Norwegian School of Economics
Bergen, Spring Semester, 2015

Commodity Currencies and Commodity Prices

An empirical analysis of the relationship between commodity currency exchange rates and commodity prices

Baba Yara Fahiz Mohammed

Branko Mirkovic

Supervisor: Dr. Michael Kisser

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

It is a well-documented fact that changes in exchange rates are very difficult to explain using macroeconomic fundamentals such as, money supply, real income, interest rate, trade balance and bond supply. Forecasting models based on macroeconomic variables, tend to do no better than a random walk model in out-of-sample exercises. This phenomenon is known as the Meese and Rogoff puzzle. We re-examine this puzzle by employing commodity prices as an alternative variable.

We find that changes in commodity prices have power in explaining fluctuations in commodity currency exchange rates both in-sample and out-of-sample. This relationship is linear in nature and strongest at the daily frequency. The relationship is present for all four studied economies and does not weaken when the GBP is used instead of USD as a base currency. The observed relationship is also robust to using either the recursive or rolling estimation scheme.

We also find that controlling for asymmetries in changes in commodity prices does not lead to any significant improvements in the performance of the commodity driven exchange rate model. The observed relationship, however, disappears when the lagged commodity price change is used as the predictor instead of the realized change.

Preface

This thesis was written as a part of our Master of Science program at the Norwegian School of Economics (NHH), and corresponds to one semester of full-time studies.

We hope this thesis will contribute to the interesting field of international finance and that it sheds light on the relationship between commodity currencies and commodity prices.

We would like to express our sincere gratitude to our supervisor Michael Kisser for his support and invaluable advice throughout the writing process. Furthermore, we are thankful to all of the lecturers and classmates, for making our time in the Norwegian School of Economics a memorable and fruitful one.

Finally, our special thanks goes out to our beloved families, for their wholehearted support and encouragement.

Bergen, June 15th 2015

Fahiz Baba Yara Mohammed

Branko Mirkovic

Content

List of Tables

List of Figures

1 Introduction

Can exchange rates be reliably forecasted out of sample? For over three decades this has been a prominent question in international finance research for which the empirical results have been generally disappointing. Consequently, many have concluded that the exchange rate is unpredictable. The recent fall in oil prices and the corresponding depreciation of currencies like the Norwegian krone and Canadian dollar, seemingly hint at a relationship between currencies of nations that are highly dependent on commodities and changes in those commodity prices.

It is against this backdrop, that we empirically investigate the nature of this relationship by exploring how changes in oil prices affect the exchange rate of Norway. We extend this analysis by examining how changes in gold prices affect the Australian dollar and South African rand and how changes in oil prices also affect the Canadian dollar. Although, the phenomenon we investigate may extend to a wider set of countries, we focus on these four countries because they have a sufficiently long history of operating a floating exchange rate regime. This provides a market based dynamic relationship between the exchange rate and commodity prices that is not marred by policy interventions.

We examine the exchange rate – commodity price relationship by conducting both in-sample and out-of-sample exercises using daily, monthly and quarterly data. We compare four model specifications of a commodity driven exchange rate prediction model against the random walk and uncovered interest rate parity benchmark models. We check the robustness of our findings by first, using an alternative reference currency, we choose GBP instead of the USD, which helps to control for a potential dollar effect. Second, we employ both the recursive and rolling estimation schemes to control for parameter estimation bias. Third, we use three different comparison statistics to better capture the alternative dimensions of the model forecast performance.

A market based argument for the existence of the relationship we investigate is that commodity prices are forward looking and as such embody information about the future movements of commodity currency exchange rates. For a commodity exporting country, global commodity price fluctuations affect a substantial portion of her exports and thus represent major-terms-of trade shocks which affects the value of her currency (Ferraro et al., 2012).

To the best of our knowledge, this paper is one of the few studies that focuses on the role of oil prices in predicting the NOK/USD exchange rate at the daily frequency. Our study is also one of the few in the exchange rate forecasting literature that employs the direction of change statistic as a comparison statistic.

1.1 Objectives and Research Questions

The primary purpose of this paper is to study the empirical relationship between exchange rates of commodity exporting nations and commodity prices by answering the following questions:

1. What is the nature of the relationship between commodity currencies and commodity prices?
2. Can the commodity driven exchange rate model forecast changes in the exchange rate of commodity exporting nations?
3. How stable are the forecasts from the commodity driven exchange rate model?

1.2 Significance of Study

This study should be of interest to several audiences. Academics will find an up to date literature review and a useful empirical framework that will help them investigate similar questions. Practitioners will be interested to know how well this non-traditional fundamental predicts changes in the exchange rate. Policymakers, for whom successful policy decisions hinges on correctly forecasting the exchange rate, will find our conclusions particularly interesting. Finally, developing countries, which are liberalising their capital markets, will be particularly interested in knowing how commodity price shocks translate into changes in exchange rates.

1.3 Limitation of study

Our study is limited by the nature of the test we carry out to answer our questions. Even though we find evidence that supports the commodity currency – commodity price relationship, we cannot conclude that there is economic causality. Fratzscher et al. (2013) point out that the identification of causality in the shock transmission mechanism is difficult because asset prices simultaneously react to each other and to changes in other observable and unobservable factors. Furthermore, our study does not rule out a portfolio rebalancing effect as a possible explanation for the observed relationship. Increasing financialisation of commodity markets which has led to increasing correlations between commodities and other asset classes (Büyükşahin and Robe, 2014) can very well be the reason for our findings.

We do not employ panel regression techniques although recent evidence suggests the potential usefulness of this specification. Finally, we study the forecasting performance of the commodity driven exchange rate model and as such our results are not necessarily indicative of the ability of the model to explain the entirety of all exchange rate behaviours. As Cheung et al. (2005) put it, “One could view this exercise as a first pass examination of these newer exchange rate models.”

1.4 Organization of Study

Chapter two of the paper reviews the international parity conditions and introduces the canonical equilibrium models of nominal exchange rate, followed by a literature review in chapter three. Chapter four presents our motivation for considering commodity prices as a possible predictor of exchange rates. In Chapter five, we present the econometric framework we use in answering our research questions. Chapter six discusses the empirical results and chapter seven concludes.

2 Theoretical Background

We begin this chapter with a brief introduction to the concept of the exchange rate, followed by a presentation of the three main international parity conditions. Subsequently, we undertake a detailed theoretical review of the main equilibrium exchange rate models.

2.1 The Exchange Rate

The bilateral exchange rate can be classified as nominal or real. The nominal exchange rate expresses how much of one currency is required to purchase another. The convention we use in this study is the direct quotation (price quotation) that expresses one unit of the foreign currency in units of the domestic currency. The exchange rate at time t, S_t, is therefore denoted as $s\left(\frac{h}{f}\right)$ where *h* is the home currency and *f* is the foreign currency. For example, an exchange rate of 7 NOK/USD means that seven Norwegian kroners are needed to purchase one US dollar, where the US dollar is the foreign currency (numeraire). This rate is constant in a fixed exchange rate regime, but determined by demand and supply in a floating exchange rate regime. An increase in the value of the domestic currency against a foreign counterpart is referred to as an appreciation whiles a decrease is called a depreciation. In a fixed rate regime, an increase in the value of the domestic currency is called a revaluation whiles its decrease is referred to as a devaluation.

The nominal exchange rate can further be divided into forward and spot rates. The bilateral forward rate is the rate negotiated today, at which foreign exchange can be bought and sold for delivery at some time in the future. In this study our primary focus is on the bilateral spot nominal exchange rate which is defined as the rate at which foreign exchange can be bought and sold for immediate delivery, usually within a day or two (Macdonald, 2007).

The real exchange rate is the nominal exchange rate adjusted for relative prices and as such shows the purchasing power of the domestic currency relative to foreign counterpart. The real exchange rate, Q, can be expressed as:

$$Q = \frac{SP^*}{P} \tag{2.01}$$

where S denotes the nominal exchange rate, P the price level in the domestic country and P^* the price level in the foreign country. An increase in the real exchange rate of the domestic currency is therefore associated with decreasing competitiveness of goods and services produced in the local economy.

2.2 The International Parity Conditions

The interrelation between the spot exchange rate, forward exchange rate, interest rate and inflation rate in two economies gives rise to the international parity conditions. These parity conditions: purchasing power parity, interest rate parity and international Fisher effect, are the central theories on which the equilibrium models, presented in the next subsection, are built.

2.2.1 Purchasing Power Parity

Purchasing power parity (PPP) states that the same basket of goods should be priced the same in different countries when measured in a common currency (Wang, 2009). The PPP condition relates the exchange rate to the ratio of national price levels. The theory is usually divided into two distinct forms: absolute and relative.

The absolute form of PPP studies the exchange rate of two currencies in terms of the absolute prices, of the same basket of goods, in the two countries. The theory posits that a homogenous product will have the same price irrespective of where it is sold, when measured in the same base currency. If we define the nominal exchange rate as S_t and designate the foreign price level of a basket of goods as P_t^* then the price of the same basket of goods in the domestic economy, P_t, will be valued as:

$$P_t = S_t * P_t^* \tag{2.02}$$

Equation 2.02 shows the relationship between PPP and the effective exchange rate. If absolute PPP holds then the effective exchange rate (equation 2.01) should be one. This version of PPP is premised on perfect markets with no frictions such as transaction costs and barriers to trade.

The other branch of the theory, relative PPP, studies the relationship between the changes in the exchange rate and changes in the aggregate price levels in two countries. Taking log differences of the absolute PPP (equation 2.02) yields:

$$\Delta s_t \approx \Delta p_t - \Delta p_t^* = \pi_t - \pi_t^*$$

(2.03)

where $\Delta s_t = \ln(S_t) - \ln(S_{t-1})$ is the percentage change in exchange rates in the period *t-1* to t, $\pi_t = \Delta p_t = \ln(p_t) - \ln(p_{t-1})$ is the percentage change in the price levels or the inflation rate in the domestic country and π_t^* is the inflation rate in the foreign country for the same period. From the mathematical representation of relative PPP (equation 2.03), the domestic currency will depreciate if inflation in the domestic country is higher than in the foreign country.

2.2.2 Interest Rate Parity

Interest rate parity is a no-arbitrage condition representing an equilibrium state under which investors are indifferent between the interest rates on similar bonds available in two different countries (Feenstra et al., 2014). The theory relies on two central assumptions: capital mobility and perfect substitutability of domestic and foreign assets. These assumptions ensure that, given foreign exchange equilibrium, the expected return on domestic assets equal the exchange rate adjusted expected return on foreign assets. Interest rate parity theory can take two forms: covered interest rate parity (CIP) and uncovered interest rate parity (UIP).

Covered interest rate parity exists when the cost of entering into a forward contract eliminates the profits from the interest rate arbitrage. In other words, the interest rate differential must offset the forward premium, otherwise there will exist exploitable arbitrage opportunities. Covered interest rate parity can be expressed mathematically as:

$$\frac{1 + r_{t,k}}{1 + {r_{t,k}}^*} = \frac{F_{t,k}}{S_t}$$

(2.04)

where $r_{t,k}$ is the domestic interest rate on a bond that matures at time k, ${r_{t,k}}^*$ is the foreign interest rate on a bond that matures at time k, $F_{t,k}$ is the forward rate contracted now to be delivered at time k and S_t is the current spot rate. Taking the log of both sides of equation 2.04 and rewriting:

$$f_{t,k} - s_t \approx r_{t,k} - r_{t,k}{}^{*} \tag{2.05}$$

where $f_{t,k} = \ln(F_{t,k})$, $s_t = \ln(S_t)$, $r_{t,k} \approx \ln(1 + r_{t,k})$ and $r_{t,k}{}^{*} \approx \ln(1 + r_{t,k}{}^{*})$. The error in this approximation increases as the interest rates get larger and so equation 2.04 is preferred to 2.05 when interest rates are high. However, the common description of the forward premium, $P_{t,k}$, (approximate) takes the form:

$$P_{t,k} = f_{t,k} - s_t = r_{t,k} - r_{t,k}{}^{*} \tag{2.06}$$

Equation 2.06 is the mathematical representation of the statement, "…the forward premium must be equal to the two countries' interest rate differential so as to eliminate any arbitrage opportunities."

Uncovered interest rate parity (UIP) asserts that there is a relationship between the expected change in the spot rate and the interest rate differential between the two countries. If UIP holds then the forward exchange rate is an unbiased predictor of the future spot exchange rate:

$$F_{t,k} = E_t(S_{t+k}) \tag{2.07}$$

where $E_t(S_{t+k})$ is the expectation held by rational economic agents at time *t* about the next period's spot rate (S_{t+k}). Substituting equation 2.07 into 2.04, we get the uncovered interest rate parity relationship:

$$\frac{1 + r_{t,k}}{1 + r_{t,k}{}^{*}} = \frac{E_t(S_{t+k})}{S_t} \tag{2.08}$$

Taking logs and rearranging yields:

$$E_t(\Delta s_{t+k}) = E_t(s_{t+k}) - s_t \approx r_{t,k} - r_{t,k}^{*} \tag{2.09}$$

where $r_{t,k} \approx \ln(1 + r_{t,k})$ and $r_{t,k}{}^{*} \approx \ln(1 + r_{t,k}{}^{*})$. This approximation is close to an equality when the interest rates are small, but the error increases as the interest rates increase. Equation 2.09 shows the commonly stated UIP relationship, which posits that the expected change in the spot exchange rate is equal to the interest rate differential between the two countries.

2.2.3 International Fisher Effect

The Fisher effect is concerned with the relationship between the real interest rate, the nominal interest rate and inflation rate in a domestic economy. If we denote the real interest rate as i, the nominal interest rate as r, and the expected inflation between $t+1$ and t as $E(\pi)$ then:

$$1 + r = (1 + i) * [1 + E(\pi)] \tag{2.10}$$

If we set $i * E(\pi)$ to zero and subtract one from both sides then 2.10 is approximately equal to:

$$r \approx i + E(\pi) \tag{2.11}$$

Equation 2.11 is the mathematical expression of the Fisher effect, which states that the nominal interest rate is the sum of the real interest rate and inflation expectations. When the interest rate and inflation expectation is low, the approximation error is negligible.

Extending this relationship to two countries leads to the International Fisher Effect (IFE). It involves combining the Fisher effect of the two countries with exchange rate expectations and PPP, assuming real interest rates are equalised across countries. We derive this parity condition by first assuming that the Fisher effect (2.11) holds in both the domestic and foreign country. Expressing relative PPP (2.03) in-terms of expectations gives:

$$E(\Delta s_t) \approx E(\pi_t) - E(\pi_t^*) \tag{2.12}$$

and substituting expression 2.11 into 2.12, while equalising real interest rate across countries $(i - i^*)$ yields:

$$E(\Delta s_t) \approx r - r^*$$
(2.13)

From 2.13, IFE suggests that the expected change in exchange rates is equal to the interest rate differential between the two countries. This statement is the same as UIP, but derived under slightly different assumptions.

The interrelation between these international parity conditions in equilibrium leads to the different models of exchange rate determination presented below.

2.3 Equilibrium Models of Nominal Exchange Rate

Before the dominance of the modern asset market theory of exchange rate determination, the traditional flow view was the norm. The traditional flow theory views exchange rates as adjusting to equilibrate international trade in goods, while the modern asset theory views exchange rates as adjusting to equilibrate international trade in financial assets (Husted and Melvin, 2012). In the wake of the collapse of the Bretton Woods system, the two major strands of the modern asset market theory have dominated the literature: the monetary and portfolio balance approaches. Both approaches focus on stocks of outside assets — money in the former and both money and bonds in the latter.

Although, both the monetary and portfolio approaches focus on stock of assets, they differ in their views of the substitutability of capital. In the former class of models, bonds are assumed to be perfect substitutes, whiles in the latter they are assumed to be imperfect substitutes. In practice, the difference amounts to whether uncovered interest rate parity (UIP) holds, or whether the forward rate differs from the expected future spot rate by an exchange rate risk premium. The monetary approach can be split into two types based on whether one assumes instantaneous (flexible) or gradual (sticky) price reaction.

2.3.1 The Monetary Exchange Rate Models

The monetary approach is one of the oldest theories of exchange rate determination. It views the exchange rate as the relative price of two currencies, monies or assets rather than two commodities (Macdonald, 2007). There are two variants of the monetary model based on whether we assume PPP holds continuously (both in the long and short run), or only in the long run. When the former assumption is made, the resulting model is the flexible price model (Bilson (1981), Frenkel (1976)), when the latter assumption is made, the resulting model is the sticky price model (Dornbusch (1976), Frankel (1979)).

The Flexible Price Monetary Model

The main assumptions of this model are that PPP holds continuously and the International Fisher Effect (IFE) holds, hence UIP also holds. As the name suggests, the model also assumes that prices are fully flexible (instantaneous adjustment). The model further assumes that money supply and real income are exogenously determined. The formal derivation of the model is as follows. Assume absolute PPP in logs:

$$s_t = p_t - p_t^* \tag{2.14}$$

where s_t is the log of the nominal exchange rate, expressed in units of the home currency per foreign currency, p_t is the log of the general price level and * is the foreign economy designator. Demand for money is defined as the desire to hold financial assets in the form of money (cash and bond deposits) and it is a function of real income, the interest rate and the price level. The velocity of money is defined as the ratio of the demand for money to the general price level and it is directly proportional to the level of real income and inversely proportional to the level of interest rate (Wang, 2009). This relationship can be summarised as:

$$\frac{M_t^D}{P_t} = \frac{Y_t^{\varphi}}{(1 + r_t)^{\lambda}} \tag{2.15}$$

where M_t^D represents the demand for money, Y_t real income, r_t nominal interest rate, P_t the general price level, φ the income elasticity of money demand and λ represent the interest rate semi-elasticity of money demand. Taking the logarithm of equation (2.15) yields the (approximate) conventional money demand equation:

$$m_t^d - p_t = \varphi y_t - \lambda r_t \tag{2.16}$$

where $ln(1 + r_t) \approx r_t$. If we assume that the money demand parameters (φ, λ) are the same across the two countries and that the money market is in equilibrium, money demand equals money supply, then equation 2.16 can be rewritten in terms of relative general price levels between the domestic and foreign country:

$$p_t - p_t^* = (m_t - m_t^*) - \varphi(y_t - y_t^*) + \lambda(r_t - r_t^*) \tag{2.17}$$

Substituting equation 2.17 into equation 2.14, we arrive at the baseline monetary equation:

$$s_t = (m_t - m_t^*) - \varphi(y_t - y_t^*) + \lambda(r_t - r_t^*) \tag{2.18}$$

Equation 2.18 states that the nominal exchange rate, ceteris paribus, is driven by the money supply, real income and interest rate differentials. The expression has three distinct implications. The first is that an increase in relative money supply leads to an increase in the exchange rate which translates into a depreciation of the domestic currency. Second, an increase in relative income induces a domestic currency appreciation. Finally, an increase in relative interest rates leads to a domestic currency depreciation.

Additional insights into the mechanisms underlining the monetarist approach can be obtained by noting that UIP implies that a higher domestic interest rate leads to a weaker currency in the future (Wang, 2009). If UIP holds then:

$$E_t(s_{t+1}) - s_t \equiv E_t(\Delta s_{t+1}) = r_t - r_t^* \tag{2.19}$$

where $E_t(s_{t+1})$ is the expected exchange rate one period from t and $E_t(\Delta s_{t+1})$ is the expected change in exchange rate between t and $t+1$. From expression 2.19, the expected change in the exchange rate, $E_t(\Delta s_{t+1})$ is equal to the interest rate differential in the baseline equation (2.18). Substituting 2.19 into 2.18, we arrive at:

$$s_t = (m_t - m_t^*) - \varphi(y_t - y_t^*) + \lambda(E_t s_{t+1} - s_t) \tag{2.20}$$

By bringing all s_t terms to the right hand side of the equation:

$$s_t = \frac{(m_t - m_t^*) - \varphi(y_t - y_t^*)}{1 + \lambda} + \left(\frac{\lambda}{1 + \lambda}\right)(E_t s_{t+1}) \tag{2.21}$$

and defining the fundamentals as:

$$F_t \equiv (m_t - m_t^*) - \varphi(y_t - y_t^*) \tag{2.22}$$

we can observe that the foreign exchange rate is determined by two terms, that is the traditional fundamentals (F_t) and the future exchange rate expectations, $E_t(s_{t+1})$. Which leads to the expression:

$$s_t = \left(\frac{1}{1+\lambda}\right) F_t + \left(\frac{\lambda}{1+\lambda}\right) E_t(s_{t+1}) \tag{2.23}$$

Imposing rational expectations, the next period exchange rate can be expressed as:

$$E_t(s_{t+1}) = \left(\frac{1}{1+\lambda}\right) E_t(F_{t+1}) + \left(\frac{\lambda}{1+\lambda}\right) E_{t+1}(s_{t+2}) \tag{2.24}$$

Substituting 2.24 into 2.23 and iterating forward, $E_{t+T}(s_{t+T+1})$ approaches zero, as $T \to \infty$, since $\left(\frac{\lambda}{1+\lambda}\right)$ is assumed to be less than one. Repeated substitution of the expected future spot rate leads to expression (2.25) which relates the current spot rate to the current and future discounted expected fundamentals ($F_{t+\tau}$). The current spot exchange rate is therefore the present value of the future stream of fundamentals, where the discount rate is a function of the interest rate semi-elasticity of money demand:

$$s_t = \sum_{\tau=0}^{T} \frac{\lambda^{\tau}}{(1+\lambda)^{\tau+1}} E_{t+\tau-1}(F_{t+\tau}) \tag{2.25}$$

Expression 2.25 shows that what matters in pricing the current spot rate is not the actual realizations of the future fundamentals, but the markets present expectation of the future fundamentals. Hence, as people’s expectation of these future fundamentals change, the exchange rate changes in line.

