Essays on the Puzzles in International Finance

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A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2015

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Abstract

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The overall theme of this dissertation is the explanation of puzzles in international finance. Empirically, exchange rates seem to be disconnected to the economic fundamentals, and it is referred to as the exchange rate disconnect puzzle. Another puzzling feature in foreign exchange market is that high interest rate currency tends to appreciate, and it is called as "uncovered interest rate parity puzzle." Chapter 1 and 3 of this dissertation examine the exchange rate disconnect puzzle, while chapter 2 investigates the explanation for the UIP puzzle.

The first chapter[1], "Imperfect Proxies for Market Expectations and the Exchange Rate Disconnect Puzzle", develop an econometric framework which can capture the relation between exchange rate and economic variables. Conventional empirical studies assume the linear relation between exchange rate and its determinants implied by the theory. I show that this linear modeling strategy leads to the spurious instance of the exchange rate disconnect puzzle and propose the new model which allows imperfectness of the macro variables as a predictor for market expectation. The proposed model provides empirical evidence that the domestic currency appreciates in response to an unanticipated increase in domestic output

[1]This chapter is based on co-authored work with Chang-Jin Kim.

growth or inflation. Furthermore, results for out-of-sample predictability tests suggest that the proposed model outperforms the random walk model over various horizons less than two years, for most of the countries under investigation.

The second chapter of my dissertation, “Is It Risk or Expectational Error? Explaining Deviation from Uncovered Interest Parity” explores the behavior of ex-ante excess return to explain the UIP puzzle. Implementing empirical models of ex-ante excess return has proven to be very difficult and previous attempts have not been successful in explaining what makes ex-ante excess return. In this chapter, I propose the new framework which estimates the ex-ante excess return more efficiently by incorporating information in economic variables. The extracted series show that high inflation or output in the foreign country raises the ex-ante excess return for holding foreign currency, while high inflation or high output in home country lowers it. Moreover, using the survey-based forecast of exchange rate data, I find that ex-ante excess return is strongly connected with the market's systematic forecast error instead of with the implied risk premium. These empirical findings suggest that the market's expectation is not fully rational, and this systematic expectational error results in the UIP puzzle.

Lastly, the third chapter, “Commodity Currency Predictions: the Role of Expectations”, examines the dynamic linkage between commodity prices and exchange rate. Even though exchange rates and commodity prices are highly correlated contemporaneously, commodity prices are not shown to have predictive power for exchange rates. With several time-series techniques and alternative data, such as survey-based forecast of exchange rate and foreign exchange option prices, I show that commodity price is linked to the future exchange rate through the market expectation: markets consider aggregate commodity prices when they form expectations of the exchange rates. These empirical findings suggest that commodity price movements are incorporated into the nominal exchange rate with lasting impact beyond one quarter.

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ACKNOWLEDGMENTS

I first want to thank two chairs of my dissertation committee Professor Chang-Jin Kim and Professor Yu-chin Chen for their support and encouragement throughout the whole process of writing my dissertation. Without two professors, I would not have completed this way. Professor Chang-Jin Kim not only taught the knowledge of Econometrics, but also showed the philosophy toward research where I should put endless effort and passion. Professor Yu-chin Chen allocated much of her time advising my dissertation and helped to maintain the balance between Econometrics and International Economics. Her intuition about Economics will have great influence on my future research.

I also want to thank my committee members Professor Eric Zivot and Professor Ji Hyung Lee for providing very helpful comments and suggestions for my study. Their contribution of their valuable time allowed me to get good feedbacks and opportunity of deeper understanding.

Last but not least, I cannot thank more to my parents for their unconditional support and love. I also thank my sisters for always being there for me.

DEDICATION

To my parents

Chapter 1

IMPERFECT PROXIES FOR MARKET EXPECTATIONS AND THE 'EXCHANGE RATE DISCONNECT PUZZLE'

1.1 Introduction

As very well documented in Engel and West (2005) and Engel et al. (2007), one puzzle in international economics has been the divergence between theoretical models and empirical models of exchange rates, i.e., 'the exchange rate disconnect puzzle'. Starting from Meese and Rogoff (1983a), researchers on international finance have reported that a random walk predicts exchange rates better than macroeconomic models of exchange rates. That is, they have failed to empirically show robust links between various exchange rates and their theory-based fundamentals such as money supplies, outputs, and interest rates.

Within the framework of a rational expectations present-value model, Engel and West (2005) show that the exchange rate follows a near random-walk process if fundamentals follow unit root processes and the factor for discounting future fundamentals is close to one. In such cases, they show that changes in the exchange rate may not be predictable by fundamentals in the short run, even when the underlying present value models of exchange rates are reasonable approximations to the real world and expectations reflect information about future fundamentals. This is because, in determining the exchange rate, current economic fundamentals have relatively little weight and much greater weight is put on expectations of future fundamentals when the discount factor is close to one.

Engel et al. (2007) thus argue that comparing the forecasting ability of a model relative to that of the random walk model may not be an appropriate way to evaluate an exchange rate model. They further conclude that macroeconomic models of exchange rates are "not so bad after all," by surveying papers that focus on evaluating the exchange rate models based on various alternative methods. For example, Engel and West (2005) and Chen et al. (2010) indirectly confirm the present value models of exchange rates by showing that there exists Granger causality from exchange rate to observable fundamentals. Anderson et al. (2003), Faust et al. (2003, 2007), and Clarida and Waldman (2008) show that, immediately after news that indicates expansion in the U.S. economy or news about higher-than-expected inflation, an appreciation of the dollar follows. These are indirect pieces of evidence that support the present value model based on the Taylor-rule of monetary policy. Engel and West (2006) and Mark (2009) indirectly test the present value model by constructing model-based exchange rates from functions of VAR forecasts of the fundamentals and by comparing them with actual exchange rates.

A major difficulty in testing the present value models of exchange rates stems from the fact that we do not have a direct measure of the market's expectation, as mentioned by Engel et al. (2007). Not all fundamentals perceived by economic agents are observable by econometricians. Money demand shocks, productivity shocks, and the risk premium are a few examples of unobservable fundamentals. The market's expectation is formed based on a larger information set than the one that consists of the current and past values of the fundamentals observable by econometricians. Thus, the observable fundamentals serve only as imperfect proxies for the market's expectation. Sometimes, even the fundamentals observed by econometricians may just be proxies for true underlying fundamentals. For example, within the framework of the Taylor-rule-based present value model, Engel and West (2006) derive inflation rate differentials and output gap differentials between the domestic and foreign countries as key fundamentals that determine exchange rates, assuming that monetary policies for the two countries involved are identical. However, if monetary policies are not the same for the two countries, observable fundamentals such as inflation differentials and output gap differentials are just imperfect proxies for true underlying fundamentals.

Under these circumstances, the dynamics of the market's expectation and those of observable fundamentals can be very different, and empirically modeling expected changes in exchange rates as a linear function of these observable fundamentals may not be an optimal strategy. We believe that such an empirical modeling strategy serves as an additional reason explaining why the existing literature has failed to find a link between exchange rates and these observable fundamentals, other than the discount factor being close to one as suggested by Engel and West (2005).

In this paper, we propose a new approach to directly evaluating present value models of exchange rates, in a situation in which observable fundamentals are just imperfect proxies for the market's expectation or true underlying fundamentals. In this case, observable fundamentals may not be perfectly correlated with the market's expectation.[1] In order to accommodate the imperfect correlation between the conditional expectation of exchange rate growth and observable fundamentals, we adopt Pastor and Stambaugh's (2009) predictive system, which can be summarized as: i) We treat the conditional expectation of exchange rate growth as a latent random variable, the dynamics of which is assumed to be known;[2] ii) The vector of observable fundamentals is assumed to follow a finite-order VAR process; iii) The link between exchange rates and these fundamentals is modeled through the correlation between the innovations to the conditional expectation of exchange rate growth and those to observable fundamentals. Within this framework, we can directly test the validity of a rational expectations present-value model by checking the significance of the correlations between innovations to observable fundamentals and those to the unobserved conditional expectation. Even though Pastor and Stambaugh's (2009) original predictive system is not identified, we present a procedure for identifying and estimating these correlations by appropriately deriving a reduced-form model.

We provide direct evidence in favor of robust and statistically significant links between various exchange rates and theory-based observable fundamentals. Our empirical results show that an unexpected increase in domestic inflation or domestic output growth results

[1] Existing present value models assume that the conditional expectation of the exchange rate growth or the market's expectation is perfectly correlated with observable fundamentals, in the sense that the conditional expectation is a linear function of these fundamentals.

[2] Modeling expected returns as a latent variable is not new in the literature on the stock market. Also refer to Brandt and Kang (2004) and Binsbergen and Koijen (2010).

in an appreciation of domestic currency in the short run. These results are obtained for the bilateral U.S. exchange rates versus those of Canada, France, Germany, Italy, Japan, Switzerland, and the United Kingdom for the period covering 1984:Q1 - 2005:Q4. Furthermore, in terms of out-of-sample predictability, our model significantly outperforms the random walk model for various short horizons less than two years, for most of the countries under consideration.

The outline of this paper is as follows. In Section 2, we first review the present value model of exchange rates by Engel and West (2005), who show that one source of the 'exchange rate disconnect puzzle' is a factor for discounting future fundamentals which is close to one. We then present an additional source of the puzzle, in a situation in which observable fundamentals are imperfect proxies for the market's expectation. In Section 3, we present a time series model of exchange rates under a realistic situation in which we have 'imperfect' proxies for the market's expectation. We then discuss the procedure for identifying and estimating of the proposed model. Section 4 presents empirical results, and Section 5 concludes the paper.

1.2 The 'Exchange Rate Disconnect Puzzle' and Its Potential Sources

1.2.1 High Discount Factor as a Source of the Puzzle: Engel and West (2005)

The term 'exchange rate disconnect puzzle' was first used by Obstfeld and Rogoff (2000) in order to cover the weak short-run relationship between the exchange rate and macroeconomic variables reported in the empirical literature on international finance. The literature reports that underlying macroeconomic fundamentals such as interest rates, inflation rates, and output fail to explain the short-term volatility in exchange rates, or equivalently, short-term forecasts of macroeconomic exchange rate models are little better than the forecasts of random walk models.

Recently, Engel and West (2005) provided a potential source of the exchange rate disconnect puzzle within the present value context. A version of the present value model considered by them is:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t[f_{t+j}], \quad 0 < b < 1, \tag{1.1}$$

where $E_t[.]$ refers to expectation conditional on information up to t; f_t is a linear combination of fundamentals perceived by economic agents; and b is a discount factor. They prove that s_{t+1} approaches a random walk process when the discount factor b approaches 1, if f_t has a unit root. Assuming that Δf_t has the following Wold representation:

$$\Delta f_t = \theta(L)\epsilon_t, \tag{1.2}$$

where ϵ_t is serially uncorrelated and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3 + ...$, with the roots of $\theta(L) = 0$ lying outside the complex unit circle, they derive the following representation for Δs_{t+1}:[3]

$$\Delta s_{t+1} = (1-b)\sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j+1}] + \theta(b)\epsilon_{t+1}. \tag{1.3}$$

If, for example, we assume that Δf_t follows an AR(1) process given below,

$$\Delta f_t = \psi \Delta f_{t-1} + \epsilon_t, \tag{1.2$'$}$$

equation (1.3) can be rewritten as:

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + \frac{1}{1-b\psi}\epsilon_{t+1}. \tag{1.3$'$}$$

Equation (1.3) or (1.3') suggests that, as the discount factor b approaches one, the exchange rate approaches a random walk process with Δs_{t+1} approaching $\theta(1)\epsilon_{t+1}$ or $\frac{1}{1-\psi}\epsilon_{t+1}$, which is serially uncorrelated. Notice also that, in this case, Δs_{t+1} may not be predictable by Δf_t, and Engel and West (2005) present a high discount factor as a potential source of the 'exchange rate disconnect puzzle.' Intuitively, this is because current economic fundamentals

[3] Refer to the Appendix for a proof.

have relatively little weight and much greater weight is put on the expectations of future fundamentals when the discount rate is close to one.[4]

1.2.2 Imperfect Proxies for Market Expectations as Additional Source of the Puzzle

In this section, we present an additional source of the 'exchange rate disconnect puzzle,' by considering a situation in which not all the fundamentals perceived by economic agents are observed by econometricians. When observable fundamentals, denoted by a vector Δx_t, are a subset of fundamentals perceived by economic agents, Δf_t and Δx_t are not perfectly correlated and their dynamics can be different. For simplicity of exposition, let us consider a simple case in which the dynamics of Δf_t is given by equation (1.2') and the dynamics of Δx_t is given by:

$$\Delta x_t = \phi \Delta x_{t-1} + \upsilon_t, \tag{1.4}$$

$$corr(\epsilon_t \upsilon_t) = \rho_{\epsilon\upsilon}, \quad |\rho_{\epsilon\upsilon}| < 1, \tag{1.5}$$

where we assume that Δx_t is 1×1, and υ_t is serially uncorrelated.

If $\psi \neq \phi$, the unconditional correlation between Δf_t and Δx_t can be very low, even when their correlation conditional on past information is close to one.[5] In this case, we may not be

[4] Engel et al. (2007) show that, if the linear combination of the fundamentals were expected to change between period t and t+1 to a new permanent value $\tilde{f}_{t+1}$, then the exchange rate would be a weighted average of the current and the future linear combination of the fundamentals, as given below:

$$s_t = (1-b)f_t + b\tilde{f}_{t+1}.$$

[5] From equations (1.2'), (1.3'), and (1.4), one can derive the relationship between the conditional and unconditional correlations between Δx_t and Δf_t, as given below:

$$corr(\Delta x_t, \Delta f_t) = \frac{\sqrt{(1-\psi^2)(1-\phi^2)}}{1-\phi\psi}\rho_{\epsilon\upsilon},$$

from which we can see that the unconditional correlation between Δx_t and Δf_t is always less than or equal to their conditional correlation $\rho_{\epsilon\upsilon}$. The equality holds when $\phi = \psi$, or equivalently, the unconditional correlation is maximized when $\phi = \psi$.

able to establish a link between the exchange rate growth and the observable fundamentals within the linear regression framework. We view this as an additional potential source of the 'exchange rate disconnect puzzle.'

In order to analytically illustrate these points, we consider a data generating process that consists of (1.2'), (1.3'), and (1.4), as given below:

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + \frac{1}{1-b\psi}\epsilon_{t+1}$$
$$\Delta f_{t+1} = \psi \Delta f_t + \epsilon_{t+1}$$
$$\Delta x_{t+1} = \phi \Delta x_t + v_{t+1},$$

where we denote the $\frac{(1-b)\psi}{1-b\psi}\Delta f_t$ term as the market's expectation, and ϵ_{t+1} and v_{t+1} are correlated. Then, in Tables A.1 and A.2, we report the correlations between Δs_{t+1} and Δf_t along with those between Δs_{t+1} and Δx_t, for different values of ψ, ϕ and b. We set $\psi = 0.1$ and $\rho_{\epsilon v} = 0.7$ for Table A.1; and we set $\psi = 0.95$ and $\rho_{\epsilon v} = 0.7$ for Table A.2.

When $\psi = 0.1$ as in Table A.1, $corr(\Delta s_{t+1}, \Delta f_t)$ is as low as 0.01 for $b = 0.9$ and it is lower at 0.006 for $b = 0.95$. We have the same pattern for the $corr(\Delta s_{t+1}, \Delta s_t)$. Based on these results, Engel and West (2005) argue that, when the discount factor b is close to 1, the exchange rate follows a near random-walk process and that it may not be predictable by the fundamentals in the short run. This may explain the 'exchange rate disconnect puzzle.'

However, when ψ is increased to 0.95, the discount factor b being close to one seems insufficient to explain the 'exchange rate disconnect puzzle,' as shown in Table A.2. In this case, even for a discount factor of 0.9, which Engel and West (2005) consider a reasonable value, $corr(\Delta s_{t+1}, \Delta f_t)$ is as high as 0.291. For a higher value of the discount factor at 0.95, it is still as high as 0.150.

When observable fundamentals are imperfect proxies for the market's expectation, the situation can be different. Even when the conditional correlation between Δf_t and the observable fundamental Δx_t is as high as 0.7 (which is the value we use for preparing Tables A.1 and A.2), the unconditional correlation between them can be as low as 0.240 (in Column 5 of Table A.1 or A.2) when the persistence of the observable fundamental is very different from that of the market's expectation (i.e., when $\phi = 0.1$ and $\psi = 0.95$ or when $\phi = 0.95$ and $\psi = 0.1$). This makes $corr(\Delta s_{t+1}, \Delta x_t)$ much lower than $corr(\Delta s_{t+1}, \Delta f_t)$. For example, for $b = 0.9$, $\psi = 0.95$, and $\phi = 0.1$, we have a $corr(\Delta s_{t+1}, \Delta x_t)$ of 0.071, even when $corr(\Delta s_{t+1}, \Delta f_t)$ is as high as 0.291. As we increase b to 0.95, $corr(\Delta s_{t+1}, \Delta x_t)$ further decreases to 0.036, even when $corr(\Delta s_{t+1}, \Delta f_t)$ is as high as 0.150. If the conditional correlation between Δf_t and Δx_t is lower than 0.7, these figures would be proportionally lower.

In order to visually illustrate the aforementioned points, we generate a set of artificial data on Δs_{t+1}, Δf_t, and Δx_t according to the data generating process used to prepare Table A.2 (the case of $\psi = 0.95$, $\phi = 0.1$, and $b = 0.9$). We then run two OLS regressions: i) a regression of Δs_{t+1} on Δf_t; and ii) a regression of Δs_{t+1} on Δx_t. The fitted values from these two regressions are depicted in Figure A.1, along with the generated Δs_{t+1} data. We can clearly see that Δf_t predicts Δs_{t+1} to a reasonable degree. However, Δx_t does not seem to have predictive power for Δs_{t+1}. Thus, in an empirical work that uses the observable fundamentals Δx_t as proxies for the market's expectation, one may not be able to find a link between Δs_{t+1} and Δx_t even when we have a valid present value model.

The analysis in this section definitely shows that a linear model that relates the exchange rate and observable fundamentals may not be an optimal strategy. In the next section, we consider a procedure for evaluating present value models of exchange rates when the observable fundamentals are imperfect proxies for the market's expectation, especially when the persistence of the market's expectation (ψ) is very different from that of the observable fundamentals (ϕ).

1.3 An Empirical Model of Exchange Rates When Observable Fundamentals are Imperfect Proxies for Market Expectations

1.3.1 Model Setup and Solving the Problem of Identification

In this section, we extend the model in Section 2.1 to include both observable and unobservable fundamentals, and we rewrite equation (1.1) as:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t[f_{1,t+j} + f_{2,t+j}], \quad 0 < b < 1, \tag{1.6}$$

where f_{1t} refers to a linear combination of observable fundamentals and f_{2t} refers to a linear combination of unobservable fundamentals. By assuming that $\Delta f_{1t} = \theta_1(L)\epsilon_{1t}$ and $\Delta f_{2t} = \theta_2(L)\epsilon_{2t}$ are the Wold representations of Δf_{1t} and Δf_{2t}, respectively, as in equation (1.2), the solution for Δs_{t+1} in equation (1.3) can be re-derived as:

$$\Delta s_{t+1} = (1-b)\sum_{j=0}^{\infty} b^j E_t[\Delta f_{1,t+j+1} + \Delta f_{2,t+j+1}] + \theta_1(b)\epsilon_{1,t+1} + \theta_2(b)\epsilon_{2,t+1}, \tag{1.7}$$

where Δf_{1t} and Δf_{2t} are potentially correlated with each other.

By defining $\mu_t = E_t[\Delta s_{t+1}] = (1-b)\sum_{j=0}^{\infty} b^j E_t[\Delta f_{1,t+j+1} + \Delta f_{2,t+j+1}]$, we can rewrite equation (1.7) as:

$$\Delta s_{t+1} = \mu_t + u_{t+1}, \tag{1.8}$$

where $u_{t+1} = \theta_1(b)\epsilon_{1,t+1} + \theta_2(b)\epsilon_{2,t+1}$ is the unexpected change in the exchange rate. As in Pastor and Stambaugh (2009), who consider a predictive system for stock returns in the presence of imperfect predictors, we specify the μ_t term, the conditional expectation of the exchange rate growth, as a latent variable. For simplicity, we assume that μ_{t+1} has the following stationary $AR(1)$ dynamics:

$$(\mu_{t+1} - \alpha_\mu) = \psi(\mu_t - \alpha_\mu) + \omega_{t+1}, \tag{1.9}$$

where ω_{t+1} is a function of the shocks to fundamentals (i.e., $\epsilon_{1,t}$ and $\epsilon_{2,t}$). Thus ω_{t+1} is correlated with u_{t+1} in equation (1.8).

According to the Engel and West Theorem (2005), as the discount factor b approaches 1, the variance of the μ_t term approaches 0, so that the serially uncorrelated u_{t+1} term will dominate the dynamics of the exchange rate dynamics in equation (1.8). Thus, for a value of the discount factor sufficiently high but less than 1, the first difference of the exchange rate may exhibit little serial correlation even when the μ_t term is highly serially correlated. The persistence of the market's expectation (μ_t) can be very different from observable fundamentals (Δx_t), as the market's expectation is formed based on both observable and unobservable fundamentals. One example of unobservable fundamentals is a risk premium, which is reported as highly persistent in the literature.[6]

Our final assumption is that Δx_{t+1}, an $n \times 1$ vector of the observable fundamentals or their proxies, follows s stationary vector autoregressive process of order 1, as given below:

$$(\Delta x_{t+1} - \alpha_x) = \Phi(\Delta x_t - \alpha_x) + v_{t+1} \tag{1.10}$$

where elements of v_{t+1} are correlated with both ω_{t+1} in equation (1.9) and u_{t+1} in equation (1.8). Note that Δx_t is only partially correlated with μ_t, as the market's expectation consists of present values of both observable and unobservable fundamentals. Furthermore, economic agents, when forming expectations about future fundamentals, employ a larger information set than the one that consists of the current and past values of the fundamentals observable by econometricians.

