Exchange rate forecasting with macro-financial data

by

Lauren S Rosborough Watt

Supervisors:
Professor Alfred Haug
Professor Dorian Owen

A thesis
submitted to the University of Otago
in fulfilment of the
requirements for the degree of
Master of Science
in Economics

University of Otago
August 2022

Abstract, non-technical introduction

This thesis examines if real-time macro-financial information observed on global financial markets are successful at predicting nominal exchange rates over short time-horizons. In the literature, exchange rate determination primarily focuses on macroeconomic data when testing the empirical success of the monetary and portfolio balance models. During the periods between macroeconomic releases, financial market participants substitute macroeconomic data with macro-financial equivalents. In the author's experience working on foreign exchange dealing floors, these macro-financial variables provide real-time proxies to guide market participants when determining a preference to buy or sell currencies in order to make profits.

Applying an augmented sticky-price asset model, I find mixed results but the forecasting performance improves when the models are characterised in an error-correction framework or by applying first differences. There is evidence of time-varying coefficients, supporting the findings found in previous studies that fixed-coefficient exchange rate models are not successful at forecasting out-of-sample. The accuracy of the directional change one week ahead is statistically significantly greater than 50 percent for many exchange rates when the exchange rate equation is estimated in first differences. More generally, a lack of cointegration and evidence of structural breaks suggests financial market participants can overstate the application of macro-financial variables as a driver of future exchange rate movements.

Acknowledgements

A huge thank you to Professor Haug and Professor Owen for supporting me as I met with new and challenging obstacles. Completing this work is testament to their patience, support, advice, feedback, and unwavering positivity. Their guidance has significantly improved the quality of this thesis. All errors remain my own.

I am grateful for the temporary free log-in provided by Bloomberg L.P. and I appreciate a discussion on random walks with Dr. Krippner.

Thank you to my family and to my children, who have encouraged me to better myself.

Thank you to the MacAndrew-Stout Postgraduate Scholarship that helped to make it possible.

Table of Contents

List of Figures

List of Tables

Section 1. Introduction and Overview

Understanding the determinants of exchange rates is a key focus for policymakers, financial market participants, and asset managers.[1] Exchange rates are widely considered to be determined by macroeconomic data, news, other asset prices, and expectations of the future path of these factors (Mussa, 1984). Relatedly, the perceived strength or weakness of a country's economic, political, and business environment is often reflected in the level of or change in its exchange rate (Canedese and Stolper, 2012; Frieden, 2016). Exchange rate misalignments are informational: in the short run (as in this study) they can provide investing opportunities for foreign exchange market participants, and in the long run (as in the Law of One Price) they can guide policymakers about domestic policy settings (Rossi, 2013).

Both economic theory and the international finance literature have long-established the importance of interest rates as a determinant of the exchange rate, and risk premia also play a part in defining the level and volatility of one currency against another. Currencies are, therefore, inherently financial assets (MacDonald, 2007). And yet, the empirical literature overwhelmingly focusses on macroeconomic

[1] A nominal exchange rate is the price a currency in one country can be converted into the currency of another country (Hubbard, 2005).

variables (for example, data released by official institutions, a statistics agency, or a central bank) as the key explanators in exchange rate models. These data, such as gross domestic product or exports, are typically reported with a time delay.

This paper takes a novel approach, testing whether macro-finance variables (asset prices that are traded on global capital markets) are successful at predicting exchange rates. This study links the macroeconomic exchange rate determination approach with that of the international finance literature and explores the relationship between the nominal exchange rate and the price of assets traded on global financial markets. Financial market participants, in lieu of real-time macroeconomic data, formulate proxies from financial market spot prices and market indices that are traded in real-time on global financial markets. In this paper's augmented sticky-price asset model, these macro-financial proxies substitute for macroeconomic data.

A model formed in this manner attempts to resolve the usual criticism of theoretical models: that of widely differing volatilities between a free-floating exchange rate and macroeconomic data (Flood and Rose, 1999). A macro-financial model also reduces many practical concerns surrounding the application of theoretical exchange rate models: for example, how to account for expectations and a risk premium, the delayed release date of published data, quasi-real-time forecasting, and the challenge of data revisions.

This approach is motivated by the author's experience working in global foreign exchange markets. The price of currency seems to adjust in real-time when expectations of future (unrealised) macroeconomic data change and exchange rates appreciate or depreciate in response to changes in market 'themes'. (A theme is the narrative considered the cause or driver of directional price movements, for example central bank interest rate rhetoric or rising uncertainty over the economic outlook). This study differs to a theoretical model that assesses the level of the exchange rate consistent with stability in a country's external balance (as in Brook and Hargreaves, 2000). Instead – and intentionally – this study has a normative focus (Ca'Zorzi *et al.*, 2020). To foreign exchange traders, the true level of relative economic activity today (as yet unknown) that influences the relevant exchange rate is secondary to the perceived level of relative economic activity today, where these perceptions are driven by themes or fads (Rosenberg, 2003). This short-termism (as defined by Callen and Fang, 2013) is in part dictated by a trader's success, where this success is often defined by the daily mark-to-market gains or losses.[2]

An important aim for empirical research is to posit varying hypotheses as to why exchange rate models poorly predict the future and to assess the relative success of new models. The purpose of this thesis is to contribute towards that aim. The literature applies macroeconomic and macro-financial data to explain exchange rate models. To the author's knowledge, considering only macro-financial data in an exchange rate model is limited and applying macro-financial data in lieu of macroeconomic data is an innovation.

---

[2] Traders also are tasked with passing on and reducing risk of foreign exchange positions at favourable levels, when foreign currency is received by corporate clients, asset managers, or hedge funds.

The thesis proceeds as follows. Section 2 discusses the literature of exchange rate determination, and the suggestions put forth as to why the models have failed to be successful. This section also discusses the burgeoning literature of macro-financial data as possible drivers of the exchange rate and describes how the approach in this paper attests to many difficulties well-known in the literature. Section 3 introduces the theoretical model and the empirical specification as it applies to this body of work. Section 4 describes the data and related considerations such as the frequency of observations and time series length. Section 5 conducts the analysis and presents the results. Section 6 explores alternative forecast specifications while Section 7 discusses and concludes.

Section 2. Literature Review and Motivation

2.1 A brief history of exchange rate model theory

Historically, the determination of exchange rates has been dominated by asset price models: the monetary and the portfolio balance models. The role of expectations is also well-documented. Despite a plethora of studies on these topics, a consensus has not formed around how best to model exchange rates (Rossi, 2013; Ca'Zorzi *et al.*, 2020).

Theoretically, the generalized monetary model is:

$$\begin{aligned} s_t = \alpha_0 + \alpha_1(m_t - m_t^*) + \alpha_2(y_t - y_t^*) + \alpha_3(i_t - i_t^*) + \alpha_4(\pi_t - \pi_t^*) \\ + \alpha_5\overline{TB}_t + \mu_t \end{aligned} \tag{1}$$

where s_t is the natural logarithm (log) of the spot exchange rate (domestic currency units per one unit of foreign currency), m_t is the log of the supply of money, y_t is the log of income (frequently in real terms), i_t is the short-term nominal interest rate, π_t is the long-run expected inflation rate, $\overline{TB}_t$ is the cumulative trade balance (either in real or nominal terms), μ_t is a disturbance term, and asterisks refer to the foreign country variables.

Equation (1) encompasses three models: the flexible price monetary model attributed to Frenkel (1976), the sticky-price monetary model (also known as the Dornbusch, 1976, or Dornbusch-Frankel, model), and the sticky-price asset model (Hooper and Morton, 1982). In all three models, the money demand function is assumed to be stable over time and uncovered interest parity holds. Frenkel's model (1976) further assumes goods prices are fully flexible and purchasing power parity (PPP) holds at all times (Frankel, 1984a). Hence, the flexible price model constrains $\alpha_4 = \alpha_5 = 0$ and expects $\alpha_1 > 0$, $\alpha_2 < 0$, and $\alpha_3 > 0$. The Dornbusch model does not assume full flexibility in prices, thus allowing the exchange rate to deviate from PPP in the short-term. Therefore, Equation (1) includes the inflation differential and imposes $\alpha_4 < 0$. The sticky-price asset model relaxes the assumption that assets are perfectly substitutable and assumes the long-run real equilibrium exchange rate can shift over time (Hooper and Morton, 1982). In the augmented portfolio balance model, risk neutrality is relaxed and its associated risk premium is accounted for within the cumulative current account balance (Hooper and Morton, 1982). Here, the exchange rate is able to respond to adjustments in the balance of payments; thus, the trade balance or current account can be included as an explanatory variable and $\alpha_5 < 0$.

Chinn (1997) substitutes the trade balance for relative non-tradeable prices as an indication of the productivity differential between countries. The terms of trade is linked to the Balassa-Samuelson (B-S) mechanism: the idea that the real exchange rate is positively related to productivity in the tradeables sector compared to that in non-tradeables (Khan and Choudhri, 2004) and the home versus foreign relative price of non-tradeables (Bordo *et al.*, 2014; Coudert *et al.*, 2008). For example, local input costs are higher in countries with higher traded-goods sector productivity growth. In turn, the prices of non-tradeable goods increase, raising the local price level, leading to a real exchange rate appreciation (Balassa, 1964; Samuelson, 1964).

The B-S effect on the nominal exchange rate is also expected to be positive, as nominal and real exchange rates tend to move together over time (Finn, 1999).

Indeed, Wu and Hu (2009) find the Balassa-Samuelson relationship holds true for both real and nominal exchange rates.

Empirical analyses suggest the B-S effect exists but is smaller than the theory would predict (see Bordo *et al.*, 2014; and Tica and Druzic, 2006, for a summary of the literature).

2.1.1 Early empirical testing of exchange rate models

Meese and Rogoff's (1983) seminal paper critiques the three monetary models of the exchange rate using out-of-sample forecasting as an evaluation criterion. The application of a random walk as a testing criterion, first used by Meese and Rogoff, is now the benchmark of success for exchange rate models. Meese and Rogoff employ macroeconomic data to explain USD/DEM, USD/JPY, USD/GBP, and the nominal U.S. trade-weighted index between March 1973 and November 1976, fitting the models to actual realised data outturns using Ordinary Least Squares (OLS), generalised least squares (GLS)[3] and Instrumental Variable (IV) estimation techniques, and a vector autoregression (VAR).[4] The resulting out-of-sample exchange rate forecasts (for the horizon from November 1976 until June 1981) are compared to a random walk and random walk plus drift at one-month, six-month,

[3] In order to account for serial correlation of the error term.

[4] The IV and VAR estimations were to account for potential endogeneity of the regressors and to obtain consistent parameter estimates.

and 12-month horizons.[5] Realised future values of each explanatory variable are used in the out-of-sample exercise to separate the success of exchange rate forecasting from the forecasting accuracy of the independent variables.

Meese and Rogoff conclude *'we can unambiguously assert that the … models do not perform significantly better than the random walk model'* (p.17). In the USD/DEM case at the one-month horizon the model improves on a random walk but overall the results are mixed. Re-estimated USD/DEM and USD/JPY models between February 1974 and July 1987 with forecasts from November 1980 to June 1984 by Meese (1990) also fail to outperform a naïve model in the general case.

2.2 The successes and failures of exchange rate models

Levich (1978) determines that the success of exchange rate determination is dependent upon the model employed. The following discusses several potential reasons why exchange rate models have historically performed poorly.

2.2.1 Omitted variable bias

Meese and Rogoff (1983) and Meese (1990) identify a number of reasons why the models may fail. One problematic aspect of the application of monetary models is omitted variable bias, potentially resulting in a regression with biased and

[5] A forward rate model and an autoregressive model were also compared but are not discussed here.

inconsistent estimates (Gujarati, 1995). Subsequently, many papers attempt to augment Meese and Rogoff's work with additional data series. An inexhaustive list of oft-tested variables includes industrial production, trade indices, and a variety of interest rates (Meese, 1990; Meese and Rose, 1991; Chinn and Meese, 1995; Schinasi and Swamy, 1987, amongst others). A Taylor rule model is frequently applied, utilising the inflation and output gaps (Molodtsova and Papell, 2009; Engel *et al.*, 2008; Chinn, 1997), while relative productivity, a wealth variable, and non-tradeables inflation are frequently employed in order to incorporate the B-S effect (Chinn and Meese, 1995; Frankel, 1982a; and Clements and Frenkel, 1980). Chinn and Meese (1995) test the producer price index as a proxy for non-tradeable goods prices in their models, while Cheung *et al.* (2005) build a Behavioural Equilibrium Exchange Rate (BEER) model, thereby including debt-to-gross domestic product (GDP) and net financial assets. More esoteric items have been added to model the exchange rate, such as house prices, as in McDonald (2012).[6]

Some out-of-sample forecasting success suggests that omitted macroeconomic variables may be a reason why the Meese and Rogoff models fail to outperform a random walk. However, it is difficult to discern given that the results vary across models, estimation techniques, exchange rates, and time periods. For example, Cheung, Chinn, and Pascual (2005) estimate three models for eight exchange rates between 1973Q2 and 2000Q4 and find some – but not overwhelming – evidence that

---

[6] Note the estimation here was not using a monetary model framework but is relevant as it seeks to explain drivers of the New Zealand dollar.

the sticky-price monetary model can predict exchange rates. The results for one-month, four-, and 20-months-ahead forecasts, based on two forecast periods – 1987Q2 to 2000Q4 and 1983Q1 to 2000Q4 – illustrate that the success of any model depends on the currency and on the sample forecast horizon.

In sum, the inability to consistently beat a random walk may suggest the variables that determine the exchange rate are not adequately captured by the theoretical suite of monetary models. Monetary models may be too restrictive and unable to represent the correct model of the real (or nominal) exchange rate, although variability between the studies in aspects such as the estimation period and econometric technique makes a definitive conclusion difficult.[7]

2.2.2 Rational expectations

An underlying assumption of exchange rate models is that expectations are rational. Thus, in a standard reduced-form equation of (1) above:

$$\Delta s_{t+1} = \beta_0 + \beta_1(i_t - i_t^*) + \beta_2 E\left((i_{t+1} - i_{t+1}^*) \mid I_t\right) + \varepsilon_t \qquad (2)$$

where $\Delta s_{t+1} = s_{t+1} - s_t$, E is the expectations operator that is made conditional on information available at time t (denoted I_t), $(i_t - i_t^*)$, and $(i_{t+1} - i_{t+1}^*)$ are the interest rate differentials at time t and $t+1$, respectively, and ε_t is an error term. If

[7] Ca'Zorzi *et al.* (2020) argue that adding variables can reduce the out-of-sample predictability of the exchange rate.

rational expectations hold all future expectations are fully captured in i_t and i_t^* and $\beta_2 = 0$ (Moosa and Bhatti, 1997).

In empirical tests, asset prices do not behave as rational expectations would suggest. Chow (1989) demonstrates that adaptive expectations explain one-month U.S. Treasury bills and 20-year Treasury bonds better. Exchange rate models that test for investor rationality typically focus on the forward rate but the general consensus concludes the forward rate is not an unbiased estimator of the future exchange rate (see Frenkel 1976; Levich, 1989; and Frankel and Chinn, 1991, for some early examples).[8]

Because the forward rate is a function of the current exchange rate and the interest rate differential (as dictated by covered interest parity),[9] testing the forward premium (the difference between spot and forward rates) is implicitly testing the relationship between the exchange rate, current interest rates, and expectations of future interest rates. In Equation (2) above: $\beta_1 = 1$ and $\beta_2 = 0$. The failure of this test is known as the forward premium puzzle (Bilson, 1980). Sercu *et al.* (2008) calculate large economic profits trading the forward premium anomaly using weekly data for ten currencies against the German mark between 1985 and 1998.

[8] A forward rate agreement is an agreement to transact a currency pair at a future date for an agreed currency amount (BIS, 2019).

[9] The exact forward rate calculation is $F_t = S_t\left(\frac{1+i_t^*}{1+i_t}\right)$, where F_t is the forward rate at time t and S_t is the spot rate. Covered interest parity is the condition whereby no arbitrage profits can be made between the spot rate today and its forward rate (Pilbeam, 1998).

Della Corte *et al.* (2009) show that the forward rate can help to predict the exchange rate at short horizons using a Bayesian model of monthly nominal exchange rates. They conclude that taking the forward premium into account for monthly returns of the USD/GBP, USD/DEM, and USD/JPY between January 1976 and December 2004 "*yield[s] large economic gains…robust to reasonably high transaction costs*" (p. 3491).

This paper innovates the asset price theory of exchange rates, recognising that the exchange rate is influenced by current information, expectations regarding future (unknown) information, and changes to these expectations. This paper contests that changes in expectations regarding future macroeconomic prospects may constitute an omitted variable in an exchange rate equation when only macroeconomic data are considered. Expectations are based on the observed information set available to the public at time *t* but the true information set of public and private information at time *t* may differ. Similarly, the information set for the same macroeconomic variable at time *t+1* may differ to that at time *t*. Relatedly, the *ex-ante* expectation formation may not equal the actual outcome. This paper contributes to the literature by utilising realised financial market data to better capture these expectations.

2.2.3 Risk premia

An alternative explanation for the forward rate bias discussed above is to assume that a premium exists, such that the forward exchange rate is not identical to the expected future spot rate. The earliest example of this is found in Fama (1984).

In its simplest logarithmic formation:

$$f_t = E(s_{t+1}|\, I_t) + \tau_t \tag{3}$$

where f_t is the forward rate in natural logarithm terms and τ_t is a risk parameter. Applying covered interest parity:

$$f_t = (i_t - i_t^*) + s_t \tag{4}$$

then:

$$E(\mathrm{s}_{\mathrm{t+1}}|\, I_t) - \mathrm{s}_{\mathrm{t}} - (i_t - i_t^*) = -\, \tau_t \tag{5}$$

If rational expectations hold:

$$E(\mathrm{s}_{\mathrm{t+1}}|\, I_t) = \mathrm{s}_{\mathrm{t+1}} \tag{6}$$

then the equation becomes:

$$\Delta \mathrm{s}_{\mathrm{t+1}} + \tau_{\mathrm{t}} = (i_t - i_t^*) \tag{7}$$

The concept of a risk premium influencing the exchange rate has been formalised by the portfolio balance approach to the exchange rate (see Frankel, 1982b as an early example). The portfolio balance model is an extension to the monetary models, where assets are not fully substitutable between domestic and foreign countries. The concept of a risk premium is readily accepted in the literature, although defining it has been elusive and generally it is considered unobservable (Engel and West, 2004). Engel and West (2004) question whether the unexplained variation in exchange rate variability is due to incorrect expectations *ex-post* or a risk premium. Frankel's (1982b) results suggest that the issue may be clouded by omitted variable bias. MacDonald (2007) surveys the literature, which is not supportive of the portfolio balance approach in determining the exchange rate. Engel *et al.* (2010) use Consensus Survey data to calculate the risk premium for eight developed country exchange rates between 1989Q4 and 2007Q2. They find that the existence of a stationary risk premium is related to the predictability of the exchange rate at long-horizons. Chen and Tsang (2013) define risk premium via the term structure of interest rates and find that it has significant explanatory power when modelling the exchange rate, even at short horizons (out to two years).[10] Munro's (2014) theoretical approach illustrates that when risk and return are separated and modeled jointly, they exhibit the correct sign (broadly in line with Fama's, 1984 proposition). Munro finds the inclusion of the CBOE Volatility Index[11] (the VIX index) is sufficient to reflect exchange rate risk, and Mallick *et al.* (2017) find the VIX index can be used as an indicator of global financial market risk aversion more broadly. The VIX index is included in this study as a way to incorporate expectations via a separate channel than the interest rate differential channel.

2.2.4 Uncovered interest parity

Closely related to the forward premium puzzle is the violation of uncovered interest rate parity (UIP).

---

[10] Similarly, Lustig *et al.* (2011) apply a slope factor derived from the forward currency curve.

[11] The CBOE Volatility Index, also known as the VIX index, measures volatility from the average of more than 23 days and less than 37 days put and call option prices on the S&P500 Index. See https://www.cboe.com/micro/vix/vixwhite.pdf.

UIP is typically written as:

$$E(\Delta s_{t+1} | I_t) = i_t - i_t^* \tag{8}$$

For UIP to hold, an unrestricted version of Equation (8) is estimated:

$$\Delta s_{t+1} = \beta_0 + \beta_1 (i_t - i_t^*) + \varepsilon_t \tag{9}$$

and tested for $\beta_0 = 0$ and $\beta_1 = 1$.

Testing UIP has had a chequered past. The literature generally concludes that UIP does not hold continuously and β_1 is often negatively signed (see Cheung *et al.*, 2005; and Mark and Sul, 2001 amongst others). This is known as the UIP puzzle (see Froot and Thaler, 1990, for an extensive discussion of the puzzles in exchange rate determination and Chinn, 2003, for a short summary of the forward premium puzzle). The prevalence of a negative slope coefficient on β_1 suggests that "*low (high) interest rate currencies offer low (high) average excess returns*" (Verdelhan, 2013, p. 30): this is the basis for the carry trade.[12] Relative interest rates are a driver of currency returns at time *t*. But under rational expectations as in Equations (2) and (6), *ex-ante* expectations may not be realised. In this study, in order for the expectations component to be captured, the coefficient on relative interest rates is not restricted to be one.

[12] The carry trade is an investing strategy that involves borrowing in low interest rate currencies to invest in high interest rate currencies (or assets). See Menkhoff *et al.* (2012).

2.2.5 Fixed-coefficients and the failure of exchange rate models

Studies show that the effect of the interest rate differential on the exchange rate is time-dependent: in the short run, β_1 is statistically significant and negative, while in the long-run UIP is expected to hold. The reasons behind the intertemporal nature of the effect of the interest rate on the exchange rate differ. Froot and Thaler (1990) assert that the interest rate differential has a different effect on the exchange rate immediately and over time due to market inefficiencies and an inability of investors to respond quickly. While this may have been true thirty years ago, technological innovations mean financial market participants and algorithms are now able to react instantaneously to changing asset prices, creating smaller market inefficiencies than in the past. More recently, Boudoukh *et al.* (2016), using G10 data[13] between 1980 and 2010, show that, in the short-run, higher interest rate differentials lead to a higher exchange rate via capital flows, but the misalignment with PPP this presents is reversed in the long-run.[14] Chinn and Meredith (2004) utilise a Taylor rule to determine the exchange rate and find the exchange rate's

[13] G10 is the Group of Ten industrialised countries, as defined by the OECD.

[14] Theoretical models of short-run exchange rate behaviour deviate from Purchasing Power Parity (PPP) – a key tenant in the theoretical underpinnings of monetary models. The general consensus is that PPP – in particular relative PPP – holds in the very long run (see Dornbusch, 1985 for a survey of the historical literature or Taylor and Taylor, 2004 for an updated summary), although the results are by no means definitive. Some reasons given for the deviations include the invoicing of trade by exporters (Goldberg and Tille, 2008) and imperfect competition (Devereux, 1997). PPP is not expected to hold in the short-run and the exchange rate has been shown to exhibit notable misalignment (Taylor and Taylor, 2004), often attributed to the existence of sticky prices. Due to this paper's focus on explaining the exchange rate over a short-time horizon, PPP is not discussed further.

sensitivity to changes in the interest rate differential varies at different time horizons.

2.2.6 Model misspecification

Model misspecification is frequently used to explain the failure of exchange rate models to outperform a random walk (see Smith and Wickens, 1986, for an early example). To resolve this concern, a lagged dependent variable is often added to the regression equation, which tends to show an improvement in the exchange rate's forecasting ability (Schinasi and Swamy, 1987). Still, the models tend to perform poorly, leading researchers to investigate possible reasons why.

A frequently estimated linear model is one oft-cited reason why exchange rate models do not perform well. This criticism can take many forms. Non-linearity may occur in a number of ways, for example regime shifts that result in non-linear formulations (such as a change in a central bank's reaction function to the exchange rate) or a non-linear relationship between the exchange rate and one or more of the regressors (nonlinearity of the underlying data generating process (DGP)). For example, Hördahl and Packer (2007) argue that fundamentals (such as inflation and gross domestic product) may not represent the exchange rate in a linear fashion.

Accounting for regime changes via Markov- or regime-switching models were popular in the 1990s. Following Engel and Hamilton's (1990) success with Markov-switching models to describe the behaviour of four exchange rates but failure of them to beat a random walk with drift, Engel (1994) re-runs the estimations for 18 exchange rates (calculated from eight major currencies against the U.S. dollar and their cross rates) over the period 1973Q3-1986Q1 (with the forecast period 1986Q2-

1991Q1) and finds the same result. Cheung and Erlandsson's (2005) use of Monte Carlo analysis demonstrates that the results from these previous tests may have been spurious because the power of finding regime switching in quarterly exchange rate data is low.[15] Cheung and Erlandsson confirm that when the time series is extended and the observations are increased then the power of the test rises.[16]

Other non-linear estimation techniques to accommodate regime changes are more successful, such as Kilian and Taylor's (2003) exponentially smoothed transitions autoregressive (ESTAR) model, also found in Taylor *et al.* (2001); Michael *et al.* (1997); and Taylor and Peel's (2000) threshold autoregressive model (TAR). In these models, the strength of an exchange rate's mean reversion differs, depending on the degree to which it is misaligned (either in terms of degrees or if above/below a threshold). Kilian and Taylor's (2003) ESTAR model looks at the PPP relationship of USD/CAD, USD/FRF, USD/DEM, USD/ITL, USD/JPY, USD/CHF, and USD/GBP exchange rates between 1973M1 and 1998M12 and its behaviour against three DGPs, at the one quarter to four-year forecast horizons. They conclude there is evidence of statistically significant non-linear mean reversion in real exchange rates of six of the currencies against the U.S. dollar at the two- to three-year forecast horizon. However, the study is unable to confirm that the models outperform a

---

[15] Power is defined as the probability of rejecting the null hypothesis when it is false. See Blough (1992).

[16] Attempting to compensate for the low power of tests in exchange rate modelling and the inability to reject a false negative of no cointegration continues to be a difficultly for the econometrician, see Sarno's (2003) summary of the literature.

random walk. Taylor, Peel, and Sarno's (2001) ESTAR results for real USD/GBP, USD/FRF, USD/DEM, and USD/JPY exchange rate estimates over 1973M1 to 1996M12 were also able to find evidence of non-linearity in exchange rate mean-reversion. Michael *et al.* (1997) estimate ESTAR models from as early as 1791 to 1992 for annual data series and between 1921M1-1925M5 or 1921M1-1923M9 for monthly data and find non-linearity for GBP/FRF and USD/FRF exchange rates at both observation frequencies. In all cases, the exchange rate behavior is mean-reverting, although deviations from PPP can remain for exceptionally long periods of time, especially when annual data are used.

Alternative formulations, such as a vector autoregressive model (VAR) may not necessarily improve current exchange rate models if leptokurtosis is not accounted for.[17] Autoregressive conditional heteroskedastic (ARCH) and generalised autoregressive conditional heteroskedastic (GARCH) processes are often employed to accommodate the non-normal distribution of the volatility of the exchange rate. However, these models are designed to identify changes in volatility regimes rather than to forecast the level of the exchange rate, and therefore are not discussed further here (see Wang *et al.*, 2001).

Because the DGP of an exchange rate model may or may not be non-linear (Mark, 1995) studies often augment a (log) linear regression in some additional non-linear

[17] A VAR assumes a standard normal or Gaussian distribution, whereas the probability distribution of some asset prices, such as exchange rates and stock prices, exhibit an unconditional distribution and fat tails, or kurtosis greater than three. See Diebold (1988) and Boothe and Glassman (1987a).

way in an attempt to capture variables that behave non-linearly with the exchange rate. Choosing a log-linear model or any other transformation has the same estimation and forecasting-error variance inadequacies as any other non-linear data transformation, if the underlying DGP is unknown (De Gooijer and Kumar, 1992). Whether one model is a better approximation of the DGP is an empirical question.

Non-linear transformations have been applied extensively in the literature: for example, Chinn (2008) applies a Taylor rule with a cubic form to an exchange rate model using quarterly data for EUR/USD between 1970Q1 and 2008Q1 to test the claim that monetary policy responds to large exchange rate changes and not small ones. They find some evidence of non-linearity but the results are not robust. Meese and Rose (1991) estimate five structural models of USD/CAD, USD/DEM, USD/JPY, and USD/GBP exchange rates between 1974M1 and 1987M12. They find a quadratic version does not improve upon a linear model using least squares estimation, and two alternating conditional expectations (ACE) algorithms (linear and non-linear) are similar in terms of forecasting abilities. They also find no evidence of non-linear cointegration using an ACE composition. Indeed, they conclude non-linearity is not a driver of the models' poor results. Diebold and Nason (1990) investigate whether the underlying DGP of weekly exchange rates is non-linear by way of a locally-weighted regression, finding an improvement to the in-sample results for the first derivative of ten currencies against the U.S. dollar between 1973 and 1987 but no improvement in out-of-sample forecasting against a random walk (at one-, two-, eight-, and 12-quarters-ahead). Chinn (1991) also applies an ACE model with rolling regressions, finding that a linear model does best for one-quarter-ahead forecasting and a non-linear compilation presents a marginal improvement at four-quarters-ahead. Burns and Moosa (2015) compare an error correction model (ECM) of 14 exchange rates estimated between 1973M1 and 2014M9 to a random walk, finding the adjustment to linearity yields no additional forecasting return in absolute root mean square error (ARMSE) terms, no greater directional accuracy in forecasting, and no improvement in information ratios (risk-adjusted return).

In sum, the results of many studies are marginal in aggregate and are specific to a particular model at a particular point in time. This lack of comprehensive statistically significant success in the non-linear exchange rate modelling literature is consistent with Meese's (1990) conclusion that non-linearity is a second-order concern in exchange rate modelling.

If the underlying DGP of exchange rate behavior is unknown, time-varying coefficients may capture a source of non-linearity. Time-varying coefficients have the added benefit of capturing periods of high/low parameter variance without having to model this explicitly, say in an ARCH or GARCH form. Schinasi and Swamy (1987) examine both flexible and sticky-price models in a nonparametric study estimating USD/JPY, USD/DEM and USD/GBP exchange rates between March 1973 and March 1980. They find that allowing the coefficients to change over time substantially improves the models' outputs compared with a random walk and random walk with drift. Chinn and Meese (1995) test for non-linearity by applying a locally-weighted regression.[18] The estimations yield poor results at the

[18] Note that this rolling window technique is a recursive or sequential estimation, also undertaken by Meese and Rogoff (1983). Recursive estimation takes a sample estimation period and then adds the subsequent data point in the series – the original sample period plus one – and the regression is re-estimated. Applied in an OLS framework, the coefficient of each additional re-estimation is a

one-month horizon forecasts, mixed results for the 12-month-ahead forecasts, whereas an alternate model (an unrestricted ECM) forecasting 36-months-ahead indicates some robust out-of-sample results for USD/DEM and USD/JPY exchange rates.[19] This contrasts to Meese and Rose's (1991) earlier paper that finds a locally-weighted regression cannot improve an exchange rate model's performance.

Related to time-varying coefficients is parameter instability, which is an econometric thorn for long-run exchange rate modelling. Wolff (1987) asserts that changes to the long-run real exchange rate over time is incongruent with the underlying money demand function (deemed fixed over time) and therefore results in unstable parameters. Long-run parameter instability results in information loss and inference errors (Hansen, 2001). Meese (1990, p. 129) notes "*[e]conometric modeling of financial markets will never be easy in an environment where the rules of the game keep changing*" while Cheung and Chinn (1999) rationalise that a time-varying parameter model may be superior for short-term forecasting due to the changing

---

(least squares) average of the relationship between macroeconomic variables and the exchange rate over the time period estimated. Consequently, each recursive or re-estimated coefficient is a diluted version of the most recent exchange rate relationship (assuming these relationships vary over time). By contrast, a rolling window sample size shifts forwards over time while retaining an unchanged or fixed sample length. If the true DGP has time-varying coefficients, then a recursive regression is less likely to perform as well as a rolling window or time-decay composition, when compared to a random walk.

[19] Chinn and Meese (1995) estimate an error-correction model (ECM) and models of first differences for USD/CAD, USD/JPY, USD/DEM, USD/GBP, and DEM/JPY exchange rates from 1973M3 to 1982M12, with two forecast periods (one month ahead from January 1983 to November 1990 and 12 months ahead from 1983M12 to 1990M11). Three models are estimated (a money demand flexible price model, a sticky-price model and a B-S formulation) using OLS and IV.

rankings of regressors in explaining the exchange rate. Sarno and Valente (2009) forecast exchange rates using a predictive procedure that allows the relationship between exchange rates and fundamentals to evolve flexibly. They conclude that the poor out-of-sample forecasting ability of exchange rate models may be caused by changing drivers, such as shifts in expectations, rather than by a lack of information embedded in the fundamentals.

This thesis applies the premise of time-varying parameters. Testing for structural breaks is sensible when the researcher suspects the long-run relationship may have changed, for example due to a regime shift (a change in monetary policy stance) or an exogenous event (for example regulatory changes). Short-run models of the exchange rate that incorporate, say, financial market variables or macro-financial variables, may also experience changing coefficients due to transitory adjustments to behavioural relationships and expectations. It is an empirical question whether these short-run changes constitute a structural break. Evolving relationships are widely acknowledged; see Froot and Obstfeld (1989) and Meese's (1990) comment above, and Chinn's (2003, p. 2) comment that "*the relative importance of individual macroeconomic variables shifts over time*". Financial market asset prices tend to respond to news and shifts in market themes – possibly due to adjustments in the expectational component of each asset price. A market theme or thematic is a general belief surrounding what news event or information (e.g., macroeconomic, relative risk preferences, politics or geopolitics) drives asset prices during a period in time. These themes, or fads, are frequently topics that dominate news headlines and are used to describe shifts in asset prices by financial market media. Themes can be persistent but are not permanent and are often associated with a common comovement between the topic and asset price movement. For example, during the period between 2000 and 2006 exchange rate movements reportedly reflected relative growth and interest rates between countries (Federal Reserve Board, 2006). By 2008, in the midst of the Global Financial Crisis, exchange rates responded more strongly to risk and safe-haven concerns (McCauley and McGuire, 2009). This is not only during the 2000s; changes to the drivers of exchange rates throughout the 1990s were discussed in Cheung and Chinn (1999) and for the 1980s by Hardouvelis (1988). Given the author's dealing floor experience, a model with time-varying coefficients reflects the real world.

2.2.7 Macroeconomic variable volatility

One of the major criticisms of monetary models is the difference between the volatility of the exchange rate and the volatility of macroeconomic variables. As Rogoff questions (1996, p. 647) *"[h]ow can one reconcile the enormous short-term volatility of real exchange rates with the extremely slow rate at which shocks appear to damp out?"* MacDonald (2007) surveys the literature and observes there is a 2x to 10x difference between the volatility of the exchange rate and that of relative prices. Meese (1990) notes how the exchange rate exhibits a larger variance than fundamental variables, such as interest rates and money supply. A frequent criticism of forecasting exchange rates is that these differing volatilities preclude exchange rate models from performing well (for example see Frankel and Rose, 1994).

Mark (2000) partially explains this phenomenon, showing how current fundamentals can have a disproportionate impact on the exchange rate due to changes in expectations. Hence, the incorporation of variables to better account for expectations potentially increases the low signal-to-noise ratio observed in exchange rate series (Chinn and Meese, 1995). To demonstrate this point, Chen and Tsang (2013) decompose the yield curve and find that both expectations and macro-fundamental data can explain the USD/CAD, USD/GBP, and USD/JPY exchange rates between 1985M8-2005M7 when forecasting out to two years out-of-sample.

This paper's novel approach – utilising financial market traded variables – better aligns the relative volatilities of each asset price with the exchange rate and may resolve some of the concern surrounding exchange rate models' in-sample performances. (This is notwithstanding that in-sample performance may have no bearing on out-of-sample forecasting ability, as noted in Engel *et al.*, 2008.)

2.2.8 Quasi-real-time data and data revisions

The inclusion of macroeconomic variables in traditional models of exchange rates may struggle to perform well out-of-sample due to two related intertemporal inconsistencies. First, macroeconomic data referenced to a set period are typically released with a multi-week (and sometimes multi-month) lag, meaning that real-time data are largely unavailable. This presents shortcomings for estimation and forecasting since the exchange rate reacts in real time to new information and surprises (Chinn, 2003). Frankel and Rose (1994) discuss approaches pertaining to how news impacts macroeconomic variables. Faust *et al.* (2001) find that forecasts based on exchange rate models using expectations of macroeconomic variables, such as inflation and economic activity (also known as fundamentals, see Hördahl and Packer, 2007) outperform forecasts based on actual (time-delayed) fundamentals, while Ehrmann and Fratzscher (2004) find a 13 percentage point improvement in the model's direction of change forecast by using real-time data compared with vintage data, when applied using a weighted least squares approach for daily USD/DEM data from 1 January 1993 to 14 February 2003.

The second related intertemporal inconsistency with standard exchange rate models occurs because events or news (shocks) that affect a macroeconomic variable may have a different time decay to that of a financial variable (such as the exchange rate), given asset prices adjust quickly (MacDonald, 2007). In the context of PPP, Taylor (2001) argues that low data frequency may explain the difficulty finding a long-run relationship. The application of higher frequency data, such as weekly rather than monthly or quarterly data, may be able to capture any rapid adjustments in the exchange rate in response to changing fundamentals or expectations of future fundamentals. For example, GDP data are typically quarterly series released with a lag but the direction of change in the data are often known in advance, due to monthly releases that inform the GDP estimate (such as industrial production and retail sales). Thus, the exchange rate may react to a weak (strong) monthly indicator one-month-ahead of the release of the official GDP figure, but then react to a different news event around the time the GDP release is published, independent of the GDP publication. In turn, the estimated exchange rate response to the GDP release will appear weaker than the true relationship. MacDonald (2007) concludes that the results from exchange rate estimates of high frequency data should be less susceptible to time averaging and Hann and Steurer (1996) find similar results when estimating a monthly linear and non-linear USD/DEM error correction model.[20] Balancing out these competing difficulties, weekly time series were employed in this study.

Relatedly, macro-financial variables are more likely to reflect changes in information more rapidly than macroeconomic data due to the components being traded in real-time on global capital markets. This paper uses financial market data for all variables and thus avoids both the intertemporal concerns discussed above.

A third explanation why monetary models using macroeconomic data may be poor performers is due to data revisions. Quasi-real-time estimation (taking the latest vintage of revised data) may not produce superior exchange rate forecasts because exchange rates react to expectations and new information; data revisions are an update of old news. Faust *et al.* (2001) show, with quarterly data from 1973Q2 to 2000Q3 using USD/JPY, USD/DEM, USD/CHF, and USD/CAD, that relative to a random walk, revised data dilute a monetary exchange rate model's performance by around a third. The paper also demonstrates that originally released data, compared with final-release (revised) data, have better predictive power for exchange rates. Molodtsova *et al.* (2008) find that using quarterly real-time indicators in a Taylor rule framework between 1979Q1 and 1998Q4 improves the

---

[20] A corollary here would be to use daily, intraday, or "tick" (individual exchange rate transaction) data. However, Juselius (2014) demonstrates in simulations that real exchange rates tend to exhibit many shocks (noise), while Zhou (1996) comments on the high degree of noise in tick exchange rate series compared with that of weekly, monthly, or quarterly time series. Vitale (2000) and Black (1986) comment that high-frequency trading is dominated by noise.

nominal USD/DEM exchange rate predictability both in- and out-of-sample (using 1989Q1–1998Q4 as the out-of-sample period). Thus, capturing the exchange rate and its response at the same time as the raw (unrevised) data are captured and reported may align a model more closely with the exchange rate's true DGP. Taking this a step further, a financial market asset price that is a representative indicator of a macroeconomic data series and the future sum of expectations pertaining to that particular macroeconomic data release is also raw, unrevised, and released in real-time. This paper tests whether these explanatory variables are successful at forecasting exchange rates in a real-time setting.

2.2.9 The random walk forecasting hurdle

A successful exchange rate model is one that beats a random walk (Meese and Rogoff, 1983). In other words, the model must perform better than a naïve no-change forecast.

Mathematically:

$$E(s_{t+1}|\, I_t) \, = s_t + E(\varepsilon_{t+1}|\, I_t) \tag{10}$$

$$= s_t \tag{11}$$

where $\varepsilon_t \sim i.i.d(0, \sigma^2)$ is serially uncorrelated with a mean of zero and constant variance.

The random walk error is therefore:

$$\varepsilon_{RW,t+1} = s_{t+1} - s_t \tag{12}$$

where RW denotes the random walk and, given (10) above:

$$E\left(\varepsilon_{RW,t+1} | I_t\right) = 0 \tag{13}$$

By contrast, if exchange rate returns are predictable, fundamentals will estimate a future exchange rate that is closer to the actual exchange rate at time *t+1* than the random walk (predicting no change).

Throughout the literature, researchers are generally unable to out-predict a random walk in out-of-sample forecasts using *ex-post* explanatory variables. Rossi (2006, p. 21), rather harshly, claims: "*economic models were completely useless for explaining exchange rates dynamics*." Moosa (2013) finds that as volatility rises, an exchange rate model error worsens compared to that of a random walk. Moosa and Burns (2014) note that many regressions apply a lagged dependent variable, which itself is a random walk component. Therefore, the random walk as a forecasting hurdle is difficult to beat.

2.3 The macro-financial literature on exchange rate modelling

By comparison to macroeconomic exchange rate estimation, the exchange rate literature on macro-financial data is burgeoning but relatively limited. Macro-finance refers to the interaction of economics and financial markets. Ponomarenko *et al.* (2018) refer to it as the interaction between the real economy and the financial sector, while Cochrane (2017) defines it as the link between asset prices and economic fluctuations. Macro-financial data are any asset price that is relevant for macroeconomic empirical analysis. Most common is relative interest rates (see Estrella and Hardouvelis, 1991, for an early example). In response to the zero-lower bound of interest rates, some studies have applied a hypothetical measure of the short-term interest rate (indicative of the country's monetary policy stance) that includes information from the term structure of interest rates, not just its level. Jensen *et al.* (2017) apply this measure of monetary policy stimulus to bond yields in Denmark, while Claus *et al.* (2016) assess the transmission of monetary policy (by way of a shadow short rate) to the USD/JPY.

Both economic theory and the international finance literature have long established the importance of interest rates as a determinant of the exchange rate but more recently, Evans and Lyons (2003) and Chen and Tsang (2011, 2013) find that other financial data, in addition to economic variables, are important factors in models of exchange rate determination. Sushko *et al.* (2016) identify that financial market proxies of risk premia can help to explain the failure of interest parity conditions.

This study defines macro-financial data narrowly. Macro-financial data defined here are prices of assets that are either tradeable on global financial markets, or where the prices are widely available to global market participants on a daily basis. This definition is applied in order to provide a direct link between exchange rates and other asset prices. The difference between the literature's wider definition and the one used in this thesis can be illustrated by two examples. Engel *et al.* (2010) conduct a survey of financial market participants as a risk premium proxy. This involves surveying participants and collating the results. The survey results are not a price that market practitioners are willing (or even able) to trade on but are their views and opinions, which may be similar, but not identical to, the perceived value (and thus price) of risk. Moreover, Engel *et al.* (2010) collate non-public information, are not capturing the universe of participants, and are equally weighting each surveyed respondent. By contrast, this paper applies the asset price of a risk variable traded on financial markets (the VIX) – a publicly available price that adjusts as participants' views adjust, and – significantly – as participants are willing to put capital against these views and expectations. To this end, a traded risk proxy is more direct than a survey measure of risk.

A second illustration is the work by Evans and Lyons (2009), who find that order-flow (actual buy and sell orders) drives exchanges rates. Unfortunately, data on buy and sell orders are not available across all asset markets, which limits the ability to apply this approach across multiple variables. However, Evans and Lyons (2003) find that order-flow is closely linked to macroeconomic-related news. Therefore, the price of the macro-financial asset encompasses the order-flow that drives the price to its new level, incorporates news, and is publicly available across all asset markets. Thus, macro-financial data as defined in this study are expected to have a more direct relationship to the exchange rate than some data used in previous studies that apply variables that are a derivative of the underlying indicator of interest.

The application of macro-financial data in exchange rate determination can yield positive results. Cheung *et al.* (2017) demonstrate how both financial market and macroeconomic variables impact on the USD/CAD, USD/JPY, USD/CHF, USD/EUR, and USD/GBP exchange rates in a first-difference and an error-correction model over various forecast periods between 1983 and 2014. Chen and Tsang (2013) find decomposing the yield curve into its slope, curvature, and level components produces excess currency returns for three exchange rates from one-month to two-years out-of-sample. Clarida *et al.* (2003) find, in a weekly regime-switching vector equilibrium correction model, the term structure of forward rates has out-of-sample informational content for USD/FRF, USD/DEM, USD/JPY, and USD/GBP exchange rates between 1996 and 1998. Engel *et al.* (2010) apply a risk variable derived from surveyed data and find it enhances long-run exchange rate forecasting. More recently, Morana (2015) estimates the USD/EUR exchange rate over three periods using both financial market and macroeconomic variables in an autoregressive distributed lag model. Morana applies variables related to the theory that the exchange rate is related to the present sum of discounted future fundamentals, and finds evidence of parameter instability throughout the three samples estimated and mixed forecasting results both in-sample and out-of-sample for the periods before, during, and after the financial crisis of 2009 (2007M8 to 2009M6; 2010M3to 2013M2; and 2013M3 to 2015M6).

This paper extends the existing empirical literature by adhering to economic theory more formally,[21] with the innovation of adding in financial market asset prices that act as proxies for macroeconomic variables when forecasting exchange rates out-of-sample. The closest applicability to this thesis from the literature is the work by Cheung *et al.* (2017). Cheung *et al.* (2017) estimate quarterly augmented sticky-price models in levels terms and by applying an error correction specification for USD/CAD, USD/GBP, USD/CHF, USD/EUR and USD/JPY exchange rates from 1973Q2 to 2014Q4. Cheung *et al.* (2017) add a risk proxy (the VIX index) and a liquidity proxy (the TED spread, or the three-month U.S. Treasury yield minus the three-month LIBOR yield). Further, the paper adds in a proxy for the slope of the

[21] Thus, avoids rendering the regression either overfitted or spurious, or both (Rossi and Sekhposyan, 2011).

Government yield curve (the 10-year sovereign bond yield minus the three-month Government bill rate) and, when the period of unconventional policy is undertaken by a number of central banks in the sample (the Bank of England, the European Central Bank, the Federal Reserve, the Swiss National Bank, and the Bank of Japan) the paper applies shadow rates (see Wu and Xia, 2016). The regressions are a rolling window with three periods of out-of-sample forecasting: 1983Q1-2014Q4, 2001Q1-2014Q4, and 2007Q4-2014Q4. Notable, given the discussion in Section 2.2.4 on time-varying parameters, Cheung *et al.* (2017) allow the long-run ECM relationship to change over time. The results are positive but not unanimous; once again, the results are exchange rate- and period-dependent.

Macro-financial data defined in this study are spot asset prices and indices for assets that are tradeable on global financial markets, where the asset prices are widely available to market participants. By utilising only publicly available asset prices, this study tests whether proxies for macroeconomic data that adjust as participants' views adjust better captures the role of expectations in an exchange rate model and if this model has predictability.

Specifically, this study attempts to attest to four common criticisms as to why exchange rate models fail in out-of-sample forecasting: only allowing the expectations component to affect the exchange rate through the relative interest rate channel; poor model performance due to delayed data releases and data revisions; failing to allow for time-varying behaviour of exchange rate drivers; and restricting the definition of success to solely a random walk. Next, Section 3 discusses the model methodology employed in this study.

Section 3. Methodology and Empirical Specification

In this section the macro-financial augmented sticky asset price model is introduced, the asset class proxies for macroeconomic data are described, and the forecasting approach is explained. Section 4 then describes the choice of data.