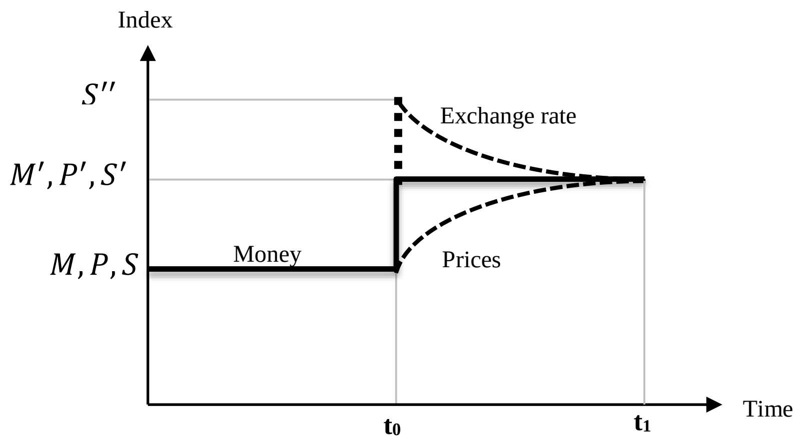
The Sticky Price Monetary Model

The assumptions of the sticky price model are slightly different from the flexible price monetary model. Whereas the supply curve is assumed to instantaneously respond to demand shocks in the flexible price model, the sticky price model allows for short-run price stickiness. In the short-run, increases in output stem from shifts in aggregate demand. In the medium term, the model allows increases in output to come from shifts in both aggregate demand and/or aggregate supply. Finally, in the long-run, only a shift in aggregate supply changes output. The model further assumes that agents are rational with perfect foresight and that uncovered interest rate parity holds. The sticky price model we discuss here is the real interest rate differential model of Frankel (1979) which resolves the apparent conflict between the flexible price monetary model and the Dornbusch sticky price model. We begin the derivation by considering a sticky price version of the monetary model (2.18) where all parity conditions hold in the long run:

$$s_t = \bar{p}_t - \bar{p}_t^* = (\bar{m}_t - \bar{m}_t^*) - \varphi(\bar{y}_t - \bar{y}_t^*) + \lambda(\bar{\pi}_t - \bar{\pi}_t^*) \tag{2.26}$$

where the bars denote the long-run values of the respective fundamentals. Since we assume the IFE holds in the long-run, the secular inflation rates replaces the long-run interest rates. Figure 1 illustrates how prices and exchange rates respond to changes in fundamental variables in the sticky price monetary framework. Assuming that the economy is in a long-run equilibrium (M, P, S), an increase in the money supply differential at time t_0 $(M' - M)$ will lead to an instant increase in the exchange rate $(S'' - S)$. This short run deviation (overshooting) of the exchange rate will be corrected by a slow convergence to the new long run equilibrium rate (S'). This reversion mechanism happens at a rate, θ. Prices will not react instantly, but follow a gradual trajectory from (P) to the new long-run value (P').

Figure 1: Exchange rate overshooting



Assuming rational expectations, this convergence mechanism will follow the process:

$$E_t(s_{t+1}) - s_t = -\theta(s_t - \bar{s}_t) + (\pi_t^e - \pi_t^{e*}) \tag{2.27}$$

where π_t^e is the inflation expectation in the domestic economy, π_t^{e*} is the inflation expectation in the foreign economy, s_t is the short-run exchange rate and $\bar{s}_t$ is the long-run exchange rate. This expression means that in the long-run equilibrium, when the actual exchange rate is at equilibrium, that is $s_t = \bar{s}_t$, the exchange rate is expected to change by an amount equal to the long-run inflation differential $(\pi_t^e - \pi_t^{e*})$. Since UIP holds, expression 2.27 can be rewritten as:

$$s_t = \bar{s}_t - \frac{1}{\theta}[(r_t - r_t^*) - (\pi_t^e - \pi_t^{e*})] \tag{2.28}$$

where $E_t(s_{t+1}) - s_t = (r_t - r_t^*)$. From 2.28, the short-run exchange rate (s_t) may be above or below the long-run equilibrium level $(\bar{s}_t)$ depending on the real interest rate differential $[(r_t - \pi_t^e) - (r_t^* - \pi_t^{e*})]$. Assuming that the long term money supply and real income differentials are determined by current actual values and $\bar{\pi}_t - \bar{\pi}_t^* = \pi_t^e - \pi_t^{e*}$, the long-run exchange rate (2.26) is:

$$\bar{s}_t = (m_t - m_t^*) - \varphi(y_t - y_t^*) + \lambda(\pi_t^e - \pi_t^{e*}) \tag{2.29}$$

Substituting 2.29 into 2.28 and rearranging yields:

$$s_t = (m_t - m_t^*) - \varphi(y_t - y_t^*) - \frac{1}{\theta}(r_t - r_t^*) + (\lambda + \frac{1}{\theta})(\pi_t^e - \pi_t^{e*}) \tag{2.30}$$

Which can be rewritten as:

$$s_t = (m_t - m_t^*) - \varphi(y_t - y_t^*) - \frac{1}{\theta}(i_t - i_t^*) + \lambda(\pi_t^e - \pi_t^{e*}) \tag{2.31}$$

where the real interest rate, i_t, is the nominal exchange rate adjusted for inflation ($i_t \equiv r_t - \pi_t^e$).

The current exchange rate (2.31) in this model is positively related to the money supply and expected inflation differentials, and negatively related to the real income and real interest rate differentials. Since, the short run inflation differentials can differ from interest rate differentials, the real interest rate sticky price model can lead to deductions that are different from the flexible monetary model.

Equation 2.32 to some extent subsumes a number of monetary models. When $\frac{1}{\theta} > 0$ and $\lambda > 0$, we are in the full real interest rate differential environment. Imposing $\frac{1}{\theta} < 0$ and $\lambda = 0$ or $\frac{1}{\theta} = 0$ and $\lambda < 0$, leads to the standard flexible price model. Restricting $\frac{1}{\theta} > 0$ and $\lambda = 0$ produces the Dornbusch sticky price model.

2.3.2 The Portfolio Balance Model

The monetary approach to exchange rate determination assumes that UIP holds and also investors are indifferent between bonds originating in either the foreign or domestic country as long as they pay the same return. This means that assets are perfectly substitutable in the monetarist framework. The portfolio balance model relaxes the perfect substitutability of assets assumption. In this environment, the returns on bonds when expressed in a common currency, may differ because of risk premium. The model also relaxes the imposition of purchasing power parity in both the short and long run because of the imperfect substitutability assumption. The derivation of the portfolio balance approach shown here is based on the work of Frankel (1984) and Dooley and Isard (1982).

We begin by assuming perfect capital mobility where covered interest parity holds, but perfect capital substitutability does not hold. We further assume that all market participants have the same portfolio preferences (β). Consequently, investors view domestic and foreign bonds as imperfect substitutes in that they differ in their currency denominations. In order to diversify the risk that comes from exchange rate variability, investors will balance their bond portfolios based on the expected relative rate of return. Thus, the risk premium (γ_t) may be expressed as a function of the relative supplies of bonds:

$$\frac{B_t}{S_t {B_t}^*} \frac{1}{\beta} = \gamma_t \tag{2.32}$$

where B_t and $B_t{}^*$ are net supplies of domestic and foreign bonds denominated in their respective currencies. When uncovered interest rate parity holds the expected change in the exchange rate equals the interest rate differential:

$$E_t(\Delta s_{t+1}) + \gamma_t = r_t - r_t^* \tag{2.33}$$

where, $\gamma_t = 0$. Deviations from UIP will imply that the risk premium is different from zero. Re-writing equation 2.33 to account for the risk premium:

$$\gamma_t = r_t - r_t^* - E_t(\Delta s_{t+1}) \tag{2.34}$$

and substituting 2.34 into 2.32 yields:

$$\frac{B_t}{S_t B_t{}^*} = \beta(r_t - r_t^* - E_t(\Delta s_{t+1})) \tag{2.35}$$

This expression shows that the holdings of domestic bonds, relative to foreign currency denominated bonds, are directly proportional to the exchange rate risk premium. An increase in the interest rate differential or a decrease in the expected change in the exchange rate will induce local investors to rebalance their portfolio holdings in favour of domestic bonds.

If we assume the functional form for relative bond demand is linear in β, after taking logs, equation 2.35 can be rewritten as:

$$s_t = \beta_0 + \beta_1\big(r_t - r_t^* - E_t(\Delta s_{t+1})\big) + b_t - b_t^* \tag{2.36}$$

The difficulty in implementing this expression is that expected change in exchange rate is not easily observable. If we assume expected change in the exchange rate is zero, we obtain an empirically testable model that is consistent with a near random walk (Chinn, 2012). The resulting expression is:

$$s_t = \beta_0 + \beta_1(r_t - r_t^*) + b_t - b_t^* \tag{2.37}$$

where increases in the stock of foreign assets held by domestic investors (b_t^*) leads to an exchange rate fall. On the other hand, an increase in the stock of domestic assets held by domestic investors leads to an exchange rate increase. If the domestic country is small, such that residents wish to hold domestically denominated assets, then one can match capital inflows with increases in the supply of foreign assets in the domestic market. If the domestic country is large relative to the foreign one, then one might want to make the opposite assumption. Since neither of these fits the typical large country, hence one usually needs to specify a separate asset-demand function for each of the two countries.

3 Empirical Evidence

In this chapter we start with a literature review of the previously presented equilibrium models. Because of the conclusions reached from the empirical review of the equilibrium models, we further examine the studies that have investigated the empirical validity of the international parity conditions. We conclude the chapter by summarizing our thoughts on the empirical evidence presented.

3.1 Review of Empirical Studies of Equilibrium Models

Although the equilibrium models, presented in the previous chapter, constitute quite a contrasting set of approaches, they can all be subsumed into the general expression:

$$s = f(\hat{m}, \hat{y}, \hat{r}, \hat{\pi}, \hat{\imath}, \omega, b, b^*) \tag{3.01}$$

where the $\hat{m}$ is the money supply differential, $\hat{y}$ is the real income differential, $\hat{r}$ is the interest rate differential, $\hat{\pi}$ is the inflation differential, $\hat{\imath}$ is the real interest rate differential, ω is the inter-country differential of tradable to non-tradable goods, b and $b^*$are domestic and foreign bond supply respectively. Researchers test for the empirically validity of the discussed models by including and dropping different sets of regressors. A long-standing puzzle in international finance, as pointed out by Engel and West (2005), is the near impossible task of tying floating exchange rates to these macroeconomic fundamentals.

We review these empirical studies chronologically which also aligns with the increasing sophistication of econometric techniques employed by researchers with the passage of time. First, we look at the early empirical studies of the monetary models from the 1970s and 1980s. A lot of the papers in this period used simple regressions disregarding the non-stationary nature of the variables and as such their findings were mostly abysmal and contrary to what theory predicted. In the 1990s, researchers turned to the co-integration technique developed in the late 1980s to handle non-stationary data. Initial applications of this methodology were positive and the results brought back some optimism to this area of research. This is the second class of studies we focus on. The third set of studies employ the panel cointegration technique, which have also proven to have strong out-of-sample predictive ability. We then turn the discussion to the set of studies that follow the Taylor-rule fundamental approach in deriving testable models. This set of studies have the highest level of success, in this literature, at predicting exchange rate at short horizons (one month). Finally, we survey the studies that have studied the special relationship between commodity currencies and commodity prices and end with a summary of the prevailing facts.

The early post Bretton Woods period saw the emergence of a number of empirical studies finding evidence in support of the classical asset market models of exchange rate. Bilson (1978) finds evidence that the flexible price monetary model is broadly consistent with DEM/GBP exchange rate from April 1970 to May 1977 and Frankel (1979), finds evidence for the sticky price model using the DEM/USD exchange rate with data from 1974 and 1978. Branson et al. (1979), extending their previous work Branson et al. (1977), find that the portfolio approach to exchange rate determination is consistent with the USD/DEM exchange rate using data from 1971 to 1978. For the JPY, FRF, ITL, CHF and GBP relative to the USD, using data from 1971 to 1976, they find estimates that are consistent with the priors from the theoretical model.

The early 1980s saw a wind of pessimism blow among economists as the discouraging results from empirical tests of existing models began to emerge. Using newer datasets, findings from Dornbusch et al. (1980), Haynes and Stone (1981) and Frankel (1983), cast serious doubts on the ability of the monetary reduced form models to track the exchange rate in-sample. To guard against the problem of over-fitting, suffered by the initial studies, researchers turned to out-of-sample tests. Among the first of these studies is the seminal works of Meese and Rogoff (1983b, 1983a). They test the out-of-sample forecasting properties of the flexible price, sticky price, the forward rate, a univariate ARIMA and a VAR model against the random walk model. Their sample consists of USD/DEM, USD/JPY and the trade weighted dollar exchange rate from 1973 to 1980. They estimate the models over a certain period, forecast one period out of sample using the realized values of the exogenous variables, then roll the regression sample up a period. This technique allowed them to account for parameter variation over the study period. Meese and Rogoff (1983b) reach the surprising conclusion that the random walk performs no worse than any of the structural models according to any of the comparison metrics. The findings of Meese and Rogoff were significant because they deliberately gave the fundamental models an unfair advantage by using actual realized data. Since the publication of the works of Meese and Rogoff, the power of an exchange rate model has been judged by how well it does against a random walk model. The random walk test has become the equivalent of the R^2 metric by which any other proposed exchange rate forecasting model is benchmarked (Macdonald, 2007). Subsequent studies tried to overturn these results, but many of the promising findings turned out to be fragile and the literature remained pessimistic about the link between exchange rates and monetary fundamentals.

The methodology employed in the exchange-rate forecasts research changed with the development of the cointegration technique. The initial popularity of the technique stems from its ability to address the potential non-stationarity of the variables used in exchange rate studies. This is essential because running regressions on non-stationary data tends to produce spurious results in the form of high R^2. In one of the earliest studies motivated by cointegration, Mark (1995) replicates the work of Meese and Rogoff and finds significant improvements in forecasts in the long run. He uses a calibrated flexible price monetary error correction model to perform out-of-sample predictions on the USD/DEM. Chinn and Meese (1995) examine a broader number of models including the flexible price, the Hooper-Merton and augmented monetary models. By imposing the cointegrating vector in an error correction framework, they also find that some of the fundamental models can outperform the random walk model over a long horizon (two to three years).

The intuition from these early studies is that the amount of news that moves exchange rates, month to month, are largely not captured in typical macroeconomic variables such as money stocks, interest rates and inflation rates. Most likely this type of news dominates at high frequencies, but is less likely to play a major role at longer horizons (Chinn, 2012). Moreover, the random walk model is a naive model that yields a no-change forecast hence, as the prediction horizon increases its forecast is more and more likely to be wrong.

Nonetheless, the results from these studies did not conclude the debate. Faust et al. (2003) show that the long horizon results are specific to the particular time period examined, especially in the case of Mark (1995). They also make the surprising finding that using real-time data that market agents had available, instead of revised numbers, increases the predictive power of exchange rate models. They conclude that data revisions, more often than not, turn out to be a hindrance rather than a help to fundamental models in forecasting. Cheung et al. (2005) study a larger set of models including the interest rate parity, productivity based models and behavioural equilibrium exchange rate models and take into account the possibility of no cointegration. They use the purchasing power parity and Dornbush-Frankel sticky price monetary models as their benchmark. They find limited evidence of improved forecasting ability at longer horizons, relative to shorter durations. Instead of estimating the cointegrating vector over the entire sample and treating it as part of the ex-ante information set, as commonly done in literature, they recursively update the cointegrating vector, thereby generating true ex ante forecasts. They analyse the results using the mean squared error, direction of change and the consistency test. Cheung et al. find that no model consistently outperforms a random walk by a mean squared error measure. Focusing on the direction of change measure, they find statistically significant evidence that some structural models do outperform the random walk. Overall, the authors find that models with different currency specifications that work well in one period does not generally work well in another period.

Very recent work focuses on using panel cointegration tests to take advantage of information across currencies. Mark and Sul (2001) use a panel of 17 bilateral exchange rates for OECD countries to implement a panel version of Mark's (1995) study. After rejecting the null hypothesis of no cointegration for the exchange rate and the monetary fundamentals, they use the estimated cointegrating vector to conduct long-horizon regressions. Monetary fundamentals outperform the random walk model at both short and long horizons over the period 1973-97. The out-performance is not statistically significant when the JPY is used as the numeraire instead of the USD. The main critique levelled against studies that employ the panel cointegration methodology is that the country samples tend to suffer from significant cross-sectional dependence. Cerra and Saxena (2010) blame this shortcoming on the fact that the panel datasets employed in previous research contain countries linked through the European Monetary System (EMS). Using data from 98 countries, to overcome this limitation, Cerra and Saxena (2010) find that fundamental-based models still outperform random walk models in out-of-sample predictions using the panel cointegration framework.

One major development in the use of macroeconomic-based models for predicting exchange rates involves the incorporation of monetary policy reaction functions (Taylor-rule) into standard exchange-rate models. Taylor (1993) formalizes the idea that the monetary authority sets the real interest rate as a function of how inflation differs from its target level and as a function of the output gap. When inflation is high, a contractionary monetary policy will be pursued by monetary authorities, while a very low inflation or deflation, will see monetary authorities pursue an expansionary policy. If output is below potential, monetary policy will be more expansionary and vice versa. Essentially, incorporating Taylor-rule fundamentals involves bringing output and inflation gaps into the determination of exchange rates. Molodtsova et al. (2008, 2011) and Molodtsova and Papell (2009) investigate the out-of-sample forecasting properties of Taylor-rule based fundamentals. They find that incorporating Taylor-rule variables improves out-of-sample forecasting at short horizons (one month), but the performance is highly dependent on the reaction function specifications. Combining monetary fundamentals and policy with yield curve factors, Chen and Tsang (2013) find that Taylor rule based fundamental models outperform the random walk. Giacomini and Rossi (2010) and Rossi and Inoue (2012) also find strong empirical evidence in favour of Taylor-rule fundamentals. However, Rogoff and Stavrakeva (2008) find that the empirical evidence in favour of Taylor-rule fundamentals is not robust to the choice of forecast window and out-of-sample forecast period variations. Some researchers also argue that Taylor-rule has been a good description of monetary policy in the past three decades, but as monetary policy changes in response to the 2008 financial crisis and the recent Euro debt crisis, these successful reaction functions may breakdown (Rossi, 2013).

Our study is located in the class of exchange rate literature that links commodity prices to exchange rates of commodity dependent economies. The motivation for such studies is the generally poor performance of traditional fundamentals and the allowance made by the forward looking expression 2.25.

One of the first papers to look at this relationship is Amano and Van Norden (1998). The authors use the cointegration framework and find a robust relationship between the oil price and the currencies of Germany, Japan and the United States. Akram (2004) explores the non-linear relationship between oil prices and NOK/USD exchange rate and finds that when there is a substantial change in the oil price, the exchange rate reacts sharply. This observation however weakens when the movement of the oil price is restricted within a normal range. Benhmad (2012) investigates the oil price and the US dollar exchange rate using the Wavelet approach. The wavelet approach involves splitting the dataset into smaller subsamples. The time series in the subsamples are then transformed from the time to frequency domain. This enables the researcher to gain more insights into the frequency components of the time series being studied. Benhmad finds evidence of a long-term relationship between the oil price and the US dollar exchange rate, but points out that there is only a one-way granger causality relationship from the oil price to the US dollar exchange rate over the short term.

Other researchers have extended the studies on the exchange rate and commodity currency relationship by using linear models. Chen et al. (2010) find that exchange rates of commodity exporting countries predict commodity price movements both in-sample and out-of-sample. Chen et al. however note that the reverse relationship, the out-of-sample predictive ability of the commodity price to predict nominal exchange rates, is weak. They employ a commodity price index, which is a weighting of several commodities for each nation. Issa et al. (2008) and Cayen et al. (2010) also consider the in-sample relationship between real oil prices and the real exchange rate and find similar results. Ferraro et al. (2015) study the CAD/USD and oil price relationship and find that commodity prices can predict daily exchange rates. The predictive power of the model they test diminishes, as they move to longer horizons. Their finding is therefore in line with the conclusions of Chen et al. (2010).

From this literature review, we are able to draw the following conclusions. First, a vast number of model specifications have been considered in the literature and the least successful at tying fundamentals to exchange rates have been the non-linear models. The most successful linear specifications have been the single-equation Error Correction Models (ECM) such as Mark (1995) and the panel ECM models such as Groen (2005) and Engel et al. (2007). These models have proven most successful at long horizons. However, this view is not held by all researchers as some have questioned the robustness of the studies. One important critique is that the positive evidence in favour of the ECM models are observed only when the cointegrating vector is calibrated and not estimated.

Second, the consensus in the literature is that Taylor-rule fundamentals have proven to be the most successful predictors (regressors) compared to traditional fundamentals (interest rate, inflation, output and money differential). Third, the class of studies that use commodity prices as macro-fundamentals have also shown some success in out-preforming the random walk benchmark although these results are mostly limited to commodity currencies. Fourth, the empirical evidence in favour of the traditional fundamentals continues to be poor with a few exceptions for some countries and time periods. Overall, traditional fundamentals perform poorly at short horizons, but their performance improves as the forecast horizon increases.

Finally, the findings of studies are strongly influenced by the choice of benchmark, evaluation method and forecast sample. For instance, choosing an inappropriate benchmark, such as the random walk with drift instead of the random walk without drift, can overstate the predictive ability of a fundamental model. In addition, a researcher may find that an interest rate differential model outperforms the random walk depending on whether or not, for example, the Clark and West statistic or the Diebold-Mariano test statistic is used. Lastly, a deeper analysis of the result may also show that a model's performance is unstable over time.

With the traditional fundamental models failing to consistently beat the random walk, one may argue that this may be a manifestation of weak form market efficiency in the foreign exchange market and therefore renders all forecasting exercises pointless. Market efficiency (Fama, 1970) asserts that financial markets, at every point in time, incorporate all available information. If this assertion is true, then changes in prices should come from unpredictable and uncorrelated events (shocks), hence the best forecast for tomorrow's price will be today's price.

A number of studies have examined market efficiency within the FX market. Meese and Singleton (1982), Corbae and Ouliaris (1986) and Zivot (2000) find unit roots in major foreign exchange rates and conclude that foreign exchange markets are predominantly weak form efficient. However, Liu and He (1991) reject the random walk hypothesis in major Asian foreign exchange rates.

