

Global Capital Flows,
Time -Varying Fundamentals and Transitional Exchange Rate Dynamics

by

Suleyman H. KAL

A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York.

2013

This manuscripts has been read and accepted for the Graduate Faculty in Economics in satisfaction of the dissertation requirements for the degree of Doctor of Philosophy.

Date

Professor Thom Thurston

Chair of Examining Committee

Date

Professor Merih Uctum

Executive Officer

Professor Thom Thurston

Professor Merih Uctum

Professor Micheal Grossman

THE CITY UNIVERSITY OF NEW YORK

Global Capital Flows,
Time -Varying Fundamentals and Transitional Exchange Rate Dynamics

by

Suleyman H. KAL

Abstract

Advisor: Professor Thom Thurston

In this paper, I investigated the effects of cross border capital flows induced by the rate of risk adjusted excess returns (Sharpe ratio) on the transitional dynamics of the nominal exchange rate's deviation from its fundamental value. For this purpose, a two state time varying transition probability Markov (TVTPM) regime switching process is added to the sticky price exchange rate model with shares (SPERS). I estimated this model using quarterly data on the four most active floating rate currencies for the years 1973 to 2009: the Australian Dollar (AUD), the Canadian Dollar (CAD), the Japanese Yen (JPY) and the British Pound (UKP). The results provide evidence that the Sharpe ratios of debt and equity investments influence the evolution of transitional dynamics of the currencies' deviation from their fundamental values. In addition, I found that the relationship between economic fundamentals and the nominal exchange rates vary depending on the overvaluation or undervaluation of the currencies.

Acknowledgements

This dissertation and ensuing papers published cannot be achieved without enduring selfless patience of my extended family, specially my wife Seyma and my two sons Mirzahan and Ahrar.

I would like to extend my gratitude to dissertation advisor, Professor Thom Thurston, who guided and shaped my dissertation through his thoughtful comments.

I also would like to thank Professor Grossman for his understanding and relentless support in this long undertaking

Contents

I. Introduction.....	1
II. The Markov Switching Approach.....	4
III. The Model.....	6
4. Estimation of the Model and Discussion of the Results.....	10
5. Testing the Markov Switching Approach.....	13
6. Data and Forecasting.....	15
6.1. Data.....	15
6.2. Forecasting Performance.....	16
6.2.1. In- Sample Forecasting.....	17
6.2.2. Out-of Sample Forecasting.....	17
7. Conclusions.....	20
Bibliography:.....	21

LIST OF TABLES

Table 1 IN-SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW	21
Table 2: Q4 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW	22
Table 3: Q8 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW	23
Table 4: Q12 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW	24
Table 5: COEFFICIENTS OF STICKY PRICE EXCHANGE RATE MODEL WITH SHARES (SPERS) ESTIMATED BY WO STATE TIME VARYING TRANSITION PROBABILITY MARKOV MODEL (TVTPM) PROCESS	25
Table 6: SHARPE RATIO OF DEBT AND EQUITY RETURNS UNDER STATE 0 AND STATE 1	26
Table 7: WALD TEST	27

I. Introduction

The dominant approach for exchange rate modeling in the Bretton Woods era of fixed exchange rates and strict capital controls was the goods market approach. According to this approach, the derived demand of currencies stemming from export and imports determine the valuation of currencies against each other. Today, the logical elegance of this approach is challenged by the fact that only a tiny fraction (less than 5% of 1.5 trillion dollar)- of daily exchange rate transactions is generated by international trade.

As the floating exchange rate era began after the collapse of Bretton Woods fixed exchange rate agreement in early 1970s, the asset approach for exchange rate modeling gained support in academic research. According to this approach, it is the demand for international financial assets not the demand for goods and services that determine the valuation of currencies against each other. Under the conditions of availability of perfect information to the public and homogenous players with rational expectations, any new information regarding the economic fundamental variables, such as interest rates, expected inflation, output, and money supply, affects the demand and supply of financial assets, and so the exchange rates. However, failure of the early models developed with this approach to explain the major exchange rates better than a “no change” random walk process (Meese and Rogoff, 1983) motivated researchers to seek non-linear applications of the asset approach.

Disconnect between the nominal exchange rates and economic variables is attributed to two basic sources. The first source is the inability of the relatively more stable economic fundamentals to explain the very volatile nominal exchange rates in a linear framework. Second

source is the evidences, which are gathered from surveys of foreign exchange traders (Cheung and Chin, 2001) and empirical studies (Frydman and Goldberg, 2001), suggest that the relationship between economic fundamentals and exchange rates is subject to frequent changes.

As the cross border capital flows increased as a consequence of liberalization in the international financial markets after 1990s, the microstructure approach (Evans and Lyon, 2001) emerged. This approach shares the basic principle of the asset approach, that the exchange rates are determined by the demand of financial assets. However, the assumptions of the asset approach, such as availability of all the information to the public, the market participants have homogenous influence on exchange rates are relaxed under the microstructure approach. Thus, the microstructure approach completes the asset approach rather than competing with it. Arguing the importance of the enormous cross border capital flows of recent decades on the exchange rate valuation, this new approach adapts the perspective of foreign exchange trading rooms to exchange rate modeling and considers order flow and order size as important factors in exchange rate determination.

