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Research article

Forecasting the Taylor rule exchange rate model using directional change tests

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Abstract: This study uses the Taylor rule model of exchange rate determination, to analyse how accurately it can predict directional changes in the exchange rate. Using bilateral exchange rate data for the US, UK, Sweden and Australia, we conduct the Pesaran-Timmermann test to determine how accurately this model can forecast changes in direction. The results suggest that although in many studies the standard out-of-sample forecasting ability of this model has been successful, the performance of the change of direction predictions are not consistently accurate over all specifications tested, in which case they may not prove profitable in a trading environment.

Key words: forecast; Taylor rule; exchange rate; prediction accuracy

JEL codes: C53, E44, F37, F41

1. Introduction

The ability to forecast directional change in exchange rates is important to asset managers and macroeconomists, with implications regarding the efficient allocation of capital and the ability to predict important economic events. This study aims to estimate the popular Taylor rule models of the exchange rate and apply an alternative measure of forecast performance to the mean square error approach commonly used, in this case forecasts of the direction of change using the Pesaran-Timmermann (1992) test. Although a number of studies have recently found the Taylor rule based model of the exchange rate, initially developed by Engel and West (2006) to be a more successful model at forecasting the exchange rate relative to more standard models, it does not imply that this will also be the case for the directional change forecasts. Unlike earlier studies of the exchange rate which largely failed to outperform the random walk (Meese and Rogoff, 1982), recent studies such as Molodstova and Papell (2009) and Ince (2014) among others have demonstrated that the Taylor rule based model can outperform the random walk in out-of-sample forecasts. This study aims to build on these results by testing whether the model can additionally accurately forecast the direction of change of the exchange rate. Forecasts based on accurately predicting movements in the direction the exchange rate moves could not only be potentially profitable for investors, but can also facilitate greater understanding of exchange rate dynamics for the monetary authorities.

The use of financial loss functions, such as the Pesaran-Timmermann (PT) test, is particularly relevant when forecasting asset prices, as forecasting the direction in which an asset moves can determine whether the trade is profitable or not, regardless of the performance using the conventional forecast errors. In addition a number of studies such as Leitch and Tanner (1991) have demonstrated that forecasting the direction of change accurately can produce more profits compared to the standard forecasting approaches.

Forecasts based on directional predictions have been conducted extensively in the literature with differing degrees of success. In general their ability to forecast varies across markets and the modelling approaches used to produce the forecasts, to this extent these results tend to reflect the results from the more conventional forecast error approaches. Studies which have attempted to forecast the direction of change have been conducted for a number of markets and series, including stock prices (Leung et al., 2000; Nyberg, 2011), crude oil prices (Knetsch, 2006), interest rates (Greer, 2003) and GDP (Pons, 2000). There have also been a number of approaches to forecasting the direction of change in exchange rates, including Qi and Wu (2003), although they find that their non-linear approach is not good at forecasting the future exchange rate or its direction. Another approach with exchange rates by Mitchell and Pearce (2007) finds that using forecasts provided by Wall Street Journal Economists can’t provide direction of change forecasts that are more accurate than a chance occurrence. The contribution of this study is that it uses a variety of Taylor rule based exchange rate models to forecast directional accuracy, to determine if the recent success from conventional forecasts with these models is also apparent with directional prediction tests.

Unlike other conventional exchange rate models, the Taylor rule type exchange rate models overcome one of the major shortcomings of traditional exchange rate models which tend to pay too little attention to the market's expectations of future values of the macroeconomic fundamentals (Bacchetta and van Wincoop, 2006; Engel and West, 2005). It reflects how monetary policy is actually conducted or evaluated and offers a different explanation of exchange rate dynamics. In addition we test a number of variations on the conventional Taylor rule model including the addition of asset market effects to the model. The use of the directional accuracy tests is particularly relevant for asset market based models and as far as we know, this is the first time it has been attempted with an exchange rate model which includes asset price measures as explanatory variables.

The theoretical basis for this study is the linear model of the exchange rate developed by Molodtsova and Papell (2009) among others. In addition, as in Wang et al. (2016), this model can be extended by the inclusion of asset market or wealth effects, including both house and stock prices, to produce a number of different variations on the main model for comparison purposes. The inclusion of asset market measures in the specification is motivated by the increasing importance of capital flows between asset markets, which inevitably influences exchange rates. As Case et al. (2005)

suggest, both housing and stock markets have varying degrees of influence on the macro-economy. As with other similar studies using the Taylor rule, the emphasis in this study is on the forecasting performance of this model rather than the estimation of the model[1].

Following the introduction we discuss the Taylor rule exchange rate models used in this study, then outline the Pesaran-Timmermann test. We then analyse the results and finish with some conclusions.

2. Materials and methods

The model used for forecasting is an amended Taylor rule model of exchange rate determination, in which the relationship between interest rates and macro fundamentals stems from the central bank's approach to monetary policy[2]. Monetary based fundamentals are a common approach to modelling the exchange rate (Beckmann et al., 2012), this can involve the monetary model approach as well as a Taylor rule model as is used in this study. According to the Taylor rule, the most basic approach to monetary policy involves setting the interest rate in response to changes in inflation and the output gap. This original specification has been further enhanced by extending the model by incorporating variables representing various asset market or wealth effects on the baseline equation, as used in other studies such as Semmler and Zhang (2007).

$$i_t^* = \pi_t + \delta\left(\pi_t - \pi_t^*\right) + \gamma y_t + \beta w_t + r^* \tag{1}$$

Where i_t^* is the target for the short-term nominal interest rate, π_t is the inflation rate, π_t^* is the target level of inflation, y_t is the output gap, or percent deviation of actual real GDP from an estimate of its potential level, and r^* is the equilibrium level of the real interest rate and w_t represents the wealth effect.