Crowder (1994) casts some doubt on the non-forecast ability of exchange rates in the foreign exchange market by pointing out that studies that find evidence of one or more cointegrating vectors within a vector autoregressive (VAR) exchange rate model, subsume at least one exchange rate forecasting the other(s). He argues that the predictability of the exchange rate is due to the presence of a forward risk premium. Dwyer and Wallace (1992) and Engel (1996) hold an even stronger position. They assert that the future exchange rate is predictable, as long as it is cointegrated with another series in a weak form efficient market, with or without a risk premium. From these arguments, it is therefore far from certain that weak form efficiency in the exchange rate market precludes all forecasting exercises and as such is not a very robust explanation of the performance of the equilibrium models in the empirical studies.

3.2 Review of Empirical Studies on Parity Conditions

Besides market efficiency, the natural avenue to look for an explanation of the poor performance of the equilibrium models is the underlying assumptions on which they are built. In deriving these models, we implicitly assume that these conditions hold or do not hold at all times. We therefore ask the question, “Are the international parity conditions valid at all times?” and briefly review the empirical studies that have attempted answering variants of this question.

The first class of studies we examine focuses on purchasing power parity which is based on the proposition that in the long run there is an equilibrium relationship between inflation, price levels and exchange rates. It asserts that market forces should push purchasing power to converge mainly through arbitrage activities. A relative price difference between two countries should therefore not be sustainable over time. A number of researchers have looked into the empirical validity of this theory and the results are broadly mixed. Engel (1999) using disaggregate price indices for the G6 currencies against the USD from 1962 to 1995, finds that 95% of the US dollar bilateral real exchange rates significantly deviate from the predictions of PPP. Froot et al. (1995) show that the evidence provided against PPP is not a recent development. Using transaction prices on eight commodities sourced in England and Holland, spanning the thirteenth to the twentieth century, the authors find that the magnitude and persistence of deviations from theory have been fairly consistent. Hakkio (1984) uses panel methods and data from 1973 to 1982 for the GBP, CAD, JPY and finds evidence in support of PPP. A more recent study, by Goldberg and Verboven (2005), analysing the European car market between 1970 to 2000, finds weak evidence in favour of the absolute form of PPP, but very strong evidence in favour of relative PPP.

Wang (2009) provides a number of intuitive explanations for these conflicting findings. First, different countries include different goods and services and assign different weights to similar goods and services when constructing their price indices. Second, the barriers to trade between two countries may be significant enough to prevent some goods and services from being traded between them. Lastly, the existence of non-traded goods and services whose prices are not linked internationally allows for systematic deviations since their prices are determined entirely by domestic supply and demand. Changes in these determinants may cause the domestic price of a basket of goods to change relative to the foreign price of the same basket.

The second class of studies focuses on covered and uncovered interest rate parity. Frenkel and Levich (1975, 1977) carry out one of the first empirical test of CIP. Using Treasury bill yields they demonstrate that CIP does not hold for both UK-US and US-Canada bill combinations. They however, point out that 80% of the “anomaly” is attributable to the transaction costs associated with covered interest rate arbitrage. These costs mainly fall under the bid-ask and lending-borrowing spreads. Using high quality matched data that was absent from the previous study, Taylor (1989) finds that covered interest rate parity holds.

Early studies, like Cumby and Obstfeld (1981) and Macdonald and Torrance (1990), cautiously reject UIP. Chaboud and Wright (2005) investigate UIP using forex data and find evidence in favour of UIP over very short horizons. They find that, as the holding period increases, the evidence in favour of UIP diminishes. Bekaert et al. (2007) examine uncovered interest rate parity and find that deviations from this parity condition are not horizon dependent, but currency dependent. Chinn and Meredith (2004) and Lothian and Wu (2011), who use very long duration bonds and long span data, find evidence in support of UIP. Lothian and Wu (2011) argue that UIP does not perform well post Bretton Woods because of the behaviour of the US dollar in the 1980s. They also note that over the entire study period (two centuries) they observe long periods of deviation from UIP.

Lastly, the Fisher effect, like all the other parity conditions, is a greatly debated concept. Over the years the specific hypothesis debated and the testing techniques used have changed. Mishkin (1984) studies the real interest rate movements in seven OECD countries from 1967 to 1979. He finds that the equality of real interest rates across countries can be statistically rejected. Peng (1995) finds a strong relationship between interest rates and expected inflation for France, UK and the US from 1957 to 1994, but he observes a much weaker relationship for Germany and Japan.

3.3 Empirical Studies: Concluding Remarks

The empirical evidence on the validity of the parity conditions are broadly mixed. A deeper reading of the presented studies shows that findings are not consistent across currencies, sample periods and exchange rate regimes. Because of this we cannot take for granted that the underlying assumptions of the equilibrium models presented in the previous chapter hold at all times. If these underlying assumptions hold ephemerally, as suggested by the literature, then the poor performance of the fundamental models are within reason.

In addition, the traditional fundamental models overlook the fact that the exchange rate and the macroeconomic variables, mainly nominal interest rates, money supply and output, are determined in equilibrium together with the exchange rate. This presents an endogeneity problem that is not so easy to overcome when using reduced form equations to test the empirical validity of these models.

Finally, expression 2.25 relates the exchange rate not only to the present realizations of the traditional fundamentals, but the markets expectation of their future realizations. Since these values are not available to the researcher, any attempt at tying fundamentals and the exchange rates is extremely difficult.

Based on these conclusions, if the purpose of a model is to examine what determines an exchange rate then the framework of the traditional models may be useful. However, if the purpose of a model is to aid forward looking decisions, then an alternative model may be preferred.

4 Foreign Exchange and Commodities

Drawing on the conclusions of the last chapter, it is natural to seek out an alternative exchange rate model that may not necessarily have a strong theoretical base as the equilibrium models, but has superior performance in aiding forward looking decision making. As an alternative, we present the commodity driven exchange rate model. We begin the chapter with a motivation followed by the Engel and West (2005) Present Value Model of exchange rate determination and show how this model subsumes a majority of the models in the literature. We end the chapter by showing how our proposed predictor fits into this framework.

4.1 Commodity Currencies: An Alternative Approach

Chen and Rogoff (2003) propose commodity prices as a potential "fundamental" for explaining changes in exchange rates. They argue that commodity price movements act as exogenous shocks for small open economies and could potentially explain a major component of the terms of trade fluctuations of these economies. Bidarkota and Crucini (2000) and Backus and Crucini (2000) show that commodity price movements indeed account for a significant portion of the variation in the terms of trade for a number of developing and developed countries.

The Chen and Rogoff (2003) proposal presents a clean relationship for investigating exchange rate forecastability. Motivated by this, we examine the nature of the relationship between changes in commodity currency exchange rates and commodity prices. We focus on the currencies of countries that earn a major part of their revenue from the export of a commodity, a group of currencies often referred to as commodity currencies. Typical examples are the currencies of Australia, Brazil, Canada, Chile, New Zealand, Norway, Russia and South Africa. For each of these countries, a decrease in the price of an important export commodity should lead to downward pressure on the demand for the country's currency, which should in turn lead to a depreciation of the currency.

One possible source of concern when using commodity prices as a fundamental in predicting exchange rates is the endogeneity problem that exists when the economy under study is a price setter. A country with market power has the potential to affect the price of its export commodity and this could cloud the commodity price – exchange rate relationship (Chen and

Rogoff, 2003). To overcome this problem, we use currencies of economies that do not account for more than ten percent of the world supply of their respective commodities, which makes them price takers. The other endogeneity problem that may weaken our study is the dollar effect. Since, both the commodity and the exchange rate are all priced in relation to the dollar, the observations being made could actually be the result of shocks to the US economy and not to the commodity, or the commodity-exporting nation. To limit the effect of this problem we follow the convention in the literature by using the GBP as an alternative numeraire.

4.2 Asset Pricing Foundation

The Engel and West (2005) asset pricing model nests and motivates a number of regressors used in the exchange rate prediction literature. This model builds on the stock pricing work of Campbell and Shiller (1987, 1988) and West (1988). The model links the exchange rate and economic fundamentals through the expression:

$$s_t = (1-b)\left(f_{1,t} + z_{1,t}\right) + b\left(f_{2,t} + z_{2,t}\right) + bE_t s_{t+1} \tag{4.01}$$

where s_t is the log of nominal exchange rate, $f_{i,t}$ $(i = 1,2)$ are the observed economic fundamentals, $z_{i,t}$ $(i = 1,2)$ are the unobserved fundamentals and shocks that drive the exchange rate and b is the discount factor. Imposing the "no-bubbles" condition and iterating forward, $b^j E_t s_{t+j}$ goes to zero as $j \to \infty$ and expression 4.01 reduces to the following present-value relationship:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j\, E_t\left(f_{1,t+j} + z_{1,t+j}\right) + b\sum_{j=0}^{\infty} b^j\, E_t\left(f_{2,t+j} + z_{2,t+j}\right) \tag{4.02}$$

The model shows that the exchange rate can be expressed as a discounted sum of current and expected future fundamentals as long as $0 < b < 1$. In Appendix A, we show how the flexible price monetary model is a special case of expression 4.02.

Expression 4.01 shows that although exchange rates are related to economic fundamentals, they may still appear to follow a random walk if the discount factor b is close to 1 and either (a) or (b) hold, where: (a) $f_{1,t} + z_{1,t} \sim I(1)$ or $f_{2,t} + z_{2,t} = 0$; (b) $f_{2,t} + z_{2,t} \sim I(1)$[1]. In light of this, the finding that the random walk model does no worse than traditional fundamental models should not be surprising. Additionally, by focusing on expression 4.02, it is evident that the contemporaneous estimation of economic fundamentals have relatively little weight in determining the exchange rate. To consistently outperform the random walk, a forecaster needs the ex-ante value of the markets expectation of the future fundamentals. Since, there is no liquid market for traditional fundamentals, it is particularly hard to obtain these estimates.

Expression 4.02 does not place any limitations on what form $f_{i,t}$ should take. We therefore argue that for predominantly commodity-exporting economies, their exchange rates should partly reflect expectations about demand and supply conditions pertaining to specific commodities. Since, the markets for the specific commodities we employ are fairly liquid, their prices should reflect the markets future expectations. This is the rationale that underpins our proposed use of commodity prices as a fundamental in determining commodity currency exchange rates.

We consider the present-value relationship between the nominal exchange rate and the discounted sum of future expected commodity prices:

$$s_t = \sum_{j=0}^{\infty} b^j \, E_t\left(f_{t+j} \middle| I_t\right) \tag{4.03}$$

where b^j is the discount factor and E_t is the expectation operator given information I_t. A careful observation of 4.03 shows that it follows from expression 2.25. Expression 2.25 explicitly defines the exchange rate as the discounted future expectations of the traditional fundamentals, whereas 4.03 defines the exchange rate as the discounted future expectations of any relevant fundamental, which in our case is the commodity price.

[1] $I(1)$ stands for “integrated of order one”

5 Econometric Framework

In this chapter we present the econometric framework that underlies the empirical analysis we carry out in this study. We first present a number of model specifications intended to best identify the nature of the relationship between commodity currency exchange rates and commodity prices. This is followed by a comprehensive discussion of the various statistical methodologies we use to evaluate the predictive power of proposed model specifications.

5.1 Model Specifications and Research Hypotheses

In chapter three we concluded that different parameterizations of the relationship between the nominal exchange rate and an economic fundamental lead to different conclusions on how successful a proposed model is. We therefore explore four different model specifications, each of which posits a unique relationship between the exchange rate and commodity prices:

The Contemporaneous Linear Model (CLM)

The contemporaneous linear model emphasises the direct effects of changes in the commodity price on the exchange rate. This is a simple model which we define as:

$$\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t \tag{5.01}$$

where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price for that commodity currency and ε_t is the error term. This model motivates our first research hypothesis:

Hypothesis 1: There is no difference between the performance of the linear commodity price model and the benchmark model.

To test this hypothesis we use the realized value of the commodity price at time *t* to predict (explain) the change in exchange rate for the same period. In the out-of-sample exercises, the α and β are estimated using in-sample (IS) data. Since, we use ex-post values of the fundamental, this is not a true out-of-sample exercise. We however use this as a natural starting point similar to Meese and Rogoff (1983a, 1983b), Cheung et al. (2005) and Ferraro et al. (2015).

One may be worried about issues of endogeneity where the error term in one period also affects the commodity price. Since a shock to an exporting economy can affect both its exchange rate and the commodity price, it makes sense to use instrumental variables. However, results from previous studies, when an instrumental variable is used, indicate that the gains in consistency are far outweighed by the loss in efficiency, in terms of prediction (Chinn and Meese, 1995). We therefore estimate the model using OLS.

The Lagged Linear Model (LLM)

Our second model explores the relationship between the lagged commodity price and the exchange rate. In reality, forecasters may not have a model that predicts the next period commodity price with a high level of accuracy. In such cases, the forecaster's next best option is to use the realized commodity price from the previous period. We define this relationship as:

$$\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t \tag{5.02}$$

where all variables are same as before and the time *t-1* change in the commodity price is used. Similar to the previous model, the α and β are estimated using in-sample (IS) data for the out-of-sample exercises. This model motivates our second research hypothesis:

Hypothesis 2: There is no difference between the performance of the one period lagged linear commodity price model and the benchmark model.

We emphasise that this is a stricter test than the previous because we use the lagged commodity price. In a sense, we give the first model an unfair advantage.

The Cointegration Model (CM)

The cointegration framework enables us to specify a single equation error correction model (ECM) that explicitly captures the long run interaction between the exchange rate and commodity price in generating forecasts (Mark, 1995). If the variables are indeed cointegrated then this model should allow us to exploit more information available in past prices. To investigate whether this is the case, we consider the specification:

$$\Delta s_t = \alpha + \beta (s_{t-1} - \lambda f_{t-1}) + \varepsilon_t \tag{5.03}$$

where all variables are same as before. We first estimate the cointegrating vector, λ, using Engle and Granger (1987) procedure and then estimate the other free parameters by using OLS. We exclude the short run dynamics of the ECM model because of estimation complications and comparability of our results to Mark (1995), Chinn and Meese (1995) and Cheung et al. (2005). Similar to the previous models, all free parameters are estimated using IS data. This specification motivates our third research hypothesis:

Hypothesis 3: There is no difference between the performance of the cointegrated commodity price - exchange rate model and the benchmark model.

Since this model specification uses only realized values in generating the next period exchange rate, the predictions are true ex ante forecasts.

The Asymmetric Commodity Currency Model (ACCM)

The asymmetric commodity currency model is based on the non-linear specification that allows for the exchange rate to respond differently to increases and decreases in commodity prices:

$$\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^{+} + \varepsilon_t \tag{5.04}$$

where $f_t^{+} = \begin{Bmatrix} \Delta f_t, & if\ \Delta f_t > 0 \\ 0, & otherwise \end{Bmatrix}$ and all other variables are as before. The goal of this model specification is to investigate if including non-linearities in the CLM specification improves forecasting ability. This motivates our fourth research hypothesis:

Hypothesis 4: There is no difference between the performance of the asymmetric commodity currency model and the benchmark model.

This asymmetric specification is motivated by Hamilton (2003) who finds significant asymmetries in oil price changes in explaining GDP growth and Akram (2004) who finds that allowing for non-linear relationships in oil prices leads to better specified NOK/USD models with stronger predictive properties. The nature of the model leads to the possible issue of multicollinearity since the second variable in the model, Δf_t^{+}, is transformation of the first Δf_t. This may lead us to making wrong inferences about, Δf_t^{+}, but due to the non-linear nature of the transformation, we do not believe this effect will be significant. Furthermore, specifying the model according to expression 5.04 reduces the inconsistencies that result from specifying the positive and negative changes separately (Kilian and Vigfusson, 2011).

The Random Walk Model (RW)

The primary benchmark in our study is the random walk without drift (RW). The random walk without drift is based on the notion that α & β in the CLM specification are equal to zero. The expected change in the exchange rate is thus:

$$E_t(s_{t+1} - s_t) = 0 \tag{5.05}$$

Since the seminal work of Meese and Rogoff (1983a, 1983b), this model has become the standard benchmark in assessing exchange rate predictability. The RW model captures the prevailing view in international finance research that exchange rates are not predictable, when conditioning on economic fundamentals, at short horizons.

The Interest Rate Differential Model (UIP)

We also consider an interest rate differential model which is based on the one traditional fundamental available at the daily frequency, as an alternative benchmark[2]. The interest rate differential model is specified as:

$$\Delta s_t = \alpha + \beta(r_t - r_t^*) + \varepsilon_t \tag{5.06}$$

where $r_t - r_t^*$ is the interest rate differential between the two relevant economies and all other variables are same. Assuming risk neutrality and rational expectations, this model implies that $\alpha = 0, \beta = 1$. We however estimate both $\alpha \, and \, \beta$ using IS data.

5.2 Model Estimation and Forecasting

We estimate all model parameters using ordinary least squares (OLS) and then run an out-of-sample forecasting exercise as in Stock and Watson (2003). Given T observations of the

[2] We do not consider money supply and output differentials because they are not observable at a high enough frequency to support our analysis.

exchange rate and commodity prices, we have *T-1* observations in first difference. With M in-sample (IS) observations, the forecasting exercise produces $P = (T - 1) - M$ distinct out-of-sample (OOS) observations.

The forecasting literature has employed both the rolling window and recursive forecasting schemes in estimating parameters. Similarly, we implement both forecasting techniques. The recursive regression methodology involves re-estimating model parameters every time a new observation is added to the IS dataset. The rolling regression methodology involves using a fixed IS observation window to estimate the model parameters. The estimation window is then rolled forward one period every time a new observation is added. The rolling regression suffers from efficiency deficiencies, but has the advantage of lessening parameter instability effects over time.

When splitting a sample into IS and OOS subsets, researchers face a trade-off between the accuracy of parameter estimation and forecast evaluation. The larger the size of the OOS observations (P), the higher the accuracy of the forecast evaluation. On the other hand, the larger the size of the IS observations (M), the higher the accuracy of parameter estimation. To reduce the impact of this trade-off, we follow the Clark and Mccracken (2013) rule-of-thumb. We split our sample in the proportion $\frac{P}{M} = 1$ under the recursive methodology and $\frac{P}{M} = 3$ under the rolling window methodology.

5.3 Model Evaluation

The success or failure of an empirical exchange rate model is usually determined by statistical tests of their out-of-sample predictive ability when compared to some benchmark, usually the random walk. As an additional benchmark we employ the interest rate differential model.

In what follows, we describe the various statistical measures used to evaluate the OOS predictive ability of the proposed models. We define $\Delta\bar{s}_{t+1|t}$ as the one-step ahead unconditional forecast from the benchmark model, $\Delta\hat{s}_{t+1|t}$ as the one-step ahead conditional forecast from the alternative model and Δs_{t+1} as the actual realization of the one-step change.

5.3.1 The Direction of Change Statistic

The first statistical criteria we use to evaluate the OOS predictive ability of our empirical exchange rate model specifications is the direction of change statistic ($\bar{d}$). Cheung et al. (2005) defines the direction of change statistic as follows:

$$d_t = \begin{cases} 1, & if\ \Delta s_{t+1} \geq 0\ and\ \Delta \hat{s}_{t+1|t} \geq 0 \\ 1, & if\ \Delta s_{t+1} < 0\ and\ \Delta \hat{s}_{t+1|t} < 0 \\ 0, & otherwise \end{cases} \tag{5.07}$$

and the mean of d_t as:

$$\bar{d} = \frac{1}{P}\sum_{t=1}^{P} d_t \tag{5.08}$$

The statistic is computed as the number of correct predictions of the direction of change over the total number of predictions. A value of $\bar{d}$ significantly above 50% is interpreted as the proposed model forecasting better than a naive model and a value significantly below 50% indicates that proposed model's forecasts tend to give the wrong direction of change more often than not. We test the null H_0: $\bar{d} = 0.5$ against the alternative H_1: $\bar{d} \neq 0.5$, using the test statistic:

$$\bar{d}_t = \frac{(\bar{d} - 0.5)}{\sqrt{0.25/P}} \tag{5.09}$$

In large samples, this test statistic is distributed as standard normal.

We include this comparison metric since the more popular mean squared error criterions may miss out on some important aspects of prediction. For instance, the direction of change metric may be more appropriate for individuals and institutions who are more concerned about predictions for profitability or economic reasons (Cheung et al., 2005). Among the conventional forecast error measures analysed by Leitch and Tanner (1991), only the direction of change metric appears to have a significant correlation with forecast profitability. This metric is also more useful to individuals who are more concerned about picking the right direction of the change as against the difference between the prediction and true change. It is theoretically possible that a model could forecast near-perfectly the direction of change in all periods and yet forecast worse than the random walk according to the more popular root mean squared forecast criterion (Rossi, 2013).

5.3.2 The Out-of-Sample R^2 (OOS R^2) Statistic

The second statistical criteria we use to evaluate the OOS predictive ability of the proposed commodity driven exchange rate model specifications is the Campbell and Thompson (2008) out-of-sample R_{oos}^2 statistic. This statistic compares the unconditional one-step ahead forecast of the benchmark model to the one-step ahead conditional forecasts of the alternative model.

The R_{oos}^2 statistic is defined as:

$$R_{oos}^2 = 1 - \frac{MSE(Alternative)}{MSE(Benchmark)} = 1 - \frac{\sum_{t=M+1}^{T-1}(\Delta s_{t+1} - \Delta\hat{s}_{t+1|t})^2}{\sum_{t=M+1}^{T-1}(\Delta s_{t+1} - \Delta\bar{s}_{t+1|t})^2} \tag{5.10}$$

The statistic is computed as the ratio of the alternative model to the benchmark model subtracted from one. A positive R_{oos}^2 estimates is interpreted as the alternative model outperforming the benchmark model.