In this paper, with an integrated view of the asset approach and the microstructure approach, I analyzed the influence of the cross border capital flows, which are induced by the risk adjusted excess returns (the Sharpe ratios) of investments in debt and equity markets, on the deviation of the nominal exchange rates from their fundamental values. To achieve this, a two state time varying transition probability (TVTPM) Markov regime switching process is added to the sticky price exchange rate model with share prices (SPERS) with the transitional dynamics of the Markov process linked to the risk adjusted excess returns (SR) to gain insight on the affects of cross border capital flows over exchange rate dynamics.

To investigate the transitional effects of global capital flows on exchange rates, I applied this model to the dollar exchange rates of the four most active (except Euro due to lack of data) currencies, AUD, CAD, JPY and UKP. Many researchers have investigated nonlinearities in exchange rates by employing a Markov regime switching process for exchange rate in a time series context. Very few papers (Frommel, MacDonald, 2005; Degrauve, 2001) have utilized the constant transition probability Markov process in the asset approach to exchange rate modeling. None have sought to model the transitional effects of the global capital flows on exchange rate valuation with time varying transition probability version of the Markov process.

My empirical results in this paper show that the global capital flows influence the transitional dynamics of the exchange rates' deviation from their fundamental values. In addition to this, I also find that the relationship between exchange rates and economic fundamental variables vary as the sign of this deviation changes.

The rest of the paper is structured as follows; Section II briefly describes the evolution of exchange rate modeling since 1970s. Section III explains the Markov switching models and Section IV establishes the model. In Section V, the data is explained. Section VI presents and analyzes the results. Section VII summarizes the main findings.

II. The Markov Switching Approach

Implementation of regime switching models in economics goes back to Quandt (1958), Godfeld and Quandt (1973). Hamilton's (1990) ground breaking work popularized Markov regime switching models in empirical economics.

Markov regime switching models assume that the observed changes in a variable between two consecutive periods are a random draw from different normal distributions. State (regime) variables (s_t) determine the distribution of each period. In a two-state case, when $s_t=1$ the observed changes y_t is a random draw from a $y_t / s_t = 1 \sim N(\mu_1, \sigma^2_1)$ distribution and when $s_t = 2$ the observed changes y_t is a random draw from a $y_t / s_t = 2 \sim N(\mu_2, \sigma^2_2)$ distribution. The unobserved state variable evolve according to Markov chain.

Mean and the variance of the y_t depend on the state. The density of y_t is conditional on s_t and is formulated as follows:

$$f(y_t | s_t = i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_t - \mu_{st})^2}{2\sigma^2}\right) \quad (1)$$

Error! Bookmark not defined.

Switching in Markov models between two states depends only on the previous state. The probability of switching from one state to another state is known as transition probability. For example switching from State (t-1) j to State (t) is shown using the following notation:

$$P\{s_t = i | s_{t-1} = j, s_{t-2} = k, \dots\} = P\{s_t = i | s_{t-1} = j\} = p_{ij} \quad (2)$$

Transition probabilities can be constant, as Hamilton suggested in his very well cited work (Hamilton, 1989), or they can be time varying, as developed by Diebold, Weinbach and Lee (1994).

In Hamiltonian framework the probabilities of switching between the states are fixed, exogenous and do not vary over the time. This limits the explanatory power of the Markov process. Diebold, Weinbach and Lee (1994) extended the Hamilton's framework to time-varying transition probabilities. In their framework, transition probabilities are estimated as logistic functions of vector of x_{t-1} as shown in the following equations:

$$p_t^{11} = P(s_t = 1 / s_{t-1} = 1, x_{t-1}; \beta_1) = \frac{\exp x_{t-1} \beta_1}{1 + \exp x_{t-1} \beta_1} \quad (3)$$

$$p_t^{01} = P(s_t = 0 / s_{t-1} = 1, x_{t-1}; \beta_1) = 1 - \frac{\exp x_{t-1} \beta_1}{1 + \exp x_{t-1} \beta_1} \quad (4)$$

$$p_t^{00} = P(s_t = 0 / s_{t-1} = 0, x_{t-1}; \beta_0) = \frac{\exp x_{t-1} \beta_0}{1 + \exp x_{t-1} \beta_0} \quad (5)$$

$$p_t^{10} = P(s_t = 1 / s_{t-1} = 0, x_{t-1}; \beta_0) = 1 - \frac{\exp x_{t-1} \beta_0}{1 + \exp x_{t-1} \beta_0} \quad (6)$$

Allowing the transition probabilities to change over time, depending on a vector of variables, further enriches the Markov process by enabling it to model the underlying process of transitional dynamics explicitly.