3.1 General model and the inclusion of expectations

The monetary model can be summarized as the exchange rate today is a function of current (relative) fundamentals and the domestic-to-foreign interest rate differential:

$$E(s_t) = \gamma' X_t + \alpha_3 (i_t - i_t^*) \tag{14}$$

where X_t is a vector of log-linear fundamental data, i_t is the domestic country nominal interest rate, and i_t^* is the foreign country nominal interest rate.

Moosa and Bhatti (2009) include expectations via the microstructure approach and describe the present value of the exchange rate as:

$$s_t = (1 - \beta_1) \sum_{i=1}^{\infty} {\beta_1}^i \, E(Z_{t+\mathrm{i}} \mid I_t) \tag{15}$$

where:

$$Z_t = f(m_t, m_t^*, y_t, y_t^*, i_t, i_t^*, \pi_t, \pi_t^* \dots) \tag{16}$$

Simply put, Equation (15) states that the spot exchange rate is a function of the expected future value of fundamental variables Z_t at time t (where Z includes interest rates) and β_1 is between 0 and 1. See Levich (1985) and Mark (2000).

As noted in MacDonald (2007) and specified in Section 2.1, the augmented sticky-price model integrates the monetary and sticky-price models to give (Frankel, 1979):

$$s_t = \alpha_0 + \alpha_1(m_t - m_t^*) + \alpha_2(y_t - y_t^*) + \alpha_3(i_t - i_t^*) + \alpha_4(\pi_t - \pi_t^*) + \alpha_5\overline{TB}_t + \mu_t \tag{17}$$

where the terms are defined in Section 2.

Equations (15) and (17) are linked. As stated by Meese (1990), the spot rate of any market asset price equates to the expected discounted sum of its future fundamental values, based on the information set available at time *t*. Thus, the current spot price of all variables can be written as a present-value reduced form representation.

The exchange rate could be determined by explicitly discounting the forwards curve of each individual regressor.[22] This is theoretically equivalent to regressing the spot exchange rate against the spot price of each right-hand-side variable. Empirically the realised future path of the asset price discounted back to $t = 0$ does not always

[22] A forwards curve is the price of the forward contract at time *t* over regular maturities dates, for example, one week, one month, two months etc., out as far as the contract is traded.

equate to the spot price today, nor indeed does the future expected price match the price of the asset in the future, as the literature shows with the forward premium puzzle (Chinn, 2003). This is because the full and true information set (both public and private) is not available *ex-ante* and expectations change from one period to the next.

To demonstrate this point, Moosa and Bhatti (2009) take Equation (15) one-period-ahead and rearrange to show:

$$\Delta s_{t+1} = \frac{1-\beta_1}{\beta_1}\left(s_t - E(Z_{t+\mathrm{i}} \mid I_t)\right) + \theta_{t+1} \tag{18}$$

where:

$$\theta_{t+1} = \frac{1-\beta_1}{\beta_1}\sum_{i=1}^{\infty} {\beta_1}^{i}\left(E(Z_{t+\mathrm{i}} \mid I_{t+1}) - E(Z_{t+\mathrm{i}} \mid I_t)\right) \tag{19}$$

That is, the change in the exchange rate is a function of expected and unexpected changes (θ_{t+1}), which in turn is in part directed by the new information set I_{t+1}. As highlighted by Sarno (2003), traditional exchange rate models may well perform poorly because of changing expectations. In Equation (18) the change in the exchange rate is in part caused by changes in expectations. Typical models of exchange rate determination include fundamentals, which, with the exception of relative interest rates, are data that do not incorporate expected future changes and cannot incorporate unexpected changes. And yet, as Moosa and Bhatti (2009, p. 299) summarise: "*if fundamentals are expected to change in the future, dealers are likely to quote different exchange rates, thereby contributing to the realized rate of change*".

This is precisely what financial market participants do. In lieu of contemporaneous macroeconomic data, market participants formulate proxies for these data – asset prices such as spot prices or market indices – and trade the corresponding assets in real time on global financial markets. Importantly, these traded asset prices include the expected future value. For example, Botman *et al.* (2013) find in risk-off periods (when global economic sentiment is declining) market players adjust their expectations around the economic outlook and re-value USD/JPY.

Macro-financial variables allow unexpected shocks and news to be reflected immediately – a form of real-time signaling regarding the prospects for their macroeconomic equivalents. The application of globally-traded asset prices instead of economic-only data allows surprises and changes in expectations to be reflected and captured in both the explanatory variables and the exchange rate at the same point in time (Mark, 2000).[23]

To the extent that it can, the spot price of the exchange rate expresses full information (both public and private) because the variable is traded and its price reflects the balance of demand and supply. Over time, the change in spot prices reflects changes in realised fundamental variables, new information, and change to

[23] This explains why event studies provide practitioners with some insights to exchange rate behaviour. Event studies compare the difference between expected macroeconomic data outturns and actual data outturns on exchange rate changes over very short periods around the time of the data release. See Kearns and Manners (2006) in the context of the New Zealand and Australian dollars.

expectations of future economic fundamentals.[24] Changes in expectations – either expected or unexpected – is reflected in the exchange rate immediately. By contrast, macroeconomic variables when applied in an exchange rate model do not incorporate expectations and are published with a time delay. The only real-time variable that incorporates expectations is relative interest rates. Thus, a model estimated with macro-financial variables is less restrictive than a traditional model based on macroeconomic data and relative interest rates, especially if the expectations formation and impact on the exchange rate differs across regressors.

3.1.1 Estimation equation and forecasting

Equation (17) determines the price of the exchange rate at time t but does not predict the spot exchange rate at $t+1$. When testing the forecasting abilities of an exchange rate model, one of three approaches is typically taken. The first is *ex-post* forecasting, where the realised future values of the exogenous variables are applied (as in Meese and Rogoff, 1983). This is appropriate for testing the in-sample properties of the regression and is the most frequently applied approach in the literature. The disadvantage with this approach is that at time $t+1$ (for a one-step-ahead forecast) the right-hand side variables are not known at time t. The second approach is where studies evaluate the accuracy of the estimation based on *ex-ante* forecasts of the independent variables. This brings uncertainty to the model, and

[24] In a similar vein, Engel *et al.* (2008) demonstrate that news about the future of the macro economy is reflected in exchange rates through surveys.

its success cannot be separated from the success of variable forecasting (Fair, 1986; Isard, 1995). This approach is not discussed further for this reason.

A third approach – typically applied in a model designed to test the equation for its forecasting ability – is:

$$s_{t+1} = \alpha_0 + \alpha_1(m_t - m_t^*) + \alpha_2(y_t - y_t^*) + \alpha_3(i_t - i_t^*) + \alpha_4(\pi_t - \pi_t^*) + \alpha_5\overline{TB}_t + \mu_{t+1} \tag{20}$$

As derived by Moosa and Bhatti (2009), there remains the potential for some distortion between $\hat{s}_{t+1}$ and s_{t+1} if $\theta_t \neq 0$.

Specifically for this study, a risk premium is included to Equations (17) and (20).

$$s_{t+1} = \alpha_0 + \alpha_1(m_t - m_t^*) + \alpha_2(y_t - y_t^*) + \alpha_3(i_t - i_t^*) + \alpha_4(\pi_t - \pi_t^*) + \alpha_5\overline{TB}_t + \alpha_6 rp_t + \mu_{t+1} \tag{21}$$

where rp_t is the risk premium variable.

In this study, the estimation is distinct to other approaches of exchange rate estimation because the regressors are no longer macroeconomic data; instead, macroeconomic data are replaced with asset price proxies traded daily on global exchanges. This has the added benefit of being forward-looking (asset prices include expectations of future values embedded in the current spot price), thus including the current and future expectations of each right-hand side variable. Replacing the independent variables with a macro-financial proxy facilitates a more parsimonious model than including a model that is not linked to the theoretical literature. This approach also reduces the risk of data snooping (White, 2000).

3.2 Choice of macro-financial regressors

This section discusses the application of macro-financial proxies, and proposes the financial market variables considered. Further information pertaining to the specific data choice and data characteristics can be found in Sections 4.5 and 4.6.

In this study, a macro-financial variable refers to a globally traded wholesale asset price or index that is considered a proxy for its macroeconomic counterpart. These proxies may not be a true substitute for the hard data they represent; they are variables that financial market participants believe are a representation of the underlying variables of interest, and variables that traders fixate on over time. Indeed, in the author's experience, these chosen proxies are not always a close alternative. For example, during the late 1990s and into the early 2000s, there was no real-time daily traded New Zealand commodity price index but foreign exchange traders understood that the New Zealand dollar is a commodity currency and thus related to commodity price movements (Cashin *et al.*, 2004). New Zealand foreign exchange traders substituted the Thomson Reuters Commodity Futures Index (CRB) as a commodity price equivalent, in order to provide guidance as to the direction of the New Zealand dollar on a daily and weekly basis (see Sullivan and Aldridge, 2011; and Tuffley, 2010, as two examples of economists implying a relationship between the series). This is despite New Zealand's primary commodity exports not forming any part of the CRB Index.[25,26]

By substituting the macroeconomic variables for macro-financial proxies, a summary of the baseline regression variables proposed is shown in Table I.

Table I. Baseline macro-financial proxies

Macroeconomic variable	Notation	Macro-financial proxy
Exchange rate	s_t	Nominal exchange rate
Money supply	$m_{p,t} - m_{p,t}{}^*$	N/A
Income	$y_{p,t} - y_{p,t}{}^*$	Major stock market index
Interest rate	$i_t - i_t{}^*$	Interest rate
Inflation	$\pi_{p,t} - \pi_{p,t}{}^*$	Breakeven inflation
Terms of trade	$c_{p,t} - c_{p,t}{}^*$	Commodity price
Risk premium	$rp_{p,t}$	Risk

[25] The CRB Index is calculated from aluminum, cocoa, coffee, copper, corn, cotton, crude oil, gold, heating oil, lean hogs, live cattle, natural gas, nickel, orange juice, RBOB gasoline, silver, soybeans, sugar, and wheat futures prices. See https://www.refinitiv.com/content/dam/marketing/en_us/documents/fact-sheets/cc-crb-total-return-index-fact-sheet.pdf.

[26] From 2002, ASB Bank started publishing a weekly NZ Commodity Price Index, which has superseded the CRB as a commodity price proxy for domestic foreign exchange traders. This index includes New Zealand export commodities, such as dairy, forestry, and fruit prices. See ASB Commodities Weekly at https://www.asb.co.nz/documents/economic-research/commodities-weekly.html.

3.2.1 Variables not included

Table I lists the theoretical explanators and the macro-financial variables of interest. Not all variables are considered, for example, relative money supply. Dornbusch (1980) argues the money supply variable is often insignificant, noting that the exchange rate is also the relative price of assets. Hartmann and Smets (2018) comment that monetary policy stimulus is driven by easing financial conditions and reduced interest rates, pointing to near-perfect multicollinearity of the right-hand side variables if money supply as well as relative interest rates and a risk variable are included, a point also made by Levich (1985). This study focuses on the period when central banks target inflation, so avoids these concerns (see Section 4.3 for a greater discussion of this point). This is further supported by Meese's (1990) comment that money demand equations are not stable and do not capture the relationship between money supply, income, and interest rates in a predictable fashion in the post-Bretton Woods era. Finally, in recent years relative money supply is not included in empirical applications of exchange rate determination and therefore is not included here.

3.2.2 Inflation

In the original flexible price model of the exchange rate, PPP is expected to hold at all times, and therefore the coefficient on the relative inflation variable is zero. Models of exchange rate determination also allow relative inflation rates to impact on the exchange rate in the short run (see Frankel, 1979; Dornbusch, 1976; MacDonald and Taylor, 1994; and Junttila and Korhonen, 2011, as some examples).

While a market-derived inflation rate, either a breakeven inflation rate[27] or an inflation swap, [28] could be applied as a macro-financial proxy, data availability constrains the use of this variable.

3.2.3 Income

Gross domestic product is the most frequently used variable for income in the literature when determining the real exchange rate. The output gap (the difference between GDP and its potential) is another variable of interest that is often used instead of GDP, especially when applied in a Taylor rule framework (such as in Molodtsova and Papell, 2009). There is no direct equivalent to income for a macro-financial variable but GDP and wealth are correlated with income and consumption (Budria Rodriguez *et al.*, 2002; Campbell and Cocco, 2007; Campbell and Cochrane, 1999) and Gavin (1989) finds the U.S. stock market is positively related to aggregate demand. Rising equity prices are positively related to consumption across developed markets.[29] Equities are often considered a reflection of the strength of an

[27] The difference between a nominal bond yield-to-maturity and an inflation-protected one of the same maturity.

[28] An interest rate swap is an agreement between two counterparties to exchange cashflows in the same currency over a set period of time. One cashflow is set to a specified interest rate (fixed rate) and one is set against a floating interest rate. See BIS (2016) for more details.

[29] Bertaut (2002) and Poterba (2000) are two of many examples. The literature on the link between stock market appreciation and consumption is large and varied. Some research argue that the transmission linkages may be indirect (for example, Jansen and Nahuis, 2003). Cooper and Dynan (2016) survey the literature on this topic, see also Sonje *et al.* (2014) for research on the short-run

economy, and economic strength is related to the currency's value (in the case of the nominal Swedish krona, see Hatemi-J and Irandoust, 2002; or the real exchange rate as in Gavin, 1989). Bahmani-Oskooee and Saha (2015) conclude that stock prices and exchange rates are jointly determined, while Kanas (2000) demonstrates how equity volatility spillover affects major developed market currencies. Ho and Huang (2015) find weekly observations show a strong relationship between the volatility of selected stock markets and the respective exchange rates, although the direction of the relationship changes across currencies and time. In this study, the primary equity index is applied as the income proxy.

3.2.4 Interest rates

As discussed in Section 2.2.4, the idea that relative interest rates affect the exchange rate is linked to UIP. However, as pointed out by Froot and Thaler (1990), higher U.S. interest rates, both nominal and real, tend to be associated with an appreciation of the U.S. dollar. Verdelhan (2018) finds the carry trade is large and significant. This study does not restrict the coefficient sign, and because interest rates are observable and traded on global financial markets, the variable does not need to be proxied.

---

relationship. In New Zealand, Wong (2017) finds a stronger relationship between financial wealth and consumption than housing wealth and consumption.

3.2.5 Commodity prices

Some countries are highly dependent on revenue from commodity exports, especially emerging economies (Cashin *et al.*, 2004). Chen and Rogoff (2003) and Chan *et al.* (2009) comment how commodity prices have a notable impact on some developed countries' exchange rates, such as New Zealand, Australia, and Canada. Cashin *et al.* (2004) find a long-run relationship between real commodity prices and the real exchange rate for one-third of the commodity-exporting countries examined. Commodity terms of trade are thus a driver of the real exchange rate.

Kohlscheen *et al.* (2016) find that rising nominal commodity prices results in the local currency strengthening in the short run, and assert that "…*key export commodities is often seen as a reasonably good proxy for terms-of-trade movements*" and "*the prices of key exports may well bear a close link with [nominal] exchange rate movements*" (p. 122). The price of each country's main export commodity, or main commodity export index, is included in this study.

3.2.6 Risk premium

International asset price co-movements are an important issue when considering the use of macro-financial variables when determining the exchange rate. If asset prices move as a result of events abroad that are expected to have consequences for the domestic economy, then this information is valuable. Flexible exchange rates are natural shock absorbers for the economy, so a variable that reflects preferences for risk-seeking or risk-aversion may add value to an exchange rate model. This risk variable is known to have different effects on exchange rates. For example, the New Zealand dollar is considered a risky currency (Cassino and Wallis, 2010), while the Japanese yen is considered a safe-haven currency and appreciates in times of market volatility (Ranaldo and Söderlind, 2010; McCauley and McGuire, 2009). A difficulty with the risk premium is that it can vary over time; see Chinn and Frankel (2019) for a survey of the historical literature, or Engel (2016) for a more recent characterisation. The existence of a currency risk premium has been found to help explain the UIP puzzle (Engel and West, 2004), and Chen and Tsang (2013) show risk drives the return of a currency portfolio. This study includes a proxy for risk that is traded on global financial markets.

3.3 Estimation approach

This paper estimates two reduced-form models applying separate estimation approaches: a full-sample fixed-coefficient (log) linear single regression and a rolling fixed-window regression.

The first reduced-form model, similar to Equation (20), is shown below as Equation (22) and the second, Equation (22a) includes the lagged dependent variable. For each of these models, the current (t) and forecasting (t+*1*), Equations (23) and (23a), versions are estimated:

$$s_t = \delta_0 + \delta_2\left(y_{p,t} - y^*_{p,t}\right) + \delta_3(i_t - i^*_t) + \delta_5\left(c_{p,t} - c^*_{p,t}\right) + \delta_6 rp_{p,t} + \varepsilon_t \qquad (22)$$

$$\begin{aligned} s_t = \delta_0 + \delta_2\left(y_{p,t} - y^*_{p,t}\right) + \delta_3(i_t - i^*_t) + \delta_5\left(c_{p,t} - c^*_{p,t}\right) \\ + \delta_6 rp_{p,t} + \delta_7 s_{t-1} + \varepsilon_t \end{aligned} \qquad (22a)$$

$$s_{t+1} = \delta_0 + \delta_2\left(y_{p,t} - y^*_{p,t}\right) + \delta_3(i_t - i^*_t) + \delta_5\left(c_{p,t} - c^*_{p,t}\right) + \delta_6 rp_{p,t} + \varepsilon_{t+1} \tag{23}$$

$$s_{t+1} = \delta_0 + \delta_2\left(y_{p,t} - y^*_{p,t}\right) + \delta_3(i_t - i^*_t) + \delta_5\left(c_{p,t} - c^*_{p,t}\right) + \delta_6 rp_{p,t} + \delta_7 s_t + \varepsilon_{t+1} \tag{23a}$$

Given the author's experience of foreign exchange trading, estimating with the lagged dependent variable is relevant from a real-world perspective, for market participants know the spot price of the recent exchange rate when they consider whether to trade a currency higher or lower. That said, there are some valid reasons to consider estimating the log-linear model without the lagged dependent variable. First, if the model is adequately identified, the right-hand side variables reflect both current and future expectations. In this way, the information in the lagged dependent variable should already be contained in the existing regressors. Second, a model including the lagged dependent variable is a more general form of a no-change model (Neely and Sarno, 2002), making the regression difficult to outperform the random walk. And finally, a lagged dependent variable is regularly excluded in the literature when exchange rate models are estimated and reported, which sets a strong precedent to do the same. Hence, both the estimation with and without the lagged dependent variable are assessed in this study.

As mentioned previously, the regressions are estimated over a set time period and also using a rolling-fixed window regression. In total, there are eight equations estimated across five currency pairs (USD/GBP, USD/EUR, USD/AUD, USD/NZD, USD/CAD, USD/JPY), for a total of 40 estimations for comparison in the first instance (see Table II).[30] The estimation technique is ordinary least squares. Each model feature is discussed

Table II. Estimations

	USD/GBP	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Full-sample fixed-coefficient 30 Jan 1998 to 28 Dec 2018						
Equation (22) Time *t*	✓	✓	✓	✓	✓	✓
Equation (23) Time *t+1*	✓	✓	✓	✓	✓	✓
Equation (22a) Time *t*, lagged dependent	✓	✓	✓	✓	✓	✓
Equation (23a) Time *t+1*, lagged dependent	✓	✓	✓	✓	✓	✓
Two-year rolling fixed-window						
Equation (22) Time *t*	✓	✓	✓	✓	✓	✓
Equation (23) Time *t+1*	✓	✓	✓	✓	✓	✓
Equation (22a) Time *t*, lagged dependent	✓	✓	✓	✓	✓	✓
Equation (23a) Time *t+1*, lagged dependent	✓	✓	✓	✓	✓	✓

3.3.1 Linear model

The choice of a linear versus a more sophisticated model has the potential to affect the results. The literature is inconclusive whether out-of-sample success is a result

[30] Section 5 also looks at the equations in first differences.

of the model employed or the transformation of the explanatory variables (see Section 2). As noted in Lopez-Suarez and Rodriguez-Lopez (2011), adjusted (non-linear) data series may have more success at fitting to the dependent variable but Zaman (2012) points out the model may lose its interpretation in the process (for example, Chinn, 2008, uses a cubic lagged exchange rate in his non-linear model). Hansen (2001) suggests that an overfitted model may perform well in-sample but is less likely to do well out-of-sample, and similarly, Neely (2016) notes that in-sample performance does not imply out-of-sample success, although this is true for all model types. Rossi (2013) surveys the literature and concludes that the model parameters are more important to determining successful results than the model form. Similarly, Froot and Obstfeld (1989) contend having a linear or non-linear model is not the primary consideration when choosing a model.

By comparison, the literature clearly shows that exchange rate models can be well-described by non-linearity (see Section 2.2.5). Despite (but notwithstanding) these valid arguments, there are three reasons why a log-linear model is employed in this study. First, a linear model is applied to focus the study on the difference in success across exchange rates when using macro-financial proxies, rather than across the type of model. Second, a linear model is the most frequently applied model-type in the literature. Third, a linear model focuses the study on the difference in success when the assumption of time-constancy is relaxed. The model form is intentionally kept simple, even though a simple ordinary least squares regression poses a number of econometric concerns, as previously discussed. A future area of research is to relax this assumption and estimate the macro-financial model in a non-linear form.

3.3.2 Full-sample fixed-coefficient versus rolling fixed-window regression

Burns and Moosa (2015), and Cheung *et al.* (2017), amongst others, show a regression estimated in one period and then applying the same coefficients onto another period can weaken the forecasting accuracy of exchange rate models. Section 3 describes the posited reasons for this, including structural breaks and changes to expectations.

Short-run models of the exchange rate that incorporate financial market (macro-financial) variables may also experience changing coefficients due to transitory adjustments to behavioural relationships and expectations. A time-varying coefficient in an exchange rate model has the additional benefit of allowing the distribution of exchange rate returns as well as the skewness of exchange rate returns (by the shifts in the sign of the coefficients) to vary (Boothe and Glassman, 1987a). There can be economic arguments for these changes. Wang *et al.* (2001) use Japan's productivity lift in the 1990s as an example for changing coefficients. Time-varying coefficients are more likely to illustrate and illuminate changes during and immediately after the occurrences, rather than averaging them out as in a full-sample fixed-coefficient regression estimation.

In conclusion, there are three sets of results presented: the full-sample fixed-coefficient results for Equation (22) and Equation (23) including the lagged dependent variable (Equations (22) and (23)), and the fixed-window rolling regressions. This paper applies a rolling regression analysis, using a fixed-window length of two years, with each roll shifted one period (one week) forward. The optimal look-back period for the fixed-roll is unknown. A long window has the benefit of increasing the power of a test but also exposes the estimation to changing coefficients over the fixed look-back period (this idea is discussed in Foster and Nelson, 1996, attributed to Fama and MacBeth, 1973). A look-back period of two years was chosen to provide a sufficient sample size, given the roll frequency (for a total of 104 periods, i.e., weeks). In New Zealand, foreign exchange traders often 're-set' at the start of the week, by comparing the exchange rate movement the week prior with movements in underlying proxies over the same period. While traders consider daily exchange rate movements in a similar fashion, the author's experience is that the start of the trading week has additional significance (Lewis and Rosborough, 2013).

Importantly, this paper does not seek to find the 'best' model (as in, say portfolio optimization or in-sample estimation), but instead directly replaces macroeconomic data with its equivalent spot asset prices and tests if this augmented model has forecasting value.

3.4 Forecasting criteria

While a random walk is considered *the* test of exchange rate predictability following Meese and Rogoff (1983), a recent trend is to compare a model's out-of-sample forecasting results to other forecasting criteria. As Engel and West (2005) note, even if an exchange rate model is predictable it may not beat a random walk if the discount factor is close to one.

Out-of-sample forecasting evidence is imperative when ranking exchange rate models in part because forecasting performance has a strong relationship to exchange rate predictability, and – importantly for practical applicability – has implications for market timing, profitability, and asset allocation decisions (Leitch and Tanner, 1991).

Profitability involves a real-world application of exchange rate models but the choices an investment manager must make are numerous. For example, how to formulate the trading strategy, such as choosing a portfolio of "buy-top-three-currencies / sell-bottom-three-currencies" (and how to define the best and worst) or a single exchange rate trade; what price to compare to (the bid-ask spread vs mid-rate, the current spot price or the current price taking into account the cost to hold the position, such as the interest rate differential gained or forgone) and so forth. Because of these decisions, profitability is difficult to compare across studies and can be subject to claims of data manipulation. Boothe and Glassman (1987b) note the difficulty of obtaining profits in exchange rate models, who calculate a cumulative profitability figure for six models of the USD/CAD and USD/DEM, over four different time periods, forecasting 1, 3, 6, and 12 months out-of-sample. The results are exchange rate-dependent and are not persistent as the forecast horizon extends. The pitfalls of creating a profit rule are avoided in this study.

Cheung *et al.* (2005) acknowledge that other forecasting criteria may be relevant; in addition to the random walk, the root mean square error (RMSE), Thiel's U, and the direction of change are popular criteria. For short-term exchange rate modelling, the correct direction matters for global foreign exchange traders. Della Corte *et al.* (2009) point out that for short horizon forecasting, the directional predictability of an exchange rate model is more valuable than the accuracy of those predictions. From a practitioner's perspective, having a small error is desired over a large error, as well as correctly predicting the direction of the exchange rate of a specified forecast period. This study compares the RMSE, Theil's U, and the direction of change (DΔAccuracy) statistic as meaningful tests of short-run exchange rate modelling accuracy, with details of each discussed. A random walk is also compared. In all cases, for comparative purposes, the forecasting criteria are used across all models.

3.4.1 Root mean square error

The RMSE, the adjusted RMSE, the mean forecast error and mean absolute error (MAE) are most frequently utilised to compare the out-of-sample exchange rate forecasts with the random walk or random walk with drift (see Meese and Rogoff, 1983; Schinasi and Swamy, 1987; and Leitch and Tanner, 1991, for some examples).

The root mean square error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} {\varepsilon_{t+1}}^2} \tag{24}$$

where $\varepsilon_{t+1} = s_{t+1} - \hat{s}_{t+1}$, s_t is the observed value at time *t+1* and $\hat{s}_{t+1}$ is the predicted value for period t. In the case of the random walk, $\hat{s}_{t+1} = s_t$.

The ratio $\frac{RMSE_{predicted}}{RMSE_{rw}}$ of less than one equates to a model that outperforms the random walk. The application of RMSE is pervasive, being reported in Meese and Rogoff's (1983) seminal paper and thereafter. The RMSE is an unbiased statistic compared with alternatives such as the mean absolute percentage error (Armstrong and Collopy, 1992) as both positive and negative errors are treated equally (Chinn and Meese, 1995). However, RMSE is not without its faults. The RSME worsens if the magnitude of forecasting errors is large, even if the direction is correct (Engel, 1994). Schinasi and Swamy (1987) point out statistically significant differences cannot be calculated across models for RMSE statistics. As noted earlier, exchange rate behaviour tends to follow a non-normal distribution (Meese and Rogoff, 1983); therefore mean-variance variables such as the RMSE can be considered an inappropriate measure of success (Della Corte *et al.*, 2009). Therefore, this measure is considered but is not the only criterion for forecast success.

3.4.2 Theil's U

The Theil's U, or coefficient of inequality, is an alternative approach to test for forecast success. There are two Theil's U statistics, U_1 and U_2. U_1 is bounded between 0 (a perfect forecast) and 1; whereas U_2 beats the random walk if it is less than one.[31] Bliemel (1973) points out that U_1 does not provide information against a no-change forecast (random walk), thus limiting its use when the random walk is considered the baseline comparator. Thus, the U_2 statistic is more meaningful, as it allows the model to be ranked against the naïve forecast result (which will be 0); in short, U_2 "*compares the RMSE for a proposed model with the RMSE for the random walk*" (Armstrong and Collopy, 1992, p. 70). Theil's U_2 statistic (RMSE adjusted for the naïve model), allows forecast errors to be compared across models and units of

[31] where $U_1 = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(s_t - \hat{s}_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}{s_t}^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}{\hat{s}_t}^2}}$

measurement (Leitch and Tanner 1991). For this reason, U_2 is applied in this study in addition to other forecasting criteria. The U_2 statistic is calculated as:

$$U_2 = \frac{\sqrt{\left[\sum_{1}^{n=1}\left(\frac{\hat{s}_{t+1} - s_{t+1}}{s_t}\right)^2\right]}}{\sqrt{\sum_{t=1}^{n}\left(\frac{s_{t+1} - s_t}{s_t}\right)^2}} \tag{25}$$

3.4.3 Accuracy of directional change

While the above two summary statistics are frequently cited in the literature, this study attempts to better understand the drivers of the exchange rate as given by macro-financial indicators and traded by financial market participants. Hence, determining the economic value of exchange rate predictability is imperative (as discussed in Della Corte *et al.*, 2009; and Leitch and Tanner, 1991).

Christoffersen and Diebold (2006) note how a model estimate is more likely to result in forecasting success if its directional change is correct. Moosa and Burns (2015) demonstrate that forecast direction can be a superior criterion to forecast error when concerned with profitability, while Leitch and Tanner (1991) find a relationship between profitability and direction of change, suggesting direction of change may be a sufficient proxy for success. The statistic is increasingly found in the exchange rate literature as a measure of forecast success; see Moosa (2013), Cheung *et al.* (2017) amongst others.

The accuracy of directional change is calculated as:

$$D\Delta A = \frac{1}{n-1}\sum_{t=1}^{n}\theta \tag{26}$$

where:

$$\theta = \begin{cases} 1 & if\ (\hat{s}_{t+1} - \hat{s}_t)(s_{t+1} - s_t) > 0 \\ 0 & (\hat{s}_{t+1} - \hat{s}_t)(s_{t+1} - s_t) < 0 \end{cases} \tag{27}$$

3.4.4 Forecast period of evaluation

The model's performance is evaluated over a forecast horizon of one year (52 weeks). Previous studies frequently compare the quarterly outcomes of one-quarter and one-year-ahead (Meese and Rogoff, 1983; Chinn and Meese, 1995; Wu and Hu, 2009, Lopez-Suarez and Rodriguez-Lopez, 2011 and Cheung *et al.*, 2017). A one-period ahead forecast for these whole-period fixed-coefficient models, for example, produces one data point, while four quarters (one year) gives four data points. Both do not provide sufficient data points to conclude whether the models perform well.

In this study, the results of the full-period fixed-coefficient models and the rolling fixed-window regressions take the out-of-sample forecast each week for 52 weeks. The sample size can be considered against other studies (one-period-ahead, one-quarter-ahead, and one-year-ahead) but also can be compared to each other as the out-of-sample period lengthens. Section 6 looks at rolling fixed-window forecasts in more detail, specifically the results of out-of-sample forecasts as the regression window rolls through time.

The literature typically tests the forecasting accuracy of the whole-period estimation is based on *ex-post* values of the regressors and the forecasting sample is typically in-sample. This gives the forecasts an "*informational advantage*" (Cheung *et al.*, 2017, p. 13) to the rolling fixed-window forecasts, which are based on data not known to the model *ex-ante*.

In order to compare like-for-like, the forecast comparison is run twice. First: the period 5 January 2018 to 28 December 2018 and then again: 4 January 2019 to 27 December 2019. In the latter period data are not known in either (fixed-coefficient or rolling fixed-window) estimation method, allowing a true test of the models' forecasting abilities.

Section 4 introduces the data, beginning with the choice of time-series length and data frequency, and discusses some difficulties with data capture. The section discusses the choice of the macro-financial data applied in the models, as well as the key advantages and disadvantages of their inclusion. The characteristics of the data are examined: over time, distributional properties, and variability. The data are tested for stationarity and multicollinearity before Section 5 discusses the results.

Section 4. Data and Related Considerations

This section describes the time series applied in the models, and discusses some notable characteristics of the data. The data are nominal, non-seasonally adjusted, weekly real-time prices as captured by Bloomberg L.P. The currencies are the euro, the Pound Sterling, the Japanese yen, the Canadian dollar, the Australian dollar, and the New Zealand dollar, each against the United States dollar.

There are several considerations with respect to the data that are discussed below.

4.1 Definition

Macro-financial data, as defined here, are spot asset prices or indices that are globally traded and available to financial market practitioners to buy or sell, or are an index where the underlying components are available to financial market practitioners to buy or sell (for example, in the case of a composite commodity index). This definition of macro-financial data is designed to have a direct relationship to exchange rates (rather than, for example, a survey). Further discussion of the motivations to use macro-financial data as compared to macroeconomic data can be found in Section 2.

4.2 Data frequency

Statistical releases of macroeconomic data are typically quarterly or monthly in frequency; restricting macroeconomic modelling to the same. By contrast, macro-financial data are traded prices and can be captured at any frequency – monthly, weekly, daily, or even at intraday intervals. Therefore, data frequency in this paper is not limited by data availability.

The choice of weekly data for this study is primarily a result of eliminating other alternatives, with the deduction process explained below.

Obtaining intraday data for the period of interest is challenging: multi-year intraday time series data are not easily available from the data provider.[32]

Daily data were not considered due to time-zone impediments. Exchange rate modelling involves cross-country comparisons and therefore time-zone differences between countries. In a pure sense, asset prices traded in London can be compared to prices traded in, say, New Zealand, when the trading and data capture occurs at the same time. But researchers need to be mindful when one country's capital market is closed. This raises two related issues: what constitute the same day when comparing asset prices globally, and how to manage the data capture at the end of a trading week.

[32] For example, Bloomberg L.P. provides 200 data points for hourly data – equating to around 13 business days. Additional data are available upon request at a prohibitive cost.

These points can be illustrated by using an example. Assume the United Kingdom (UK) global fixed income (Gilts) market reacts to information and news during the London trading day (*t=0*) in the afternoon when New Zealand's (NZ's) bond market has just opened (*t=0*). Any information or news released should be reflected in the movement of prices in both countries. Now consider the situation when the UK market is open and the NZ one is closed. Any information and news that moves interest rates in the UK is not reflected in New Zealand's local bond prices until the following morning in NZ's time zone when the New Zealand market opens (*t+1*). Practically, NZ bond yields tend to re-set upon the open, with the size and direction of this re-set being strongly influenced by global overnight moves (Lewis and Rosborough, 2013). During the NZ day (*t+1*), local news events influence the direction of local yields. Thus, movements in NZ fixed income yields over the NZ trading day are a combination of the offshore moves plus the reaction to any local releases. In this example, the behaviour of the NZ fixed income market movements lags that of the UK, despite NZ's time zone being around 12 hours ahead. In the case of the U.S., the UK, Japan, and Germany there is evidence of co-movement between interest rates (see Brzoza-Brzezina and Crespo Cuaresma, 2007; Del Negro *et al.*, 2018; and Rachel and Smith, 2015). It is now widely accepted that trends in interest rates are largely determined by common factors (IMF, 2014).

For the purposes of this study, a daily dataset utilising macro-financial data requires the closing price for some data and a snapshot immediately after the opening for others, which, in turn, will require either intraday or lagged daily data for some (but not all) countries. The former is computationally time-consuming and, as previously mentioned, multi-year intraday data series are not readily available.

Lewis and Rosborough (2013) adopt the latter approach by lagging data for some countries in order to create a global interest rate via principal components analysis.

Weekly data observations (taking a snapshot at the end of the working week) do not eliminate the timing of price movements across countries but the impact of this one day on the overall regression results is reduced. A weekly series also avoids the practical difficulties with daily data. A Friday closing price, for example, is Friday, regardless of the country of origin. Even if one country's exchange opens and closes at a different time to another, the first country remains closed (i.e., it is Saturday). While there is the potential for a 'catch up' period on the Monday open (i.e., Monday trading), the effect of the 'catch up' is priced into the asset price well before the following Friday, since the half-life of news priced into asset prices is estimated to be rapid (Evans and Lyons, 2003). Hence, compared to daily data, weekly observations are a 'cleaner' data series.

When choosing the data frequency there is a tradeoff between information and noise. In the short-term, macro-finance data and the price of foreign exchange are influenced by a variety of temporary factors such as: market positioning (Fratzscher, 2008); order flow (Neely, 2011; and Evans and Lyons, 2009); large one-off investments; 'technicals' (for example a psychological level or strength of momentum); and idiosyncratic risk (for example central bank intervention, a speech, an upcoming political event risk and so forth; see Fratzscher, 2008; Chaboud and LeBaron, 2001; Chaboud and Humpage, 2005; and Neely and Dey, 2010).[33] If the factors listed above (order flow etc.) are related to the exchange rate in the short-run, then estimation using weekly data will increase the power of the statistical tests and decrease estimation error compared with monthly or quarterly outturns *ceteris paribus*, assuming information flow is irregular and information shifts both the regressor and the explanatory variables concurrently.[34] By contrast, if microstructure effects are statistically independent from the determination of the exchange rate (that is, the volatility is noise) then a lower data frequency will be able to "look through" this volatility and better predict exchange rate behaviour (Mark, 1995).

Balancing these considerations, this study uses end-of-week data in its analysis, specifically Friday financial market closing prices, as given by Bloomberg L.P.

4.3 Time series length

An econometrician prefers a longer time series to a shorter one. The period considered in this study is from 30 January 1998 to 28 December 2018.

[33] See Cheung and Chinn (1999) for a survey of the literature regarding the type of and rapidity of information dissemination to exchange rates.

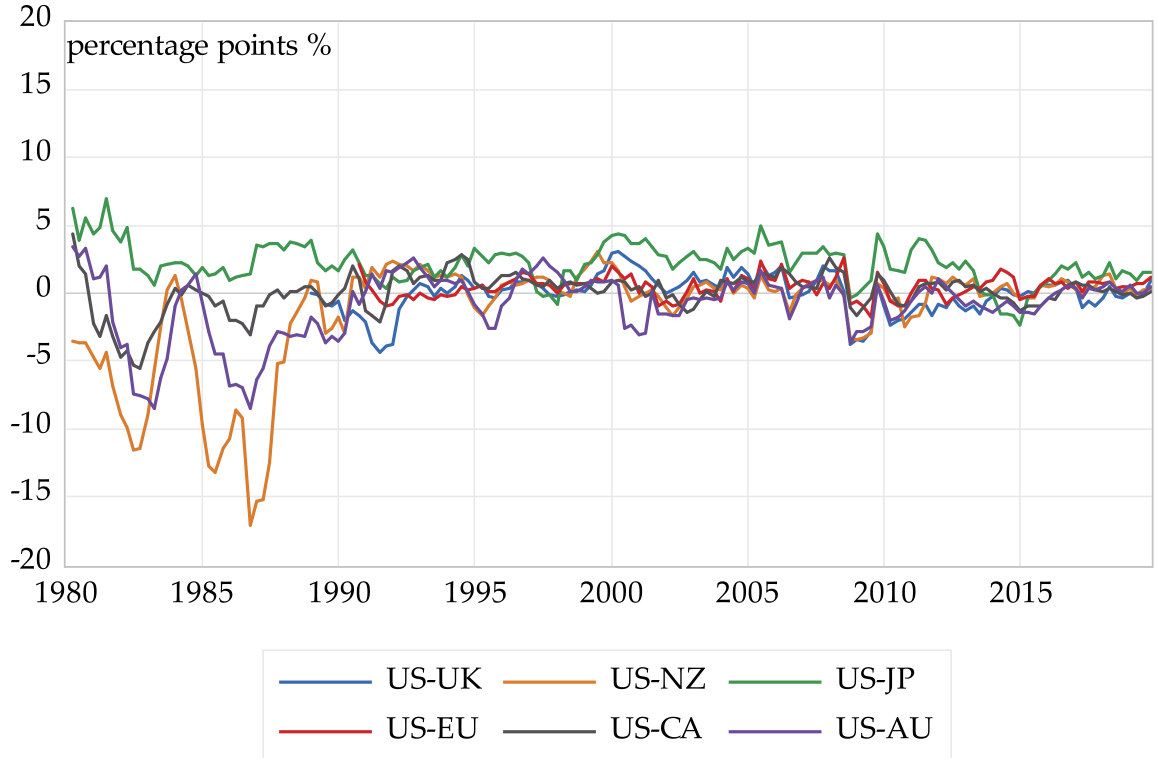
[34] Zhou (1996) notes that that information flow is not constant. He also argues even a daily frequency is too low to capture changes in the information flow over time.

The beginning date trades off several different aspects. Data availability is the key constraint on the start date for most countries.

To ensure relative prices are not a significant driver of divergences in nominal exchange rates, unvarying inflation rates and a stable monetary policy regime is desirable. The study is short-term in its application and it is a reasonable assumption that prices are sticky in the short run (Mussa, 1986); therefore, relative inflation rates have little impact over a weekly period. Devereux (1997) observes that nominal and real exchange rates tend to move closely over time; however, persistent differences in relative inflation rates across countries can incrementally have an impact over a long time series. Vlieghe (2017) observes that the early 1990s were the beginning of the current global monetary regime, confirmed by a cross-country study undertaken by Wood and Reddell (2014). This is aligned with the period of inflation targeting, which New Zealand started in 1990 (RBNZ, 1990) and in most other countries was implemented the early 1990s (Roger, 2010; RBA, n.d.).

Subsequently, from the mid-1990s headline inflation rates were relatively stable, as shown in Figure I and Table III. Table III identifies a notably higher relative inflation rate and standard deviation for the period pre-1990 compared to 1991 onwards, with the exception of the United States-Japan (possibly due to the Bank of Japan's quantitative easing; see Andolfatto and Li, 2014). The time series starting period in 1998 is therefore during a period of stable relative inflation rates, lending some confidence that nominal exchange rates can be considered.

Figure I. Relative inflation rates, 1980-2019



Notes: UK series from 1988Q1 and EU series from 1990Q1. Source: Bloomberg L.P.

Relative inflation rates remain stable over the estimation period, yet an obvious complication is whether there has been a change in the monetary policy regime potentially impacting the relationship between the explanatory variables and the nominal exchange rate. In the post-2009 period, some central banks engaged in unconventional policy stimulus in order to ease financial conditions when the target interest rate was already at very low levels (Potter, 2019). The prevailing view is that during this period central bank inflation targeting mandates have not markedly changed and central bank policies remain credible (Borio *et al.*, 2021; Martinez-Garcia *et al.*, 2021). Hameed and Rose (2018) do not find exchange rates behave differently across 61 currencies between 2010 and 2016 even when interest rates are negative, and Arteta *et al.* (2018) conclude that the global negative interest rate policy has broadly the same impact on global assets as more conventional policy stimuli. The implications of the past decade on exchange rate determination and forecasting are discussed when conducting structural break tests in Section 5.

Table III. Average relative inflation rates, 1980-2019

	1980-1990		1991-2006		2007-2019	
	average percentage point difference (%)	std. dev.	average percentage point difference (%)	std. dev.	average percentage point difference (%)	std. dev.
US – UK	…	…	-.45	1.5	.48	1.3
US – AU	-2.81	3.4	.18	1.4	-.41	1.1
US – NZ	-5.87	5.1	.64	1.1	-.01	1.3
US - EU	…	...	.39	.8	.38	.9
US – CA	-.81	2.2	.65	1.0	.15	.9
US – JP	2.93	1.6	2.33	1.2	1.49	1.6

Notes: UK from 1988Q1 and EU from 1990Q1. Source: Bloomberg L.P.

Country- and global-specific events also affect the estimation period. Floating exchange rate data are utilised in this study, presenting two complications: the Japanese yen and the Euro. The Japanese yen was not fully free-floating until the early 2000s (IMF, 2004); it was considered a dirty float or a managed exchange rate (see BBC News, 1999; and Bank of Japan, 2000).[35] In the case of the Euro, it began

[35] This suggests an *a priori* expectation that the results may be biased and inconsistent due to omitted variable bias (Gujarati, 1995). A dummy variable or a real-time macro-financial proxy for intervention could be considered and left for future research.

trading as one currency unit on 1 January 1999, although a back-cast exchange rate series is available on Bloomberg L.P.[36]

Reducing the length of the estimation period increases the risk of small-sample bias.[37] The use of weekly data over the time period estimated – over a thousand data points – provides a sufficiently large sample (compared to say, monthly or quarterly data).

There is a second small-sample bias that a time-series econometrician must be wary of: the number of cycles in the data. The two business cycles observed in the post-2002 period are colloquially known as The Great Moderation (Bernanke, 2004), followed by the Global Financial Crisis (GFC): the worst crisis since The Great Depression (Draghi, 2019). This business cycle small sample of two is unlikely to impact on an exchange rate regression when estimated with weekly observations. However, if the data are subject to one large cycle or discrete event, this event can dominate the empirical relationship between the dependent and explanatory variables over the entire estimation period, thereby distorting the results and forecasting validity. The GFC could be one of those discrete events; see Contessi *et al.* (2014) for a discussion of the changing asset class correlations during the GFC, and Melvin and Taylor (2009) for a discussion of the impact of the GFC on foreign

[36] Trading the Euro in wholesale foreign exchange markets began three years prior to the physical currency in circulation (EU Commission, n.d.).

[37] Small-sample bias occurs when the number of observations in the sample over which the model is estimated is not large enough to ensure the sample distribution equals that of the population and the expected mean of the sample draw equals the population mean (Stock and Watson, 2011).

exchange markets. The GFC began in credit and liquidity markets in mid-2007 (Draghi, 2008) and spread to currency markets in mid-2008 (Cusbert and Rohling, 2013), evidenced by the rapid appreciation of the U.S. dollar at this time (illustrated using the U.S. Trade Weighted Index, shown in Figure II). The IMF (2009) notes how financial markets remained in a stressed state until mid-2009. For these reasons, the estimation period begins as early as practically possible. The estimation period is 30 January 1998 to 28 December 2018, to allow for a year of out-of-sample analysis.

Figure II. United States trade weighted index

Notes: Weekly observations from 30 January 1998 to 27 December 2019. Source: Bloomberg L.P.

An additional concern surrounding the GFC period is the impact it had on financial market participants' expectations surrounding either the underlying DGP or the distribution of future shocks. This is known as the 'peso problem' (Evans, 1996). Berger *et al.* (2006) observe, with reference to volatility clustering of the EUR/USD, how market participants' sensitivities to information changes over time. Meese (1990) argues that this can "*distort statistical inference*" (p. 128), in particular via persistent serially correlated errors (Mark, 2000). To avoid the empirical complication of the peso problem, this paper estimates both full-period fixed-coefficient regressions and rolling fixed-window regressions (Rossi, 2013; and Cheung *et al.*, 2017, also estimate rolling fixed-length regressions). Relaxing the assumption that the estimation coefficients are constant over time has the potential to account for changes in both the coefficient and changes in its standard deviation.[38]

The out-of-sample observation period is 52 data points – one year of data, while the rolling window moves at one-week observation increments. This choice balances the weekly data with the forecast horizon, as is noted in Rossi (2013).

4.4 Data provider limitations

This study looks at what financial market participants' focus on to determine the value of the exchange rate. For trading data, most financial market participants use Reuters or Bloomberg platforms (or sometimes both, see wallstreetprep.com, 2021). The data provider used in this study, Bloomberg L.P., records closing prices for individual series as given by the underlying exchange. However, these times are not the same across countries. Table IV illustrates the various closing times.

[38] To see how asset price correlations change during period of market stress, see IMF (2015).

Table IV. Closing times, as given by Bloomberg L.P.

Country / Asset class	FX	Government bonds	Interest rate swaps	Stock market
US	1700 EST	1700 EST	1700 EST	1600 EST
UK	1700 EST	1615 BST	1700 EST	1630 BST
AU	1700 EST	1630 AEST	1700 EST	1600 AEST
NZ	1700 EST	1645 NZST	1700 EST	1645 NZST
EU	1700 EST	1730 CET	1700 EST	1730 CET
CA	1700 EST	1630 EST	1700 EST	1600 EST
JP	1700 EST	1515 JST	1700 EST	1500 JST
Exchange	**Closing time**	**Asset price**		
CBOE	1600 EST	VIX		
NY Mercantile	1430 EST	West Texas Oil		
Chicago Mercantile	1645 EST	S&P GSCI		
N/A	1700 EST	ASB NZ Commodity Index		
N/A	1700 EST	Westpac Commodity Index		

Notes: EST is Eastern Standard Time, BST is British Standard Time, NZST is New Zealand Standard Time, AEST is Australian Eastern Standard Time, CET is Central European Time, and JST is Japan Standard Time.