We also assess the statistical significance of the R_{oos}^2 point estimate using the Clark and West (2006, 2007) and Giacomini and White (2006) inference procedures. Both of these tests are fundamentally testing the null hypothesis $H_0: MSE(Alternative) = MSE(Benchmark)$. They however differ in the details; whereas Clark and West (2006, 2007) operates in an environment where parameter estimates converge to their true population values, Giacomini and White (2006) operate in an environment with asymptotically non-vanishing estimation uncertainty. Hence, the former test is appropriate when the underlying research question is one of Granger causality, whereas the latter is more appropriate for addressing the normatively oriented question of whether one forecast model performs better than the other (Paye, 2012).

5.3.2.1 The Clark and West Inference Test (CW_t)

The Clark and West (2006, 2007) inference procedure, CW_t, is particularly useful because it accounts for testing the null of equal predictive ability of two nested models where the more popular Diebold and Mariano (1995) test fails. When the RW is the benchmark, the test of equal predictive ability reduces to comparing the performance of a parsimonious restricted null model (the RW, where $\alpha = \beta = 0$) to a set of larger alternative unrestricted models that nest the more parsimonious model (where $\alpha \neq \beta \neq 0$). The CW_t procedure acknowledges the fact that under H_0, the MSE from the alternative model is expected to be greater than that of the random walk model. This is because the alternative model introduces noise into the forecasting process by estimating a parameter vector that may not be helpful in prediction. Finding a negative R^2_{oos} is therefore not clear evidence against the alternative model. The CW_t inference procedure tests the null:

$$H_0\colon MSE\left(\Delta\hat{s}_{t+1|t}\right) = MSE\left(\Delta\bar{s}_{t+1|t}\right) \tag{5.11}$$

against the alternative hypothesis that the alterative model has a lower mean squared error. Clark and West (2006, 2007) suggest to adjust the MSE as follows:

$$MSE_{c\&w} = \frac{1}{P}\sum_{t=M+1}^{T-1}(\Delta s_{t+1} - \Delta\hat{s}_{t+1|t})^2 - \frac{1}{P}\sum_{t=M+1}^{T-1}(\Delta\bar{s}_{t+1|t} - \Delta\hat{s}_{t+1|t})^2 \tag{5.12}$$

Then, a computationally convenient way of testing for equal MSE, that is whether or not the R^2_{oos} estimate is statistically different from zero, is to define:

$$\widehat{test}_{t+1|t} = (\Delta s_{t+1} - \Delta\bar{s}_{t+1|t})^2 - \left[(\Delta s_{t+1} - \Delta\hat{s}_{t+1|t})^2 - \left(\Delta\bar{s}_{t+1|t} - \Delta\hat{s}_{t+1|t}\right)^2\right] \tag{5.13}$$

and to regress $\widehat{test}_{t+1|t}$ obtained from 5.13 on a constant for $n = 1, .., P$ where MSE-*t* is the t-statistic corresponding to the constant. Clark and West (2006, 2007) and Mccracken (2007) show that although the asymptotic distribution of this test is nonstandard, standard normal critical values provide a good approximation. They therefore recommend rejecting the null if the test statistic is greater than +1.282 (for a one-sided 0.10 test), +1.645 (for a one-sided 0.05 test) and +2.326(for a one-sided 0.01 test). The Clark and West (2006, 2007) inference procedure is asymptotic, thus it relies on the population values of estimated coefficients. This means that the power of the test increases as M→ ∞, hence we restrict the use of the Clark and West (2006, 2007) inference procedure to the recursive scheme. We must also stress that the R^2_{oos} statistic is a predictive ability estimate designed to assess the accuracy of a model in a finite sample. This implies that a rejection of the null hypothesis by the CW_t test may occasionally be associated with a negative R^2_{oos}.

5.3.2.2 The Giacomini and White Inference Test (GW_t)

The second inference technique we use is the Giacomini and White (2006) (GW_t) conditional testing procedure. The GW_t test is constructed for forecasts generated with a rolling window. Consider the general loss differential function: $d_t = (\Delta s_{t+1} - \bar{s}_{t+1|t})^2 - (\Delta s_{t+1} - \Delta\hat{s}_{t+1|t})^2$. The null hypothesis of equal forecasting accuracy can be written as:

$$H_0: E[d_{t+\tau}|h_t] = 0 \tag{5.14}$$

where h_t denotes an information set available to the forecasting agent at time t and τ is the forecast horizon. We test this null against an alternative hypothesis of unequal forecasting accuracy. When $\tau = 1$, the GW test statistic GW_t can be computed as:

$$GW_t = P\left(P^{-1}\sum_{t=M+1}^{T-1} h_t\, d_{t+1}\right)\widehat{\Omega}_P^{-1}\left(P^{-1}\sum_{t=M+1}^{T-1} h_t\, d_{t+1}\right) \tag{5.15}$$

where $\widehat{\Omega}_T^{-1}$ is a heteroskedastic autocorrelation consistent (HAC) estimator of the asymptotic variance of $h_t d_{t+\tau}$. Under modest mixing and moment conditions the GW_t statistic is asymptotically $\mathcal{X}^2$ distributed with two degrees of freedom.

This test addresses the question of outperformance in the more realistic environment since it uses finite-sample estimated coefficients. In this regard, this inference procedure might be more useful to determine which model will provide a more accurate set of forecasts in a real time application. In addition, a forecasting methodology is a broad concept that encompasses not only a set of model specifications, but also the detailed procedure used to obtain forecasts. Therefore, for a testing framework to effectively compare one forecasting methodology to another, it should able to account for differences in the forecasting models, parameter estimation procedures and the size of rolling windows. The GW_t testing procedure is one of the few tests that correctly accounts for all these details. The main weakness of the Giacomini and White (2006) testing procedure is that the model used to construct the forecasts must be estimated using a rolling window of observations of size M that is finite and small relative to the prediction sample P. In line with this, we restrict its application to making inferences about the statistical significance of the R^2_{oos} statistic when the rolling window is employed.

5.3.3 Forecast Stability Statistic

We use the formal testing procedure of Giacomini and Rossi (2009), GR_t, to test for the stability of the forecasts produced by the various commodity driven model specifications. They propose a theoretical framework for assessing whether or not a forecast model estimated over one period can provide good forecasts over a subsequent period. They formalize this concept by defining a forecast breakdown as a situation in which the OOS performance of the model, judged by some loss function, is significantly worse than the IS performance. Giacomini and Rossi (2009) analyse the expectation of the difference between the OOS forecast error relative to the average loss computed over the IS period. Their test for accessing forecast stability is obtained as follows. Define surprise losses, SL_{t+1}, as:

$$SL_{t+1} = L_{t+1} - \bar{L}_t \tag{5.16}$$

where L_{t+1} is the OOS forecast error loss and $\bar{L}_t$ is the IS average loss. In our implementation, we use the MSE as the loss function and compute the OOS mean surprise losses as:

$$\overline{SL}_p \equiv P^{-1} \sum_{t=M}^{T-1} SL_{t+1} \tag{5.17}$$

If a forecasting technique is reliable, then the mean should be close to zero. Specifically we test the null hypothesis:

$$H_0 \colon E\left(P^{-1} \sum_{t=M}^{T-1} SL_{t+1}\right) = 0 \tag{5.18}$$

against the alternative of deteriorating performance. The forecast breakdown test statistic is computed as:

$$\overline{SL}_t = \sqrt{P} * \frac{\overline{SL}_p}{\hat{\sigma}_{SL}} \tag{5.19}$$

which has an asymptotic normal distribution. By failing to reject the null, we find evidence that the alternative model has a stable or improving forecasting quality.

6 Empirical Results

In this chapter we report the results of our analyses. We start with the data description and then present the results from the various empirical tests. We conclude the section with a discussion of the results in relation to the hypothesis set out in the previous chapter.

6.1 Data

Our study focuses primarily on Norway for three reasons. First, crude oil represents 31 percent of Norway's total exports over the period 2002-2013. Second, Norway is a small open economy whose size in the world oil market is relatively small to justify the assumption that it is a price-taker in this market. Norway's average share of the global crude market between 2002 and 2013 was four percent. Table 9 in Appendix B shows that Australia, Canada and South Africa fit the same narrative. Finally, Norway has a long history of market-based floating exchange rate.

The empirical analysis uses NOK/USD and NOK/GBP spot exchange rates; crude oil prices and Norwegian, American and British interest rate data. The study covers the period 01/12/1992 to 31/12/2014, representing 22 years of data. We acknowledge the availability of Norwegian exchange rate data for periods before December 1992, but we restrict our sample to the recent floating exchange rate regime period which officially commenced on the 10th of December, 1992 (Kleivset, 2012). The dataset in levels consists of 5762 daily observations, 265 monthly observations and 89 quarterly observations. This reduces to 5761 daily observations, 264 monthly observations and 88 quarterly observations in first difference. We therefore produce 2881 daily, 132 monthly and 44 quarterly forecasts under the recursive scheme and 4320 daily, 198 monthly and 66 quarterly forecasts under the rolling scheme. The oil price series is the price of Brent crude oil, which is the benchmark for Europe. We use the NIBOR rates as the riskless interest rate for Norway and the Euro-deposit rates as proxies for the U.S. and UK riskless rates in computing the interest rate differential, as is the convention in the literature. We subtract the period specific U.S. or British interest rate from the Norwegian equivalent.

We also consider the commodity currency-commodity price relationships for Australia, Canada and South Africa. For nominal spot rates, we use the USD and GBP crosses for each country's currency. For commodity prices, we use the commodity that makes up the largest share of the respective country's total exports: Gold[3] (Australia), Crude Oil (Canada), Crude Oil (Norway) and Gold (South Africa).

The exchange rate, commodity price and interest rate data were collected from DataStream. The exchange rate is defined as the domestic currency price of a unit of USD or GBP. For interest rates we use the Euro-deposit rate equivalent for most of the countries. Table 10 in Appendix B, provides a detailed description of all data sources we use. We do not detrend, filter or seasonally adjust the data. We follow the end of period convention in determining the daily, monthly and quarterly exchange rates and commodity prices. More precisely, we use the end of day observation as daily, end of month observation as monthly and end of quarter observation as the quarterly observation, respectively.

All analysis presented in this chapter is for daily and monthly data and USD as numeraire. The results for quarterly frequency and GBP numeraire are placed in appendixes. We convert all the data, except the interest rates, by taking natural logs and first differencing to arrive at percentage equivalents. Throughout the rest of the study, the symbols, s_t, r_t^d and f_t refer to transformed spot exchange rate, nominal interest rate differential and commodity price, respectively. Tables 11 and 12 in Appendix C, show that the commodity and currency series contain unit roots and their first difference is stationary.

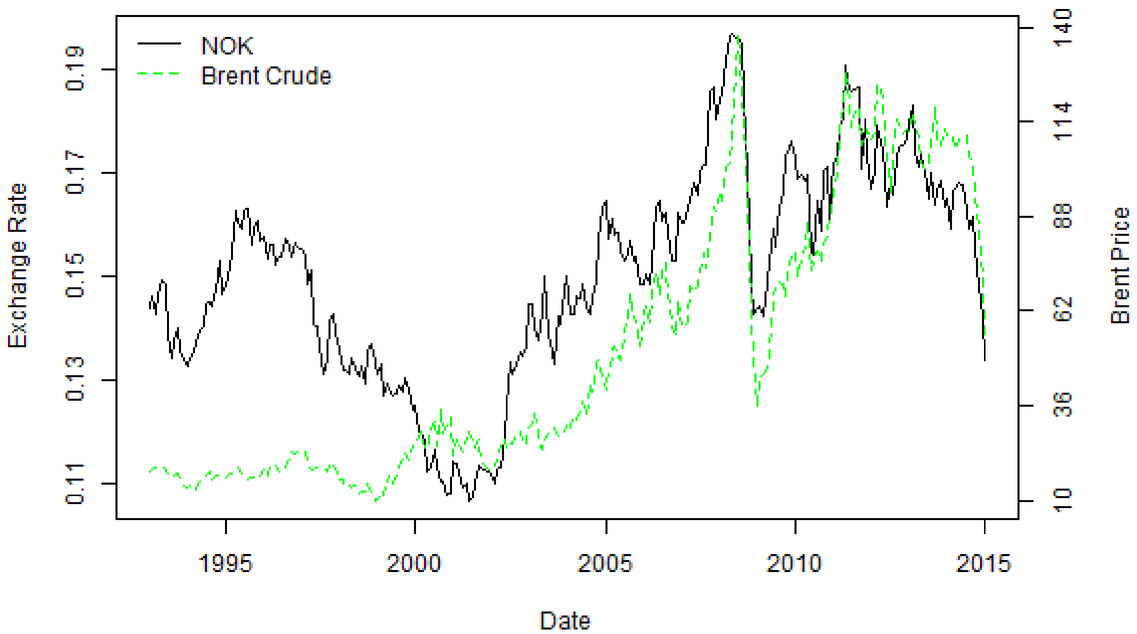
The Norwegian Krone and the Brent crude oil price

Before 10th December, 1992, the Norwegian krone was pegged to the ECU index. Figure 2 shows the time series plot of the monthly observations of the cost of one Norwegian Krone and a barrel of Brent crude oil priced in USD from this date[4]. Before 2001, the NOK co-moves with crude oil but does not show the same level of variability as crude oil. The direct relationship between the two series is more apparent after 2001. Beyond this period, the krone becomes more volatile and the exchange rate-crude relationship becomes more obvious. We hypothesize that this could be due to the increasing financialisation of commodity markets and the inflation targeting policy adopted by the Norges Bank in March 2001 (Kleivset, 2012).

[3] We use Gold instead of Coal or Iron ore for Australia because we could not get access to daily price series for any of these two commodities

[4] We change the quoting mechanism to highlight the nature of the relationship between the commodity currency and the commodity.

Figure 2: Time Series plot of NOK and Brent crude priced in USD



This plot shows the evolution of the NOK and Brent crude, priced in USD through time, using end of month observations from December 1992 to December 2014. A direct relationship between NOK and Brent crude can be observed especially after 2001.

A similar time series plot for the other three currency-commodity pairs are presented in Appendix D. Overall, the plots exhibit a similar trend as the NOK/USD-Brent relationship. With the exception of the ZAR/USD-Gold, all the others show a pronounced correlation after 2001.

6.2 Statistical Evaluation

6.2.1 In-Sample Granger-Casuality Analysis

We test the empirical performance of the commodity driven exchange rate model by first estimating the four proposed model specifications using the full dataset. This exercise is commonly known in the literature as a traditional in-sample Granger-causality test. Table 1 shows the OLS estimates for the four proposed model specifications with heteroskedastic and autocorrelation consistent standard errors[5].

[5] Appendix C shows the results for stationarity, homoscedasticity and autocorrelation tests.

6.2.1.1 Slope Coefficient Analysis

We start our analysis by focusing on the significance of the slope coefficients (β). Slope coefficients provide some preliminary insights into which of the model specifications best captures the commodity currency - commodity price relationship.

Table 1: OLS estimation using full sample

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Daily				Monthly			
CLM	α	0.00004	0.00002	-0.00001	0.0003^b	0.001	0.001	0.00002	0.006^b
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.002)	(0.001)	(0.003)
	β	-0.067^a	-0.257^a	-0.053^a	-0.239^a	-0.108^a	-0.325^a	-0.094^a	-0.258^a
		(0.006)	(0.017)	(0.004)	(0.019)	(0.028)	(0.053)	(0.023)	(0.068)
	R^2	0.041	0.114	0.060	0.064	0.123	0.179	0.134	0.072
LLM	α	0.00003	-0.00003	-0.00002	0.0002^c	0.001	-0.001	-0.0002	0.005^c
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.002)	(0.001)	(0.003)
	β	-0.0004	-0.008	0.003	0.009	-0.037	-0.003	-0.024	0.043
		(0.005)	(0.016)	(0.003)	(0.016)	(0.023)	(0.057)	(0.019)	(0.067)
	R^2	-0.0002	-0.0001	0.00001	-0.0001	0.011	-0.004	0.005	-0.002
CM	α	0.005^b	0.007^b	0.002^a	0.0004^a	0.075^a	0.128^a	0.043^a	0.010^a
		(0.002)	(0.003)	(0.001)	(0.0001)	(0.043)	(0.043)	(0.016)	(0.003)
	β	-0.002^b	-0.003^b	-0.002^a	-0.001^b	-0.031^c	-0.063^a	-0.045^a	-0.016
		(0.001)	(0.001)	(0.001)	(0.0004)	(0.018)	(0.022)	(0.016)	(0.010)
	R^2	0.001	0.001	0.001	0.0004	0.006	0.026	0.016	0.009
ACCM	α	0.0001	-0.00004	-0.0001	0.00003	-0.001	-0.005	0.001	0.001
		(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.003)	(0.003)	(0.003)	(0.004)
	β	-0.061^a	-0.266^a	-0.058^a	-0.276^a	-0.132^b	-0.511^a	-0.081	-0.420^b
		(0.009)	(0.027)	(0.007)	(0.033)	(0.057)	(0.133)	(0.053)	(0.169)
	D	-0.012	0.018	0.010	0.076	0.054	0.342^c	-0.029	0.297
		(0.013)	(0.047)	(0.012)	(0.053)	(0.080)	(0.200)	(0.086)	(0.248)
	R^2	0.041	0.114	0.060	0.065	0.123	0.198	0.132	0.079

The table reports the least squares estimates of the proposed model specifications, by using daily and monthly data and USD as a numeraire. Heteroskedasticity and autocorrelation consistent standard errors are reported in parentheses. The adjusted R^2 is reported in place of the regular R^2. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively.

If the estimated coefficient (beta) is statistically different from zero, then this provides evidence that the model specification captures some underlying relationship between the commodity currency and the commodity price.

The Contemporaneous Linear Model (CLM) exhibits the highest in-sample success. This model specification has a 1% statistically significant slope coefficient for all four currency pairs at both the daily and monthly frequencies. The highest cross-elasticity coefficient for the daily frequency is 25.7% (AUD), 32.5% (AUD) for monthly and 34.4% (NOK) for quarterly frequency. Using the GBP to control for the dollar effect, most of daily and monthly regressions retain the significant slope coefficients (Appendix E, Table 16). The results in favour of the CLM specification are however less pronounced at the quarterly frequency (Appendix E, Table 17). The Asymmetric Commodity Currency Model (ACCM) shows that controlling for asymmetries in crude oil price changes does not improve the fit of the model. The Cointegration Model (CM) shows weak signs of correctly capturing the commodity currency – commodity price relationship. For the daily forecast horizon, the slope coefficient is statistically significant at the 5% level for both numeraires. The Lagged Linear Model (LLM) specification exhibits the least success. For both currency crosses and all forecast horizons, none of the beta estimates are statistically significant at conventional levels. Overall, the estimated slope coefficients for all commodity driven model specifications are negative, which correctly captures the direct relationship observable in Figure 2.

6.2.1.2 Adjusted R-Square Analysis

To identify signs of model over-fitting, we analyse the adjusted R-Square of the different model specifications. Model over-fitting usually occurs when a researcher includes too many independent variables in a regression. If the commodity currencies generally follow a random walk then the adjusted R-Square for the proposed model specification should, in theory, be negative. The results from the regressions, presented in Table 1, show that the CLM specification has the highest level of success. For all frequencies and both crosses, the adjusted R-Square for this model specification is positive. The highest adjusted R-Square for the daily frequency is 11.4% (AUD), 17.9% (AUD) for monthly and 26.4% (NOK) for quarterly frequency. Including asymmetries (ACCM), does not improve the fit of the CLM specification. The CM specification has very low adjusted R-Squares, but they are all positive. The LLM specification, again, shows strong signs of model misspecification with two forecast horizon regressions recording negative adjusted R-Squares. It is also interesting to note that the adjusted R-Square estimate tends to increase with increasing forecast horizons.

Based on the in-sample analysis, the Contemporaneous Linear Model is the best specification in explaining the commodity currency – commodity price relationship, followed by the Cointegration Model. Including asymmetries does not consistently improve the fit of the CLM specification. With some minor exceptions, the Linear Lagged Model shows the least sign of correctly capturing the relationship. The commodity currency – commodity price relationship is more pronounced at the daily frequency compared to the monthly and quarterly.

6.2.2 Out-of-Sample Analysis

We assess the out-of-sample statistical performance of the proposed model specifications by first analysing the direction of change ($\bar{d}$) and the out-of-sample R-Square (R^2_{oos}) statistics. Afterwards, we investigate how the estimation window size affects the forecasting power of the best performing model specification, under the rolling estimation scheme. We end the out-of-sample statistical analysis by evaluating the forecasting stability of the different model specifications.

We focus mainly on the out-of-sample forecasts as a basis for judging the relative merits of the different model specifications. This is not because we believe that we can necessarily out-perform the market in real time, but rather as a means of guarding against data mining that might occur when one relies solely on in-sample inferences.

6.2.2.1 Direction of Change Analysis

Recall that a $\bar{d}$ greater than 0.5 provides evidence that the model specification out-performs a naive model that can correctly predict the direction of change of the exchange rate 50 percent of the time. The superscripts next to the $\bar{d}$ estimates report the p-value of the hypothesis test with a null, that the direction of change estimate is equal to 0.5. Table 2 displays the direction of change statistics for the four different model specifications and for all the currency pairs at the daily and monthly frequency.

For all currency pairs, the CLM specification predicts the correct direction of change more than 50 percent of the time using both daily and monthly data. The finding remains unchanged for the daily frequency when use GBP cross but weakens at the monthly frequency (Appendix F, Table 18). We therefore find evidence that the statistical significance of the estimate fades with decreasing data frequency. Including asymmetries (ACCM) does not greatly improve the direction of change estimate of the model. Both the LLM and CM specifications fail to consistently predict the correct direction of change more than 50% of the time.

Based on these insights, we can conclude that the commodity driven model does not show signs of real-time profitability, as all the model specifications (LLM & CM) that can generate true ex-ante forecasts fail to consistently cross the 50% threshold.