As in Pastor and Stambaugh's (2009) predictive system, not all the correlations among the disturbance terms in equations (1.8)-(1.10) are identified. However, we only need to identify the correlation between ω_{t+1} and v_{t+1} in equations (1.9) and (1.10), for evaluating the validity of the present value model. This is possible by adopting the following three steps, assuming that the disturbance terms are normally distributed:

Step 1 We consider an orthogonal projection of ω_{t+1} in equation (1.9) on v_{t+1} in equation (1.10): $\omega_{t+1} = \gamma' v_{t+1} + \omega^*_{t+1}$. This allows us to rewrite equation (1.9) as follows:

$$(\mu_{t+1} - \alpha_\mu) = \psi(\mu_t - \alpha_\mu) + \gamma' v_{t+1} + \omega^*_{t+1}, \tag{1.11}$$

[6] Refer to a survey paper by Engel (2014).

where ω^*_{t+1} is not correlated with v_{t+1}, and $\gamma = var(v_{t+1})^{-\frac{1}{2}} corr(v_{t+1}, \omega_{t+1}) var(\omega_{t+1})^{\frac{1}{2}}$.

Step 2 We consider an orthogonal projection of u_{t+1} in equation (1.8) on v_{t+1} in equation (1.10): $u_{t+1} = \delta' v_{t+1} + u^*_{t+1}$. This allows us to rewrite equation (1.8) as follows:

$$\Delta s_{t+1} = \mu_t + \delta' v_{t+1} + u^*_{t+1}, \tag{1.12}$$

where u^*_{t+1} is not correlated with v_{t+1}, and $\delta = var(v_{t+1})^{-\frac{1}{2}} corr(v_{t+1}, u_{t+1}) var(u_{t+1})^{\frac{1}{2}}$.

Step 3 We multiply both sides of equation (1.12) by $(1 - \psi L)$ to get:

$$\begin{aligned} (1-\psi L)\Delta s_{t+1} &= (1-\psi L)\mu_t + \delta'(1-\psi L)v_{t+1} + (1-\psi L)u^*_{t+1} \\ &= \gamma' v_t + \omega^*_t + \delta'(1-\psi L)v_{t+1} + (1-\psi L)u^*_{t+1} \end{aligned} \tag{1.13}$$

which can be rewritten as:

$$\Delta s_{t+1} = (1-\psi)\alpha_\mu + \psi \Delta s_t + (\gamma' - \psi\delta')v_t + \delta' v_{t+1} + e_{t+1} - \theta e_t, \tag{1.14}$$

where $e_{t+1} - \theta e_t = \omega^*_t + u^*_{t+1} - \psi u^*_t$. Here, as both ω^*_{t+1} and u^*_{t+1} are uncorrelated with v_{t+j}, for all j, e_{t+1} is not correlated with v_{t+j} for all j.

Then, equations (1.10) and (1.14) form our reduced-form model. To estimate the reduced-form model, we can apply the Kalman filter and the maximum likelihood estimation procedure to the state-space model provided in the Appendix. The validity of the present value model can then be tested by the statistical significance of the estimate of the γ coefficients in equation (1.14). Note that γ is a function of the correlation between ω_t and v_t, and δ is a function of the correlation between u_t and v_t.

1.3.2 Performance of the Proposed Model in Comparison to OLS: Monte Carlo Experiment

In order to evaluate the performance of the proposed model in Section 3.1, we conduct Monte Carlo experiments in this section. We consider the following data generating process:

Data Generating Process[7]

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + u_{t+1}$$

$$\Delta f_{t+1} = \psi \Delta f_t + \epsilon_{t+1}$$

$$\Delta x_{t+1} = \phi \Delta x_t + v_{t+1}$$

$$\begin{bmatrix} u_{t+1} \\ \epsilon_{t+1} \\ v_{t+1} \end{bmatrix} \sim i.i.d.N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \rho_{u\epsilon}\sigma_u\sigma_\epsilon & \rho_{uv}\sigma_u\sigma_v \\ \rho_{u\epsilon}\sigma_u\sigma_\epsilon & \sigma_\epsilon^2 & \rho_{\epsilon v}\sigma_\epsilon\sigma_v \\ \rho_{uv}\sigma_e\sigma_v & \rho_{\epsilon v}\sigma_\epsilon\sigma_v & \sigma_v^2 \end{bmatrix} \right)$$

$$b = 0.9; \quad \psi = 0.95; \qquad \sigma_v^2 = 0.1; \quad \sigma_\epsilon^2 = 0.1; \quad \sigma_u^2 = 1;$$

$$\rho_{uv} = 0.1; \quad \rho_{u\epsilon} = 0.3; \quad \rho_{\epsilon v} = 0.5.$$

We fix parameter values for b, ψ, σ_v^2, σ_ϵ^2, σ_u^2, ρ_{uv} and $\rho_{u\epsilon}$ as given above. We then consider three alternative cases that differ in the values for the ϕ parameter ($\phi = 0.95,\ 0.5,\ or\ 0.1$). We fix the discount factor b at 0.9, as it is the value Engel and West (2005) suggest as a reasonable one.[8] For the values of ψ and $\rho_{\epsilon v}$ fixed at 0.95 and 0.7, respectively, as the value

[7] If we define $\mu_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_{t+1}$, the first two equations in the data generating process are given by:

$$\Delta s_{t+1} = \mu_t + u_{t+1}$$

$$\mu_{t+1} = \psi\mu_t + \omega_{t+1}, \quad \omega_{t+1} \sim i.i.d.N\left(0, \frac{(1-b)^2\psi^2}{(1-b\psi)^2}\sigma_\epsilon^2\right).$$

[8] We also conducted the simulation studies by fixing $b = 0.95$. But the results were qualitatively almost identical.

of ϕ decreases from 0.95 to 0.5 or 0.1, the unconditional correlation between Δx_t and Δf_t decreases considerably, even though their conditional correlation is fixed at 0.7. We generate 5,000 sets of data for each of the three cases, and for each data set generated, we run the following regressions:

<u>OLS with True Fundamental</u>

$$\Delta s_{t+1} = \beta \Delta f_t + \eta_{f,t+1}$$

<u>OLS with Observable Fundamental</u>

$$\Delta s_{t+1} = \beta \Delta x_t + \eta_{x,t+1}$$

<u>Proposed Model (Reduced-Form Model)</u>

$$\Delta s_{t+1} = \psi \Delta s_t + (\gamma - \psi\delta) v_t + \delta v_{t+1} + e_{t+1} - \theta e_t$$

$$\Delta x_{t+1} = \phi \Delta x_t + v_{t+1},$$

where e_{t+1} and v_{t+1} are uncorrelated with each other.

Table A.3 reports the mean and standard deviation of the R^2 values from each regression, as well as the estimates for the key parameters. If the Δf_t were observed, an OLS regression would result in an R^2 as high as 0.268 on average, as reported in the third column of Table A.3. The mean for the estimates of β is close to the true value with small standard deviation. This re-confirms that a discount factor as high as 0.9 may be insufficient to explain the 'exchange rate disconnect puzzle,' at least for the parameter values we assign to generate data.

However, if Δf_t is unobserved and if we run an OLS regression using only the observable fundamental Δx_t, the results are discouraging. Even for the most favorable situation in which $\phi = 0.95$, the average R^2 values drop to 0.086. For the least favorable situation in which

$\phi = 0.1$, the average R^2 value decreases dramatically to 0.014. In this case, the mean for the estimates of β is much smaller than the true value and it is not statistically different from zero. These suggest that an OLS regression may result in spurious instances of the 'exchange rate disconnect puzzle,' when observable fundamentals are used as imperfect proxies for the market's expectation.

In the last column of Table A.3, we report results from the proposed model. The parameters of the proposed model are estimated with little bias. A very important finding is that the mean of the R^2 values is around 0.204, regardless of the value of the ϕ parameter. This suggests that the proposed model appropriately captures the information in the conditional correlation between Δx_t and Δf_t. The goodness of fit is worse than that in the case of OLS with Δf_t, because the conditional correlation between Δx_t and Δf_t is less than 1.

1.4 Uncovering the Short-Run Relationship between Exchange Rates and Macroeconomic Fundamentals: Empirical Results

1.4.1 Data Description

We study bilateral U.S. exchange rates versus those of 7 countries: Canada, France, Germany, Italy, Japan, Switzerland, and the United Kingdom. The observable fundamentals that we consider are 'real output growth differentials' and 'inflation differentials' between the two countries involved. In our empirical analysis, the industrial production index and the consumer price index (CPI) are employed to construct these fundamentals.

The data frequency is quarterly, and the sample period is 1984:Q1-2005:Q4. All the data are obtained from the International Financial Statistics CD-Rom. The exchange rate is measured in dollars per unit of foreign currency, such that the exchange rate decreases when the US dollar appreciates. The logs of the industrial production index, CPI, and exchange rates are multiplied by 100 so that their first differences are interpretable as percentage changes.

1.4.2 Empirical Results

We consider two alternative estimation strategies: i) OLS regression of a linear model, in which μ_t, the conditional expectation of exchange rate growth, is a linear function of the the observable fundamentals and ii) Maximum likelihood estimation of the proposed model, in which μ_t is assumed to be partially correlated with observable fundamentals. For our model, we assume that μ_t follows an AR(1) process as in equation (1.9) and that the two observable fundamentals follow AR(1) processes.[9] The linear model and the model proposed in this paper are given by:

Linear Model

$$\Delta s_{t+1} = \alpha + \beta_y(\Delta y_t - \Delta y_t^*) + \beta_p(\Delta p_t - \Delta p_t^*) + e_{t+1}^{ols}, \tag{1.15}$$

Proposed Model

$$\begin{aligned}\Delta s_{t+1} =&(1-\psi)\alpha_\mu + \psi\Delta s_t + (\gamma_y - \delta_y\psi)v_{yt} \\ &+ (\gamma_p - \delta_p\psi)v_{pt} + \delta_y v_{y,t+1} + \delta_p v_{p,t+1} + e_{t+1} - \theta e_t,\end{aligned} \tag{1.16}$$

$$(\Delta y_{t+1} - \Delta y_{t+1}^*) = (1-\phi_y)\alpha_y + \phi_y(\Delta y_t - \Delta y_t^*) + v_{y,t+1}, \tag{1.17}$$

$$(\Delta p_{t+1} - \Delta p_{t+1}^*) = (1-\phi_p)\alpha_p + \phi_p(\Delta p_t - \Delta p_t^*) + v_{p,t+1}, \tag{1.18}$$

where Δy_t and Δy_t^* are the growth rates of the industrial production index for the home and the foreign countries; Δp_t and Δp_t^* are the inflation rates for the home and the foreign countries as measured by the CPI. Again, $(\Delta y_t - \Delta y_t^*)$ and $(\Delta p_t - \Delta p_t^*)$ are imperfect proxies for the market's expectation.

In Table A.4, we report estimates of the key parameters for two models. For the linear model, $\hat{\beta}_y$ is insignificant at the 5% level for all the countries under consideration. $\hat{\beta}_p$ is

[9] We also estimated the proposed model employing a VAR(1) process for the observable fundamentals. But the results were almost identical.

significant at the 5% level only for France. The R^2 values range between 0.007 and 0.051. We cannot find any significant link between the exchange rate and the observable fundamentals for any of the countries except for France.

Such a weak link between the exchange rates and the observable fundamentals within the linear model can be partially explained by the discrepancy between the estimates of the ψ coefficient (i.e., a measure of persistence for latent conditional expectations μ_t) and those of the ϕ_y and the ϕ_p coefficients (i.e., measures of the persistence for the observable fundamentals). The estimates of the ψ coefficient are very high, ranging between 0.808 and 0.948, while the estimates of the ϕ_y and ϕ_p coefficients range between 0.011 and 0.592 in absolute values. When the persistence of μ_t is very different from that of the observable fundamentals, the unconditional correlation between μ_t and the observable fundamentals may be low, even when their correlation is very high conditional on past information. This contributes to the poor performance of the linear model.[10]

For the model proposed in this paper, as we estimate the conditional correlation between the conditional expectation and the observable fundamentals, our results do not depend upon their persistence levels. We find evidence that shocks to the inflation differentials and the output growth differentials have predictive power for future exchange rate changes. We obtain considerable increases in the R^2 values for this model over the linear model for all the countries. The improvement of the R^2 values for our model relative to the linear model ranges between 0.023 and 0.093.

$\hat{\gamma}_p$ is negative for all the countries except the U.K., and it is statistically significant at the 5% level for France, Germany, and Japan. $\hat{\gamma}_y$ is also negative for all the countries, and it is statistically significant at the 5% level for all the countries except Japan. A negative sign of $\hat{\gamma}_p$ or $\hat{\gamma}_y$ suggests that the U.S. (home country) currency appreciates in response to an unanticipated increase in U.S. inflation or output growth, foreign inflation or output growth being constant. In order to visually compare the performance of our model relative to the

[10]Refer to our Monte Carlo experiment results in the fourth column of Table A.3.

linear model, we obtain measures of one-step-ahead conditional expectations of exchange rate growth from each model. These measures are depicted in Figure 2 along with actual data. We clearly see the differences in the dynamics of the conditional expectations from the two alternative models. In particular, we can observe that the conditional expectations from the linear model cannot capture the dynamics of exchange rate growth at a low frequency, while those from the proposed approach do.

The results in this section are consistent with those from recent research based on high frequency data. For example, Anderson et al. (2003), Clarida and Waldman (2008), and Faust et al. (2003, 2007) examine the response of the exchange rates to announcements of macroeconomic news. As surveyed in Engel et al. (2007), they all find that unexpectedly strong announcements regarding real activity or reports of unexpectedly high inflation in the U.S. lead to short-run appreciation of the dollar.[11] Their results as well as ours are in line the predictions of the Taylor rule model. Within the Taylor rule model, in response to higher-than-expected output growth or inflation, the Fed is expected to increase interest rates. This makes U.S. assets more attractive, which in turn results in an appreciation of the dollar in the short run.

Explicit in our model is the channel through which unexpected changes in inflation differentials or output growth differentials affects exchange rates in the short run. We find it very interesting that the results of recent research based on high frequency data carry on to those based on quarterly data in this paper.

1.4.3 Out-of-Sample Forecasting Performance of the Proposed Model

In this section, we evaluate the out-of-sample forecasting performance of our model relative to the random walk model. For this purpose, we employ a test proposed by Clark and West (2007), for which we calculate rolling out-of-sample forecasts from both models. We use a rolling window of 40 quarters, and our first rolling sample is from 1984:Q1 to 1993:Q3. Table

[11] Clarida and Waldman (2008), unlike the other studies, investigate the effect of the macroeconomic announcements from non-U.S. countries. The results are the same.

A.5 reports the Clark and West test statistics. A negative value implies that our model performs better than the random walk model. The results suggest that our model outperforms the random walk model at horizons 4 to 8 quarters for most countries. Even though our model does not offer a statistically significant improvement in the forecasting performance over the random walk model at shorter horizons (except for Canada and Germany), the results are still very encouraging. This is especially so in light of Engel and West (2005) and Engel et al. (2007), who suggest that, with the discount factor close to one, even a valid present-value model may not outperform the random walk model in terms of out-of-sample predictability.

1.5 Summary and Conclusions

As Engel and West (2005) show, a high discount factor in the presence of a unit root in fundamentals may serve as an important source of the 'exchange rate disconnect puzzle' or the near random-walk behavior of the exchange rate reported in the literature. In this paper, we show that an empirical evaluation of the exchange rate models based on observable fundamentals or imperfect proxies for the market's expectation can serve as an additional source of the 'exchange rate disconnect puzzle.' Under this situation, the latent conditional expectation of exchange rate changes (μ_t) is not perfectly correlated with observable fundamentals (Δx_t), and this results in the poor performance of the linear model.

We present a new approach to empirical evaluation of the present value model, by adopting Pastor and Stambaugh's (2009) predictive system. In particular, we present a procedure for identifying and estimating the correlation between μ_t and Δx_t conditional on past information. This procedure provides us with a partial solution to the 'exchange rate disconnect puzzle.' By employing output growth differentials and inflation differentials as observable fundamentals, we confirm that the latent conditional expectations of exchange rate changes are very persistent, while the observable fundamentals exhibit little persistence. These differences in the persistence levels also contribute to spurious instances of the 'exchange rate disconnect puzzle' in a linear model.

Our empirical results suggest that the domestic currency appreciates in response to an unanticipated increase in domestic output growth or inflation. These results are consistent with those from recent research based on high frequency data, and are in line with the predictions of the Taylor rule model. The results for out-of-sample predictability tests suggest that our model beats the random walk model over various forecasting horizons less than two years. Recently, Molodtsova and Papell (2009) investigated predictability of exchange rate models that incorporate Taylor rule fundamentals, and they find evidence of short-term predictability. Chen and Tsang (2013) show that cross-country yield curve differences can proxy expected movements in future exchange rate fundamentals and that they have predictive power for future exchange rate changes. Engel et al. (2007), in their survey paper, also provide various pieces of indirect evidence that "exchange rate models are not so bad after all." The approach proposed in this paper and the empirical results provide us with direct evidence in support of their conclusion.

Finally, we hope that the proposed approach will serve as a first step in developing a general tool for empirically evaluating and comparing the competing exchange rate models, in the presence of imperfect proxies for the market's expectation.

Chapter 2

IS IT RISK OR EXPECTATIONAL ERROR? EXPLAINING DEVIATION FROM UNCOVERED INTEREST PARITY

2.1 Introduction

The uncovered interest rate parity (UIP) condition implies that the expected change in exchange rates should be equal to the interest rate differential between two countries. Since Hansen and Hodrick (1980), Bilson (1981), and Fama (1984), however, empirical studies have found that the high interest rate currency tends to appreciate, rather than depreciate as the UIP condition would predict. Investors in foreign one-period discount bonds thus earn the interest rate spread, which is known at the time of their investment, plus the bonus from the currency appreciating during the holding period. As a result, the forward premium anomaly implies positive predictable excess returns for investments in high interest rate currencies and negative predictable excess returns for investment in low interest rate currencies.

The most extensively explored explanation for the UIP puzzle is that it reflect time-varying risk premia. But fully rational models with time-varying risk premia have had difficulties explaining these puzzles away. Successful attempts are Verdelhan (2010) when consumption is habit-persistent; Bacchetta and Van Wincoop (2009) when inattention is rational; Basal and Yaron (2004), and Bansal and Shaliastovich (2008), and Colacito (2011) when long-run risk plays an important role. Another line of research focuses on systematic forecast error, based on imperfect rationality which can potentially offer new insight into the puzzle. Frankel and Froot (1989), Chinn and Frankel (1993, 1994, 2002) and Cavaglia et al. (1994) are older empirical studies, that emphasize the role of systematic expectational error in explaining the UIP puzzle and predictable excess return. More recently, Bacchetta et al.

(2009) demonstrate that deviations from strong rationality are behind the predictability of excess return in foreign exchange market. However, arguing expectational error requires one to confront difficulties measuring market expectations; most of the empirical studies depend on survey-based expectation.

In this paper, we first estimate the predictable excess return using a pure time series model and investigate what accounts for the extracted predictable excess return. Several previous studies, including Wolff (1989), Bekaert (1992), Canova (1991), Cheung (1993) and Mark et al. (1993) have examined the properties of time series estimates of ex-ante excess return. These studies decompose ex-post excess return into predictable part and unpredictable shock. Treating predictable excess return as a latent variable, they estimate ex-ante excess return by using the conditional on time t information. However, previous models do not incorporate the macro variables which might help to predict excess return. Moreover, they cannot account for what they estimated–they cannot find any linkage between extracted series and macro variables implied by the theory. Building upon the previous models, we employ a new state-space model developed by Pastor and Stambaugh (2009) and Kim and Lee (2014). Within this framework, unobserved predictable excess return is constructed to link to the economic variable implied by theory, in the channel of the conditional correlation between these two. Since it allows nonlinearity in relation to predictable excess return and macro variables, this gives a more efficient predictor for ex-post excess returns.

We conduct an empirical analysis with five currency pairs: the Australian, Canadian, and New Zealand dollars, the Japanese yen, and the United Kingdom pound, each relative to the U.S. dollar. The first four currencies are known as typical "carry trade" country-pairs.[1] Our results indicate that the estimated series from the new framework is a good predictor for the currency excess return: the R^2 from the new model to explain ex post excess return improves to 33%, while R^2 from the simple ARMA model, which does not incorporate any information from the macro variable, is near zero. New frameworks also provide the empirical

[1]Backus, Gavazzoni, Telmer, and Zin (2013) conduct a calibration with those four currency pairs considering "carry trade" funding and recipient currencies.

evidence of connection between economic variables, such as inflation or output, and excess return in foreign markets. Notably, for all five currency pairs, the sign of the coefficients is matched to the intuition or theory implied: high inflation or output growth in a foreign country raises the predictable excess return for holding foreign currency, while high inflation or output growth in the home country lowers it.

By extracting the statistically predictable excess return, we can examine what accounts for the predictable excess return: is it risk premium or systematic forecast error? Allowing market expectation to deviate from the rational expectation or statistical expectation, predictable excess return is decomposed into the risk premium part and the expectation error part. We regress a survey-based expected excess return that represents the risk premium on the extracted series, but cannot find any linkage between them for all countries. In contrast, regressing a surveyed forecast error on the extracted series, coefficients are significantly different from zero with relatively high explanatory power. These empirical results support the view that predictable excess return is related with systematic forecast error. Moreover, empirical results indicate that these expectational errors stem from the economic conditions, such as inflation and output growth.