Following the approach of Clarida et al. (1998), several modifications which are typically included in the estimation have been included. This includes the real exchange rate in the specification of the foreign country, where it is assumed the central bank targets the level of the exchange rate to ensure long-run PPP holds. Combining the parameters π_t^* and r^* from equation (1) into one constant term: $\mu = r^* - \delta\pi^*$, we can derive the following version of the Taylor rule model:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t + \beta w_t + \phi q_t \tag{2}$$

[1] Although this is the case in most studies, an exception is Chen et al. (2017), who have used a SVAR and a Taylor rule based model to analyse exchange rate policy, with respect to foreign exchange intervention and capital controls.

[2] The Taylor rule approach to monetary policy is widely used, including in the countries tested in this study. It allows US variables to be included in all the specifications, in effect acting as a proxy for the impact from the rest of the world, either in a restricted or unrestricted format. However there are many other approaches that could be incorporated into exchange rate modelling such as the issue of global liquidity (Beckmann et al., 2014), current account imbalances (Beckmann et al., 2013) and productivity shocks (Beckmann et al., 2015).

Where q_t is the real exchange rate.

A lagged interest rate is also incorporated into the Taylor rule to account for the Federal Reserve following the Taylor rule, while responding gradually to changes in the inflation and output gaps. The observable interest rate i_t follows a partial adjustment to the target rate as follows:

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + v_t \tag{3}$$

Where ρ denotes the extent of interest rate smoothing and v_t is the error term also known as the interest rate smoothing shock. Substituting (2) into (3) gives the following equation for the actual short-term interest rate:

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t + \beta w_t + \phi q_t) + \rho i_{t-1} + v_t \tag{4}$$

Taking the U.S. as the benchmark country, equation (4) as the interest rate reaction function for the foreign country, then the monetary policy reaction function for the US would be the same as equation (4) but with $\phi = 0$.

2.1. The exchange rate models

Deriving the Taylor rule based exchange rate model requires generating the implied interest rate differential. Where ~ denotes variables for the foreign country; the interest rate differential is produced by subtracting the Taylor rule equation for the foreign country from that of the domestic country, in this case the US.

$$i_t - \tilde{i}_t = \psi + (\psi_{u\pi}\pi_t - \psi_{f\pi}\tilde{\pi}_t) + (\psi_{uy}y_t - \psi_{fy}\tilde{y}_t) + (\psi_{uw}w_t - \psi_{fw}\tilde{w}_t) - \psi_q\tilde{q}_t + \rho_u i_{t-1} - \rho_f\tilde{i}_{t-1} + \eta_t \tag{5}$$

Where u and f are coefficients for the U.S. and the foreign country respectively. ψ is a constant, $\psi_\pi = \lambda(1-\rho)$, $\psi_y = \gamma(1-\rho)$ and $\psi_w = \beta(1-\rho)$ for both countries, and $\psi_q = \phi(1-\rho)$ for the foreign country.

Finally we assume that the expected rate of exchange rate depreciation is proportional to the interest rate differential:

$$E(\Delta s_{t+1}) = \beta(i_t - \tilde{i}_t) \tag{6}$$

Where Δs_{t+1} represents the logarithmic difference of the nominal exchange rate; specified as the price of the home currency in terms of the foreign currency, and E denotes the expectations operator. If we Assume Uncovered Interest Parity (UIP) holds with rational expectations, then $\beta = 1$, producing the following Taylor rule based exchange rate equation:

$$\Delta s_{t+1} = \psi + \psi_{u\pi}\pi_t - \psi_{f\pi}\tilde{\pi}_t + \psi_{uy}y_t - \psi_{fy}\tilde{y}_t + \psi_{uw}w_t - \psi_{fw}\tilde{w}_t - \psi_q\tilde{q}_t + \rho_u i_{t-1} - \rho_f\tilde{i}_{t-1} + \eta_t \tag{7}$$

Where s_t is the natural log of the U.S. nominal exchange rate, defined as the US dollar per unit of foreign currency, meaning a rise in s_t implies a depreciation of the American dollar. This specification using UIP, follows other similar approaches such as the Dornbusch (1976) overshooting model which provides a link for the monetary policy reaction function to the exchange rate behaviour through UIP. It has also previously been used in other Taylor rule based exchange rate models, such as Jian and Wu (2009) and Molodtsova and Papell (2009).

