-term exchange rate volatility, which is mainly influenced by short-term speculators' expectation. However, the expectations of longer-term investors converge to the long-term trend and long-run equilibrium in the foreign exchange market and are less likely to be affected by short-run policy interventions.

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NOTES

1. Triennial Central Bank Survey (*http://www.bis.org/publ/rpfx13fx.pdf*), Bank for International Settlements, September 2013.
2. Among others, these models are described in Williamson (2008) and Lam *et al.* (2008).
3. See, for example, Evans and Lyons (2002), Bacchetta and Wincoop (2006), Rime *et al.* (2007), Berger *et al.* (2008), Gyntelberg *et al.* (2009a, 2009b), Dunne *et al.* (2010), and Evans (2010).
4. Menkhoff and 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.
5. Examples of studies developing Markov switching models of the exchange rate with two states of the world, i.e., chartist-expectation-only and fundamentalist-expectation-only states, are Vigfusson (1997), Ahrens and Reitz (2005), and Li (2008).
6. Levin (1997) develops two theoretical models based on the Dornbusch model. The results indicate that when there are two different groups of traders, one employing a chartist rule and another employing a fundamentalist rule, market dynamics always converge to the long-run equilibrium. However, if the same group of traders employs both chartist and fundamentalist rules to form their expectations, the market can move along either a stable path or an unstable path, which can produce market bubbles.
7. 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 five most traded currency pairs are considered because daily data for quantitative easing and FX market interventions in these developed markets are available.
8. We could consider other technical strategies to represent a chartist rule, such as a moving average rule, a filter rule, etc. In the real world, there are many technical rules and the use of these strategies in the market varies from time to time. Therefore, this study opts to employ the past movement of exchange rate to represent a chartist rule because it is easy to interpret and provides consistent results for the considered currency pairs.
9. This variable is the value, measured in billions JPY, of the ministry of finance (MOF) of Japan interventionsin 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.

10. 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.
11. 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.
12. For the sake of brevity, some empirical results of this study which are mentioned but not presented here are available upon request.
13. Since there is no common criterion to pre-determine the value of lambda 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, 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. When the lambda used for the HP filter varies, values of 50, 100, and 200 were used, the qualitative results hold. However, the empirical results presented in this paper employ lambda = 100; the results of lambda = 50 and lambda = 200 are available upon request.

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APPENDIX

Description 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	none	daily, monthly	calculation
DLN_XXX_USD	Difference of ln_XXX_USD from period t-1 to t	none	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
DEV_XXX_PPP	Deviation of actual LN_XXX_USD from fundamental LN_XXX_USD in the Purchasing Power Parity (PPP) Model	none	daily	calculation
ABS_DEV_XXX_PPP	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	31Dec 87=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)

contd.

BOE_QE	Outright asset purchases by the Bank of England (BOE)	million GBP	daily	Bank of England (BOE)
BOJ_QE	Outright asset purchases by the Bank of Japan (BOJ)	100 million JPY	daily	Bank of Japan (BOJ)
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	none	daily	Hodrick-Prescott (HP) filter
DLN_FX_SM	Change in the natural logarithm of the smoothed series of each LN_XXX_ USD series	none	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).