For example, the S&P500 stock index trades on the New York Stock Exchange, which closes at 1600 Eastern Standard Time, whereas the UK Gilts market closes at 1615 British Standard Time, and the closing price of the Standard&Poor's commodity index is recorded at 1645 Eastern Standard Time. The U.S. Treasury bond market trades over-the-counter and is not on a centralized exchange. Its closing price, as given by Bloomberg L.P., is 1700 Eastern Standard Time. This snapshot is also the weekly closing time recorded for foreign exchange by Bloomberg L.P., even though exchange rates trade globally 24 hours during business days.

Daylight saving periods further shift the closing times of different exchanges. Public holidays equate to nine days in a given year, on average, with no more than two consecutive business days closed in most centres (not all these days are a Friday). The exception is Japan, which is affected to a greater degree over New Year's holiday and Golden Week.[39]

Without intraday data, streamlining the closing prices is not possible. With these limitations in mind, the data are applied as given. When there is a public holiday in one region, the previous trading day's closing price (so the final closing price of the week) is applied.

4.5 Data selection

There are six exchange rates estimated: USD/GBP, USD/EUR, USD/AUD, USD/NZD, USD/CAD, and USD/JPY. All exchange rates are quoted in the usual manner: the number of domestic (local) currency units per unit of foreign exchange where the United States is the local country.

---

[39] Europe, the UK, and New Zealand data are affected by two consecutive closing days for Easter, Christmas, and New Year's holiday. Australia's capital markets are typically closed for two days over Easter and Christmas. In the United States, the bond market is closed for two days over Thanksgiving (but not the stock market), while Japan is closed for a week over the New Year period and a week for Golden Week. See bankofcanada.ca, sifma.org, nyse.org, asx.com.au, jpx.co.jp, nzx.com, and clearstream.com.

4.5.1 Nominal interest rates

In the literature, the short-term interest rate is often the three-month government bill or the interbank equivalent (see Meese and Rogoff, 1983, for an early example). However, Aliber (1973) and MacDonald (2007) point out that these bills are subject to sovereign and political risk.[40] Over the sample period, a sufficiently long three-month government bill time series is not always available, for example in New Zealand. The equivalent-duration bank bill swap rate is one short-term instrument that could be considered, in particular because it has sufficient history in New Zealand and is highly liquid (primarily because bank paper is frequently issued for short-term funding). However, this wholesale market interest rate is not universal across all countries – for example, in Japan there is no generic bank bill swap series available. In the case of the U.S., the bank bill equivalent is the three-month certificate of deposit (CD), although it ceased to trade for a period over the GFC, making empirical analysis difficult.[41,42] Importantly for this study, a bank bill yield may not provide an accurate reading of monetary policy due to credit risk (Joyce and Meldrum 2008; Joyce *et al.*, 2008), which at times can be substantial.[43]

---

[40] Specifically, Aliber (1973) is concerned with the risk of exchange rate controls. It is expected that sovereign risk is low in the countries under consideration here.

[41] Both bank bill paper and certificates of deposits are short-term claims against a specific bank.

[42] See FDIC (2017) for details of the market freeze during that period.

[43] For example, in February 2019 the New Zealand generic three-month bank bill (maturity May 2019) yielded 1.885 percent, while the closest equivalent Treasury bill (maturity 14 August 2019) had a yield to maturity 0.249 percent lower, at 1.636 percent.

An alternative short-term interest rate used in some studies is the futures rate, for example the Federal Funds future (Kearns and Manners, 2006).[44] But for New Zealand, the short-term futures contract is a derivative against the underlying 90-day bank bill (because is it a more liquid instrument), which is not an equivalent to the United States (where the derivative trades against the effective 30-day federal funds rate).

The emergence of the overnight index swap (OIS) market is an alternative.[45] It has revolutionized the ability to price the market's expectation for future monetary policy decisions more accurately (Lloyd, 2018), but the OIS maturities across countries differ. In the case of the UK and New Zealand, each OIS maturity matches the date of the respective central bank monetary policy decision. By contrast, in Australia, the OIS swaps are standarised monthly maturity dates. Backing out the comparator rate for each country deviates from this study's focus: applying widely-known market instruments that market participants trade actively. Finally, the history of the OIS market is relatively short (Choy, 2003).

Until the GFC, the three-month London interbank offered rate (LIBOR) was a frequently-used market instrument well-known and traded by market

[44] A futures contract is an agreement to buy or sell a specific asset at a set date for a pre-determined price. They are often standardised and trade on an exchange (Frankel, 1984b).

[45] An OIS is an interest rate swap in which daily payments of a reference overnight rate, such as the effective central bank rate, are exchanged for a fixed rate over the contract period. The OIS rate is the fixed leg of such a swap, and captures the expected path of the rate over the contract term (Choy, 2003).

participants.[46] The ICE exchange published three-month LIBOR rates for most countries but in recent years it emerged that LIBOR rates were being manipulated (see McBride, 2016; and Hou and Skeie, 2014, for background information) and LIBOR is discontinued in some countries (for example, in New Zealand and Australia). In addition, LIBOR is also subject to credit and liquidity premia (Bailey, 2017; Gyntelberg and Wooldridge, 2008).

A notable limitation of using short-term interest rate differentials is the period after 2008, when interest rates in major developed market economies were close to zero. The central banks of half of the countries considered in this paper (the US, the UK, and Europe) began utlising unconventional monetary policy tools such as quantitative easing (QE), while Japan was already undertaking QE (Fawley and Neely, 2013). This has the potential to reduce the contribution of relative short-dated interest rates in determining movements in the exchange rate. Implied short-dated interest rates (negative rates or shadow rates) are not considered for this study, primarily because they are not directly observable and tradeable prices are not readily available to financial market participants.[47]

By contrast, financial market participants often consider two-year interest rate swaps as a relevant proxy for a short-dated interest rate that remains influenced by monetary policy. Swaps are often substituted for bonds due to greater liquidity

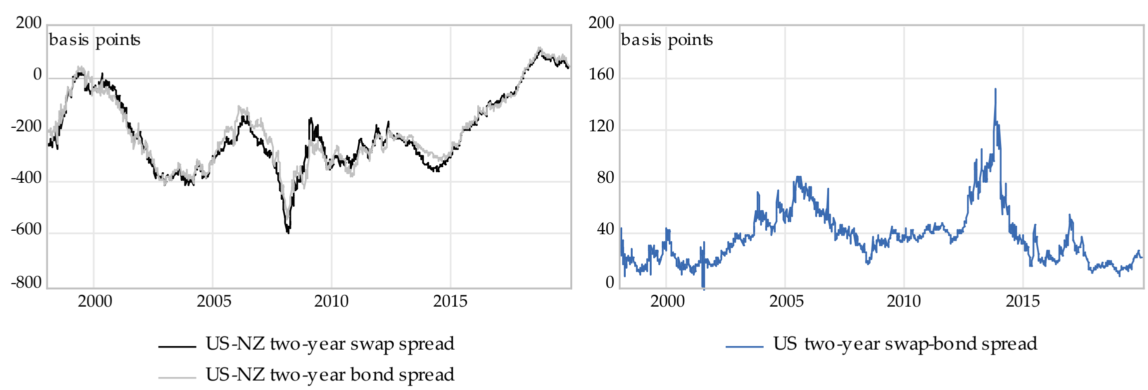
[46] LIBOR is a weighted average unsecured funding rate, where the rate is provided by major interbank players in the London market (Osborne, 2016).

[47] For example, Krippner's (2015) shadow short rate time series are available on a monthly basis.

(BIS, 2016) and more efficient pricing (via a reduction in the illiquidity premium and narrower bid-ask spreads, see Wooldridge, 2001).

For the most part, the counterparty risk premium is very low (Joyce *et al.*, 2008) but this risk premium can change over time, most notably during times of stress. For example, during the GFC, the differential between the swap rate and its equivalent bond widened (see Figure III, right-hand chart). However, because the crisis was global across countries and assets, the cross-country swap spreads (for example, US-NZ) remained close to the levels of the equivalent bond spreads, as shown in Figure III (left-hand chart, difference between the two lines).

Figure III. U.S. swap-bond spread and US-NZ cross-country spreads, 1998-2019



Sources: Bloomberg L.P., Reserve Bank of New Zealand.

The other notable spike in the US swap-bond spread was following the Federal Reserve's surprise announcement in 2013 that it would taper its asset purchases (Fischer, 2017). On this occasion, the cross-country swap spread widened more notably to the US-NZ bond spread before converging again. Despite these differences, the swap spread was chosen because it is highly liquid and is closely watched by market participants as an indicator of relative interest rates. The two-year maturity was chosen as it is market convention as a proxy for monetary policy (Hanson and Stein, 2012; Leombroni *et al.*, 2018).[48]

4.5.2 Stock price indices

The macro-financial proxy for income or wealth is the major share price index for each country. Details of the indices are in Appendix A. In New Zealand, the NZSE Top 40 Index is considered the key market index but this changed once the S&P/NZX50 Index was introduced on 5 January 2001. The two series are spliced together and backdated to 1998.

4.5.3 Commodity price indices

For financial market participants, the price of a country's major commodity is considered a good proxy for the terms of trade, given export prices tend to vary more than import prices (Kohlscheen *et al.*, 2016). Indeed, Zou *et al.* (2017) find

[48] In recent empirical publications, monetary policy is frequently controlled by including relative interest rates and the term structure of the yield curve (slope spread). The slope spread is the differential between the yield-to-maturity of a long-dated maturity bond (e.g. 10-years) and a short-dated maturity bond (e.g. two-years or a three-month Government Treasury bill). The slope between the 10-year bond and the two-year bond is widely used by market participants when discussing the yield curve slope (Kishan, 2018; The Financial Times 2018; Vlieghe, 2018) but it exhibits high multicollinearity with the relative interest rate series and was therefore not included. Accounting for the yield curve slope is recommended as future research – the slope of the yield curve has the benefit of capturing the expected future path of relative interest rates (Krippner, 2010; Bauer and Rudebusch, 2015) and, through this, currency returns (Ang and Chen, 2010).

commodity prices improve exchange rate forecasting for the Australian and New Zealand dollars.

Following other studies, the primary commodity considered for the United States is the West Texas intermediate spot oil price.[49,50] The Westpac Commodity Futures Index is used as the Australian commodity proxy,[51] and the ASB / CBA commodity price index is applied for the New Zealand commodity proxy. Europe, Japan, and the UK's primary export commodity are manufactures, so the Dow Jones / UBS Industrial metals index is applied.[52] In the case of the USD/CAD the oil price is used.

4.5.4 A risk variable

This paper takes the approach utilised by Cheung *et al*. (2017), Munro (2014), and Lustig *et al.* (2011) by applying a financial market variable that market participants

---

[49] Traders are only concerned with a few major relevant commodity prices at a high frequency (such as weekly), whereas in lower frequency studies, terms of trade data are most commonly applied.

[50] Although the United States has reduced its oil dependency over the period of this thesis (Neff and Coleman, 2014), the relationship between oil and the US dollar (proxied by the Dollar Index) has also varied but remains negative on average (see Fratzscher *et al*., 2014). This point is illustrated in Appendix B2, Figure B2.

[51] A spot price equivalent is not available for Australia in a timely manner. The WCFI is a daily series that is frequently watched by market participants, and therefore is included.

[52] See https://ec.europa.eu/eurostat, https://www.stat.go.jp/english/, and http://ons.gov.uk, respectively.

consider akin to a risk premium: the CBOE Volatility Index, colloquially known as the VIX.[53]

4.6 Data characteristics

4.6.1 Data overview

This section examines the basic characteristics of the time series. Both levels and first differences, $z_t - z_{t-1}$, are discussed. The variable definitions and time series charts of both levels and first differences are found in Appendix A.

The exchange rates levels, volatilities, and trends are different across currency pairs and also throughout the time series considered (see Appendix A, Figure A1). For example, the USD/NZD appears to have an upward trend from the early 2000s, other than a brief period during the GFC when the New Zealand dollar (NZD) depreciated before rebounding. By contrast, the USD/GBP appears to have a downward trend, while the direction of the USD/EUR is not visually clear. The lower chart of Figure A1 depicts the one week change of the variable.

With respect to the two-year swap spreads (Appendix A, Figure A2), some relative series look to trend down (US-JP), while others oscillate (US-CA). There are

[53] Note that risk premia differ from risk-taking or risk-aversion, which may be expressed directly in the price of an individual asset. In this paper, the coefficients on each explanatory variable is not constrained, so to allow risk-taking / risk-aversion to express (if relevant) via the coefficient on the asset's spot price at time *t*.

distinctive differences between some relative swap spreads, for example the US-NZ has notably larger daily fluctuations than US-AU, as well as throughout time, as in the US-JP case.

Appendix A, Figure A3 shows the individual stock indices and the difference between the United States and each country. For most relative series, the S&P500 outperforms the foreign country from 2010, except in the case of New Zealand.

Finally, Appendix A, Figure A4 plots the risk premium (VIX), commodity indices, and relative commodity series. The VIX has greater short-term variability, with a notable peak during the GFC. The commodity indices have different time trend paths, with the oil price, and CBA and Westpac commodity price indices trending up over the period of consideration; while the industrial metals index rises into the pre-GFC period and depreciates thereafter. All commodity indices and oil prices fell rapidly during 2008-2009 before subsequently recovering. Seasonality was not assessed given the series are a weekly frequency.

The visual assessment of the one-period (first difference) change time series shows irregularity, with evidence of some large changes around the GFC period. In the case of the exchange rate series (Appendix A, Figure A1, lower group of charts), the USD/EUR and USD/NZD have larger positive and negative weekly changes than the other currency crosses, with the exception of the GFC period. In particular, the USD/AUD has an exceptionally large drop the week of 10 October 2008. Similarly, in Appendix A, Figure A3, the US-AU and US-JP weekly changes in stock market indices show higher one-period changes early in the period under consideration, a reduction in the weekly change around 2005, before widening out again around the GFC. A notable characteristic of the one-week change in the relative stock price series is some series exhibit larger weekly changes on average than others, for example US-JP compared with US-UK.

A more detailed assessment of the distribution of the times series can be found in Table V and Table VI.

Table V describes the data in levels and log level terms. One observation is the lack of similarity in the series, both across countries and across asset types. The skew of the variables changes through asset types (with the exception of relative commodity prices) and is both greater and less than zero, indicating asymmetry in the distribution, and to varying degrees. Appendix B, Figure B1 illustrates the histograms of the exchange rate time series and reports the Jarque-Bera statistic; indicating the exchange rates reject the null hypothesis of a normal distribution.[54] High kurtosis of exchange rates and financial data are well described in the literature (Leon *et al.*, 2005; Clark and Baccar, 2018; Kim and White, 2004; Gkillas *et al.*, 2019). A non-normal distribution of the underlying time series does not preclude normality of the regression error but it is less likely the residual is also normally distributed (Tabachinck and Fidell, 1996). Table VI presents the descriptive statistics of the one-week change of each variable.

[54] The statistics here are a generic output from EViews and are shown for illustrative purposes, although the Shapiro-Wilk test is considered to have a higher power than the Jarque-Bera test (Thadewald and Buening, 2007; Yap and Sim, 2010).

Table V. Descriptive statistics - level/log level: 30 Jan 1998 to 27 Dec 2019

	Mean	Std dev	Min	Max	Skew	Kurtosis
USD/GBP	.46	.12	.19	.74	.01	2.56
USD/EUR	.17	.14	-.18	.47	-.45	2.69
USD/AUD	-.28	.19	-.72	.09	-.11	2.38
USD/NZD	-.43	.20	-.93	-.13	-.80	2.74
USD/CAD	-.21	.15	-.48	.07	.03	1.77
USD/JPY	-4.67	.13	-4.99	-4.33	.81	3.22
US-UK 2yr swap spread	-.47	1.06	-2.93	1.97	-.02	2.66
US-EU 2yr swap spread	.64	1.26	-2.07	3.24	.15	1.90
US-AU 2yr swap spread	-1.68	1.59	-5.36	.95	-.12	1.99
US-NZ 2yr swap spread	-2.12	1.45	-5.98	1.08	.36	2.50
US-CA 2yr swap spread	-.09	.70	-2.11	1.18	-.29	2.34
US-JP 2yr swap spread	2.40	1.86	.09	7.13	.56	2.19
US-UK relative equity indices	.33	.20	.00	.88	.98	2.86
US-EU relative equity indices	-.21	.33	-.36	.87	.45	1.93
US-AU relative equity indices	-.11	.22	-.52	.26	-.11	1.75
US-NZ relative equity indices	-.19	.27	-.61	.52	1.08	3.19
US-CA relative equity indices	-.11	.21	-.52	.31	-.10	2.02
US-JP relative equity indices	.43	.25	-.06	.94	.16	1.76
CBOE Volatility Index	19.8	8.43	9.14	79.13	2.11	10.73
US Crude West Texas Oil*	3.92	.56	2.39	4.98	-.60	2.65
Bloomberg industrial metals index	4.73	.39	3.99	5.59	.03	2.03
ASB New Zealand Commodity Price Index	4.28	.37	3.64	4.83	-.37	1.60
Westpac Commodity Futures Index	5.41	.45	4.54	6.09	-.50	1.81
US-UK relative commodity indices**	-.81	.30	-1.80	-.17	-.80	4.07
US-AU relative commodity indices	-1.49	.20	-2.20	-1.04	-.89	4.06
US-NZ relative commodity indices	-.37	.30	-1.31	.36	-.54	3.15

Notes: * Indicates is also the commodity series for Canada. ** Indicates the relative commodity series are identical for the United Kingdom, Europe, and Japan. Sample size N = 1145. Data to 2 d.p.

Table VI. Descriptive statistics - first differences: 30 Jan 1998 to 27 Dec 2019

	Mean	Std dev	Min	Max	Skew	Kurtosis
ΔUSD/GBP	-.00	.01	-.08	.05	-.49	5.92
ΔUSD/EUR	.00	.01	-.06	.05	-.22	4.09
ΔUSD/AUD	.00	.02	-.19	.07	-1.36	16.27
ΔUSD/NZD	.00	.02	-.11	.06	-.67	5.72
ΔUSD/CAD	.00	.01	-.08	.05	-.76	8.48
ΔUSD/JPY	.00	.02	-.06	.15	1.07	11.71
ΔUS-UK 2yr swap spread	.00	.09	-.54	.46	-.07	6.92
ΔUS-EU 2yr swap spread	.00	.09	-.53	.60	-.18	7.71
ΔUS-AU 2yr swap spread	.00	.13	-.52	1.05	.34	8.72
ΔUS-NZ 2yr swap spread	.00	.13	-.76	.57	-.01	5.67
ΔUS-CA 2yr swap spread	.00	.01	-.08	.05	-.76	8.48
ΔUS-JP 2yr swap spread	-.00	.11	-.52	.63	.23	6.84
ΔUS-UK relative equity indices	.00	.02	-.08	.08	-.05	5.44
ΔUS-EU relative equity indices	.00	.02	-.08	.12	.20	6.23
ΔUS-AU relative equity indices	.00	.02	-.09	.08	.14	4.07
ΔUS-NZ relative equity indices	-.00	.02	-.09	.09	.04	4.58
ΔUS-CA relative equity indices	.00	.02	-.07	.11	.49	7.79
ΔUS-JP relative equity indices	.00	.13	-.10	.13	.13	4.35
ΔCBOE volatility index	-.01	3.08	-19.24	24.8	.58	11.29
ΔUS-UK relative commodity indices*	.01	.05	-.30	.27	-.25	6.62
ΔUS-AU relative commodity indices	.00	.04	-.26	.23	-.22	8.38
ΔUS-NZ relative commodity indices	.00	.05	-.32	.34	-.24	7.43

* The relative commodity series are identical for the United Kingdom, Europe, and Japan. Sample size N = 1144. Data to 2 d.p.

The primary takeaway from Table VI is the series' means and skew are closer to a normal distribution (where the mean and skew are zero). Still, the fourth moment (kurtosis) is consistently larger than that of a normal distribution (Bai and Ng, 2012). Some notable outliers are the ΔVIX and ΔUSD/JPY. This poses a particular problem for Ordinary Least Squares analysis, as the estimation is sensitive to outliers (Stock and Watson, 2011).[55]

4.6.2 Volatility

Table VII illustrates that, similar to earlier studies (see Meese, 1990; MacDonald, 2007; and Della Corte *et al.*, 2009, amongst others), exchange rates display higher volatility than macroeconomic data. This is often cited as a reason why exchange rate models are unsuccessful at forecasting (Flood and Rose, 1999).

Table VII updates and extends Meese's (1990, p. 119) Table 1 illustrating the variability range between exchange rates and fundamentals frequently used in exchange rate valuations. The table updates exchange rates, real gross domestic product (GDP), and M1 data. Relative terms of trade are included, as is nominal GDP (to compare to the nominal exchange rates), and the macro-financial proxies applied in this study are compared. Industrial production was not included due to a lack of data availability.

The standard deviation shows, as noted by the literature, the greater volatility across relative exchange rates and relative interest rates compared with relative GDP. Importantly, all macro-financial data have greater variability than the

---

[55] Appendix B1 Table B1 considers the possibility that the excess kurtosis (kurtosis – 3) is a result of the exceptional volatility in all asset markets during the GFC (Bastianin, 2020). The results indicate that excluding the GFC period from the analysis reduces the kurtosis, but inconsistently. It is not clear, therefore, if the regression results would be improved by this adjustment.

macroeconomic data displayed, with the exception of relative money supply, which is comparable (in some instances), to the relative exchange rate standard deviations.

Table VII. Volatility of selected time series: 1998Q1 – 2019Q4

Macro-financial	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Relative exchange rates							
Mean	.46	.17	-.28	-.43	-.21	-4.67	
Standard deviation	.12	.14	.19	.20	.15	.14	
Relative interest rates							
Mean	-.58	.61	-1.68	-2.11	-.10	2.37	
Standard deviation	1.43	1.27	1.60	1.46	.71	1.85	
Relative stock indices							
Mean	.29	-.18	-.11	-.18	-.10	.37	
Standard deviation	.20	.28	.23	.28	.22	.26	
Relative commodity prices							
Mean	-1.86	-1.86	-2.57	-.18	3.92	-1.86	
Standard deviation	.39	.39	.45	.38	.55	.39	
Risk							
Mean							20.6
Standard deviation							8.42
Macroeconomic	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Relative real GDP							
Mean	.012	.017	.002	.003	.008	.025	
Standard deviation	.02	.01	.02	.02	.02	.02	
Relative nominal GDP							
Mean	.012	.004	.002	.010	.051	.022	
Standard deviation	.02	.02	.02	.03	.02	.02	
Relative terms of trade							
Mean	.11	-.01	.10	.19	.11	-.13	
Standard deviation	.05	.02	.06	.13	.06	.15	
Relative money supply							
Mean	.02	.24	.46	.22	.16	.22	
Standard deviation	.15	.17	.17	.15	.09	.16	

Notes: All variables in log levels, except interest rates and the risk premium. Data are quarterly observations, hence some differences between this table and Table V. All data sources from Bloomberg L.P., except EU and Japan terms of trade indices, from OECD, found at https://data.oecd.org/trade/terms-of-trade.htm. Japan M1 data from 2003Q3.

Meese (1990) claims exchange rate models fail due to the different variability between the macroeconomics variables (bottom half of Table VII) compared to the variability of the exchange rate. Therefore, the utilisation of macro-financial variables (which display larger standard deviations, shown in the top half of Table VII) may help to improve upon the models' poor forecasting performances. This study implicitly tests this hypothesis.

4.6.3 Pairwise correlation

Next, the pairwise correlations are discussed. Assessing cross-correlations provides guidance on the degree of pairwise multicollinearity of the right-hand-side variables.[56] If expectations or other events and news impact concurrently across the explanatory variables, the variables may have a high contemporaneous correlation. If multicollinearity exists, the standard error will increase on the right-hand variable, reducing the *t*-statistics and statistical significance (Allen, 1997). The Pearson correlations are reported in Table VIII, with correlations greater than ±.70 in bold text.

In two situations, the bivariate correlations between the United States and each country's two-year swap spread and the corresponding relative equity indices, is greater than .70 in absolute terms. In all cases, the correlation falls when the

[56] Multicollinearity can also occur between combinations of more than two variables.

correlation of weekly changes is assessed. There are no other cases of high collinearity between the variables.

Table VIII. Descriptive statistics - correlation level/log level and first difference: 30 Jan 1998 to 27 Dec 2019

		Swap	Equity	Commodity	Risk	
US – UK	Swap		.60	.05	-.32	*Levels / Log levels*
	Equity	-.06		.34	-.44	
	Commodity	.01	-.03		-.15	
	Risk	-.04	-.18	-.02		
			First differences			
US-EU	Swap		.28	-.35	-.35	*Levels / Log levels*
	Equity	-.02		-.45	-.38	
	Commodity	-.06	.01		-.15	
	Risk	-.06	.07	-.02		
			First differences			
US-AU	Swap		**.72**	-.40	-.22	*Levels / Log levels*
	Equity	-.02		-.47	-.31	
	Commodity	-.02	.05		.10	
	Risk	.08	-.41	-.13		
			First differences			
US-NZ	Swap		.07	-.46	-.14	*Levels / Log levels*
	Equity	-.05		-.29	.24	
	Commodity	.05	.12		-.08	
	Risk	-.03	-.59	-.16		
			First differences			
US-CA	Swap		.19	-.24	-.07	*Levels / Log levels*
	Equity	-.07		-.61	-.19	
	Commodity	-.06	-.17		-.26	
	Risk	.06	-.29	-.13		
			First differences			
US-JP	Swap		**-.71**	-.64	.04	*Levels / Log levels*
	Equity	.01		.53	-.24	
	Commodity	-.01	.02		-.14	
	Risk	-.16	-.27	-.02		
			First differences			

Notes: For levels and log levels, the sample size is N = 1145. For the first period change, the sample size is N = 1144. Correlations greater than ±0.70 are in bold text.

4.6.4 Stationarity

To perform regressions and apply other econometric techniques, variables should be covariance stationary. A stochastic series is covariance stationary if it has a constant mean, constant and finite variance, and a covariance structure that is invariant with respect to time (Mills, 1990). A non-stationary process, by contrast, is a series that has a tendency to move away from its initial state over time (McDermott, 1990).

Macro-financial time series frequently display a varying mean over time, which in turn can be trend stationary (if the series does not have a constant mean) or the series may be non-stationary and has a unit root (Kennedy, 2003). Because the distribution of a non-stationary process is non-normal (Kremers *et al.*, 1992), conventional *t*-statistics will tend to report that a series is stationary, when it really is not (Nelson and Plosser, 1982). To account for the non-normal sample distribution, two frequently-used approaches to test of a unit root are the Augmented Dickey-Fuller test (ADF), which compares standard *t*-statistics with a non-stationary distribution under the null hypothesis (Dickey and Fuller, 1979); and the Phillips-Perron test (PP), a non-parametric test that adjusts for serial correlation and heteroskedasticity (Phillips and Perron, 1988; Leybourne and Newbold, 1999). However, these are also not infallible. Macro-financial data tend to cycle over time, which can affect the properties of the test results (Del Barrio Castro *et al.*, 2015). DeJong *et al.* (1992) show the existence of autocorrelation can lead to low power when a Phillips-Perron unit root test is applied and Del Barrio Castro *et al.* (2015) point out that Phillips-Perron unit roots tests perform poorly when using time series that exhibit cyclical behaviour. Schwert (1989) concludes ADF has smaller size distortions than the PP test; thus, the ADF test is applied here.[57,58]

This paper examines each data series individually and concludes all time series are not integrated of order two;[59] the exchange rates are I(1); while the right-hand-side variables are integrated of order one or zero. The test results suggest the log levels of the exchange rates and relative equity prices are non-stationary. For the level of the swap spreads, the results predominately suggest the series are integrated of order one. The exception is the US-CA relative interest rate time series that does not have a unit root at the 10% significance level. For relative commodity prices, the null hypothesis of a unit root is rejected but cannot be rejected at the 5% significance level. In all cases, the risk variable does not exhibit a unit root process.

Regarding these series in first differences, all tests suggest that the first differences of all series are stationary. Details of the tests can be found in Appendix B3. The results in levels/log level results are in Appendix B3, Table B2, while the first differenced results are in Appendix B3, Table B3.

Meese and Singleton (1982) note there is little agreement whether exchange rates indeed exhibit a unit root, primarily because macroeconomic and macro-financial

---

[57] Elliot *et al.* (1996) propose an efficient unit root test that exhibits maximum power.

[58] Both tests were considered as a robustness check for stationarity.

[59] The I(2) results are not reported to save space. The Phillips-Perron results give qualitatively similar conclusions but are not reported to save space.

time series are often near a unit root (Engel and West, 2004). The common technique to difference the time series is debated too; for example, Moosa and Bhatti (1997) show how differencing long-run relationships can equate to a loss of information and Hendry (1995) comments how a differenced series implies agents ignore long-run equilibrium levels relationships.[60]

Granger (1981) concludes that if two or more time series are integrated of order I(1) and the residual of the relationship is integrated of order zero, then the dependent and right-hand-side variables are cointegrated. Alternatively characterised, if there is a true long-run equilibrium relationship between the variables, the residual will be stationary.

With these considerations in mind, researchers frequently approach non-stationarity in a variety of ways. Some studies do not test for non-stationarity but instead make assumptions of the DGP based on economic theory, or ignore stationary tests altogether, believing that stationary or non-stationary processes are indistinguishable (Neely and Sarno, 2002). Others proceed to test whether a series is non-stationary (often against the alternative of trend stationary) and apply a Monte Carlo simulation to build the appropriate critical values, as applied in Taylor *et al.* (2001). Some papers test only the model's regression errors (for example, Chinn and Meese, 1995).[61] A notable feature of the time series, as stipulated in

---

[60] Assuming the relationship is cointegrated.

[61] Clemente *et al.* (2018) provide a good summary of the varying approaches with reference to real interest rates and the Fisher effect.

Section 4.6.1, is the distinctive change in the series – both in levels/log levels and in one-week changes, around the time of the GFC. Time series with structural changes and unit roots share similar features that make it difficult to discriminate between a stationary and non-stationary process (Perron, 1989). In the presences of structural breaks, a unit root test is biased to fail to reject a unit root (Type II error). As a check, Appendix B3, Table B4 and Table B5 show the results from breakpoint unit root tests as per Perron (1989) and Perron (1997) and structural breaks of the models are discussed in Section 5.

The results of these tests clearly show that all linear and log linear series have a break point and a unit root, with the exception of the risk variable; and the null hypothesis can be rejected in the first difference series. These results suggest the exchange rate model should be tested for cointegration and, if cointegration exists, then tested for structural breaks. The *a priori* expectation that a breakpoint might show around 2007 or 2008 is not realised. Indeed, the breakpoint date varies across data in levels and log/level terms. In first differences, many series pointed to a break in 1998.

The next section presents the results from the fixed-coefficient and rolling regressions, it explores evidence of structural breaks over the whole-period sample in more detail, and discusses forecasting accuracy of the macro-financial models.

Section 5. Empirical Analysis and Results

This section reports the results from the full-sample fixed-coefficient and fixed-window rolling sample exchange rate models, for both the concurrent formulation and forecasting formulation, both with and without a lagged dependent variable. The full-sample regression is tested for a cointegrating relationship and an error-correction model is estimated. The models including the lagged dependent variable are estimated in first differences. The appropriate models are tested for a structural break with unknown breakpoint. The out-of-sample forecasting results of all sets of regressions are discussed.

5.1 Level/Log level: Full-sample fixed-coefficient estimation

Table IX reports the results of estimations of the multivariate models specified by Equations (22) and (23) – the regressions estimated at time *t* in contemporaneous format and estimated in a forecasting framework.[62] The exchange rates are USD/GBP, USD/EUR, USD/AUD, USD/CAD, USD/NZD, and USD/JPY and the models are estimated over the period 30 January 1998 to 28 December 2018. The

---

[62] The results and forecasting success of Equations (22a) and (23a) – contemporaneous and forecasting with a lagged dependent variable – are discussed in Section 5.2.

standard errors are adjusted to account for heteroskedasticity and autocorrelation by applying the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator (Newey and West, 1987; Andrews, 1991), to derive inference from OLS.[63,64] Heteroskedasticity and autocorrelation renders OLS estimators inefficient (Asteriou and Hall, 2007; Kennedy, 2003) and OLS standard errors are biased (Imbens and Kolesar, 2012; Cochrane and Orcutt, 1949).

5.1.1 Results

The results of the log-level regressions, shown in Table IX, are similar to previous studies.[65]

The regressions show that UIP does not hold: $\delta_3 < 0$ in the case of USD/GBP and USD/EUR. A negative coefficient on relative interest rates suggests the carry trade is a better representation than UIP, as found in previous studies, for example, Verdelhan (2013). With respect to other coefficients, some have the expected sign but there is a lack of consistency across countries and regressors. For example, the sign on relative equity prices – the proxy for relative economic activity – is, at times,

---

[63] An OLS estimation plus HAC adjustment was chosen instead of Generalised Least Squares (GLS) as the latter requires strict exogeneity of regressors (Stock and Watson, 2011).

[64] The HAC adjustment involves pre-whitening lags, chosen using the AIC criterion, undertaking the Newey-West HAC covariance method, with a quadratic-spectral kernel (k), and applying an automatic truncation parameter or user bandwidth (L), as given by Andrews (1991).

[65] Restrictions are not imposed on the coefficients and data determine the size and sign. Previous work (see Section 2) suggests that the size and sign of the coefficients can vary widely.

negative (as theory predicts). That is, as the U.S. equity price improves relative to the equivalent in the foreign country, one foreign currency unit is worth fewer U.S. dollars; hence the U.S. dollar has appreciated. The exceptions are in the case of the USD/EUR and USD/JPY regressions in Equations (22) and (23), shown in Table IX, although these estimates are not significantly different from zero. The sample size is 1092 observations over 20 years, which is a reasonable length to expect the estimates are precise and to have confidence in the coefficients.

In the case of USD/CAD, the commodity proxy is the natural log of the oil price, which is in U.S. dollar terms. The positive relationship between USD/CAD and oil prices could be due to the local currency pricing effect (Casas *et al.*, 2016) or because Canada is a net oil exporter (Government of Canada, 2022). A depreciation in the U.S. dollar in response to an increase in oil prices is well documented (Lizardo and Mollick, 2010; Fratzscher *et al.*, 2014; and Beckmann *et al.*, 2017, amongst others).

The coefficient on the proxy for the risk premium is significant and negative in the majority of estimations, suggesting that, as uncertainty increases the U.S. dollar strengthens as a safe-haven asset, which is a widely known phenomenon (Lilley *et al*., 2019; Maggiori, 2013; and Ranaldo and Söderlind, 2010, amongst others). The one currency pair that moves in the opposite direction to the U.S. dollar in times of rising volatility is the Japanese yen. This also aligns with research demonstrating that the yen is a safe-haven asset compared to the U.S. dollar (Botman *et al.*, 2013; and Lee, 2017). In the case of the USD/EUR regressions, the risk premium proxy is not significant, which is unexpected.

Table IX. Full-sample fixed-coefficient estimation: Estimation period 30 Jan 1998 to 28 Dec 2018

		USD/GBP	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Equation (22)		$s_t = \delta_0 + \delta_2(y_{p,t} - y^*_{p,t}) + \delta_3(i_t - i^*_t) + \delta_5(c_{p,t} - c^*_{p,t}) + \delta_6 rp_{p,t} + \varepsilon_t$					
Estimated coefficients							
Constant	δ_0	.594	.242	-.232	-.386	-.898	-4.676
		(.072) ***	(.115) **	(.253)	(.082) ***	(.154) ***	(.123) ***
Equity	δ_2	-2.231	.122	-.088	-.465	-.236	.167
		(.110) **	(.157)	(.314)	(.125) ***	(.049) ***	(.233)
Interest rates	δ_3	-.056	-.051	-.070	-.020	-.013	-.015
		(.019) ***	(.024) **	(.056)	(.019)	(-.019)	(.032)
Commodity	δ_5	-.010	.022	.004	.094	.176	.114
		(.052)	(.084)	(.145)	(.108)	(.0385) ***	(.077)
Risk	δ_6	-.005	-.002	-.009	-.007	-.001	.003
		(.002) **	(.002)	(.004) **	(.002) ***	(.0008) **	(.002) *
Adjusted R²		.459	.252	.478	.689	.887	.430
Breusch-Godfrey Chi		.000	.000	.000	.000	.000	.000
Equation (23)		$s_{t+1} = \delta_0 + \delta_2(y_{p,t} - y^*_{p,t}) + \delta_3(i_t - i^*_t) + \delta_5(c_{p,t} - c^*_{p,t}) + \delta_6 rp_{p,t} + \varepsilon_{t+1}$					
Estimated coefficients							
Constant	δ_0	.060	.243	-.243	-.388	-.886	-4.67
		(.067) ***	(.120) **	(.225)	(.084) ***	(.120) ***	(.120) ***
Equity	δ_2	-.238	.120	-.097	-.467	-.243	.166
		(.103) ***	(.160)	(.319)	(.122) ***	(.050) ***	(.221)
Interest rates	δ_3	-.0564	-.051	-.070	-.020	-.014	-.015
		(.002) ***	(.025) **	(.059)	(.019)	(.018)	(.030)
Commodity	δ_5	-.010	.021	-.0002	.092	.173	.112
		(.052)	(.087)	(.141)	(.102)	(.038) ***	(.078)
Risk	δ_6	-.0048	-.002	-.009	-.007	-.002	.003
		(.002) ***	(.002)	(.004) **	(.002) ***	(.0007) **	(.002) *
Adjusted R²		.465	.256	.478	.693	.864	.426
Breusch-Godfrey Chi		.000	.000	.000	.000	.000	.000

Notes: Standard errors in parentheses. * *t*-statistic is significant at 10%, ** *t*-statistic is significant at 5%, *** *t*-statistic is significant at 1%. Sample size of N = 1092. The Newey-West HAC adjustment was applied using the quadratic-spectral kernel with the bandwidth automatically selected as per Andrews (1991), given by EViews. HAC also pre-whitens using the automatic lag selection based on AIC. The Breusch-Godfrey Chi is the *p*-value for the Chi-square distributed test statistic with the number of lags *p*=2. The number of lags (*p*) was determined by visual assessment of the correlogram of regression residuals up to 36 lags.

An interesting observation is how similar the regressions appear visually, either using current regressors or the forecasting estimation Equation (23), as shown in Figure IV and Figure V. The results in Section 5.1.2 show there are differences when forecasting and the Appendix charts these differences. An alternative specification in Section 5.5 illustrates large differences between the two estimation approaches when forecasting the exchange rate in first difference terms.

The adjusted coefficient of determination for Equations (22) and (23) in Table IX, with the exception of the USD/CAD relationship, demonstrates how poorly the variation of the right-hand side variables explain the variation in the exchange rate. There is also notable positive autocorrelation, as shown by the Breusch-Godfrey serial correlation test statistics and the noticeable positive and negative runs of residuals in Figures IV and V.[66]

Hendry (1995, p. 60) discusses the disadvantages of the model structure estimated in Equation (22) and Equation (23) and dismisses their use "*for policy, for predictions, or even for testing theories*". Notwithstanding this salient point, the forecasting results are reported here, primarily to follow the literature and to compare the forecasting ability of the models. However, it should be stressed that the results do not

---

[66] Under the null hypothesis of no serial correlation, the Breusch-Godfrey test (calculated as the number of observations x R^2 from a regression of the OLS residuals on the explanatory variables and lags of the residuals) is a Chi-square distribution with the degrees of freedom equal to the order of autocorrelations considered (Breusch, 1978; Godfrey, 1978).

necessarily suggest the models are a good characterisation of the true DGP nor should the results be relied upon for future inference.

Figure IV. Equation (22) Full-sample fixed-coefficient estimation output: Estimation period 30 Jan 1998 to 28 Dec 2018

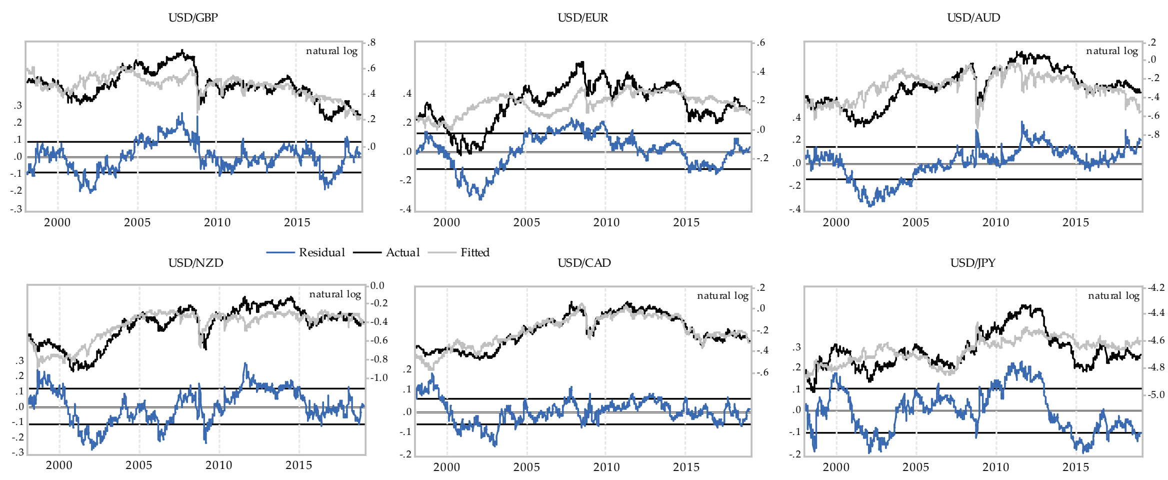
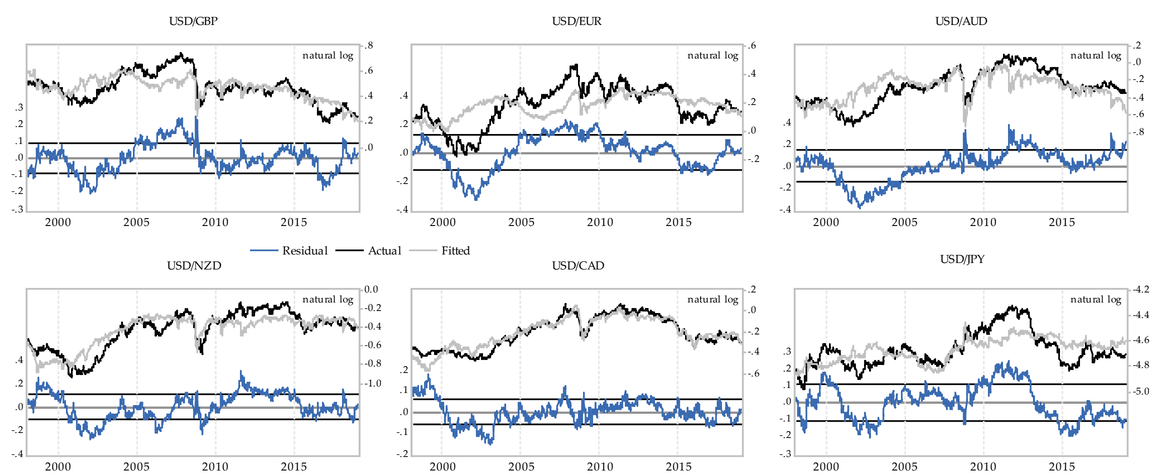


Figure V. Equation (23) Full-sample fixed-coefficient estimation output: Estimation period 30 Jan 1998 to 28 Dec 2018



5.1.2 Forecasting performance: Full-sample fixed-coefficient estimation and rolling fixed-window estimation

The performance of the forecasts for all exchange rates estimated in Equations (22) and (23) is reported in Table X. The sample size of the forecast period is 52 weeks and two periods were selected: 5 January 2018 to 28 December 2018 (in-sample) and 4 January 2019 to 27 December 2019 (out-of-sample). The forecast criteria are based on the average one-step ahead (one-week) exchange rate prediction for each regression 52 weeks out-of-sample. Three criteria are selected to compare with a random walk without drift.[67]

In the literature, the forecasting accuracy of the whole-period estimation is typically based on *ex-post* values of the regressors (see Section 3.1.1). This in-sample forecasting provides the model with an advantage. To compare, and to align with the focus on applicability for financial market participants, a second forecast period is evaluated, 4 January 2019 to 27 December 2019, using *ex-ante* time series only.

Examining the results for both sets of forecast periods, the root mean square errors of the forecast prediction compared with the random walk are not favourable for the estimated models. In a similar vein, the predicted values do not improve upon the random walk under the Theil's U criterion in all cases.

---

[67] Appendix C, Figure C1 and Figure C2 illustrate the results from the rolling fixed-window estimations for both equations. Further discussion of the rolling fixed-window regressions when the equation includes a lagged dependent variable can be found in Section 5.2.

Table X. Forecasting comparison: Equations (22) and (23) levels relationship

Exchange rate / Model	Forecast period 5 Jan 18 – 28 Dec 18			Forecast period 4 Jan 19 – 27 Dec 19		
	RMSE	Theil's U	DΔA %	RMSE	Theil's U	DΔA %
USD/GBP						
Random walk	.010	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22)	.044	4.30	61	.047	4.13	41
Rolling fixed-window, Eqn (22)	.047	5.51	61	.037	2.93	55
Full-sample fixed-coefficient, Eqn (23)	.046	4.45	47	.045	3.93	49
Rolling fixed-window, Eqn (23)	.042	4.98	47	.035	2.75	65
USD/EUR						
Random walk	.008	1.00		.007	1.00	
Full-sample fixed-coefficient, Eqn (22)	.037	3.80	43	.008	10.8	41
Rolling fixed-window, Eqn (22)	.049	7.30	49	.039	3.09	52
Full-sample fixed-coefficient, Eqn (23)	.038	3.84	53	.068	10.2	43
Rolling fixed-window, Eqn (23)	.044	6.53	51	.025	3.20	57
USD/AUD						
Random walk	.011	1.00		.009	1.00	
Full-sample fixed-coefficient, Eqn (22)	.153	14.5	48	.084	8.87	61
Rolling fixed-window, Eqn (22)	.030	2.47	75	.020	2.07	65
Full-sample fixed-coefficient, Eqn (23)	.154	14.3	37	.094	9.74	57
Rolling fixed-window, Eqn (23)	.029	2.34	57	.019	1.94	47
USD/NZD						
Random walk	.012	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22)	.063	5.26	56	.123	9.93	59
Rolling fixed-window, Eqn (22)	.032	2.54	57	.019	1.52	60
Full-sample fixed-coefficient, Eqn (23)	.065	5.34	35	.094	9.86	61
Rolling fixed-window, Eqn (23)	.028	2.24	76	.019	1.50	61
USD/CAD						
Random walk	.009	1.00		.007	1.00	
Full-sample fixed-coefficient, Eqn (22)	.035	3.83	59	.028	4.17	34
Rolling fixed-window, Eqn (22)	.014	1.57	80	.023	3.20	63
Full-sample fixed-coefficient, Eqn (23)	.033	3.61	41	.027	3.71	53
Rolling fixed-window, Eqn (23)	.015	1.58	55	.02	2.73	53
USD/JPY						
Random walk	.010	1.00		.008	1.00	
Full-sample fixed-coefficient, Eqn (22)	.088	9.12	47	.095	13.1	50
Rolling fixed-window, Eqn (22)	.034	3.54	73	.065	8.62	77
Full-sample fixed-coefficient, Eqn (23)	.090	10.1	58	.094	16.7	52
Rolling fixed-window, Eqn (23)	.030	3.10	39	.010	1.31	55

Notes: Forecast sample size N = 52. Forecast sample on one-week-ahead results. DΔA is the directional change accuracy, shown as a percentage. The predicted change in the estimated exchange rate is correct 50% of the time when DΔA is 50. See Section 3.4.3 for details.