The transition probabilities are collected in P, a (2×2) matrix called the transition matrix:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix} \text{ and } \sum_{j=1}^2 p_{ij} = 1, \quad 0 \leq p_{ij} \leq 1$$

III. The Model

The exchange rate model used in this paper is the sticky price exchange rate model with stock prices (SPERS) and is represented by the following equation:

$$\Delta e_t = a_0 + a_1(\Delta m_t - \Delta m_t^*) - a_2(\Delta y_t - \Delta y_t^*) + a_3(i_t - i_t^*) + a_4(\Delta p_t - \Delta p_t^*) + a_5(SMY_t - SMY_t^*) \quad (7)$$

where Δe_t is the rate of change of the nominal exchange rate, defined as the price of foreign currency (the US dollar in this paper) in terms of the domestic currency, Δm_t is the rate of change of domestic money supply, i_t is the domestic short term interest rate (treasury bill rate), Δp_t is the rate of change of domestic price level, and SMY_t is the yield of domestic stock market. The variables with asterisks represent the same variables for the foreign country (the US in this paper).

The exchange rate (e_t) and the fundamental variables are calculated as rates of change instead of levels. For example, the rate of change in money supply is calculated as follows:

$$\Delta m_t = \frac{m_t - m_{t-1}}{m_{t-1}} \quad (8)$$

All other variables, except the interest rate, are calculated analogously.

This approach is used in this paper because it helps to avoid the seasonal effects in the data and thereby reducing the noise from short-term movements in the exchange rates and the fundamental. As a consequence this approach produces more stable results.

The expected signs of the coefficients in the sticky price exchange rate model with shares (SPERS) are as follows:

$$a_1(\text{MSD}) \quad a_2(\text{GD}) \quad a_3(\text{IRD}) \quad a_4(\text{IFD}) \quad a_5(\text{SMYD})$$

Sticky Price Mon. Model: 1 - - + -

The model posits that the risk adjusted excess return in each period changes the expectations of the global investors and influence the position of the change observed in exchange rate relative to the change to its fundamentally determined value. The deviation of the observed exchange rate from its fundamentally determined value is defined as follows:

$$d_t = \Delta C_t - \Delta e_t \tag{9}$$

ΔC_t is the observed change in exchange rate and Δe_t is the change determined by fundamental variables .

The overvalued state, (S0), is identified as when deviation (d_t) parameter is below zero. In other words, the overvalued state is when the fundamentally determined change is greater than the observed change in the exchange rate.

The undervalued state, (S1), is identified as when deviation (d_t) parameter is above zero. In other words, the undervalued state is when the fundamentally determined change is smaller than the observed change in the exchange rate.

Therefore the Equation 11 can be written as:

$$a^0_0 + a^0_1(\Delta m_t - \Delta m^*_t) - a^0_2(\Delta y_t - \Delta y^*_t) + a^0_3(i_t - i^*_t) + a^0_4(\Delta p_t - \Delta p^*_t) + a^0_5(SMY_t - SMYp^*_t) + \varepsilon^0_t$$

$\Delta C_t = \{$

$$a^1_0 + a^1_1(\Delta m_t - \Delta m^*_t) - a^1_2(\Delta y_t - \Delta y^*_t) + a^1_3(i_t - i^*_t) + a^1_4(\Delta p_t - \Delta p^*_t) + a^1_5(SMY_t - SMYp^*_t) + \varepsilon^1_t \tag{10}$$

In the time varying transition probability Markov process utilized in this paper, transition probabilities determine the likelihood of remaining in the same state or switching between the undervalued and overvalued states. The time varying transition probabilities defined as logistic functions (Equations 3-6). The risk adjusted excess return in (the Sharpe ratios) of investing in the domestic debt and equity markets of each currency are employed as the vector of governing variables (x_{t-1}) of the logistic functions.

The Sharpe ratios (x_{t-1}) are formulated as follows:

$$SharpRatio_{(t)} = \frac{E[R_C] - R_{ft}}{\sigma_C} \quad (11)$$

$E[R_s]$ is the expected rate of return from investments in the domestic debt market or equity markets described as :

$$E[R_C] = - E \left[\frac{S_{t+1} - S_t}{S_t} \right] + (i_t - i_t^*) \text{ for debt market,}$$

$$E[R_C] = - E \left[\frac{S_{t+1} - S_t}{S_t} \right] + SMY_t - SMY_t^* \text{ for equity market.} \quad (12)$$

The first term ($- E \left[\frac{C_{t+1} - C_t}{C_t} \right]$) is the expected return due to appreciation of the domestic currency ($i_t - i_t^*$) is interest rate differential between domestic and foreign currencies and ($SMYD = SMY_t - SMY_t^*$) is stock market yield differential between domestic and foreign currencies (US Dollar). I

R_f , is risk free interest rate (US treasury rate) and σ_C , is the standard deviation of expected return of the investment strategy.

The mechanics of the transition dynamics work as follows: When the coefficient (β) of the Sharpe ratios (x_{t-1}) is positive and the Sharpe ratio gets larger the numerator and denominator of the logistic function converge to each other and the logistic function approaches to 1 (100%). Since the sum of the probability of staying in the same state and the probability of transition to the other state is equal to 1 ($p_{01} = 1 - p_{11}$ and $p_{10} = 1 - p_{00}$), when the logistic function gets closer to 1, the probability of staying in the same state, (p_{11}, p_{00}), gets larger and probability of transition between the states gets smaller. On the other hand, when the coefficient (β) is negative and the Sharpe ratio gets larger, the opposite happens; the probability of staying in the same regime decreases and the probability of transition between the regimes increases.