The Taylor rule forecasting model has the following form[3]:

$$\Delta s_{t+1} = \alpha_m + \beta_m X_{m,t} + \eta_{m,t+1} \tag{8}$$

where Δs_{t+1} is the change in the log of the nominal exchange rate determined as the domestic price of foreign currency. $X_{m,t}$ is a vector contains different economic variables. A general form of our forecasting model is given by the following equation:

$$\Delta s_{t+1} = \alpha - \alpha_{u\pi}\pi_t + \alpha_{f\pi}\tilde{\pi}_t - \alpha_{uy}y_t + \alpha_{fy}\tilde{y}_t - \alpha_{uw}w_t + \alpha_{fw}\tilde{w}_t + \alpha_q\tilde{q}_t - \alpha_{ui}i_{t-1} + \alpha_{fi}\tilde{i}_{t-1} + \eta_t \tag{9}$$

To produce the forecasts rolling regressions have been conducted with a moving window of 40 quarters (10 years) to produce one quarter ahead forecasts. Covering the time period from 1989Q1 to 2008Q4, forecasts are generated of the exchange rate and this forecast is then compared to the actual data, where the initial estimation period is from1979Q1 to 1988Q4 (except Australia which begins in 1983Q4). Depending on different assumptions regarding the coefficients, including the addition of stock prices and house prices as the wealth effect, there are sixteen models embedded in the above equation, which can be used for forecasting.

Model 1: asymmetric, with smoothing, heterogeneous coefficients with stock prices

[3] The models were also estimated and used for forecasting with lags of the variables included, but this had little effect on the forecasts.

$$X_{1,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} \quad \tilde{i}_{t-1} \quad w_t(stock) \quad \tilde{w}_t(stock)]$$

Model 2: asymmetric, with smoothing, heterogeneous coefficients with house prices

$$X_{2,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} \quad \tilde{i}_{t-1} \quad w_t(house) \quad \tilde{w}_t(house)]$$

Model 3: asymmetric, with smoothing, homogeneous coefficients with stock prices

$$X_{3,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{i}_{t-1} \quad w_t(s) - \tilde{w}_t(s)]$$

Model 4: asymmetric, with smoothing, homogeneous coefficients with house prices

$$X_{4,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{i}_{t-1} \quad w_t(h) - \tilde{w}_t(h)]$$

Model 5: Symmetric with smoothing, heterogeneous coefficients with stock prices

$$X_{5,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad i_{t-1} \quad \tilde{i}_{t-1} \quad w_t(stock) \quad \tilde{w}_t(stock)]$$

Model 6: Symmetric with smoothing, heterogeneous coefficients with house prices

$$X_{6,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad i_{t-1} \quad \tilde{i}_{t-1} \quad w_t(house) \quad \tilde{w}_t(house)]$$

Model 7: Symmetric with smoothing, homogeneous coefficients with stock prices

$$X_{7,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad i_{t-1} - \tilde{i}_{t-1} \quad w_t(s) - \tilde{w}_t(s)]$$

Model 8: Symmetric with smoothing, homogeneous coefficients with house prices

$$X_{8,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad i_{t-1} - \tilde{i}_{t-1} \quad w_t(h) - \tilde{w}_t(h)]$$

Model 9: Asymmetric, no smoothing, heterogeneous coefficients with stock prices

$$X_{9,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad w_t(stock) \quad \tilde{w}_t(stock)]$$

Model 10: Asymmetric, no smoothing, heterogeneous coefficients with house prices

$$X_{10,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad w_t(house) \quad \tilde{w}_t(house)]$$

Model 11: Asymmetric, no smoothing, homogeneous coefficients with stock prices

$$X_{11,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad w_t(s) - \tilde{w}_t(s)]$$

Model 12: Asymmetric, no smoothing, homogeneous coefficients with house prices

$$X_{12,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad w_t(h) - \tilde{w}_t(h)]$$

Model 13: Symmetric, no smoothing, heterogeneous coefficients with stock prices

$$X_{13,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad w_t(stock) \quad \tilde{w}_t(stock)]$$

Model 14: Symmetric, no smoothing, heterogeneous coefficients with house prices

$$X_{14,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad w_t(house) \quad \tilde{w}_t(house)]$$

Model 15: Symmetric, no smoothing, homogeneous coefficients with stock prices

$$X_{15,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t(s) - \tilde{w}_t(s)]$$

Model 16: Symmetric, no smoothing, homogeneous coefficients with house prices

$$X_{15,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t(house) - \tilde{w}_t(house)\,]$$

2.2. Methodology

The Pesaran-Timmermann test is a directional prediction test which focuses on correctly forecasting the direction of change in the variables being considered. The null hypothesis is that there is no relationship between actual and predicted directional changes. The procedure is distribution free and based on the proportion of times the direction of change in y_t is correctly predicted in the sample, as specified in Pesaran and Timmermann (1992). There are a number of economic theories that suggest predicting directional changes can be effective. As Hong and Chung (2003) point out, one example is the overreaction theory, whereby there are reversals in price movements following an overreaction by the market to a news announcement. With exchange rates the overshooting approach, as developed by Dornbusch (1976) would be an example of when directional change in the exchange rate could potentially be predictable. Similarly with the contagion theory, where adverse movements in one market could cause similar movements in another related market.