The directional change accuracy criterion shows little consistency through models or across exchange rates. The directional change accuracy percentage is not more likely to be over 50 percent than below it. The statistic also does not repeatedly worsen for the full-sample fixed-coefficient exchange rate estimates when moving from the 2018 forecast period to the 2019 forecast period – it could reasonably be expected that the *ex-ante* forecasting outcomes (for 2019) may underperform the *ex-post* forecast period in 2018 but this is not consistently the case. For example, the forecast results for USD/AUD and USD/GBP improve from the 2018 forecast sample to the 2019 forecast period. The results also seem to improve with the rolling fixed-window regressions compared with the full-sample fixed-coefficient estimation, for both equations, for the USD/AUD, USD/CAD, USD/NZD, and USD/JPY regressions. The results are mixed for the USD/GBP and USD/EUR across these criteria; for example, in the *ex-ante* forecast period a rolling regression improves the forecasting performance but this performance is still poor (for example, the directional change accuracy figures are equally as likely to be above 50 percent as below it).

In the context of this study's focus, financial market participants cannot depend on these specifications of exchange rate models to be profitable. More research is needed to verify the robustness of these results and to compare to previous studies, for example changing the data frequency to quarterly to be directly comparable to other studies; changing time periods, and to test if the results are sensitive to the time period examined.

5.2 Level/Log level: Full-sample fixed-coefficient estimation with lagged dependent variable

Table XI reports the results of estimations of the multivariate models specified by Equations (22a) – the regressions including a lagged dependent variable estimated at time *t* (contemporaneous format) and Equation (23a) – estimated in a forecasting framework. The exchange rates are USD/GBP, USD/EUR, USD/AUD, USD/CAD, USD/NZD, and USD/JPY and the models are estimated over the period 30 January 1998 to 28 December 2018. The regressions are estimated including the lagged dependent variable to account for serial correlation, as is typically applied in the literature. The estimation results are graphed in Figure VI and Figure VII and the rolling fixed-window results in Appendix C1, Figure C4 and Figure C5.

5.2.1 Results

The inclusion of the lagged dependent variable in Equations (22a) and (23a) improves Equations (22) and (23). In many regressions, there is no longer evidence of serial correlation (the USD/GBP regression is one exception). The regression equations fit reasonably well, and the goodness of fit (adjusted-R^2) of the equations in Table XI suggests the vast majority of the variation in the exchange rate is explained by the variation in the right-hand side variables. However, the only consistently significant parameter estimate is the coefficient on the lagged exchange rate. In the extreme case of Equation (23a) – the USD/JPY – only the constant and the lagged dependent variables are statistically significant at the 5% level or better.[68] Note also some parameter signs change from negative to positive once the lagged dependent variable is included, for example in the case of the relative equity regressors or relative commodity price indices. This could suggest there is some combination of regressors that jointly explain the exchange rate, either via collinearity (although recall Section 4.6.3, Table VIII did not show notable multicollinearity) or that the variables are related in some non-linear way. More generally, the changing signs suggest the potential of time-varying parameter estimates or model misspecification.

Time-varying coefficients driving exchange rate movements, such as changing fads or themes, are demonstrated here via a rolling fixed-window estimation. If a relationship is stable over time, the estimated coefficients will also be relatively stable. Changes to the size of the coefficients in an augmented sticky-price asset model, by contrast, will show changes in the estimated coefficients as the rolling window moves through the sample period.

[68] A common next step, when a number of parameter estimates are not significantly different from zero, is to test if they are jointly significant. A Wald test is valid when the regression is cointegrated. Cointegration is discussed in Section 5.3.

Table XI. Full-sample fixed-coefficient estimation included lagged dependent: Estimation period 30 Jan 1998 to 28 Dec 2018

		USD/GBP	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Equation (22a)		$s_t = \delta_0 + \delta_2(y_{p,t} - y^*_{p,t}) + \delta_3(i_t - i^*_t) + \delta_5(c_{p,t} - c^*_{p,t}) + \delta_6 rp_{p,t} + \delta_7 s_{t-1} + \varepsilon_t$					
Estimated coefficients							
Constant	δ_0	.016	.003	-.015	-.007	-.009	-.07
		(.005) ***	(.003)	(.005) ***	(.003) **	(.010)	(.021) ***
Equity	δ_2	-.008	.0010	-.0078	-.010	-.018	.002
		(.004) **	(.002)	(.003) **	(.004) ***	(.005) ***	(.003)
Interest rates	δ_3	-.002	-.002	-.002	-.002	-.002	-.0005
		(.0005) ***	(.0004) ***	(.0006) ***	(.0004) ***	(.0006) ***	(.0004)
Commodity	δ_5	-.001	-.003	-.009	-.004	.002	.0005
		(.001)	(0.002) *	(.003) ***	(.002)	(.002)	(.002)
Risk	δ_6	-.0003	-.0002	-.0005	-.0004	-.0004	.0003
		(.0008) ***	(.00008) *	(.00001) ***	(.0001) ***	(.0001) ***	(.0008) ***
Lagged dependent	δ_7	.979	.991	.979	.975	.966	.986
		(.006) ***	(.004) ***	(.004) ***	(.005) ***	(.010) ***	(.004) ***
Adjusted R^2		.989	.991	.993	.992	.994	0988
Breusch-Godfrey Chi		.022	.984	.320	.855	.533	.067
Equation (23a)		$s_{t+1} = \delta_0 + \delta_2(y_{p,t} - y^*_{p,t}) + \delta_3(i_t - i^*_t) + \delta_5(c_{p,t} - c^*_{p,t}) + \delta_6 rp_{p,t} + \delta_7 s_t + \varepsilon_{t+1}$					
Estimated coefficients							
Constant	δ_0	.014	.003	-.014	-.009	-.003	-.045
		(.003) ***	(.002)	(.005) ***	(.003) ***	(.007) ***	(.022) **
Equity	δ_2	-.010	-.0003	-.009	-.011	-.012	-.002
		(.003) ***	(.002)	(.003) ***	(.004) ***	(.003) ***	(.003)
Interest rates	δ_3	-.0009	-.0009	-.001	-.0007	-.0005	-.0005
		(.0005) *	(.0004) *	(.0005)	(.0004) *	(.0005)	(.0004)
Commodity	δ_5	-.0004	-.001	-.007	.00001	.0006	-.0005
		(.0011)	(.002)	(.004) *	(.002)	(.0014)	(.002)
Risk	δ_6	-.0002	-.0001	-.0001	-.0001	-.0001	.0008
		(.00006) ***	(.0008)	(.0001)	(.0001)	(.00008)	(.0007)
Lagged dependent	δ_7	.014	.993	.991	.981	.982	.990
		(.003) ***	(.003) ***	(.003) ***	(.005) ***	(.006) ***	(.004) ***
Adjusted R^2		.989	.991	.992	.992	.994	.987
Breusch-Godfrey Chi		.012	.991	.320	.730	.123	.037

Notes: See notes to Table IX. Sample size = 1091.

Figure VI. Equation (22a) Full-period fixed-coefficient estimation output: Estimation period 30 Jan 1998 to 28 Dec 2018

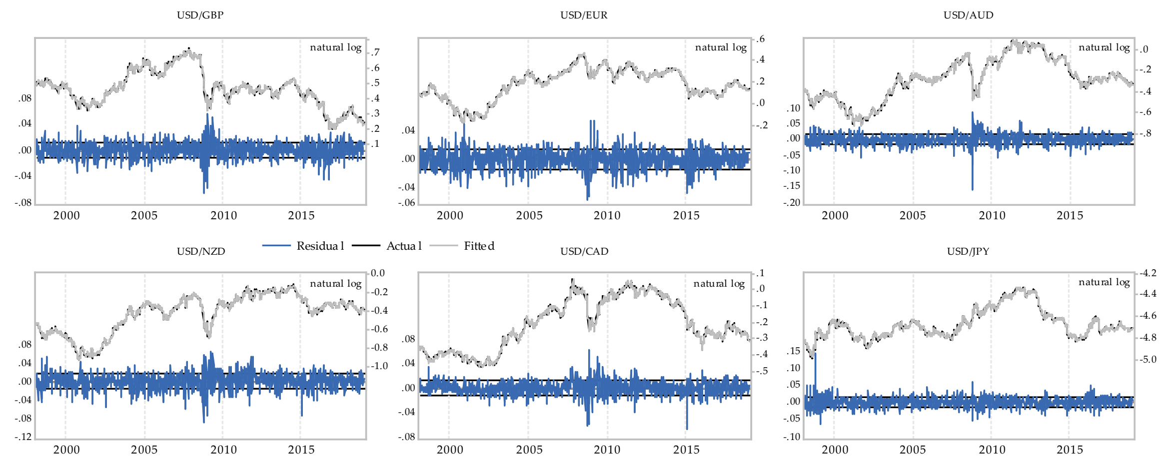
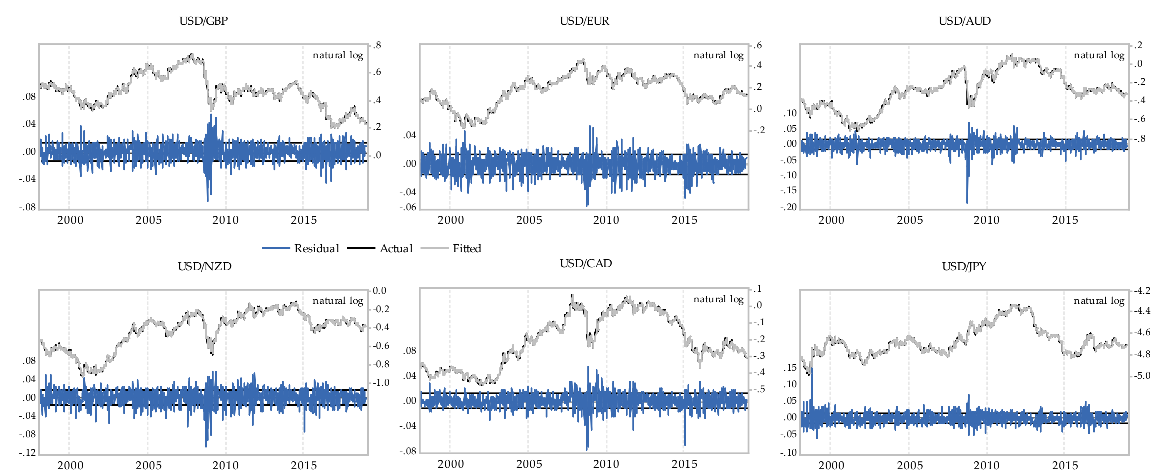


Figure VII. Equation (23a) Full-period fixed-coefficient estimation output: Estimation period 30 Jan 1998 to 28 Dec 2018



5.2.2 Forecasting performance: Full-sample fixed-coefficient estimation and rolling fixed-window estimation with lagged dependent variable

The parameter estimates from Equations (22a) and (23a), the regressions including the lagged dependent variables, are obtained employing OLS for the period 30 January 1998 to 28 December 2018. Equations (22a) and (23a) are re-estimated using a rolling regression framework, with the length of the fixed-window set at 104 periods (two years). The coefficients on all exchange rate regressors are time-varying, with a wide variation, including changing of signs. Figure VIII charts the estimated exchange rate coefficients and standard deviations for Equation (23a) for the USD/NZD as an example. The remaining sample coefficients are displayed in Appendix C1 Figure C6 and Figure C7. With respect to the USD/NZD rolling regression, the coefficients on relative interest rates are not consistently negative over the sample period, and the coefficient on the risk premium proxy also varies over the sample estimation period. This variability in sign occurs across a number of other regressors.

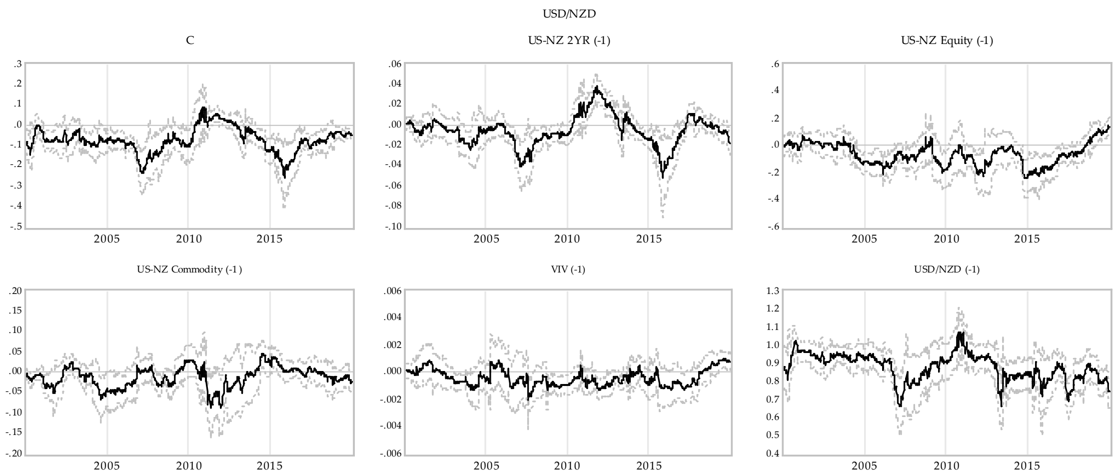
Table XII presents the forecasting results of Equations (22a) and (23a), the full-sample fixed-coefficient estimations and the rolling fixed-window estimations. The results consider whether or not the exchange rate equations with a lagged dependent variable contain information that can be used by analysts and traders to improve short-term exchange-rate forecasts.

Table XII. Forecasting comparison: Equations (22a) and (23a) levels relationship

Exchange rate / Model	Forecast period 5 Jan 18 – 28 Dec 18			Forecast period 4 Jan 19 – 27 Dec 19		
	RMSE	Theil's U	DΔA %	RMSE	Theil's U	DΔA %
USD/GBP						
Random walk	.010	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.010	1.01	59	.012	1.00	45
Rolling fixed-window, Eqn (22a)	.012	1.24	47	.014	1.05	51
Full-sample fixed-coefficient, Eqn (23a)	.010	1.01	59	.013	1.03	47
Rolling fixed-window, Eqn (23a)	.014	1.53	57	.016	1.28	57
USD/EUR						
Random walk	.008	1.00		.007	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.008	1.01	51	.007	1.02	31
Rolling fixed-window, Eqn (22a)	.009	1.08	46	.009	1.12	49
Full-sample fixed-coefficient, Eqn (23a)	.008	.970	43	.007	1.01	31
Rolling fixed-window, Eqn (23a)	.015	1.40	55	.008	1.07	49
USD/AUD						
Random walk	.011	1.00		.009	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.011	.979	51	.010	1.02	59
Rolling fixed-window, Eqn (22a)	.011	.975	75	.008	1.02	67
Full-sample fixed-coefficient, Eqn (23a)	.011	.986	48	.005	1.01	59
Rolling fixed-window, Eqn (23a)	.014	1.23	47	.011	1.20	49
USD/NZD						
Random walk	.012	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.012	.999	57	.001	.995	51
Rolling fixed-window, Eqn (22a)	.012	1.01	56	.011	.943	52
Full-sample fixed-coefficient, Eqn (23a)	.012	1.08	26	.012	1.02	51
Rolling fixed-window, Eqn (23a)	.016	1.31	49	.012	1.02	57
USD/CAD						
Random walk	.009	1.00		.007	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.008	.972	27	.007	1.03	26
Rolling fixed-window, Eqn (22a)	.009	.962	69	.009	1.23	51
Full-sample fixed-coefficient, Eqn (23a)	.009	.970	51	.008	1.07	51
Rolling fixed-window, Eqn (23a)	.011	1.27	49	.008	1.11	59
USD/JPY						
Random walk	.010	1.00		.008	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.009	.957	69	.007	.966	48
Rolling fixed-window, Eqn (22a)	.012	1.21	65	.006	.846	53
Full-sample fixed-coefficient, Eqn (23a)	.010	.993	57	.008	1.00	56
Rolling fixed-window, Eqn (23a)	.011	1.15	65	.009	1.17	56

Notes: Forecast sample size of N = 52. See Table X for more details.

Figure VIII. Equation (23a) Rolling coefficient estimates of the level/log level USD/NZD estimation parameters: Estimation sample 30 Jan 1998 to 28 Dec 2018



Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, (-1) refers to the lagged variable

Examining the results in Table XII, the root mean square errors of the forecast predictions compared with the random walks are wide and varied. At times, the RMSE for some exchange rate regressions improves upon the RMSE of the random walk. On occasion, the Theil's U criterion improves upon the random walk, and this occurs more frequently during the 2018 forecast period (for example with the USD/AUD regressions). Generally, the RMSE and Theil's U results improve during the *ex-post* forecasting period (2018) compared with 2019, as expected. However, this is not always the case – the full-sample and rolling USD/NZD regressions (both contemporaneous and the forecasting approach) improve as the forecast window moves to 2019. In contrast with the results from Equations (22) and (23), there is no clear indication that the forecasting performance of the rolling fixed-window regressions are better at predicting directional change than the fixed-coefficient estimations.

Broadly speaking, the forecast performance improves when the lagged dependent variable is included in the regression (compared to Table X) but the results overall remain variable.

Comparing the out-of-sample forecasts from the full-sample fixed-coefficient results to the rolling regression forecast results implicitly tests whether a longer sample period provides more or less accurate forecasts of exchange rates than a shorter estimation period. The results suggest that the shorter window does not improve the forecasting ability of the exchange rate regressions, in contrast to the results for Equations (22) and (23) from Table X.

The forecasting assessment of all four equation specifications is performed to compare to other studies of exchange rate determination. The results are not directly comparable to the literature but do suggest that macro-financial variables alone do not consistently forecast exchange rates out-of-sample. In keeping with the literature more generally, the results are not consistent over time or across currency pairs. There is some indication that macro-financial variables contemporaneously reflect the current level of the exchange rate.

A final salient point: while these results follow the process typically applied in the literature, the literature assumes that a long-run cointegrating relationship exists. The issue of cointegration is discussed in the following section.

5.3 Cointegration

The variables in the exchange rate model are relevant in levels and are cointegrated if, jointly, they exhibit a long-run relationship; that is, the time series do not wander apart without bound. In order to determine if there is a long-term relationship in an exchange rate model when the variables of interest are non-stationary, there must be some linear combination that is stationary (Banerjee *et al.*, 1993). If there is not a long-run relationship amongst variables, the time-series are not cointegrated and the error term in the model is not covariance stationary; any apparent relationship may be spurious (Stock and Watson, 2011; Granger and Newbold, 1974).[69] For this study, if the variables are not cointegrated, foreign exchange traders cannot have confidence that the exchange rate model will be profitable into the future, even if it was in the past.

The decision about which cointegration test to apply is motivated by the mixed results for unit root tests on the individual time series. Granger (1981) proved a regression based on both I(1) and I(0) time series can exhibit stationary regression residuals, yet research points to its low power (Frankel and Rose, 1994).

[69] Trending time series can appear to be related but this also may be spurious (Asteriou and Hall, 2007).

The Engle-Granger cointegration test (Engle and Granger, 1987) is appropriate for single-equation regressions when all variables are integrated of the same order.[70] In level or log level terms, the data in this study are not all unequivocally I(1), so the Engle-Granger approach is not applied.

This study applies Autoregressive Distributed Lag (ARDL) bounds testing, given the mixed order of integration of the underlying data and the dependent variables exhibiting integration of order one (McNown *et al.*, 2016). The procedure follows Phillips (2018).

An unrestricted ARDL regression model, ARDL(*p, q; k*), is:

$$s_t = \phi_0 + \sum_{i=1}^{p} \phi_i \, s_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q} \phi_{ji} \, z_{jt-i} + \epsilon_t \tag{28}$$

where ϕ_0 is a constant, p (q) is the number of lags on the dependent (right-hand side) variable(s); *z* are the explanatory variables, *j* is each explanatory variable while *k* is the total number of right-hand side variables, ϵ_t is the error and $\epsilon_t \sim IID(0, \sigma^2)$ (Pesaran *et al.*, 2001; Kennedy, 2003). When the underlying series are not I(2) and ϵ_t

[70] Johansen's cointegration test (Johansen, 1988; Johansen and Juselius, 1990), another alternative, allows for more than one cointegrating vector (long-run relationship) but within a system of equations (a VAR), which is not applied in this study.

is white noise and independent of s and z, the ARDL can be estimated using ordinary least squares.[71]

The cointegration technique detects a long-run equilibrating relationship by testing the null hypothesis of no cointegrating levels relationship (irrespective of the order of integration of the underlying time series) against the alternative that there is a long-run equilibrium relationship. The ARDL bounds approach tests the joint significance of the lagged levels of the regressors in an unrestricted error correction model (ECM), such as:

$$\Delta s_t = \mu + \sum_{i=1}^{p} \nu_i \Delta\, s_{t-i} + \sum_{j=1}^{k}\sum_{i=0}^{q} \nu_{ji} \Delta\, z_{jt-} + \upsilon s_{t-1} + \sum_{j=1}^{k} \nu_k\, z_{kt-1} + \epsilon_t \qquad (29)$$

where:

$$H_0\colon \nu = \nu_1 = \nu_2 = \cdots = \nu_k = 0 \qquad (30)$$

The distribution of the F-statistic is non-standard and provided by Pesaran *et al.* (2001).[72] The number of lags is set at 12, the highest number provided by EViews, to assist with the most appropriate model selection (reducing autocorrelation).

[71] It is not a prerequisite to re- for the order of integration, assuming the time series are not I(2).

[72] Pesaran *et al.* (2001) assume a sample size of 1000. The regressions in this study have a sample size of more than 1000, therefore Narayan's (2005) critical values for smaller sample sizes are not applied. Critical values are given by EViews.

EViews re-estimates the ARDL equation using a general-to-specific procedure until the number of lags on each lagged term is significant.

The results of the ARDL bounds tests are found in Table XIII.[73] The USD/GBP model rejects the null hypothesis that there is no equilibrating relationship at the 5% level of significance. The USD/CAD and USD/AUD results are inconclusive, with the critical value falling between the I(1) and I(0) critical bands. The *F*-statistic on all other exchange rate models fails to reject the null hypothesis of no equilibrating relationship. The broad conclusion here is there is little evidence of a long-run relationship between the exchange rate and its regressors using a macro-financial augmented sticky-price model when estimated between 30 January 1998 and 28 December 2018.

Cointegration is essential and yet previous studies at times do not discuss or report the tests of cointegration. For example, Neely and Sarno (2002) dismiss cointegration as an important condition for monetary fundamentals to predict the exchange rate. Cheung *et al.* (2017) apply a theoretical framework that implies cointegration but do not formally test for it. It is more common for studies to fail to discuss the concept and its relevance to exchange rate determination or its forecasting than to test for cointegration.

[73] This ARDL model is based on Equation (22), that being the regression including current values of the right-hand side variables and a lagged dependent variable. Equation (23) was also considered and the primary outcome is unchanged, see Appendix C1, Table C1.

Table XIII. Autoregressive Distributed Lag Model (ARDL) cointegration bounds test, Equation (22)

	USD/GBP	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Estimated ARDL model						
ARDL lags	(9,1,7,0,1)	(1,2,1,0,2)	(11,3,0,0,4)	(3,2,0,0,3)	(3,3,0,2,2)	(2,1,2,0,11)
F-statistic	4.65 **	1.40	3.11	2.65	3.45	1.27
Critical bound I(0)						
1% significance	3.29	3.29	3.29	3.29	3.29	3.29
5% significance	2.56	2.56	2.56	2.56	2.56	2.56
10% significance	2.2	2.2	2.2	2.2	2.2	2.2
Critical bound I(1)						
1% significance	4.37	4.37	4.37	4.37	4.37	4.37
5% significance	3.49	3.49	3.49	3.49	3.49	3.49
10% significance	3.09	3.09	3.09	3.09	3.09	3.09
Adjusted R^2	.991	.992	.995	.992	.996	.990
Breusch-Godfrey Chi	.811	.513	.8744	.715	.221	.626
Actual sample size	1083	1090	1081	1086	1089	1081

Notes: The Newey-West HAC adjustment was applied using the quadratic-spectral kernel and automatic bandwidth selection as given by EViews. The ARDL null hypothesis is of no cointegrating level relationship. Estimated with an unrestricted constant and trend and maximum allowable lags of $k = 12$. Critical values of the F-test statistic. * Can reject null hypothesis at 10% level. ** Can reject at 5% level. Critical values from Pesaran *et al.* (2001). The Breusch-Godfrey Chi is the p-value for a Chi-square distributed test statistic, with the number of lags $p = 2$. The number of lags (p) was determined by visual assessment of the correlogram of regression residuals up to 36 lags. Lags (in parentheses) are in order of s_t, y_t-y_t*, i_t-i_t*, c_t-c_t*, rp_t. Sample size N = 1091.

The results of the cointegration bounds tests are at odds with the literature's discussions on exchange rate modelling. Perhaps cointegration is not found because the series are close to a unit root but not integrated of order one. Elliott and Stock (1994) show that highly persistent predictors (close to a unit root) can lead to inference errors and Campbell and Perron (1991) argue it is difficult to determine the number of cointegrating relationships. Demetrescu and Hassler (2016) demonstrate that a shift in the mean of a model may keep OLS estimation consistent but a break in dynamics of a model will lead to biases in forecasting – implying a break in a relationship may not impact the econometric results, depending on its source. For example, the presence of heteroskedastic shocks, which are common in financial market variables, are known to reduce the power of an Augmented Dickey Fuller unit root test, making an appropriate order of integration determination difficult (Cavaliere *et al.*, 2015). Hendry and Massmann (2007) warn that if a structural break is not appropriately taken into account, unit root tests can mistake a break for a unit root.[74] Campos *et al.* (1993) and Gregory *et al.* (1996) show tests have low power when breaks are present.

These last points, and the lack of evidence of a long-run relationship in macro-financial exchange rate modelling, may indicate structural breaks in the equations of interest. A structural break is a permanent change in a regression coefficient, rendering the prior DGP inaccurate (Park, 2015). A difficulty with testing for structural breaks is that it requires the relationship to be covariance stationary, that is, cointegrated (Haug *et al.*, 2011).[75]

At the very least, the ARDL bounds tests suggest the linear methodology applied may be insufficient to capture the correct functional form. Augmented derivations of the standard sticky-price asset model could express the relationships in first differences terms (thereby avoiding the issue of different orders of integration), or

[74] This could explain why many researchers ignore unit root tests.

[75] Carrion-i-Silvestre and Sansó (2006) devise a technique to test for possible cointegration in the presence of breaks.

apply an error correction model to allow for a long-run relationship and short-run deviations.[76]

The next sections explore these alternative specifications and tests for the existence of structural breaks.

5.4 Error-Correction Model, USD/GBP

The forecasting performance of the USD/GBP regression is assessed via an error-correction model (ECM). The ECM is built using the variables and lags identified in the ARDL model, both the long-run equilibrium relationship and the short-run dynamics. The sample period runs from 10 April 1998 to 28 December 2018, due to the lags in the construction of the model. The forecast periods are unchanged, the *ex-post* forecast period is from 5 January 2018 to 28 December 2018, and the *ex-ante* period from 4 January 2019 to 27 December 2019.

5.4.1 Results

The long-run equilibrium formulation is:

$$s_t = \delta_0 + \delta_2\left(y_{p,t} - y_{p,t}^*\right) + \delta_3(i_t - i_t^*) + \delta_5\left(c_{p,t} - c_{p,t}^*\right) + \delta_6 rp_{p,t} + \varepsilon_t \qquad (31)$$

[76] Non-linear applications – such as regime-switching (Engel and Hamilton, 1990) – are recommended as an area for future research.

with the usual terminology, as noted in Section 3.3. The estimated coefficients in the equilibrium relationship from the ARDL model are reported in Table XIV.

Table XIV. Equation (22) Long-run relationship

		USD/GBP
Estimated coefficients		
Constant	δ_0	.898 (.163) ***
Equity	δ_2	-.570 (.220) ***
Interest rates	δ_3	-.088 (.042) ***
Commodity	δ_5	-.051 (.094)
Risk	δ_6	-.019 (.006) ***

Notes: Standard errors in parentheses. *** *t*-statistic is significant at 1%. Sample size of N = 1083.

Similar signs on the parameters are found generally in the literature on relative interest rates, relative income (proxied by relative equity indices), and a risk premium proxy. The negative coefficient on relative commodity prices is not significant at the 5% level.[77] The error correction term ($ECT_t = s_t - \hat{s}_t$), based on the ARDL bounds test, is stationary, making the least squares estimator super

[77] Even though the regressor is not significant at the 5% level, it forms part of the ECM, as defined by EViews in the ARDL estimation. The variable was not excluded as it does not materially affect the long-run relationship.

consistent (Stock, 1987) and able to be directly inserted into the short-run dynamic relationship. Table XI shows the ARDL formulation of the error-correction model.

Table XV. Equation (22) USD/GBP Error-Correction Model: Estimation period 30 Jan 1998 to 28 Dec 2018

	Variable	Coefficient	Standard Error
Long-Run	ECT_{t-1}	-.013	(.006) **
Short-Run Dynamics	c	-.0004	(.004)
	Δs_{t-1}	-.0219	(.004)
	Δs_{t-2}	-.064	(.028) **
	Δs_{t-3}	.026	(.057)
	Δs_{t-4}	.020	(.028)
	Δs_{t-5}	-.050	(.029) *
	Δs_{t-6}	.0002	(.031)
	Δs_{t-7}	.021	(.028)
	Δs_{t-8}	-.067	(.031) **
	$\Delta(i-i^*)_t$	-.046	(.006) ***
	$\Delta\left(y_p-y_p^*\right)_t$	.123	(.031) ***
	$\Delta\left(y_p-y_p^*\right)_{t-1}$	.079	(.036) **
	$\Delta\left(y_p-y_p^*\right)_{t-2}$	.033	(.024)
	$\Delta\left(y_p-y_p^*\right)_{t-3}$	.0009	(.030)
	$\Delta\left(y_p-y_p^*\right)_{t-4}$	-.019	(.037)
	$\Delta\left(y_p-y_p^*\right)_{t-5}$	.010	(.026)
	$\Delta\left(y_p-y_p^*\right)_{t-6}$	.070	(.050)
	ΔVIX_t	-.0003	(.0002) *
	Adjusted R^2	.197	
	Breusch-Godfrey Chi	.879	

Notes: See notes to Table IX. Sample size of N=1083.

The ECT coefficient is negative, as expected, indicating the model will converge in the long-run to its equilibrium. The parameter coefficient on the ECT is significant but is small, suggesting 1.3 percent of any disequilibrium is reduced each week, with the half-life of the disequilibrium taking just over one year. [78,79,80] Not all parameter estimates are significant, although they are identified as relevant by the ARDL.[81]

Further, with respect to Table XV, the oscillating signs on the lags of the dependent variable in first difference terms suggest the first difference of USD/GBP is related to its recent changes. This oscillation tentatively suggests that there could be an improved model specification that would better represent the time series exchange rate relationship. Finally, the Breusch-Godfrey Chi statistic cannot reject the null hypothesis of no autocorrelation in the residuals. Figure IX shows visually the model fit and the ECT.

---

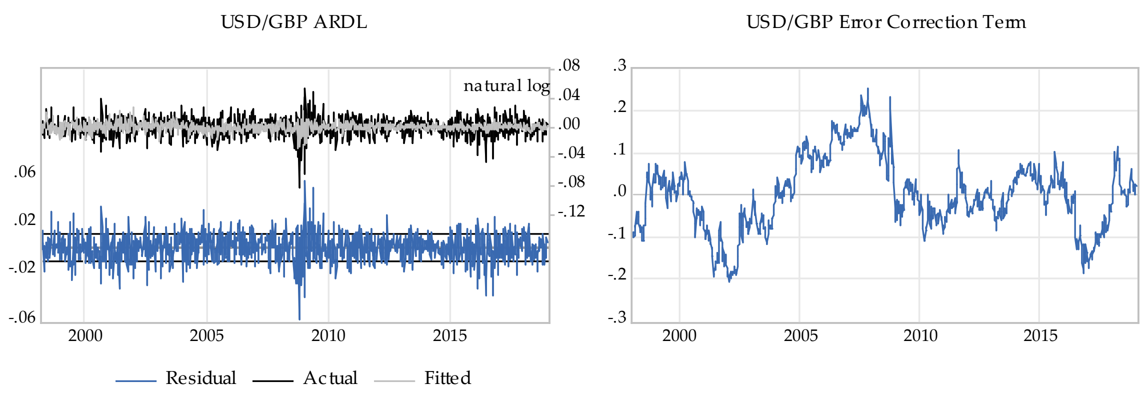
[78] This error-correction form allows for a constant but not a deterministic time trend.

[79] A check on the bounds test by applying the Ericsson and MacKinnon (2002) critical values to the error-correction coefficient t-statistic fails to reject the null hypothesis of the coefficient is equal to zero against the alternative hypothesis it is less than zero (applying $k = 5$ and asymptotic critical values, the Ericsson and MacKinnon critical value is -3.99, with the test statistic of -2.17). Conflicting cointegration test results are not unusual (Gregory *et al.*, 2004), in particular because the true underlying DGP is unknown (Hendry, 1986). Ericsson and MacKinnon's (2002) critical values attest to the non-standard distribution of the error-correction coefficient test statistic (Kremers *et al.*, 1992) but the critical values rely on I(1) variables, which is not the case for the VIX regressor. Hence, the cointegration result from the ARDL bounds test is assumed to be correct.

[80] $(1 - .013)^n = .5; n = 53$ periods (weeks).

[81] The results from Equation (22) are displayed here. There is little difference in the results from an ECM applying Equation (23) and so this was not included. The similarities are not unexpected, given the one additional variable in the former equation, that being the contemporaneous values of the regressors. The ECM is also similar to Equation (22a) because of the lagged dependent variable (although Equations (22a) and (23a) exclude lags of the explanatory variables).

Figure IX. Equation (22): Estimation period 30 Jan 1998 to 28 Dec 2018



5.4.2 Structural break with unknown breakpoint

Testing for structural breaks is sensible when the researcher suspects the long-run relationship may have changed; take for example government or fiscal regime changes, exchange rate intervention, changes to regulation, or changes in the central bank's monetary policy reaction function. These are exogenous breaks – the break point is unique and known *a priori*. In this circumstance, a Chow test can be applied. Figure IX shows a notable change in the regression errors around 2008 suggesting a change in the relationship around the GFC. However, even if a date is suspected or visually noticeable, there is a risk of data mining and Andrews (1993) argues it would be inappropriate to use the standard critical values based on a Chow test. To circumvent this problem, the procedure devised by Bai and Perron (1998, 2003a) allows multiple breaks in the parameters of a linear regression when the break date is unknown. This procedure is applied in this study.

In the basic model, Bai and Perron (1998) assume that the DGP of s_t is linear in time t, so that:

$$s_t = x_t'\beta + z_t'\delta_j + u_t \qquad (32)$$

for j = 1…ℓ+1, where j is the index of a regime, ℓ is the number of breaks with j regimes, $t = T_{j-1} + 1, \dots, T_j$, x_t and z_t are vectors of covariates (variables) with β and δ vectors of coefficients, and u_t is the error.[82] Bai and Perron (1998) minimise the sum of squared residuals and the associated least squares estimators of β and δ are substituted into the objective function to provide estimated breakpoints:

$$(\hat{T}_1, \dots, \hat{T}_m) = \arg min_{T_{1,\dots,}T_m}[RSS\,(T_1, \dots, T_m)] \qquad (33)$$

where *arg min* is the argument of minimum and *RSS* is the residual sum of squares with *m* the maximum number of breaks.

The estimation procedure can take one of three forms: no break versus a fixed number of breaks, a double maximum test, and a sequential test. Perron (2006) warns that tests for a fixed number of breakpoints may have power problems if the actual number of breakpoints is greater than the number tested. This situation is a risk in this study, given the high data frequency, raising the possibility of frequent breaks.

---

[82] This description relies heavily on Casini and Perron (2018).

Thus, the double maximum test is first applied to test the null hypothesis of no breaks against the alternative hypothesis of one or more breakpoints (ℓ) (Bai and Perron, 2003a). Two test statistics are calculated – the equal-weight (*UDmax*) that minimises the sum of square residuals (Andrews *et al.*, 1996), and (*WDmax*), where the *p*-values of the sup-Wald statistic are equal across the number of breaks (Bai and Perron, 1998). Finding that $\ell > 0$, the sequential Bai and Perron test is next applied to the model. The existence of a lagged dependent variable in the model requires the model to be pre-whitened: the Bai and Perron (2003a) structural break test requires no serial correlation in the regression error. The Breusch-Godfrey test statistic in Table II does not reject the null hypothesis of no serial correlation. The results are shown in Table XVI, with the critical values provided by Bai and Perron (2003b), due to the asymptotic distribution of the test statistics.

Upon determining the existence of at least one break applying the double maximum test, the sequential procedure is applied to test if there are ℓ breaks against an alternative hypothesis of (ℓ+1) breaks to find the number of breaks and the associated break dates. A maximum number of *m* breaks is considered. Each (ℓ+1) segment is tested for an additional break (see Casini and Perron, 2018 for a detailed explanation) and this sequencing continues (one break versus more than one break, two breaks versus more than two breaks and so on) until there is a failure to reject the null hypothesis. If ℓ against ℓ+1 is not rejected then the approach constructs the critical values using estimates of the break dates obtained from a global minimization of the sum of squared residuals. The double maximum test followed by the sequential test allows the data to define the break dates, rather than pre-determining how many or where these breaks may occur (Bai and Perron, 1998).

Table XVI reports the Bai and Perron (1998) double maximum statistics (*UDmax* and *WDmax*) of no structural break against the alternative of an unknown number of breaks. There is strong evidence of at least one structural break in the weekly USD/GBP ECM model. The sequential breakpoint procedure is then applied, and the breakpoint dates are listed.[83]

Bai and Perron (2003a) apply this two-step procedure to two data sets and recommend a trimming parameter of .15 with a maximum of m = 5 breaks so that the sample size in each segment is large enough not to lead to size distortions. Kennedy (2003) notes the trimming factor balances off the power of the tests against the number of breaks. In larger sample sizes, Bai and Perron (2006) comment that when the errors are adjusted for autocorrelation and heteroskedasticity, a smaller trimming parameter may be relevant, and Bai and Perron (1998) provide an example using a .05 trimming parameter. The results below apply a trimming parameter of .15, with the maximum number of breaks of five ($m \leq 5$). If the results reach the maximum number of breaks, the test could be run with a smaller trimming parameter (because the sample size is large) to check if there are more than five breaks in the series. However, this is not necessary, as the number of breaks identified is three.

[83] It is reasonable to set the starting value of $\ell \geq 1$ once the global test shows at least one break. The test of zero breaks versus at least one break in the sequential test above is therefore unnecessary, given the results of the double maximum test. It is reported here in order to present the breakdate for discussion.

Table XVI. USD/GBP Error correction model breakpoint dates, $m \leq 5$

	USD/GBP
UDmax	116.91 *
WDmax	137.59 *
Break dates	
0 vs 1	28 Mar 2003
1 vs 2	1 Aug 2008
2 vs 3	7 Oct 2011

Notes: For the globally determined break the null hypothesis is no breaks versus one or more. *UDmax* and *WDmax* are one-sided (upper-tail) tests of the hypothesis of an unknown number of breaks given an upper bound, where *UDmax* is the equal-weighted test result and the *WDmax* test statistic weighs the statistics to equalise their *p*-values (Bai and Perron, 2003a). * *F*-statistic is significant at the 5% level, with critical values given by Bai and Perron (2003b). Break dates are only recorded if they are significant at the 5% level. Heterogeneous error distributions are allowed across breaks. The breakpoint date sequential test is a one-sided (upper-tail) test of the null hypothesis of ℓ breaks against the alternative of $\ell+1$ breaks given an upper bound of $m = 5$ where the trimming parameter is .15.

As previously stated, the Bai and Perron procedure identifies three break dates across the sample period for the error-correction model. These dates line up with significant news or financial market events, as witnessed by the author. The first date – March 2003 – aligns with the week following President Bush's announcement of the U.S. invasion of Iraq (The White House, 2003). The second break date (August 2008) identified in Table XVI is notable, especially for foreign exchange traders. The week of 3 August 2008 signalled the spread of the GFC – which until that time had been evident in mortgage-backed securities and U.S. collateralised loan obligations[84] – into foreign exchange markets. The Pound Sterling in particular depreciated rapidly against the U.S. dollar: in early August 2008 one Pound Sterling was worth two U.S. dollars; by early 2009 it was being exchanged for US$1.30. The final date identified by the Bai and Perron unknown breakpoint date selection procedure – October 2011 – was during the European Sovereign Debt Crisis, a tumultuous time for financial markets (BIS, 2011).

Two of these dates (2003 and 2011) refer to non-U.K. events and yet are identified as a structural break in the USD/GBP exchange rate relationship, possibly due to the U.S. side of the exchange rate or because of U.K.'s close relationship with Europe. The indirect but significant impact of these events on the USD/GBP relationship indicates global common factors or themes could be driving financial market asset price valuations and their relationships with one another (Miranda-Agrippino and Rey, 2020; and Rey, 2013).[85] Possibly, the conditional expectations component of the macro-financial variables could be driving these breaks. The macro-financial price is based on forward-looking conditional expectations and these expectations change regularly. This is also recommended as an area of future research.

The forecasting performance of the ECM is discussed next.

---

[84] Collaterised loan obligations are pools of leveraged loans wrapped into tranches of bonds (Federal Reserve, 2019).

[85] If indeed this is the case, the estimation may be better explained as a system or as a panel regression. A systems approach will also allow the drivers of exchange rates to be determined (Kilian and Lütkepohl, 2017). This is recommended as an area of future research.

5.4.3 Forecasting performance: Error-correction model

The forecasting performance of the USD/GBP ECM is shown in Figure X, forecasting out 52 weeks (one year). Graphically, the estimated model looks similar to the actual level of the USD/GBP during both 2018 and 2019, with a greater deviation between the actual and forecast lines in 2019 than in 2018.[86]

Figure X. Equation (22) Error-correction models, USD/GBP

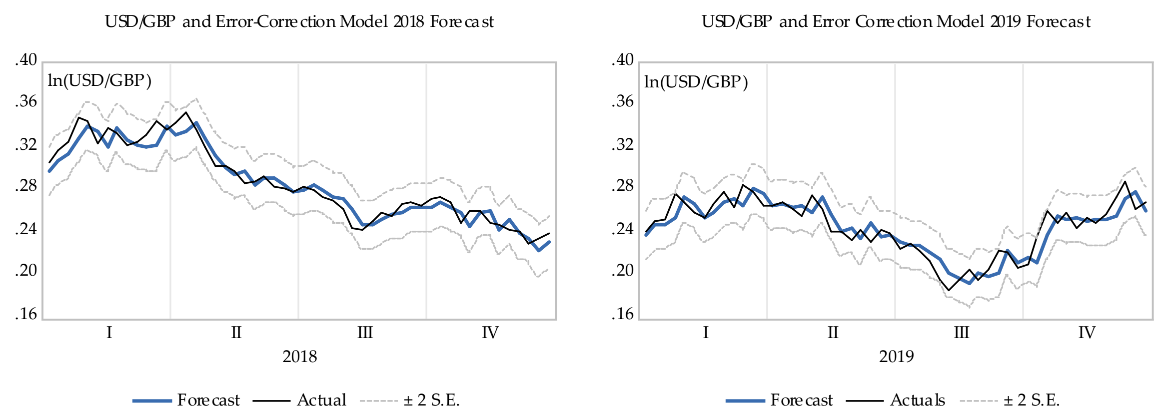


Table XVII confirms this visual assessment – the directional change statistic is below 50 percent in 2019. The forecasting performance in general is notable – the RMSE and the Theil's U of the ECM improve upon a random walk across both periods assessed. In the case of the directional change statistic for 2018, 61 percent of the

[86] This was a static forecasting approach, assuming that market participants 'reset' each week but assessing the actual value of the regressors when forecasting one-week ahead. A static forecasting approach is closer to the approach taken by foreign exchange traders, and is consistent with the forecasting approach applied in Section 5 for comparative purposes.

time the model correctly forecasts the change in the direction in the USD/GBP one week ahead.

Table XVII. Forecasting comparison: error-correction model

Model	Forecast period 5 Jan 18 – 28 Dec 18			Forecast period 4 Jan 19 – 27 Dec 19		
	RMSE	Theil's U	DΔA %	RMSE	Theil's U	DΔA %
Random Walk	.009	1.00		.035	1.00	
Error Correction Model	.009	.952	61	.011	.904	45

Notes: Forecast sample period N = 52. DΔA is the directional change accuracy indicator in percent terms.

The results indicate a dynamic relationship between the USD/GBP exchange rate and macro-financial proxies of macroeconomic variables is a better model specification than a static augmented sticky-price model when forecasting the exchange rate. However, while the USD/GBP model consistently outperforms a random walk, it does not consistently predict the subsequent direction of the exchange rate out-of-sample. The non-stationary behaviour of the variables, as shown by the structural break procedure, could explain why the short-term forecasting performance of this model varies over time.

Next, a first differences estimation is considered for the full-sample and on a weekly rolling fixed-window basis.

5.5 First difference estimation with lagged dependent variable

For all exchange rate models other than the USD/GBP exchange rate, the ARDL bounds tests do not indicate a cointegrating relationship but unit root tests indicate several variables are I(1). A natural next step is to re-estimate the models in first difference terms, as a more appropriate non-spurious specification. This section focuses on the equations that include a lagged dependent variable, thereby accounting for autocorrelation. The model and the out-of-sample forecasting results, for both the contemporaneous model and the forecasting approach, are discussed.[87] The models are also tested for structural breaks when the break date is unknown, and the predictability of the models is explored.

5.5.1 Results

The results for the equations with the lagged dependent variable included are shown in Table XVIII.[88] The results are startling. One-week changes in the underlying variables of interest do not explain concurrent or one-week-ahead changes in the nominal exchange rate. Relative interest rates, relative equity indices, and the risk premium regressors are significant parameters in the contemporaneous set of regressions. Again, the Breusch-Godfrey Chi *p*-value points to notable serial correlation and the coefficient of determination is low.

---

[87] The results for Equations (22) and (23) are not shown here due to the lack of explanatory power. The results for these equations do not add to the discussion other than to support the results reported.

[88] For brevity, only the table of results is presented here. A graphical view can be found in Appendix C2: Figures C8, and C9, with the differences between the two estimations illustrated in Figure C10.