4. Estimation of the Model and Discussion of the Results

I estimated the SPERS with TVTPM approach for each currency. I used the expected maximum likelihood algorithm developed by Diebold et al to estimate the model. This algorithm depends on maximizing the incomplete log likelihood function by iterating the expected complete data log likelihood of e_t conditioned on the data observed. Using the observed data, smoothed state probabilities, that can be defined as the unconditional probability of being in a particular state, are calculated. Then the expected complete likelihood function is found by using the transition probabilities. This step is called the expectation step. The next step is the maximization step at which the expected complete likelihood function is maximized to find updated estimates of the parameters. These updated parameter estimates are used to find new smoothed probabilities which in turn are used as inputs in the expected likelihood function. Finally, this expected likelihood function is maximized till convergence.

Estimated coefficients of the TVTPM application of SPERS are shown in Table 5. The results indicate that the economic fundamental variables do have more influence on the exchange rates when the exchange rates are in the undervalued regime (State 0) than when they are in the overvalued regime. SMYD emerges as the most significant variable for all the currencies across the states. MSD and IRD are both significant for all the currencies except the CAD in the undervalued state. Both of these variables are significant for only one currency (MSD for the CAD and IRD for the UKS) in the overvalued state. GD is statistically significant for only the CAD in both of the states. INFD is significant only in the overvalued state for two currencies (the AUD and the CAD)

As seen in the tables, the statistical significance all variables and the sign of most of them are state dependent and subject to change between the states. These results are in-line with the

previous papers and surveys conducted among the currency traders, who indicated that they attribute different importance of the economic fundamentals vary depending on the economic conditions (See Frommel and MacDonald,2005).

As stated above, the relations between the economic fundamentals and exchange rates are much stronger in the undervalued state. This relation weakens as the currencies get overvalued. Among other possible explanations, is the conclusion that higher excess returns in the debt markets attract global capital flows which cause the overvaluation of the currencies and the link between the economic fundamentals and exchange rates weakens and disappears for most of the currencies studied in this paper.

In this paper, the transitional dynamics of the Markovian switching process is linked to Sharp ratios domestic debt and equity investments via logistic functions (Equation 3 and 6). The time varying transition probabilities, formulated as logistic functions, indicate that with positive coefficients (betas), higher SRs increase the likelihood of staying in the same state. With negative coefficients, higher SRs increase the likelihood of switching to the other state. The coefficients of the SRs (betas) of domestic debt investments are statistically significant for all currencies in both states with positive signs in the overvalued state and negative signs in undervalued state. This result is very helpful in understanding the impact that foreign capital flows attracted by debt markets have on the exchange rates. According to this evidence, higher risk adjusted excess yield in the overvalued state increases the staying probability of the currency in that overvalued state by attracting foreign capital flows. The negative beta of the SR in the undervalued state increases the likelihood of transition from the undervalued state to the overvalued state by attracting foreign capital flow. The coefficients (beta) of the SRs for equity investments have a negative sign and are significant for all currencies except the UKS in the

overvalued state. In the undervalued state however, they have a positive sign and are significant for the CAD and the UKS. It is relatively easy to interpret the negative sign in overvalued state (State 0), since overvalued currency make the share prices expensive and cause capital out-flow and increases the likelihood of switching to the undervalued state.

5. Testing the Markov Switching Approach

Testing whether the exchange rate follows a single regime with the same mean in both of the states versus a two state Markov process is important, However, such test is not straightforward, because the constant coefficient model with one regime does not have transition probabilities, whereas the Markov model has transition probabilities. Two tests are utilized for this purpose: likelihood ratio test and Wald test (See, Engel and Hamilton, 1983). In this paper, I employed the Wald test to test the null hypothesis that the means of the two states are equal to each other against the alternative hypothesis that they are different from each other.

$$H_{0r} : \mu_0 = \mu_1$$

$$H_1 : \mu_0 \neq \mu_1$$

The Wald statistics used is

$$\frac{(\hat{\mu}_1 - \hat{\mu}_2)}{\sqrt{\hat{\text{var}}(\hat{\mu}_1) + \hat{\text{var}}(\hat{\mu}_2) - 2\hat{\text{cov}}(\hat{\mu}_1, \hat{\mu}_2)}} \approx \chi^2 \quad (13)$$

For the adequacy of the model, it is also important to understand whether there are any links between the regimes and the economic fundamentals. Following MacDonald and Frommel,(2005) I also use a Wald test to assess the significance of differences in the coefficients. The null and the alternative hypothesis for the coefficients are as follows:

$$H_{0r} : a_0^0 = a_0^1 \quad H_{0r} : a_1^0 = a_1^1 \quad H_{0r} : a_2^0 = a_2^1 \quad H_{0r} : a_3^0 = a_3^1 \quad H_{0r} : a_4^0 = a_4^1$$

$$H_1 : a_0^0 \neq a_0^1 \quad H_1 : a_1^0 \neq a_1^1 \quad H_1 : a_2^0 \neq a_2^1 \quad H_1 : a_3^0 \neq a_3^1 \quad H_1 : a_4^0 \neq a_4^1$$

Table 7 reports the Wald test results. According to this, the means of the regimes for all currencies are significantly different from each other. Similarly, the intercepts for all currencies are also different. According to the results in Table 7 IRD with highest Wald test score is the most important variable that causes the regime change and MSD is the second one. Coefficients of SMYD are not significantly different in between the states.