Assuming the following:

y_t: Actual value at time t

$\hat{y}_t$: The predictor value of y_t based on information available at time $t-1$

n: Total number of observations in the forecast series

Set: $Y_t = \begin{cases} 1 & y_t > 0 \\ 0 & otherwise \end{cases}$, $\hat{Y}_t = \begin{cases} 1 & \hat{y}_t > 0 \\ 0 & otherwise \end{cases}$ and

$$Z_t = \begin{cases} 1 & y_t\hat{y}_t > 0 \\ 0 & otherwise \end{cases}$$

Let $P_y = Pr(y_t > 0)$, $P_{\hat{y}} = Pr(\hat{y}_t > 0)$ and $\hat{P}$ be the proportion of time that the sign of y_t is correctly predicted. On the assumption that y_t and $\hat{y}_t$ are independently distributed of each other, the number of correct sign predictions has a binominal distribution with n trials and a success probability equal to:

$$\begin{aligned} P_* = \Pr(Z_t = 1) = Pr(y_t\hat{y}_t > 0) &= Pr(y_t > 0,\ \hat{y}_t > 0) + Pr(y_t < 0,\ \hat{y}_t < 0) \\ &= P_y P_{\hat{y}} + (1 - P_y)(1 - P_{\hat{y}}) \end{aligned}$$

Estimating these probabilities with their samples, we have:

$$\hat{P}_y = \frac{\sum_{t=1}^{n} y_t}{n},\ \hat{P}_{\hat{y}} = \frac{\sum_{t=1}^{n} \hat{y}_t}{n} \quad and \quad \hat{P}_* = \hat{P}_y\hat{P}_{\hat{y}} + (1 - \hat{P}_y)(1 - \hat{P}_{\hat{y}})$$

Under the null hypothesis that y_t and $\hat{y}_t$ are independently distributed, i.e. $\hat{y}_t$ has no power in forecasting y_t, the test statistic is:

$$PT = \frac{\hat{P} - \hat{P}_*}{\left(v\hat{a}r(\hat{P}) - v\,\hat{a}r(\hat{P}_*)\right)^{1/2}}$$

Where $v\hat{a}r(\hat{P}) = n^{-1}\hat{P}_*(1 - \hat{P}_*)$,

$$v\hat{a}r(\hat{P}_*) = n^{-1}(2\hat{P}_y - 1)^2\hat{P}_{\hat{y}}(1 - \hat{P}_{\hat{y}}) + n^{-1}(2\hat{P}_{\hat{y}} - 1)^2\hat{P}_y(1 - \hat{P}_y) + 4n^{-2}\hat{P}_y\hat{P}_{\hat{y}}(1 - \hat{P}_y)(1 - \hat{P}_{\hat{y}})$$

Pesaran-Timmermann (1992) have shown that the PT statistics converge to a standard normal distribution. The critical values at 95% and 99% are 1.64 and 2.33 respectively.

3. Data and Results

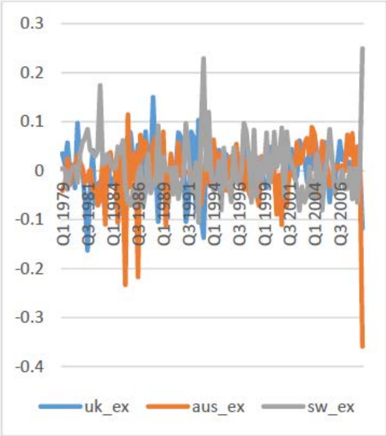
3.1. Data

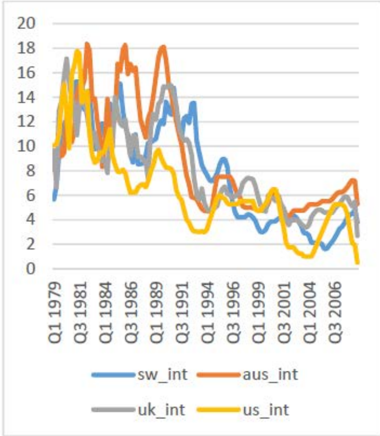
The data is all quarterly and consists of the exchange rates returns measured in log-differences, and the standard Taylor rule economic fundamentals for the United States, the United Kingdom, Sweden and Australia. Due to data availability, the time period for these countries differs depending on the measure of the wealth effect, which in the case of stock prices representing the wealth effect, the data runs from 1975Q1 to 2008Q4. Whereas when house prices are used, the data runs from 1980Q1 to 2008Q4 (The Australian data is estimated from 1983 quarter 4, reflecting the move to a floating exchange rate in that year). These four countries were selected partly because they have strong housing markets and therefore plentiful housing data and also because the UK, US and Australia have large internationally traded stock markets. As the interest rates approached their zero bounds after the financial crisis, the models are only estimated up to 2008. However a separate set of tests for robustness has been conducted on the shadow interest rate for the UK/US exchange rate to allow a data series to continue past 2008 (until 2015 Q4) and predict exchange rate movements after the financial crisis. The shadow interest rate is estimated and made available by Wu and Xia (2016).

All variables except interest rates are in logarithms[4]. The inflation rate is the annual inflation rate calculated using the CPI over the previous 4 quarters and we have used real GDP to measure the level of output. As in other similar studies, the output gap is constructed as the percentage deviation of actual output from a Hodrick Prescott (1997) (HP) generated trend.[5] The real foreign/U.S. exchange rate is calculated as the percentage deviation of the nominal exchange rate from a target, which is defined by

[4] The data was taken from the *International Financial Statistics (IMF),* except the exchange rate and main stock market indices which are from *Datastream* and the house price series from *Oxford Economics*. Summary statistics of the data are contained in tables A1 to A4 in the appendices and plots in Figure 1.