Table XVIII. Full-sample fixed-coefficient estimation, first difference: Estimation period 30 Jan 1998 to 28 Dec 2018

		USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
				Equation (22a)		

$$\Delta s_t = \delta_0 + \delta_2 \Delta(y_{p,t} - y_{p,t}{}^*) + \delta_3 \Delta(i_t - i_t{}^*) + \delta_5 \Delta(c_{p,t} - c_{p,t}{}^*) + \delta_6 \Delta rp_{p,t} + + \delta_7 \Delta s_{t-1} + \varepsilon_t$$

Estimated coefficients		USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Constant	δ_0	.0003	.007	.0003	.0003	-.0003
		(.004)	(.004)	(.0004)	(.003)	(.0004)
Equity	δ_2	.098	-.038	.029	-.0118	.112
		(.031) **	(.040)	(.056)	(.041) ***	(.029) ***
Interest rates	δ_3	-.048	-.05	-.04	-.032	-.0005
		(.007) ***	(.009) ***	(.010) ***	(.009) ***	(.0004) ***
Commodity	δ_5	-.007	.0009	-.012	.052	.0006
		(.0009)	(.016)	(.013)	(.011) ***	(.008)
Risk	δ_6	-.003	-.002	-.002	-.002	.001
		(.0003)	(.0003) ***	(.0003) ***	(.0003) ***	(.0001) ***
Lagged dependent	δ_7	-.005	-.005	-.003	-.006	-.068
		(.030)	(.028)	(.023)	(.025)	(.036) *
Adjusted R^2		.114	.307	.189	.237	.17
Breusch-Godfrey Chi		.061	.0013	.003	.009	.003

Equation (23a)

$$\Delta s_{t+1} = \delta_0 + \delta_2 \Delta(y_{p,t} - y_{p,t}{}^*) + \delta_3 \Delta(i_t - i_t{}^*) + \delta_5 \Delta(c_{p,t} - c_{p,t}{}^*) + \delta_6 \Delta rp_{p,t} + + \delta_7 \Delta s_t + \varepsilon_t$$

Estimated coefficients		USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Constant	δ_0	-.0004	.004	.0001	.0005	.0006
		(.004)	(.005)	(.005)	(.107)	(.0005)
Equity	δ_2	.005	.021	-.0004	-.029	.067
		(.023)	(.034)	(.034)	(.036)	(.021) ***
Interest rates	δ_3	-.001	.004	.0008	.003	-.010
		(.005)	(.005)	(.005)	(.007)	(.007)
Commodity	δ_5	.0008	-.018	-.004	-.005	-.007
		(.008)	(.015)	(.011)	(.011)	(.008)
Risk	δ_6	-.0002	-.0008	-.0001	-.0002	.0001
		(.0001) *	(.0002)	(.0002)	(.0002)	(.0002)
Lagged dependent	δ_7	-.002	-.026	-.034	-.038	-.110
		(.030)	(.035)	(.03)	(.038)	(.047) ***
Adjusted R^2		-.0003	-.005	-.003	-.002	.017
Breusch-Godfrey Chi		.061	.222	.307	.524	.822

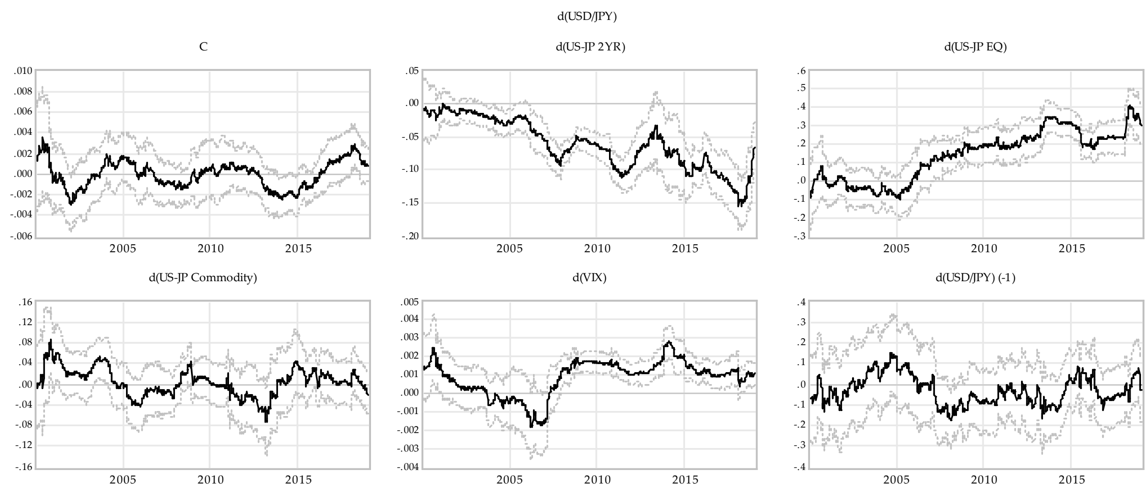
Notes: See Table IX for details. Sample size of N = 1090.

The lack of coefficient significance in the forecasting approach, Equation (23a), is notable. The USD/JPY equation displays the coefficients on relative equity indices and the lagged dependent as significant but many other exchange rates do not have any significant parameters. Equally concerning is the adjusted coefficient of determination, which is low and frequently negative. A negative value indicates there is little explanatory power in the regressions using this formulation over this period of estimation at this data frequency. A reason to apply macro-financial variables in lieu of macroeconomic variables in this framework is to see if the higher volatility of the macro-financial regressors relative to the macroeconomic equivalents improves the fit and forecasting performance of exchange rate models. In first difference terms, these models suggest the opposite.

5.5.2 Forecasting performance: First difference full-sample fixed-coefficient estimation and rolling fixed-window estimation with lagged dependent variable

An evaluation of the predictability of the first difference models is discussed, with the results in Table XIX. The time-varying parameters of the USD/JPY model are shown in Figure XI, as an example. The coefficients vary markedly throughout the estimation period, as expected. At times, the coefficients change sign. For example, the coefficient on the risk premium variable is negative around 2006 but exert a positive impact on the change in the USD/JPY by 2014. The remaining coefficients for the other exchange rates can be found in Appendix C2, Figures C11 and C12.

Figure XI. Equation (22a) Rolling coefficient estimates of the first difference USD/NZD estimation parameters: Estimation sample 30 Jan 1998 to 28 Dec 2018



Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, d = first difference, (-1) refers to the lagged variable.

It is questionable whether the forecasting results should even be calculated, given the poor in-sample outcomes. For completeness they are, and, in contrast to previous studies and the results for the level/log level models, the results for the first difference regressions on an RMSE basis (see Table XIX) tend to be homogeneous in their predictive ability that the models improve on a random walk. Compared to the log level regression results reported in Section 5.1.2 and 5.2.2, the RMSE of the first difference model is frequently close to or smaller than the random walk RMSE. Such a result typically would be considered impressive, given the history of publications unable to outperform a random walk, but the model's small (and at times negative) coefficient of determination in the estimated equations negates this interpretation. The inability of the models to adequately explain the variation in the underlying dependent variables is more telling as to the adequacies of the model than a small RMSE forecasting result.

Table XIX. Forecasting comparison: first differences relationship

Exchange rate / Model	Forecast period 5 Jan 18 – 28 Dec 18			Forecast period 4 Jan 19 – 27 Dec 19		
	RMSE	Theil's U	DΔA %	RMSE	Theil's U	DΔA %
USD/EUR						
Random walk	.012	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.008	.995	63	.008	.982	63
Rolling fixed-window, Eqn (22a)	.009	1.15	49	.008	.974	54
Full-sample fixed-coefficient, Eqn (23a)	.008	.995	63	.007	.980	51
Rolling fixed-window, Eqn (23a)	.008	.974	54	.007	.960	48
USD/AUD						
Random walk	.016	1.00		.014	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.009	.672	77	.078	.995	67
Rolling fixed-window, Eqn (22a)	.013	1.24	37	.009	1.21	57
Full-sample fixed-coefficient, Eqn (23a)	.011	.932	57	.010	1.03	67
Rolling fixed-window, Eqn (23a)	.010	.881	57	.011	1.25	40
USD/NZD						
Random walk	.017	1.00		.019	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.010	1.21	67	.010	.760	67
Rolling fixed-window, Eqn (22a)	.010	.972	58	.015	1.15	41
Full-sample fixed-coefficient, Eqn (23a)	.012	1.01	49	.010	1.01	65
Rolling fixed-window, Eqn (23a)	.011	1.23	68	.013	1.07	35
USD/CAD						
Random walk	.013	1.00		.011	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.035	.979	67	.009	1.35	69
Rolling fixed-window, Eqn (22a)	.010	2.10	65	.008	1.16	35
Full-sample fixed-coefficient, Eqn (23a)	.010	.987	67	.009	1.05	59
Rolling fixed-window, Eqn (23a)	.010	1.10	35	.005	1.52	69
USD/JPY						
Random walk	.015	1.00		.012	1.00	
Full-sample fixed-coefficient, Eqn (22a)	.008	.935	80	.011	1.08	83
Rolling fixed-window, Eqn (22a)	.014	.798	33	.011	.913	71
Full-sample fixed-coefficient, Eqn (23a)	.009	.982	57	.007	.822	58
Rolling fixed-window, Eqn (23a)	.010	1.16	37	.008	.964	60

Notes: Forecast sample size of N = 52.

In a similar manner, the Theil's U statistic points to superior relative forecasting ability on many occasions compared to the random walk. For example, in the USD/EUR results, across both model types and forecast sample periods, the model outperforms a random walk in all but on one occasion (Equation (22a), rolling fixed-window during 2018).

From a financial market trader's perspective (and advocated by Moose and Burns, 2015), the direction of change statistic is more useful than the other forecasting criteria – the direction of change is more important than the size of the change in any given week. The direction of change statistics are frequently above 50 percent, and as high as 83 percent for the USD/JPY contemporaneous regression but again, the impressive forecasting performance based on weak model results gives pause. Section 6 addresses the question of the consistency of the directional change accuracy statistic for the rolling fixed-window regressions.

In previous studies, typically the in-sample model is robust but performs poorly when it is used for out-of-sample forecasting, which Inoue and Rossi (2005) attribute to overfitted models. In this study, the basic models were intentionally parsimonious to avoid the criticism of data mining or overfitting. There still remains a difference between the in-sample performance, the in-sample forecasting accuracy and the out-of-sample results but the ordering is switched – the in-sample models perform poorly while forecasting performs (relatively) well.

With respect to the 2018 forecasting performance compared to the random walk, the 2018 results (both fixed-coefficient and fixed-window estimations) are at an informational advantage (that being, the estimation period includes the forecast sample period). Not surprisingly then, during the 2018 forecasting sample period, the results for the majority of exchange rates estimated over the 1998 to 2018 period have a smaller RMSE and Theil's U than a random walk (the USD/NZD and USD/JPY are two exceptions).

The results for the 2018 forecasting period (both fixed-coefficient and fixed-window estimations) are also expected to outperform the 2019 forecasting sample period, due to the same informational advantage. However, the results show the 2019 forecast period (the true out-of-sample period) at times outperforms that of 2018. For example, in the case of the USD/NZD and USD/EUR equations, the RMSE and Theil's U forecast results improve in 2019 over the 2018 sample period the case of the full-sample fixed-coefficient models.

Finally, as noted earlier, the difference in predictability between the full-sample fixed-period and rolling fixed-window results is implicitly testing whether the past two years (the rolling regression look-back period) is better at explaining the exchange rate relationship than the full-sample estimation. The model formation in this study was in part to test if time-varying parameters help to explain why exchange rate models forecast poorly. If market themes drive exchange rate movements, the shorter regression should be more accurate at predicting short-term future exchange rate movements. Over the two forecast periods chosen in this study, the rolling fixed-window first difference regression estimations do not consistently outperform the full-sample fixed-coefficient one-period change regressions.

The mixed, but promising predictive ability of the models in first difference formulation warrants further research. It would be useful to examine the forecasting performance over a variety of forecasting periods and adjust the length of the look-back. This is left for future research. Parameter instability is also an issue to consider, which is discussed next.

5.5.3 Structural break with unknown breakpoint

As discussed in Section 5.4.2, cointegration tests may not reject the null hypthesis of no cointegration due to breaks in the relationship (Carrion-i-Silvestre and Sansó, 2006). A first-difference model is stationary when the underlying (level) time series regressors are I(1), as many are in this study, and although this study does not test explicity for a different form of the underlying (but unknown) DGP, a structural break test is implicitly investigating if there are non-linearities in the functional form (Kennedy, 2003).[89] The structural break process follows that described previously, first obtaining the global minimised sum of squared residuals to test if there are no breaks and, if the null hypothesis is rejected, to subsquently test for the number of breaks and break dates via the Bai and Perron (2003a) sequential test. The results are found in Table XX.

The calculated values of the global maximum test (*UDmax* and *WDmax*) point to at least one break in the first difference models for all exchange rates when estimated in the contemporaneous format. This result is not surprising. As far back as Wolff (1987), the concept of changing parameters has been highlighted (in his case via a

[89] The basic motivation is to replace macroeconomic variables with a macro-financial proxy and test if this improves forecasting out-of-sample.

recursive regression) as a reason for the poor out-of-sample performance of empirical models of exchange rates.

Table XX. Full-sample fixed-coefficient first difference breakpoint dates, $m \leq 5$

	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
			Equation (22a)		
UDmax	71.96 *	49.73*	84.49 *	22.76 *	136.4 *
WDmax	78.71 *	53.19 *	89.31 *	31.14 *	136.4 *
Break dates					
0 vs 1	25 Mar 2005	3 Jan 2003	3 Oct 2003		4 Nov 2005
1 vs 2	21 May 2010	25 Jul 2008	25 May 2012		
2 vs 3	23 Jan 2015				
			Equation (23a)		
UDmax	9.51	15.19	17.21	71.92 *	16.74
WDmax	13.46	24.07 *	17.21	83.14 *	22.64 *
Break dates					
0 vs 1				31 Aug 2001	
1 vs 2				26 Sep 2008	
2 vs 3				25 Dec 2009	

Notes: See Table XVI for details.

For the Equation (22a) regressions, there are many breaks identified. The break dates show little consistency across countries, years, and months.[90] Even around the time of the GFC, the sequential break test does not consistently pick up a break

[90] The test results show conflict for the USD/CAD regressions. The double maximum test indicates at least one break in each model but the sequential test fails to find a break (and thus breakdate). Bai and Perron (1998) acknowledge the sequential test is subject to a lack of power in certain circumstances, such as highly persistent time series (Prodan, 2008).

date across the exchange rate models (the only date identified is 25 July 2008 for the USD/AUD regression). The concept of varying breakdates is not unusual with financial time series data. Rapach and Wohar (2005) find various breaks in the mean of inflation and real interest rates, although some of these breaks align across countries in the samples considered.

Caporale and Grier (2000) argue that any theoretical model will not be consistent with the empirical evidence if the coefficients remain constant over the length of the sample. In other words, breaks in time series data can be expected. Sarno and Valente (2009) posit that a model's frequently poor out-of-sample forecasting ability is caused by shifts in fundamentals (resulting in an inadequate selection of the best in-sample predictive model). This is possibly the circumstance with the Equation (22a) results; that is, the poor in-sample results and variability in the out-of-sample forecasts could be a result of structural breaks.[91]

However, this is not the case for Equation (23a), where there is a dearth of breaks. Only in one case – the USD/CAD model – is a structural break evident.[92] The inadequate model results (by way of a lack of significant coefficients and the low

---

[91] Evidence of structural breaks in the historical data is useful and might explain why models perform poorly compared to a random walk (Rossi, 2005). However, as Clark and McCracken (2005) highlight, the future predictive ability depends on the timing of the structural break but structural breaks are not known *ex-ante*.

[92] Bai and Perron (2006) note that in larger sample sizes without the presence of serial correlation and/or heterogeneity in the data the trimming parameter can be reduced (to .10 or .05). This modification was adjusted and the results are sensitive to the choice of trimming parameter. See Appendix C2, Table C2.

and frequently adjusted coefficient of determination) across all exchange rates when estimated in the Equation (23a) format (as shown in Table XXI) are somewhat validated by the lack of structural breaks in the regression. In short – structural breaks cannot be the excuse for the poor in-sample relationships for this model specification estimated over these dates.

By deduction, time-varying coefficients are therefore a legitimate model specification for USD/EUR, USD/GBP, USD/AUD, USD/NZD, and USD/JPY when estimated with Equation (23a) because this variability does not trigger a structural change using the Bai and Perron (2003a) procedure (which would render the model and forecast results suspect). Bacchetta and van Wincoop (2004) hypothesise the predictability of a model improves when the coefficients are allowed to vary over time. Rossi (2006) finds that the parameters of monetary fundamentals are unstable when applied to the nominal exchange rate using monthly data between March 1973 and December 1998. She demonstrates that in some cases time-varying models can outperform a time-varying random walk. In contrast to these authors, the out-of-sample performance of the rolling fixed-window Equation (23a) predictability does not outperform the performance of the full-sample fixed-coefficient equations (Table XIX). The rolling fixed-window prediction performance does generally improve upon a random walk for the RMSE indicator, but does not for Theil's U or the directional change accuracy indicator. It is difficult to know if these results are related to model misspecification, a structural break in the out-of-sample forecast period, or due to the small sample size of the out-of-sample forecast period. The reliability of the forecasting results over time is explored in Section 5.6.

5.6 Summary and discussion of results

This section summarises the results from the estimations and discusses the implications for exchange rate models and forecasting.

The in-sample results show that macro-financial models explain the behaviour of exchange rates in a levels/log levels relationship, with the sign of the coefficients consistent with the literature. However, unit root tests and ARDL inference suggests many of the relationships are subject to spurious findings. There is evidence of a long-run equilibrium relationship in only one exchange rate (USD/GBP) over the time period estimated when applying macro-financial proxies aligned with an augmented sticky-price exchange rate model. The first difference specification of the in-sample models does not explain one-week changes in the exchange rates well and many regressors are not significant. In all cases, the exchange rates are better represented in-sample when the lagged dependent variable is included, which is also consistent with the literature – the in-sample models have a higher coefficient of determination when estimated concurrently (recent level/changes in regressors explain current level/changes in the exchange rate, as is regularly applied in the literature), compared with a forward-looking forecasting approach (the current levels of or changes in regressors explain the future levels or changes in the exchange rate).

There are a variety of interpretations as to why the results from the contemporaneous models have a superior fit to the forward-looking models. One is that financial market participants trade current themes (Cheung and Chinn, 1999; Chinn, 2003; Bacchetta and van Wincoop, 2004) or that a global factor is driving financial variables (Claessens and Rose, 2017; Jordà *et al.*, 2019). A second potential reason is that the models are misspecified (Rogoff and Meese, 1983). Alternatively, the forward-looking approach suggests exchange rates just cannot consistently be explained by these macro-financial variables over the time period examined.

As Rapach and Wohar (2002) warn, it is recommended to test for cointegration and structural breaks before proceeding to exchange rate forecasting. Despite the potential for spurious relationships, the forecasting procedure was applied to all model specifications in order to align with the literature and because tests of cointegration are known to have low power when the series are close to a unit root (Kremers *et al.*, 1992; Zhou, 2001). The forecasting results were also considered as it matches behaviour of financial market participants, as observed by the author working on foreign exchange trading floors. If market participants (erroneously) believe the model specification is correct and trade accordingly, the predictions could become self-fulfilling. In this respect, this thesis is normative in its focus.

The in-sample forecasting and out-of-sample predictive ability of the levels/log levels relationships is mixed across exchange rates, forecasting indicator, and forecast sample periods. In the case of the USD/GBP error-correction model, which integrates the long-run (cointegrated) relationship with the short-run dynamics, the forecasting results are also mixed and it is unknown if a structural break is evident in the out-of-sample forecast period. For the contemporaneous first difference equations, Equation (22a), the out-of-sample forecasting results also bear no uniformity over time, across a particular predictive indicator, or with a specific exchange rate. These results align with Rossi's (2013) conclusion following her survey of the literature.

The set of equations where the forecasting results are unaffected by cointegration and structural breaks are the forecasting model approach equations in first difference format: model specification Equation (23a). For this group of regressions, the in-sample model results are particularly weak. Nevertheless, the in-sample and out-of-sample forecasting results regularly outperform a random walk, and the directional change indicator is frequently above 50 percent.

There are reasons to be skeptical of these promising first difference out-of-sample predictive results. If a random walk is the true DGP of nominal exchange rates or if foreign exchange traders have a naïve expectation of no change in the subsequent trading period, then changes in the exchange rate are driven by an unexplained or unexpected component. By definition then, exchange rates changes cannot be predictable and results that suggest otherwise are not repeatable. From an econometric standpoint, the first difference regressions exhibit a poor fit of the data, and there is evidence of serial correlation even when the lagged dependent variable is incorporated (Hendry, 1995).

An aspect of this thesis is to test if time-varying parameters improve the forecasting performance of exchange rate models. In contrast to Bacchetta *et al.* (2010), rolling regressions in this study do not consistently improve upon a random walk. In line with their conclusion, time-varying parameters have a negligible impact on the prediction performance compared to a fixed-sample regression.

A final area to explore is the sensitivity of the forecasting approach on the predictive success of exchange rate models. This is discussed in Section 6.

Section 6. Alternative Forecast Specifications

A model that accounts for time-varying parameters mimics changing market themes. While an exchange rate model can exhibit time variation, the forecasting period should be clear of a structural break. The situation of both occurring in time series data is plausible; for example, the exchange rate may evolve slowly (with changing coefficients driving these shifts) and occasionally exhibit a discontinuous change (a structural break). Failure to account for structural breaks could lead to the erroneous conclusion that the exchange rates perform no better than a random walk. As previously discussed, a structural break is not known *ex-ante* but reporting the out-of-sample predictions, as in Section 5, without knowing if a structural break has occurred reduces the reliability of the out-of-sample predictive outcomes. This section undertakes a true out-of-sample forecast procedure to test the reliability of the model's predictive accuracy and applies this approach retrospectively, ensuring the model is locally stationary (Vogt, 2014).

An additional concern (about whether the prediction of the models is or could be reliable) is that finding predictors that work well in one forecast period does not guarantee that such predictors will continue to be successful in subsequent periods. Cheung, Chinn, and Pascual (2005) find the good (poor) forecasting ability of a predictor in one sub-sample is uncorrelated with its forecasting ability in the second sub-sample. Rossi (2013) evaluates the literature on the choice of forecast sample and concludes it is a key contributor to the inconsistency in exchange rate results across studies. The choice of two sample periods in this study for forecasting (weekly results for 52 periods over 2018 and 2019) present a snapshot but the promising (and poor) results do not provide any indication whether these results are persistent over time.

In order to attest to the above concerns, in this section the forecasting method is adjusted slightly and applied to the first difference Equation (23a) rolling fixed-window regressions.[93] Specifically, the consistency of the rolling regression predictability over time is assessed.

6.1.1 One-week-ahead predictive accuracy

The forecast method follows the iterative approach discussed in Marcellino *et al.* (2006). This approach runs a rolling fixed-window regression (in this case with a two-year look-back window), calculates the *t*-step-ahead prediction, then re-estimates the rolling regression one period ahead, and calculates the next (iterative) prediction, and so forth. As a result, each forecast estimation is a true *ex-ante* forecast. The results are calculated for the exchange rate first difference models with lagged dependent variable, Equation (23a), where no structural breaks are evident, and for the periods between structural breaks, in the case of the USD/CAD.[94] The

[93] The full-sample fixed-period and the contemporaneous first difference models are not considered here as the former is not a true out-of-sample test of predictability (the latter cannot be applied in a real-life setting by financial market participants to forecast changes in exchange rates).

[94] With a fixed-window of two years (104 periods), the USD/CAD results are calculated and reported from 7 September 2001 to 29 August 2003 (the regression sample) and rolled forwards until 19 September 2008, with a sample size of N = 264. The second period without a structural

rolling estimation period is broadly unchanged: 30 January 1998 to 21 December 2018 (ending one period earlier to create the one-step ahead forecast). The two-year rolling RMSEs are calculated, from 25 January 2002. The results are shown below.

Figure XII. First difference Equation (23a) rolling two-year forecast errors, RMSE: Estimation period 30 Jan 1998 to 21 Dec 2018

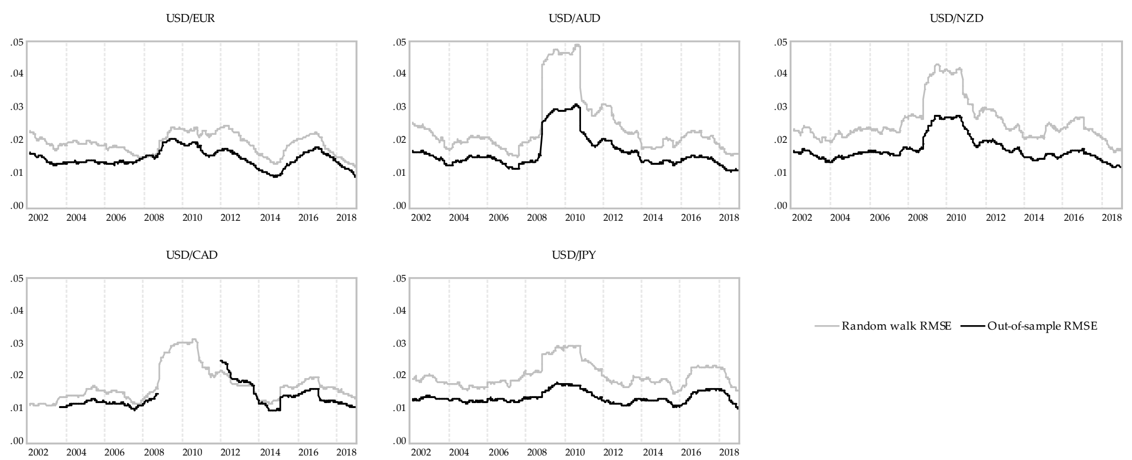
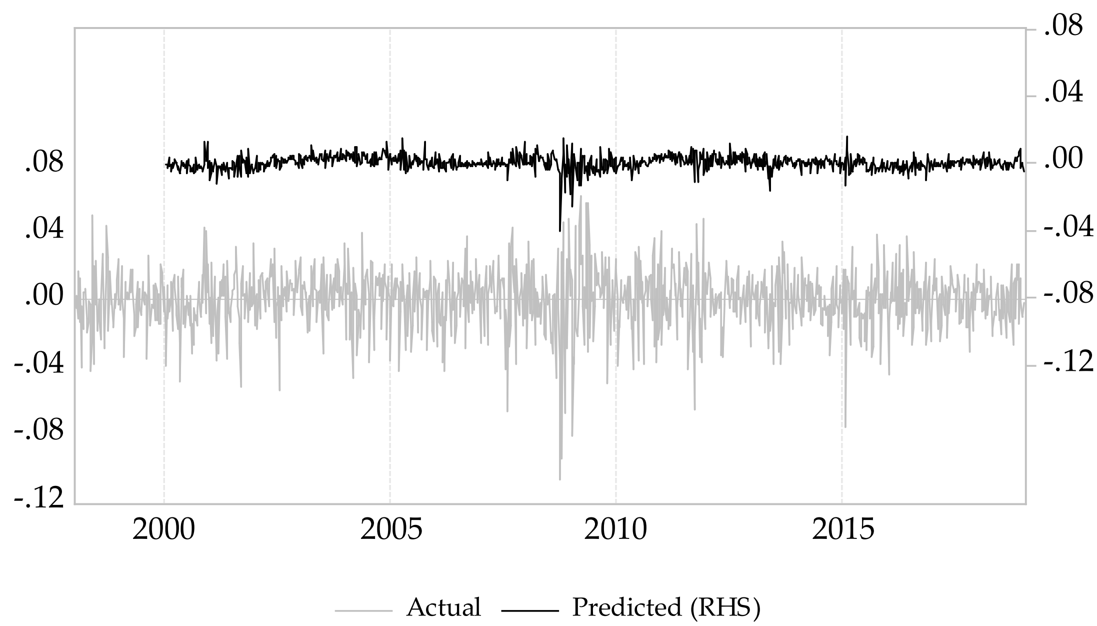


Figure XII shows the rolling two-year RMSE for the first difference in the one-week-ahead predicted exchange rate change $(s_{t+1} - \hat{s}_{t+1})$ compared to the actual change $(s_{t+1} - s_t)$ in each exchange rate based on Equation (23a). Across all exchange rates, the predicted RMSE is typically smaller than that of a random walk. However, this result does not suggest the model performs well; instead, it is a function of the poor in-sample results. In Appendix C2, Figure C9, and replicated below in Figure XIII

break is a regression first estimated between 1 January 2010 and 16 December 2011 and rolled forwards until 21 December 2018, with a sample size of N = 366.

for illustrative purposes, the variability of the USD/NZD in-sample prediction for the one-period change in the exchange rate is smaller than the underlying data series. Consequently, the ratio of the two-year rolling relative RMSE results: $\left(\frac{RMSE_{predicted}}{RMSE_{rw}}\right)$, for the change in each exchange rate based on Equation (23a) will also tend to be biased downwards. Hence, in the case of the first-difference change in the exchange rates, a low RMSE is not providing insightful conclusions.

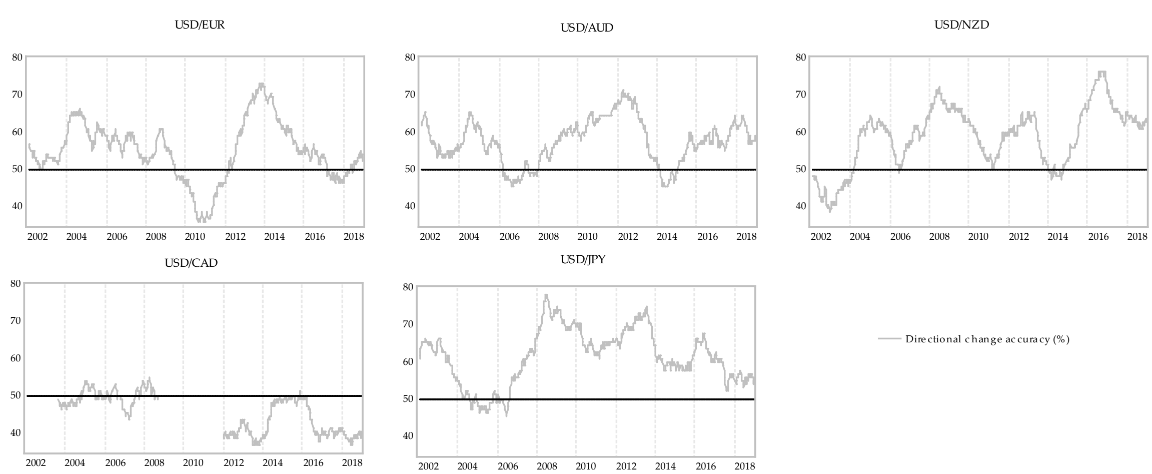
Figure XIII. Level/log level rolling fixed-window estimation output, Equation (23a) for USD/NZD



Instead, the directional change accuracy indicator is applied to see if the rolling fixed-window estimations can accurately – and reliably – predict the future direction of the exchange rate over time. The directional change accuracy is calculated as a two-year rolling average, with the results shown in Figure XIV.

Figure XIV shows the directional change accuracy indicator for each exchange rate, as well as the 50 percent baseline, which delineates between success and failure for a foreign exchange trader. The results show a wide variation in the correct directional prediction both across exchange rates and across time. For example, the USD/AUD, USD/NZD, and USD/JPY results are generally above 50 percent, whereas the USD/CAD is regularly below 50 percent accuracy. The results for USD/EUR alternate widely over the sample period, between 35 percent to 73 percent.

Figure XIV. First difference Equation (23a) rolling two-year direction change accuracy one week ahead: Estimation period 30 Jan 1998 to 21 Dec 2018



It is difficult to surmise reasons for the relative predictability outperformance of the USD/NZD, USD/AUD, and USD/JPY. Cashin *et al.* (2003) explain how currencies are more reflective of commodity price movements when the economy is a large commodity exporter, but this does not explain the poor USD/CAD results (IMF, n.d.). Devereux *et al.* (2006) show that monetary policy in small open economies has a stronger pass-through to exchange rates, which could explain the relative underperformance of USD/EUR. Mishkin (2009) speculates that the monetary policy channel has a stronger link to exchange rates over the past two decades, which could explain the promising performance of the one-week-ahead directional change statistic more generally. Each possible explanation relies on the assumption that the choice of macro-financial proxy applied is correct and that the proxies correctly reflect the related fundamentals.

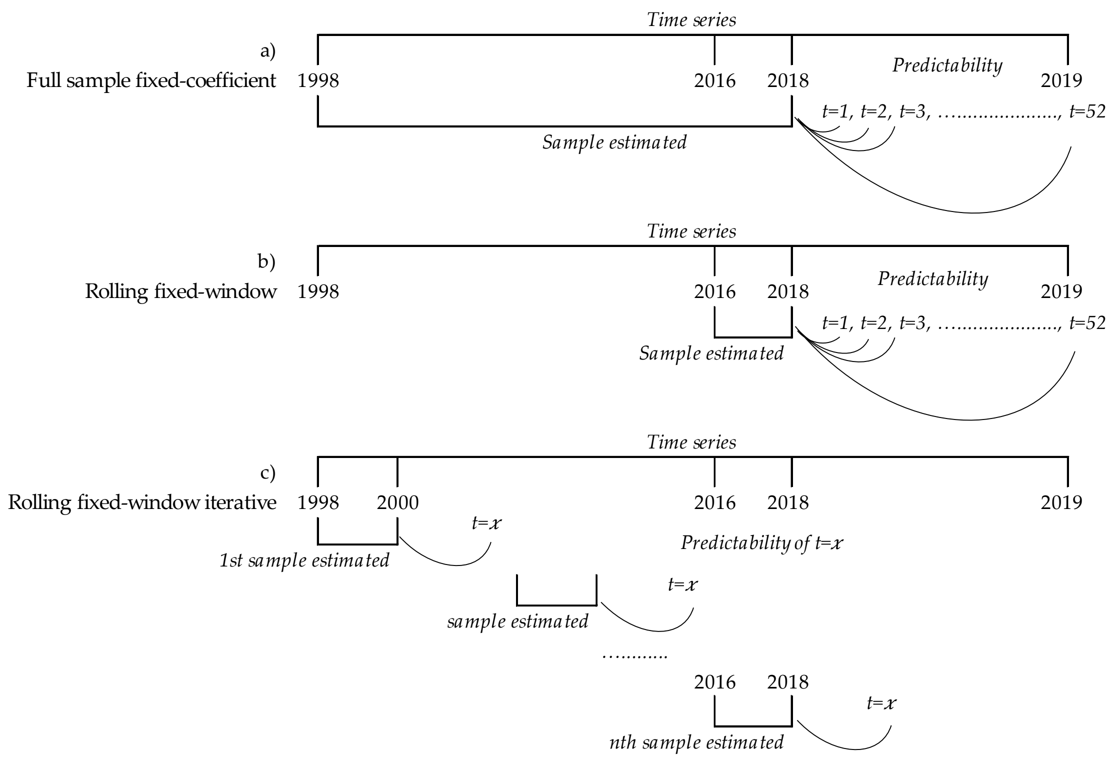
Based on these results, the out-of-sample forecasts suggest financial market participants can, according to this specification across these dates estimated, use macro-financial variables as proxies for macroeconomic variables to correctly predict the one-week-ahead direction of the exchange rate. This may explain the interest by financial market participants, as observed by the author, to focus on macro-financial variables as short-term drivers of exchange rates.

6.1.2 Multi-week ahead predictive accuracy

The one-week-ahead out-of-sample predictive accuracy results in Section 6.1.1 are promising and counter the mixed directional change accuracy forecasting results in Section 5. The rolling fixed-window results cannot be directly compared to the full-sample results but the forecasting accuracy can be compared for the rolling regressions across different forecast horizons, creating a directly comparable set of forecast results. This section explores whether the robust out-of-sample directional change accuracy results in Section 6.1.1 but mixed performance overall is a result of the forecast horizon.

To better explain this concept, consider the graphic in Figure XV. This graphic shows three examples. Each indicates the length of the data time series, the estimation sample period, and the 2019 out-of-sample forecast period.[95] The first two illustrations; a) and b), visually explain the forecasting process applied in Section 5.

Figure XV. Illustration of out-of-sample forecast approaches



As noted in Section 5.5.2, comparing the rolling fixed-window estimation forecasting results with the full-sample fixed-coefficient results is implicitly testing whether a shorter sample size (2016 – 2018), with potentially different regressor

[95] The 2019 forecast sample is relevant as is it out-of-sample.

coefficients to the coefficients in the full-sample estimation, better reflects current thematics that drive exchange rates than the forecasts based on the full-sample estimation (1998 – 2018). The predictability results from Section 6.1.1 correspond to example c) in Figure XV, where $x = 1$.

The results for the directional change accuracy for Equation (23a) when $x = 1, 12, 26,$ and 52 (one week, three months, six months, and one year) are displayed in Table XXII.

Table XXII. Average directional change accuracy (%) for the first difference

$t = x$	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
$x = 1$	55 (2.87)*	57 (4.59)*	58 (5.16)*	46 (-2.18)	60 (6.46)*
$x = 12$	50 (-.29)	48 (-1.1)	49 (-.61)	49 (-.50)	51 (.80)
$x = 26$	53 (1.88)	47 (-1.988)	53 (1.81)	47 (-1.55)	46 (-2.34)*
$x = 52$	50 (.23)	52 (1.01)	49 (-.69)	54 (1.70)	50 (.03)

Notes: t denotes the length of the step-ahead predictions. The USD/EUR, USD/AUD, USD/NZD, and USD/JPY forecast horizons are: 28 Jan 2000 to 28 Dec 2018 for $x = 1$, with a sample size N = 988; 14 Apr 2000 to 28 Dec 2018 for $x = 12$, with a sample size N = 977; 21 Jul 2000 to 28 Dec 2018 for $x = 26$, with N = 963; and 19 Jan 2001 to 28 Dec 2018 for $x = 52$, for N = 937. The forecast sample for USD/CAD for $x = 1$ is 28 January 2000 to 24 August 2001, 29 Aug 2003 to 19 Sep 2008, and 23 Dec 2011 to 28 Dec 2018, where the total sample size N = 715; for $x = 12$ the forecast observations are 14 Apr 2000 to 24 Aug 2001, 14 Nov 2003 to 19 Sep 2008, and 9 Mar 2012 to 28 Dec 2018 for a total sample size of N = 682; for $x = 26$ the forecast observations are 21 Jul 2000 to 24 Aug 2001, 20 Feb 2004 to 19 Sep 2008, and 15 Jun 201 to 28 Dec 2018 with a total sample size of N = 640; for $x = 52$ the forecast observations are 20 Aug 2004 to 19 Sep 2008 and 7 Dec 2012 to 28 Dec 2018, where the total sample size N = 531. Data in parentheses refer to the two-sided t-test where the null hypothesis is the mean is equal to 50 percent. * Indicates significance at the 5% level with d.f. >100.

A benefit of separating the out-of-sample forecast horizon in this way is to increase the number of forecasts, thereby improving the accuracy of the reported results

(Clark and McCracken, 2012). It also reduces the averaging effect (if any exists) of the predictions as the forecast horizon lengthens.

In aggregate, the results suggest that as the forecast horizon lengthens, the predictive accuracy weakens. The USD/CAD is an exception but in general the predictive accuracy of the USD/CAD model is close to 50 percent.

These outturns can be tested to see if they are statistically different to 50 percent or statistically different over forecast time-horizons. A Diebold-Mariano (DM) test (Diebold and Mariano, 1995) is frequently applied to determine if two competing set of forecasts are statistically different (Diebold, 2012). A benefit of the DM test is that it allows the forecast errors to have a non-normal distribution (Gilleland and Roux, 2015). However, the DM test cannot be applied to the directional change statistics because the loss function is bimodal (correct directional change or incorrect change) and the RMSE is biased, as demonstrated above. For the same reasons (bimodal distribution), non-parametric hypothesis tests cannot be applied.

Instead, the two-sided *t*-test is applied. A Student *t*-test assumes a normal distribution but is less sensitive to non-normal data when the sample size is large (Canavos, 1988). The results, based on the null hypothesis that the directional change is equal to 50 percent with the alternative hypothesis that they are different, are shown in parentheses in Table XXII. In the one-week-ahead forecasts the directional change accuracy is statistically significantly different to 50 percent for all exchange rates, with the exception of the USD/CAD. The null hypothesis of the mean equal to 50 percent is not rejected for the remaining forecast horizons, except the USD/JPY when the out-of-sample forecast horizon extends to six months.

This result has important implications. It raises questions around the reliability (and significance) of any of the directional change accuracy indicators discussed in Section 5, both due to the lack of statistical significance as the forecast window lengthens, and because of the small sample size of the true out-of-sample period (2019). The results here indicate that the averaging effect of multiple step-ahead forecasts dilute information surrounding the predictability of exchange rate models. The RMSE result also casts doubt over interpretations of the first difference models.

These results, however, do not explain why more generally the in-sample model performance of Equation (23a) in first difference terms is particularly poor (suggesting the regressors do not describe future exchange rate movements well) and yet the predictive accuracy improves upon all other models considered. These conflicting results are left for future research.

Section 7. Discussion and Conclusions

This thesis uses macro-finance variables to analyse the out-of-sample forecasting performance of a traditional reduced-form augmented sticky-price exchange rate model. The model choice is motivated to be consistent with previous studies, to implicitly test if macro-financial variables explain exchange rates well and if time-varying coefficients improve the out-of-sample predictability. The study focuses on short-term (weekly) data frequency and substitutes macroeconomic variables for macro-financial proxies. In the author's experience, financial market participants use these macro-financial variables as proxies for the macroeconomic equivalents between the official statistic agency publication releases. Asset prices utilised as macro-financial proxies have the additional benefit of allowing the expectations component to affect the exchange rate through a variety of channels (in addition to relative interest rates), they exhibit greater volatility than macroeconomic time series and thus align more closely with the variability of exchange rates, and macro-financial data avoid the usual criticisms of data publication lags and revisions. This study defines forecasting success by the forecast predictions compared with a random walk as well as a measure of the accuracy of directional change.

The model estimates the USD/GBP, USD/EUR, USD/AUD, USD/NZD, USD/CAD, and USD/JPY exchange rates between 30 January 1998 and 28 December 2018. The in-sample results show that macro-financial models explain the behaviour of exchange rates in a levels/log levels relationship, consistent with the literature, but further investigation indicates the relationships are subject to spurious findings.

There is evidence of a long-run equilibrium relationship in only one exchange rate (USD/GBP) over the time period estimated. Despite the potential for spurious relationships, the forecasting analyses are applied to all model specifications in order to align with the literature and because it matches behaviour by financial market participants, which the author experienced when working on foreign exchange trading floors. The results show, in both levels/log levels and in an error-correction framework, there is little consistency across or between the full-sample fixed-coefficient and the rolling fixed-window (time-varying parameter) specification, across currency pairs, time periods, or equation type. When a lagged dependent variable is included in the regression, some explanatory variables remain statistically significant, possibly indicating a market inefficiency in foreign exchange markets. At times the predictions beat a random walk, using two forecast sample periods (5 January 2018 to 28 December 2018 and 4 January 2019 to 27 December 2019) and frequently, but not consistently, the predictions are more accurate than expected by chance. These results are consistent with publications that apply macroeconomic data to predict exchange rates and do not provide additional insights for researchers interested in exchange rate determination and exchange rate forecasting.

The exchange rates are also modelled in a first difference specification. The regressors are poor at explaining the in-sample change in exchange rates – either in concurrent terms (recent changes in regressors explain current changes in the exchange rate, as is regularly applied in the literature) and especially in the case of a forecasting formulation (current changes in regressors explain future changes in the exchange rate). Nevertheless, the out-of-sample forecasting results regularly outperform a random walk and the directional change indicator is frequently above

50 percent. A deeper dive into the reliability of the out-of-sample forecast shows financial market participants can apply macro-financial variables as proxies for macroeconomic variables, utilising a time-varying first-difference specification across the dates estimated, to correctly predict the week-ahead change in most nominal exchange rates.

However, there remain reasons to be skeptical of these promising first difference results. The robust out-of-sample results are contrary to the poor in-sample fit. Even when the lagged dependent variable is incorporated, the regressions frequently show residual serial correlation and there are lingering concerns around model misspecification. Evidence of structural breaks suggest the model would be better estimated in a non-linear model form.

This thesis identifies several areas for future research. The in-sample model may benefit by including the term structure of the yield curve or different relative tradeable prices, especially for countries such as Japan and the Eurozone that are not significant commodity-exporters. Another avenue for future research is relaxing the linearity of a macro-financial model specification to possibly better explain the unknown underlying DGP, such as a time-varying vector autoregression (VAR) or a Markov-switching model. A time-varying VAR or a systems approach to exchange rate estimation using macro-financial data may help researchers identify the drivers of exchange rates and the persistence of these drivers over time.

This paper focuses on whether globally-traded assets are useful variables for predicting the exchange rate over short horizons. The answer is: possibly, but further research is warranted.

References

Aliber, R. Z. (1973) The interest rate parity theorem: A reinterpretation. *Journal of Political Economy*, 81(6), pp. 1451-1459, Nov/Dec.

Allen, M. P. (1997) *Understanding regression analysis*. New York, Plenum Press.

Andolfatto, D. & Li, L. (2014) Quantitative easing in Japan: Past and present. *St Louis Federal Reserve Economic Synopses*, number 1, January.

Andrews, D. W. K. (1991) Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica*, 59(3), pp. 817-858, May.

Andrews, D. W. K. (1993) Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61(4), pp. 821-856.

Andrews, D. W. K., Lee, I. & Ploberger, W. (1996) Optimal changepoint tests for normal linear regression, *Journal of Econometrics*, 70(1), pp. 9-38.

Ang, A. & Chen, J. (2010) Yield curve predictors of foreign exchange returns. *AFA 2011 Denver Meetings Papers*, Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1542342 [Accessed 13 September 2021], 13 March.

Armstrong, J. S. & Collopy, F. (1992) Error measures for generalizing about forecasting methods: Empirical comparisons. *International Journal of Forecasting*, 8(1), pp. 69-80, June.

Arteta, C., Kose, M. A., Stocker, M. & Taskin, T. (2018) Implications of negative interest rate policies: An early assessment, *Pacific Economic Review*, 23, pp. 8-26.

Asteriou, D. & Hall, S. G. (2007) *Applied Econometrics, a modern approach using EViews and Microfit*. Basingstoke, Palgrave MacMillan.

Bacchetta, P. & van Wincoop, E. (2004) A scapegoat model of exchange-rate fluctuations. *The American Economic Review*, 94(2), pp. 114-118, May.

Bacchetta, P., van Wincoop, E., & Beutler, T. (2010) Can parameter instability explain the Meese-Rogoff puzzle? *NBER International Seminar on Macroeconomics*, 6(1), pp. 125-173.

Bahmani-Oskooee, M. & Saha, S. (2015) On the relation between stock prices and exchange rates: a review article. *Journal of Economic Studies*, 42(4), pp. 707-732.

Bai, J. & Ng, S. (2012) Tests for skewness, kurtosis, and normality for time series data. *Journal of Business & Economics Statistics*, 23(1), pp. 49-60.

Bai, J. & Perron, P. (1998) Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1), pp. 47-78.

Bai, J. & Perron, P. (2003a) Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18, pp. 1-22, Jan/Feb.

Bai, J. & Perron, P. (2003b) Critical Values for Multiple Structural Change Tests. *Econometrics Journal*, 6, pp. 72-78.

Bai, J. & Perron, P. (2006) Multiple structural change models: A simulation analysis. In: Corbae, D., Durlauf, S. & Hansen, B. (eds.), *Econometric Theory and Practice: Frontiers of Analysis and Applied Research*, Cambridge: Cambridge University Press, pp. 212-238.

Bailey, A. (2017) The future of LIBOR. Speech at *Bloomberg*, London, 27 July 2017.

Balassa, B. (1964) The purchasing-power parity doctrine: A reappraisal. *Journal of Political Economy*, 72(6), pp. 584-596.

Banerjee, A., Dolado, J., Galbraith, J. W. & Hendry, D. F. (1993) *Co-integration, error-correction, and the econometric analysis of non-stationary data*. New York, Oxford University press Inc.

Bank of Japan. (2000) Outline of the Bank of Japan's foreign exchange intervention operations. [Online]. Available from: https://www.boj.or.jp/en/intl_finance/outline/expkainyu.htm/ [Accessed: 28 January 2019], July.

Bastianin, A. (2020) Robust measures of skewness and kurtosis for macroeconomic and financial time series. *Applied Economics*, 52(7), pp. 637-670.

Bauer, M. D. & Rudebush, G. D. (2015) Optimal monetary policy and market-based expectations. *Federal Reserve Bank of San Francisco Economic Letter, 2015-12, April.* Available from: https://www.frbsf.org/economic-research/publications/economic-letter/2015/april/monetary-policy-market-based-expectations/ [Accessed 4 June 2019].