6. Data and Forecasting

6.1. Data

The dataset used in this paper covers quarterly observations of four bilateral nominal exchange rates (price of US dollar in terms of each currency): Australian dollar (AUD), Canadian dollar (CAD), Japanese Yen (JPY), British Pound (BP). In addition to this, five macroeconomic measurements for these four countries and US are used: money supply, income, inflation rates, short term interest rates, and share prices. The data are acquired from the web site of International Financial Statistics (IFS) of International Monetary Fund (IMF).

The in-sample sample period covers the 130 end-of-period observations for the post Bretton Wood period beginning with the first quarter of 1973 and ending with the second quarter of 2005. The money supply variable is seasonally adjusted M2+CDS for Japan, seasonally adjusted M2 for US, seasonally adjusted gross M2 for Canada, and seasonally adjusted M3 for Australia. Since there are some discontinuities for UK monetary aggregate data in IFS, I acquired data on M4 for the UK from the Statistical Data Base of Bank of England. GDP chain volume with 2002 reference prices is used as the income measure for Australia. GDP chain volume with 2002 prices is used as income measure for Canada. Nominal GDP is used as income measure for Japan. GDP chain volumes with 2000 prices used are as income measures for UK and US. The Three Year Government Bond Yield is used as the short term interest rate for Australia, The Treasury Bill rate is used as the short term interest rate for Canada. The Money Market Rate is used as short term interest rate for Japan. The Treasury Bill rate is used as short run interest rate for UK and US. The price level in each economy is measured by quarterly CPI. Inflation is calculated as quarterly percentage change . Share prices are the end of quarter share prices for each country.

6.2. Forecasting Performance

Since seminal study of Meese and Rogoff (1983), comparing the out-of-sample forecast performance of exchange rate models with a simple random walk model has become the convention. In this paper, I compared the forecast accuracy of in-sample and 4, 8 and 12 quarters a head out-of-sample forecasting accuracy of this model in terms of mean squared errors (MSE) with a random walk and a random walk with drift. I also use the forecasts of constant coefficients version (OLS) of the model to use as a benchmark for measuring the improvement of the Markov process over constant coefficient model.

Tables 1 to 4 report the mean squared errors of competing models (TVTPM, Constant Coefficient, RW and RWD); mean squared error ratios, defined as the ratio of mean squared error of OLS, RW or RWD to that of TVTPM; and Diebold Mariano (DM) statistics.

(DM) statistics test the significance of the difference between MSE of the model and a random walk and a random walk with drift. DM statistic is a t-type statistic asymptotically normal. Under the null population MSE's are equal. DM test statistic is defined by the following equations (Look Ince, 2010):

$$\hat{f}_t = \hat{MSE}_{t,TVTPM} - \hat{MSE}_{t,RW} \quad (14)$$

$$\bar{f}_t = N^{-1} \sum_{t=N-P+1}^N \hat{f}_{t+1} = \sigma_{TVTPM}^2 - \sigma_{RW}^2 \quad (15)$$

$$\hat{V} = N^{-1} \sum_{t=N-P+1}^N (\hat{f}_{t+1} - \bar{f})^2 \quad (16)$$

$$DM = \frac{\bar{f}}{\sqrt{N^{-1} \hat{V}}} \quad (17)$$

N is the sample size, P is number of forecasts.

6.2.1. In- Sample Forecasting

Table 1 reports in-sample-forecasting results of the model against a random walk, a random walk with drift and the model with the constant coefficients. With respect to in-sample forecasts the sticky price exchange rate model with shares (SPERS) with Markov specification and without Markov specification statistically significantly outperforms a random walk and a random walk with shares.

The addition of the Markov process improves the in-sample forecasting ability of the SPERS model with constant coefficients. The Markov specification of the model produces substantially lower (fifty percent or less) mean squared errors than the constant coefficient version of the model.

6.2.2. Out-of Sample Forecasting

To produce out-of-sample forecasts, I divided the sample is into two sections: in-sample and out-of-sample. I estimated the parameters of the equation with the in-sample section and used the remaining part of the sample to estimate the out-of-sample forecasting for all three horizons. The in-sample period covers the dates between Q1 of 1973 to Q2 of 2005. The in-sample section is then extended recursively by adding one quarter each time to Q3 of 2006 and this continues to the last observation Q4 of 2009 for 12 quarter ahead forecasting. A total of 120

out-of sample forecasts are done for the Markov model, the constant coefficient model, the random walk and the random walk with drift.

Table 2 reports 4 quarter ahead out-of-sample forecasting. The Markov specification of the SPERS model produces lower mean squared errors than the random walk. The Diebold Mariano statistics indicate that means error squared differences between the Markov model and the random walk are statistically significant for all the currencies except for the Australian dollar. Compared to the random walk with drift, the Markov model produces lower mean squared errors for all the currencies except for Australian dollar, but the differences are not significant statistically for any of the currencies. The Markov specification also produces at least fifty percent or lower mean squared errors than the constant coefficient specification of the model.