To check if the extracted predictable return can explain the UIP puzzle, we insert this series into the original UIP regression model and estimate the UIP slop coefficient. We observe that it mitigates the UIP puzzle: coefficients change from negative to positive. Even though it is not significantly different from zero in most of the cases, our model holds great potential for explaining the UIP puzzle. This result implies that estimated ex-ante excess return is the omitted variable that is negatively correlated with forward premium, resulting in the UIP puzzle. In other words, macro variables such as inflation and output growth in each country are key to explaining the UIP puzzle.

The remainder of this paper is organized as follow: In section 2, we review the properties of the UIP puzzle and introduce the background of excess return, risk premium and forecast error. In section 3, we present the state-space model in which predictable excess return is assumed to be conditionally correlated with the macro variables and has its own dynamics.

In section 4, we report the relationship between estimated predictable excess return on macro variables, and results of UIP relevant regressions. Section 5 is the conclusion of this paper.

2.2 Ex-ante Excess Returns and the Uncovered Interest Parity Puzzle

2.2.1 Predictable Excess Return

Fama (1984) tests uncovered interest by using following simple regression model.

$$s_{t+1} - s_t = a + b(i_t - i_t^*) + e_{t+1} \tag{2.1}$$

where s_{t+1} is log of spot exchange rate at time $t+1$, i_t is domestic one-period continuously compounded nominal interest rate, and its foreign equivalent is i_t^*. Under the null, the regression coefficients should be $a = 0$ and $b = 1$. However, a long history of empirical work has found that the estimated value of b is less than one, and even negative. Hodrick (1987), Froot and Thaler (1990), and Engel (1996, 2013) survey empirical support for the UIP puzzle, and more recently, Burnside et al. (2006) report that slope coefficients are still significantly less than zero.

Several recent studies have measured the economic return from taking positions based on the deviation from the uncovered interest parity implied by the empirical findings of equation (2.1). Let us define excess return for holding foreign currency, er_{t+1}, as:

$$er_{t+1} = s_{t+1} - s_t - (i_t - i_t^*) = s_{t+1} - f_t \tag{2.2}$$

where f_t is forward exchange rate at time t. Excess return is interest gained from holding foreign deposit as well as earning from exchange rate changes. The left side of the equation (2.2) can be derived by substituting $f_t - s_t$ for the interest rate differential, assuming that the covered interest rate parity is held. (i.e., $i_t - i_t^* = f_t - s_t$).Since the excess return is not known at the time of taking out the contract t, analyzing any behavioral aspects of these returns depends upon measures of expected excess returns. One such measure is the statistically predicted value of the excess return based upon time t information:

$$\Lambda_t \equiv E_t(er_{t+1}) = E_t s_{t+1} - f_t \tag{2.3}$$

where E_t is the statistical expectations operator conditional on time t information. Thus,

$$er_{t+1} = \Lambda_t + \epsilon_{t+1} \tag{2.4}$$

where the last term is the statistical forecast error, $\epsilon_{t+1} \equiv s_{t+1} - E_t s_{t+1}$.

Many studies such as Lewis (1995), Gourinchas and Tornell (2004), and Engel (2013) point out that the market expectation, E_t^m is not necessarily the statistical expectation conditional on the information up to time t, E_t. Gourinchas and Tornell propose that the foreign exchange arbitrage condition holds under the market's subjective expectation and risk premium as below:

$$E_t^m s_{t+1} - s_t = i_t - i_t^* - \rho_t \tag{2.5}$$

where E_t^m represents the subjective expectation of next period's exchange rate, and ρ_t is risk premia perceived by agents. Equation (2.5) implies that market adjust their expected depreciation rate, $E_t^m s_{t+1} - s_t$, considering return on the short domestic and foreign bonds as well as the risk premium of holding foreign currency. Predictable excess return is then,

$$\Lambda_t = E_t s_{t+1} - s_t - (i_t - i_t^*) = E_t s_{t+1} - E_t^m s_{t+1} + \rho_t \tag{2.6}$$

Substituting for $(i_t - i_t^*)$ using equation (2.5), we can decompose predictable excess return into two parts: subjective expected excess return, $\Lambda_t^s = E_t^m s_{t+1} - s_t - (i_t - i_t^*) = \rho_t$, and expectation error, $E_t s_{t+1} - E_t^m s_{t+1} = \Lambda_t - \Lambda_t^m$.

If we assume that expectations are rational ($E_t^m s_{t+1} = E_t s_{t+1}$) and there is no risk premium ($\rho_t = 0$), the rational expected rate of depreciation $E_t s_{t+1} - s_t$ is equal to the forward premium $i_t - i_t^*$. In this case, there are no predictable excess returns ($\Lambda_t = 0$). On the other hand, if market expectation deviate from the rational expectation, predictable excess return are driven by either risk premium or expectational error, or by both. Risk premia and systematic forecast errors are not mutually exclusive and the behavior of predictable excess returns could result from a combination of these two factors. However, most studies tend to assume one or the other. In this paper, we measure the predictable excess return more efficiently than previous literature, and then investigate what accounts for the predictable excess return.

2.2.2 Predictable Excess Return and Macro Linkage

The extensive literature for explaining the risk premium of currency excess returns tends to models risk premium as a function of consumption and inflation. In standard asset pricing theory, risk premia derive from the conditional covariance between asset returns and the marginal intertemporal rate of substitution (e.g., Cochrane (2001), or Campbell et al. (1997)). Assuming log-normality, the risk premium can be reduced as the conditional volatility of each country's pricing kernel. However, implementing empirical models of time-varying risk premia has proven to be very difficult in general, and previous attempts have not been successful in explaining returns to forward speculation. Even though risk premia in the literature are derived in terms of higher moment of macro economic variables, such as conditional volatility of inflation between two countries, it seems to be common intuition that good economic conditions, such as moderate inflation and high output growth in the U.S., should lower the risk premium on dollar assets. Empirically, Faust et al. (2003) show that stronger-than-expected real U.S. macro news leads to declines in the premium required for holding foreign rather than dollar-denominated assets. Chen and Tsang (2013) also provide the evidence that expected high inflation or high output growth raises the ex-post excess return by using the yield curve factors as a proxy. Even though theory does not provide much guidance on how the level of macro variables affect the covariance or eventually the risk premium, empirical studies constantly show that inflation or output growth have an effect on the market expectation and risk premium on currency.

Regarding systematic expectational error, several papers propose the model in which systematic forecast error stems from economic variables. For example, Gourinchas and Tornell

(2003) propose that the deviation from the UIP condition or non-zero predictable excess return results from the distortion in beliefs about future interest rate. Considering that short-term interest rates are strongly affected by monetary policy, their model implies that the source of the distorted beliefs stems from the inflation and output gap. Burnside et al (2009) offer an explanation for the UIP puzzle in foreign exchange markets based upon investor over confidence. They suggest that when monetary policy determines the nominal interest rate, inflation and output growth affect the degree of investors' over confidence, which creates the systematic forecast error.

Both explanations, risk premium and expectational error, consider that macro variables such as inflation or output growth affect predictable excess return. Therefore, we treat predictable excess return as a latent variable which is conditionally correlated with inflation and output growth. With extracted series, we examine the behavior of the ex-ante returns over time.

2.3 Estimation Strategies

2.3.1 Measuring Ex-ante Currency Excess Return

A pure time series studies is conducted to estimate the ex-ante excess return. Wolff (1987) treats the predictable excess return as an unobserved variable and implements the Kalman Filter model to measure it. The main advantage of the state-space model is that it enables us to empirically characterize the temporal behavior of predictable return without the strong assumption associated with the structural model. Assuming a fully rational market that predictable excess return is equal to the risk premium, subsequent empirical papers develop state-space models to investigate the risk premium in currency excess return. Cheung (1994) develops an original model further, by allowing innovations in the risk premium to be correlated with the error from the previous period forecast. Bekaert (1994b) replicates Cheung's results that estimated risk premium to have high degree of serial correlation and found that the conditional variance of these series exhibits clustering. Canova and Marrinan (1993) confirm these basic characteristics for predictable excess return: it has a large variance, it is highly serially correlated and it exhibits heteroskedasticity due to volatility clustering. However, the extracted ex-ante excess return series from the state-space model fail to find the linkage connection between economic variables that the theory says should be related. In other words, a pure time series study provide no evidence that the measure of Λ_t in equation (2.3) is a measure of a risk premium. Moreover, the state-space model presented in previous literature uses only ex-post excess return as the information set which produces the conditional prediction update every period. It implies that if we use the information on the economic variable, we can get a good predictor for the ex-post excess return.

Building on the previous model, we propose a new version of the state-space model by involving the macro variable which is considered to be crucial in forming the predictable excess return. This state-space model was originally developed by Pastor and Stambaugh (2009).

$$er_{t+1} = \Lambda_t + u_{t+1} \tag{2.7}$$

$$\Lambda_{t+1} = (1-\psi)E_{er} + \psi\Lambda_t + w_{t+1} \tag{2.8}$$

$$x_{t+1} = (I-\phi)E_x + \phi x_t + v_{t+1} \tag{2.9}$$

where

$$er_{t+1} \equiv s_{t+1} - s_t - (i_t - i_t^*)$$
$$\Lambda_t \equiv E_t(er_{t+1}) = E_t s_{t+1} - s_t - (i_t - i_t^*)$$

where er_{t+1} is ex post currency excess return, Λ_t is statistical predictable excess return conditional on the information set at time t, and u_{t+1} is unexpected error term. x_t is a set of macro variables, which contains the k predictors based on the theory. Here, x_t consists of the inflation rate and output growth of each country: $[\pi_t, \Delta y_t, \pi_t^*, \Delta y_t^*]'$. E_{er} and E_x are unconditional means of the ex-post excess return and of the predictors, respectively. Equation (2.7) defines the unobserved conditional expected excess return Λ_t. Equation (2.8) describes a simple persistent process for Λ_t. Equation (2.9) is a standard VAR model, to describe the dynamics of macro variables. A special case of this model arises when there are no predictors, in which case equation (2.9) is absent and the data include only excess returns. Note that Wolff (1987)'s model and Cheung (1994)'s model demonstrate the case with no predictor, in which equation (2.9) is omitted. Note that no restrictions are imposed in this framework except $0 < \psi < 1$ and $0 < \phi < 1$.

The residuals in this state-space model are assume to be identically and independently distributed across $t + 1$ as follow.

$$\begin{bmatrix} u_{t+1} \\ w_{t+1} \\ v_{t+1} \end{bmatrix} \sim \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \sigma_{uw} & \sigma_{uv} \\ \sigma_{uw} & \sigma_w^2 & \sigma_{wv} \\ \sigma_{uv} & \sigma_{wv} & \Sigma_{vv} \end{bmatrix} \right)$$

Compared to the previous model in the absence of equation (2.9), a new version of state space model has two benefits:

(i) It enables us to measure the predictable excess return more efficiently, using additional information contained in macro variables. Note that Λ_t is generally unobservable, even with complete knowledge of all the parameters in the state-space model. Those parameters do, however, imply a value of $E(\Lambda_t|D_t) = E(er_{t+1}|D_t)$, where D_t incorporates the data we use: our model incorporate all of the history of the ex-post excess return as well as macro variables, while the previous version contains only the past value of the realized excess return. It implies that the filtered series from new model would be a better predictors of realized excess return with higher explanatory power. Of course, if macro variables convey no additional information for explaining predictable excess return, the proposed model would be converge to the model presented in the previous literature.

(ii) The proposed framework enable us to investigate the connection between predictors in x_t and Λ_t directly. The proposed model does not impose any specific relationship between Λ_t and x_t, but they are connected to each other via the correlation between their shocks, w_t and v_t. Thus, $corr(w_t, v_t)$ verifies the relationship between expectation and predictors. As mentioned in section 2.2, many models suggest that inflation or output growth are related to the risk premium or expectational error, but a variety of models impose different functional forms of these variables. Our modeling strategy is that, predictable excess return is an unknown function of macro variables, which covers not only the linear relationship but also the nonlinear.

2.3.2 Identification and Maximum Likelihood Estimation

As Pastor and Stambaugh (2009) stated, one of the parameters in the covariance matrix is identified. To solve this problem, Kim and Lee (2015) propose a reduced form, by incorporating a control function that resolves the endogenous problem in the time series model.

First, shocks on the predictable excess return w_{t+1} in equation (2.8) can be decomposed into the correlated with v_{t+1} term and independent term, w^*_{t+1}. Then, $w_{t+1} = \gamma' v_{t+1} + w^*_{t+1}$, where $\gamma = var(v_{t+1})^{-\frac{1}{2}} corr(v_{t+1}, w_{t+1}) var(w_{t+1})^{\frac{1}{2}}$. In the same procedure, the unexpected shock on the ex-post excess return u_{t+1} can be decomposed as correlated with v_{t+1} and not correlated with v_{t+1}. Then, $u_{t+1} = \delta' v_{t+1} + u^*_{t+1}$, where $\delta = var(v_{t+1})^{-\frac{1}{2}} corr(v_{t+1}, u_{t+1}) var(u_{t+1})^{\frac{1}{2}}$. Replacing w_{t+1} and u_{t+1} with the control function, then multiplying both sides in equation (2.7) by $(1 - \phi L)$, we can obtain the reduced form model as below:

$$er_{t+1} = \psi er_t + (\gamma' - \psi\delta')v_t + \delta' v_{t+1} + e_{t+1} - \theta e_t \tag{2.10}$$

$$x_{t+1} = (I - \phi)E_x + \phi(x_t - \alpha_x) + v_{t+1} \tag{2.11}$$

where $e_{t+1} - \theta e_t = w^*_t + u^*_{t+1} - \psi u^*_t$. Note that e_{t+1} and v_{t+1} are distributed identically and independently across $t+1$, since w^*_{t+1} and u^*_{t+1} in e_{t+1} are uncorrelated with v_{t+1}.

$$\begin{bmatrix} e_t \\ v_t \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_e^2 & 0 \\ 0 & \Sigma_{vv} \end{bmatrix} \right) \tag{2.12}$$

The parameters in the two equations, along with the covariance matrix of $[e_t \quad v_t']$ are identified. As all equations are linear, we can compute the likelihood of the model using the Kalman filter, and use conditional Maximum Likelihood Estimation to estimate the parameters and extract Λ_t series conditional on the data we have.

2.4 Empirical Results

2.4.1 Data Description

We study bilateral U.S. exchange rates versus those of the other five countries: Australia, Canada, Japan, New Zealand, and the United Kingdom. All country pairs, except the UK pound, are typically considered as "carry trade" currency-pairs. In normal conditions, forward rates satisfy the covered interest rate parity conditions: the forward discount on foreign currency is equal to the interest rate differential, $f_t - s_t = i_t^* - i_t$, where f_t is the log of the forward exchange rate in units of the foreign currency per U.S. dollar. We collect daily spot and forward exchange rates in U.S. dollars, then build end-of-quarter series from December 1984 to March 2008 for Australia, Canada, and New Zealand, and from December 1983 to March 2008 for Japan and the UK. These data are collected by Barclays and Reuters and available on Datastream. The basic macro data source is International Financial Statistics, supplemented on occasion by national sources. The price level is the CPI in the last month of quarter and output is industrial production in last month of quarter. We convert all data by taking logs and multiplying by 100. Throughout the rest of the paper, the symbols defined in this paragraph (s_t, f_t, y_t, and π_t) refer to the transformed data.

Table B.1 reports summary statistics for the exchange rate changes, interest rate differential (i.e., forward premium), and excess return on foreign exchange market. Depreciation rates are highly volatile. Interest rate differential, measured by forward premium $(f_t - s_t)$, is less volatile and highly persistent. The excess return for holding foreign deposits for three months is positive, especially for Australia and New Zealand dollars.

2.4.2 Main Results

In Table B.2, we compare the R^2 values from the proposed model $R^2_{predictor}$ and from the conventional state-space model, which does not incorporate the macro variables, $R^2_{nopredictor}$. We compute the explanatory power of both filtered series as

$$R^2 = \frac{v\hat{a}r(\hat{\Lambda}_t)}{v\hat{a}r(er_{t+1})}$$

where $\hat{\Lambda}_t$ is the predictable excess return estimated from Kalman filtering. For all five-currency pairs, $R^2_{predictor}$ is significantly higher than $R^2_{nopredictor}$. Especially, in case of Australia, the explanatory power of the proposed model is 0.267, compared to 0.015 in the simple ARMA model. The highest R^2 is obtained from the New Zealand currency excess return: 0.333 within the proposed model. Thus, incorporating macro variables, we can have a good predictors of excess return with higher accuracy. This result implies that economic variables help to predict excess currency return, since information about macro fundamentals affects the markets when they form their expectation.

In Figure B.1, we plot the filtered series from both the state-space model as well as the realized excess return. The predictable excess return series of our filtering procedure is different from the simple ARMA model. The filtered series from our model picks up a large fraction of the variation in ex-post excess return. Further, it appears that it has a positive and high autocorrelation, while the persistence of the filtered series from previous studies is not as high as that of the proposed model. This implies that a substantial fraction of currency excess return is predictable within our framework.

We can see the same implication from the maximum likelihood estimation. In Table B.2, we report Maximum-Likelihood Estimates of the state-space model in equations (2.10)-(2.11). No predictor implies that no macro variables are involved, so that the state-space model consists of equations (2.7) and (2.8) only, and we do not have γ term in equation (2.10). The autoregressive parameter estimates within the proposed model show that the predictable excess returns have a statistically significant high degree of persistence, ranging from 0.81 to 0.93. For all currency pairs, the persistence of predictable excess return is always higher than that of the no predictor model. We also conduct an augmented Dickey-Fuller test to determine whether the estimated series contains a unit root. It turns out that, for all the filtered series, the unit root hypothesis was rejected at the 1% level of significance. That is, the estimated series exhibit only short-run but not unit root persistence, and indicates that the persistent agents' expectation in foreign asset market. This result is consistent with the findings of Wolff (1989) and Cheung (1994).

In addition, one of the merits of the proposed model is that we can investigate the relationship between macro variables and predictable excess return directly. The lower panel of Table B.2 reports the results of the estimated parameters in equation (2.10). As illustrated in the previous section, γ is defined as $\gamma = var(v_{t+1})^{-\frac{1}{2}}corr(v_{t+1}, w_{t+1})var(w_{t+1})^{\frac{1}{2}}$, where w_t is the unexpected shocks on the predictable excess return and v_t are the shocks on the macro variables. In this paper, we use $\pi_t, \pi_t^*, \Delta y_t$ and Δy_t^* as the predictors, we have 4 v_t's and their correspondings γ's: $[\gamma_\pi, \gamma_{\pi^*}, \gamma_{\Delta y}, \gamma_{\Delta y^*}]$.

Estimated coefficients have a consistent pattern in all five currency-pairs: $\gamma_{\pi^*} > 0$, $\gamma_\pi < 0$, $\gamma_{\Delta y^*} > 0$ and $\gamma_{\Delta y} < 0$. This pattern is to the same as in previous empirical studies. Faust et. al. (2003) and Chen and Tsang (2013) support the view that low output growth affects the market expectation, and induce higher perceived risk associated with holding the domestic currency, due to its payoff being negatively correlated with the marginal utility of consumption. In this case, the risk premium associated with holding domestic currency rises. Gourincahs and Tornell (2003)'s and Burnside et al. (2009)'s models predict that high output or high inflation increases interest rates according to the Taylor rule. However, the market is not fully rational, so that systematic expectational error exists. The sign of the estimated coefficient indicates that high inflation or output growth in the foreign country raises the predictable excess return, while high inflation or output in domestic country lowers the predictable excess return for holding foreign currency.

Under rational expectation, higher moments of macro variables, such as conditional volatility of inflation or that of output, can be the determinants of predictable return or time-varying risk premium, but this does not address the mechanism between the first moment of the economic variables and predictable return. From these estimated results, we find that the levels of inflation and output growth in the home and foreign country are important factors in predictable excess return. It implies that market form their expectations based on current macro variables, but these can be different from rational expectations. Within this channel, we can explain the negative coefficients for domestic inflation and the output gap, and the positive coefficients for foreign inflation and the output gap.

2.5 Discussion

2.5.1 Explanation of the UIP Puzzle

The necessary condition for solving UIP puzzle is the negative correlation between predictable excess return Λ_t and the interest rate differential $(i_t - i_t^*)$. In Table B.4, we report the correlation between the interest rate differential and the extracted series from the filtering procedure. As documented in Table B.4, $corr(i_t - i_t^*, \hat{\Lambda}_t)$ is negative for all five currency-pairs. Our results suggest that an increase in domestic inflation and/or output and a decrease in foreign inflation and/or output increases the interest rate differential, while the predictable excess return on foreign asset decreases at the same time.

In addition, we conduct two types of UIP coefficient estimates, with and without predictable excess return.

$$s_{t+1} - s_t = a_1 + a_2(i_t - i_t^*) + \epsilon_{1,t+1} \tag{2.13}$$

$$s_{t+1} - s_t = b_1 + b_2(i_t - i_t^*) + a_3\hat{\Lambda}_t + \epsilon_{2,t+1} \tag{2.14}$$

Equation (2.13) is the original UIP regression and Equation (2.14) is adjusted UIP regression with additional regressors, estimated predictable return $\hat{\Lambda}_t$:

As shown in Table B.5, the slope coefficient a_2 are all negative under the original UIP specification, confirming the puzzle. Our conjecture is that by omitting the Λ_t, which is negatively correlated with $(i_t - i_t^*)$, the estimated coefficient for the interest differential term would be biased downward from 1 and might turn negative, resulting in the UIP puzzle. We insert estimated $\hat{\Lambda}_t$ from our framework to control this omitted variable problem. As a result, coefficients are either turn positive or become insignificantly different from zero. In the case of New Zealand, a_2 rises from -0.951 to 0.614. We also conduct Equation (2.14) under restriction such as $a_3 = 1$. Interestingly, all of the UIP coefficients, a_2, are positive. In particular, for the Australia and New Zealand dollars, a_2 is statistically significant and approaches 1.