BBC News. (1999) *Business: The economy Japan's 'managed float' for yen*. [Online]. Available from: http://news.bbc.co.uk/2/hi/business/395148.stm [Accessed 28 January 2019], 15 July.

Beckmann, J., Czudaj, R. & Arora, V. (2017) The relationship between oil prices and exchange rates: Theory and evidence. *EIA Working Paper*, July. Available from: https://www.eia.gov/workingpapers/pdf/oil_exchangerates_61317.pdf [Accessed 26 February 2022].

Berger, D., Chaboud, A., Hjalmarsson, E. & Howorka, E. (2006) What drives volatility persistence in the foreign exchange market? *Federal Reserve International Finance Discussion Papers*, number 862, May.

Bernanke, B. S. (2004) The Great Moderation. Speech to the *Eastern Economic Association*, 20 February 2004.

Bertaut, C. C. (2002) Equity prices, household wealth, and consumption growth in foreign industrial countries: Wealth effects in the 1990s. *Board of Governors of the Federal Reserve System International Finance Discussion Papers*, number 724, April.

Bilson, J. F. O. (1980) The 'speculative efficiency' hypothesis. *NBER Working Paper*, number 474, April.

BIS. (2011) Euro area sovereign crisis drives global financial markets, *BIS Quarterly Review*, December.

BIS. (2016) Foreign exchange turnover in April 2016. *BIS Triennial Central Bank Survey*, September.

BIS. (2019) Foreign exchange turnover in April 2019. *BIS Triennial Central Bank Survey*, September.

Black, F. (1986) Noise. *Journal of Finance*, 41(3), pp. 528-543, July.

Bliemel, F. (1973) Theil's forecast accuracy coefficient: A clarification. *Journal of Marketing Research*, 10, pp. 444-446, November.

Blough, S. R. (1992) The relationship between power and level for generic unit root tests in finite samples. *Journal of Applied Econometrics*, 7, pp. 295-308.

Boothe, P. & Glassman, D. (1987a) The statistical distribution of exchange rates. *Journal of International Economics*, 22(3-4), pp. 297-319.

Boothe, P. & Glassman, D. (1987b) Comparing exchange rate forecasting models: Accuracy versus profitability. *International Journal of Forecasting*, 3(1), pp. 65-79.

Bordo, M. D., Choudhri, E. U., Fazio, G. & MacDonald, R. (2014) The real exchange-rate in the long run: Balassa-Samuelon effects reconsidered. *NBER Working Paper*, number 20228, June.

Borio, C., Disyatat, P., Xia, D. & Zakrajšek, E. (2021) Monetary policy, relative prices and inflation control: flexibility born out of success. *BIS Quarterly Review*, pp. 14-29, September.

Botman, D., de Carvalho Filho, I. & Lam. W. R. (2013) The curious case of yen as safe haven currency: A forensic analysis. *IMF Working Paper*, WP/13/228, November.

Boudoukh, J., Richardson, M. & Whitelaw, R. F. (2016) New evidence on the forward premium puzzle. *Journal of Financial and Quantitative Analysis*, 51(3), pp. 875-987, June.

Breusch, T. S. (1978) Testing for autocorrelation in dynamic linear models. *Australian Economic Papers*, 17(31), pp. 334-355.

Brook, A-M. & Hargreaves, D. (2000) A macroeconomics balance measure of New Zealand's equilibrium exchange rate. *Reserve Bank of New Zealand Discussion Paper*, DP2000/09, December.

Brzoza-Brzezina, M. & Crespo Cuaresma, J. (2007) Mr. Wicksell and the global economy: What drives real interest rates. *Austrian Central Bank Working Paper*, number 139.

Budria Rodriguez, S., Diaz-Gimenez, J., Quadrini, V. & Rios-Rull, J-V. (2002) Updated factors on the U.S. distributions of earnings, income, and wealth. *Federal Reserve Bank of Minneapolis Quarterly Review*, 26(3), pp. 2-35, Summer.

Burns, K. & Moosa, I. A. (2015) Enhancing the forecasting power of exchange rate models by introducing nonlinearity: Does it work? *Economic Modelling*, 50, pp. 27-39.

Ca'Zorzi, M., Cap, A., Majakovic, A. & Rubaszek, M. (2020) The predictive power of equilibrium exchange rate models. *ECB Working* Paper, number 2359, January.

Callen, J. L. & Fang, X. (2013) Institutional investor stability and crash risk: Monitoring versus short-termism?, *Journal of Banking and Finance*, 37, pp. 3047-3063.

Campbell, J. Y. & Cocco, J. F. (2007) How do house prices affect consumption? Evidence from micro data. *Journal of Monetary Economics*, 54(3), pp. 591-621, April.

Campbell, J. Y. & Cochrane, J. H. (1999) By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2), pp. 205-251.

Campbell, J. Y. & Perron, P. (1991) Pitfalls and opportunities: What macroeconomists should know about unit roots. In: Blanchard, O. J. & Fischer, S.

(eds.), *NBER Macroeconomics Annual 1991* (vol. 6). Cambridge: The MIT Press, pp. 141-220.

Campos, J., Ericsson, N. R. & Hendry, D. F. (1993) Cointegration tests in the presence of structural breaks, *Federal Reserve International Finance Discussion Papers*, number 440, February.

Canavos, G. C. (1988) The sensitivity of the one-sample and two-sample student t statistics, *Computational Statistics & Data Analysis*, 6(1), pp. 39-46, January.

Canedese, G. & Stopler, T. (2012) Currency fair value models. In James, J., March, I. W. & Sarno, L. (eds.), *Handbook of Exchange Rates* (1st ed.). New Jersey: John Wiley & Sons, Inc., pp. 313-342.

Caporale, T. & Grier, K. (2000) Political regime changes and the real interest rate. *Journal of Money, Credit, and Banking*, 32(3), pp. 320-334.

Carrion-i-Silvestre, J. L. & Sansó, A. (2006) Testing the null of cointegration with structural breaks. *Oxford Bulleting of Economics and Statistics*, 68(5), pp. 623-646.

Casas, C., Diez, F., Gopinath, G. & Gourinchas, P-O. (2016) Dollar pricing redux. *BIS Working Paper*, number 653, August.

Cashin, P., Céspedes, L. F. & Sahay, R. (2003) Commodity currencies. *IMF Finance & Development quarterly 7magazine*, 40(1).

Cashin, P., Céspedes, L. F. & Sahay, R. (2004) Commodity currencies and the real exchange rate. *Journal of Development Economics*, 75, pp. 239-268.

Casini, A. & Perron, P. (2018) Structural breaks in time series. *Boston University Department of Economics Working Paper*, WP2019-02, Boston University, Department of Economics. [Online.] Available from: https://ideas.repec.org/p/bos/wpaper/wp2019-002.html. [Accessed 5 March 2022].

Cassino, E. & Wallis, Z. (2010) The New Zealand dollar through the global financial crisis. *RBNZ Bulletin*, 73(3), pp. 20-30, September.

Cavaliere, G., Phillips, P. C. B., Smeekes, S. & Taylor, A. M. R. (2015) Lag length selection for unit root tests in the presence of nonstationary volatility. *Economics Reviews*, 34(4), pp. 512-536.

Chaboud, A. P. & Humpage, O. F. (2005) An assessment of the impact of Japanese foreign exchange intervention: 1991-2004. *Board of Governors of the Federal Reserve System International Finance Discussion Papers*, number 824, January.

Chaboud, A. & LeBaron, B. D. (2001) Foreign-exchange market trading volume and Federal Reserve intervention. *The Journal of Futures Markets*, 21(9), pp. 851-860.

Chan, K., Tse, K. & Williams, M. (2009) The relationship between commodity prices and currency exchange rates: Evidence from the futures markets. In: Ito, T. & Rose, A. K. (eds.), *Commodity prices and markets, East Asia seminar on Economics* (vol. 20). Chicago: University of Chicago Press, pp. 47-71.

Charemza, W. W. & Deadman, D. F. (1997) New Directions in Econometric Practice: General to Specific Modelling, Cointegration, and Vector Autoregression (2nd ed.). Cheltenham: Edward Elgar Publishing Limited.

Chen, Y-C. & Rogoff, K. (2003) Commodity currencies. *Journal of International Economics*, 60(10), pp. 133-160.

Chen, Y. & Tsang, K. P. (2011) A macro-finance approach to exchange rate determination. *HKIMR Working Paper*, number 01/2011. Available from: http://www.hkimr.org/uploads/publication/78/ub_full_0_2_265_wp-no-1_2011-final-.pdf. [Accessed 4 May 2016].

Chen, Y. & Tsang, K. P. (2013) What does the yield curve tell us about exchange rate predictability? *The Review of Economics and Statistics*, 95(1), pp. 185-205, March.

Cheung, Y-W. & Chinn, M. D. (1999) Macroeconomic implications of the beliefs and behaviour of foreign exchange traders. *NBER Working Paper*, number 7417, November.

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, pp. 1150-1175.

Cheung, Y-W., Chinn, M. D., Pascual, A. G. & Zhang, Y. (2017) Exchange rate prediction redux: new models, new data, new currencies. *ECB Working Paper*, 2018, February.

Cheung, Y-W. & Erlandsson, U. G. (2005) Exchange rates and markov switching dynamics. *Journal of Business & Economic Statistics*, 23(3), pp. 314-320.

Chinn, M. D. (1991) Some linear and nonlinear thoughts on exchange rates. *Journal of International Money and Finance*, 10, pp. 214-230.

Chinn, M. D. (1997) Paper pushers of paper money? Empirical assessment of fiscal and monetary models of exchange rate determination. *Journal of Policy Modeling*, 19(1), pp. 51-78.

Chinn, M. D. (2003) Explaining exchange rate behaviour. *NBER Reporter: Research Summary*, Spring, Available from:

http://www.nber.org/reporter/spring03/explaininge.html. [Accessed 7 March 2016].

Chinn, M. D. (2008) Nonlinearities, business cycles and exchange rates. *Economic Notes*, 37(3), pp. 219-239.

Chinn, M. D. & Frankel, J. (2019) A third of a Century of currency expectations data: The carry trade and the risk premium. *mimeo* (January). Available from: https://scholar.harvard.edu/files/frankel/files/cf_quartercentexpectns_2019jan2.pdf . [Accessed 13 March 2021].

Chinn, M. D. & Meese, R. A. (1995) Banking on currency forecasts: How predictable is change in money? *Journal of International Economics*, 38, pp. 161-178.

Chinn, M. D. & Meredith, G. (2004) Monetary policy and long-horizon uncovered interest rate parity. *IMF Staff Papers*, 51(3), pp. 409-430.

Chow, G. C. (1989) Rational versus adaptive expectations in present value models. *The Review of Economics and Statistics*, 71(3), pp. 376-684, August.

Choy, W. K. (2003) Introducing overnight indexed swaps. *Reserve Bank of New Zealand Bulletin*, 66(1), pp. 34-39.

Christoffersen, P. F. & Diebold, F. X. (2006) Financial asset returns, direction-of-change forecasting, and volatility dynamics. *Management Science*, 52, pp. 1273-1287, August.

Claessens, S. & Rose, M. A. (2017) Asset prices and macroeconomic outcomes: A survey, *BIS Working Paper*, number 676, November.

Clarida, R. H., Sarno, L., Taylor, M. P. & Valente, G. (2003) The out-of-sample success of term structure models as exchange rate predictors: a step beyond. *Journal of International Economics*, 60, pp. 61-83.

Clark, E. & Baccar, S. (2018) Modelling credit spreads with time volatility, skewness, and kurtosis. *Annals of Operations Research*, 262, pp. 431-461.

Clark, T. E. & McCracken, M. W. (2005) The power of tests of predictive ability in the presence of structural breaks. *Journal of Econometrics*, 124, pp. 1-31.

Clark, T. E. & McCracken, M. W. (2012) Advances in forecast evaluation. In: Elliot, G. & Timmermann, A. (eds.), *Handbook of Economic Forecasting* (vol. 2, part B.). pp. 1107-1201. Available from: https://www.sciencedirect.com/handbook/handbook-of-economic-forecasting/vol/2/part/PB. [Accessed: 20 August 2022].

Claus, E., Claus, I. & Krippner, L. (2016) Monetary policy spillovers across the Pacific when interest rates are at the zero lower bound. *Asian Economic Papers*, 15(3), pp. 1-27.

Clemente, J., Gadea, M. D., Montanes, A. & Reyes, M. (2018) Structural breaks, inflation and interest rates: Evidence from the G7 countries. In: Perron, P. (ed.), *Unit Roots and Structural Breaks*. MDPI: Basel, pp. 141-157. Available from: http://www.mdpi.com/journal/econometrics/special issues/unit roots structural breaks. [Accessed: 13 March 2022].

Clements, K. W. & Frenkel, J. A. (1980) Exchange rates, money, and relative prices: The dollar-pound in the 1920s. *Journal of International Economics*, 10, pp. 249-262.

Cochrane, J. H. (2017) Macro-finance. *Review of Finance*, 21(3), pp. 945-985.

Cochrane, D. & Orcutt, G. H. (1949) Application of least squares regression to relationships containing auto-correlated error terms. *Journal of the American Statistical Association*, 44(245), pp. 32-61, March.

Contessi, S., De Pace, P. & Guidolin, M. (2014) How did the financial crisis alter the correlations of U.S. yield spreads? *Journal of Empirical Literature*, 28, pp. 362-385, April.

Cooper, D. & Dynan, K. (2016) Wealth effects and macroeconomic dynamics. *Journal of Economic Surveys*, 30(1), pp. 34-55.

Coudert, V., Couharde, C. & Mignon, V. (2008) Do terms of trade drive real exchange rates? Comparing oil and commodity currencies. *CEPII Working Paper*, number 2008-32, Available from: http://www.cepii.fr/PDF_PUB/wp/2008/wp2008-32.pdf [Accessed 13 March 2021].

Cusbert, T. & Rohling, T. (2013) Currency demand during the Global Financial Crisis: Evidence from Australia. *Reserve Bank of Australia Discussion Paper*, number 2013-01, January.

De Gooijer, J. G. & Kumar, K. (1992) Some recent developments in non-linear time series modelling, testing, and forecasting. *International Journal of Forecasting*, 8, pp. 135-156.

DeCarlo, L. T. (1997) On the meaning and use of kurtosis. *Psychological Methods*, 2(3), pp. 292-307.

DeJong, D. N., Nankervis, J. C., Savin, N. E. & Whiteman, C. H. (1992) The power problems of unit root test in time series with autoregressive errors. *Journal of Econometrics*, 51(1-3), pp. 323-343, July-September.

Del Barrio Castro, T., Rodrigues, P. M. M. & Taylor, A. M. R. (2015) On the behaviour of Phillips-Perron tests in the presence of persistent cycles. *Oxford Bulletin of Economics and Statistics*, 77(4), pp. 495-511.

Del Negro, M., Giannone, D., Giannoni, M. P. & Tambalotti, A. (2018) Global trends in interest rates. *Federal Reserve Bank of New York Staff Reports*, number 886, September.

Della Corte, P. D., Sarno, L. & Tsiakas, I. (2009) An economic evaluation of empirical exchange rate models. *The Society for Financial Studies*, 22 (9), pp. 3491-3530.

Demetrescu, M. & Hassler, U. (2016) (when) do long autoregressions account for neglected changes in parameters? *Econometric Theory*, 32, pp. 1317-1348.

Devereux, M. (1997) Real exchange rates and macroeconomics: Evidence and theory. *The Canadian Journal of Economics,* 30(4a), pp. 773-808.

Devereux, M. B., Lane, P. R., Juanyi, X. (2006) Exchange rates and monetary policy in Emerging Market economies*, The Economic Journal, 116(511), pp. 478-506.*

Dickey, D. A. & Fuller, W. A. (1979) Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427-431, June.

Dickey, D. A. & Pantula, S. G. (1987) Determining the order of differencing in autoregressive processes. *Journal of Business & Economic Statistics*, 5(4), pp. 455-461, October.

Diebold, F. X. (1988) *Empirical Modeling of Exchange Rate Dynamics*, Berlin, Springer-Verlag.

Diebold, F. X. (2012) Comparing predictive accuracy, Twenty years later: A personal perspective on the use and abuse of Diebold-Mariano tests, *NBER Working Paper*, number 18391, September.

Diebold, F. X. & Mariano, R. S. (1995) Comparing predictive accuracy*, Journal of Business and Economic Statistics*, 13(3), pp. 253-263, July.

Diebold, F. X. & Nason, J. A. (1990) Nonparametric exchange rate prediction? *Journal of International Economics*, 28, pp. 315-332.

Dornbusch, R. (1976) Expectations and exchange rates. *Journal of Political Economy*, 84 (6), pp. 1161-1176, December.

Dornbusch, R. (1980) Exchange rate economics: Where do we stand? *Brookings Papers on Economic Activity*, 2, pp. 143-185.

Dornbusch, R. (1985) Purchasing power parity. *NBER Working Paper*, number 1591, March.

Draghi, M. (2008) *Combating the global financial crisis – the role of international cooperation*, lecture to HKMA Distinguished Lecture, Hong Kong, 16 December 2008. Available from: https://www.bis.org/review/r081218b.pdf. [Accessed 2 December 2017].

Draghi, M. (2019) *Statement to the Hearing of the Committee on Economic and Monetary Affairs of the European Parliament*, 28 January 2019. [Online]. Available from: https://www.ecb.europa.eu/press/key/date/2019/html/ecb.sp190128~8b43137b4f.en.html [Accessed 28 January 2019].

Ehrmann, M. & Fratzscher, M. (2004) Exchange rates and fundamentals: new evidence from real-time data. *ECB Working Paper*, number 365, May.

Elliot, G., Rothenberg, T. J. & Stock, J. H. (1996) Efficient tests for an autoregressive unit root. *Econometrica*, 64(4), pp. 813-836, July.

Elliot, G. & Stock, J. H. (1994) Inference in time series regressions when the order of integration of a regressor is unknown. *Econometric Theory*, 10(3-4), pp. 672-700, August.

Engel, C. (1994) Can the Markov switching model forecast exchange rates? *Journal of International Economics*, 36, pp. 151-165.

Engel, C. (2016) Exchange rates, interest rates, and the risk premium. *American Economic Review*, 106(2), pp. 436-474, February.

Engel, C. & Hamilton, J. D. (1990) Long swings in the Dollar: Are they in the data and do markets know it? *American Economic Review*, 80(4), pp. 689-713.

Engel, C., Mark, N. C. & West, K. D. (2008) Exchange rate models are not as bad as you think. In: Acemoglu, D., Rogoff, K. & Woodford, M. (eds.), *NBER Macroeconomics Annual* 2007 (vol. 22). Chicago: University of Chicago Press, pp. 381-441.

Engel, C., Wang, J. & Wu, J. (2010) Long-horizon forecasts of asset prices when the discount factor is close to unity. *Federal Reserve Bank of Dallas Working Paper*, number 36, September.

Engel, C. & West, K. D. (2004) Accounting for exchange-rate variability in present-value models when the discount factor is near 1. *American Economic Review Paper and Proceedings*, 94, pp. 119-125, May.

Engel, C. & West, K. D. (2005) Exchange rates and fundamentals. *Journal of Political Economy*, 113(3), pp. 485-517.

Engle, R. F. & Granger, C. W. J. (1987) Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), pp. 251-276, March.

Ericsson, N. R. & MacKinnon, J. G. (2002) Distributions of error correction tests for cointegration, *Econometrics Journal*, 5, pp. 285-318.

Estrella, A. & Hardouvelis, G. A. (1991) The term structure as a predictor of real economic activity. *The Journal of Finance*, 46(2), pp. 555-576, June.

EU Commission. *The history of the euro*. [Online]. Available from: https://ec.europa.eu/info/about-european-union/euro/history-euro/history-euro_en. [Accessed 9 October 2017].

Evans, M. D. D. (1996) Peso problems: Their theoretical and empirical implications. In: Maddala, G. S. & Rao, C. R. (eds.), *Handbook of Statistics: Statistical Methods in Finance* (vol. 14). Amsterdam: Elsevier Science B.V., pp. 613-646.

Evans, M. D. D. & Lyons, R. K. (2003) How is macro news transmitted to exchange rates? *NBER Working Paper*, Number 9433, January.

Evans, M. D. D. & Lyons, R. K. (2009) Forecasting exchange rate fundamentals with order flow. *CiteSeerX*. Available from: https://core.ac.uk/download/files/145/21172766.pdf. [Accessed: 14 October 2014].

Fair, R. C. (1986) Evaluating the predictive accuracy of models. In: Griliches, Z. & Intriligator, M. D (eds.), *Handbook of Econometrics* (vol. 3). Amsterdam, Elsevier Science Publishers B.V., pp. 1979-1995.

Fama, E. F. (1984) Forward and spot exchange rates. *Journal of Monetary Economics,* 14, pp. 319-338.

Fama, E. F. & MacBeth, J. D. (1973) Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), pp. 607-636, May.

Faust, J., Rogers, J. H. & Wright, J. H. (2001) Exchange rate forecasting: The errors we've really made. *Federal Reserve Board International Finance Discussion Papers*, number 714, December.

Fawley, B. W. & Neely, C. J. (2013) Four stories of quantitative easing. *Federal Reserve Bank of St. Louise Review*, 95(10), pp. 51-88, January/February.

Federal Deposit Insurance Corporation (FDIC). (2017) *Crisis and Response: An FDIC History, 2008–2013.* Washington, DC: FDIC. [Online.] Available at:

https://www.fdic.gov/bank/historical/crisis/crisis-complete.pdf. [Accessed: 17 October 2021].

Federal Reserve Board. (2006) *Monetary policy report submitted to the Congress*, 15 February. Online. Available from: https://www.federalreserve.gov/boarddocs/hh/2006/february/ReportSection2.htm. [Accessed 3 May 2022].

Federal Reserve. (2019) Collateralized loan obligations in the financial accounts of the United States, *FEDS Notes*, 20 September 2019. Available from: https://www.federalreserve.gov/econres/notes/feds-notes/collateralized-loan-obligations-in-the-financial-accounts-of-the-united-states-20190920.htm. [Accessed 4 March 2019].

Finn, M. G. (1999) An equilibrium theory of nominal and real exchange rate comovement. *Journal of Monetary Economics*, 44(3), pp. 453-475, December.

Fischer, S. (2017) Monetary policy expectations and surprises. Speech to *Columbia University School of International and Public Affairs*, 17 April 2017. Available from: https://www.federalreserve.gov/newsevents/speech/fischer20170417a.htm. [Accessed 1 November 2021].

Flood, R. P. & Rose, A. K. (1999) Understanding exchange rate volatility without the contrivance of macroeconomics. *The Economic Journal*, 109(459), F660-F672, November.

Foster, D. P. & Nelson, D. B. (1996) Continuous record asymptotics for rolling sample variance estimators. *Econometrica*, 64(1), pp. 139-174, January.

Frankel, A. B. (1984a) Tests of monetary and portfolio balance models of exchange rate determination. In: Bilson, J. F. O. and Marston, R. C. (eds.), *Exchange rate theory and practice*. University Chicago Press, pp. 239-260.

Frankel, A. B. (1984b) Interest rate futures: An innovation in financial techniques for the management of risk. *BIS Economic Papers*, number 12, September.

Frankel, J. A. (1979) On the mark: A theory of floating exchange rates based on real interest differentials. *American Economic Association*, 69(4), pp. 610-622, September.

Frankel, J. A. (1982a) The mystery of the multiplying marks: A modification of the monetary model. *The Review of Economics and Statistics*, 64(3), pp. 515-519, August.

Frankel, J. A. (1982b) In search of the exchange rate risk premium: A six-currency test assuming mean-variance optimization. *Journal of International Money and Finance*, 1, pp. 255-274.

Frankel, J. & Chinn, M. (1991) Exchange rate expectations and the risk premium: Tests for a cross-section of 17 currencies. *NBER Working Paper*, number 3809, August.

Frankel, J. A. & Rose, A. K. (1994) A survey of empirical research on nominal exchange rates. *NBER Working Paper*, number 4865, September.

Fratzscher, M. (2008) Communication and exchange rate policy. *Journal of Macroeconomics*, 30(4), pp. 1651-1672, December.

Fratzscher, M., Schneider, D. & Van Robays, I. (2014) Oil prices, exchange rates, and asset prices. *ECB Working Paper*, number 1689, July.

Frenkel, J. A. (1976) A monetary approach to the exchange rate: Doctrinal aspects and empirical evidence. *The Scandinavian Journal of Economics*, 78(2), pp. 200-224, June.

Frieden, J. A. (2016) *Currency politics: The political economy of exchange rate policy*, Princeton Scholarship online: Princeton University Press. Available from: http://assets.press.princeton.edu/chapters/i10364.pdf. [Accessed 18 February 2021].

Froot, K. A. & Obstfeld, M. (1989) Intrinsic bubbles: The case of stock prices. *NBER Working Paper*, number 3091, September.

Froot, K. A. & Thaler, R. H. (1990) Anomalies: Foreign exchange. *Journal of Economic Perspectives*, 4(3), pp. 179-192, Summer.

Gavin, M. (1989) The stock market and exchange rate dynamics. *Journal of International Money and Finance*, 8(2), pp. 181-200, June.

Gilleland, E. & Roux, G. (2015) A new approach to testing forecast predictive accuracy*, Meteorological Applications*, 22, pp. 534-543.

Gkillas, K., Gupta, R. & Pierdzioch, C. (2019) Forecasting (downside and upside) realized exchange-rate volatility: Is there are a role for realized skewness and kurtosis? *Physica A*, 523, pp. 1-11.

Godfrey, L. G. (1978) Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica*, 46(6), pp. 1293-1301.

Goldberg, L. S. & Tille, C. (2008) Macroeconomic interdependence and the international role of the dollar. *NBER Working Paper*, number 13820, February.

Government of Canada. (2022) *Oil demand and supply*. [Online]. Available from: https://www.nrcan.gc.ca/our-natural-resources/energy-sources-distribution/clean-fossil-fuels/oil-supply-demand/18086 [Accessed 26 February 2022].

Granger, C. W. J. (1981) Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, 16, pp. 121-130.

Granger, C. W. J. & Newbold, P. (1974) Spurious regressions in econometrics. *Journal of Econometrics*, 2(2), pp. 111-120, May.

Gregory, A., Haug, A. A. & Lomuto, N. (2004) Mixed signals among tests for cointegration, *Journal of Applied Econometrics*, 19, pp. 89-98, Jan/Feb.

Gregory, A. W., Mason, J. M. & Watt, D. G. (1996) Testing for structural breaks in cointegrated relationships, *Journal of Econometrics*, 71, pp. 321-341.

Gujarati, D. N. (1995) *Basic Econometrics* (3rd ed.). New York, McGraw-Hill.

Gyntelberg, J. & Wooldridge, P. (2008) Interbank rate fixings during the recent turmoil. *BIS Quarterly Review*, pp. 59-72, March.

Hameed, A. & Rose, A. K. (2018) Exchange rate behaviour with negative interest rates: Some early negative observations, *Pacific Economic Review*, 23, pp. 27-42.

Hann, T. H. & Steurer, E. (1996) Much ado about nothing? Exchange rate forecasting: Neural networks vs. linear models using monthly and weekly data. *Neurocomputing*, 10, pp. 323-339.

Hansen, B. E. (2001) The new econometrics of structural change: Dating breaks in U.S. labor productivity. *Journal of Economic Perspectives*, 15(4), pp. 117-128, Fall.

Hanson, S. G. & Stein, J. C. (2012) Monetary policy and long-term real rates. *Federal Reserve Board Finance and Economics Discussion*, number 46, July.

Hardouvelis, G. A. (1988) Economic news, exchange rates and interest rates. *Journal of International Money and Finance*, 7(1), pp. 23-25, March.

Hartmann, P. & Smets, F. (2018) The first twenty years of the European Central Bank: Monetary policy. *ECB Working Paper*, number 2219, December.

Hatemi-J, A. & Irandoust, M. (2002) On the causality between exchange rates and stock prices: A note. *Bulletin of Economic Research*, 54(2), pp. 197-203.

Haug, A. A., Beyer, A. & Dewald, W. (2011) Structural breaks and the Fisher effect. *The B.E. Journal of Macroeconomics*, 11(1), article 9.

Hendry, D. F. (1986) Econometric modelling with cointegrated variables: An overview, *Oxford Bulletin of Economics and Statistics*, 48(3), pp. 201-212, August.

Hendry, D. F. (1995) A typology of linear dynamic equations. In: Hendry, D. F. (ed.) *Dynamic Econometrics*. New York, Oxford University Press Inc. pp. 321-328.

Hendry, D. F. & Massmann, M. (2007) Co-breaking: Recent advances and a synopsis of the literature, *Journal of Business & Economic Statistics*, 25(1), pp. 33-51, January.

Ho, L-C. & Huang, C-H. (2015) The nonlinear relationships between stock indexes and exchange rates. *Japan and the World Economy*, 33, pp. 20-27.

Hooper, P. & Morton, J. (1982) Fluctuations in the Dollar: A model of nominal and real exchange rate determination. *Journal of International Money and Finance*, 1, pp. 39-56.

Hördahl, P. & Packer, F. (2007) Understanding asset prices: an overview. *BIS Working Paper*, number 34, March.

Hou, D. & Skeie, D. (2014) LIBOR: Origins, economics, crisis, scandal, and reform. *Federal Reserve Bank of New York Staff Papers*, number 667, March.

Hubbard, R. G. (2005) *Money, the Financial System, and the Economy*, 5th edition, Boston, Pearson Publishing.

Imbens, G. W. & Kolesar, M. (2012) Robust standard errors in small samples: Some practical advice. *NBER Working Paper*, number 18478, October.

IMF. Direction of Trade Statistics (DOTS). Available from: https://data.imf.org/?sk=9D6028D4-F14A-464C-A2F2-59B2CD424B85.

IMF. (2004) *Classification of exchange rate arrangement and monetary policy frameworks*. [Online]. Available from: https://www.imf.org/external/np/mfd/er/2004/eng/0604.htm. [Accessed 28 January 2019], June.

IMF. (2009) *Annual Report: Fighting the Global Crisis.* [Online]. Available from https://www.imf.org/~/media/Websites/IMF/imported-flagship-issues/external/pubs/ft/ar/2009/eng/pdf/_ar09engpdf.ashx. [Accessed 16 October 2021], June.

IMF. (2014) Perspectives on global real interest rates. In: *World Economic Outlook*, April.

IMF. (2015) Enhancing policy traction and reducing risks. In: *Global Financial Stability Report*, 1-54, April.

Inoue, A. & Rossi, B. (2005) Recursive predictability tests for real-time data, *Journal of Business & Economic Statistics*, 23(3), pp. 336-345, July.

Isard, P. (1995) *Exchange rate economics*. Cambridge, Cambridge University Press.

Jansen, W. J. & Nahuis, N. J. (2003) The stock market and consumer confidence: European evidence. *Economics Letters*, 79, pp. 89-98.

Jarque, C. M. & Bera, A. K. (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3), pp. 225-259.

Jensen, J. R., Mikkelsen, J. G. & Spange, M. (2017) The ECB's unconventional monetary policy and the role of exchange rate regimes in cross-country spillovers. *Danmarks Nationalbank Working Paper*, number 119. Available from: https://www.econstor.eu/handle/10419/202859. [Accessed: 13 September 2021].

Johansen, S. (1988) Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3), pp. 231-254, June-September.

Johansen, S. & Juselius, K. (1990) the maximum likelihood estimation and inference on cointegration – with applications to demand for money. *Oxford Bulleting of Economics and Statistics*, 52(2), pp. 169-210.

Jordà, O., Schularick, M., Taylor, A. M., & Ward, F. (2019) Global financial cycles and risk premiums, *IMF Economic Review*, 67, pp. 109-150.

Joyce, M. & Meldrum, A. (2008) Market expectations of future Bank Rate. *Bank of England Quarterly Review*, Q3, pp. 274-282.

Joyce, M., Relleen, J. & Sorensen, S. (2008) Measuring monetary policy expectations from financial market instruments. *ECB Working Paper*, number 978, December.

Junttila, J. & Korhonen, M. (2011) Utilizing financial market information in forecasting real growth, inflation and real exchange rate. *International Review of Economics and Finance*, 20(2), pp. 281-301.

Juselius, K. (2014) Testing for near I(2) trends when the signal-to-noise ratio is small. *Economics: The open-access, open-assessment e-journal*, 8(21), pp. 1-30.

Kanas, A. (2000) Volatility spillovers between stock returns and exchange rate changes: International evidence. *Journal of Business Finance & Accounting*, 27(3-4), pp. 447-467, April/May.

Kearns, J. & Manners, P. (2006) The impact of monetary policy on the exchange rate: A study using intraday data. *International Journal of Central Banking*, 2(4), pp. 157-183, December.

Kennedy, P. (2003) *A guide to econometrics* (5th ed.). Cambridge, The MIT Press.

Khan, M. S. & Choudhri, E. U. (2004) Real exchange rates in developing countries: Are Balassa-Samuelson effects present? *IMF Working Paper*, WP/04/188, October.

Kim, T-H. & White, H. (2004) On more robust estimation of skewness and kurtosis. *Finance Research Letters*, 1(1), pp. 56-73, March.

Kilian, L., & Lütkepohl, H. (2017) *Structural Vector Autoregressive Analysis* (2nd ed.). Cambridge: Cambridge University Press.

Kilian, L. & Taylor, M. P. (2003) Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics*, 60, pp. 85-107.

Kishan, H. (2018) US yield curve to invest in 2019, recession to follow: Reuters poll, *Reuters*, 12 December 2018. [Online]. Available from: https://www.reuters.com/article/us-markets-bonds-poll/u-s-yield-curve-to-invert-in-2019-recession-to-follow-reuters-poll-idUSKBN1OC00S [Accessed: 4 March 2019].

Kohlscheen, E., Avalos, F. H. & Schrimpf, A. (2016) When the walk is not random: Commodity prices and exchange rates. *BIS Working Paper*, number 551, March.

Kremers, J. J. M., Ericsson, N. R. & Dolado, J. J. (1992) The power of cointegration tests, *Oxford Bulletin of Economics and Statistics*, 54(3), pp. 325-348.

Krippner, L. (2010) Connecting the dots: A yield curve perspective on New Zealand's interest rates. *RBNZ Bulletin*, 73(3), pp. 5-58.

Krippner, L. (2015) *Zero Lower Bound Term Structure Modeling: A Practitioner's Guide*. Palgrave: Macmillan.

Lee, K-S. (2017) Safe-haven currency: An empirical identification. *Review of International Economics*, 25(4), pp. 924-947.

Leitch, G. & Tanner, J. E. (1991) Economic forecast evaluation: Profits versus the conventional error measures. *American Economic Review*, 81(3), pp. 580-590.

Leombroni, M., Vedolin, A., Venter, G. & Whelan, P. (2018) Central bank communication and the yield curve. *CEPR Discussion Paper*, number DP12970, June.

Leon, A., Rubio, G. & Serna, G. (2005) Autoregressive conditional volatility skewness and kurtosis. *The Quarterly Review of Economics and Statistics*, 45, pp. 599-618.

Levich, R. (1978) Further results on the efficiency of markets for foreign exchange. In: Federal Reserve Bank of Boston Conference Series¸ *Managed Exchange-Rate Flexibility: The Recent Experience*, number 20. Available from: https://www.bostonfed.org/-/media/Documents/conference/20/conf20d.pdf. [Accessed: 9 November 2018].

Levich, R. (1985) Empirical studies of exchange rates: Price behavior, rate determination and market efficiency. In: Jones, R. W. & Kenen, P. B. (eds.) *Handbook of International Economics* (vol 2). Amsterdam, Elsevier Science Publishers B.V., pp. 979-1040.

Levich, R. M. (1989) Forward rates as the optimal future spot rate forecast. In: Dunis, C. & Feeny, M. (eds.), *Exchange Rate Forecasting*, Cambridge, Woodhead-Faulkner Limited., pp. 75-98.

Lewis, M. & Rosborough, L. (2013) What in the world moves bond yields? *RBNZ Analytical Note*, AN2013/08.

Leybourne, S. & Newbold, P. (1999) One the size properties of Phillips-Perron tests. *Journal of Time Series Analysis*, 20(1), pp. 51-61.

Lilley, A., Maggiori, M., Neiman, B. & Schreger, J. (2019) Exchange rate reconnect. *Stanford Graduate School of Business Working Paper*, number 3842, June.

Lizardo, R. A. & Mollick, A. V. (2010) Oil price fluctuations and U.S. dollar exchange rates. *Energy Economics*, 32(2), pp. 399-409, March.

Lloyd, S. P. (2018) Overnight index swap market-based measures of monetary policy expectations. *Bank of England Working Paper*, number 709, February.

Lopez-Suarez, C. & Rodriguez-Lopez, J. A. (2011) Nonlinear exchange rate predictability. *Journal of International Money and Finance*, 30, pp. 877-895.

Lustig, H., Roussanov, N. & Verdelhan, A. (2011) Common risk factors in currency markets. *The Review of Financial Studies*, 24(11), pp. 3731-3777, November.

MacDonald, R. (2007) *Exchange rate economics: Theories and evidence*. New York, Routledge.

MacDonald, R. & Taylor, M. (1994) The monetary model of the exchange rate: Long-run relationships, short-run dynamics and how to beat a random walk. *Journal of International Money and Finance*, 13(3), pp. 276-290.

MacKinnon, J. G. (1996) Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Economics*, 11(6), pp. 601-618.

Maggiori, M. (2013) The U.S. dollar safety premium, Federal Reserve Bank of Dallas: International Conference on Capital Flow and Safe Assets, 26-27 May 2013, Fudan University, Shanghai. [Online] Available from: https://www.dallasfed.org/institute/events/2013/13capitalflows.aspx [Accessed 12 January 2022].

Mallick, S. K., Mohanty, M. S. & Zampolli, F. (2017) Market volatility, monetary policy and the term premium. *BIS Working Paper*, number 606, January.

Marcellino, M., Stock, J. H., & Watson, M. W. (2006) A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series, *Journal of Econometrics*, 135, pp. 499-526.

Mark, N. C. (1995) Exchange rates and fundamentals: Evidence on long-horizon predictability. *American Economic Review*, 85(1), pp. 201-218, March.

Mark, N. C. (2000) *International Macroeconomics and Finance: Theory and Econometric Methods*. Oxford: Blackwell. Available from: http://www.emu.edu.tr/mbalcilar/books/Site/Books_files/Economics%20-%20International%20Macroeconomics%20and%20Finance.pdf. [Accessed 26 September 2016].

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, pp. 29-52.

Martinez-Garcia, E., Coutler, J. & Grossman, V. (2021) Fed's new inflation targeting policy seeks to maintain well-anchored expectations. *Federal Reserve Bank of Dallas Economics Notes*, April 6. [Online]. Available from: https://www.dallasfed.org/research/economics/2021/0406. [Accessed 27 September 2021].

McBride, J. (2016) Understanding the libor scandal. *Council on Foreign Relations*. [Online]. Available from https://www.cfr.org/backgrounder/understanding-libor-scandal. [Accessed 4 March 2019].

McCauley, R. N. & McGuire, P. (2009) Dollar appreciation in 2008: Safe haven, carry trades, dollar shortage and overhedging. *BIS Quarterly Review*, pp. 85-93, December.

McDermott, C. J. (1990) Cointegration: Origins and significance for economists. *New Zealand Economic Papers*, 24, pp. 1-23.

McDonald, C. (2012) Kiwi drivers – the New Zealand dollar experience. *RBNZ Analytical Note*, AN2012/02.

McNown, R., Sam, C. Y. & Goh, S. K. (2016) Bootstrapping the autoregressive distributed lag test for cointegration. *University of Colorado Working Paper*, number 16-08, November. [Online]. Available from: https://www.colorado.edu/economics/sites/default/files/attached-files/wp16-08.pdf. [Accessed 7 March 2022].

Meese, R. (1990) Currency fluctuations in the post-Bretton Woods era. *The Journal of Economic Perspectives*, 4(1), pp. 117-134.

Meese, R. A. & Rogoff, K. (1983) Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics*, 14, pp. 3-24.

Meese, R. A. & Rose, A. K. (1991) An empirical assessment of non-linearities in models of exchange rate determination. *The Review of Economic Studies Special Issue: The Econometrics of Financial Markets*, 58(3), pp. 603-619.

Meese, R. A. & Singleton, K. J. (1982) On unit roots and the empirical modeling of exchange rates. *The Journal of Finance*, 37(4), pp. 1029-1035, September.

Melvin, M. & Taylor, M. P. (2009) The crisis in the foreign exchange market. *The Journal of International Money and Finance*, 28, pp. 1317-1330.

Menkhoff, L., Sarno, L., Schmeling, M. & Schrimpf, A. (2012) Carry trades and global foreign exchange volatility. *Journal of Finance*, 67(2), pp. 681-718, April.

Michael, P., Nobay, A. R. & Peel, D. A. (1997) Transaction costs and nonlinear adjustment in real exchange rates: An empirical investigation. *Journal of Political Economy*, 105(4), pp. 862-879, August.

Mills, T. C. (1990) *Time Series Techniques for Economists*, Cambridge, Cambridge University Press.

Miranda-Agrippino, S. & Rey, H. (2020) U.S. monetary policy and the global financial cycle. *Review of Economic Studies*, 87, pp. 2754-2776.

Mishkin, F. S. (2009) Globalization, macroeconomic performance, and monetary policy, *Journal of Money, Credit and Banking*, 41(1), pp. 187-196, February.

Molodtsova, T., Nikolsko-Rzhevskyy, D. & Papell, D. H. (2008) Taylor rules with real-time data: A tale of two countries and one exchange rate. *Journal of Monetary Economics*, 55, S63–S79.

Molodtsova, T. & Papell, D. H. (2009) Out-of-sample exchange rate predictability with Taylor rule fundamentals. *Journal of International Economics*, 77, pp. 167-180.

Moosa, I. (2013) Why is it so difficult to outperform the random walk in exchange rate forecasting? *Applied Economics*, 45(23), pp. 3340-3346.

Moosa, I. A. & Bhatti, R. H. (1997) *International Parity Conditions: Theory, econometric testing and empirical evidence*, New York: St. Martin's Press, Inc.

Moosa, I. A. & Bhatti, R. H. (2009) *The theory and empirics of exchange rates*. World Scientific Publishing Company. Online. Available from https://www.worldscientific.com/worldscibooks/10.1142/7213#:~:text=Exchange%20rate%20economics%20is%20an,and%20effects%20of%20exchange%20rates. [Accessed 12 December 2021].

Moosa, I. & Burns, K. (2014) The unbeatable random walk in exchange rate forecasting: Reality or myth? *Journal of Macroeconomics*, 40, pp. 69-81.

Moosa, I. & Burns, K. (2015) Can exchange rate models outperform the random walk? Magnitude, direction and profitability as criteria. *Economia Internazional*, 65(3), pp. 473-490.

Morana, C. (2015) The US$/€ exchange rate: Structural modeling and forecasting during the recent financial crises. *University of Milan Bicocca Department of Economics, Management and Statistics Working Paper*, number 321.

Munro, A. (2014) Exchange rates, expected returns and risk. *RBNZ Discussion Paper*, DP2014/01, April.

Mussa, M. (1984) The Theory of Exchange Rate Determination. In: Bilson, J. F. O., & Marston, R. C. (eds.), *Exchange Rate Theory and Practice*. Chicago, University of Chicago Press, pp. 13-78.

Mussa, M. (1986) Nominal exchange rate regimes and the behavior of real exchange rates: Evidence and implications. *Carnegie-Rochester Conference Series on Public Policy*, 25, 117-214, Autumn.

Narayan, P. K. (2005) The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics*, 37(17), pp. 1979-1990.

Neely, C. J. (2011) A survey of announcement effects on foreign exchange volatility and jumps. *Federal Reserve Bank of St. Louis Review*, 93(5), pp. 361-407, September/October.

Neely, C. J. (2016) How persistent are unconventional monetary policy effects? *Federal Reserve Bank of St. Louis Working Paper*, 2014-004C, October.

Neely, C. J. & Dey, S. R. (2010) A survey of announcement effects on foreign exchange returns. *Federal Reserve Bank of St. Louis Review*, 92(5), pp. 417-463, September/October.

Neely, C. J. & Sarno, L. (2002) How well do monetary fundamentals forecast exchange rates? *Federal Reserve Bank of St Louis Review*, pp. 51-74, September/October.

Neff, S. & Coleman, M. (2014) EIA outlook: reversal in U.S. oil import dependency. *Energy Strategy Reviews*, 5, pp. 6-13.

Nelson, C. R. & Plosser, C. I. (1982) Trends and random walks in macroeconomic time series: Some evidence and implications. *Journal of Monetary Economics*, 10, pp. 139-162.

Newey, W. & West, K. (1987) A simple positive semi-definite, heteroskedastic and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), pp. 703-708, May.

Ng, S. & Perron, P. (1995) Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag. *Journal of the American Statistical Association*, 90(429), pp. 268-281, March.

Osborne, M. (2016) Monetary policy and volatility in the sterling money market. *Bank of England Staff Working Paper*, number 588, April.

Park, J. S. (2015) The duration analysis of structural breaks: is stability destabilizing? *Applied Econometrics*, 47(9), pp. 940-954.

Perron, P. (1988) Trends and random walks in macroeconomic time series. *Journal of Economic Dynamics and Control*, 12, pp. 297-332.

Perron, P. (1989) The great crash, the oil price shock, and the unit root process. *Econometrica*, 57(6), pp. 1361-1401, November.

Perron, P. (1997) Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics*, 80(2), pp. 355-385, October.

Perron, P. (2006) Dealing with structural breaks. In Mills, T. C. & Patterson, K. (eds.), *Palgrave Handbook of Econometrics* (vol. 1). London: Palgrave Macmillan, pp. 278–352.

Perron, P. & Vogelsang, T. J. (1998) Additional test for a unit root allowing for a break in the trend function at an unknown time. *International Economic Review*, 39(4), pp. 1073-1100, November.

Pesaran, M. H., Shin, Y. & Smith, R. J. (2001) Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), pp. 289-326.

Phillips, A. Q. (2018) Have your cake and eat it too? Cointegration and dynamic inference from autoregressive distributed lag models. *American Journal of Political Science,* 62(1), pp. 230-244.

Phillips, P. C. B. & Perron, P. (1988) Testing for a unit root in time series regression. *Biometrika*, 75(2), pp. 335-346.

Pilbeam, K. (1998) *International Finance* (2nd ed.). Basingstoke, Macmillan Press Ltd.

Ponomarenko, A., Rozhkova, A. & Seleznev, S. (2018) Macro-financial linkages: The role of liquidity dependence. *BIS Working Paper*, number 716, April.

Poterba, J. M. (2000) Stock market wealth and consumption. *Journal of Economic Perspectives*, 14(2), pp. 99-118, Spring.

Potter, S. (2019) Unconventional monetary policy tools: A cross-country analysis. *BIS CGFS Papers*, number 63, October.

Prodan, R. (2008) Potential pitfalls in determining multiple structural changes with an application to purchasing power parity, *Journal of Business & Economic Studies*, 26(1), pp. 50-65.

Rachel, L. & Smith, T. D. (2015) Secular drivers of the global real interest rate. *Bank of England Staff Working Paper*, number 571, December.

Ranaldo, A. & Söderlind, P. (2010) Safe haven currencies. *Review of Finance*, 14(3), pp. 385-407, July.

Rapach, D. E. & Wohar, M. E. (2002) Testing the monetary model of exchange rate determination: new evidence from a century of data. *Journal of International Economics*, 58(2), pp. 359-385, December.

Rapach, D. E. & Wohar, M. E. (2005) Regime changes in international real interest rates: Are they a monetary phenomenon? *Journal of Money, Credit and Banking*, 37(5), pp. 887-906, October.