Table 2: Direction of change statistic

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	$\bar{d}$	0.58[a]	0.63[a]	0.62[a]	0.58[a]	0.63[a]	0.63[a]	0.67[a]	0.57[c]
LLM	$\bar{d}$	0.48	0.49	0.51	0.48	0.58[b]	0.51	0.58[b]	0.50
CM	$\bar{d}$	0.50	0.51	0.48	0.49	0.45	0.53	0.42	0.57[c]
ACCM	$\bar{d}$	0.58[a]	0.63[a]	0.62[a]	0.59[a]	0.65[a]	0.67[a]	0.60[a]	0.56[c]
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	$\bar{d}$	0.55[a]	0.62[a]	0.58[a]	0.56[a]	0.61[a]	0.64[a]	0.64[a]	0.60[a]
LLM	$\bar{d}$	0.49	0.49	0.51	0.48	0.49	0.51	0.53	0.49
CM	$\bar{d}$	0.50	0.49	0.50	0.48	0.50	0.47	0.51	0.46
ACCM	$\bar{d}$	0.55[a]	0.62[a]	0.58[a]	0.56[a]	0.62[a]	0.66[a]	0.60[a]	0.58[b]

The table displays the direction of change statistic $(\bar{d})$ by using daily and monthly data and USD as a numeraire. Direction of change is the proportion of forecasts that correctly predict the direction of the exchange rate movement. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a*, *b* and *c* report the results for the two-sided test of a null of $\bar{d} = 0.5$ against the alternative $\bar{d} \neq 0.5$.

6.2.2.2 Out-Of-Sample R-Square Analysis

The second statistic we use to evaluate the out-of-sample statistical performance of the proposed model specifications is the out-of-sample R-Square (R^2_{oos}) statistic. A positive R^2_{oos} implies that the proposed model specification has a lower MSE than the benchmark model hence a higher forecast accuracy. The superscripts next to the R^2_{oos} estimate report the p-values from a null hypothesis test of equal predictive ability. By rejecting the null, we conclude that the alternative model or proposed model specification out-performs the benchmark. Table 3, displays the R^2_{oos} results for all four currencies when the random walk (RW) is used as the benchmark.

Table 3: Out-of-Sample R Square for RW Benchmark

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.06[a]	0.13[a]	0.08[a]	0.10[a]	0.18[a]	0.19[a]	0.15[a]	0.10[a]
LLM	R^2_{oos}	0.00	0.00	0.00	0.00	0.01[c]	-0.02	0.00	-0.01
CM	R^2_{oos}	0.00	0.00	0.00	0.00	-0.01	0.00	-0.02	-0.01
ACCM	R^2_{oos}	0.06[a]	0.13[a]	0.08[a]	0.10[a]	0.16[a]	0.20[a]	0.09[b]	0.09[b]
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.07[a]	0.11[a]	0.11[a]	0.06[a]	0.15[b]	0.13[b]	0.16[a]	0.03
LLM	R^2_{oos}	0.00	0.00	0.00	0.00	-0.03	-0.05	-0.05	-0.05
CM	R^2_{oos}	0.00	0.00	0.00	-0.01	-0.13	-0.07	-0.08	-0.13
ACCM	R^2_{oos}	0.07[a]	0.11[a]	0.11[a]	0.06[a]	0.14[c]	0.14[b]	0.08[b]	0.03

The table displays the Out-Of-Sample R squared statistic(R^2_{oos}), for RW benchmark, by using daily and monthly data and USD as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a, b* and *c* in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a RW. The superscripts *a, b* and *c* in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a random walk.

The out-of-sample R-Square estimates show the CLM specification statistically out-performs the random walk model for all four currencies using both daily and monthly data. The out-performance is however less robust for monthly forecasts when the reference currency is changed (Appendix F, Table 20). Including asymmetries (ACCM) does not lead to any improvement in the performance of the commodity driven model. The LLM and CM specifications fail to out-perform the random walk and record negative R^2_{oos} for most forecast horizons, crosses and estimation schemes.

Table 4 displays the R^2_{oos} estimates for all four currencies when the interest rate differential model (UIP) is used as the benchmark. The CLM specification again shows strong evidence of out-performing the UIP model in this forecasting exercise. Under both estimation schemes, it mostly records statistically significant and positive R^2_{oos} for all four currencies at the daily and monthly frequencies.

Table 4: Out-of-Sample R Square for UIP Benchmark

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.06[a]	0.10[a]	0.08[a]	0.09[a]	0.20[a]	0.20[a]	0.16[a]	0.07[b]
LLM	R^2_{oos}	0.00	0.00	0.00[c]	0.00	0.04[a]	0.01[c]	0.01	0.00
CM	R^2_{oos}	0.00[c]	0.00[b]	0.00	0.00	0.02[c]	0.03[b]	0.00	-0.01
ACCM	R^2_{oos}	0.06[a]	0.10[a]	0.08[a]	0.09[a]	0.18[a]	0.22[a]	0.10[a]	0.07[b]
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.07[a]	0.12[a]	0.11[a]	0.08[a]	0.18[a]	0.16[b]	0.18[a]	0.08[c]
LLM	R^2_{oos}	0.00	0.00	0.00	0.00[c]	0.00	-0.01	-0.02	0.02
CM	R^2_{oos}	0.00	0.00	0.00	-0.01	-0.10	-0.02	-0.05	-0.08
ACCM	R^2_{oos}	0.07[a]	0.12[a]	0.11[a]	0.08[a]	0.16[b]	0.17[b]	0.11[b]	0.10

The table displays Out-Of-Sample R squared statistic (R^2_{oos}), for UIP benchmark, by using daily and monthly data and USD as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts a, b and c statistical significance at the 1%, 5% and 10% level, respectively. The superscripts a, b and c for R^2_{oos} in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark. The superscripts a, b and c for R^2_{oos} in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark.

The ACCM specification again does not improve the performance of the CLM model. The LLM and CM specifications repeatedly fail to out-perform the benchmark model although the CM specification does show some very weak signs for the NOK and AUD under the recursive scheme. Tables 22 in Appendix F, shows that these findings holds for the GBP cross.

Overall, the commodity driven model performs better than the UIP model under the recursive scheme compared to the rolling scheme but this out-performance deteriorates as we decrease the data frequency.

Our findings under the out-of-sample forecast analysis can be summarized as follows. The Contemporaneous Linear Model best captures the commodity currency – commodity price relationship. This inference strongly holds at the daily level, but weakens as the data frequency is reduced. Controlling for asymmetries in changes in commodity prices does not improve the CLM specification's out of sample performance. The Lagged Linear Model and the Cointegration Model specifications exhibit the least sign of correctly capturing the commodity currency – commodity price relationship.

6.2.2.3 Forecast Stability Analysis

To investigate the stability of the forecasts produced by the different model specifications, we use the Giacomini and Rossi (2009) *t*-statistics, displayed in Table 5. Overall, the results show that we can strongly reject the null of no forecast breakdown or forecast stability across different forecasting frequencies, estimation schemes and numeraires. This reveals instabilities in the commodity driven model's forecasting performance over time. The strong rejection of the null hypothesis appears to be exclusive to the USD cross. Table 24 in Appendix F shows that for the GBP crosses we mostly fail to reject the null of no forecast breakdown for a majority of the currencies. From this we can conclude that forecasts of the commodity driven model when the GBP cross is the numeraire are more stable then when the USD cross is used as a numeraire.

Table 5: Testing for forecast breakdown

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	GR_t	5.57[a]	3.81[a]	10.45[a]	4.01[a]	1.35[c]	2.23[a]	2.31[a]	1.61[b]
LLM	GR_t	6.21[a]	4.59[a]	10.95[a]	4.66[a]	1.74[b]	2.04[b]	2.46[a]	1.71[b]
CM	GR_t	6.23[a]	4.56[a]	11.00[a]	4.66[a]	1.83[b]	1.97[b]	2.53[a]	1.68[b]
ACCM	GR_t	5.57[a]	3.81[a]	10.45[a]	4.01[a]	1.35[c]	2.23[a]	2.31[a]	1.61[b]
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	GR_t	2.63[a]	1.22[c]	4.74[a]	3.59[a]	2.41[a]	2.19[a]	2.08[a]	1.66[b]
LLM	GR_t	2.26[a]	1.25[c]	4.43[a]	3.38[a]	2.05[a]	1.77[b]	1.60[b]	1.79[a]
CM	GR_t	2.55[a]	1.42[c]	4.63[a]	3.62[a]	3.34[a]	2.41[a]	1.98[a]	3.38[a]
ACCM	GR_t	2.68[a]	1.33[c]	4.90[a]	3.67[a]	3.26[a]	2.70[a]	2.85[a]	2.68[a]

The table reports the Giacomini and Rossi (2009) t-statistic(GR_t) by using daily and monthly data and USD as a numeraire. This is a test for stability of the forecasting ability of a model, where the null is that the out-of-sample MSE of the model is equal to the in-sample MSE. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively, for a one-sided test.

6.2.2.4 Estimation Window Size Analysis

We revisit the question of the CLM specification performance under the rolling estimation scheme by varying the size of the in-sample window size and observing how this affects the model's performance and our conclusions.

Table 6 shows the average slope coefficients of the CLM specification and the result of the null test of the mean of the slope coefficient being equal to zero as we reduce the window size under the rolling estimation scheme. From the results, we can see that the average of the slope coefficients are fairly stable for each currency as we change the estimation window size. Most of the estimates are negative fitting the narrative expounded earlier. For the two cases where the average is positive, we cannot reject the null hypothesis that the estimate is statistically indistinguishable from zero. Tables 26 and 27 in Appendix F present the same results but for the GBP cross and the quarterly frequency variant respectively. The results support the conclusions we draw for USD cross.

Table 6: Average Beta estimate

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Daily				Monthly			
1/2	-0.03[a]	-0.28[a]	-0.02[a]	-0.18[a]	0.01	-0.24[a]	0.00	0.04
1/3	-0.02[a]	-0.29[a]	-0.01[a]	-0.15[a]	-0.03[a]	-0.30[a]	-0.03[a]	-0.27[a]
1/4	-0.03[a]	-0.33[a]	-0.01[a]	-0.16[a]	-0.06[a]	-0.36[a]	-0.02[a]	-0.20[a]
1/5	-0.03[a]	-0.28[a]	-0.01[a]	-0.12[a]	-0.07[a]	-0.30[a]	-0.05[a]	-0.21[a]

The table reports the average slope coefficient estimated via OLS using daily and monthly data and USD as a numeraire. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Table 7 shows the same information as Table 6, but this time we use a sub-sample (2002 – 2014) that covers the period of increasing financialisation of commodity markets and inflation targeting regime in Norway. The results are similar to the previous exercise, but now the estimates are much more pronounced (higher absolute values). We can therefore conclude that there has been an increase in the cross-elasticity between commodity currencies and the respective commodity prices post 2002. Tables 26 to 29 in Appendix F show that for the GBP cross and quarterly frequency the same conclusion holds.

Table 7: Average Beta estimate (2002-2014)

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Daily				Monthly			
1/2	-0.08[a]	-0.27[a]	-0.06[a]	-0.26[a]	-0.11[a]	-0.28[a]	-0.19[a]	-0.10[a]
1/3	-0.07[a]	-0.29[a]	-0.07[a]	-0.36[a]	-0.13[a]	-0.41[a]	0.00	-0.41[a]
1/4	-0.07[a]	-0.36[a]	-0.07[a]	-0.43[a]	-0.10[a]	-0.37[a]	-0.06	-0.54[a]
1/5	-0.08[a]	-0.37[a]	-0.06[a]	-0.42[a]	-0.07[a]	-0.30[a]	-0.07[a]	-0.45[a]

The table reports the average slope coefficient estimated via OLS using daily and monthly data and USD as a numeraire, for the period 2002-2014. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Figure 3 shows the time series evolution of the slope coefficient for the one quarter rolling window size that we predominantly used in the study. Although the estimates between 2001 and 2005 are highly unstable, the periods before and after are fairly stable. We can see that for all four currencies the overall trend of the slope coefficient has been downwards, post 2006, which confirms the increasing strength of the relationship.

Figure 3: Slope Coefficient Plot

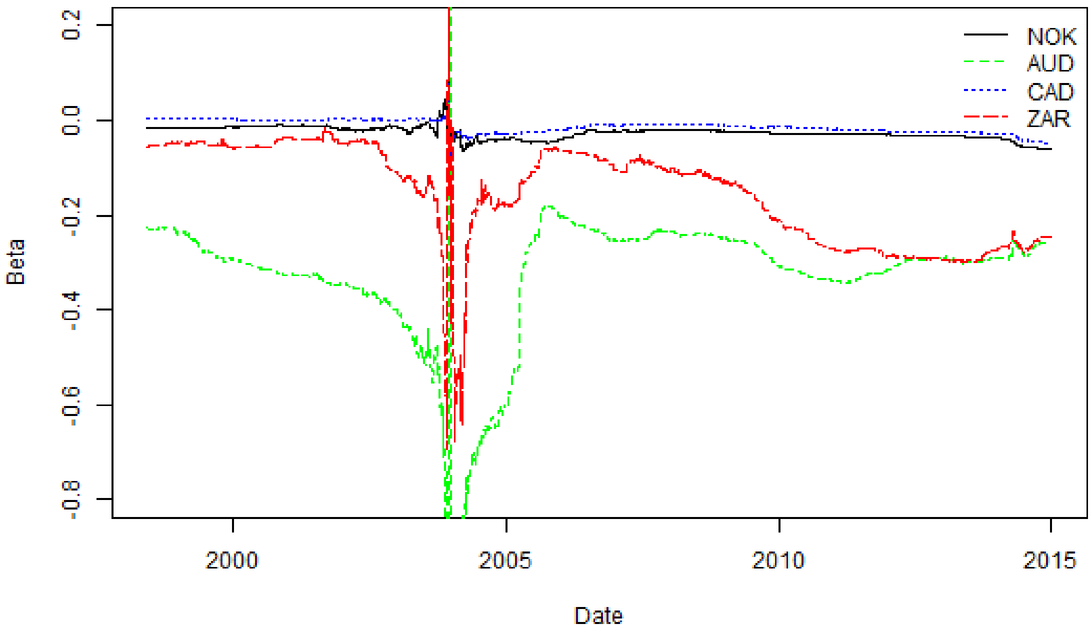


Figure 3 shows a plot of the CLM slope coefficient against time estimated via OLS using daily data and USD as a numeraire, covering the period 1992-2014. Each slope coefficient is obtained using rolling regressions, which involve successively re-estimating the model parameters using a fixed in-sample window size, of one fourth of the data, every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively.

We hypothesize that the observed instability in the parameters may be due to the dotcom bubble burst and increased volatility in commodity prices that happened in that period. For crude linked economies, NOK and CAD, the level of the parameter instability is not as pronounced as for the gold linked economies. Using the GBP as an alternative numeraire (Appendix F, Figure 5) does not lessen the extent of the parameter instability observed between 2002 and 2005 nor the other conclusions drawn.

Table 8, shows the p-values from the Giacomini and White (2006) one-sided test of out-performance for the CLM specification against both the RW and UIP benchmarks. Overall, the CLM specification out-performs both benchmarks at the daily frequency, across all estimation window sizes we study. As before, the evidence of out-performance weakens as the data frequency is decreased.

Table 8: Giacomini and White (2006) test p-values

	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Panel A: RW Benchmark							
Window Size	Daily				Monthly			
1/2	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.20
1/3	0.00	0.00	0.00	0.00	0.03	0.03	0.00	0.23
1/4	0.00	0.00	0.00	0.00	0.02	0.03	0.01	0.20
1/5	0.00	0.00	0.00	0.00	0.02	0.03	0.01	0.24
	Panel B: UIP Benchmark							
	Daily				Monthly			
1/2	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.32
1/3	0.00	0.00	0.00	0.00	0.01	0.06	0.00	0.02
1/4	0.00	0.00	0.00	0.00	0.01	0.05	0.01	0.08
1/5	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.19

The table reports the Giacomini and White (2006) test *p*-values by using daily and monthly data and USD as a numeraire. *P*-values from test of a null hypothesis of equal predictive ability between the CLM specification and the benchmark. By rejecting the null hypothesis of equal forecasting ability, we conclude that the CLM specification has a better forecasting power. The out-of-sample forecasts are obtained using rolling regressions which involve generating forecasts by successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively.

6.3 Discussion

Several aspects of the preceding analysis merit a discussion and this follows from the four hypotheses posited in section 5.1.

Results for Hypothesis 1

We test Hypothesis 1 by evaluating the results from the in-sample and out-of-sample exercises for the Contemporaneous Linear Model specification. Overall, we can strongly reject the null that the CLM specification does no better than the random walk and UIP benchmarks at the daily frequency. The evidence in favour of the CLM specification is much weaker at the monthly frequency and we fail to reject the null at the quarterly.

Recall that the CLM specification uses ex-post values of the commodity prices and so the finding of predictive ability is more a co-movement or contemporaneous relationship. This model specification follows from the work of Meese and Rogoff (1983b, 1983a) who demonstrate that even when using ex-post values as regressors, traditional fundamentals fail to outperform the random walk model. We have however shown that when using a non-traditional fundamental, commodity prices, for commodity exporting nations such as Australia, Canada, Norway and South Africa, we find strong evidence of predictability of the exchange rate at high frequencies. This model specification does not only out-perform the traditional UIP model, but the more difficult random walk benchmark. The evidence of predictability does not disappear when the GBP is used as the reference currency to control for the dollar effect. The evidence in favour of the CLM specification is also robust to the choice of estimation scheme. The CLM specification does not show only a strong out-sample performance, but also exhibits strong in-sample fit. The model specification however suffers from unstable forecasts over time, as indicated by the Giacomini and Rossi (2009) test.

We have to point out that this model specification is not a tradable strategy. Since the forecaster does not typically know the end of period commodity price, she cannot employ this model real time. To use this model successfully, one would also need a model that can forecast the commodity price with a very high level of accuracy.

Results for Hypothesis 2

Whiles the results for the CLM specification are encouraging, in reality forecasters do not have access to realized values of commodity prices when predicting future exchange rates. The evaluation of Hypothesis 2 answers the more realistic question of whether or not the one period lag change in commodity price can be used to predict the future exchange rate. From the in-sample and out-of-sample exercises, we fail to reject the null hypothesis that there is no difference between the performance of the Lagged Linear Model specification and the random walk and UIP benchmarks. This specification is a stricter test since we postulate that the change in lagged commodity price contains information about future exchange rates.

The results are not surprising given the liquid nature of both the currency and commodity markets. We have earlier on argued that the present market price of the commodity reflects the markets expectation of the future and so the same will hold for the exchange rate if the FX market is just as liquid. We should therefore only expect the lagged linear model to out-perform the RW benchmark if the exchange rate market is at least not as liquid as the commodity market. Given that the currency market is the most liquid market in the world, this result is plausible.

Results for Hypothesis 3

We test Hypothesis 3 by evaluating the results from the in-sample and out-of-sample exercises for the Cointegration Model specification. We fail to reject the null hypothesis that there is no difference between the performance of the CM specification against the random walk and UIP benchmarks. This result is in contrast to the general findings of Cheung et al. (2005), where they conclude that error correction models show the best results of predicting changes in the exchange rate. However, when viewed in terms of frequency, our finding is reasonable since cointegration is long-term feature of time series observed at lower frequencies whereas we mainly focus on the higher frequency data.

The model specification does show weak signs of an in-sample fit, but fails in all of the out-of-sample tests. This insight is in line with several findings in the literature: while several predictors and model specifications display in-sample predictive ability for future exchange rates, they fail in out-of-sample tests (Rossi, 2013).

Results for Hypothesis 4

To test Hypothesis 4, we evaluate the results from the in-sample and out-of-sample exercises for the Asymmetric Commodity Currency Model specification. The evaluation of this model specification tells us whether or not controlling for asymmetric effects in the commodity prices, improves the performance of the CLM specification. The empirical evidence shows that although we can reject the null of no difference in out-of-sample performance, the ACCM specification fails to improve the performance of the CLM specification. This suggests that there are no non-linearities in the commodity currency – commodity price relationship.

Summary

A large part of the empirical exchange rate literature has documented the difficulty of establishing a relationship between fundamentals and movements in the exchange rate. Some of the explanations that have been put forward include parameter instability in the predictive regressions which manifests in the form of high variation in the period by period OOS beta estimates (Li et al., 2014). Another explanation offered is based on the asset pricing model of Engel and West (2005). Their model shows that if exchange rates are related to economic fundamentals they may still appear to follow a random walk, if the discount factor is close to one and economic fundamentals are near unit-root processes. Therefore, under certain conditions, exchange rates may appear as random walks but this will still be consistent with an asset pricing model that links fundamentals to exchange rates. Yet again, some have argued that researchers cannot tie fundamentals to exchange rates because exchange rates are partly forward looking and traditional fundamentals are mostly lagging measures.

In this study, we have found that economic fundamentals are contemporaneously related to exchange rate movements and the key to revealing this connection is to use the right model specification and the right forward looking fundamental.

Comparing our results to other studies in the literature, we find that using the realized value of the fundamental instead of its lag matters in finding predictability, unlike Cerra and Saxena (2010) who find positive evidence no matter the predictor (lag or contemporaneous) they use. As opposed to Cheung et al. (2005) who find that the same model specification and fundamental does not consistently outperform the random walk, we find that the CLM specification of the commodity driven exchange rate model consistently outperforms the RW at the daily frequency across all four studied commodity currencies. The strength of the relationship however weakens as we decrease the frequency.

The fact that we find stronger evidence of outperformance at higher frequencies is contrary to the prevailing notion in the literature which is that predictability appears at longer horizons. We however stress that these studies predominantly use macroeconomic data which are fundamentally different from market data. Zhang et al. (2013) similarly argue that movements in highly active financial markets can be quite fast or short-lived, so frequency matters. The speculative nature of the exchange rate markets along with efficient market arguments suggest that any form of predictability will be aggregated away in lower frequency data.

A great deal of our findings are analogous to the findings of Ferraro et al. (2015) because we ask similar questions, but our work differs in the empirical techniques we employ to investigate the issues and the conclusions we draw from the results. The evidence of a strong in-sample connection is also in line with the in-sample conclusions of Chen and Rogoff (2003).