Moreover, we observe that the predict ability of exchange rate movement improve significantly when controlling omitted variables. As shown in Table B.5, the R^2s in the original UIP regression are very small, while the R^2s in the UIP regression with $\hat{\Lambda}_t$ increase by 18.5%. The difference between the R^2s from the regressions with and without $\hat{\Lambda}_t$, indicates the contribution of $\hat{\Lambda}_t$ in explaining the exchange rate. The statistically significant coefficient of $\hat{\Lambda}_t$ in the adjusted UIP regression and the higher R^2s indicates that filtered series capture the determinants of exchange rate movement. In short, our results suggest that macro variables directly link to the nominal exchange rate, and it can be potential resolution of exchange rate disconnect puzzle.

2.5.2 Is It Risk or Expectataional Error?

According to Equation (2.6), predictable excess return contains both a risk premium, $\rho_t = E_t^m s_{t+1} - s_t - (i_t - i_t^*) = \Lambda_t^m$, and expectational error, $E_t s_{t+1} - E_t^m s_{t+1}$. Bacchetta et al. (2009) state that a number of studies have documented a close relationship between the predictability of excess returns and the predictability of expectational errors about excess returns. This empirical result indicates that deviations from strong rationality are behind the predictability of excess returns. By using the survey data and extracting predictable excess return from the proposed model, we investigate what account for our extracted predictable excess return.

Several studies, such as Dominguez (1986), Ito (1990), Frankel and Froot (1987, 1989) and more recently, Bacchetta et al. (2009) use survey-based forecast of foreign exchange rates. They run the following three sets of regressions, in accordance with the discussion above, to evaluate the information embodied in forward premia or interest differentials as predictor.

$$er_{t+1} = s_{t+1} - s_t - (i_t - i_t^*) = a_0 + a_1(f_t - s_t) + e_{1,t+1} \tag{2.15}$$

$$\rho_t = E_t^m s_{t+1} - s_t - (i_t - i_t^*) = b_0 + b_1(f_t - s_t) + e_{2,t+1} \tag{2.16}$$

$$s_{t+1} - E_t^m s_{t+1} = c_0 + c_1(f_t - s_t) + e_{3,t+1} \tag{2.17}$$

where $E_t^m er_{t+1} = E_t^m s_{t+1} - s_t - (i_t - i_t^*)$ is implied risk premium perceived by the market or subjective predictable excess return. Then, the first equation is for excess return predictability, the second is for survey-expected excess return or implied risk premium, and the third is for survey error predictability. Bacchetta et al. (2009) verify that predictability of excess return on foreign exchange market comes from the forecast error by showing that expectational errors of excess returns are predictable with the same sign and even with similar magnitude. For example, a_1 in equation (2.15) and c_1 in equation (2.17) have same sign and similar value.

In this subsection, instead of forward discount, we use the extract predictable excess return series to verify what the estimated predictable excess return is. The regression model is simple as seen below:

$$\rho_t = E_t^m s_{t+1} - s_t - (i_t - i_t^*) = b_1 + b_2\hat{\Lambda}_t + \eta_{2,t+1} \tag{2.18}$$

$$s_{t+1} - s_{t+1}^m = c_1 + c_2\hat{\Lambda}_t + \eta_{3,t+1} \tag{2.19}$$

Note that when markets are fully rational, $E_t^m = E_t$ which implies $\Lambda_t = \Lambda_t^m$. In this paper, we use the survey-based forecast of a quarter-ahead exchange rate from Consensus Economic Inc. Panel A and B in Table B.6 gives the estimates of equation (2.18) and (2.19) respectively. Presented in Table B.6, for all currencies, a_2 are insignificant, while b_2 are consistently significant at the 1% level. If the reason for excess return predictability is time varying premia, then the coefficient in panel A would be significantly different from zero. This is clearly not the case. The expected excess return is not systematically related to the predictable excess return obtained statistically.

To check the relationship between forecast error and predictable excess return, we also compose another equation as below:

$$s_{t+1} - E_t^m s_{t+1} = d_1 + d_2(\hat{\Lambda}_t - \rho_t) + \eta_{4,t+1} \tag{2.20}$$

More interestingly, when regressing the survey forecast error on expectational error, $\hat{\Lambda}_t - \rho_t = E_t s_{t+1} - E_t^m s_{t+1}$, all the coefficients are significantly different from zero and consistently near one. This supports the view that statistical expectational excess return is strongly connected to the market's systematic forecast error, rather than to the risk premium. This empirical results suggests that understanding what determines expectational errors is crucial in explaining excess return predictability. Since predictable return are affected by macro variables such as inflation and output growth in each country, this result suggests that macro variables produce the expectational errors.

2.6 Conclusion

Implementing empirical models of the predictable excess return has proven to be very difficult in general and previous attempts have not been successful in explaining returns. In this paper, we propose the state-space model to extract the predicted part of the ex-post excess return more efficiently by incorporating economic variables. With the extracted series, we examine the characteristic of predictable excess return. First, predictable excess return are highly persistent. Second, they are significantly correlated with inflation and output growth both in the U.S. and in foreign countries. Specifically,the predicted excess return from holding foreign currency is high in times of low domestic inflation and/or output and high foreign inflation and/or output. These results are consistent with the previous literature, considering both time-varying risk premium and systematic expectational error to explain the deviation from the UIP condition.

Moreover, using the survey-based forecast of exchange rate data, we show that ex-ante excess return is strongly connected with the market's systematic errors instead of with the implied risk premium. This results confirms the existence of forecast error as well as the mechanism of systematic forecast error. Since extracted predictable return series incorporate information from each country's inflation and output levels, a significant relationship between this series and forecast errors shows that forecast error are formed by these variables. This result directly explains the UIP puzzle: our estimated predictable excess return represents the omitted variable in the original UIP regression. We empirically show that omitting predictable return can be a potential explanation for the UIP puzzle.

Chapter 3

COMMODITY CURRENCY PREDICTIONS: THE ROLE OF EXPECTATIONS

3.1 Introduction

One of the well known puzzle in international finance is that empirically, exchange rates do not seem to be connected to economic fundamentals as implied theoretically. Many researchers have tried to find the explanation for this puzzle, and one line of research has related exchange rates for commodity-exporting countries to the price of those commodities. Chen and Rogoff (2003) uncover the empirical links between real exchange rates for commodity exporting countries and the price of the commodities that they export. Because commodity price fluctuations affect a share of their exports for the commodity exporters, it is considered as major terms of trade shocks to the value of their currencies. Chen, Rogoff, and Rossi (2010) extend this finding with evidence that exchange rates have forecasting power for commodity prices at short horizons in commodity-exporting countries.

Even though exchange rate and commodity prices are highly correlated contemporaneously, this correlation disappears very quickly and commodity prices do not have a lasting impact on future exchange rates. We investigate if commodity price predict the exchange rates for Australia, Canada, Chile, New Zealand, and South Africa, which are commonly known as the commodity currencies. With a simple predictive regression model or error correction model, commodity prices are not shown to have predictive power for exchange rates.

In this paper, we take a new line of attack on the question of the link between commodity prices and exchange rates. We first work with a pure time-series model in which we explore the dynamic linkage between commodity prices and commodity currencies though their shocks. We perform a Beveridge-Nelson decomposition, expressing each series as the sum of a random walk component and a transitory component. By separating transitory movement from the random walk components, we can see that commodity prices have predictive power for future exchange rate movements. The next question is why linear model cannot capture this relation. To answer this question, we employ another time-series model that emphasizes the role of market expectation in the exchange rate. From a theoretical standpoint, the nominal exchange rate is viewed as an asset prices, so that it can be decomposed into two parts: market expectation conditional on the information up to t, and unexpected shock or forecast error. Note that the expected part is key to understanding the connection between current commodity price and future exchange rate. To investigate this mechanism, we employ a state-space framework, developed by Kim and Lee (2015). Within their model, we can see the commodity price influence on exchange rate at $t+1$ in two ways: (i) commodity price at time t is linked to the market expectation about exchange rate conditional on time t though the co-movement of their shocks, and (ii) commodity price changes at time $t+1$ are connected to the exchange rate fluctuation at time $t+1$ though contemporaneous shocks. We should pay special attention to addressing the first point, because it is not observable from a simple regression model, even with structural breaks, or an error correction model. We find that estimated parameters which represent correlation between shocks on market expectation and commodity price are statistically significant, and R^2 values is higher than both simple ARMA model and conventional OLS regression model. In addition, we find the explanation for why commodity price does not seem to predict the exchange rate. Compared to the effect of commodity price on a quarter-ahead exchange rate though market expectation, the impact of contemporaneous shocks is very large. Given this empirical result, we conjecture that the dynamic linkage between commodity price and exchange rate exists, but it is not observable within a conventional predictive regression model because of strong and volatile contemporaneous shocks.

Using survey data, we provide empirical support for the view that the market expectation of future exchange rates reflects commodity price changes, in the direction discussed above. In particular, quarterly commodity price growth rate is strongly related to the market forecast of exchange rates at longer horizons, such as one-year- or two-year-ahead forecasts. But some argue that survey data has a measurement problem, since the data is collected from several large professional forecasters/companies, not the all market participants. Thus, we use foreign exchange option data as an alternative way to measure the market expectation for future exchange rates. Using daily options data, Chen and Gwati (2014) show that the cross-section and term structure of options-implied standard deviation, skewness and kurtosis explain foreign exchange expectations and risks. With structural breaks, we confirm that even with an extended period, from 2003 to 2014, higher moments extracted from foreign exchange option data capture the expected exchange rate. Next, we evaluate the connection between market expectation and commodity price though the relationship between option implied moments and commodity price. Interestingly, we find a significant relationship between commodity price and option-implied standard deviation, which is most important in predicting exchange rate changes with quantitatively significant effect among second to fourth moments. These empirical results consistently indicates that commodity prices help to predict exchange rate through market expectations.

The paper is organized as follows. Section 2 explain why we focus on commodity price as the determinants of exchange rate for several countries; Section 3 demonstrate the time-series model and its results for exploring the relationship between exchange rates and commodity prices; Section 4 presents the direct evidence that commodity price is connected to the market expectation with alternative data, such as survey forecasts and foreign exchange option; and Section 5 presents conclusions.

3.2 Background and Data Description

3.2.1 Commodity Currencies

Most empirical studies on exchange rate models have focused on finding better tests for uncovering the link between economic fundamentals and exchange rates. As one of the resolutions of the "exchange rate disconnect puzzle", Chen and Rogoff (2003) show that the exchange rates of Australia, Canada, and New Zealand, which are known as commodity export countries, exhibit significant co-movement with world commodity prices. For Australia, Canada, and New Zealand, commodity price potentially explain a major component of their terms-of-trade fluctuation, due to the large share of their production and exports accounted for by primary commodity products. For example,[1] more than 60% of Australia's total exports are wool, wheat, and various metals. In New Zealand, the primary commodities, such as lamb and mutton, account for more than half of its total exports. In the case of Canada, it relies on commodity products such as base metals, forestry products, and crude oil for more than a quarter of its exports. Despite the relatively small size of their overall economies, these countries retain a significant share of the global market for a few of their export products. As Chen and Rogoff (2003) state, however, country specific commodity price can have an endogenous problem, because these countries have market power in their country specific commodity products. For instance, because New Zealand controls a near majority of the global sheep market, the world price of sheep may be significantly influenced by the value of the New Zealand dollar. To address this potential form of endogeneity, Chen and Rogoff use a broader "world commodity price index" as an instrument for the country production-weighted price index. The world commodity price index is the "non-fuel primary commodity price index" from the IMF, and contains the US dollar prices of about 40 globally traded commodities. Thus, global commodity price fluctuation serve as an easily observable and essentially exogenous terms-of-trade shock to these countries exchange rate.

Chen, Rogoff, and Rossi (2010) further show that commodity currency exchange rates have surprisingly robust power in predicting global commodity prices. These empirical results support the present value model, in which exchange rates are strongly forward-looking and embody the expectation of future determinants. Work that attempts to use commodity price to predict future exchange rates, however, has been limited in its success.

[1] See Chen and Rogoff (2003).

In summary, exchange rate and commodity price are highly correlated contemporaneously. In particular, if one looks at real exchange rate, it may be somewhat surprising that commodity price movements are incorporated into real exchange rate so quickly, with no lasting impact beyond the quarter, given likely price rigidity in the real exchange rate. However, using a linear predictive regression model, we find that commodity price does not predict exchange rate at monthly or quarterly frequency. In this paper, we focus on uncovering the lack of dynamic connection between commodity currencies and commodity price.

3.2.2 Data Description

Following Chen et al. (2010, 2015), we focus on five small commodity-exporting countries with a sufficiently long history of market-based floating exchange rates, and explores the dynamic relationship between exchange rates and world commodity prices.

We study bilateral U.S. exchange rates versus those of five countries, which are known as commodity currencies: Australia (from 1984Q1 to 2013:Q3), Canada(from 1980Q1 to 2013Q3), Chile (from 1989Q3 to 2013Q3), New Zealand (from 1987Q1 to 2013Q3), and South Africa (from 1994Q1 to 2013Q3). Global Financial Data is the source of the end-of-quarter exchange rate. We also use the nominal effective exchange rate, from International Finance Statistics, and cross rates relative to the British pound and Japanese yen, from Global Financial Data, as the robustness checks for eliminating the dollar effect. For the overall aggregate world commodity price, we use the aggregate commodity price index from the IMF, which is a world export-earnings-weighted price index for over forty products traded on various exchanges.

We convert all data by taking logs and multiplying by 100. Through the rest of the paper, the symbols defined in this paragraph (s_t and cp_t) refer to the transformed data.

3.3 Exchange Rates and Commodity Prices

3.3.1 Can Commodity Price Predict Exchange Rate?

We first examine whether the current and past commodity price can predict movement in the exchange rate by using a simple regression model.

$$\Delta s_t = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta cp_{t-1} + \beta_3 \Delta cp_{t-2} + \beta_4 \Delta cp_{t-3} + e_t \tag{3.1}$$

where s_t is the log of the end-of-quarter nominal exchange rate at time t, U.S. dollar per unit of foreign currency, and cp_t is log of world commodity price at time t. In this paper, we use a broader "world commodity price index" as an instrument for the country production-weighted price index to deal with the endogeneity problem. As standard unit root tests cannot reject the hypothesis that these series contain unit roots, we proceed to analyze the data in first differences, which we denote with a preceding Δ.

Table C.1 presents the estimated results of equation (3.1). Consistent with Chen and Rogoff (2003), contemporaneous commodity price changes are statistically important at predicting exchange rate changes, but the lagged value of commodity prices changes are not significantly different from zero. This result confirms that current and past commodity price does not help to predict future exchange rate changes, even though there are highly correlated contemporaneously.

We next extend the analysis to focus on the relationship between current commodity price and the one-quarter ahead exchange rate. We conduct the Bai and Perron Test (2003) to identify the possible structural breaks in their relationship. As shown in Table C.2, all countries have one significant break point, within 2000Q4 and 2001 Q4 for Australia, New Zealand, South Africa, and Chile, and 2005Q4 for Canada. Next, we includes interactions with structural break indicator variables in the regression:

$$\Delta s_{t+1} = \beta_0 + \beta_1 D1 + \beta_2 \Delta cp_t + D1 * \beta_3 \Delta cp_t + e_{t+1} \tag{3.2}$$

where $D1$ is an indicator variable that is zero before the break date and equal to one otherwise. Table C.2 presents the estimated result: Except Canada, all countries have similar break points between 2000Q4 and 2001Q4. In contrast, the break date for Canada is 2005Q4. Even with the structural break, we cannot find any significant relationship between current commodity price changes and a quarter-ahead exchange rate changes.

We then look into a model that includes an error correction term. The basic idea of the Error Correction Model (ECM) is that the exchange rate returns to its fundamental value over time so that its current state of evolution can be characterized by deviations from the dependent variables. Mark (1995) uses the monetary model of exchange rates, and displays the evidence that long-horizon changes in nominal exchange rates contain an economically significant predictable component. In this paper, using commodity price as fundamentals, we project the m-month-ahead change in the nominal exchange rate on its current deviation from the commodity prices as below:

$$\Delta s_{t+m} = \beta_0 + \beta_1(cp_t - s_t) + e_{t+m} \tag{3.3}$$

Table C.3 shows that in case of Canada and South Africa, exchange rate are predictable from the deviation of the current commodity currency exchange rate from the commodity price. However, for other three countries, we cannot find evidence that long-horizon changes in the spot exchange rate are predictable.

The goal of these three regression models is to examine the predictive power of current commodity price on one-quarter-ahead exchange rates. All three regression models consistently confirm that the current commodity price does not help to predict exchange rate changes in a short horizon.

3.3.2 Trend and Cyclical Component

Since the augmented Dickey Fuller Test provides the empirical evidence that commodity price and nominal exchange rate possess a unit root, we take the first difference for these two series to investigate the relationship between these two. However, we can examine these I(1) series more specifically, by using Beveridge-Nelson decomposition. Beveridge and Nelson (1981) decompose non-stationary time series into two components: a stochastic trend component, and a stationary component. The Stochastic trend component of exchange rate and that of commodity prices is defined as

$$s_t^{trend} = s_t + E(\Sigma_{j=1}^{\infty}(\Delta s_{t+j}|I_t) \tag{3.4}$$

$$cp_t^{trend} = cp_t + E\Sigma_{j=1}^{\infty}(\Delta cp_{t+j} - E(\Delta cp_t)|I_t) \tag{3.5}$$

where I_t is the information up to time t. The trend component is interpreted as the infinite horizon forecast of the level of the I(1) process, conditional on information up to time t. $E(\Delta cp_t) \neq 0$ is the case when we control the effect of the time trend. The stationary or cyclical component is defined as the transitory departure from its expected long-run equilibrium as below:

$$s_t^{cycle} = -E_t(\Sigma_{j=1}^{\infty}\Delta s_{t+j}|I_t) \tag{3.6}$$

$$cp_t^{cycle} = -E_t(\Sigma_{j=1}^{\infty}\Delta cp_{t+j}|I_t) \tag{3.7}$$

The stochastic trend component is a pure random walk, while the stationary part is defined to be the forecastable momentum in the series at each point in time.

We first examine the relationship between trend component extracted from both series.

$$\Delta s_t^{trend} = \beta_0 + \beta_1 \Delta cp_t^{trend} + \beta_2 \Delta cp_{t-1}^{trend} + \beta_3 \Delta cp_{t-2}^{trend} + e_t \tag{3.8}$$

Note that taking the first difference of the trend component is an innovation in the random walk part, which is not predictable from the past. Table C.4 presents the estimated parameters of equation (3.8). For all currency pairs, only β_1 is negative and significantly differ from zero. It implies that shocks on the stochastic process of commodity price and exchange rates are highly correlated contemporaneously. However, the lagged shocks on the long-run expected commodity price have no lasting impact on the exchange rate– β_2, β_3 are very small and not significantly different from zero.

Eliminating the random walk process and the time trend from commodity prices and exchange rates, we re-examine their relationship by running the following regression.

$$s_t^{cycle} = \beta_0 + \beta_1 cp_t^{cycle} + \beta_2 cp_{t-1}^{cycle} + \beta_3 cp_{t-2}^{cycle} + \beta_4 cp_{t-3}^{cycle} + \beta_5 cp_{t-4}^{cycle} + e_t \tag{3.9}$$

Interestingly, as shown in the Table C.5, the lagged value of cp^{cycle} and its contemporaneous value have explanatory power for the transitory component of exchange rates. In particular, in case of Australia, Canada, and New Zealand, β_1, β_2 and β_3 are all significant with high R^2s. It implies that over- or under-valuation of the commodity price (i.e.,the cyclical component of the commodity price is positive or negative) predicts over- or under valuation of the future exchange rate (i.e., the cyclical component of exchange rate would be positive or negative.)

With this practice, we can see that commodity price and exchange rate are highly correlated contemporaneously, both in stochastic and cyclical components. In particular, contemporaneous shocks that have a permanent effect on each series are strongly correlated. Eliminating the effect of contemporaneous permanent shocks, we can observe the existence of a dynamic connection between exchange rate and commodity price more clearly.

3.3.3 State-Space Representation

A. Modeling Strategy

To better understand the temporal relationship between exchange rate and commodity price shocks, we use a time-series framework, which decomposes the exchange rate to the expected part and the unexpected part (or forecast error). We start from the framework developed by Pastor and Stambaugh (2009). They introduce a predictive system for estimating expected returns in the stock market. Since the exchange rate is also known as one of the asset prices, we employ their framework in the foreign exchange market.

$$\Delta s_{t+1} = \mu_t + u_{t+1} \tag{3.10}$$

$$\mu_{t+1} = \psi \mu_t + w_{t+1} \tag{3.11}$$

$$\Delta cp_{t+1} = (1-\phi)E_{cp} + \phi \Delta cp_t + v_{t+1} \tag{3.12}$$

where

$$\mu_t \equiv E(\Delta s_{t+1} | I_t)$$

In this state-space model, μ_t is the conditional expectation about one-quarter-ahead exchange rate movement, using all the information up to time t. E_{cp} is the unconditional mean of the commodity price. Equation (3.10) decomposes the exchange rate changes to expectation formed at time t and unexpected shock realized at time $t+1$. Equation (3.11) postulates a simple persistent process for the conditional expectation, μ_{t+1}. This equation assumes that an agent's expectation is affected both by both previous expectation and innovation on the expectation, w_{t+1}. Note that no strict assumption is made about the persistence of the expectation, but ψ should be between 0 and 1.[2] Equation (3.12) is a dynamics of commodity price changes: follow AR(1) process, with shock at time $t+1$. Keep in mind that the Δs_{t+1} and Δcp_t series are observable but the μ_t are not.