RBA. Inflation Target. [Online]. Available from https://www.rba.gov.au/inflation/inflation-target.html. [Accessed 3 October 2021].

RBNZ. (1990) Reserve Bank of New Zealand targets agreement. *RBNZ Bulletin*, 53(1), pp. 26-28, March.

Rey, H. (2013) Dilemma not trilemma: The global financial cycle and monetary policy independence. In *Proceedings of the 2013 Federal Reserve Bank of Kansas City Economic Symposium at Jackson Hole*, pp. 285-333.

Roger, S. (2010) Inflation targeting turns 20. *IMF Finance and Development*, 47(1), pp. 46-49, March.

Rogoff, K. (1996) The purchasing power parity puzzle. *Journal of Economic Literature,* 34(2), pp. 647-668, June.

Rogoff, K. & Meese, R. (1983) The out-of-sample failure of empirical exchange rate models: Sampling error or misspecification? In: Frenkel, J. A. (ed.), *Exchange Rates and International Macroeconomics*. Chicago, University of Chicago Press, pp. 67-112.

Rosenberg, M. R. (2003) *Exchange rate determination*. New York: McGraw-Hill.

Rossi, B. (2005) Optimal tests for nested model selection with underlying parameter instability, *Econometric Theory*, 21(5), pp. 962-990, October.

Rossi, B. (2006) Are exchange rates really random walks? Some evidence robust to parameter instability. *Macroeconomic Dynamics*, 10(1), pp. 20-38.

Rossi, B. (2013) Exchange rate predictability. *Journal of Economic Literature*, 51(4), pp. 1063-1119, December.

Rossi, B. & Sekhposyan, T. (2011) Understanding models' forecasting performance. *Journal of Econometrics*, 164(1), pp. 158-172.

Samuelson, P. A. (1964) Theoretical notes on trade problems. *The Review of Economics and Statistics*, 46(2), pp. 145-154.

Sarno, L. (2003) Nonlinear exchange rate models: A selective overview. *International Monetary Fund Working Paper*, WP/03/111.

Sarno, L. & Valente, G. (2009) Exchange rates and fundamentals: Footloose or evolving relationship? *Journal of the European Economic Association*, 7(4), pp. 786-830.

Sercu, P., Vandebroek, M. & Wu, X. (2008) Is the forward bias economically small? Evidence from European rates. *Journal of International Money and Finance*, 27, pp. 1284-1302.

Schinasi, G. J. & Swamy, P. A. V. B. (1987) The out-of-sample forecasting performance of exchange rate models when coefficients are allowed to change. *Board of Governors of the Federal Reserve System International Finance Discussion Papers*, number 301, January.

Schwert, G. W. (1989) Tests for unit roots A Monte Carlo investigation, *Journal of Business & Economic Statistics*, 7(2), pp. 147-159.

Smith, P. N. & Wickens, M. R. (1986) An empirical investigation into the causes of failure of the monetary models of the exchange rate. *Journal of Applied Econometrics*, 1, pp. 143-162.

Sonje, A. A., Casni, A. C. & Vizek, M. (2014) The effect of housing and stock market wealth on consumption in emerging and developed countries. *Economic Systems*, 38, pp. 433-450.

Stock, J. H. (1987) Asymptotic properties of least squares estimators of cointegrating vectors, *Econometrica*, 55(5), pp. 1035-1056, September.

Stock, J. H. & Watson, M. W. (2011) *Introduction to Econometrics* (3rd ed.). Boston, Addison-Wesley.

Sullivan, R. & Aldridge, T. (2011) The outlook for commodity prices and implications for New Zealand monetary policy. *RBNZ Note*, [Online]. Available from: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/the-outlook-for-commodity-prices-and-implications-for-new-zealand-monetary-policy [Accessed 18 February 2021].

Sushko, V., Borio, C., McCauley, R. & McGuire, P. (2016) The failure of covered interest rate parity: FX hedging demand and costly balance sheets. *BIS Working Paper*, number 590, October.

Tabachnick, B. G. & Fidell, L. S. (1996) *Using Multivariate Statistics* (3rd ed.). New York: Harper Collings College Publishers.

Taylor, M. P. (2001) Potential pitfalls for the purchasing-power parity puzzle: sampling and specification biases in mean-reversion tests of the law of one price. *Econometrica*, 64, pp. 1067-1084.

Taylor, M. P. & Peel, D. A. (2000) Nonlinear adjustment, long-run equilibrium and exchange rate fundamentals. *Journal of International Money and Finance*, 19, pp. 33-53.

Taylor, M. P., Peel, D. A. & Sarno, L. (2001) Nonlinear mean-reversion in real exchange rates: toward a solution to the purchase power parity puzzles. *International Economic Review*, 42(4), 1015-1042, November.

Taylor, A. M. & Taylor, M. P. (2004) The purchasing power parity debate. *Journal of Economic Perspectives*, 18(4), pp. 135-158.

Thadewald, T. & Bűning, H. (2007) Jarque-Bera test and its competitors for testing normality – A power comparison, *Journal of Applied Statistics*, 34(1), pp. 87-105.

The Financial Times. (2018) US Treasury yield curves nears flattest point in 10 years. *FastFT Markets*, 16 January 2018. [Online]. Available from: https://www.ft.com/content/456d463e-b94f-39fa-af4f-bacffe59d6a0 [Accessed: 4 March 2019].

The White House. (2003) *Operation Iraqi Freedom*. [Online]. Available from: https://georgewbush-whitehouse.archives.gov/news/releases/2003/03/20030319-17.html. [Accessed 24 June 2022].

Tica, J. & Druzic, I. (2006) The Harrod-Balassa-Samuelson effect: A survey of empirical evidence. *EFZG Working Paper*, 6-7(686), pp. 1-38.

Tuffley, N. (2010) ASB Quarterly Economic Forecasts: Looking for the exit. *scoop.co.nz*, 19 April 2010. [Online]. Available from: https://img.scoop.co.nz/media/pdfs/1004/ASB_Quarterly_Economic_Forecast_April_2010.pdf. [Accessed: 18 February 2021].

Verdelhan, A. (2013) The share of systematic variation in bilateral exchange rates. In: European Central Bank Workshop, *Exchange rates: a global perspective*, 27-28 June 2013, Frankfurt am Main, Germany. Available from: https://www.ecb.europa.eu/events/pdf/conferences/130627/2.1a_A.Verdelhan_Paper.pdf. [Accessed November 2014].

Verdelhan, A. (2018) The share of systematic variation in bilateral exchange rates. *Journal of Finance*, 73(1), pp. 375-418.

Vitale, P. (2000) Speculative noise trading and manipulation in the foreign exchange market. *Journal of International Money and Finance*, 19(5), pp. 689-712, October.

Vlieghe, G. (2017) Real interest rates and risk. Speech to *Society of Business Economists' Annual Conference*, London, 15 September 2017. Available from: http://www.bankofengland.co.uk/publications/Documents/speeches/2017/speech995.pdf. [Accessed 18 September 2017].

Vlieghe, G. (2018) The yield curve and QE. Speech to *Imperial College Business School*, 25 September 2018. Available from: https://www.bankofengland.co.uk/-/media/boe/files/speech/2018/the-yield-curve-and-qe-speech-by-gertjan-vlieghe.pdf. [Accessed 4 March 2019].

Vogt, M. (2014) Testing for structural change in time-varying nonparametric regression models, *Econometric Theory*, 31(4), pp. 811-859.

wallstreetprep.com. (2021) Bloomberg vs. Capital IQ vs. FactSet vs. Thomson Reuters Eikon. [Online.] Available from: https://www.wallstreetprep.com/knowledge/bloomberg-vs-capital-iq-vs-factset-vs-thomson-reuters-eikon/ [Accessed: 10 October 2021].

Wang, K-L., Fawson, C., Barrett, C. B. & McDonald, J. B. (2001) A flexible parametric GARCH model with an application to exchange rates. *Journal of Applied Econometrics*, 16, pp. 521-536.

White, H. (2000) A reality check for data snooping. *Econometrica*, 68(5), pp. 1097-1126.

Wolff, C. C. P. (1987) Time-varying parameters and the out-of-sample forecasting performance of structural exchange rate models. *Journal of Business & Economic Statistics*, 5(1), pp. 87-97.

Wong, M. (2017) Revisiting the wealth effect on consumption in New Zealand. *RBNZ Analytical Note*, AN2017/3, March.

Wood, A. & Reddell, M. (2014) Documenting the goals for monetary policy: some cross-country comparisons. *RBNZ Bulletin*, 77(5), pp. 1-15, October.

Wooldridge, P. D. (2001) The emergence of new benchmark yield curves. *BIS Quarterly Review*, pp. 48-57, December.

Wu, J-L. & Hu, Y-H. (2009) New evidence on nominal exchange rate predictability. *Journal of International Money and Finance*, 28, pp. 1045-1063.

Wu, J. C. & Xia, F. D. (2016) Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3), pp. 253-291.

Yap, B. W. & Sim, C. H. (2010) Comparisons of various types of normality tests. *Journal of Statistical Computation and Simulation*, 81(12), pp. 2141-2155, December.

Zaman, A. (2012) Methodological Mistakes and Econometric Consequences. *International Econometric Review*, 4(2), pp. 99-122.

Zhou, B. (1996) High-frequency data and volatility in foreign-exchange rates. *Journal of Business & Economic Statistics*, 14(1), pp. 45-52, January.

Zhou, S. (2001) The power of cointegration tests versus data frequency and time spans, *Southern Economic Journal*, 67(4), pp. 906-921.

Zou, L. P., Zheng, B. L. & Li, X. M. (2017) The commodity price and exchange rate dynamics. *Theoretical Economics Letters*, 7, pp. 1770-1793.

Appendix A. Data

A1. Data sources and definitions

BBG: Bloomberg L.P. All data were downloaded using the ticker field =BDP("xxx","BLOOMBERG_CLOSE_TIME_RT"), where xxx is the ticker of the variable of interest.

RBNZ: Reserve Bank of New Zealand. Available at: https://www.rbnz.govt.nz/statistics/b2.

OECD: Organisation for Economic Co-operation and Development. Available at: https://data.oecd.org/trade/terms-of-trade.htm.

Table A1. Data tickers and definitions: Currencies and interest rate swaps

Acronym	Title	Additional detail	Ticker
USDGBP	USD/GBP	Price of 1 USD in GBP	USDGBP Curncy
USDJPY	JPY/USD	Price of 1 USD in JPY	JPY Curncy
USDEUR	USD/EUR	Price of 1 USD in EUR	USDEUR Curncy
USDCAD	CAD/USD	Price of 1 USD in CAD	CAD Curncy
USDAUD	USD/AUD	Price of 1 USD in AUD	USDAUD Curncy
USDNZD	USD/NZD	Price of 1 USD in NZD	USDNZD Curncy
US TWI	US trade-weighted index, Major country	100 = January 2006	USTW$ Index
US2	US fixed/floating semi-annual two-year interest rate swap	30/360: actual/360 day count basis	USSW2 Curncy
UK2	UK fixed/floating semi-annual two-year interest rates swap	actual/365: actual/365 day count basis	BPSW2 Curncy
JP2	Japan fixed/floating semi-annual two-year interest rates swap	actual/365: actual/360 day count basis	JYSW2 Curncy
EU2	Europe fixed/floating annual/semi-annual two-year interest rates swap	30/360: actual/360 day count basis	EUSA2 Curncy
CA2	Canada fixed/floating semi-annual two-year interest rates swap	actual/365: actual/365 day count basis	CDSW2 Curncy
AU2	Australia fixed/floating semi-annual two-year interest rates swap	actual/365: actual/365 day count basis	ADSW2 Curncy
NZ2	New Zealand fixed/floating semi-annual/quarterly two-year interest rates swap	actual/365: actual/365 day count basis	NDSW2 Curncy

Table A2. Data tickers and definitions: Consumer price indices, commodities, and risk

Acronym	Title	Additional detail	Ticker
US CPI	US Consumer Price Index	urban consumers, s.a. 1982-1984=100	CPI INDX Index
UK CPI	UK EU Harmonized Consumer Price Index	not s.a., 2015=100	UKRPCHVJ Index
JP CPI	Japan Nationwide General Consumer Price Index	not s.a., 2015=100	JCPNGEN Index
EU CPI	Euro Area Consumer Price Index	annual percent change	EHPIEU Index
CA CPI	Canada Consumer Price Index	not s.a., 2002=100	CACPI Index
AU CPI	Australia Consumer Price Index, All Groups,	not s.a., 3Q2011-2Q2012=100	AUCPI Index
NZ CPI	New Zealand Consumer Price Index, All Groups	not s.a., 2Q2006=1000	NZCPCCPI Index
OIL	UK Crude West Texas Intermediate Cushing OK	spot price in US dollars per barrel	USCRWTIC Index
MET	Bloomberg (previously Dow Jones-UBS) industrial metals index	US dollars	BCOMIN Index
WCFI	Westpac Commodity Futures Index	export-weighted in Australian dollars	WCFIINDX Index
CRB	Thomson Reuters/Core Commodity CRB Index	arithmetic average of commodity futures prices in US dollars	CRY Index
CBA	ASB New Zealand Commodity Price Index	in US dollars	CBANZUSD Index
VIX	CBOE Volatility Index	points, where one point is one percent per annum	VIX Index

Table A3. Data tickers and definitions: Government bonds and stock markets

Acronym	Title	Additional detail	Ticker
US2	US on-the-run two-year government bond indices	yield to maturity	USGG2YR Index
UK2	UK two-year government bond	yield to maturity	GTGBP2YR Govt
NZ2	New Zealand two-year government bond	yield to maturity	GNZBG2 Index
NZ2	New Zealand two-year government bond	yield to maturity	INM.DG102.N
US10	US on-the-run ten-year government bond	yield to maturity	USGG10YR Index
NZ10	New Zealand ten-year government bond	yield to maturity	GTNZD2Y Govt
USEQ	S&P500 Index		SPX Index
EUEQ	Euro Stoxx 50 Index		SX5E Index
UKEQ	FTSE100 Index		UKX Index
JPEQ	TOPIX/Tokyo Stock Exchange Index		TPX Index
CAEQ	S&P / Toronto Stock Exchange Index		SPTSX Index
AUEQ	All Ordinaries Index		AS30 Index
NZEQ	S&P / NZX 50 Gross Index		NZSE50FG Index
NZEQ	New Zealand Top 40 Index		NZSE40 Index

A2. Data transformations

Table A4. Data transformations: Exchange rates and interest rate swaps

Acronym	Unit	Transformation / Calculation
USDGBP	price of 1 USD in GBP	natural log
USDJPY	price of 1 USD in JPY	natural log
USDEUR	price of 1 USD in EUR	natural log
USDCAD	price of 1 USD in CAD	natural log
USDAUD	price of 1 USD in AUD	natural log
USDNZD	price of 1 USD in NZD	natural log
US2	percent	
UK2	percent	
JP2	percent	
EU2	percent	
CA2	percent	
AU2	percent	
NZ2	percent	

Table A5. Data transformations: Inflation, commodities, and risk

Acronym	Unit	Transformation / Calculation
US INFL	percent	$((US\ CPI_t - US\ CPI_{t-4})/US\ CPI_{t-4})$ X 100
UK INFL	percent	$((UK\ CPI_t - UK\ CPI_{t-4})/UK\ CPI_{t-4})$ X 100
JP INFL	percent	$((JP\ CPI_t - JP\ CPI_{t-4})/JP\ CPI_{t-4})$ X 100
EU INFL	percent	$((EU\ CPI_t - EU\ CPI_{t-4})/EU\ CPI_{t-4})$ X 100
CA INFL	percent	$((CA\ CPI_t - CA\ CPI_{t-4})/CA\ CPI_{t-4})$ X 100
AU INFL	percent	$((AU\ CPI_t - AU\ CPI_{t-4})/AU\ CPI_{t-4})$ X 100
NZ INFL	percent	$((NZ\ CPI_t - NZ\ CPI_{t-4})/NZ\ CPI_{t-4})$ X 100
OIL	US dollars per barrel	natural log
WCFI	index	natural log
CRB	index	natural log
CBA	index	natural log
VIX	index	

Table A6. Data transformations: Government bonds and stock markets

Acronym	Unit	Transformation / Calculation
US2	percent	
NZ2	percent	When Bloomberg data were not recorded, replaced with the Friday closing price from RBNZ. Between 17 October 2013 and 13 December 2014 the three-year bond was substituted due to no two-year bond recorded.
US10	percent	
NZ10	percent	
USEQ	natural log	rebased to 100 as at 30 January 1998
EUEQ	natural log	rebased to 100 as at 30 January 1998
UKEQ	natural log	rebased to 100 as at 30 January 1998
JPEQ	natural log	rebased to 100 as at 30 January 1998
CAEQ	natural log	rebased to 100 as at 30 January 1998
AUEQ	natural log	rebased to 100 as at 30 January 1998
NZEQ	natural log	NZX 50 Gross Index spliced with New Zealand Top 40 Index as at 5 January 2001. Rebased to 100 as at 30 January 1998

A3. Graphical representation

Figure A1. Exchange rates

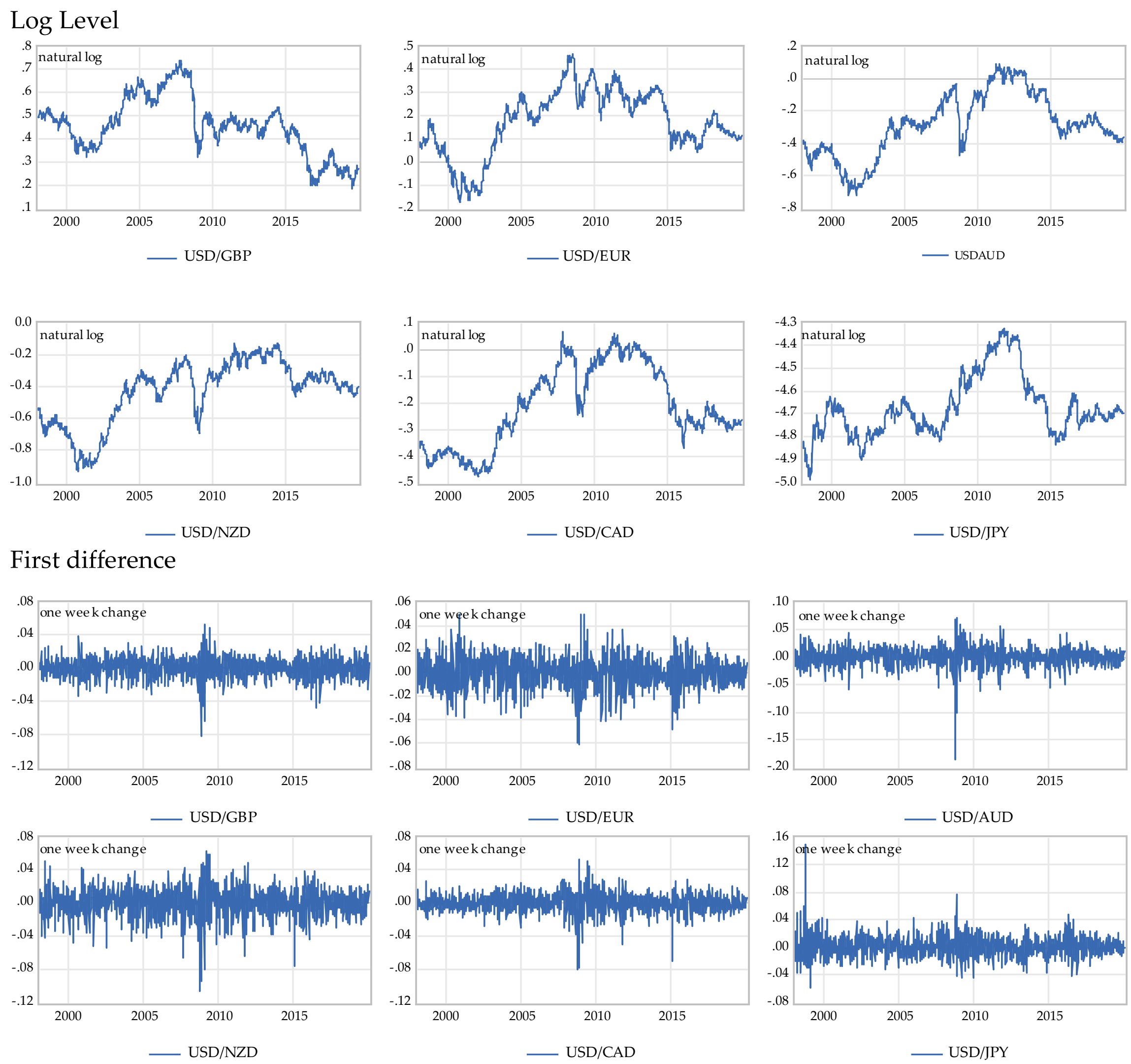
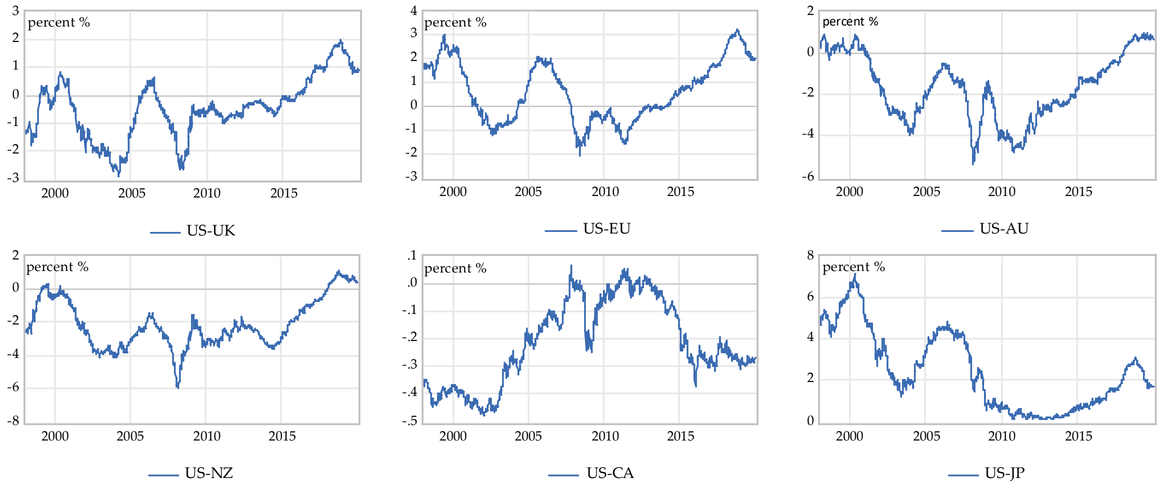


Figure A2. Two-year swap spreads

Level



First difference

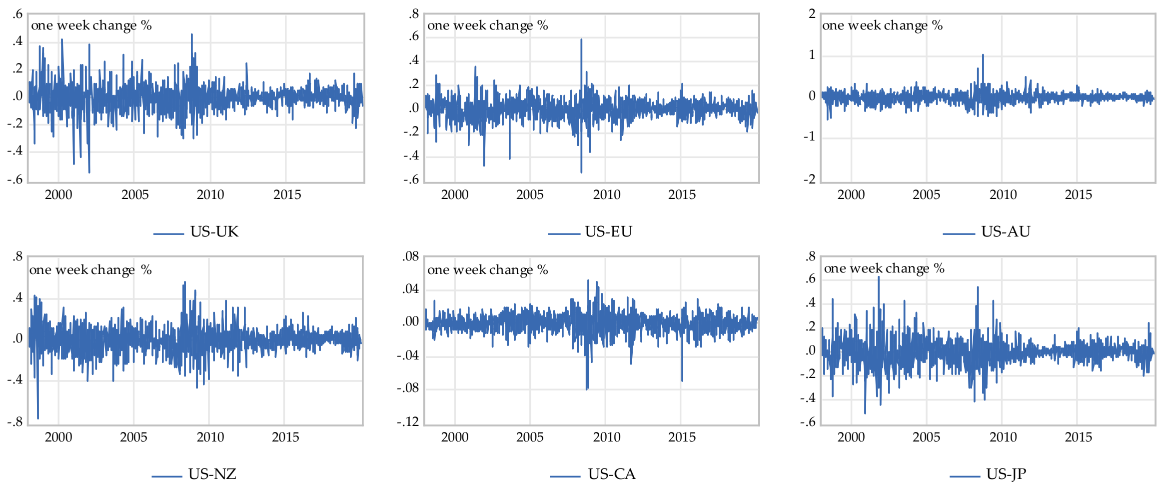
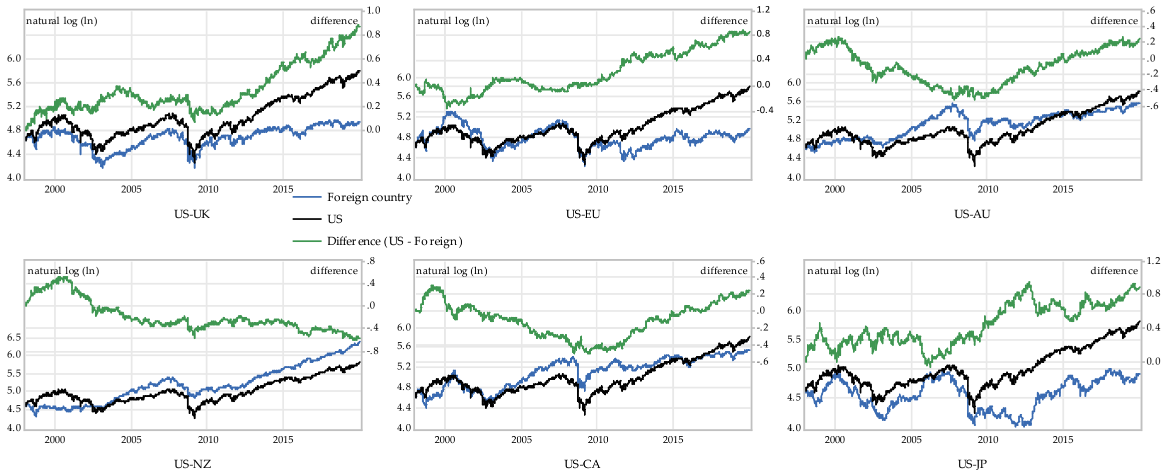


Figure A3. Stock market and relative stock market indices

Level



First difference

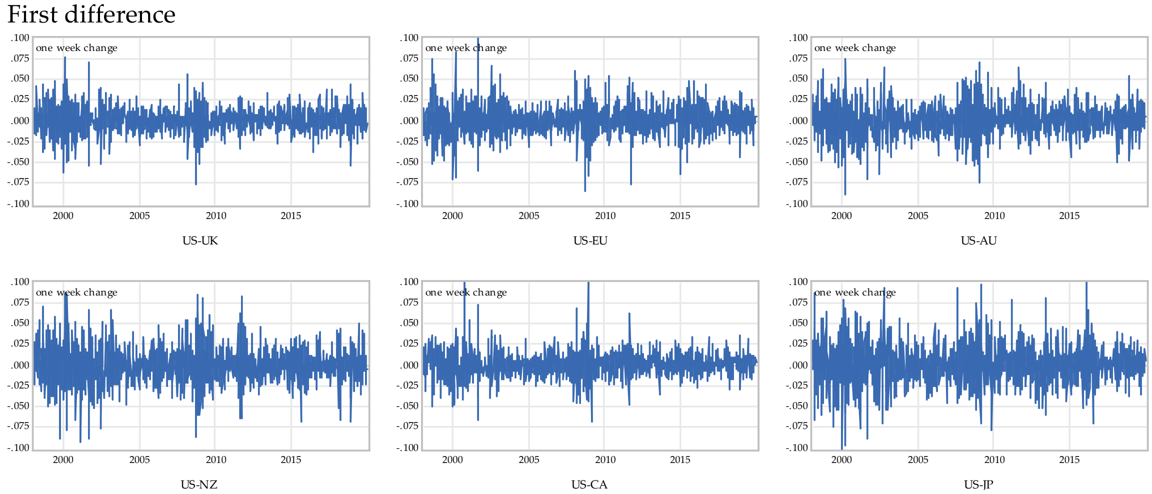
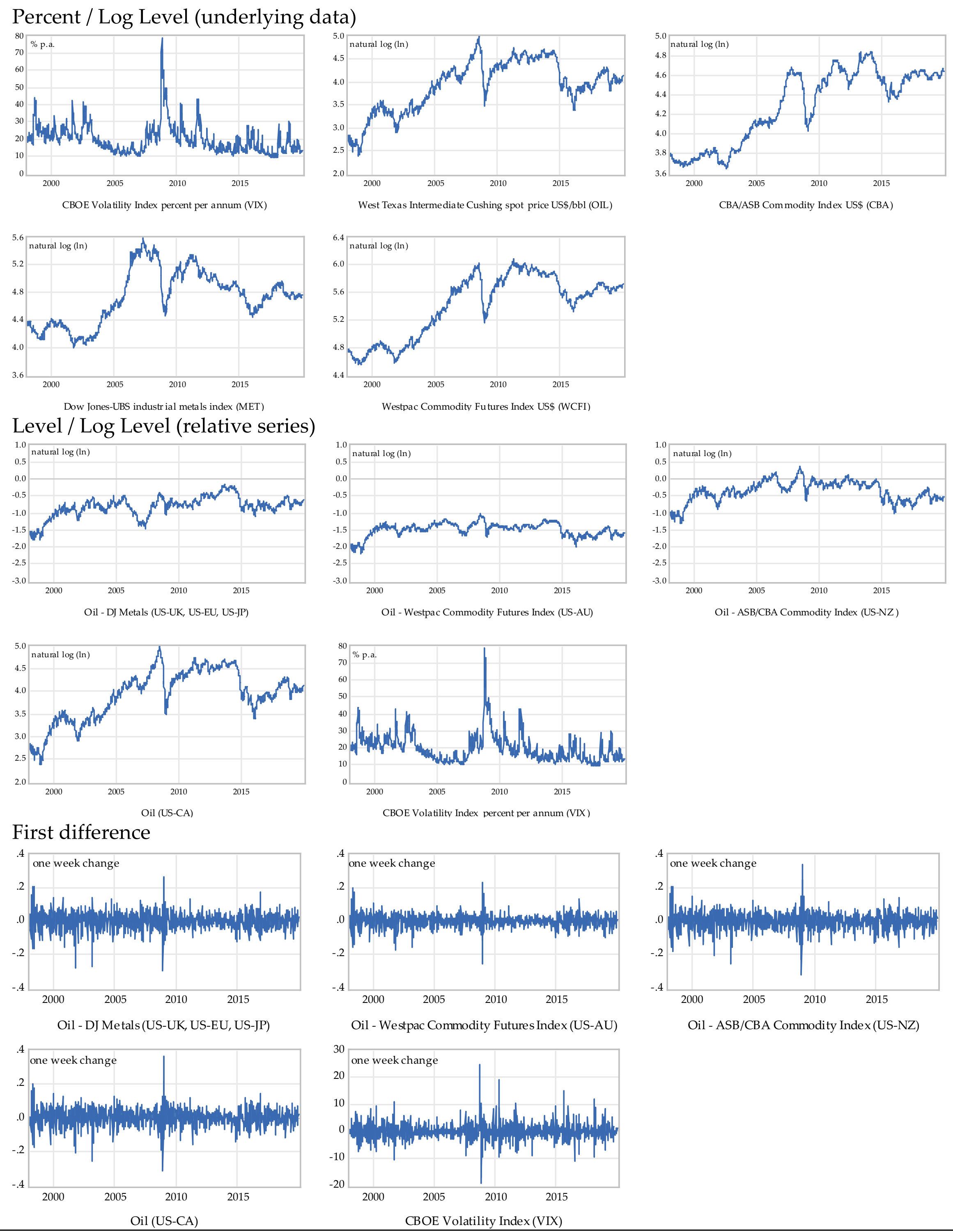


Figure A4. Commodity indices and risk premium



Appendix B. Hypothesis testing

B1. Exchange rate distribution: Jarque-Bera test

Below presents the Jarque-Bera normality test (Jarque and Bera, 1980). This test analyses the sample distribution over two aspects: skewness and kurtosis. The first measures the extent to which the distribution has symmetry around its mean. The second compares the sample's distribution of frequencies against the normal distribution.[96]

The Jarque-Bera test is:

$$W = \frac{N}{6}\left(S^2 + \left(\frac{(K-3)^2}{4}\right)\right) \tag{A1}$$

where W is the test statistic, N is the sample size, S is sample skewness, and K is sample kurtosis. Here, the null hypothesis is for W = 3; or a zero skewness and zero kurtosis compared to a normal distribution with a (one-tailed) Chi-squared distribution with 2 d.f. The null hypothesis is rejected at the 1% level for all the exchange rates in Figure B1.

[96] Skewness and kurtosis are the third and fourth moment of a probability distribution, respectively. Excess kurtosis, also known as positive kurtosis, is typically described as having light tails. This differs from the visual representation: positive kurtosis tends to show heavier extreme tails at the edges of the distribution (DeCarlo, 1997).

Figure B1. Exchange rate histograms and Jarque-Bera hypothesis test of a normal distribution

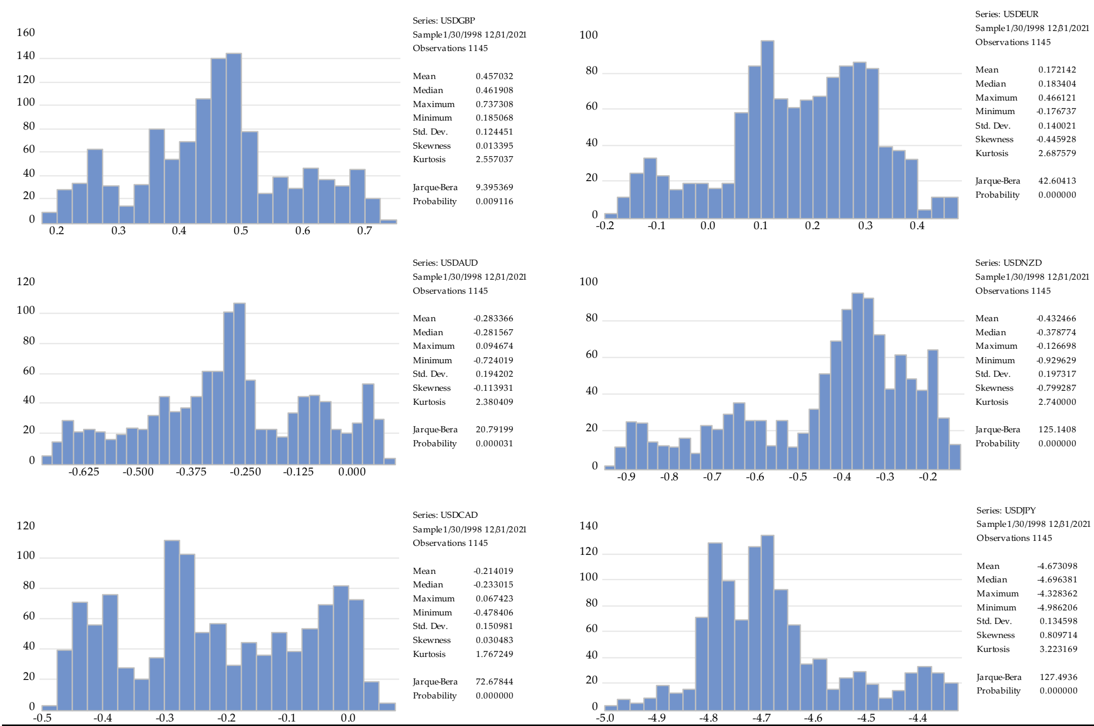


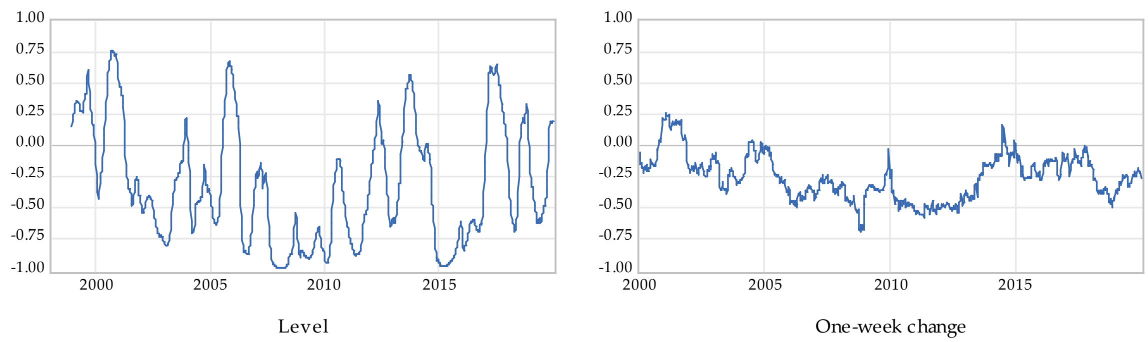
Table B1. Excess kurtosis, excluding 2007-2009

ΔUSDGBP	.26	ΔUSUK2	5.00
ΔUSDEUR	.42	ΔUSEU2	2.74
ΔUSDAUD	1.09	ΔUSAU2	2.21
ΔUSDNZD	.94	ΔUSNZ2	3.15
ΔUSDCAD	2.72	ΔUSCA2	11.18
ΔUSDJPY	10.81	ΔUSJP2	4.29
ΔUSUKEQ	2.22	ΔVIX	4.67
ΔUSEUEQ	3.23	ΔUSUKC	2.63
ΔUSAUEQ	1.55	ΔUSAUC	3.13
ΔUSNZEQ	1.68	ΔUSNZC	1.89
ΔUSCAEQ	3.65	ΔUSCAC	73.67
ΔUSJPEQ	1.46		

Notes: Excess kurtosis is defined as kurtosis minus 3 (Tabachnick and Fidell, 1996). The excluded period was 2007 – 2009 inclusive.

B2. Exchange rate and spot oil price correction

Figure B2. One-year correlation between West Texas crude oil price and U.S. Dollar Index (DXY)



B3. Unit root tests

Dickey and Fuller (1979) first described the unit root test. The generalised case is:

$$\Delta y_t = \mu + \lambda t + \psi y_{t-1} + \sum_{j=1}^{p} d_j \Delta y_{t-j} + \varepsilon_t \tag{A2}$$

where μ is a drift term t is a time trend, ε_t is the (stationary) error term, p is the order of autoregressive process that is tested and d is the order of integration.

The null hypothesis is the series is non-stationary (has a unit root), or that $\psi = 0$, with the alternative is where $\psi < 0$. EViews provides an add-in procedure that tests both the Augmented Dickey Fuller and Phillips-Perron unit root tests on all variables simultaneously for three regression equations (random walk, random walk with drift, and random walk with drift and a linear time trend). This significantly reduces the time taken to test each time series individually but does not allow the researcher to follow a sequential order (Dickey and Pantula, 1987; and

Ng and Perron, 1995) to ensure the distribution of the test statistic is independent of the parameters in the DGP, i.e., to produce a similar test (Banerjee *et al.*, 1993).

The testing procedure includes the random walk with drift and a time trend. Failing to include time trend when one exists biases the results towards a unit root whereas including one when it is not necessary reduces the power of the test (Perron, 1988).

Table B2. Augmented Dickey-Fuller unit root tests, levels: 30 Jan 1998 to 27 Dec 2019

	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Random walk							
Exchange rate	-.921	-.956	-.880	-849	-1.09	-.347	
Swap spread	-2.13	-1.81†	-1.05	-1.23	-2.52††	-1.49	
Equity	2.48	.960	-.646	.006	-.697	.299	
Commodity	-1.65†	-1.65†	-.824	-2.24††	.457	-1.65†	
Risk							-1.41
Random walk with drift							
Exchange rate	-1.74	-1.80	-1.51	-1.57	-1.42	-1.96	
Swap spread	-2.18	-2.02	-2.19	-1.46	-2.59†	-1.35	
Equity	.553	.164	-.510	-.729	-.474	-1.31	
Commodity	-3.07††	-3.07††	-3.50†††	-3.18††	-2.10	-3.07††	
Risk							-3.67†††
Random walk with drift and time trend							
Exchange rate	-2.22	-1.76	-1.46	-1.93	-1.16	-1.87	
Swap spread	-2.83	-2.14	-1.55	-1.67	-2.56	-1.19	
Equity	-.610	-2.69	-.628	-2.05	-2.40	-2.49	
Commodity	-3.28†	-3.28†	-3.48††	-3.11	-2.04	-3.28†	
Risk							-5.65†††

Notes: The null hypothesis of a unit root is tested. The *t*-statistic used is based on the AIC lag length criterion up to maximum of 21, as given by EViews. † *t*-statistic is significant at 10%, †† *t*-statistic is significant at 5%, ††† *t*-statistic is significant at 1%. Critical values from MacKinnon (1996).

The EViews procedure allows the researcher to choose between the Akaike Information criterion (AIC) and the Schwarz Bayesian criterion (SIC) when deciding the lag length for the unit root test. AIC tends to choose too many lags, whereas

SIC can choose too few. Too many lags can reduce the power of the test (Ng and Perron, 1995), whereas the error term may not be white noise if too few lags are chosen, increasing the size of the test (Charemza and Deadman, 1997).[97] Because of the risk of serial correlation in the errors, a longer lag selection is chosen (both here and throughout the paper), with the unit root results shown Tables B2 and B3.

Table B3. Augmented Dickey-Fuller unit root tests, first differences: 30 Jan 1998 to 27 Dec 2019

	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Random walk							
Exchange rate	-7.89†††	-16.4†††	-34.9†††	-34.7†††	-10.7†††	-36.4†††	
Swap spread	-5.83†††	-5.51†††	-10.8†††	-8.07†††	-10.2†††	-22.4†††	
Equity	-20.2†††	-37.7†††	-19.6†††	-19.4†††	-39.4†††	-15.1†††	
Commodity	-20.7†††	-20.7†††	-9.4†††	-10.5†††	-9.7†††	-20.3†††	
Risk							-13.18†††
Random walk with drift							
Exchange rate	-7.90†††	-16.4†††	-34.9†††	-34.7†††	-10.7†††	-36.4†††	
Swap spread	-5.84†††	-5.51†††	-10.84†††	-8.08†††	-10.2†††	-22.4†††	
Equity	-8.35†††	-3.80†††	-19-56†††	-19.4†††	-39.4†††	-15.2†††	
Commodity	-20.7†††	-20.7†††	-9.44†††	-10.5†††	-9.8†††	-20.7†††	
Risk							-13.18†††
Random walk with drift and time trend							
Exchange rate	-7.91†††	-16.4†††	-34.85†††	-34.7†††	-10.7†††	-36.4†††	
Swap spread	-5.84†††	-5.57†††	-10.99†††	-8.11†††	-10.2†††	-22.4†††	
Equity	-8.51†††	-37.8†††	-10.72†††	-19.4†††	-39.5†††	-15.2†††	
Commodity	-20.7†††	-20.7†††	-9.50†††	-10.5†††	-9.80†††	-20.7†††	
Risk							-13.18†††

Notes: The null hypothesis of a unit root is tested. The *t*-statistic used is based on the AIC lag length criterion up to maximum of 21, as given by EViews. † *t*-statistic is significant at 10%, †† *t*-statistic is significant at 10%, ††† *t*-statistic is significant at 10%. Critical values from MacKinnon (1996).

[97] Where size is the probability of rejecting the null hypothesis of a unit root when it is true.

Table B4. Augmented Dickey-Fuller unit root with unknown breakpoint tests, levels: 30 Jan 1998 to 27 Dec 2019

	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Exchange rate	-4.53	-3.74	-3.96	-3.86	-4.04	-3.84	
Lag length	19	15	10	14	20	21	
Break date	29Aug'03	12Apr'02	27Feb'09	27Sep'02	6Mar'09	22Aug'08	
Swap spread	-4.84	-3.43	-4.44	-3.66	-3.55	-3.28	
Lag length	20	16	1	15	17	15	
Break date	17Sep'04	6Jul'07	6Mar'09	21Dec'01	6Mar'09	20Jun'08	
Equity	-5.45***	-3.56	-4.20	-4.50	-6.53***	-4.28	
Lag length	1	22	13	16	17	21	
Break date	8Mar'13	29Apr'05	22Sep'06	6Mar'09	5Dec'08	3Jul'09	
Commodity	-4.25	-4.25	-4.84	-4.74	-4.58	-4.25	
Lag length	0	0	20	9	9	0	
Break date	19Jun'98	19Jun'98	3Oct'14	19Dec'08	25Jul'14	19Jun'98	
Risk							-6.77***
Lag length							0
Break date							17Jul'98

Notes: The trend specification is with a trend and intercept, with break specification of trend and intercept. Based on the Schwarz criterion with a maximum lag length of 22. * Indicates test statistic value significant at 10%. ** Indicates test statistic value significant at 5%. ** Indicates test statistic value significant at 1%. Critical values are from Perron and Vogelsang (1998) one-sided *t*-statistic with the null of a unit root with at least one break. Maximum sample size of N = 1144.

Table B5. Augmented Dickey-Fuller unit root with unknown breakpoint tests, first differences: 30 Jan 1998 to 27 Dec 2019

	US-UK	US-EU	US-AU	US-NZ	US-CA	US-JP	
Exchange rate	-33.9***	-33.8***	-35.0***	-35.1***	-38.0***	-36.6***	
Lag length	0	0	0	0	0	0	
Break date	19Jun’98	8May’98	19Jun’98	20Mar’09	10Oct’08	12Jun’98	
Swap spread	-38.0***	-39.2***	-40.8***	-38.1***	-36.7***	-35.9***	
Lag length	0	0	0	0	0	0	
Break date	19Jun’98	24Apr’98	12Jun’98	26Jun’98	27Mar’98	12Jun’98	
Equity	-41.8***	-37.9***	-44.1***	-42.3***	-39.6***	-40.4***	
Lag length	0	0	0	0	0	0	
Break date	1May’98	12Jun’98	26Jun’98	26Jun’98	17Jul’98	3Apr’98	
Commodity	-35.8***	-35.9***	-36.0***	-36.6***	-35.5***	-35.9***	
Lag length	0	0	0	0	0	0	
Break date	27Mar’98	27Mar’98	24Apr’98	27Mar’98	12Jun’98	27Mar’98	
Risk							-40.66***
Lag length							0
Break date							24Jul’98

Notes: The trend specification is with a trend and intercept, with break specification of trend and intercept. Based on the Schwarz criterion with a maximum lag length of 22. * test statistic value significant at 10%. ** test statistic value significant at 5%. ** test statistic value significant at 1%. Critical values are from Perron and Vogelsang (1998) one-sided *t*-statistic with the null of a unit root with at least one break. Maximum sample size of N = 1144.