Our findings to some degree provide a resolution to the Meese and Rogoff puzzle. The puzzle can be summarized as the finding, that although “traditional” fundamentals are significant predictors of exchange rates in-sample, their out-of-sample predictive ability is not superior to that a random walk benchmark (Rossi, 2013). We have however shown that the contemporaneous linear specification of the commodity driven exchange rate model shows strong in-sample fit and out-performs the random walk in a rigorous out-of-sample exercise.

To explicitly answer our research questions, we have found that, first, the relationship between commodity currencies and commodity prices is linear and contemporaneous in nature. Second, true forecast models (lag linear model and cointegration models) are no good in forecasting changes in the exchange rate. Finally, the commodity driven exchange rate model produces unstable forecasts.

7 Conclusion

This paper focuses on the structural link between exchange rates and commodity prices by empirically investigating the dynamic relationship between commodity price movements and commodity currency exchange rate fluctuations.

After controlling for the dollar effect and estimation scheme bias, we find a very robust linear contemporaneous relationship between commodity prices and commodity currency exchange rates at the daily frequency. When using the one period lagged changes in commodity price to predict exchange rate, this relationship disappears. We find in-sample evidence that suggests a cointegration relationship between the commodity currency exchange rate and commodity prices. However, this cointegration relationship does not translate into out-of-sample success as this specification does no better than a random walk or UIP benchmark. Furthermore, controlling for asymmetries in the commodity price changes does not improve the performance of the simple linear model. Overall, the commodity driven exchange rate model shows signs of forecast instability.

Our results confirm Ferraro et al. (2015) suggestion that the existing literature has been unable to find strong out-of-sample evidence of exchange rate predictability by using commodity prices, mainly because these studies employed low frequency data.

While our study focuses on a statistical evaluation of the proposed models, it would be interesting to investigate model predictability in the economic sense (trading strategies) by using the econometric framework provided by Della Corte and Tsiakas (2012). Further robustness tests in the form of newer test statistics and testing of alternative specifications will also be informative. We leave these potentially interesting issues for the future research.

References

Akram, Q. F. 2004. Oil Prices and Exchange Rates: Norwegian Evidence. *The Econometrics Journal,* 7(2)**,** 476-504.

Amano, R. A. & Van Norden, S. 1998. Exchange Rates and Oil Prices. *Review of International Economics,* 6(4)**,** 683-694.

Backus, D. K. & Crucini, M. J. 2000. Oil Prices and the Terms of Trade. *Journal of International Economics,* 50(1)**,** 185-213.

Bekaert, G., Wei, M. & Xing, Y. 2007. Uncovered Interest Rate Parity and the Term Structure. *Journal of International Money and Finance,* 26(6)**,** 1038-1069.

Benhmad, F. 2012. Modeling Nonlinear Granger Causality between the Oil Price and Us Dollar: A Wavelet Based Approach. *Economic Modelling,* 29(4)**,** 1505-1514.

Bidarkota, P. & Crucini, M. J. 2000. Commodity Prices and the Terms of Trade. *Review of International Economics,* 8(4)**,** 647-666.

Bilson, J. F. 1978. The Monetary Approach to the Exchange Rate: Some Empirical Evidence. *Staff Papers-International Monetary Fund,* 48-75.

Bilson, J. F. 1981. The" Speculative Efficiency" Hypothesis. *Journal of Business,* 435-451.

Branson, W. H., Halttunen, H. & Masson, P. 1977. Exchange Rates in the Short Run: The Dollar-Dentschemark Rate. *European Economic Review,* 10(3)**,** 303-324.

Branson, W. H., Halttunen, H. & Masson, P. 1979. Exchange Rates in the Short Run: Some Further Results. *European Economic Review,* 12(4)**,** 395-402.

Breusch, T. S. & Pagan, A. R. 1979. A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica: Journal of the Econometric Society,* 1287-1294.

Büyükşahin, B. & Robe, M. A. 2014. Speculators, Commodities and Cross-Market Linkages. *Journal of International Money and Finance,* 4238-70.

Campbell, J. Y. & Shiller, R. J. 1987. Cointegration and Tests of Present Value Models. *The Journal of Political Economy,* 95(5)**,** 1062-1088.

Campbell, J. Y. & Shiller, R. J. 1988. Stock Prices, Earnings, and Expected Dividends. *The Journal of Finance,* 43(3)**,** 661-676.

Campbell, J. Y. & Thompson, S. B. 2008. Predicting Excess Stock Returns out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies,* 21(4)**,** 1509-1531.

Cayen, J.-P., Coletti, D., Lalonde, R. & Maier, P. 2010. What Drives Exchange Rates? New Evidence from a Panel of Us Dollar Bilateral Exchange Rates. Bank of Canada Working Paper.

Cerra, V. & Saxena, S. C. 2010. The Monetary Model Strikes Back: Evidence from the World. *Journal of International Economics,* 81(2)**,** 184-196.

Chaboud, A. P. & Wright, J. H. 2005. Uncovered Interest Parity: It Works, but Not for Long. *Journal of International Economics,* 66(2)**,** 349-362.

Chen, Y.-C. & Rogoff, K. 2003. Commodity Currencies. *Journal of International Economics,* 60(1)**,** 133-160.

Chen, Y.-C., Rogoff, K. & Rossi, B. 2010. Can Exchange Rates Forecast Commodity Prices? *Quarterly Journal of Economics,* 125(3)**,** 1145-1194.

Chen, Y.-C. & Tsang, K. P. 2013. What Does the Yield Curve Tell Us About Exchange Rate Predictability? *Review of Economics and Statistics,* 95(1)**,** 185-205.

Cheung, Y.-W., Chinn, M. D. & Pascual, A. G. 2005. Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive? *Journal of International Money and Finance,* 24(7)**,** 1150-1175.

Chinn, M. D. 2012. Macro Approaches to Foreign Exchange Determination. *J. James, I. Marsh, L. Sarno, Handbook of Exchange Rates, Wiley,* 45-72.

Chinn, M. D. & Meese, R. A. 1995. Banking on Currency Forecasts: How Predictable Is Change in Money? *Journal of International Economics,* 38(1)**,** 161-178.

Chinn, M. D. & Meredith, G. 2004. Monetary Policy and Long-Horizon Uncovered Interest Parity. *IMF staff papers,* 409-430.

Clark, T. & Mccracken, M. 2013. Advances in Forecast Evaluation. *Handbook of Economic Forecasting,* 21107.

Clark, T. E. & West, K. D. 2006. Using out-of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis. *Journal of Econometrics,* 135(1)**,** 155-186.

Clark, T. E. & West, K. D. 2007. Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of econometrics,* 138(1)**,** 291-311.

Corbae, D. & Ouliaris, S. 1986. Robust Tests for Unit Roots in the Foreign Exchange Market. *Economics Letters,* 22(4)**,** 375-380.

Crowder, W. J. 1994. Foreign Exchange Market Efficiency and Common Stochastic Trends. *Journal of International Money and Finance,* 13(5)**,** 551-564.

Cumby, R. E. & Obstfeld, M. 1981. A Note on Exchange-Rate Expectations and Nominal Interest Differentials: A Test of the Fisher Hypothesis. *The Journal of Finance,* 36(3)**,** 697-703.

Della Corte, P. & Tsiakas, I. 2012. Statistical and Economic Methods for Evaluating Exchange Rate Predictability. *In:* James, J. M., Ian;Sarno, Lucio; (ed.) *Handbook of Exchange Rates.* New Jersey: John Wiley & Sons.

Dickey, D. A. & Fuller, W. A. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica: Journal of the Econometric Society,* 1057-1072.

Diebold, F. X. & Mariano, R. S. 1995. Comparing Predictive Accuracy. *Journal of Business & Economic Statistics,* 13(3).

Dooley, M. & Isard, P. 1982. A Portfolio-Balance Rational-Expectations Model of the Dollar-Mark Exchange Rate. *Journal of International Economics,* 12(3)**,** 257-276.

Dornbusch, R. 1976. Expectations and Exchange Rate Dynamics. *The Journal of Political Economy,* 1161-1176.

Dornbusch, R., Branson, W. H., Kenen, P., Houthakker, H., Hall, R. E., Lawrence, R., Perry, G., Fellner, W., Brainard, W. & Von Furstenburg, G. 1980. Exchange Rate Economics: Where Do We Stand? *Brookings Papers on Economic Activity,* 143-205.

Durbin, J. & Watson, G. S. 1950. Testing for Serial Correlation in Least Squares Regression: I. *Biometrika,* 409-428.

Durbin, J. & Watson, G. S. 1951. Testing for Serial Correlation in Least Squares Regression. Ii. *Biometrika,* 159-177.

Dwyer, G. P. & Wallace, M. S. 1992. Cointegration and Market Efficiency. *Journal of International Money and Finance,* 11(4)**,** 318-327.

Engel, C. 1996. A Note on Cointegration and International Capital Market Efficiency. *Journal of International Money and Finance,* 15(4)**,** 657-660.

Engel, C. 1999. Accounting for Us Real Exchange Rate Changes. *Journal of Political Economy,* 107(3).

Engel, C., Mark, N. C. & West, K. D. 2007. Exchange Rate Models Are Not as Bad as You Think. National Bureau of Economic Research, Inc.

Engel, C. & West, K. D. 2005. Exchange Rates and Fundamentals. 113(3).

Engle, R. F. & Granger, C. W. J. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica,* 55(2)**,** 251-276.

Fama, E. F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work*. *The journal of Finance,* 25(2)**,** 383-417.

Faust, J., Rogers, J. H. & H Wright, J. 2003. Exchange Rate Forecasting: The Errors We've Really Made. *Journal of International Economics,* 60(1)**,** 35-59.

Feenstra, R. C., Taylor, A. M. & Taylor, J. 2014. *International Macroeconomics,* Worth Publishers.

Ferraro, D., Rogoff, K. S. & Rossi, B. 2012. Can Oil Prices Forecast Exchange Rates? : National Bureau of Economic Research.

Ferraro, D., Rogoff, K. S. & Rossi, B. 2015. Can Oil Prices Forecast Exchange Rates? *National Bureau of Economic Research Working Paper,* (w17998).

Frankel, J. A. 1979. On the Mark: A Theory of Floating Exchange Rates Based on Real Interest Differentials. *American Economic Review,* 69(4)**,** 610-22.

Frankel, J. A. 1983. Monetary and Portfolio-Balance Models of Exchange Rate Determination. National Bureau of Economic Research.

Frankel, J. A. 1984. Tests of Monetary and Portfolio Balance Models of Exchange Rate Determination. *Exchange Rate Theory and Practice.* University of Chicago Press.

Fratzscher, M., Schneider, D. & Van Robays, I. 2013. Oil Prices, Exchange Rates and Asset Prices. Discussion Papers, DIW Berlin.

Frenkel, J. A. 1976. A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence. *the scandinavian Journal of economics,* 200-224.

Frenkel, J. A. & Levich, R. M. 1975. Covered Interest Arbitrage: Unexploited Profits? *The Journal of Political Economy,* 325-338.

Frenkel, J. A. & Levich, R. M. 1977. Transaction Costs and Interest Arbitrage: Tranquil Versus Turbulent Periods. *The Journal of Political Economy,* 1209-1226.

Fuller, W. 1976. Introduce to Statistical Time Series. New York: John Wiley.

Giacomini, R. & Rossi, B. 2009. Detecting and Predicting Forecast Breakdowns. *The Review of Economic Studies,* 76(2)**,** 669-705.

Giacomini, R. & Rossi, B. 2010. Forecast Comparisons in Unstable Environments. *Journal of Applied Econometrics,* 25(4)**,** 595-620.

Giacomini, R. & White, H. 2006. Tests of Conditional Predictive Ability. *Econometrica,* 74(6)**,** 1545-1578.

Goldberg, P. K. & Verboven, F. 2005. Market Integration and Convergence to the Law of One Price: Evidence from the European Car Market. *Journal of international Economics,* 65(1)**,** 49-73.

Groen, J. J. 2005. Exchange Rate Predictability and Monetary Fundamentals in a Small Multi-Country Panel. *Journal of Money, Credit, and Banking,* 37(3)**,** 495-516.

Hakkio, C. S. 1984. A Re-Examination of Purchasing Power Parity: A Multi-Country and Multi-Period Study. *Journal of International Economics,* 17(3)**,** 265-277.

Hamilton, J. D. 2003. What Is an Oil Shock? *Journal of econometrics,* 113(2)**,** 363-398.

Haynes, S. E. & Stone, J. A. 1981. On the Mark: Comment. *The American Economic Review,* 71(5)**,** 1060-1067.

Husted, S. L. & Melvin, M. 2012. *International Economics*, Pearson.

Issa, R., Lafrance, R. & Murray, J. 2008. The Turning Black Tide: Energy Prices and the Canadian Dollar. *Canadian Journal of Economics/Revue canadienne d'économique,* 41(3)**,** 737-759.

Kilian, L. & Vigfusson, R. J. 2011. Are the Responses of the Us Economy Asymmetric in Energy Price Increases and Decreases? *Quantitative Economics,* 2(3)**,** 419-453.

Kleivset, C. 2012. *From a Fixed Exchange Rate Regime to Inflation Targeting* [Online]. Oslo, Norway: Norges Bank.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. & Shin, Y. 1992. Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root? *Journal of econometrics,* 54(1)**,** 159-178.

Leitch, G. & Tanner, E. J. 1991. Economic Forecast Evaluation: Profits Versus the Conventional Error Measures. *American Economic Review,* 81(3)**,** 580-90.

Li, J., Tsiakas, I. & Wang, W. 2014. Predicting Exchange Rates out of Sample: Can Economic Fundamentals Beat the Random Walk? *Journal of Financial Econometrics,* nbu007.

Liu, C. Y. & He, J. 1991. A Variance-Ratio Test of Random Walks in Foreign Exchange Rates. *The Journal of Finance,* 46(2)**,** 773-785.

Lothian, J. R. & Wu, L. 2011. Uncovered Interest-Rate Parity over the Past Two Centuries. *Journal of International Money and Finance,* 30(3)**,** 448-473.

Macdonald, R. 2007. *Exchange Rate Economics: Theories and Evidence,* New York, Routledge.

Macdonald, R. & Torrance, T. S. 1990. Expectations Formation and Risk in Four Foreign Exchange Markets. *Oxford Economic Papers,* 544-561.

Mark, N. C. 1995. Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability. *The American Economic Review,* 201-218.

Mark, N. C. & Sul, D. 2001. Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post-Bretton Woods Panel. *Journal of International Economics,* 53(1)**,** 29-52.

Mccracken, M. W. 2007. Asymptotics for out of Sample Tests of Granger Causality. *Journal of Econometrics,* 140(2)**,** 719-752.

Meese, R. & Rogoff, K. 1983a. The out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification? *Exchange Rates and International Macroeconomics.* University of Chicago Press.

Meese, R. A. & Rogoff, K. 1983b. Empirical Exchange Rate Models of the Seventies: Do They Fit out of Sample? *Journal of international economics,* 14(1)**,** 3-24.

Meese, R. A. & Singleton, K. J. 1982. On Unit Roots and the Empirical Modeling of Exchange Rates. *the Journal of Finance,* 37(4)**,** 1029-1035.

Mishkin, F. S. 1984. Are Real Interest Rates Equal across Countries? An Empirical Investigation of International Parity Conditions. *The Journal of Finance,* 39(5)**,** 1345-1357.

Molodtsova, T., Nikolsko-Rzhevskyy, A. & Papell, D. H. 2008. Taylor Rules with Real-Time Data: A Tale of Two Countries and One Exchange Rate. *Journal of Monetary Economics,* 55S63-S79.

Molodtsova, T., Nikolsko-Rzhevskyy, A. & Papell, D. H. 2011. Taylor Rules and the Euro. *Journal of Money, Credit and Banking,* 43(2-3)**,** 535-552.

Molodtsova, T. & Papell, D. H. 2009. Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals. *Journal of International Economics,* 77(2)**,** 167-180.

Paye, B. S. 2012. 'Déjà Vol': Predictive Regressions for Aggregate Stock Market Volatility Using Macroeconomic Variables. *Journal of Financial Economics,* 106(3)**,** 527-546.

Peng, W. 1995. The Fisher Hypothesis and Inflation Persistence: Evidence from Five Major Industrial Countries.

Rogoff, K. S. & Stavrakeva, V. 2008. The Continuing Puzzle of Short Horizon Exchange Rate Forecasting. National Bureau of Economic Research, Inc.

Rossi, B. 2013. Exchange Rate Predictability. *Journal of Economic Literature,* 51(4)**,** 1063-1119.

Rossi, B. & Inoue, A. 2012. Out-of-Sample Forecast Tests Robust to the Choice of Window Size. *Journal of Business & Economic Statistics,* 30(3)**,** 432-453.

Schwarz, G. 1978. Estimating the Dimension of a Model. *The annals of statistics,* 6(2)**,** 461-464.

Stock, J. H. & Watson, M. W. 2003. Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature,* 41788-829.

Taylor, J. B. Discretion Versus Policy Rules in Practice. Carnegie-Rochester conference series on public policy, 1993. Elsevier, 195-214.

Taylor, M. P. 1989. Covered Interest Arbitrage and Market Turbulence. *The Economic Journal,* 376-391.

Wang, P. 2009. *The Economics of Foreign Exchange and Global Finance,* Hull, United Kingdom, Springer.

West, K. D. 1988. Dividend Innovations and Stock Price Volatility. *Econometrica: Journal of the Econometric Society,* 37-61.

White, H. 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica: Journal of the Econometric Society,* 817-838.

Zhang, H. J., Dufour, J.-M. & Galbraith, J. W. 2013. Exchange Rates and Commodity Prices: Measuring Causality at Multiple Horizons. *CIRANO-Scientific Publications 2013s-39*.

Zivot, E. 2000. Cointegration and Forward and Spot Exchange Rate Regressions. *Journal of International Money and Finance,* 19(6)**,** 785-812.

Appendix A: Example of Engel and West (2005) Asset Pricing Model

The Engel and West (2005) asset pricing model nests a number of empirical models, one of which we is the monetary fundamental model present in chapter 2.

We consider the familiar sticky price monetary model and show how it is a special case of expression 4.01. We start the derivation by assuming the money market is described by the relationship:

$$m_t = p_t + \varphi y_t - \lambda r_t + \varepsilon_{m,t} \tag{A.1}$$

Expression A.1 is the same as equation 2.03 with one modification. We introduce $\varepsilon_{m,t}$, which is the unobserved shock to domestic money demand at time *t*. We again assume money demand equals money supply and that a similar relationship holds for the foreign economy, where the corresponding variables are denoted by $m_t^*, p_t^*, y_t^*, r_t^*$ and $\varepsilon_{m,t}^*$. We further assume that the income elasticity of money demand (φ) and the interest rate semi-elasticity of money demand (λ) are the same across economies.

From the real exchange rate expression in chapter two we have:

$$s_t = p_t - p_t^* + q_t \tag{A.2}$$

If uncovered interest rate parity does not hold then the UIP expression can be rewritten as:

$$E_t s_{t+1} - s_t - p_t = r_t - r_t^* \tag{A.3}$$

where p_t is the deviation from the UIP condition and interpreted as the risk premium. As before, rearranging equation A.1 in-terms of p_t and p_t^* and substituting this A.3 we get:

$$s_t = \left(\frac{1}{1+\lambda}\right)\left[(m_t - m_t^*) - \varphi(y_t - y_t^*) + q_t - \left(\varepsilon_{m,t} - \varepsilon_{m,t}^*\right) - \lambda p_t\right] + \left(\frac{\lambda}{1+\lambda}\right) E_t s_{t+1} \tag{A.4}$$

This equation takes the form of the original model in equation 4.01 where the discount factor b is given by $\left(\frac{\lambda}{1+\lambda}\right)$, the observed fundamentals $f_{1,t}$ are $(m_t - m_t^*) - \varphi(y_t - y_t^*)$ and the unobserved fundamentals are $z_{1,t} = q_t - \left(\varepsilon_{m,t} - \varepsilon_{m,t}^*\right)$ and $z_{2,t} = -p_t$.

Appendix B: Data Description

Table 9: Country's commodity as a percent of total export / world production

Country	Australia	Canada	Norway	South Africa
Commodity	*Gold******	*Crude Oil*	*Crude Oil*	*Gold*
Commodity as a percent of country's total exports	4%	9%	31%	7%
Country commodity production as percent of the total world production	9%*	4%**	4%**	6%*

Sources: International Trade Statistics Yearbook (2002-2013), *U.S. Department of the Interior – U.S. Geological Survey, ** BP Statistical Review of world energy June 2013 (1992-2012) ***Gold is used due to the unavailability of the long time series of daily observations for iron ore and coal.