Table 3 reports the 8 quarter ahead out-of-sample forecasting. At this horizon, the Markov model produces lower a mean squared error than the random walk for all the currencies, and the difference between the Markov forecast and the random walk forecast is significant for all the currencies except the Japanese yen. Again, the Markov model produces lower mean squared errors than the random walk with drift, but the difference between errors of the Markov model and of the random walk with drift is statistically significant only for the British pound. The Markov specification also improves forecasting performance of the constant coefficient version of the model at least fifty percent or more.

Table 4 reports the 12 quarter ahead out-of-sample forecasting. It is noteworthy that at this forecasting horizon the forecasting performance of the Markov model gets better in comparison with both versions of the random walk and the constant coefficient version of SPERS model. The differences between the Markov and the random walk models are all

statistically significant for all currencies except the random walk with drift of the Japanese yen. Again, the Markov model produces substantially lower mean squared errors than the constant coefficient model relative to the other horizons.

7. Conclusions

In this paper, I investigated whether the deviation of the exchange rates from their fundamental values affect the relationship between the economic fundamentals and exchange rates by extending the sticky price exchange rate model with shares with a time varying transition probability Markov (TVTPM) regime switching process. In this model, risk adjusted excess rate of return (SR) of debt and equity investments in the currencies are utilized as signals by which the investors direct the cross border capital flows.

The results I report show that the cross border capital flows influence the exchange rate valuation by changing the transition dynamics of the deviation of currencies from their fundamental values causing overvaluation and undervaluation. The results also reveal that the relationship between economic fundamental variables and exchange rates depends on whether the exchange rates are overvalued or undervalued. Thus, the cross border capital flows indirectly affect the relationship between exchange rates and economic fundamentals.

In addition, the model used in this paper substantially increases the forecasting power over the constant coefficient version of SPERS model and it promises a bright perspective on exchange rate modeling by producing lower out-of sample forecasting errors than that of a random walk or a random walk with drift. For future research, a three state version of the same model can provide more refined insight to the exchange rate economic fundamental relation as well as it may further increase the forecasting power of the model.

TABLE 1 IN-SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW

	TVTPM	Constant Coefficient	RW	RWD	RW MSER	RW DM	RWD MSER	RWD DM
Australian Dollar	0.0007	0.0020	0.0046	0.0023	0.1409	8.1027	0.2822	6.5064
Canadian Dollar	0.0002	0.0004	0.0012	0.0006	0.1318	6.9848	0.2470	6.7675
Japanese Yen	0.0008	0.0019	0.0060	0.0033	0.1319	7.3142	0.2365	8.9832
British Pound	0.0006	0.0016	0.0044	0.0025	0.1288	7.4328	0.2232	10.0186

Note: The table reports in-sample the mean squared error (MSE) of Markov switching model (MS), constant coefficient model, random walk (RW), random walk with drift (RWD), mean squared error ratio of MS against RW (RW MSER), mean squared error of MS against (RWD MSER), Diebold-Mariano test statistic MS against RW (RW DMW) and Diebold-Mariano test statistic TVPTPM against RWD (RWD DMW)

MSER (mean squared error ratio) is defined as the ratio of MSE of Markov model to that of RW (random walk) and RWD (random walk with drift). According to this, MSER less than one means that TVTPM outperforms RW and RWD. A significant Diebold Marino (DM) test statistic implies that TVTPM produces statistically significantly lower mean squared error than RW and RWD.

Bold numbers indicate statistical significance at 10 % level according to t-test

TABLE 2: Q4 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARED ERROR RATIO AND DMW

	TVTPM	Constant Coefficient	RW	RWD	RW MSER	RW DMW	RWD MSER	RWD DMWD
Australian Dollar	0.00093	0.00153	0.00340	0.00098	0.53345	0.75940	1.7296	-0.4585
Canadian Dollar	0.00010	0.00048	0.00215	0.00075	0.04263	2.22993	0.12093	0.98013
Japanese Yen	0.00020	0.00145	0.00405	0.00140	0.04700	1.93435	0.13765	0.78940
British Pound	0.00025	0.00118	0.00368	0.00123	0.06863	1.85235	0.47620	0.64530

Note: The table reports 4Q ahead out-of-sample the mean squared error (MSE) of Markov switching model (TVTPM), constant coefficient model, random walk (RW), random walk with drift (RWD), mean squared error ratio of MS against RW (RW MSER), mean squared error of MS against (RWD MSER), Diebold-Mariano test statistic MS against RW (RW DMW) and Diebold-Mariano test statistic TVTPM against RWD (RWD DMW)

MSER (mean squared error ratio) is defined as the ratio of MSE of TVTPM to that of RW (random walk) and RWD (random walk with drift). According to this MSER less than one means that TVTPM outperforms RW and RWD. A significant Diebold Marino (DM) test statistic implies that the model (TVTPM) produces statistically significantly lower mean squared error than RW and RWD.