The residuals in this state space model are assumed to be identically and independently distributed across $t+1$ as

$$\begin{bmatrix} u_{t+1} \\ w_{t+1} \\ v_{t+1} \end{bmatrix} \sim \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} \sigma_u^2 & \sigma_{uw} & \sigma_{uv} \\ \sigma_{uw} & \sigma_w^2 & \sigma_{wv} \\ \sigma_{uv} & \sigma_{wv} & \sigma_{vv} \end{bmatrix} \right) \tag{3.13}$$

The advantage of this state-space model is that we can avoid the limitations of specifying the underlying relationship or strong assumptions associated with the regression-based approach. In addition, it allows for a nonlinear relationship between commodity price and

[2]We relax this assumption and conduct the case when μ_t follow AR(2) and AR(3), but results do not change significantly

expected or realized exchange rate. Note that Δs_{t+1} are connected to both Δcp_t and Δcp_{t+1} in this framework. The first channel is σ_{wv}, the conditional correlation between μ_t and Δcp_t. Note that the market forms its expectation about a quarter-ahead exchange rate movement at time t, using all the information including commodity price changes at time t. This relationship is captured by co-movement of their shocks at time t, which is represented by σ_{wv}. The second channel is σ_{uv}, which represent the contemporaneous relationship between commodity price and exchange rate. Comparing σ_{wv} and σ_{uv}, we can see the dynamic impact of commodity price on exchange rate.

As Pastor and Stambaugh state in their paper, all but one of the parameters in the covariance matrix are identified. To solve this problem, Kim and Lee (2015) propose the reduced form as follow:

$$\Delta s_{t+1} = \psi \Delta s_t + (\gamma - \psi\delta) v_t + \delta v_{t+1} + e_{t+1} - \theta e_t \tag{3.14}$$

$$(\Delta cp_{t+1} - E_{cp}) = \phi(\Delta cp_t - E_{cp}) + v_{t+1} \tag{3.15}$$

where e_{t+1} and v_{t+1} are independent. We should note that γ capture the relationship between μ_t and Δcp_t, defined as $\gamma = var(v_t)^{-\frac{1}{2}} corr(v_t, w_t) var(w_t)^{\frac{1}{2}}$. The pure effect of the contemporaneous shock on commodity price is δ, a function of u_{t+1} and v_{t+1}. Kim and Lee derived that $\delta = var(v_{t+1})^{-\frac{1}{2}} corr(v_{t+1}, u_{t+1}) var(u_{t+1})^{\frac{1}{2}}$. By estimating γ and δ in equation (3.14), we can evaluate the dynamic impact of commodity price on the exchange rate.

3.3.4 Estimation Results

In the state-space model, we compute the R^2 values for exchange rate changes as

$$R^2 = 1 - \frac{v\hat{a}r(\Delta s_{t+1} - \mu_t^F)}{v\hat{a}r(\Delta s_{t+1})}$$

where $v\hat{a}r$ is the sample variance, μ_t^F is the filtered series for changes in exchange rate. We also report R^2 values from two alternatives as a benchmark as below:

$$\Delta s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + e_t^{ols} \tag{3.16}$$

$$\Delta s_{t+1} = \psi \Delta s_t + e_{t+1} - \theta e_t^{ARMA} \tag{3.17}$$

Equation (3.16) is OLS regression model, which assumes a linear relationship between Δcp_t and Δs_{t+1}. Equation (3.17) is simple ARMA(1,1) process, a special case of the state-space model in equation (3.14) and (3.15), with no information from the Δcp_t. Thus, comparing R^2 obtained from equation (3.14) and from equation (3.17), we can see the explanatory power of Δcp_t.

The results are summarized in Table C.6. For Australia, Canada and New Zealand, R^2 from the state-space model is always higher than other two benchmark model. (i) $R^2_{nonlinear} > R^2_{OLS}$ implies that nonlinear relation between Δcp_t and Δs_{t+1} exists and it help to improve the predictability of exchange rate and (ii) $R^2_{nonlinear} > R^2_{ARMA}$ confirm that Δcp_t help to predict a quarter-ahead exchange rate changes.

The state-space model enables us to explore how the market expectation changes in response to commodity price changes and to compare the magnitude of the dynamic influence of commodity price on the exchange rate. The estimated results are summarized in Table C.7. The upper panel is the estimated parameter before the break date, and lower panel is that after the break date. We use the same structural break in section 2, using the methods presented in Bai and Perron (2003).

Here, note again that γ gives us the empirical evidence of a connection between Δcp_t and Δs_{t+1}, while δ captures relationship between Δcp_{t+1} and Δs_{t+1}. Before the break time, γ_0's have a consistent pattern: negative for all currency pairs. It implies that market expectation reflect the commodity price– when the commodity price rises, the market expects that the commodity currency will be stronger than before. δ_0 also shows the consistent pattern: negative for all commodity currencies. Especially for Australia and New Zealand, δ_0's are statistically significant. After the break, we can see δ_1's become significant and have negative values for all currencies but Chile, and γ's become insignificant and positive for all but

Canada. It implies that after the structural break, the link between market expectation and commodity price is weaker than before the break point, and contemporaneous shocks dominate the relationship between commodity price and exchange rate.

These empirical results shows the dynamic linkage between commodity price and nominal exchange rate, which is not observed in the conventional OLS regression model.

3.4 Expectation and Commodity Prices

3.4.1 Survey Data

Section 3 summarized prior research showing commodity price as a predictor for future exchange rate through the market expectation. We conduct a simple test here to evaluate our argument using survey data obtained from Economic Consensus Inc, which contains forecasts of a wide range of economic indicators including foreign exchange rates from a large group of private sector and institutional economists. Monthly data is available from October 1990 to October 2014. The survey reports the average forecast of the spot exchange rate 3, 12, and 24 months ahead. We report the summary statistics in the first half of the Table C.8 and correlation coefficients among the nine survey forecasts are reported in the second half of the Table C.8. We note that forecast for the commodity currencies are positively correlated, and Australia and New Zealand are especially highly correlated in all three horizons. Theses results reflect that investors expect very similar movements among commodity currencies.

First, we test if the survey-based market expectation predicts one-quarter ahead exchange rate movement.

$$s_{t+1} - s_t = \beta_0 + \beta_1(E_t^s s_{t+1} - s_t) + e_{t+1} \tag{3.18}$$

$E_t^s s_{t+1} - s_t$ is the period t survey based expected deprecation from time period t to t+1. Thus, the left side of equation (3.18) shows ex-post exchange rate changes, while the right side is the survey-based forecast. The unbiasedness hypothesis is represent by the null hypothesis that $\beta = 1$. We report the estimated results in Table C.8. Surprisingly, expected exchange rate changes do not help to predict one-quarter-ahead exchange rate. The regression results in a predictive coefficient of $\beta_1 = -0.178$ with $R^2 = 0.005$ for Australia, $\beta_1 = -0.223$ with $R^2 = 0.006$ for Canada, and $\beta_1 = -0.003$ with $R^2 = 0.000$ for New Zealand. All of these coefficients are insignificant and seems to have the wrong sign in the sense that an ex-post exchange rate moves in the opposite direction to market expectations. However, this result is consistent with the previous literature. Frankel and Froot (1987) run the equation (3.19) with survey data and show that coefficients are significantly less than zero and the unbiasedness hypothesis fails in most of the data sets.

Next, we investigate if the expectation reflects the commodity price changes as following two regressions:

$$E_t^s s_{t+1} - s_t = \alpha_0 + \alpha_1 \Delta cp_t + \zeta_{1,t+1} \tag{3.19}$$

$$s_{t+1} - E_t^s s_{t+1} = \beta_0 + \beta_1 \Delta cp_t + \zeta_{2,t+1} \tag{3.20}$$

where $s_{t+m} - E_t^s s_{t+m}$ is forecast error. Panel B of the Table C.9 present the estimated coefficient for regression (15). Only in the case of Canada was there a significant coefficient at the 1% level, whereas the other two countries shows no significant relationship between commodity price and survey-based exchange rate changes. In panel C, estimated results support the view that exchange rate changes are predictable by the lagged value of commodity price. In a short horizon, expectation does not seem to be strongly affected by commodity price. However, our empirical results suggest that Δcp_t is the determinant of Δs_{t+1} through the unexpected shock/forecast error. This result confirms the existence of a dynamic connection between commodity price and exchange rate.

Next, we look into the impact of commodity price shock on the 12-month and 24-month-ahead forecast of exchange rate movement. We test this relationship with two equations:

$$E_t^s \Delta s_{t+m} = \alpha_0 + \alpha_1 \Delta cp_t + \zeta_{1,t+m} \tag{3.21}$$

$$E_t^s \Delta s_{t+m} = \beta_0 + \beta_1 (cp_t - s_t) + \zeta_{2,t+1,} \tag{3.22}$$

where m is a 3, 12 and 24 months horizon. Since markets use all the information up to time t, we use quarterly commodity price growth rate as the predictor, instead of matching the frequencies to the forecast horizons. Tables C.10 and C.11 presents the estimated results. For all currencies, we can find a significant relationship between commodity price and exchange rate forecast– one-year-ahead or two-year-ahead expected exchange rates are strongly related to the current commodity price changes for all currencies. The estimated result from the Error Correction Models shows even stronger correlation between expectations about future exchange rates and current commodity prices. For all currency pairs and all horizons, information about commodity prices is significantly linked to the market forecast of future exchange rates. We also observe a consistent pattern across currency pairs: the effect of the commodity price is positive for all cases, and tend to be larger for longer horizon forecast. Again, this results confirms that commodity price is the one of the main agents in determining the future exchange rate, as expected. It implies that we cannot see the dynamic linkage between commodity price and exchange rate, because the impact of contemporaneous shocks dominates the effect of Δcp_t through the expectation channel.

However, survey data has been criticized because of potential measurement problems. So, in next section, we will check the relation between commodity price and market expectation with alternative data and methods.

3.4.2 Foreign Exchange Option Data

Chen and Gwati (2015) shows that foreign exchange options with different strike price and maturity capture both foreign exchange expectation and risks. Since payoffs of option contracts depend on the uncertain future realization of the price of the underlying asset, option prices must reflect market beliefs about probability of future payoffs. With daily option data, they extract the ex ante standard deviations, skewness, and kurtosis of the distribution of exchange rate movements. They show that these market-based ex-ante measures of FX volatility, crash and tail risk can explain the deviation from the UIP, which is interpreted as a risk premium under rational expectation. They test their argument as below:

$$\Delta s_{t+1} = \alpha_0 + \alpha_1(f_t - s_t) + \alpha_2 stdev_t + \alpha_3 skew_t + \alpha_4 kurt_t + e_{t+1} \tag{3.23}$$

where $stdev_t$, $skew_t$, and $kurt_t$ are extracted option implied moments, which capture perceived FX volatility, tail and crash risk. A daily option data set for Australia and Canada, covers from 05/14/2003 to 02/13/2013, which includes the well known global financial crisis. Thus, by using the method presented by Bai and Perron, we estimate the structural break first. Bai and Perron test capture two break points for each country: 05/12/2008, 09/04/2009 for Australia, and 10/03/2006 and 01/29/2009 for Canada. Estimated coefficient considering structural breaks are reported in Table C.12. All these 2nd-4th moments are statistically important in predicting one-quarter-ahead exchange rate movement–coefficients are significant under 1% level, and R^2 is very high, 0.520 and 0.425 for Australia and for Canada respectively.

To capture the pure effect of the option implied moments on market expectation, we omit the forward premium $(f_t - s_t)$ in equation (3.23) and run the regression below:

$$\Delta s_{t+1} = \beta_0 + \beta_1 stdev_t + \beta_2 skew_t + \beta_3 kurt_t + e_{t+1} \tag{3.24}$$

Estimated results are reported in Table C.13. The results do not change much– estimated structural breaks are very similar, coefficients are consistently significant, and even R^2 values are almost same as before. These results confirm that option implied moments capture the market expectation of exchange rate movement.

Next, we explore if these option implied moments response to the commodity prices. We run the following three sets of regressions to evaluate the relationship between market expectation captured by $stdev_t$, $skew_t$, $kurt_t$, and Δcp_t.

$$stdev_t = a_0 + a_1 \Delta cp_t + e_t^{stdev} \tag{3.25}$$

$$skew_t = b_0 + b_1 \Delta cp_t + e_t^{skew} \tag{3.26}$$

$$kurt_t = c_0 + c_1 \Delta cp_t + e_t^{kurt} \tag{3.27}$$

Δcp_t is quarterly data, whereas extracted moments from option data are daily frequency. To match the frequency, we use the end-of-quarter $stdev_t$, $skew_t$ and $kurt_t$ as the dependent variable, so that the observation number is reduced to 39. Table C.14 show that Δcp_t is linked to the $stdev_t$, but there is no significant relationship with $skew_t$ and $kurt_t$. The explanatory power of Δcp_t for $stdev_t$ is high, above 15%, while very small for $skew_t$ and $kurt_t$. Note that in Table C.12 and C.13, $stdev_t$ is the most important factors for explaining or predicting future exchange rate among the 2nd -4th moments extracted from FX option data. Thus, the statistically significant relationship between Δcp_t and $stdev_t$ confirm our argument that commodity price is linked to the one-quarter-ahead exchange rate though expectation.

3.5 Conclusion

Within a simple regression approach, commodity price seems to have no forecasting power for exchange rate movement at short horizon. We argue that the lack of dynamic linkage between commodity price and exchange rate is because of the huge impact of contemporaneous shocks relative to the effect of the lagged value of the commodity prices. We support this argument with a time-series technique first: (i) Using Beveridge-Nelson decomposition, we show that permanent shocks on exchange rate and commodity price are highly correlated. Then, eliminating this contemporaneous and dominant shock, we can see that exchange rate responds to the lagged value of commodity prices. (ii) Estimating the conditional correlation between market expectation and commodity price changes, we can directly observe how the lagged commodity price help to predict a quarter-ahead exchange rate changes. With these empirical results, we focus on the relationship between market expectation and commodity price, as the channel of connecting commodity price and future exchange rate. With survey-based market expectation and extracted expectation measured by option implied moments, we can find consistent results that markets consider aggregate commodity prices when they form expectations of the future exchange rates of commodity currencies. Thus, our empirical results suggest that commodity price movements are incorporated into the nominal exchange rate with lasting impact beyond the quarter.

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Appendix A

APPENDIX TO CHAPTER I

A.1 Mathematical Appendix

A.1.1 Deriving Present Value of Exchange Rate Changes

Consider the following simplified version of the present value model investigated by Engel and West (2005):

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t[f_{t+j}], \quad 0 < b < 1, \tag{A.1}$$

where f_t is a linear combination of fundamentals, and b is discount factor. Suppose further that there is a unit root in f_t, such that Δf_t has the following Wold representation:

$$Delta f_t = \theta(L)\epsilon_t, \tag{A.2}$$

where ϵ_t is serially uncorrelated and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3 + ...$, with the roots of $\theta(L) = 0$ lying outside the complex unit circle.

Then, we have the following expression for s_t and Δs_t:

$$\begin{aligned} s_t &= (1-b)\sum_{j=0}^{\infty} b^j E_t[f_{t+j}] \\ &= \sum_{j=0}^{\infty} b^j E_t[f_{t+j}] - b\sum_{j=0}^{\infty} b^j E_t[f_{t+j}] \\ &= \sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j}] + \sum_{j=0}^{\infty} b^j E_t[f_{t+j-1}] - b\sum_{j=0}^{\infty} b^j E_t[f_{t+j}] \\ &= \sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j}] + f_{t-1}, \end{aligned} \tag{A.3}$$

$$\begin{aligned}\Delta s_t &= \sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j}] - \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j-1}] + \Delta f_{t-1} \\ &= \sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j}] - b \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j}],\end{aligned} \tag{A.4}$$

Due to law of iterative expectations, we have:

$$E_{t-1}[\Delta s_t] = (1-b) \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j}], \tag{A.5}$$

and by combining equations (A.4) and (A.5), we have:

$$\begin{aligned}\Delta s_t - E_{t-1}[\Delta s_t] &= \sum_{j=0}^{\infty} b^j E_t[\Delta f_{t+j}] - b \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j}] - (1-b) \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j}] \\ &= \sum_{j=0}^{\infty} b^j \{E_t[\Delta f_{t+j}] - E_{t-1}[\Delta f_{t+j}]\} \\ &= \sum_{j=0}^{\infty} b^j \theta_j \epsilon_t = \theta(b)\epsilon_t,\end{aligned} \tag{A.6}$$

which allows us to rewrite Δs_t as:

$$\Delta s_t = (1-b) \sum_{j=0}^{\infty} b^j E_{t-1}[\Delta f_{t+j}] + \theta(b)\epsilon_t. \tag{A.7}$$

A.1.2 State-space Model

The reduced-form model that consists of equations (10) and (14) can be cast into the following state-space model:

<u>*Measurement Equation*</u>

$$\begin{pmatrix} \Delta x_{t+1} \\ \Delta s_{t+1} \end{pmatrix} = \begin{pmatrix} \alpha_x \\ \alpha_\mu \end{pmatrix} + \begin{pmatrix} I_n & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} \Delta \tilde{x}_{t+1} \\ \Delta \tilde{s}_{t+1} \\ e_{t+1} \\ v_{t+1} \end{pmatrix}$$

$$(\quad Y_t = \tilde{\alpha} + H\xi_t \quad)$$

<u>*Transition Equation*</u>

$$\begin{pmatrix} \Delta \tilde{x}_{t+1} \\ \Delta \tilde{s}_{t+1} \\ e_{t+1} \\ v_{t+1} \end{pmatrix} = \begin{pmatrix} \Phi & 0 & 0 & 0 \\ 0 & \psi & -\theta & (\gamma' - \psi\delta') \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \Delta \tilde{x}_{t} \\ \Delta \tilde{s}_{t} \\ e_{t} \\ v_{t} \end{pmatrix} + \begin{pmatrix} I_n & 0 \\ \delta' & 1 \\ 0 & 1 \\ I_n & 0 \end{pmatrix} \begin{pmatrix} v_{t+1} \\ e_{t+1} \end{pmatrix}$$

$$\left(\quad \xi_t = F\xi_{t-1} + R\tilde{U}_t, \quad \tilde{U}_t \sim i.i.d.N(0, \Omega), \quad \right)$$

where $\Omega = \begin{pmatrix} \Sigma_v & 0 \\ 0 & \sigma_e^2 \end{pmatrix}$.

A.2 Figures and Tables

Table A.1: Autocorrelations and Cross Correlation of Δs_{t+1} $[\psi = 0.1]$

- **Data Generating Process:**

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + \frac{1}{1-b\psi}\epsilon_{t+1}$$

$$\Delta f_{t+1} = \psi \Delta f_t + \epsilon_{t+1}$$

$$x_{t+1} = \phi x_t + v_{t+1}$$

$$\begin{bmatrix} \epsilon_{t+1} \\ v_{t+1} \end{bmatrix} = \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\epsilon^2 & \rho_{\epsilon v}\sigma_\epsilon\sigma_v \\ \rho_{\epsilon v}\sigma_\epsilon\sigma_v & \sigma_v^2 \end{bmatrix} \right)$$

$$\rho_{\epsilon v} = 0.7$$

ψ	ϕ	$corr(\Delta s_{t+1}, \Delta s_t)$	$corr(\Delta s_{t+1}, \Delta f_t)$	$corr(\Delta f_t, x_t)$	$corr(\Delta s_{t+1}, x_t)$
			b=0.7		
0.1	0.95	0.030	0.030	0.241	0.008
0.1	0.5	0.030	0.030	0.635	0.019
0.1	0.1	0.030	0.030	0.700	0.021
			b=0.9		
0.1	0.95	0.010	0.010	0.240	0.002
0.1	0.5	0.010	0.010	0.635	0.006
0.1	0.1	0.010	0.010	0.700	0.007
			b=0.95		
0.1	0.95	0.006	0.006	0.240	0.000
0.1	0.5	0.006	0.006	0.635	0.004
0.1	0.1	0.006	0.006	0.700	0.004

Table A.2: Autocorrelations and Cross Correlation of Δs_{t+1} [$\psi = 0.95$]

- **Data Generating Process:**

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + \frac{1}{1-b\psi}\epsilon_{t+1}$$
$$\Delta f_{t+1} = \psi \Delta f_t + \epsilon_{t+1}$$
$$x_{t+1} = \phi x_t + v_{t+1}$$

$$\begin{bmatrix}\epsilon_{t+1}\\ v_{t+1}\end{bmatrix} = \left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_\epsilon^2 & \rho_{\epsilon v}\sigma_\epsilon\sigma_v \\ \rho_{\epsilon v}\sigma_\epsilon\sigma_v & \sigma_v^2\end{bmatrix}\right)$$

$\rho_{\epsilon v} = 0.7$

ψ	ϕ	$corr(\Delta s_{t+1}, \Delta s_t)$	$corr(\Delta s_{t+1}, \Delta f_t)$	$corr(\Delta f_t, \mathrm{x}_t)$	$corr(\Delta s_{t+1}, x_t)$
			<u>b=0.7</u>		
0.95	0.95	0.587	0.674	0.700	0.472
0.95	0.5	0.587	0.674	0.361	0.243
0.95	0.1	0.587	0.674	0.241	0.162
			<u>b=0.9</u>		
0.95	0.95	0.168	0.291	0.700	0.203
0.95	0.5	0.168	0.291	0.361	0.106
0.95	0.1	0.168	0.291	0.240	0.071
			<u>b=0.95</u>		
0.95	0.95	0.067	0.150	0.699	0.105
0.95	0.5	0.067	0.150	0.361	0.054
0.95	0.1	0.067	0.150	0.240	0.036

Table A.3: Performance of Alternative Models: Monte Carlo Experiments [$\rho_{\epsilon v} = 0.5, \psi = 0.95$]

- **Data Generating Process:**

$$\Delta s_{t+1} = \frac{(1-b)\psi}{1-b\psi}\Delta f_t + u_{t+1}$$
$$\Delta f_{t+1} = \psi \Delta f_t + \epsilon_{t+1}$$
$$x_{t+1} = \phi x_t + v_{t+1}$$
$$\begin{bmatrix} u_{t+1} \\ \epsilon_{t+1} \\ v_{t+1} \end{bmatrix} = \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \rho_{u\epsilon}\sigma_u\sigma_\epsilon & \rho_{uv}\sigma_u\sigma_v \\ \rho_{u\epsilon}\sigma_u\sigma_\epsilon & \sigma_\epsilon^2 & \rho_{\epsilon v}\sigma_\epsilon\sigma_v \\ \rho_{uv}\sigma_u\sigma_v & \rho_{\epsilon v}\sigma_\epsilon\sigma_v & \sigma_v^2 \end{bmatrix} \right)$$
$$(\rho_{\epsilon v} = 0.5, \rho_{u\epsilon} = 0.3,\ \rho_{uv} = 0.1,\ \sigma_u^2 = 1,\ \sigma_\epsilon^2 = 0.1,\ \sigma_v^2 = 0.1)$$

- **True Parameter Values**: $\beta = 0.655,\ \gamma = 0.328,\ \psi = 0.95$

		OLS with Δf_t	OLS with Δx_t	Proposed Model
	$\hat{\beta}$	0.648(0.067)	0.326(0.185)	-
	γ	-	-	0.335(0.145)
$\phi = 0.95$	$\hat{\psi}$	-	-	0.939(0.044)
	θ	-	-	0.808(0.074)
	R^2	**0.269(0.089)**	**0.086(0.075)**	**0.205(0.087)**
	$\hat{\beta}$	0.649(0.066)	0.459(0.265)	-
	γ	-	-	0.338(0.146)
$\phi = 0.5$	$\hat{\psi}$	-	-	0.939(0.043)
	θ	-	-	0.809(0.074)
	R^2	**0.268(0.088)**	**0.027(0.025)**	**0.204(0.086)**
	$\hat{\beta}$	0.648(0.067)	0.358(0.248)	-
	γ	-	-	0.337(0.145)
$\phi = 0.1$	$\hat{\psi}$	-	-	0.938(0.045)
	θ	-	-	0.806(0.075)
	R^2	**0.268(0.088)**	**0.014(0.014)**	**0.202(0.085)**

Notes: Sample size =250; Iterations =5,000;   In the parentheses are standard deviations.