Table 10: Data Sources

Country	Description	Source	Range	Frequency	Series
			Nominal Exchange Rate		
Australia	Spot AUD/USD	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (AUUSBOE)
	Spot AUD/GBP	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (AUSTBOE)
Canada	Spot CAD/USD	IMF	01.12.1992-31.12.2014	Daily	DataStream (RCADUSD)
	Spot CAD/GBP	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (CNSTBOE)
Norway	Spot NOK/USD	IMF	01.12.1992-31.12.2014	Daily	DataStream (RNOKUSD)
	Spot NOK/GBP	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (NWSTBOE)
South Africa	Spot ZAR/USD	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (SAUSBOE)
	Spot ZAR/GBP	Bank of England	01.12.1992-31.12.2014	Daily	DataStream (SASTBOE)
			Commodity Price		
Australia	Gold $	London Bullion Market	01.12.1992-31.12.2014	Daily	DataStream (GOLDBLN)
Canada	Crude Oil WTI $	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (CRUDOIL)
Norway	Crude Oil Brent $	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (OILBRDT)
South Africa	Gold $	London Bullion Market	01.12.1992-31.12.2014	Daily	DataStream (GOLDBLN)
			Interest Rates		
Australia	Australian $ S/T Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECAUDST)
	Australian $ 1m Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECAUD1M)
	Australian $ 3m Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECAUD3M)
Canada	Canadian $ S/T Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCADST)
	Canadian $ 1m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCAD1M)
	Canadian $ 3m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCAD3M)

Table 10: Continued

Country	Description	Source	Range	Frequency	Series
Canada	Canadian $ S/T Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCADST)
	Canadian $ 1m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCAD1M)
	Canadian $ 3m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECCAD3M)
Norway	Norway O/N Lending	Norges Bank	01.12.1992-31.12.2014	Daily	DataStream (NWDINTN)
	Norway Interbank 1m	Norges Bank	01.12.1992-31.12.2014	Daily	DataStream (NWIBK1M)
	Norway Interbank 3m	Norges Bank	01.12.1992-31.12.2014	Daily	DataStream (NWIBK3M)
South Africa	S. African Rand S/T Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECSARST)
	S. African Rand 1m Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECSAR1M)
	S. African Rand 3m Deposit	Thomson Reuters	01.04.1997-31.12.2014	Daily	DataStream (ECSAR3M)
United Kingdom	UK Sterling S/T Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUKPST)
	UK Sterling 1m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUKP1M)
	UK Sterling 3m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUKP3M)
USA	US Dollar S/T Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUSDST)
	US Dollar 1m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUSD1M)
	US Dollar 3m Deposit	Thomson Reuters	01.12.1992-31.12.2014	Daily	DataStream (ECUSD3M)

The table displays a detailed description of the sources of raw data. The exchange rate data is from December 1992 to December 2014. The riskless rate and the commodity price data have a starting range of December 1992 to October 1997 and end in December 2014.

Appendix C: OLS Assumption tests

Correctly estimating the parameters of a regression using Ordinary Least Squares (OLS) is predicated on a set of assumptions. The validity of the estimates and inferences based on the results of the regression therefore rests on whether or not the OLS assumptions hold. In this appendix we undertake a number of formal diagnostic test on the data we use and the contemporaneous model specification to verify the validity of the underlying OLS assumptions.

Unit Root Tests

We use the Augmented Dickey Fuller (Dickey and Fuller, 1981) and the Kwiatkowski, Phillips, Schmidt and Shin test (Kwiatkowski et al., 1992) stationarity tests to test for the presence of a unit root in the levels and logs of all the price series we use in the regressions.

Augmented Dickey Fuller Test (ADF)

Under the ADF procedure, we test the null hypothesis of unit root by estimating the following regression equation; $\Delta x_t = \alpha_0 + \alpha_1 t + \gamma x_{t-1} - \sum_{j=1}^{k} \beta \Delta x_{t-j} + \varepsilon_t$, where *x* is the series, Δ is the difference operator, k is the optimal lag length selected to ensure ε_t is a white noise process. The decision to set $\alpha_0\ and/or\ \alpha_1$ to 0, is based on visual inspection. Rejecting the null hypothesis, $\boldsymbol{H_0}: \boldsymbol{\gamma} = \boldsymbol{0}$, means the series is stationary. The distribution of the *t*-statistic for $\boldsymbol{\gamma}$ in the regression is provided by Fuller (1976). We select the optimal lag using the Schwert information criterion (Schwarz, 1978).

KPSS Stationarity Test

The test involves decomposing the time series into the sum of a deterministic trend, a random walk and a stationary error component as: $y_t = \delta t + r_t + \varepsilon_t$, where r_t is a random walk: $r_t = r_{t-1} + \mu_t$ and $\mu_t$is independent identically distributed $(0, \sigma_\mu^2)$. The initial value of r_t, r_0, is treated as fixed and serves the role of an intercept in the model. *t* is treated as the time index in the model. The null hypothesis is H_0: $\sigma_u = 0$ meaning the unit process is fixed at the initial value of r_0 and y_t is stationary. The alternative hypothesis is that y_t contains a unit root. The KPSS test statistic is the Lagrange multiplier (LM) or score statistic for testing $\sigma_u{}^2 = 0$ against the alternative $\sigma_u{}^2 > 0$. We specify the optimal lag length using the the Schwert information criterion (Schwarz, 1978).

Table 11: Augmented Dickey-Fuller Unit Root test

Variable	Logs of Variables			First Difference of Logs		
	Lags	Test Statistic	5% Critical Value	Lags	Test Statistic	5% Critical Value
			Currencies			
AUDUSD	1	-1.094	-1.950	1	-54.922	-1.950
AUDGBP	1	-0.638	-1.950	1	-55.100	-1.950
CADUSD	1	-0.868	-1.950	1	-53.651	-1.950
CADGBP	1	-0.497	-1.950	1	-54.962	-1.950
NOKUSD	1	0.137	-1.950	1	-55.249	-1.950
NOKGBP	1	0.243	-1.950	1	-54.549	-1.950
ZARUSD	1	-2.028	-3.410	1	-55.785	-1.950
ZARGBP	1	-2.105	-3.410	1	-54.887	-1.950
			Commodities			
Brent Crude	1	-2.445	-3.410	1	-53.396	-1.950
Gold	1	-1.560	-3.410	1	-53.687	-1.950
WTI Crude	1	-2.760	-3.410	1	-55.510	-1.950

The table displays the optimal lag, ADF *t*-statistic and the 5% critical value for testing for unit root. Reject the null of unit root when the test statistic is greater than the critical value.

Table 12: KPSS Unit Root test

Variable	Logs of Variables			First Difference of Logs		
	Lags	Test Statistic	5% Critical Value	Lags	Test Statistic	5% Critical Value
			Currencies			
AUDUSD	1	148	0.463	1	0.083	0.463
AUDGBP	1	127.781	0.463	1	0.100	0.463
CADUSD	1	205.198	0.463	1	0.134	0.463
CADGBP	1	163.209	0.463	1	0.110	0.463
NOKUSD	1	122.875	0.463	1	0.098	0.463
NOKGBP	1	104.393	0.463	1	0.111	0.463
ZARUSD	1	186.094	0.463	1	0.120	0.463
ZARGBP	1	204.309	0.463	1	0.143	0.463
			Commodities			
Brent Crude	1	263.842	0.463	1	0.096	0.463
Gold	1	239.842	0.463	1	0.251	0.463
WTI Crude	1	262.005	0.463	1	0.077	0.463

The table displays the optimal lag, *test* statistic and the 5% critical value for testing for the KPSS stationarity test. Reject the null of sationarity when the test statistic is greater than the critical value.

Autocorrelation

One violation of the normality assumption expresses itself in the form of correlation in the error terms/disturbance. Since this is more likely to occur with time-series data, we formally test for this. The presence of autocorrelation in the error term does not lead to biased estimates but reduces the validity of inferences made using the uncorrected standard errors. Serial correlation means that the error terms are related by a relationship similar to: $\varepsilon_t = \rho\varepsilon_{t-1} + error$, where ε_t is the error term at time t. The null hypothesis is that: $H_0: \rho = 0$ which is tested against a two sided alternative of: $H_A: \rho \neq 0$. We do not estimate the relationship using OLS but use the Durbin and Watson (1950, 1951) autocorrelation testing framework. Table 19 shows the bootstrapped p-values of the Durbin-Watson statistic for the different pairs and different forecast horizons, we study. When p-value is less than 0.05, we can safely reject the null hypothesis of no serial correlation. Besides the daily CLM specification for the USD, the results surprisingly show very little evidence of serial correlation.

Table 13: Durbin-Watson test

	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	USD				GBP			
Daily	0.039[b]	0.002[a]	0.002[a]	0.076[c]	0.169	0.194	0.230	0.770
Monthly	0.409	0.133	0.036[b]	0.848	0.195	0.246	0.061	0.223
Quarterly	0.366	0.950	0.716	0.481	0.046	0.028	0.661	0.482

The table reports the p-values for the Durbin and Watson (1950, 1951) test for autocorrelation. This is a test for the presence of serial correlation in the error terms of the estimated model which means that inference made using the OLS estimation results are no longer valid. By rejecting the null, we find evidence of autocorrelation. The full sample set is used in conducting the test based on the Contemporaneous Linear Model (CLM) which is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10%.

Heteroskedasticity

Violation of the Homoscedastic assumption means that the error terms have a varying variance. When this happens, the OLS estimates remain unbiased but the variance of the estimate and statistical inference based on these variances are now incorrect. We formally check for this using Breusch-Pagan test and White test.

The Breusch-Pagan test

This test starts with a null hypothesis of homoscedasticity: $H_0: Var(\varepsilon|x_1, x_2, \dots, x_k) = \sigma^2$. Which says that the variance of the error term given the observations is constant. Given the zero conditional mean assumption of the model, this is equivalent to: $H_0: E(\varepsilon^2|x_1, x_2, \dots, x_k) = E(\sigma^2) = \sigma^2$. This also means that the squared error terms should be uncorrelated with all the explanatory variables if the null hypothesis is true. Since the true ε^2 is unobserved but its sample counterpart is, we use the sample counterpart in the formal test. If there is heteroscedasticity, $\hat{\varepsilon}^2$ could be any function of the explanatory variables, for simplicity the linear function we test is: $\varepsilon^2 = \delta_0 + \delta_1 x_1 + error$, thus the test of the null hypothesis is now: $H_0: \delta_1 = 0$ which is tested with an F-test for the overall significance of the regression. Table 20 shows the P-values of conducting the BP test on the CLM specification for different pairs and different forecast horizons. If the recorded p-value is less than 0.05, we can safely reject the null hypothesis of constant variance. The results show that aside the daily and monthly USD and GBP cross for the Canadian dollar and Norwegian krone, the null of homoscedasticity is not rejected for the rest of the pairs.

Table 14: Breusch-Pagan test

	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	USD				GBP			
Daily	0.017[b]	0.218	0.007[a]	0.545	0.012[b]	0.952	0.000[a]	0.727
Monthly	0.004[a]	0.196	0.044[b]	0.075[c]	0.631	0.861	0.918	0.978
Quarterly	0.405	0.889	0.654	0.467	0.169	0.177	0.806	0.773

The table reports the p-values for the Breusch and Pagan (1979) test for homoscedasticity. This is a test for the presence of heteroscedasticity which means that inference made using the OLS estimation results are no longer valid. By rejecting the null, we find evidence of heteroscedasticity. The full sample set is used in conducting the test based on the Contemporaneous Linear Model (CLM) which is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively, for a one-sided test.

The White-test

This is a test based on a null hypothesis of homoscedasticity but with a weaker restriction of $Var(\varepsilon|x_1, x_2, \ldots, x_k) = \sigma^2$. The White (1980) test is based on estimating: $\varepsilon^2 = \delta_0 + \delta_1 y + \delta_1 y^2 + error$, where ε^2 the squared residuals and y is is the fitted dependent variable. Under the null, all coefficients are statistically zero ($\delta_1 = \delta_2 = 0$). Table 12 reports the p-values of conducting the White test on the CLM specification for the different pairs and different forecast horizons. If the recorded p-value is less than 0.05, we can safely reject the null hypothesis of homoscedasticity. The results show a number of the models estimated suffer from heteroscedasticity.

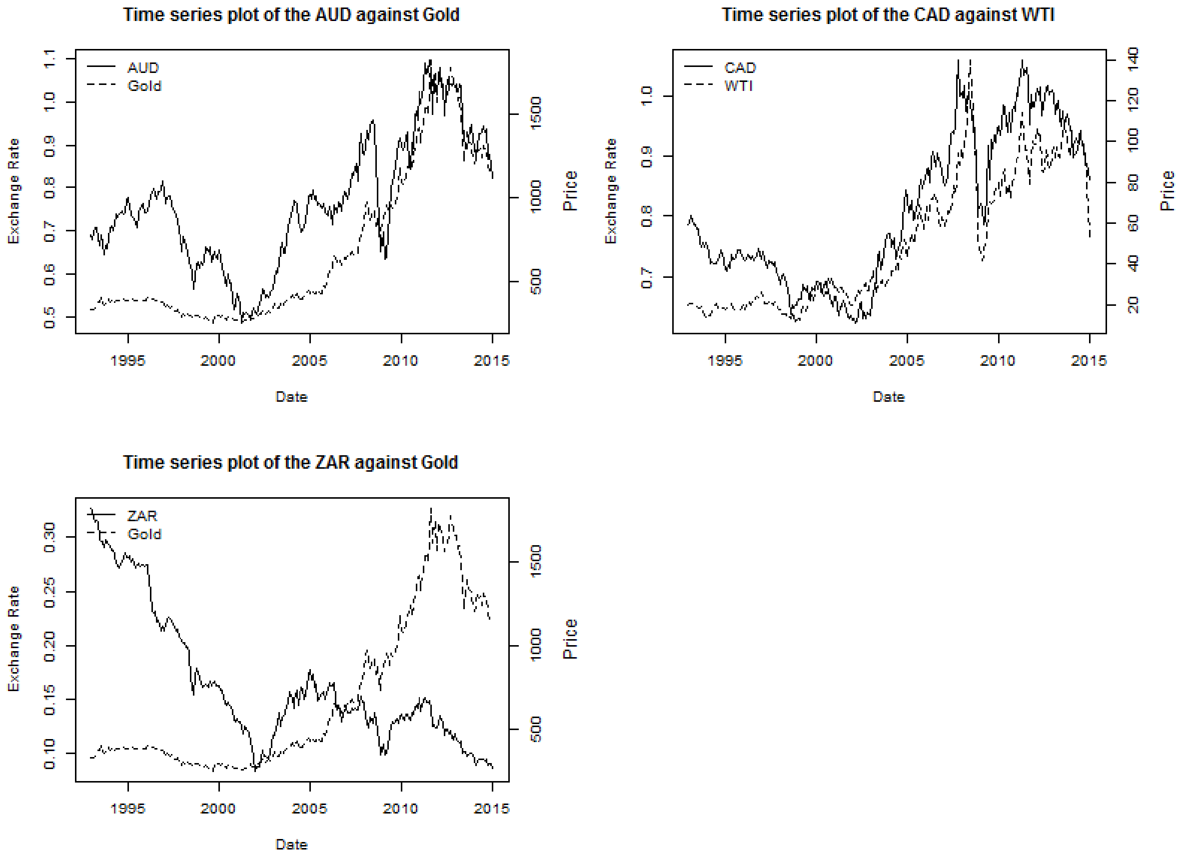
Table 15: White test

	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	USD				GBP			
Daily	0.059^c	0.468	0.026^b	0.833	0.044^b	0.998	0.001^a	0.941
Monthly	0.014^b	0.434	0.132	0.205	0.891	0.985	0.995	1.000
Quarterly	0.707	0.990	0.904	0.768	0.389	0.403	0.970	0.959

The table reports the p-values from the White (1980) test for homoscedasticity. This is a test for the presence of heteroscedasticity which means that inference made using the OLS estimation results are no longer valid. By rejecting the null, we find evidence of heteroscedasticity. The full sample set is used in conducting the test based on the Contemporaneous Linear Model (CLM) which is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively, for a one-sided test.

Appendix D

Figure 4: Time Series plots of the various commodity currency and commodity pairs



This plot shows the evolution of the various commodity currency and commodity pairs. Except for the South African rand, all the other pairs show a pronounced trend following 2001, which we hypothesize could be due to the financialisation of the commodity markets following the 2000 dot com crush. All the data series start from December 1992 and end in December 2014.

Appendix E

Table 16: OLS estimates using full sample (GBP)

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Daily				Monthly			
CLM	α	0.00003	-0.00000	-0.00001	0.0003[b]	0.001	0.0003	-0.0002	0.006[b]
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.003)
	β	-0.032 [a]	-0.109 [a]	-0.020 [a]	-0.091 [a]	-0.053 [a]	-0.178 [a]	-0.018	-0.111 [c]
		(0.004)	(0.014)	(0.004)	(0.016)	(0.016)	(0.044)	(0.016)	(0.062)
	R^2	0.015	0.023	0.005	0.010	0.042	0.061	0.0001	0.010
LLM	α	0.00003	-0.00003	-0.00001	0.0002[c]	0.0004	-0.001	-0.0003	0.005[b]
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.002)
	β	-0.006	-0.001	-0.012 [a]	0.015	0.016	-0.003	0.026	0.043
		(0.004)	(0.013)	(0.004)	(0.014)	(0.015)	(0.041)	(0.021)	(0.059)
	R^2	0.0004	-0.0002	0.002	0.0001	0.0002	-0.004	0.004	-0.002
CM	α	0.005[b]	0.007[a]	0.003[b]	0.001[a]	0.085[b]	0.152[a]	0.054[a]	0.016[a]
		(0.002)	(0.002)	(0.001)	(0.0002)	(0.034)	(0.050)	(0.018)	(0.005)
	β	-0.002[b]	-0.003[a]	-0.002[b]	-0.001[c]	-0.031[b]	-0.064[a]	-0.043[a]	-0.017[b]
		(0.001)	(0.001)	(0.001)	(0.0004)	(0.012)	(0.021)	(0.014)	(0.008)
	R^2	0.001	0.002	0.001	0.0005	0.012	0.034	0.026	0.011
ACCM	α	0.0001	-0.0001	-0.00003	-0.0001	0.001	-0.003	0.003	0.003
		(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.002)	(0.003)	(0.003)	(0.004)
	β	-0.031 [a]	-0.126 [a]	-0.021 [b]	-0.136 [a]	-0.050	-0.289 [a]	0.025	-0.197
		(0.008)	(0.020)	(0.009)	(0.028)	(0.032)	(0.076)	(0.032)	(0.121)
	D	-0.003	0.035	0.002	0.093 [b]	-0.007	0.203 [c]	-0.094 [c]	0.160
		(0.012)	(0.035)	(0.013)	(0.047)	(0.052)	(0.119)	(0.057)	(0.183)
	R^2	0.014	0.023	0.005	0.011	0.039	0.067	0.007	0.010

The table reports the least squares estimates of the proposed model specifications, by using daily and monthly data and GBP as a numeraire. Heteroskedasticity and autocorrelation consistent standard errors are reported in parentheses. The adjusted R^2 is reported. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 17: OLS estimates using full sample

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Quarterly (USD)				Quarterly (GBP)			
CLM	α	0.003	0.003	0.0001	0.019[b]	0.002	0.001	-0.001	0.017[b]
		(0.005)	(0.006)	(0.004)	(0.008)	(0.004)	(0.005)	(0.004)	(0.008)
	β	-0.145[a]	-0.344[a]	-0.100[a]	-0.286[a]	-0.035	-0.197[b]	0.011	-0.139
		(0.029)	(0.087)	(0.022)	(0.094)	(0.030)	(0.095)	(0.032)	(0.093)
	R^2	0.264	0.137	0.206	0.058	0.016	0.051	-0.009	0.006
LLM	α	0.002	0.0001	0.0005	0.015[b]	0.002	-0.0005	0.0002	0.014[b]
		(0.006)	(0.007)	(0.004)	(0.007)	(0.004)	(0.005)	(0.005)	(0.007)
	β	-0.046	-0.126	-0.078[a]	-0.006	-0.013	-0.055	-0.040	0.065
		(0.028)	(0.083)	(0.016)	(0.101)	(0.034)	(0.070)	(0.025)	(0.121)
	R^2	0.013	0.008	0.107	-0.012	-0.008	-0.007	0.015	-0.008
CM	α	0.213	0.387[a]	0.116[b]	0.027[a]	0.232[b]	0.441[a]	0.163[a]	0.044[a]
		(0.152)	(0.120)	(0.048)	(0.008)	(0.102)	(0.117)	(0.046)	(0.015)
	β	-0.089	-0.190[a]	-0.122[b]	-0.044	-0.085[b]	-0.182[a]	-0.128[a]	-0.044[c]
		(0.064)	(0.059)	(0.052)	(0.032)	(0.037)	(0.048)	(0.037)	(0.024)
	R^2	0.014	0.078	0.041	0.022	0.032	0.101	0.094	0.027
ACCM	α	-0.009	-0.017[c]	-0.005	0.016	0.001	-0.022[a]	0.006	0.012
		(0.007)	(0.009)	(0.006)	(0.010)	(0.008)	(0.008)	(0.008)	(0.011)
	β	-0.207[a]	-0.748[a]	-0.131[a]	-0.341[b]	-0.036	-0.649[a]	0.055	-0.242[b]
		(0.029)	(0.159)	(0.031)	(0.135)	(0.055)	(0.117)	(0.038)	(0.112)
	D	0.164[a]	0.772[a]	0.080	0.105	0.003	0.863[a]	-0.113	0.196
		(0.059)	(0.249)	(0.060)	(0.244)	(0.099)	(0.198)	(0.080)	(0.233)
	R^2	0.296	0.203	0.213	0.048	0.004	0.161	0.006	-0.002

The table reports the least squares estimates of the proposed model specifications, by using quarterly data, USD and GBP as a numeraire. Heteroskedasticity and autocorrelation consistent standard errors are reported in parentheses. The adjusted R^2 is reported. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

Appendix F

Table 18: Direction of Change Statistic (GBP)

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	$\bar{d}$	0.55 [a]	0.55 [a]	0.52 [b]	0.54[a]	0.56 [c]	0.60 [a]	0.54	0.52
LLM	$\bar{d}$	0.48	0.48	0.50	0.49	0.52	0.43	0.48	0.48
CM	$\bar{d}$	0.47	0.49	0.48	0.48	0.51	0.52	0.53	0.54
ACCM	$\bar{d}$	0.55 [a]	0.54 [a]	0.52 [a]	0.53[a]	0.57 [c]	0.60 [a]	0.55	0.49
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	$\bar{d}$	0.54 [a]	0.54 [a]	0.51[c]	0.52[a]	0.57 [b]	0.60 [a]	0.46	0.52
LLM	$\bar{d}$	0.49	0.48	0.49	0.49	0.48	0.45	0.45	0.51
CM	$\bar{d}$	0.49	0.48	0.48	0.46	0.52	0.54	0.56 [c]	0.43
ACCM	$\bar{d}$	0.54 [a]	0.54 [a]	0.51[c]	0.52[a]	0.51	0.58 [b]	0.47	0.50

The table displays the direction of change statistic $(\bar{d})$ by using daily and monthly data and GBP as a numeraire. Direction of change is the proportion of forecasts that correctly predict the direction of the exchange rate movement. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a*, *b* and *c* report the results for the two-sided test of a null of $\bar{d} = 0.5$ against the alternative $\bar{d} \neq 0.5$.