Bold numbers indicate statistical significance at 10% level according to t-test

TABLE 3: Q8 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARED ERROR RATIO AND DMW

	TVTPM	Constant Coefficient	RW	RWD	RW MSER	RW DMW	RWD MSER	RWD DMWD
Australian Dollar	0.00063	0.00143	0.00258	0.00115	0.26815	1.60265	0.54605	0.90743
Canadian Dollar	0.00030	0.00070	0.00210	0.00075	0.13178	3.22198	0.37003	0.87320
Japanese Yen	0.00095	0.00255	0.00250	0.00105	0.39135	1.01035	0.94310	0.06250
British Pound	0.00023	0.00115	0.00238	0.00130	0.08985	2.08455	0.17105	1.73218

Note: The table reports 8Q ahead out-of-sample the mean squared error (MSE) of Markov switching model (TVTPM), constant coefficient model, random walk (RW), random walk with drift (RWD), mean squared error ratio of MS against RW (RW MSER), mean squared error of MS against (RWD MSER), Diebold-Mariano test statistic MS against RW (RW DMW) and Diebold-Mariano test statistic TVPTPM against RWD (RWD DMW)

MSER (mean squared error ratio) is defined as the ratio of MSE of TVTPM to that of RW (random walk) and RWD (random walk with drift). According to this MSER less than one means that TVTPM outperforms RW and RWD. A significant Diebold Marino (DM) test statistic implies that the model (TVTPM) produces statistically significantly lower mean squared error than RW and RWD.

Bold numbers indicate statistical significance at 10% level according to t-test

TABLE 4: Q12 HORIZON OUT-OF SAMPLE MEAN SQUARED ERROR AND MEAN SQUARRED ERROR RATIO AND DMW

	TVTPM	Constant Coefficient	RW	RWD	RW MSER	RW DMW	RWD MSER	RWD DMWD
Australian Dollar	0.00095	0.00368	0.00328	0.00198	0.27568	1.69750	0.50113	1.33925
Canadian Dollar	0.00050	0.00118	0.00225	0.00125	0.21275	3.80253	0.38638	1.82778
Japanese Yen	0.00090	0.00193	0.00283	0.00125	0.32053	1.52015	0.79390	0.36280
British Pound	0.00023	0.00118	0.00203	0.00110	0.11300	2.43460	0.21260	1.96608

Note: The table reports 12Q ahead out-of-sample the mean squared error (MSE) of Markov switching model (TVTPM), constant coefficient model, random walk (RW), random walk with drift (RWD), mean squared error ratio of MS against RW (RW MSER), mean squared error of MS against (RWD MSER), Diebold-Mariano test statistic MS against RW (RW DMW) and Diebold-Mariano test statistic TVPTPM against RWD (RWD DMW)

MSER (mean squared error ratio) is defined as the ratio of MSE of TVTPM to that of RW (random walk) and RWD (random walk with drift). According to this MSER less than one means that TVTPM outperforms RW and RWD. A significant Diebold Marino (DM) test statistic implies that the model (TVTPM) produces statistically significantly lower mean squared error than RW and RWD.

Bold numbers indicate statistical significance at 10% level according to t-test

TABLE 5: COEFFICIENTS OF STICKY PRICE EXCHANGE RATE MODEL WITH SHARES (SPERS) ESTIMATED BY TWO STATE TIME VARYING TRANSITION PROBABILITY MARKOV MODEL (TVTPM) PROCESS

	Australia		Canada		Japan		UK	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
<i>Constant0</i>	-0.0395	-4.0166	-0.0156	-3.4921	-0.0428	-4.0869	-0.0203	-2.9038
<i>MSD 0</i>	0.2969	1.0789	0.2689	1.3935	-0.3113	-0.4497	0.1114	0.467
<i>GD 0</i>	-0.2426	-0.5398	-0.6085	-1.8072	-0.1836	-0.4146	0.0984	0.3503
<i>IRD 0</i>	0.3746	0.3367	-0.2706	-0.3796	0.3437	0.297	-1.5938	-2.417
<i>INFD 0</i>	-1.4576	-2.7921	-0.7984	-1.3731	-0.4615	-0.6206	-0.0779	-0.3006
<i>SMYD 0</i>	-0.1523	-4.2825	-0.2143	-6.2361	-0.3782	-5.2459	-0.4387	-7.7877
<i>Sigma 0</i>	0.0009	3.7388	0.0002	3.7065	0.0013	3.0451	0.0004	3.8003
<i>Constant1</i>	0.014	1.3038	0.0171	5.6441	0.0091	1.4087	0.0228	1.7541
<i>MSD 1</i>	0.3397	1.1971	0.1128	0.6784	0.669	1.629	0.5046	1.4243
<i>GD 1</i>	0.5017	0.7977	-0.5038	-2.785	0.2328	0.971	0.3385	0.594
<i>IRD 1</i>	1.1091	1.1509	-0.0861	-0.127	-1.2507	-1.576	0.9126	0.9729
<i>INFD 1</i>	0.09	0.1442	-0.0081	-0.0211	-0.2723	-0.4678	0.2771	0.5527
<i>SMYD 1</i>	-0.1275	-2.4771	-0.1572	-4.7915	-0.3573	-7.7265	-0.3198	-4.9862
<i>Sigma 1</i>	0.0008	3.0929	-0.0156	-3.4921	0.0005	3.995	0.001	3.2378

Notes: There are two sets of coefficients for SPERS estimated with two state TVTPM process. One, for State 0 the state in which the observed change in exchange rate is less than the change suggested by the economic fundamentals. Two, State 1 the state in which the observed change in exchange rate is more than the change suggested by the economic fundamentals.