Appendix C. Results

C1. Level/log level output

Figure C1. Level/log level rolling fixed-window estimation output, Equation (22): Estimation sample 30 Jan 1998 to 28 Dec 2018

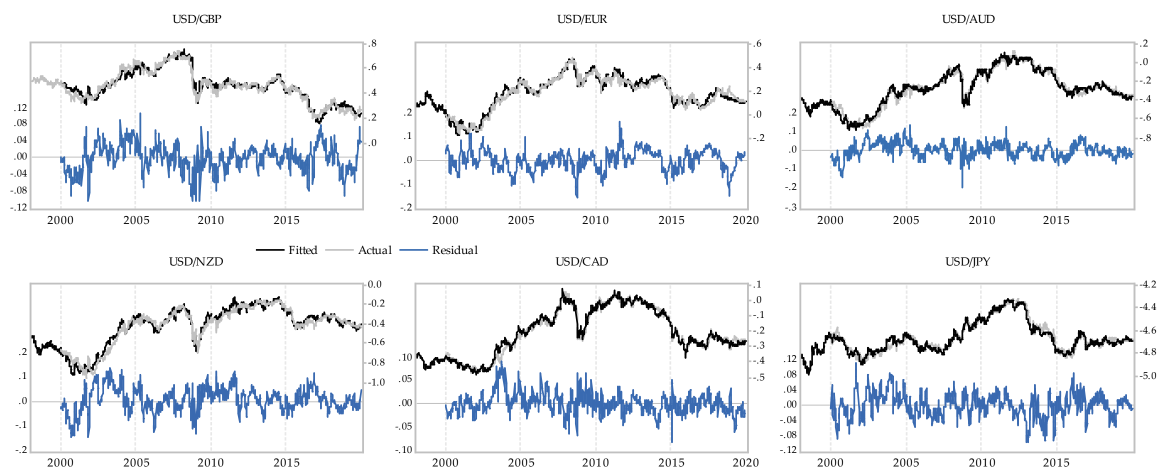


Figure C2. Level/log level rolling fixed-window estimation output, Equation (23): Estimation sample 30 Jan 1998 to 28 Dec 2018

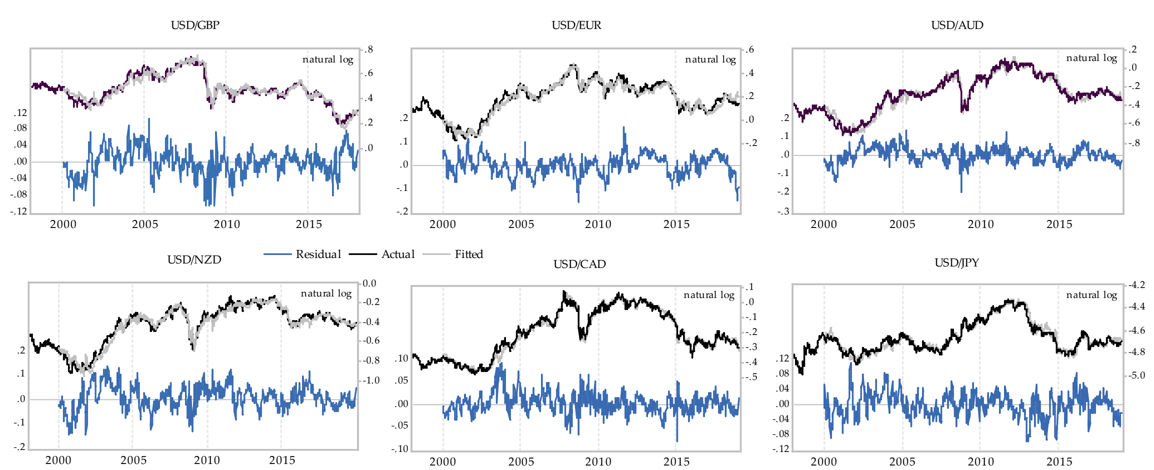


Figure C3. Difference between Equations (22) and (23) rolling fixed-window estimation residuals

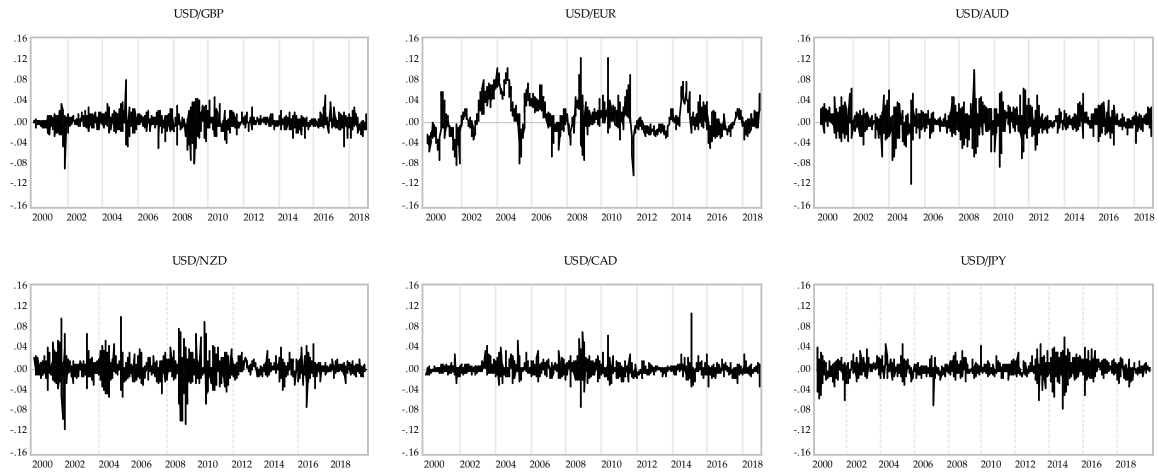


Figure C4. Level/log level rolling fixed-window estimation output, Equation (22a): Estimation sample 30 Jan 1998 to 28 Dec 2018

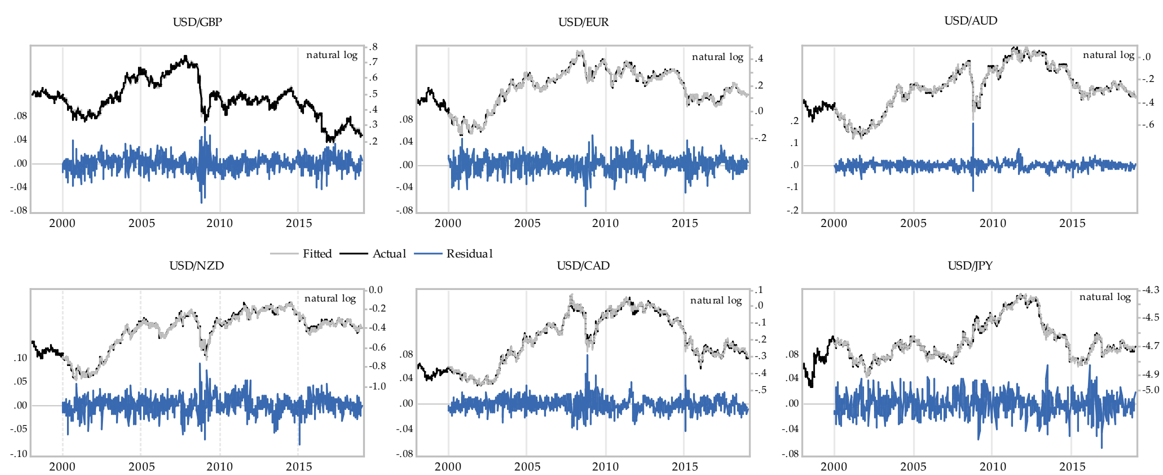


Figure C5.Level/log level rolling fixed-window estimation output, Equation (23a): Estimation sample 30 Jan 1998 to 28 Dec 2018

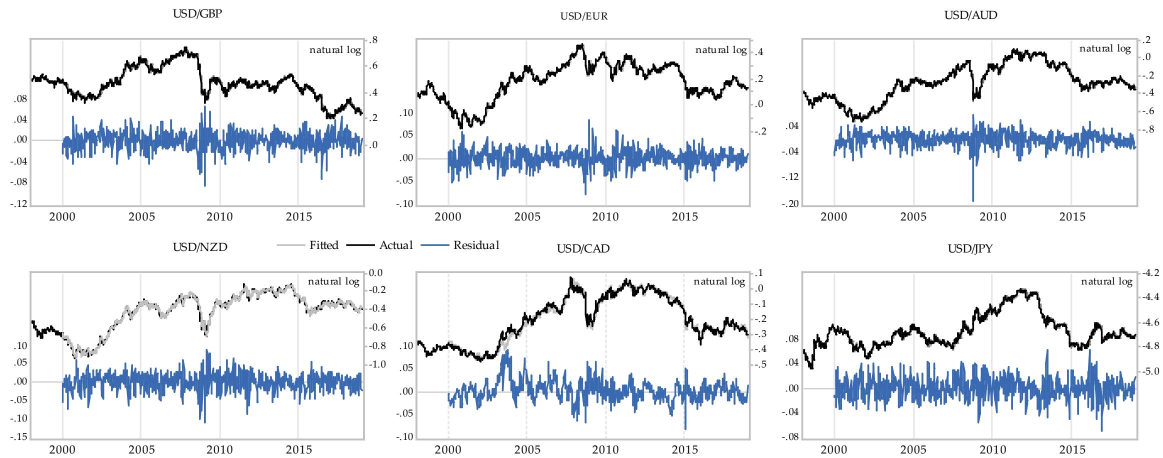
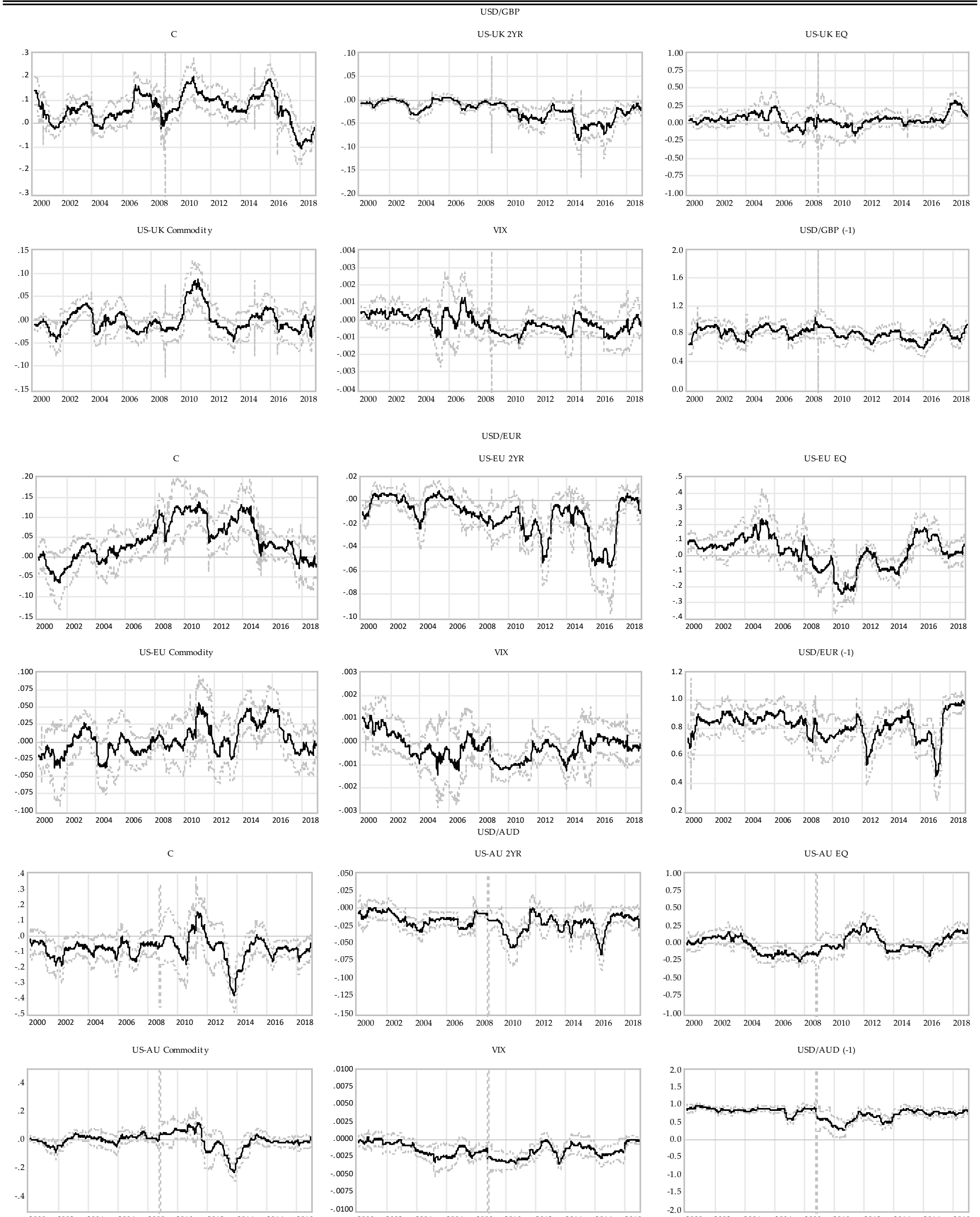
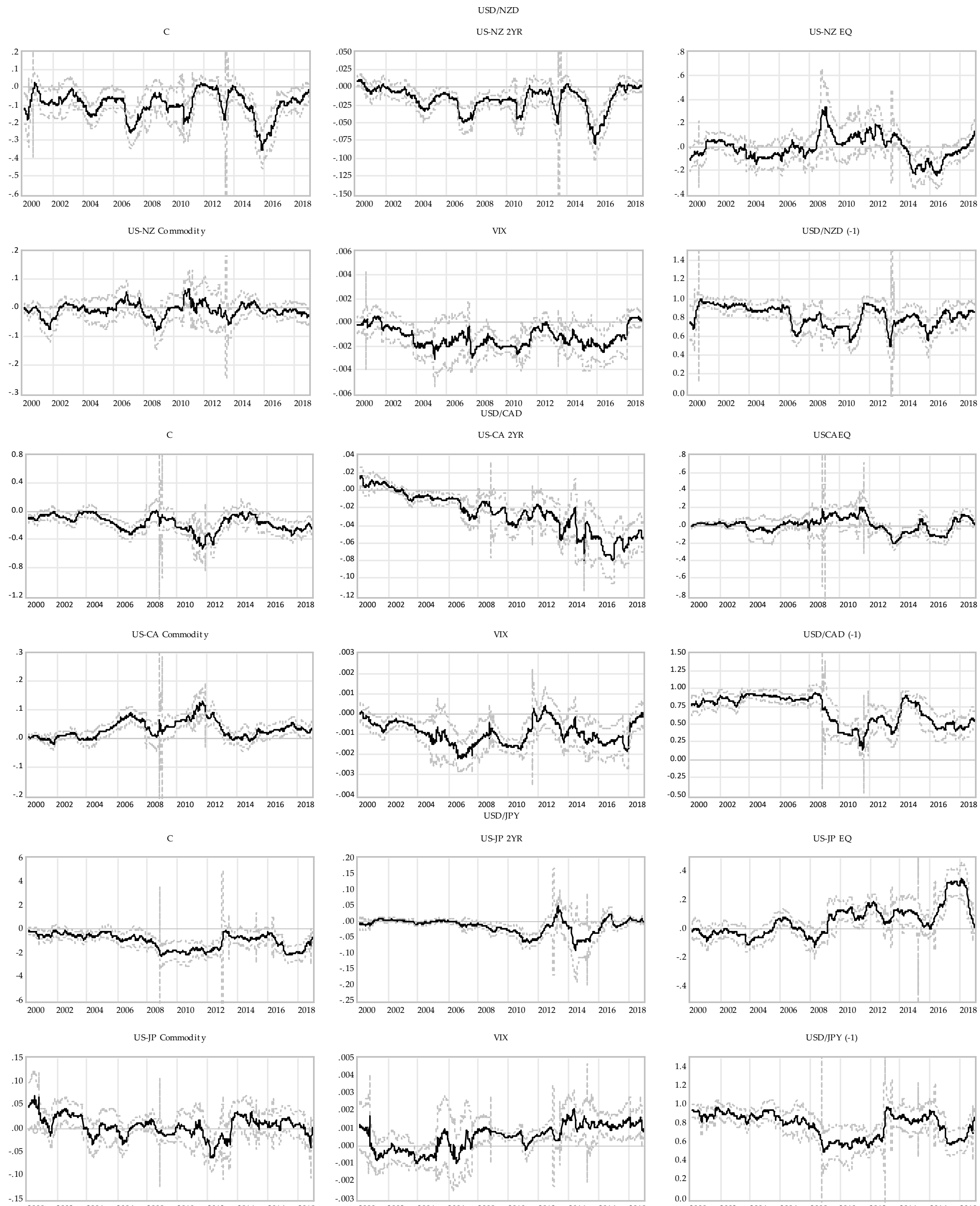


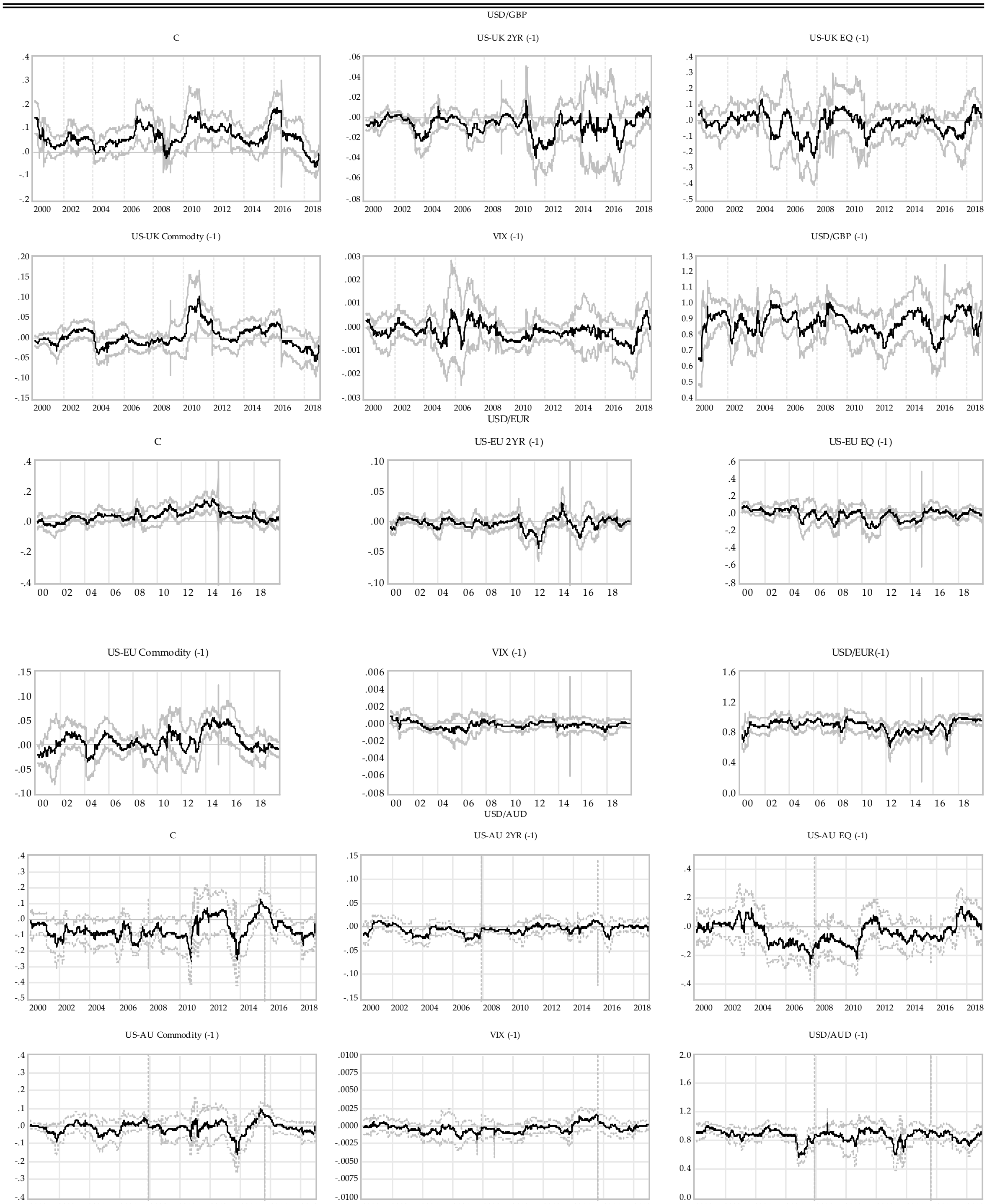
Figure C6. Level/log level rolling fixed-window estimation coefficients, Equation (22a): Estimation sample 30 Jan 1998 to 28 Dec 2018

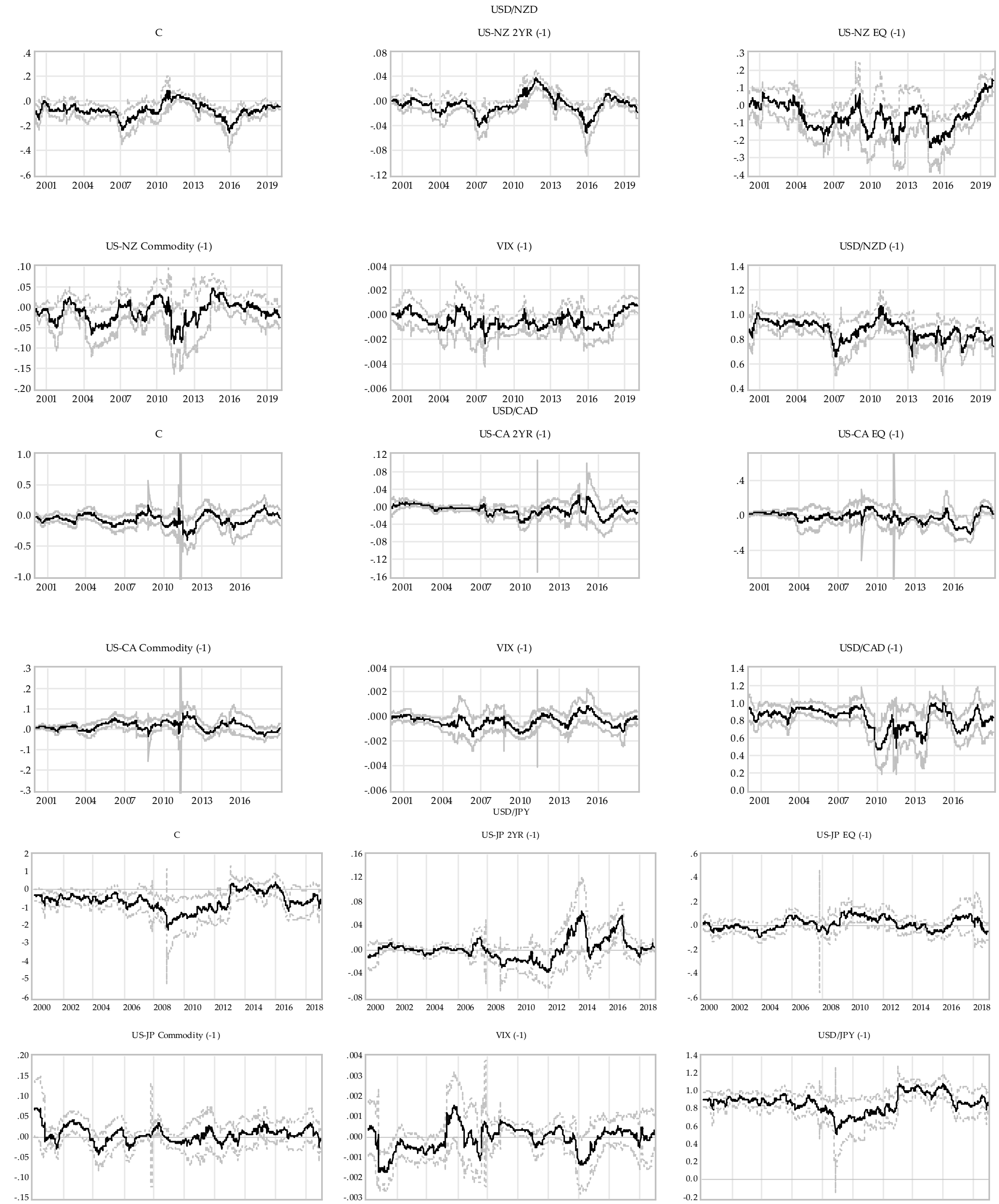




Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, (-1) refers to the lagged variable.

Figure C7. Level/log level rolling fixed-window coefficients, Equation (23a): Estimation sample 30 Jan 1998 to 28 Dec 2018





Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, (-1) refers to the lagged variable.

Table C1. Autoregressive Distributed Lag Model (ARDL) cointegration bounds test, Equation (23)

	USD/GBP	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
Estimated ARDL model						
ARDL lags	(3,2,1,0,1)	(5,0,0,3,10)	(11,2,0,0,3)	(3,3,2,0,4)	(11,2,3,0,3)	(2,0,1,3,10)
F-statistic	5.67 ***	1.20	2.74	2.80	1.93	1.44
Critical bound I(0)						
1% significance	3.29	3.29	3.29	3.29	3.29	3.29
5% significance	2.56	2.56	2.56	2.56	2.56	2.56
10% significance	2.2	2.2	2.2	2.2	2.2	2.2
Critical bound I(1)						
1% significance	4.37	4.37	4.37	4.37	4.37	4.37
5% significance	3.49	3.49	3.49	3.49	3.49	3.49
10% significance	3.09	3.09	3.09	3.09	3.09	3.09
Adjusted R^2	.989	.991	.993	.994	.994	.988
Breusch-Godfrey Chi	.289	.795	.595	.610	.097	.856
Actual sample size	1089	1090	1081	1086	1081	1081

The Newey-West HAC adjustment was applied using the quadratic-spectral kernel and automatic bandwidth selection as given by EViews. The ARDL null hypothesis is of no cointegrating level relationship. Estimated with an unrestricted constant and trend and lags *=12*. Critical values two-sided *t* test statistic with *N-k* d.f. Sample size N= 1091. * Can reject null hypothesis at 10% level. ** Can reject at 5% level. *** Can reject at 1% level. Critical values from Pesaran, Shin, and Smith (2001). The Breusch-Godfrey Chi is a Chi-square distribution with *p*=2. The number of lags (*p*) was determined by visual assessment of the correlogram of regression residuals up to 36 lags. Lags (in parentheses) are in order of s_t, y_t-y_t*, i_t-i_t*, c_t-c_t*, rp_t.

C2. First difference output

Figure C8. First difference rolling fixed-window estimation output, Equation (22a): Estimation sample 30 Jan 1998 to 28 Dec 2018

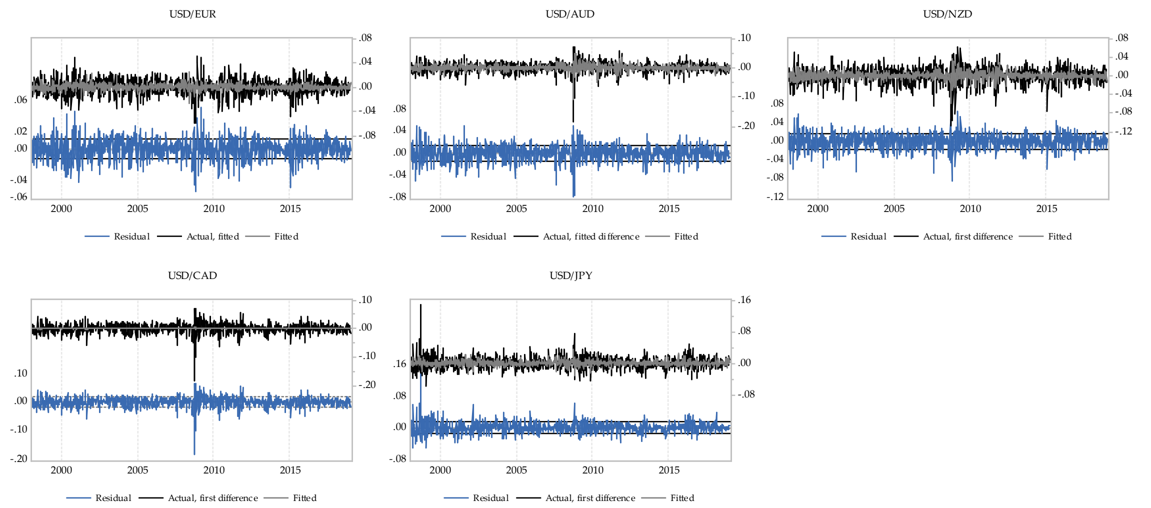


Figure C9. First difference rolling fixed-window estimation output, Equation (23a): Estimation sample 30 Jan 1998 to 28 Dec 2018

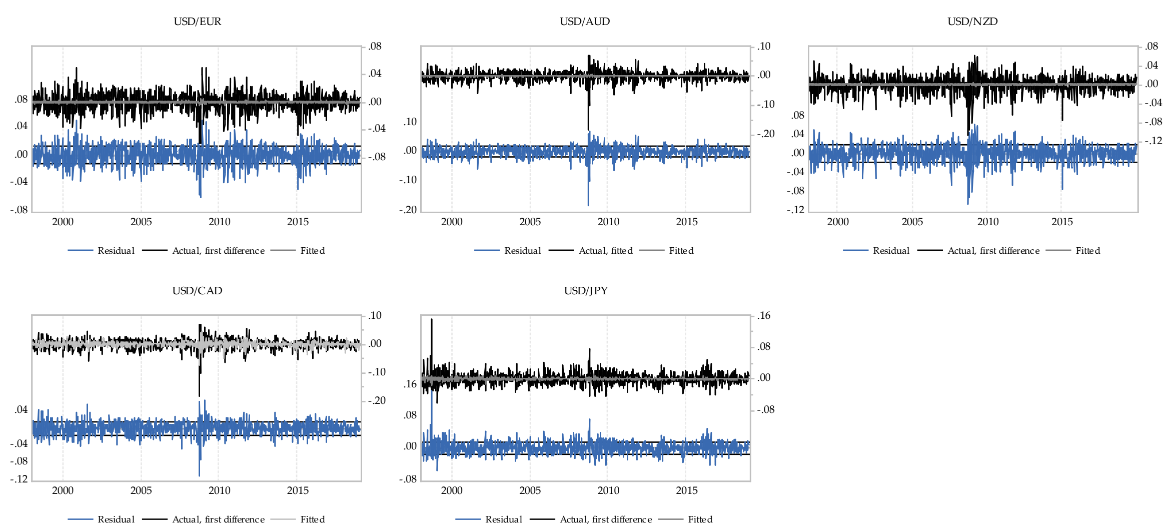


Figure C10. Difference between Equations (22a) and (23a) first difference rolling fixed-window estimation residuals

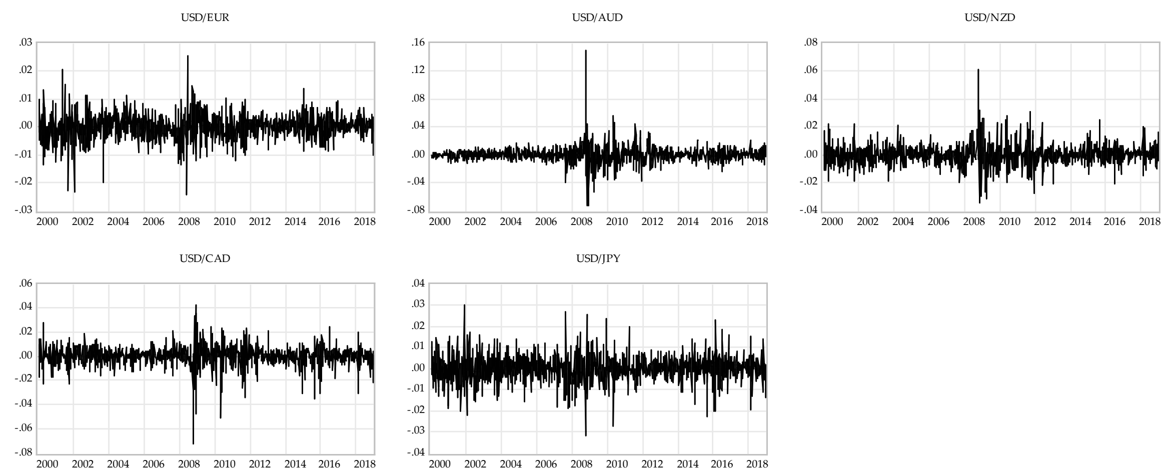
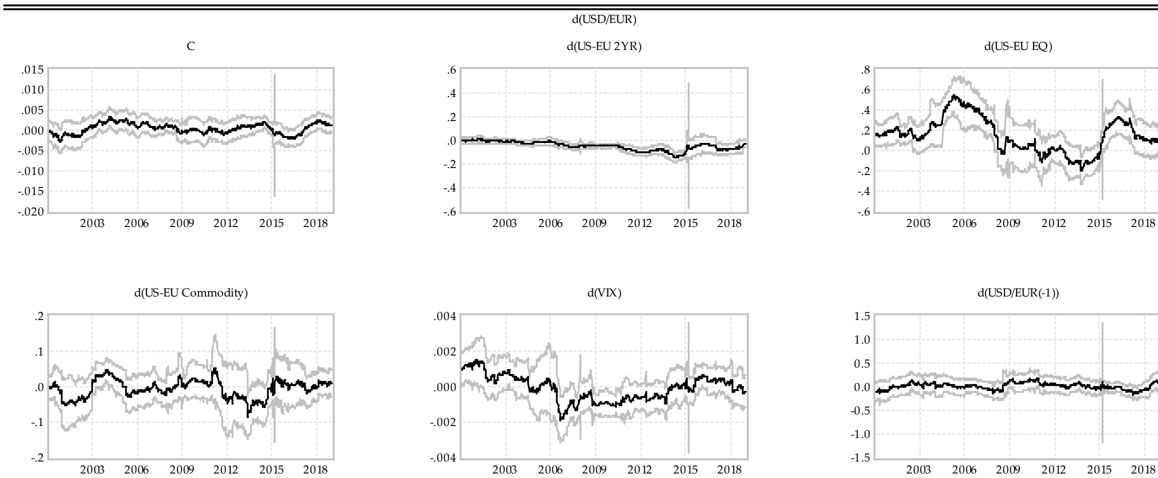
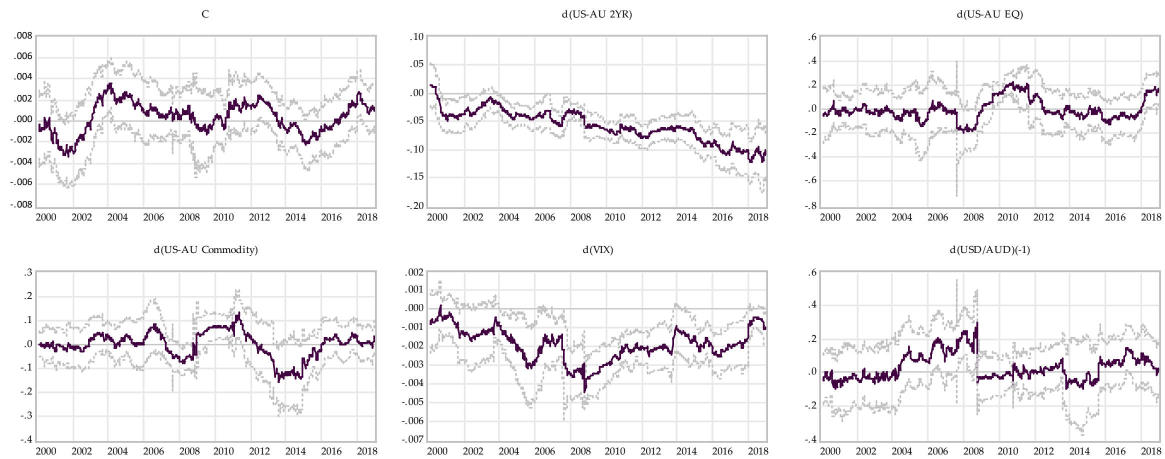


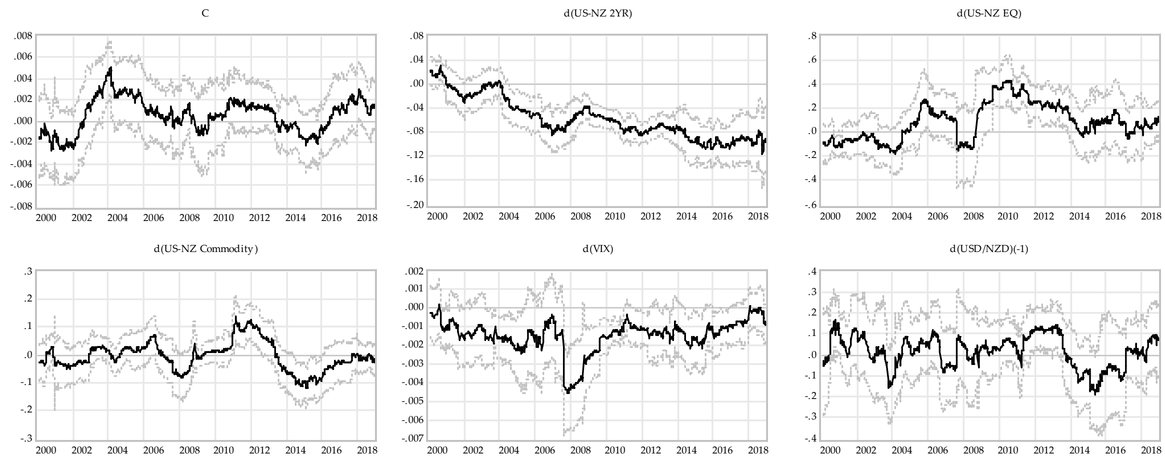
Figure C11. First difference rolling fixed-window-coefficients, Equation (22a): Estimation sample 30 Jan 1998 to 28 Dec 2018



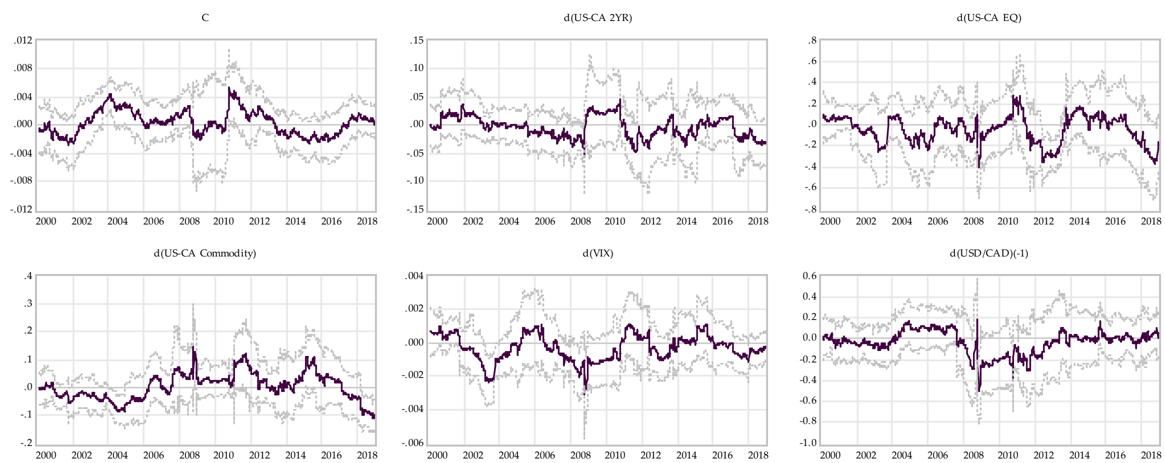
d(USD/AUD)



d(USD/NZD)

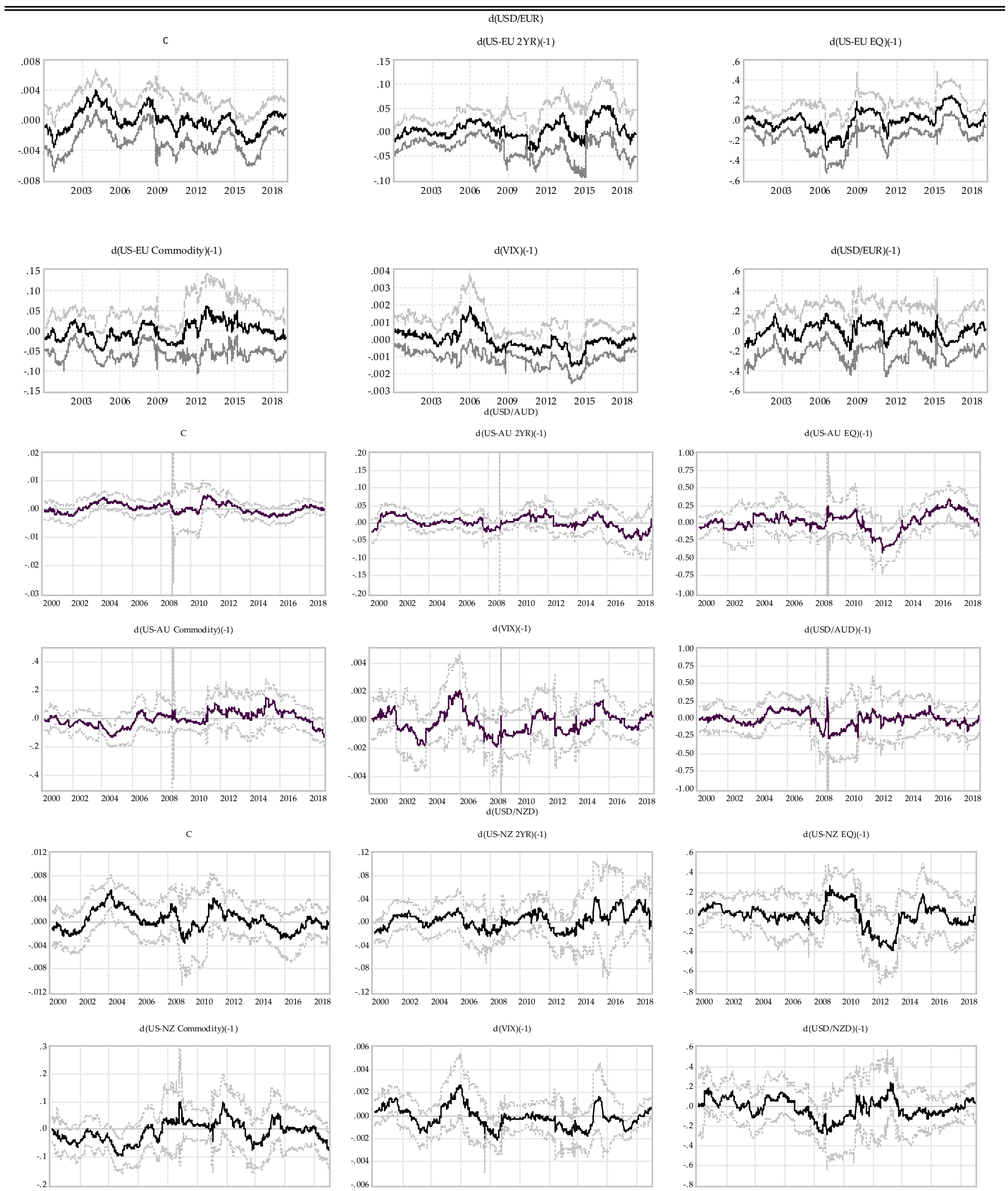


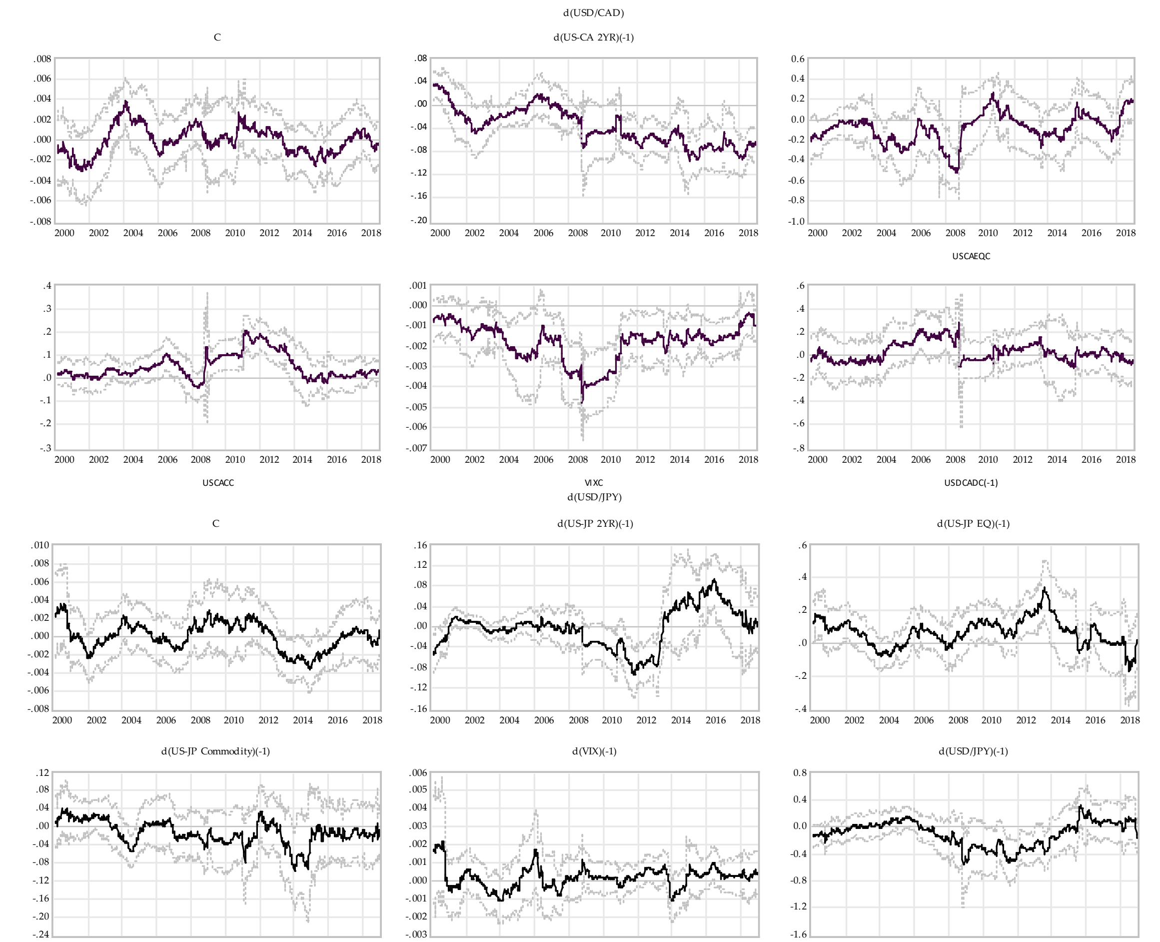
d(USD/CAD)



Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, d = first difference, (-1) refers to the lagged variable.

Figure C12. First difference rolling fixed-window coefficients, Equation (23a): Estimation sample 30 Jan 1998 to 28 Dec 2018





Notes: Black line is coefficient estimate for each two-year window regression. The grey dotted lines are confidence bands. c = constant, d = first difference, (-1) refers to the lagged variable.

Table C2. Full-sample fixed-coefficient first difference breakpoint dates, m ≤ 15

	USD/EUR	USD/AUD	USD/NZD	USD/CAD	USD/JPY
			Equation (22a)		
UDmax	71.96 *	63.35*	84.49 *	22.1 *	136.4 *
WDmax	84.09 *	77.86 *	89.06 *	26.5 *	136.4 *
Break dates					
0 vs 1	1 Nov 2002	26 Feb 1999	3 Oct 2003		4 Nov 2005
1 vs 2	19 May 2006	3 Oct 2008	25 May 2012		
2 vs 3	20 Mar 2009	29 July 2011			
3 vs 4	14 May 2010				
4 vs 5	23 Jan 2015				
			Equation (23a)		
UDmax	23.00 *	33.63 *	17.13	530.6 *	22.07 *
WDmax	27.23 *	42.05 *	25.35 *	663.28 *	27.71 *
Break dates					
0 vs 1				31 Aug 2001	26 Feb 1999
1 vs 2				26 Sep 2008	
2 vs 3				25 Dec 2009	
3 vs 4				10 Aug 2012	
4 vs 5					

Notes: The globally determined break is the null hypothesis of no breaks versus one or more. *UDmax* and *WDmax* is a one-sided (upper-tail) test of the hypothesis of an unknown number of breaks given an upper bound, where *UDmax* is the equal-weighted test result and the *WDmax* test statistic weights the statistics to equalise their p-values (Bai and Perron, 2003a). * F-statistic is significant at the 5% level. Break dates are only recorded if they are significant at the 5% level. Critical values are given by Bai and Perron (2003b). Heterogeneous error distributions are allowed across breaks. The breakpoint date sequential test is a one-sided (upper-tail) test of the null hypothesis of ℓ breaks against the alternative of $\ell+1$ breaks given an upper bound of 15 (m) where the trimming parameter is .05.