Table 19: Direction of Change Statistic

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	$\bar{d}$	0.64 [b]	0.73 [a]	0.66 [b]	0.61 [c]	0.52	0.57	0.41	0.55
LLM	$\bar{d}$	0.48	0.55	0.59	0.57	0.45	0.43	0.50	0.48
CM	$\bar{d}$	0.52	0.59	0.45	0.59	0.43	0.55	0.59	0.55
ACCM	$\bar{d}$	0.64 [b]	0.73 [a]	0.59	0.59	0.59	0.59	0.61 [c]	0.57
		Panel B: Rolling Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	$\bar{d}$	0.56	0.65 [a]	0.56	0.62 [b]	0.55	0.50	0.47	0.50
LLM	$\bar{d}$	0.48	0.48	0.56	0.47	0.47	0.50	0.41	0.48
CM	$\bar{d}$	0.52	0.56	0.52	0.47	0.48	0.55	0.47	0.45
ACCM	$\bar{d}$	0.59 [c]	0.64 [b]	0.52	0.65 [a]	0.48	0.53	0.41	0.55

The table displays the direction of change statistic $(\bar{d})$ by using quarterly data, USD and GBP as a numeraire. Direction of change is the proportion of forecasts that correctly predict the direction of the exchange rate movement. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a*, *b* and *c* report the results for the two-sided test of a null of $\bar{d} = 0.5$ against the alternative $\bar{d} \neq 0.5$.

Table 20: Out-of-Sample R Square Statistic for RW Benchmark (GBP)

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.02 [a]	0.02 [a]	0.01 [a]	0.02[a]	0.03 [b]	0.09 [a]	-0.01	0.01[c]
LLM	R^2_{oos}	0.00	0.00	0.00	0.00	-0.01	-0.02	0.00	-0.01
CM	R^2_{oos}	0.00	0.00	0.00	0.00	-0.02	-0.05	-0.09	-0.02
ACCM	R^2_{oos}	0.02 [a]	0.02 [a]	0.01 [a]	0.02[a]	0.02 [c]	0.08 [a]	-0.01	0.01
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.07 [a]	0.02 [a]	0.01	0.01[b]	0.03 [a]	0.02	-0.03	-0.03
LLM	R^2_{oos}	0.00	0.00	0.00	0.00	0.00	-0.05	-0.02	-0.04
CM	R^2_{oos}	0.00	0.00	0.00	-0.01	-0.01	-0.07	-0.08	-0.14
ACCM	R^2_{oos}	0.07 [a]	0.02 [a]	0.01	0.01[b]	0.02 [a]	0.00	-0.03	-0.06

The table displays the Out-Of-Sample R squared statistic(R^2_{oos}), for RW benchmark, by using daily and monthly data and GBP as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a*, *b* and *c* in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a RW. The superscripts *a*, *b* and *c* in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a random walk.

Table 21: Out-of-Sample R Square Statistic for RW Benchmark

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	R^2_{oos}	0.34 [b]	0.14 [a]	0.25 [a]	0.03 [b]	-0.09	0.06 [c]	-0.06	-0.03
LLM	R^2_{oos}	-0.04	0.00	0.09 [b]	-0.02	-0.04	-0.02	-0.01	-0.07
CM	R^2_{oos}	-0.02	0.03	-0.08	-0.02	-0.06	-0.16	-0.24	-0.05
ACCM	R^2_{oos}	0.40 [b]	0.15 [b]	0.24 [b]	0.01 [b]	-0.17	0.24 [c]	-0.01	-0.03
		Panel B: Rolling Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	R^2_{oos}	0.20 [c]	-0.01	0.15	-0.03	-0.22	-0.24	-0.13	-0.16
LLM	R^2_{oos}	-0.21	-0.28	-0.02	-0.17	-0.07	-0.10	-0.12	-0.09
CM	R^2_{oos}	-0.26	-0.15	-0.21	-0.46	-0.39	-0.22	-0.19	-0.54
ACCM	R^2_{oos}	0.12	-0.62	0.08	-0.52	-0.33	-0.04	-0.31	-0.18

The table displays the Out-Of-Sample R squared statistic(R^2_{oos}), for RW benchmark, by using quarterly data, USD and GBP as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observations every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a, b* and *c* in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a RW. The superscripts *a, b* and *c* in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the benchmark of a random walk.

Table 22: Out-of-Sample R Square Statistic for UIP Benchmark (GBP)

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.02[a]	0.02[a]	0.01[a]	0.02[a]	0.05[b]	0.10[a]	0.02[b]	0.00
LLM	R^2_{oos}	0.00	0.00	0.00	0.00	0.01[c]	0.00	0.02[c]	-0.01
CM	R^2_{oos}	0.00	0.00[b]	0.00	0.00	0.00	0.00[b]	-0.07	-0.02
ACCM	R^2_{oos}	0.02[a]	0.01[a]	0.01[a]	0.02[a]	0.04[b]	0.11[a]	0.01	-0.01
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	R^2_{oos}	0.03[a]	0.02[a]	0.01[b]	0.01[a]	0.05	0.11[b]	0.02	0.02
LLM	R^2_{oos}	0.00	0.00[a]	0.00	0.00	0.02	0.04[c]	0.02	0.01
CM	R^2_{oos}	0.00	0.00	0.00	-0.01	-0.06	0.00	-0.04	-0.10
ACCM	R^2_{oos}	0.03[a]	0.02[a]	0.01[b]	0.01[a]	0.04	0.07[b]	0.01	0.01

The table displays the Out-Of-Sample R squared statistic(R^2_{oos}), for UIP benchmark, by using daily and monthly data and GBP as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observation number every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a, b* and *c* statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a, b* and *c* for R^2_{oos} in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark. The superscripts *a, b* and *c* for R^2_{oos} in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark.

Table 23: Out-of-Sample R Square Statistic for UIP Benchmark

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	R^2_{oos}	0.38[a]	0.23[a]	0.28[a]	0.01	-0.01	0.15[b]	-0.01	-0.11
LLM	R^2_{oos}	0.03[c]	0.09[b]	0.12[b]	-0.01	0.03	0.05[b]	0.05[c]	-0.09
CM	R^2_{oos}	0.05[c]	0.14[a]	-0.04	-0.04	0.02[c]	0.05[b]	-0.18	-0.13
ACCM	R^2_{oos}	0.44[b]	0.21[b]	0.27[b]	-0.02[c]	-0.08	0.29[c]	0.04	-0.11
		Panel B: Rolling Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	R^2_{oos}	0.27[b]	0.05	0.24[b]	0.12	-0.12	-0.01	-0.02	-0.03
LLM	R^2_{oos}	-0.11	-0.30	0.09	0.00	0.02	0.04	-0.02	0.03
CM	R^2_{oos}	-0.16	-0.11	-0.08	-0.25	-0.27	-0.08	-0.07	-0.39
ACCM	R^2_{oos}	0.20[b]	-0.69	0.18	-0.30	-0.22	0.13	-0.18	-0.05

The table displays the Out-Of-Sample R squared statistic(R^2_{oos}), for UIP benchmark, by using quarterly data, USD and GBP as a numeraire. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observation number every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \gamma \Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a, b* and *c* statistical significance at the 1%, 5% and 10% level, respectively. The superscripts *a, b* and *c* for R^2_{oos} in Panel A are obtained from the Clark and West (2006, 2007) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark. The superscripts *a, b* and *c* for R^2_{oos} in Panel B are obtained from the Giacomini and White (2006) test of a null that the alternative model specification has a lower mean squared error compared to the UIP benchmark.

Table 24: Testing for forecast breakdown (GBP)

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Daily				Monthly			
CLM	GR_t	5.21^a	-0.56	0.91	-0.31	1.52^c	-0.29	-0.43	-0.21
LLM	GR_t	5.56^a	-0.59	1.10	-0.02	1.67^b	0.01	-0.48	-0.12
CM	GR_t	5.55^a	-0.55	1.14	0.00	1.81^b	0.41	0.42	0.01
ACCM	GR_t	5.21^a	-0.56	0.91	-0.31	1.52^c	-0.29	-0.43	-0.21
		Panel B: Rolling Estimation							
		Daily				Monthly			
CLM	GR_t	1.71^b	-1.54	-2.48	1.64^b	1.05^c	0.40	-1.26	-0.03
LLM	GR_t	2.01^b	-1.76	-2.33	1.59^b	1.26^b	0.60	-0.74	0.23
CM	GR_t	2.12^a	-1.56	-1.93	1.83^b	3.40^a	2.26^a	0.90^c	2.59^a
ACCM	GR_t	1.79^b	-1.48	-2.34	1.72^b	1.54^b	0.94^c	-0.89	0.85^c

The table reports the Giacomini and Rossi (2009) t-statistic(GR_t) by using daily and monthly data and GBP as a numeraire. This is a test for stability of the forecasting ability of a model, where the null is that the out-of-sample MSE of the model is equal to the in-sample MSE. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observation number every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^{+} + \varepsilon_t$ where all variables are same as before and $\Delta f_t^{+} = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively, for a one-sided test.

Table 25: Testing for forecast breakdown

		NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
		Panel A: Recursive Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	GR_t	0.61	0.77	1.20[c]	0.05	1.30[c]	-0.84	0.56	-0.79
LLM	GR_t	1.49[c]	0.98	1.81[b]	-0.08	1.09	-0.53	0.38	-0.97
CM	GR_t	1.40[c]	1.12	1.91[b]	0.16	1.27[c]	0.57	1.30[c]	-0.66
ACCM	GR_t	0.61	0.77	1.20[c]	0.05	1.30[c]	-0.84	0.56	-0.79
		Panel B: Rolling Estimation							
		Quarterly (USD)				Quarterly (GBP)			
CLM	GR_t	1.34[b]	1.27[b]	3.02[a]	0.68[c]	1.44[a]	2.03[a]	0.98[b]	0.58[c]
LLM	GR_t	2.33[a]	2.61[a]	1.97[a]	1.25[b]	0.15	0.66[b]	0.84[b]	0.26
CM	GR_t	2.92[a]	3.14[a]	2.83[a]	4.56[a]	3.26[a]	4.34[a]	2.97[a]	3.28[a]
ACCM	GR_t	2.36[a]	3.12[a]	3.75[a]	2.53[a]	2.28[a]	2.19[a]	2.93[a]	0.92[c]

The table reports the Giacomini and Rossi (2009) *t*-statistic(GR_t) by using quarterly data, USD and GBP as a numeraire. This is a test for stability of the forecasting ability of a model, where the null is that the out-of-sample MSE of the model is equal to the in-sample MSE. The out-of-sample forecasts obtained using recursive regressions involve generating forecasts by successively re-estimating the model parameters every time a new observation is added to the sample. The out-of-sample forecasts obtained using rolling regressions involve generating forecasts by successively re-estimating the model parameters using the same in-sample observation number every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The Lagged Linear Model (LLM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_{t-1} + \varepsilon_t$ where Δs_t is the first difference of the logarithm of the exchange rate and Δf_{t-1} is the one period lagged first difference of the logarithm of the commodity price. The Cointegration Model (CM) is based on the regression $\Delta s_t = \alpha + \beta(s_{t-1} - \lambda f_{t-1}) + \varepsilon_t$ where all variables are same as before and λ is the cointegrating vector. The Asymmetric Commodity Currency Model (ACCM) is based on the regression $\Delta s_t = \alpha + \beta\Delta f_t + \gamma\Delta f_t^+ + \varepsilon_t$ where all variables are same as before and $\Delta f_t^+ = \Delta f_t$, when the change in the commodity is positive and zero otherwise. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively, for a one-sided test.

Table 26: Average Beta estimate (GBP)

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Daily				Monthly			
1/2	-0.02[a]	-0.14[a]	-0.02[a]	-0.05[a]	0.00	-0.07[a]	0.00	0.21[a]
1/3	-0.01[a]	-0.18[a]	-0.01[a]	-0.04[a]	-0.05[a]	-0.06	-0.04[a]	-0.02
1/4	-0.02[a]	-0.23[a]	-0.01[a]	-0.06[a]	-0.07[a]	-0.21[a]	-0.2[a]	-0.04[a]
1/5	-0.01[a]	-0.18[a]	-0.02[a]	-0.01[a]	-0.07[a]	-0.14[a]	-0.02[a]	-0.05[a]

The table reports the average slope coefficient estimated via OLS using daily and monthly data and GBP as a numeraire. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Table 27: Average Beta estimate

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Quarterly (USD)				Quarterly (GBP)			
1/2	-0.09[a]	-0.16	0.01	-0.66[a]	-0.03[a]	0.02	0.05	-0.48
1/3	-0.04[a]	-0.51[a]	0.03	-0.47[a]	-0.06[a]	-0.34[a]	0.02	-0.30[a]
1/4	-0.04	-0.24	-0.01	-0.96	0.00	0.12	-0.01	-0.59
1/5	-0.09[a]	-0.37[a]	-0.03[a]	-0.01	-0.06[b]	-0.13	-0.01	0.23

The table reports the average slope coefficient estimated via OLS using quarterly data, USD and GBP as a numeraire. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a*, *b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Table 28: Average Beta estimate 2002-2014 (GBP)

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Daily				Monthly			
1/2	-0.05[a]	-0.07[a]	-0.01[a]	-0.07[a]	-0.08[a]	-0.15[a]	-0.17[a]	0.03
1/3	-0.03[a]	-0.08[a]	-0.03[a]	-0.15[a]	-0.07[a]	-0.15[a]	0.01	-0.15[a]
1/4	-0.03[a]	-0.11[a]	-0.02[a]	-0.18[a]	-0.04[a]	-0.12[a]	0.08	-0.30[a]
1/5	-0.03[a]	-0.13[a]	-0.02[a]	-0.17[a]	-0.02[a]	-0.10[a]	-0.02[a]	-0.25[a]

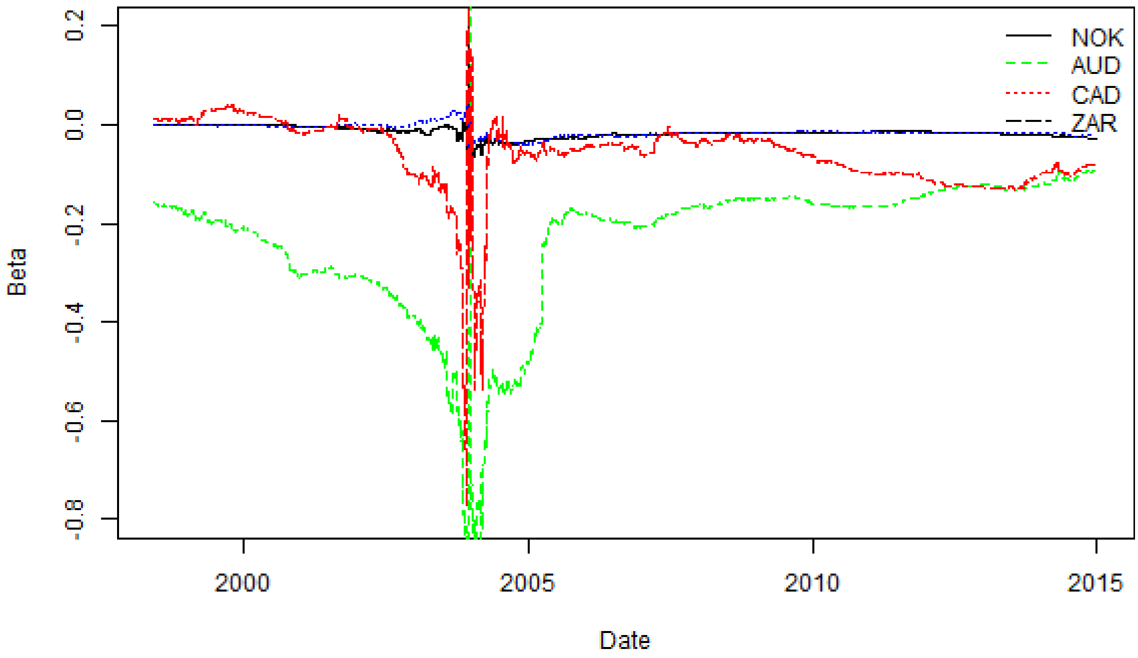
The table reports the average slope coefficient estimated via OLS using daily and monthly data and GBP as a numeraire, for the period 2002-2014. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Table 29: Average Beta estimate 2002-2014

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Quarterly (USD)				Quarterly (GBP)			
1/2	0.03	0.03	-0.05[a]	0.12	-0.08[a]	0.01	-0.11[a]	0.10
1/3	-0.05	-0.10[c]	-0.18[b]	-0.43[a]	-0.10[c]	0.09[c]	-0.02	-0.24[b]
1/4	-0.02	-0.36[a]	-0.06[a]	-0.64[a]	0.02	-0.12[b]	-0.02	-0.40[a]
1/5	-0.10[c]	-0.53[a]	-0.06[b]	-0.26[a]	0.13	-0.30[a]	0.08[c]	-0.02

The table reports the average slope coefficient estimated via OLS using quarterly data, USD and GBP as a numeraire, for the period 2002-2014. Each slope coefficient is obtained using rolling regressions which involves successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively. The superscripts *a, b* and *c* denote statistical significance at the 1%, 5% and 10% level, respectively which is for the null test of the average coefficient equals zero.

Figure 5: Slope Coefficient Plot (GBP)



The figure shows a plot of the CLM slope coefficient against time estimated via OLS using daily data and GBP as a numeraire, covering the period 1992-2014. Each slope coefficient is obtained using rolling regressions which involve successively re-estimating the model parameters using a fixed in-sample window size, of one fourth of the data, every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively.

Table 30: Giacomini and White (2006) test p-values (GBP)

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Panel A: RW Benchmark							
	Daily				Monthly			
1/2	0.00	0.00	0.02	0.00	0.15	0.20	0.58	0.71
1/3	0.00	0.00	0.08	0.00	0.39	0.27	0.91	0.67
1/4	0.00	0.00	0.14	0.02	0.49	0.45	0.79	0.78
1/5	0.00	0.00	0.23	0.08	0.46	0.43	0.94	0.86
	Panel B: UIP Benchmark							
	Daily				Monthly			
1/2	0.00	0.00	0.00	0.00	0.04	0.06	0.11	0.85
1/3	0.00	0.00	0.02	0.00	0.20	0.05	0.65	0.14
1/4	0.00	0.00	0.03	0.00	0.17	0.03	0.32	0.35
1/5	0.00	0.00	0.07	0.00	0.19	0.07	0.70	0.65

The table reports the Giacomini and White (2006) test p-values by using daily and monthly data and GBP as a numeraire. P-values from test of a null hypothesis of equal predictive ability between the CLM specification and the benchmark. By rejecting the null hypothesis of equal forecasting ability, we conclude that the CLM specification has a better forecasting power. The out-of-sample forecasts are obtained using rolling regressions which involve generating forecasts by successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively.

Table 31: Giacomini and White (2006) test p-values

Window Size	NOK	AUD	CAD	ZAR	NOK	AUD	CAD	ZAR
	Panel A: RW Benchmark							
	Quarterly (USD)				Quarterly (GBP)			
1/2	0.01	0.07	0.00	0.24	0.70	0.39	0.98	0.88
1/3	0.07	0.11	0.05	0.20	0.79	0.64	0.99	0.93
1/4	0.06	0.43	0.23	0.56	0.93	0.97	0.99	0.99
1/5	0.04	0.51	0.33	0.46	0.74	0.90	1.00	0.98
	Panel B: UIP Benchmark							
	Quarterly (USD)				Quarterly (GBP)			
1/2	0.00	0.09	0.00	0.25	0.45	0.19	0.48	0.97
1/3	0.04	0.17	0.03	0.08	0.62	0.17	0.69	0.73
1/4	0.02	0.33	0.03	0.21	0.76	0.53	0.57	0.55
1/5	0.01	0.14	0.03	0.30	0.31	0.34	0.94	0.55

The table reports the Giacomini and White (2006) test p-values by using quarterly data, USD and GBP as a numeraire. P-values from test of a null hypothesis of equal predictive ability between the CLM specification and the benchmark. By rejecting the null hypothesis of equal forecasting ability, we conclude that the CLM specification has a better forecasting power. The out-of-sample forecasts are obtained using rolling regressions which involve generating forecasts by successively re-estimating the model parameters using the fixed in-sample window size every time a new observation is added to the sample. The Contemporaneous Linear Model (CLM) is based on the regression $\Delta s_t = \alpha + \beta \Delta f_t + \varepsilon_t$ where Δs_t and Δf_t are the first difference of the logarithm of the exchange rate and the commodity price respectively.

Abbreviations

ACCM	Asymmetric Commodity Currency Model
ARIMA	Autoregressive Integrated Moving Average model
BIS	Bank for International Settlements
CAD	Canadian Dollar
CHF	Swiss Franc
CIP	Covered Interest rate Parity
CLM	Contemporaneous Linear Model
CM	Cointegration Model
CPI	Consumer Price Index
CW	Clark and West statistics
DEM	German Mark
DW	Durbin–Watson statistic
ECM	Error Correction Model
ECU	European Currency Unit
EMS	European Monetary System
EUR	Euro
FRF	French Franc
FX	Foreign Exchange
GBP	Great Britain Pound
GDP	Gross Domestic Product
GR	Giacomini and Rossi
GW	Giacomini and White statistics
HAC	Heteroskedastic Autocorrelation Consistent
IFE	International Fisher Effect
IS	In-sample
ITL	Italian Lira
JPY	Japanese Yen
LLM	Lagged Linear Model
MDD	Maximum Drawdown
MSE	Mean Square Error
NOK	Norwegian Krone
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squared
OOS	Out-of-Sample
PPI	Producer Price Index
PPP	Purchasing Power Parity
RMSE	Root Mean Squared Error
RW	Random Walk
SR	Sharpe Ratio
UIP	Uncovered Interest rate Parity
UK	United Kingdom
US	United States
USD	United States Dollar
VAR	Vector Autoregressive model
ZAR	South African Rand
WPI	Wholesale Price Index