OLS with Δf_t: $\Delta s_{t+1} = \beta \Delta f_t + \eta_{f,t+1}$;

OLS with Δx_t: $\Delta s_{t+1} = \beta \Delta x_t + \eta_{x,t+1}$;

Proposed Model:

$$\Delta s_{t+1} = \psi \Delta s_t + (\gamma - \delta\psi)v_t + \delta v_{t+1} + e_{t+1} - \theta e_t$$
$$x_{t+1} = \phi x_t + v_{t+1}$$

Table A.4: Estimation of Models: Comparison between Linear Model and Proposed Model

	CANADA	FRANCE	GERMANY	ITALY	JAPAN	SWITZERLAND	UK
Linear Model: $\Delta s_{t+1} = \alpha + \beta_p(\Delta p_t - \Delta p_t^*) + \beta_y(\Delta y_t - \Delta y_t^*) + e_{t+1}^{ols}$							
β_p	-0.570	-3.331**	0.048	-0.258	0.000	0.762	-0.852
	(0.654)	(1.459)	(1.305)	(1.154)	(1.095)	(1.315)	(0.735)
β_y	-0.239	-0.047	-0.175	-0.341	0.342	0.184	-0.364
	(0.230)	(0.322)	(0.401)	(0.470)	(0.425)	(0.294)	(0.434)
$\mathbf{R^2_{ols}}$	0.022	0.051	0.003	0.007	0.008	0.009	0.027
Proposed Model: $\Delta s_{t+1} = \alpha + \psi\Delta s_t + (\gamma_p - \delta_p\psi)v_{pt} + (\gamma_y - \delta_y\psi)v_{yt} + \delta_p v_{p,t+1} + \delta_y v_{y,t+1} + e_{t+1} - \theta e_t$; $\Delta y_{t+1} - \Delta y_{t+1}^* = \alpha_y + \phi_y(\Delta y_t - \Delta y_t^*) + v_{y,t+1}$; $\Delta p_{t+1} - p_{t+1}^* = \alpha_p + \phi_p(\Delta p_t - \Delta p_t^*) + v_{p,t+1}$							
γ_p	-0.305	-2.253***	-0.793*	-0.216	-0.845**	-0.368	0.335
	(0.289)	(0.920)	(0.487)	(0.417)	(0.379)	(0.383)	(0.226)
γ_y	-0.224***	-0.310***	-0.484**	-0.689***	-0.128	-0.207**	-0.471**
	(0.089)	(0.139)	(0.191)	(0.280)	(0.132)	(0.144)	(0.229)
ψ	0.925***	0.808***	0.948***	0.808***	0.927***	0.904***	0.839***
	(0.040)	(0.066)	(0.041)	(0.073)	(0.030)	(0.072)	(0.064)
θ	0.926***	0.890***	0.999***	0.852***	0.999***	0.962***	0.972***
	(0.050)	(0.059)	(0.009)	(0.089)	(0.007)	(0.066)	(0.046)
ϕ_p	0.274***	0.379***	0.254***	0.592***	-0.321**	-0.013	-0.217**
	(0.102)	(0.097)	(0.099)	(0.091)	(0.097)	(0.142)	(0.103)
ϕ_y	0.150*	0.050	0.241***	0.191**	0.455***	-0.234**	0.256***
	(0.110)	(0.102)	(0.097)	(0.105)	(0.091)	(0.104)	(0.101)
$\boldsymbol{R^2_{ML}}$	0.115	0.122	0.065	0.083	0.041	0.032	0.085

Note: Standard errors are reported in the parentheses. Asterisks denote significance at levels 1%(***), 5%(**), and 10%(*), respectively.

Table A.5: Test for Out-Of-Sample Forecasting Performance

HORIZON	CANADA	FRANCE	GERMANY	ITALY	JAPAN	SWITZERLAND	UK
Panel A: Proposed Model vs. Random Walk with Drift Model							
1 Quarter	-1.123	0.349	**-1.405***	0.649	-0.841	-0.155	-0.979
2 Quarter	**-1.483***	0.438	-1.143	0.261	-0.530	-0.186	0.281
3 Quarter	**-2.193****	0.687	-0.574	-0.261	-0.590	-0.067	0.653
4 Quarter	**-2.894****	-0.547	-1.410	**-1.967****	-0.910	-1.230	**-1.378***
5 Quarter	**-3.127****	**-1.584***	**-2.178****	**-3.717****	-1.230	**-2.112****	**-2.344****
6 Quarter	**-2.854****	**-1.778****	**-2.122****	**-3.526****	-1.122	**-2.23****	**-2.190****
7 Quarter	**-2.956****	**-1.634***	**-2.013****	**-3.250****	-1.158	**-2.284****	**-2.504****
8 Quarter	**-2.219****	**-2.651****	**-2.377****	**-3.347****	**-1.537****	**-2.428****	**-3.009****
Panel B: Proposed Model vs. Random Walk without Drift Model							
1 Quarter	-0.157	0.643	-0.545	1.038	-0.583	0.261	-0.365
2 Quarter	-0.258	0.868	-0.274	0.923	-0.496	0.249	0.939
3 Quarter	-0.542	1.042	0.046	0.609	-0.494	0.365	1.421
4 Quarter	-1.039	-0.136	-0.729	-0.672	-0.983	-0.650	-0.293
5 Quarter	-1.049	-1.015	-1.220	**-1.963****	-1.175	-1.203	**-1.437***
6 Quarter	-1.287	**-1.423***	**-1.589***	**-2.008****	**-1.917****	**-1.934****	**-1.593***
7 Quarter	**-1.316***	**-1.471***	**-1.600****	**-2.405****	**-1.708****	**-2.094****	**-1.970****
8 Quarter	**-1.321***	**-2.107****	**-2.021****	**-2.066****	**-2.316****	**-2.353****	**-2.540****

Note: This table reports Clark and West test statistics (Clark and West 2007) to compare the forecast ability between the proposed model and benchmark forecasts (i.e., random walk or random walk with drift model). We adopt a rolling window procedure, with window size 40 of quarters, starting from 1984Q1-1993Q4. Negative values imply that the proposed model forecasts better than the benchmark model. Asterisks denote rejections of the null hypothesis that random walk is better in favor of the alternative hypothesis that the fundamental-based model is better at 5 %(**), 10 %(*) significance levels, respectively.

Figure A.1: Generated Exchange Rate and its Prediction from OLS Regressions

- **Data Generating Process:**

$$\Delta s_{t+1} = \frac{(1-b)\cdot}{1-b\cdot}\Delta f_t + \frac{1}{1-b\cdot}\epsilon_{t+1}$$

$$\Delta f_{t+1} = \cdot\,\Delta f_t + \epsilon_{t+1}$$

$$x_{t+1} = \text{¤}\, x_t + v_{t+1}$$

$$\begin{bmatrix}\epsilon_{t+1}\\ v_{t+1}\end{bmatrix} = \left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\pm^2_\epsilon & {}^\circ_{\epsilon v}\pm_\epsilon\pm_v \\ {}^\circ_{\epsilon v}\pm_\epsilon\pm_v & \pm^2_v\end{bmatrix}\right)$$

$$(\,b = 0.9,\ \cdot\ = 0.95,\ \text{¤} = 0.1,\ {}^\circ_{\epsilon v} = 0.7,\ \pm^2_\epsilon = 1,\ \pm^2_v = 0.5\,)$$

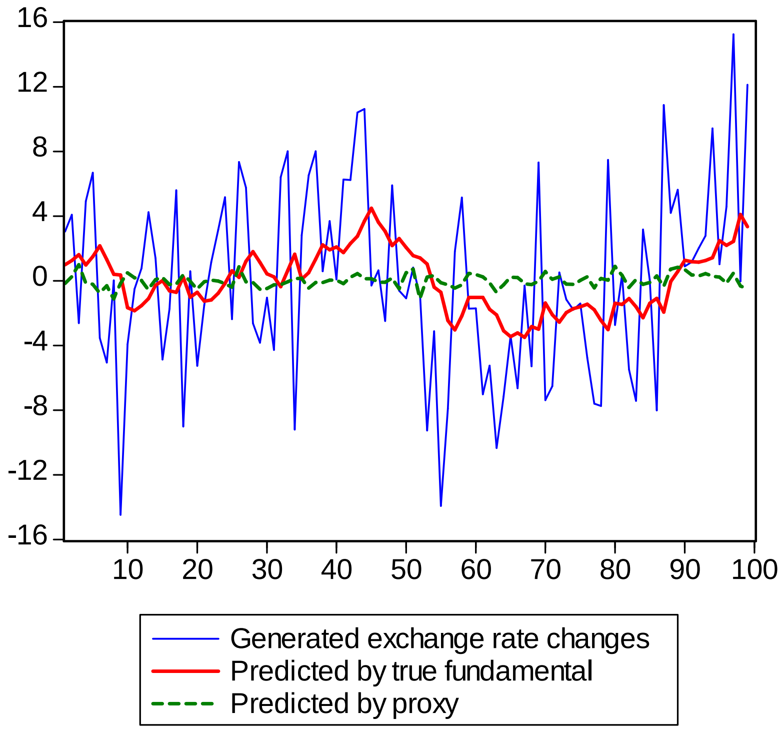
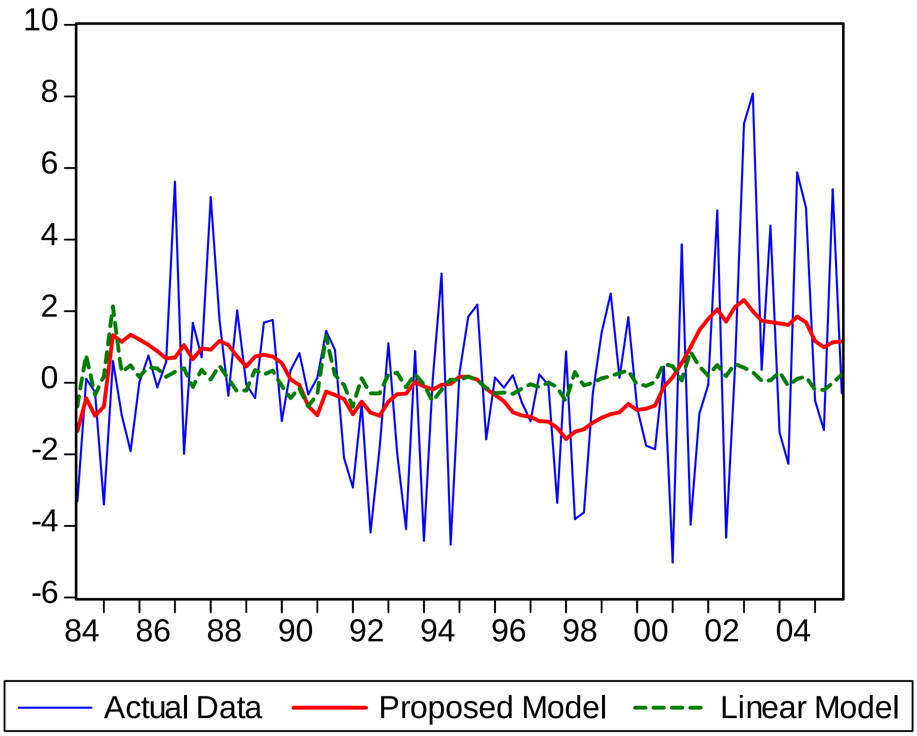
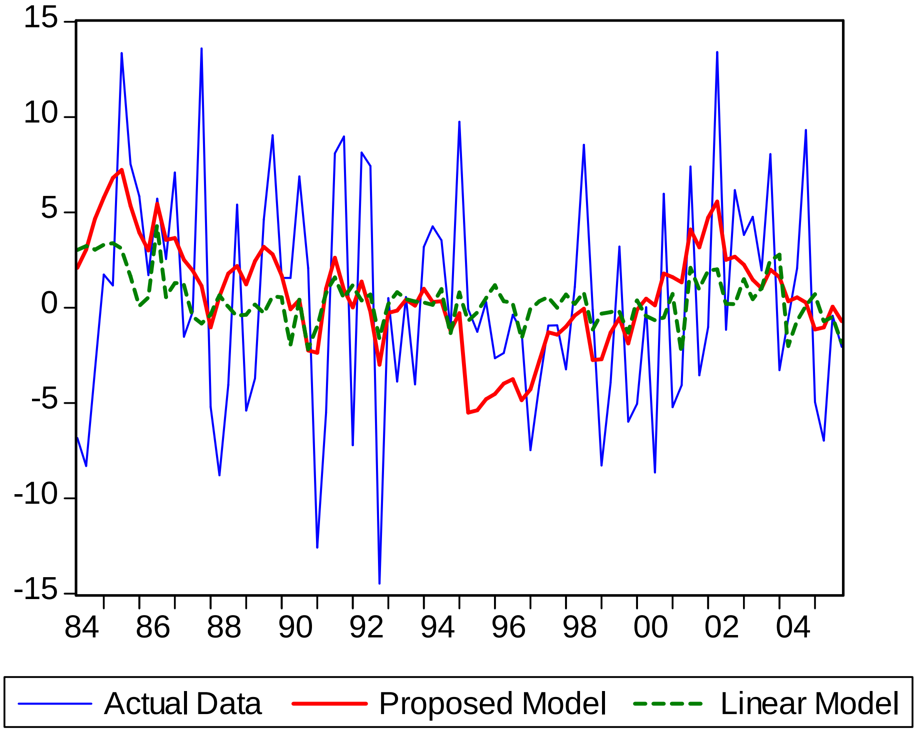