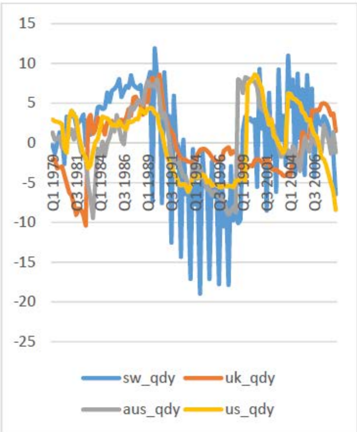
[5] Quarterly data was used, as the GDP data was not available on a monthly basis.

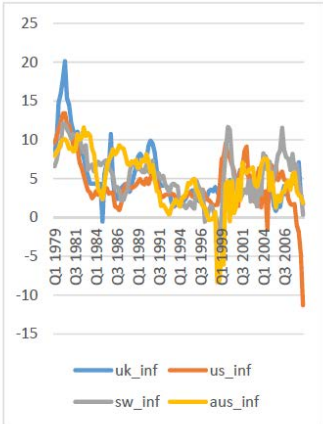




a) Plot of exchange rates.

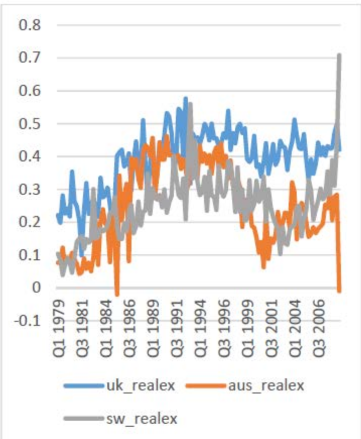
b) Plot of interest rates.

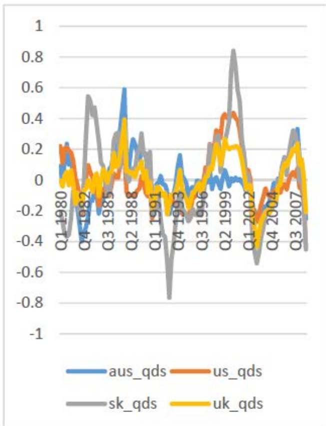




c) Output gaps.

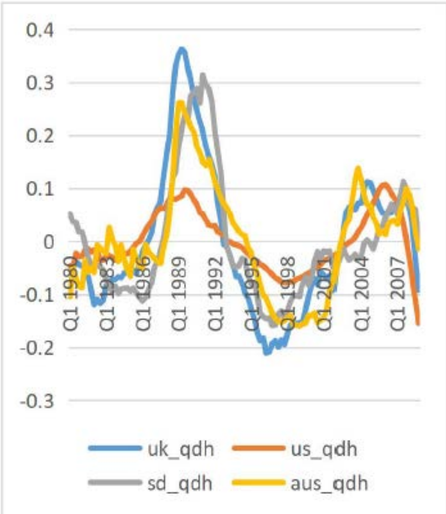
d) Inflation rates.





e) Real exchange rates.

f) Stock price.



g) House prices.

Figure 1. Plots of the data.

purchasing power parity (PPP) (i.e., $\tilde{q}_t = s_t - (p_t - p_t^*)$, where p_t and p_t^* are natural logarithms for U.S. and foreign price levels, respectively, as measured by respective CPI levels. The money market interest rates are used as a measure of the short-term interest rates. The nominal exchange rate is defined as the U.S. dollar price of foreign currency and is taken as the end-of-month exchange rate.

Similar studies, such as Molodtsova and Papell (2009) have emphasised the importance of real-time data in the use of Taylor rule-based models for forecasting the exchange rate. Real-time data use vintages of data which are available to researchers at each point in time (i.e., before any revisions to the data are applied). We have followed the approach of Molodtsova and Papell (2009) and used quasi-real time data for the output gap. In this case, current vintage data has been used and the trends at period t were calculated based on observations 1 to t-1.

4. Discussion

4.1. Structural breaks

As Pesaran and Timmermann (2004) and Sinclair et al. (2008) have indicated, the presence of structural breaks can affect forecasts and Beckmann et al. (2011) have emphasised the importance of testing for structural breaks in exchange rate models. To determine if there are structural breaks present and also whether the data is stationary, we have employed the Lee-Strazicich (2003) test for unit roots and structural breaks in the dataset. The Lee-Strazicich (2003) test starts with the assumption that the null hypothesis is a unit root with up to two breaks. Compared to the other ADF-type endogenous break unit root tests, it not only endogenously determines the structural breaks, but the alternative hypothesis also implies the series is trend stationary (Glynn et al., 2007). The ability to permit up to two breaks in the null and two breaks in the level or slope of the alternative make this approach particularly flexible and attractive.

Table 1a. One Break Lee Strazicich Test.