TABLE 6: SHARPE RATIO OF DEBT AND EQUITY RETURNS UNDER STATE 0 AND STATE 1

	Beta Debt 0	t-stat	Beta Equity 0	t-stat	Beta Debt 1	t-stat	Beta Equity 1	t-stat
Australian Dollar	3.4661	1.3482	-1.3177	-1.2689	-3.4482	-1.3633	0.7845	0.7095
Canadian Dollar	3.5243	1.4944	-1.4898	-1.3592	-4.7459	-1.4424	2.5729	1.3064
Japanese Yen	3.7509	1.3837	-2.6877	-1.2684	-3.7801	-1.2309	2.6654	0.9066
British Pound	2.9172	1.8156	0.3481	0.4273	-2.6761	-1.6373	1.0637	1.4532

Note: Betas are the coefficients of governing variables (x_{t-1} =Sharpe Ratio ($SR_{(t)} = \frac{E[R_{st}] - R_{ft}}{\sigma_s}$)) of time varying transition probability which is formulated as logistic function ($p_t^{11} = \frac{\exp x_{t-1}\beta_1}{1 + \exp x_{t-1}\beta_1}$). According to this, if the beta is positive higher SR increases the likelihood of staying in the same regime and decreases the likelihood of transition to the other regime ($p_t^{01} = 1 - p_t^{11}$).

TABLE 7: WALD TEST

	Mean	Constant	MSD	GD	IRD	INFD	SMYD	Beta
Australian Dollar	3.1837	29.506	0.0506	1.7738	1.4428	1.2412	4.70E-03	4.79E+06
Canadian Dollar	2.7628	82.7053	3.2073	1.03E+00	1.372	9.08E-01	0.0298	3.19E+05
Japanese Yen	2.2869	39.0826	1.0047	0.3066	1.832	0.002	0.007	5.14E+02
British Pound	3.1299	29.1971	1.5800	0.1369	9.9728	0.1753	0.0413	4.19E+03

Bold numbers indicate statistical significance at 10% level

Bibliography:

- [1] Boothe, P. and Glasmann, D (1987). 'The Statistical Distribution of Exchange Rates,' *Journal of International Economics*, 22: 297-319.
- [2] Clarida, Richard H., Lucio Sarno, Mark P. Taylor and Giorgio Valente (2003). "The Out-of Sample Success of Term Structure Models as Exchange Rate Predictors: A step beyond." *Journal of International Economics*, 60, 61-83
- [3] De Grauwe, Paul and Vansteenkiste, Isabel, (2001). "Exchange Rates and Fundamentals a Non-Linear Relationship?" (October 2001). *CESifo Working Paper Series No. 577*
- [4] Diebold, F.X., J.H. Lee, G.C. Weinbach (1994), Regime switching with time-varying transition probabilities, in: C. Hargreaves (ed.), *Nonstationary Time Series Analysis and Cointegration*, Oxford: Oxford University Press, 283-302.
- [5] Engel, Charles and Hamilton James D. (1990) "Long Swings in the Dollar: Are They in the Data and Do Markets Know It?", *The American Economic Review*, 80, 689-711.
- [6] Frommel, Michael & MacDonald, Ronald & Menkhoff, Lukas, 2005. "Markov switching regimes in a monetary exchange rate model" *Economic Modeling*, 22(3), 485-502,
- [7] Goldberg, Michael D. and Frydman Roman (2001), "Macroeconomic Fundamentals and DM/\$ Exchange Rate: Temporal Instability and the Monetary Model" *International Journal and Finance and Economics*, 6,421-435.
- [8] Goldfeld, Stephen M. and Richard E. Quandt (1973), "A Markov Model for Switching Regressions," *Journal of Econometrics*, 1, 3-16.
- [9] Hamilton, James D. (1990), "Analysis of Time Series Subject to Changes in Regime,"

Journal of Econometrics, 45, 39-70.

[10] Hamilton, James D. (1994), *Time Series Analysis*, Princeton University Press, New Jersey.

[11] Ince Onur (2010), "Forecasting Exchange Rates Out-of-Sample with Panel Methods and Real-Time Data", submitted, 2010

[12] Lyons, Richard K. (2001), *The Microstructure Approach To Exchange Rate*, The MIT Press, Cambridge, Massachusetts

[13] Meese Richard A., Rogoff K. (1983) "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics* 14,3-24.

[14] Meese, Richard A., Rose Andrew K. (1990) "Empirical Assessment of Non-Linearities in Models of Exchange Rate Determination", *Review of Economic Studies*, 58, 603-619.

[15] Peel David A, Sarno Lucio, Taylor Mark P. (2001) "Nonlinear Mean-Reversion in Real Exchange Rates: Toward a Solution To the Purchasing Power Parity Puzzles" *International Economic Review* 42, 1015-1042

[16] Quandt, Richard E. (1958), "The Estimation of Parameters of Linear Regression System Obeying Two Separate Regimes," *Journal of the American Statistical Association*, 55, 873-880.