Figure A.2: In-Sample Prediction

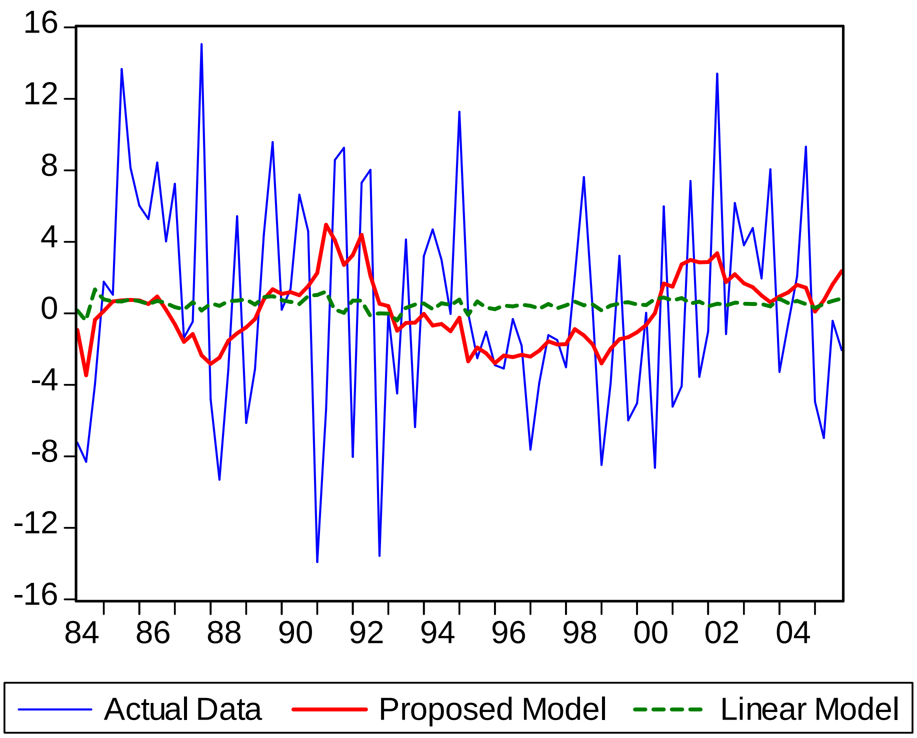
A. CANADA



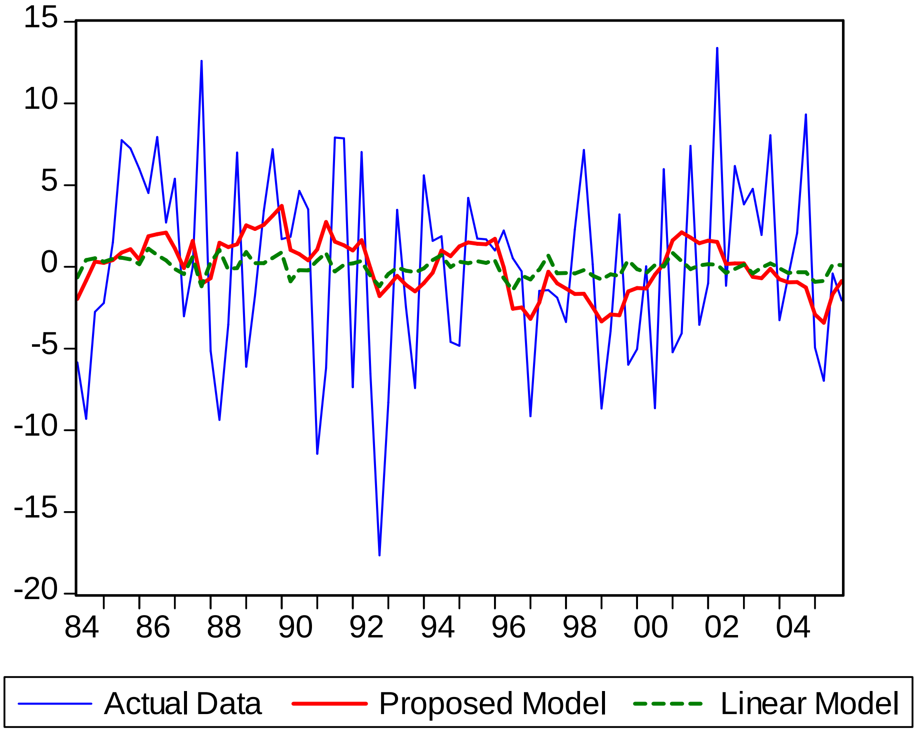
B. FRANCE



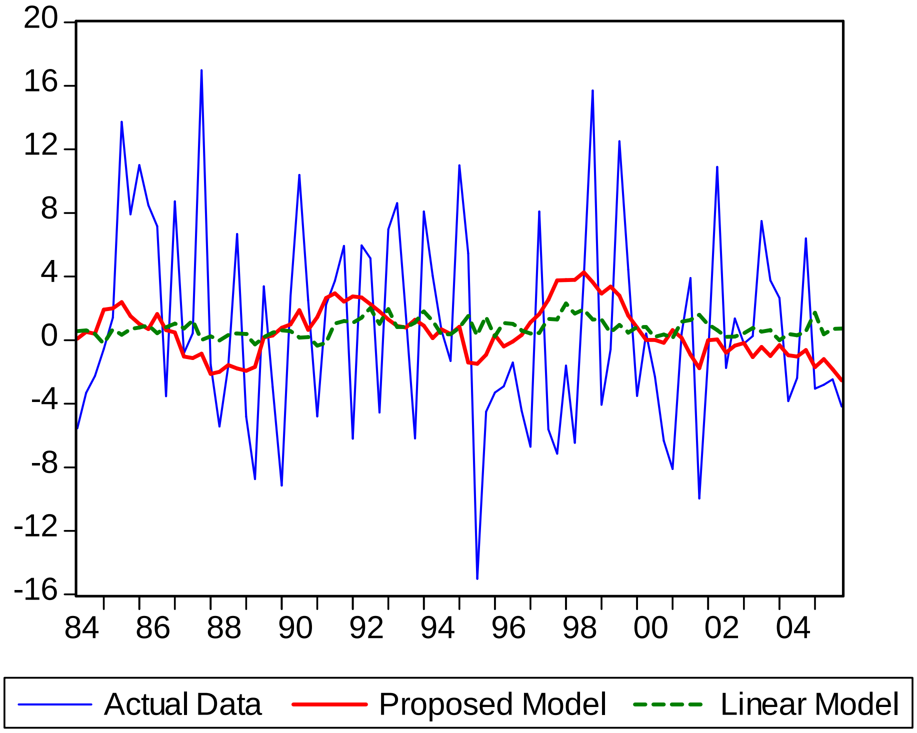
C. GERMANY



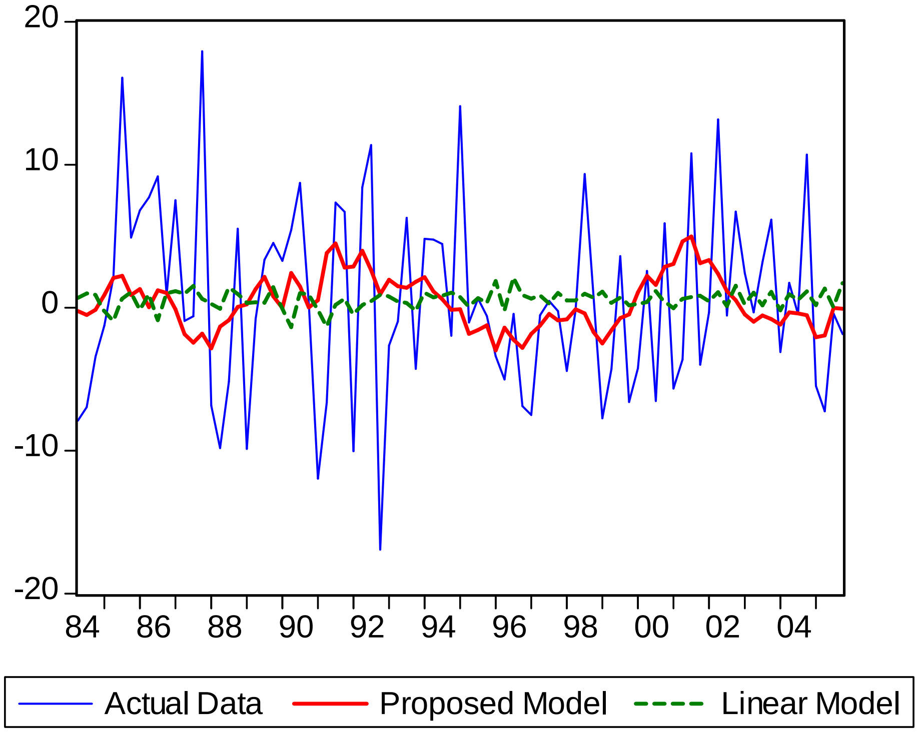
D. ITALY



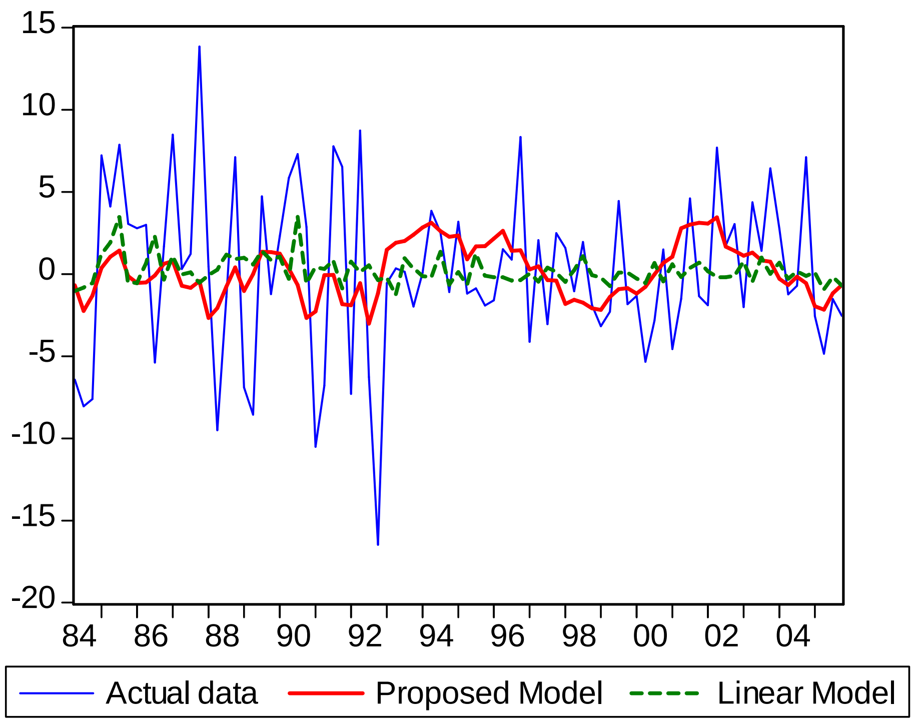
E. JAPAN



F. SWITZERLAND



G. UNITED KINGDOM



Appendix B

APPENDIX TO CHAPTER II

B.1 Figures and Tables

Table B.1: Summary Statistics

Currency	Mean	Std Deviation	Autocorrelation
I. Excess return: $s_{t+1} - f_t$			
Australia dollar	0.821	5.220	0.071
Canadian dollar	0.493	2.937	0.111
New Zealand dollar	1.631	5.504	0.150
Japanese yen	0.106	6.464	0.123
UK pound	0.841	5.016	0.119
II. Forward premium, $f_t - s_t = i_t - i_t^*$			
Australia dollar	0.718	0.711	0.909
Canadian dollar	0.224	0.417	0.818
New Zealand dollar	1.096	1.000	0.870
Japanese yen	-0.760	0.527	0.913
UK pound	0.531	0.532	0.892
III. Depreciation rates, $s_{t+1} - s_t$			
Australia dollar	-0.108	5.094	0.036
Canadian dollar	-0.269	2.884	0.099
New Zealand dollar	-0.540	5.234	0.046
Japanese yen	-0.869	6.330	0.075
UK pound	-0.322	4.927	0.091

Notes. Data are quarterly, end of the period, from the Barclay and Reuters via Datastream. The letter s and f denote the logarithms of spot and three-month forward exchange rate, respectively, measured in dollars per unit of foreign currency. Mean is the sample mean, Std Deviation the sample standard deviation, and Autocorrelation the first autocorrelation. Sample period depends on the data available in Datasteam: Australia (1986Q1-2008Q1), Canada (1990Q1-2008Q1), New Zealand (1986Q1-2008Q1), Japan (1989Q1-2008Q1), UK(1984Q1-2008Q1)

Table B.2: Comparison with Simple ARMA Model

	Australia	Canada	New Zealand	Japan	UK
			I. R^2 Values		
$R^2_{predictor}$	**0.267**	**0.139**	**0.333**	**0.147**	**0.135**
$R^2_{no\ predictor}$	0.015	0.008	0.055	0.082	0.003
			II. Persistence of the Predictable Excess Return		
$\psi_{predictor}$	**0.932*** **	**0.933*** **	**0.866*** **	**0.888*** **	**0.810*** **
	(0.038)	(0.035)	(0.035)	(0.042)	(0.055)
$\psi_{no\ predictor}$	**0.628*** **	0.490	**0.784*** **	**0.597*** **	**0.627*** **
	(0.127)	(0.589)	(0.108)	(0.261)	(0.140)

Notes. The numbers in parentheses under the means are the standard deviations of the indicated variable. Asterisks mark the significant level and 1% (***), 5% (**), and 10% (*) respectively. $R^2_{predictor}$ refers to the R^2 value obtained from the proposed model, $R^2_{no\ predictor}$ is from state-space model without economic variables, developed by Wolff (1987).

Table B.3: Estimated Results from the Proposed Model

	Australia	Canada	New Zealand	Japan	UK
γ_{π^*}	**2.295*** **	**1.414** **	**2.498*** **	**3.703*** **	0.850
	(0.981)	(0.749)	(0.749)	(1.291)	(0.844)
γ_{π}	**-3.534*** **	**-2.334*** **	-1.149	**-7.411*** **	**-3.349* **
	(1.091)	(0.829)	(0.959)	(2.821)	(0.604)
$\gamma_{\Delta y^*}$	0.370	+0.009	**1.113*** **	0.912	0.790
	(0.662)	(0.170)	(0.396)	(0.752)	(0.767)
$\gamma_{\Delta y}$	**-2.239*** **	-0.622	**-2.768*** **	**-3.582*** **	**-2.340*** **
	(0.768)	(0.448)	(0.623)	(1.093)	(1.591)

Notes. It reports the resulting coefficients of the proposed model, presented in equation (10)-(12), estimated by Maximum Likelihood and Kalman Filtering. One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at 5% level, and three asterisks indicate significance at the 1% level.

Table B.4: Correlation between Estimated Predictable Excess Return and Interest Rate Differential

	Australia	Canada	New Zealand	Japan	UK
$var(i_t - i_t^*)$	0.509	0.178	0.932	0.278	0.277
$var(\Lambda_t)$	7.208	1.183	10.051	6.095	3.364
$\text{cov}(i_t - i_t^*, \Lambda_t)$	-1.244	-0.093	-2.047	-0.691	-0.233
$corr(i_t - i_t^*, \Lambda_t)$	-0.652	-0.205	-0.669	-0.531	-0.242

Notes. $var(i_t - i_t^*)$ is unconditional variance of interest rate differential between domestic and foreign country, $var(\Lambda_{t|t})$ is unconditional variance of extracted predictable excess return from the proposed model. Last two rows report the covariance and correlation between interest rate differential and estimated predictable excess return: $\text{cov}(i_t - i_t^*, \Lambda_t)$ and $corr(i_t - i_t^*, \Lambda_t)$. These statistics show that estimated series is more volatile, and is negatively correlated with interest rate differential.

Table B.5: UIP Regression and Controlling Predictable Excess Return

UIP regression: $\Delta s_{t+1} = a_1 + a_2(i_t - i_t^*) + residuals$

Controlling omitted variable $\Delta s_{t+1} = a_1 + a_s(i_t - i_t^*) + a_3\,\Lambda_t + residuals$

	AUSTRALIA		CANADA		NEW ZEALAND		JAPAN		UK	
	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t
a_1	0.448	-0.274	-0.189	0.281	0.461	0.101	-2.819**	-1.900	0.241	0.503
	(0.748)	(0.727)	(0.341)	(0.339)	(0.798)	(0.742)	(1.111)	(1.225)	(0.705)	(0.687)
a_2	**-0.779**	**1.494***	**-0.359**	**0.234**	**-0.951***	**0.614**	**-2.557****	**-1.234**	**-1.065**	**-0.355**
	(0.744)	(0.925)	(0.720)	(0686)	(0.539)	(0.631)	(1.199)	(1.417)	(0.940)	(0.942)
a_3	**-**	**0.913*****	**-**	**1.032*****	**-**	**0.808*****	**-**	**0.517***	**-**	**0.768*****
	-	(0.245)	-	(0.263)	-	(0.200)	-	(0.302)	-	(0.273)
R^2	0.012	0.144	0.003	0.148	0.033	0.185	0.046	0.074	0.013	0.090
Adj.R^2	0.001	0.125	-0.008	0.129	0.022	0.166	0.036	0.054	0.003	0.071

Notes. The UIP regression exclude the predictable excess return Λ_t . Λ_t extracted from the proposed model is added as a proxy the Λ_t . One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at 5% level, and three asterisks indicate significance at the 1% level.

Table B.6: UIP Regression and Controlling Predictable Excess Return with Restriction: $a_3 = 1$

UIP regression: $\Delta s_{t+1} = a_1 + a_2(i_t - i_t^*) + residuals$

Controlling omitted variable $\Delta s_{t+1} = a_1 + a_s(i_t - i_t^*) + a_3\Lambda_t + residuals$

	AUSTRALIA		CANADA		NEW ZEALAND		JAPAN		UK	
	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t	UIP	With Λ_t
a_1	0.448	-0.343	-0.189	0.267	0.487	0.016	-2.819**	-1.038	0.241	0.582
	(0.748)	(0.697)	(0.341)	(0.315)	(0.795)	(0.737)	(1.111)	(1.109)	(0.705)	(0.679)
a_2	**-0.779**	**1.711****	**-0.359**	**0.213**	**-0.941***	**0.984***	**-2.557****	**0.004**	**-1.065**	**0.141**
	(0.744)	(0.692)	(0.720)	(0.665)	(0.537)	(0.498)	(1.199)	(1.196)	(0.940)	(0.906)

Notes. The UIP regression exclude the predictable excess return Λ_t . Λ_t extracted from the proposed model is added as a proxy the Λ_t . One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at 5% level, and three asterisks indicate significance at the 1% level.

Table B.7: Predictable Excess Return and Survey Data

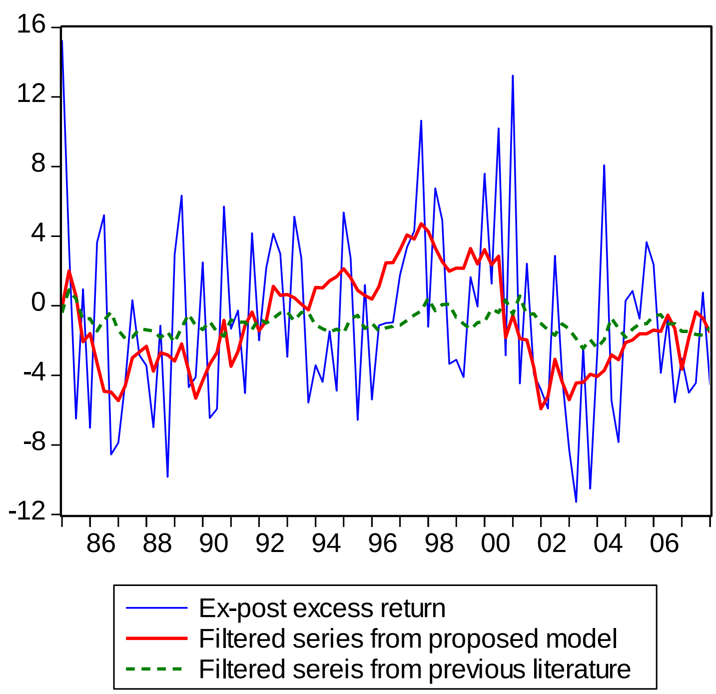
	Australia	Canada	New Zealand	Japan	UK
A. Risk premium and predictable excess return: $(E_t^m s_{t+1} - f_t) = \beta_0 + \beta_1 \lambda_t + e_{t+1}$					
β_0	-1.206	-0.530	-0.715	0.756	0.520
	(0.380)	(0.234)	(0.457)	(0.454)	(0.401)
β_1	0.113	-0.115	0.124	0.095	0.203
	(0.143)	(0.190)	(0.160)	(0.205)	(0.202)
R^2	0.009	0.005	0.009	0.003	0.014
B. Forecast error and predictable excess return: $s_{t+1} - E_t^m s_{t+1} = \beta_0 + \beta_1 \lambda_t + e_t$					
β_0	0.910	0.703	0.540	-0.396	-0.679
	(0.641)	(0.437)	(0.761)	(0.857)	(0.764)
β_1	0.793***	1.215***	0.872***	0.676*	0.426
	(0.240)	(0.355)	(0.265)	(0.387)	(0.385)
R^2	0.135	0.142	0.134	0.041	0.017
C Forecast Error and subjective expectation error: $s_{t+1} - E_t^m s_{t+1} = \beta_0 + \beta_1(\lambda_t - \rho_t) + e_{t+1} = \beta_0 + \beta_1 \eta_t + e_{t+1}$					
β_0	-0.214	0.125	-0.155	0.390	0.386
	(0.526)	(0.333)	(0.495)	(0.724)	(0.546)
β_1	0.950***	1.074***	1.147***	0.997***	1.137***
	(0.132)	(0.149)	(0.114)	(0.165)	(0.156)
R^2	0.427	0.421	0.590	0.341	0.427

Notes. $E_t^m \Delta s_{t+m}$ denote the survey-based forecast of m-month ahead exchange rate movement. The numbers in parentheses are the standard error. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

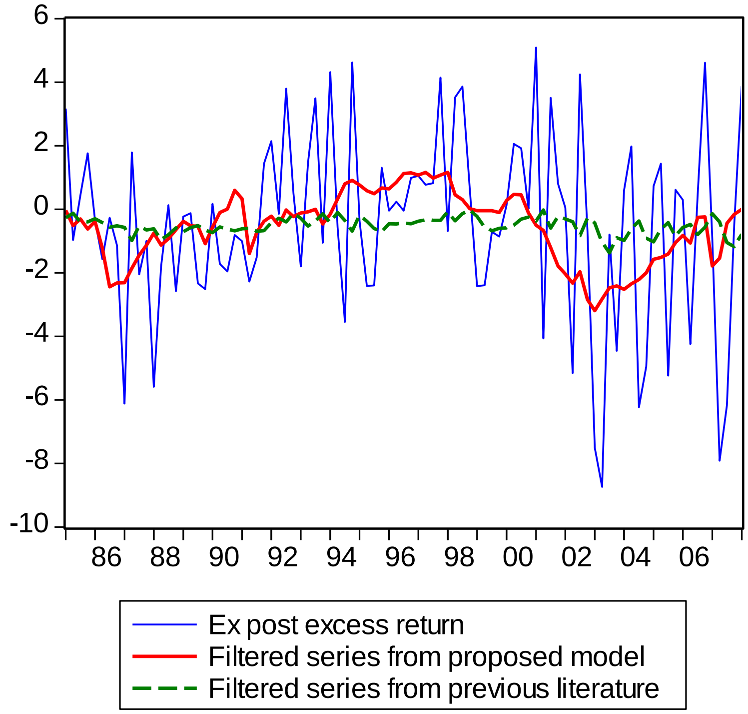
Figure B.1: Realized Excess Return and Estimated Predictable Excess Return

The graph plots the extracted predictable excess return from the proposed state space model. The graph also plots the realized currency excess return as well as the filtered series from model proposed by Wolff (1989), which does not involve macro variables in the state-space model.

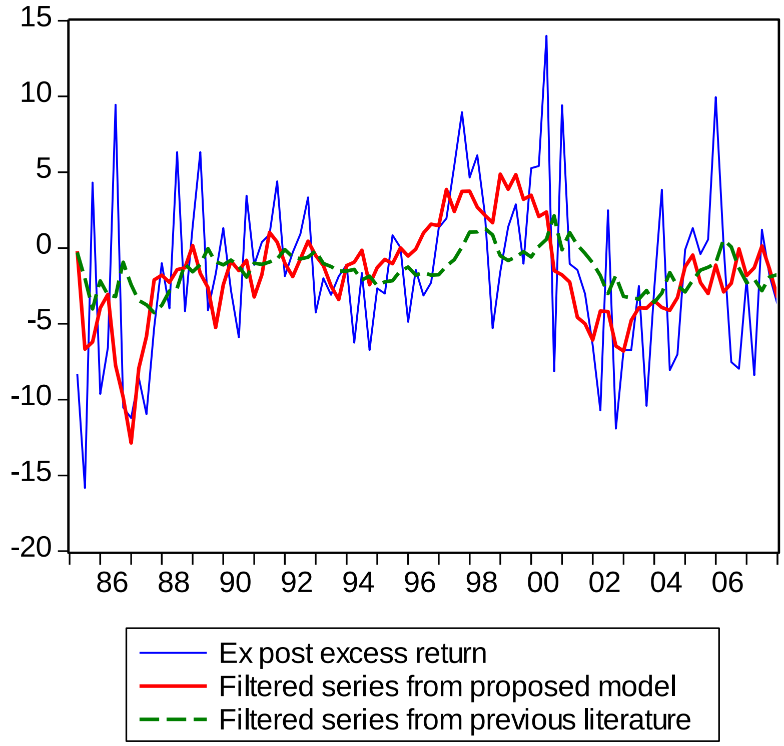
A. Australia



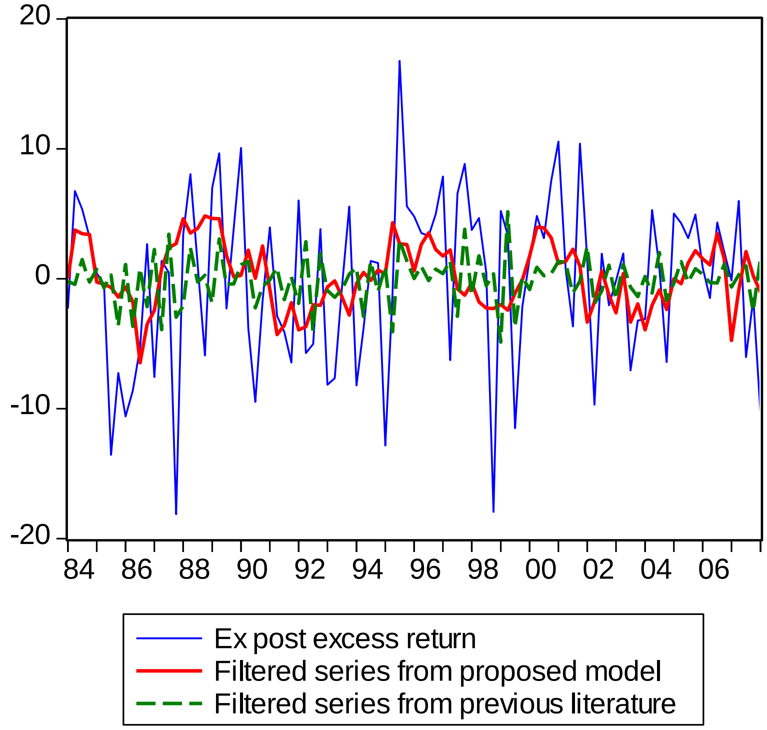
B. Canada



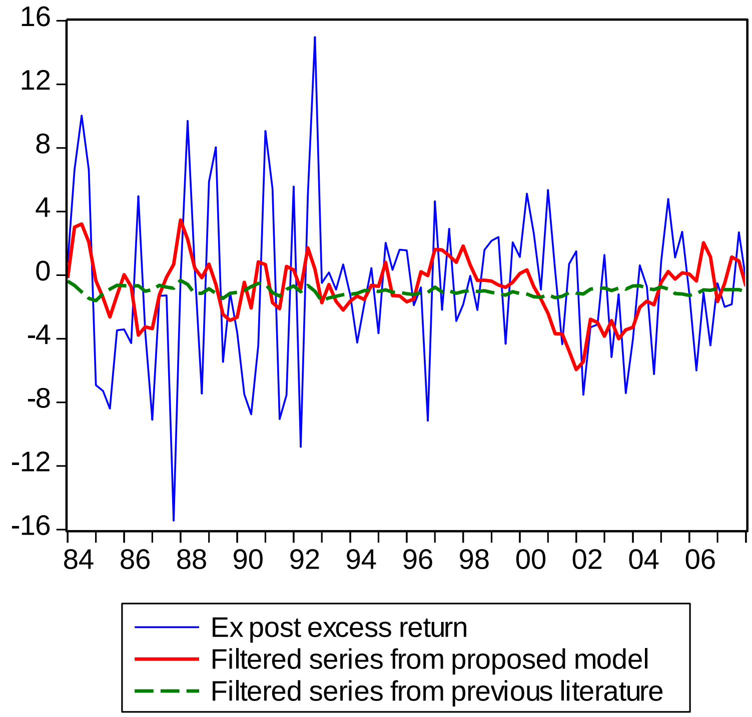
C. New Zealand



D. Japan



E. United Kingdom



Appendix C

APPENDIX TO CHAPTER III

C.1 Figures and Tables

Table C.1: Exchange Rates and Commodity Prices: Simple Regression Model

$$\Delta s_t = \beta_0 + \beta_1 \Delta cp_t + \beta_2 \Delta cp_{t-1} + \beta_3 \Delta cp_{t-2} + \beta_4 \Delta cp_{t-3} + \beta_5 \Delta cp_{t-4} + e_t$$

	Australia	Canada	New Zealand	South Africa	Chile
β_1	**-0.386*** **	**-0.169*** **	**-0.366*** **	**-0.324** **	**-0.478*** **
	(0.087)	(0.048)	(0.083)	(0.143)	(0.084)
β_2	-0.053	-0.077	-0.038	-0.101	0.269
	(0.089)	(0.049)	(0.085)	(0.150)	(0.086)
β_3 .	-0.053	0.007	0.057	0.188	-0.019
	(0.089)	(0.049)	(0.084)	(0.150)	(0.086)
β_4	0.094	0.078	0.034	-0.036	-0.081
	(0.089)	(0.049)	(0.085)	(0.150)	(0.086)
β_5	0.009	-0.018	0.036	0.017	0.061
.	(0.086)	(0.047)	(0.082)	(0.143)	(0.083)
obs	118	130	100	78	95
R^2	0.183	0.163	0.201	0.115	0.287
Prob(F-stat)	0.000	0.000	0.000	0.110	0.000

Notes. The numbers in parentheses are the standard error F-stats report Wald test of the null that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$. Asterisks indicate significance at 1% (***), 5% (**), and 10%(*) level.