		UK		*Sweden*		*Australian*	
variables	*model*	*t-statistics*	*break date*	*t-statistics*	*break date*	*t-statistics*	*Break date*
Δs_{t+1}	A	-4.0101*	1980:01	-6.6866*	2001:01	-6.9187*	1985:01
π_t	A	-5.1396*	1985:02	-6.2031*	1994:03	-5.8468*	2000:01
y_t	A	-4.1115	1978:04	-6.8584*	2005:02	-5.1151*	1985:02
$\tilde{q}_t$	A	-4.0772*	1986:03	-2.9814	1984:04	-3.274**	1985:02
i_{t-1}	A	-4.5221*	1992:03	-7.1603*	1993:02	-3.5384	1991:01
$w_t(house)$	C	-4.8287*	1987:02	-4.8584*	1988:01	-3.9666	1988:01
$w_t(stock)$	C	-5.5372*	2002:04	-5.4708*	1982:01	-5.6244*	2005:03
$\pi_t - \tilde{\pi}_t$	A	-7.5086*	1991:02	-5.8380*	1993:01	-3.7506	2001:02
$y_t - \tilde{y}_t$	A	-5.3955*	1983:03	-5.8464*	1992:02	-5.3360*	1982:01
$i_{t-1} - \tilde{i}_{t-1}$	A	-4.8120*	1992:03	-4.2090*	1993:02	-3.0798	1990:01
$w_t - \tilde{w}_t(H)$	A	-5.0372*	2004:01	-4.8003*	1992:01	5.7839*	2005:01
$w_t - \tilde{w}_t(S)$	A	-6.9614*	1979:02	-5.6860*	1982:01	-5.0880*	1986:02

Notes: we only consider breaks if a variable is concluded to be non-stationary in the conventional tests. * ,** denote the unit root is rejected if allowed for 1 structural break at the 5% and 10% significance level.

Table 1b. One Break Lee Strazicich Test (continued).

		U.S.	
variables	*model*	*t-statistics*	*break date*
π_t	A	-4.7665*	1982:02
y_t	A	-5.2147*	2004:03
i_{t-1}	A	-5.0039*	1980:02
$w_t(house)$	C	-6.1388*	2004:02
$w_t(stock)$	C	-4.9267*	1982:02

Notes: * ,** denote the unit root is rejected if allowed for 1 structural break at the 5% and 10% significance level.

The results are shown in Table 1. For variables that are expected to grow over time, we allow for a constant and a time trend under the alternative hypothesis. Those series are the stock price and house price. For the exchange rate differences, inflation, interest rate, output gap and real exchange rate, we expect a long-run equilibrium value which does not grow over time and these tests have been specified with a constant but no time trend; Table 1 lists the test results and break points we considered for each of the countries measured at the 95% confidence interval[6]. In the presence of breaks for these variables, we have re-estimated the models including dummy variables to account for the breaks and ensure the data is stationary.

Most of the break dates can be explained by changes in the exchange rate regime or monetary policies in these countries. For example, For the UK, the first break corresponds with the abandoning of the £M3 target in October 1985. This is part of the MTFS the government announced in March 1980. It was originally aiming to reduce inflation and create conditions for sustainable economic growth. However, with the overshooting of the £M3 target, the UK economy went into a deep recession. The authorities had then successively downgraded its importance and by October 1985, the plan was finally

[6] We also used the Perron-NG test for a unit root, results available on request. For the real Swedish exchange rate, as it was non-stationary even with two structural breaks, we included it in first-differenced form.

abandoned. The second breaks can be viewed as a result of the UK leaving the ERM[7]. Sweden has a single break in 1994 Q3, when their economy began recovering after the severe banking crisis in the early 1990s. Australia has a break in 1985 Q2, when Australia adopted a flexible exchange rate. For the US there was a break in 1980 Q2, when the Treasury Department and the Federal Reserve announced a package of measures to strengthen the Dollar.

4.2. Results from the PT test

Table 2 contains the results over the extended time period using the shadow interest rates and Tables 3 and 4 report the results from our analysis of the predictive power of the exchange rate models for different countries over the standard time period. The column labelled "directional accuracy" shows the percentage of exchange rate changes that were accurately forecast by different models over the one quarter interval. The PT statistics measure the significance in the predictability of the direction of exchange rate changes. Results in general vary with different countries and the different model specifications, in particular whether stock prices or house prices are used as the wealth effect. The standard forecast error tests, using the mean square error (MSE) type statistic have not been included here, as there is a substantial body of literature which has already shown that forecasts from this Taylor rule based model outperform a random walk and the results of conducting the same tests on the models used here mirrored those results[8].

Table 2. Results for the Pesaran-Timmermann (PT) test using USUK with the shadow interest rate.

	Directional Accuracy	*PT statistic*
Model 1	50.0%	-0.1304
Model 2	42.2%	-1.9639
Model 3	54.7%	0.9757
Model 4	53.1%	0.6207
Model 5	54.7%	0.6611
Model 6	43.8%	-1.7218
Model 7	56.3%	1.2977
Model 8	53.1%	0.6712
Model 9	56.3%	1.0973
Model 10	54.7%	0.7190
Model 11	60.9%	1.9379*
Model 12	53.1%	0.6207
Model 13	62.5%	2.2624*
Model 14	53.1%	0.4760
Model 15	64.1%	2.5124*
Model 16	57.8%	1.5380

Note*:* Directional accuracy is the percentage of exchange rate changes that were accurately forecast. * and ** indicates model can correctly forecast the direction of change at the 5% and 1% significance level. The critical values of the PT-test at 95% and 99% are 1.64 and 2.33 respectively.

[7] The European exchange rate mechanism; Within the ERM, Germany was dominant and other countries followed German interest rate policy.

[8] Results are available on request.

For the UK and US exchange rates[9], the rolling predictions attain the sign of the exchange rate changes correctly in at least 50% of all quarters over the period 2000 to 2008. We have based the selection criteria on the models which perform best simply on the one with the highest percentage of correct predictions. We have in addition provided information on the explanatory power of these models in tables 5 to 7, but as with similar studies we concentrate on the forecast performance rather than the models explanatory powers.

Table 3. Non-parametric Statistics for the Pesaran-Timmermann (PT) test.

	UK		*Sweden*		*Australia*	
	Directional Accuracy	*PT statistic*	*Directional Accuracy*	*PT statistic*	*Directional Accuracy*	*PT statistic*
Model 1	58.3%	1.1198	44.4%	-1.0934	47.2%	-1.1931
Model 2	58.3%	1.0306	63.9%	1.7889*	55.6%	-0.0926
Model 3	52.8%	0.3912	33.3%	-2.1552	47.2%	0.0401
Model 4	58.3%	1.0725	58.3%	1.1198	47.2%	-0.1173
Model 5	63.9%	1.7889*	44.4%	-1.0934	69.4%	2.3371**
Model 6	61.1%	1.4255	69.4%	2.6186**	55.6%	0.0862
Model 7	61.1%	1.5597	36.1%	-1.7889	52.8%	1.1932
Model 8	66.7%	2.3047*	63.9%	1.9270*	33.3%	-1.8073
Model 9	55.6%	0.6981	50.0%	0	47.2%	-0.1173
Model 10	58.3%	1.1198	63.8%	1.7889*	63.9%	1.1809
Model 11	50.0%	0	33.3%	-2.2180	50.0%	0.4887
Model 12	58.3%	1.0725	52.8%	0.3912	44.4%	-0.5462
Model 13	61.1%	1.5597	44.4%	-0.6848	61.1%	1.7870*
Model 14	63.9%	2.0641*	66.7%	2.1704*	58.3%	1.3088
Model 15	72.2%	3.2660**	33.3%	-2.6701	58.3%	1.7371*
Model 16	63.8%	1.8405*	52.8%	0.4282	30.6%	-2.2731

Note: Directional accuracy is the percentage of exchange rate changes that were accurately forecast. * and ** indicates the model can correctly forecast the direction of change at the 5% and 1% significance level. The critical values of the PT-test at 95% and 99% are 1.64 and 2.33 respectively.

In table 2 we find that only 3 models predict the directional change when using the shadow interest rate on post-crisis data with model 15 performing best, this is less than the UK/US model for the pre-crisis data suggesting directional change is now less easy to predict in the post-crisis monetary regime for these two countries. In Table 3, again for the UK/US model 15 (symmetric, no smoothing, homogeneous coefficients with stock prices) gives the highest directional prediction accuracy, with 72.2 percent of actual exchange rate changes correctly predicted. The PT test statistics show that only for 5 out of the 14 models, are the predicted changes significantly associated with the actual changes. A common feature shared by the successful results is that they are all symmetric models, without the real exchange rate. For the PT results confirming the directional accuracy,

[9] The implied restrictions on the coefficients were tested using Wald tests and models 5 and 13 in the cases of the US/UK exchange rate and Models 9, 10, 13 and 14 in the case of US/Sweden exchange rate the restrictions could not be rejected, so the unrestricted results of these tests have not been reported.

models with significant PT statistics tend to have a higher proportion of successful directional prediction than the others.

Table 4. Non-parametric Statistics for the Pesaran-Timmermann (PT) test after incorporating structural breaks.

	UK		*Sweden*		*Australia*	
	Directional Accuracy	*PT statistic*	*Directional Accuracy*	*PT statistic*	*Directional Accuracy*	*PT statistic*
Model 1	47.2%	-0.3391	58.3%	1.0725	52.8%	0.2705
Model 2	63.9%	1.7646*	63.8%	2.0641*	61.1%	0.6375
Model 3	52.8%	0.3912	33.3%	-2.1552	47.2%	0.0401
Model 4	58.3%	1.0725	58.3%	1.1198	47.2%	-0.1173
Model 5	63.9%	1.7646*	63.9%	1.9270*	69.4%	2.3371**
Model 6	63.9%	1.7646*	69.4%	2.6186**	58.3%	0.4049
Model 7	61.1%	1.5597	36.1%	-1.7889	52.8%	1.1932
Model 8	66.7%	2.3047*	63.9%	1.9270*	33.3%	-1.8073
Model 9	47.2%	-0.3434	47.2%	-0.3525	55.5%	0.8583
Model 10	58.3%	1.0306	63.8%	1.7889*	50.0%	-0.6836
Model 11	50.0%	0	33.3%	-2.2180	50.0%	0.4887
Model 12	58.3%	1.0725	52.8%	0.3912	44.4%	-0.5462
Model 13	61.1%	1.5597	47.2%	-0.3525	61.1%	1.7870*
Model 14	69.4%	3.0693**	66.7%	2.1704*	55.6%	0.5462
Model 15	72.2%	3.2660**	33.3%	-2.6701	58.3%	1.7371*
Model 16	63.8%	1.8405*	52.8%	0.4282	30.6%	-2.2731

Note: Directional accuracy is the percentage of exchange rate changes that were accurately forecast. * and ** indicates model can correctly forecast the direction of change at the 5% and 1% significant level. The critical values of the PT-test at 95% and 99% are 1.64 and 2.33 respectively. Dummy variable added for AUS: 85Q2; Dummy variable added for Sweden: 94Q3 and 80Q2; Dummy variable added for UK: 85Q2, 92Q3 and 80Q2.