Table C.2: Exchange Rates and Commodity Prices: Structural Breaks

$$\Delta s_{t+1} = \beta_0 + \beta_1 D_1 + \beta_2 \ \Delta cp_t + \ D_1 * \beta_3 \, \Delta cp_t + e_{t+1}$$

	Australia	Canada	New Zealand	South Africa	Chile
β_0	0.847	0.013	0.694	3.633	1.760
	(2.004))	(0.310)	(1.000)	(16.483)	(0.493)
β_1	-1.120	-0.102	-1.275	-0.316	-1.044
	(1.083)	(13.189)	(7.407)	(2.884)	(15.931)
β_2	-0.042	0.017	-0.050	-0.516	-0.280**
	(0.199)	(0.046)	(0.195)	(0.584)	(0.125)
β_3	-0.121	-0.206	-0.112	-0.036	0.246
	(0.081)	(0.164)	(0.290)	(0.055)	(0.508)
Obs.	117	129	105	77	94
R^2	0.045	0.081	0.052	0.093	0.135
F-stat	1.335	2.582	1.372	1.874	0.010
Prob(F-stat)	0.261	0.026	0.249	0.124	94
Sample period	1984Q1:2013Q3	1980Q1:2013Q3	1987Q1:2013Q3	1994Q1:2013Q3	1989Q3:2013Q3
Break Date	2000Q4	2005Q4	2000Q4	2001Q3	2001Q1

Notes. D1 is the break date selected by Bai and Perron (2003) test, allowing for maximum of five breaks. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_2 = \beta_3 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.3: Exchange Rates and Commodity Prices: Error Correction Model

$$(s_{t+m} - s_t) = \beta_0 + \beta_1(\mathrm{cp}_t - s_t) + e_{t+1}$$

	Australia	Canada	New Zealand	South Africa	Chile
			M=3		
β_1	0.011	0.061***	0.004	0.049*	0.020
	(0.013)	(0.021)	(0.021)	(0.023)	(0.016)
R^2	0.006	0.069	0.000	0.050	0.016
Prob(F-stat)	0.415	0.004	0.863	0.050	0.215
Obs.	118	118	106	78	95
			M=12		
β_1	0.040	0.073**	0.045	0.054**	0.010
	(0.028)	(0.029)	(0.035)	(0.023)	(0.017)
R^2	0.017	0.055	0.016	0.064	0.004
Prob(F-stat)	0.163	0.012	0.196	0.027	0.562
Obs.	115	115	103	75	92
			M=24		
β_1	0.082	0.085**	0.102**	0.050**	0.020
	(0.042)	(0.039)	(0.048)	(0.025)	(0.017)
R^2	0.034	0.041	0.044	0.056	0.014
Prob(F-stat)	3.857	0.033	0.037	0.047	0.277
Obs.	111	111	99	71	88

Notes. M is the m-month horizon. (e.g., Here, s_{t+3} is a quarter ahead exchange rate.) The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_2 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.4: Beveridge-Nelson Decomposition: Trend Component

$$\Delta s_t^{trend} = \beta_0 + \beta_1 \Delta cp_t^{trend} + \beta_2 \Delta cp_{t-1}^{trend} + \beta_3 \Delta cp_{t-2}^{trend} + e_t$$

	Australia	Canada	New Zealand	South Africa	Chile
β_1	**-0.338*** **	**-0.141*** **	**-0.365*** **	**-0.276** **	0.093
	(0.078)	(0.040)	(0.088)	(0.123)	(0.097)
β_2	-0.128	-0.088**	-0.066	-0.144	0.010
	(0.078)	(0.040)	(0.088)	(0.126)	(0.097)
β_3 .	0.099	0.015	0.128	0.158	0.029
	(0.077)	(0.040)	(0.087)	(0.127)	(0.097)
obs	115	129	103	75	93
R^2	0.17	0.123	0.167	0.104	0.011
Prob(F-stat)	0.000	0.000	0.000	0.050	0.794

Notes. Beveridge-Nelson decomposition express non-stationary time series into a random walk component and a transitory component. We assume ARIMA(2,1,0) process for both exchange rate and commodity price series, and separate cyclical component from trend component. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = \beta_2 = \beta_3 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.5: Beveridge-Nelson Decomposition: Cyclical Component

$$s_t^{cycle} = \beta_0 + \beta_1 cp_t^{cycle} + \beta_2 cp_{t-1}^{cycle} + \beta_3 cp_{t-2}^{cycle} + \beta_4 cp_{t-3}^{cycle} + \beta_5 cp_{t-4}^{cycle} + e_t$$

	Australia	Canada	New Zealand	South Africa	Chile
β_1	**-0.118*** **	**0.089** **	**-0.613*** **	-0.001	0.193
	(0.025)	(0.045)	(0.125)	(0.069)	(0.156)
β_2	**-0.109*** **	**0.201*** **	**-0.620*** **	0.086	-0.142
	(0.026)	(0.048)	(0.135)	(0.072)	(0.164)
β_3 .	**-0.045* **	**0.211*** **	**-0.355*** **	**0.159* **	-0.104
	(0.026)	(0.048)	(0.134)	(0.072)	(0.162)
β_4	-0.020	**0.140*** **	-0.183	0.031	-0.113
	(0.026)	(0.048)	(0.133)	(0.072)	(0.164)
β_5	0.007	0.012	-0.008	0.032	-0.015
.	(0.024)	(0.044)	(0.124)	(0.069)	(0.155)
obs	116	128	104	76	94
R^2	0.234	0.193	0.271	0.082	0.05
Prob(F-stat)	0.000	0.000	0.000	0.294	0.459

Notes. Beveridge-Nelson decomposition express non-stationary time series into a random walk component and a transitory component. We assume ARIMA(2,1,0) process for both exchange rate and commodity price series, and separate cyclical component from trend component. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.6: Compare R^2 values: Nonlinear Model, OLS Model and ARMA(1,1) Model

	Australia	Canada	New Zealand	South Africa	Chile
$R^2_{nonlinear}$	0.082	0.150	0.070	0.072	0.007
R^2_{OLS}	0.045	0.081	0.052	0.093	0.135
R^2_{ARMA}	0.028	0.039	0.034	0.049	0.054

Notes $R^2_{nonlinear}$ is obtained from the state-space model, equation (20) and (21). R^2_{OLS} is from OLS regression model which regress exchange rate changes on lagged commodity price changes, equation (30). R^2_{ARMA} is from ARMA (1,1) process of exchange rate changes, special case of the proposed model with no predictor.

Table C.7: Estimated Parameters in Nonlinear Model

$$\Delta s_{t+1} = \psi \Delta s_t + (\gamma - \psi\delta) v_t + \delta v_{t+1} + e_{t+1} - \theta e_t$$
$$\Delta cp_t = \phi_1 \Delta cp_{t-1} + v_t$$
$$\begin{bmatrix} e_{t+1} \\ v_{t+1} \end{bmatrix} \sim \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_e^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix} \right)$$

	Australia	Canada	New Zealand	South Africa	Chile
γ_0	**-0.182*** **	**-0.057***	-0.053	-0.014	**-0.181** **
	(0.074)	(0.037)	0.070	(0.126)	(0.086)
δ_0	**-0.283*** **	-0.045	**-0.468*** **	-0.255	-0.151
	(0.130)	(0.062)	0.133	(0.241)	(0.148)
ψ_0	0.740***	0.877***	0.893***	0.687***	0.786***
	(0.084)	(0.081)	(0.090)	(0.134)	(0.098)
γ_1	0.038	**-0.274*** **	0.085	0.073	0.287
	(0.084)	(0.092)	(0.069)	(0.129)	(0.174)
δ_1	**-0.477*** **	**-0.284*** **	**-0.336*** **	**-0.354** **	**0.262** **
	(0.112)	(0.072)	(0.109)	(0.178)	(0.109)
ψ_1	0.723***	0.337***	0.886***	0.898***	0.595***
	(0.105)	(0.125)	(0.068)	(0.079)	(0.135)
R^2	0.082	0.150	0.070	0.072	0.007
Break Date	2000Q4	2005Q4	2000Q4	2001Q3	2001Q1

Notes. We present the estimation results of the state-space model in equation (20)-(22). The model is estimate by conditional maximum likelihood. γ is a function of conditional correlation between market expectation, μ_t and commodity price changes, Δcp_t, while δ is a function of conditional correlation between exchange rate fluctuation, Δs_{t+1} and commodity price changes at time t+1, Δcp_{t+1}. Thus, γ capture the relation between lagged commodity price and exchange rate, while δ represent the contemrpoaus relation between commodity price and exchange rate. Upper panel is estimated parameters before the break point and bottom panel is after the break point. Break date is selected by Bai and Perron (2003) test, allowing for maximum of five breaks. The numbers in parentheses are the standard error. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.8: Summary Statistics and Correlations for the Survey-Expected Exchange Rates

A. Summary Statistics

	Australia			Canada			New Zealand		
	m=3	m=12	m=24	m=3	m=12	m=24	m=3	m=12	m=24
Mean	-0.569	-1.408	-1.137	-0.346	-1.076	-0.984	0.087	-0.183	-0.011
Median	-0.431	0.215	1.428	-0.275	-1.360	-0.955	0.075	-0.060	1.081
Max	5.602	8.653	13.338	3.414	4.889	9.104	6.179	12.381	16.244
Min	-6.409	-13.377	-18.721	-3.071	-5.373	-8.673	-7.444	-15.181	-23.293
SD	2.478	5.368	8.528	1.307	2.445	3.586	2.691	6.185	9.568
Skewness	-0.096	-0.453	-0.420	0.400	0.272	0.196	-0.419	-0.285	-0.338
Kurtosis	3.051	2.362	2.040	2.807	2.164	2.585	3.200	2.613	2.282

B. Correlations between the surveyed forecasts

	3m aus	12m aus	24m asu	3m can	12m can	24m can	3m nz	12m nz	24m nz
3m Australia	1.000								
12m Australia	0.787	1.000							
24m Australia	0.642	0.963	1.000						
3m Canada	0.553	0.529	0.467	1.000					
12m Canada	0.468	0.773	0.788	0.787	1.000				
24m Canada	0.397	0.759	0.825	0.628	0.888	1.000			
3m New Zealand	0.791	0.733	0.633	0.434	0.479	0.411	1.000		
12m New Zealand	0.644	0.899	0.873	0.439	0.731	0.679	0.828	1.000	
24m New Zealand	0.558	0.894	0.930	0.445	0.774	0.769	0.696	0.953	1.000

Notes Survey data is from Consensus Economic Inc., monthly over the following time periods: Australia, New Zealand(3 month, 12 month: Jan.1990-Oct.2014, 24 month: Dec.1994-Oct.2014), Canada (3 month, 12 month: Oct.1989-Oct.2014, 24 month: Dec.1994-Oct.2014). To match the frequencies, we collect the end-of-quarter exchange rate forecasts.

Table C.9: Survey-Expected Exchange Rates

	Australia	Canada	New Zealand
A. Ex post data and expectation: $\Delta s_{t+1} = \beta_0 + \beta_1 E_t^s s_{t+1} + e_t$			
β_1	-0.178	-0.223	-0.003
	(0.264)	(0.303)	(0.230)
obs	94	94	94
R^2	0.005	0.006	0.000
Prob(F-stat)	0.502	0.465	0.989
B. Expectation and commodity price: $E_t^s \Delta s_{t+1} = \alpha + \beta_1 \Delta cp_t + e_{t+1}$			
β_1	0.004	**0.060*** **	0.048
	0.039	(0.020)	(0.042)
Obs	95	95	95
R^2	0.000	0.090	0.014
Prob(F-stat)	0.926	0.003	0.257
C. Forecast Error and commodity price: $s_{t+1} - E_t^s s_{t+1} = \alpha + \beta_1 \Delta cp_t + e_{t+1}$			
β_1	-0.106	**-0.116***	**-0.224****
	(0.108)	(0.068)	(0.112)
obs	94	94	94
R^2	0.023	0.033	0.042
Prob(F-stat)	0.142	0.077	0.048

Notes. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.10: Survey-Expected Exchange Rates and Commodity Prices: Simple Regression Model

$$E_t^s \Delta s_{t+m} = \alpha + \beta_1 \Delta cp_t + e_{t+m}$$

	Australia	Canada	New Zealand
		M=3	
β_1	0.004	**0.060*** **	0.048
	0.039	(0.020)	(0.042)
obs	95	95	95
R^2	0.000	0.090	0.014
Prob(F-stat)	0.926	0.003	0.257
		M=12	
β_1	**0.160***	**0.120*** **	**0.220** **
	(0.084)	(0.039)	(0.093)
Obs	95	95	95
R^2	0.038	0.093	0.056
Prob(F-stat)	0.059	0.003	0.021
		M=24	
β_1	**0.400*** **	**0.205*** **	**0.472*** **
	(0.142)	(0.058)	(0.159)
Obs	76	76	76
R^2	0.100	0.144	0.110
Prob(F-stat)	0.006	0.001	0.004

Notes. $E_t^s \Delta s_{t+m}$ denote the survey-based forecast of m-month ahead exchange rate movement. Since market form their expectation using all the information up to time t, we use the quarterly growth rate of commodity price, Δcp_t. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.11: Survey-Expected Exchange Rates and Commodity Prices: Error Correction Model

$$E_t^s \Delta s_{t+m} = \beta_0 + \beta_1 (cp_t - s_t) + e_{t+m}$$

	Australia	Canada	New Zealand
		M=3	
β_1	**0.027*****	**0.011*****	**0.025*****
	(0.005)	(0.003)	(0.005)
obs	95	95	95
R^2	0.271	0.150	0.190
Prob(F-stat)	0.000	0.000	0.000
		M=12	
β_1	**0.086*****	**0.036*****	**0.080*****
	(0.007)	(0.005)	(0.010)
obs	95	95	95
R^2	0.585	0.376	0.394
Prob(F-stat)	0.000	0.000	0.000
		M=24	
β_1	**0.149*****	**0.055*****	**0.157*****
	(0.011)	(0.006)	(0.015)
obs	76	76	76
R^2	0.731	0.491	0.604
Prob(F-stat)	0.000	0.000	0.000

Notes. $E_t^s \Delta s_{t+m}$ denote the survey-based forecast of m-month ahead exchange rate movement. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.12: Option Implied Moments and FX Return

$$\Delta s_{t+1} = D_i * \beta_{i,0} + D_i * \beta_{i,1}(i_t - i_t^*) + D_i * \beta_{i,2} Stdev_t + D_i * \beta_{i,3} skew_t + D_i * \beta_{i,4} kurt_t + e_{t+1}$$

	Australia	Canada
β_{00}	-0.234***	-0.396***
	(0.026)	(0.029)
β_{01}	1.112***	-2.873***
	(0.438)	(0.595)
β_{02}	**1.547*** **	**7.435*** **
	(0.221)	(0.508)
β_{03} .	0.048***	-0.119***
	(0.009)	(0.008)
β_{04}	0.037***	-0.002
	(0.004)	(0.002)
β_{10}	-0.383***	0.173***
	(0.012)	(0.011)
β_{11}	1.493***	11.355***
	(0.300)	(1.070)
β_{12}	**3.795*** **	**-1.547*** **
	(0.121)	(0.116)
β_{13} .	0.384***	0.152***
	(0.012)	(0.009)
β_{14}	0.0638***	0.007***
	(0.003)	(0.002)
β_{20}	-0.020***	0.003
	(0.013)	(0.015)
β_{21}	0.637	-2.704
	(0.500)	(1.784)
β_{22}	**1.239*** **	**-1.345*** **
	(0.119)	(0.104)
β_{23}	-0.001	0.025***
	(0.016)	(0.005)
β_{24}	-0.010***	0.013***
	(0.002)	(0.003)
R^2	0.520	0.425
Prob(F-stat)	0.000	0.000
Break dates	T_1: 05/12/2008, T_2: 09/04/2009	T_1: 10/3/2006, T_2: 1/29/2009

Notes. "Stdev", "Skew", and "Kurt" are the implied standard deviation, skewness, and kurtosis of the risk-neutral distribution of exchange rate growth. Di is the break date selected by Bai and Perron (2003) test, allowing for maximum of five breaks. Estimated break date is reported in the bottom line. The numbers in parentheses are the standard error. F-stats report Wald test of the null that all the coefficients are equal to zero. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.13: Option Implied Moments and Exchange Rates

$$\Delta s_{t+1} = \beta_{i,0} + D_i * \beta_{i,1} Stdev_t + D_i * \beta_{i,2} skew_t + D_i * \beta_{i,3} kurt_t + e_{t+1}$$

	Australia	Canada
β_{00}	-0.191***	-0.325***
	(0.025)	(0.024)
β_{01}	**1.353*** **	**6.703*** **
	(0.209)	(0.434)
β_{02}	0.037***	-0.086***
	(0.007)	(0.010)
β_{03} .	0.034***	-0.008***
	(0.004)	(0.002)
β_{10}	-0.411***	0.192***
	(0.011)	(0.011)
β_{11}	0.389***	-1.528***
	(0.120)	(0.119)
β_{12}	0.392***	0.170***
	(0.012)	(0.008)
β_{13} .	0.066***	0.004***
	(0.003)	(0.001)
β_{20}	-0.023*	0.002
	(0.013)	(0.157)
β_{21}	1.198***	-1.235***
	(0.116)	(0.076)
β_{22}	-0.003	0.022***
	(0.016)	(0.005)
β_{23}	-0.011***	0.011***
	(0.002)	(0.003)
R^2	0.513	0.394
Prob(F-stat)	0.000	0.000
Break date	T_1: 05/11/2008, T_2: 09/04/2009	T_1: 4/10/2006, T_2: 1/29/2009

Notes. “Stdev”, “Skew”, and “Kurt” are the implied standard deviation, skewness, and kurtosis of the risk-neutral distribution of exchange rate growth. Di is the break date selected by Bai and Perron (2003) test, allowing for maximum of five breaks. Estimated break date is reported in the bottom line. The numbers in parentheses are the standard error. F-stats report Wald test of the null that all the coefficients are equal to zero. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.

Table C.14: Option Implied Moments and Commodity Prices

	Australia	Canada
A. $Stdve_t = \beta_0 + \beta_1 \Delta cp_t + e_t$		
β_1	**-0.001****	**-0.0008****
	(0.0004)	(0.0003)
obs	39	39
R^2	0.159	0.156
Prob(F-stat)	0.012	0.012
B. $Skew_t = \beta_0 + \beta_1 \Delta cp_t + e_t$		
β_1	0.005	-0.008
	(0.007)	(0.011)
obs	39	39
R^2	0.015	0.014
Prob(F-stat)	0.463	0.467
C. $Kurt_t = \beta_0 + \beta_1 \Delta cp_t + e_t$		
β_1	-0.014	0.006
	0.016	(0.011)
obs	39	39
R^2	0.020	0.007
Prob(F-stat)	0.391	0.618

Notes. "Stdev", "Skew", and "Kurt" are the implied standard deviation, skewness, and kurtosis of the risk-neutral distribution of exchange rate growth. The numbers in parentheses are the standard error. F-stats report Wald test of the null that $\beta_1 = 0$. Asterisks indicate significance at 1% (***), 5 (**), and 10% (*) level.