According to the results in Tables 3 and 4, the model which gives the best forecast of directional change for the Sweden/US exchange rate is the symmetric, with smoothing and heterogeneous coefficient model with house prices representing the wealth effect (see Model 6). It gives the highest fraction of successful directional prediction at 66.7% and the PT statistic is well above the 95% critical value for a one sided standard normal test, leading to a strong rejection of the hypothesis that actual and predicted exchange rates are independently distributed. The PT statistics show that 5 models provide evidence of predictive power in exchange rate direction movements. All the best performing Swedish models have house prices representing the wealth effect. Therefore, exchange rate forecasting models incorporating house prices are the most accurate approach to forecasting the direction of exchange rate changes, which reflects the relative importance of housing to the Swedish economy relative to the stock market.

The difference between the Swedish and the UK/Australian results can be explained by reference to the underlying structure of the Swedish economy. There are several reasons why house prices are more significant than stock prices in explaining the US-Swedish exchange rate. Firstly, Swedish stock market wealth accounts for only a small proportion of the total household financial wealth, as estimated by Chen (2006). This study found that 0.08–0.2% of total financial wealth in Sweden is from the stock market. In contrast, housing wealth takes up a much a larger proportion, again according to Chen (2006), about 50–70% of non-stock wealth originates from housing for the period 1980 to 2004. As housing wealth takes up a large proportion of household asset wealth, changes in house prices will have a more significant impact on consumption and therefore output, as well as a more substantial effect on inflation. Secondly, house prices often indirectly influence consumption through credit loans, as it is often used as collateral. Sweden has a large and liquid housing finance market and its mortgage bond market ranks as the third largest in Europe.

For the Australian data, the PT test statistics show that only models 5, 13 and 15 have significant statistics and so we reject the null hypothesis for only these three models. Since model 13 is an unrestricted version of model 15, and Model 13 has a higher directional accuracy and PT statistic than model 15, we conclude that symmetric models with heterogenous coefficients and stock prices are better in predicting directional changes for Australia. Table 4 contains the results from including dummy variables in those series where a structural break was found based on the Lee-Stazichich test. Where no structural breaks were found the test statistic is the same as in the previous table. In general there is a slight improvement in the forecasting performance for the UK and Swedish tests in terms of significant forecasts, but no difference for Australia.

Table 5. Estimation of Taylor rule exchange rate models for the UK.

Heterogeneous coefficient	*Model 1*	*Model 2*	*Model 5*	*Model 6*	*Model 9*	*Model 10*	*Model 13*	*Model 14*
R-squared	0.262	0.438	0.144	0.193	0.204	0.350	0.087	0.143
Adj. R-squared	0.168	0.354	0.044	0.081	0.146	0.294	0.029	0.078
$\hat{\sigma}$	0.047	0.042	0.051	0.050	0.048	0.044	0.051	0.050
Log likelihood	227.327	209.501	217.459	188.648	224.255	201.063	215.058	185.168
F-statistic	1.758	5.072*	0.629	0.595	2.787*	4.827*	0.245	3.197*
Homogenous coefficient	*Model 3*	*Model 4*	*Model 7*	*Model 8*	*Model 11*	*Model 12*	*Model 15*	*Model 16*
R-squared	0.142	0.150	0.088	0.049	0.112	0.124	0.058	0.026
Adj. R-squared	0.109	0.111	0.051	0.015	0.084	0.093	0.037	-0.001
$\hat{\sigma}$	0.0489	0.049	0.050	0.052	0.049	0.050	0.051	0.052
Log likelihood	217.252	185.654	213.136	179.223	216.866	183.931	212.933	177.785
F-statistic	0.142	0.150	0.088	0.049	0.112	0.124	0.058	0.026

Note: Models are estimated by OLS where standard errors have been Newey-West corrected. Dummies are only included in ones that have structural breaks (i.e. heterogeneous models) $\hat{\sigma}$ is the standard error of the regression. F-statistics is the Wald test for coefficient equality restriction. *and **means significance at 5% and 1% significant level, respectively.

From the above PT test results, we conclude that not all Taylor rule models are effective in predicting the direction of the exchange rate changes. For almost two thirds of the models studied, the direction of exchange rate changes predicted from the Taylor rule models is uncorrelated with the actual directional changes. This mirrors other studies such as Qi and Wu (2003) who found using their model to predict the direction of change of the exchange rate was not successful, although in their case, it also failed to consistently predict the future value of the exchange rate. Among the three countries that have been studied, the PT statistics show that Taylor rule models give the highest predictive power for the UK/US data. Model 15 in general works well for both the UK/US and Australia/US exchange rate predictions. In addition to these forecasts Tables 5, 6 and 7 provide statistical analysis of the estimated models.

When accounting for the structural breaks in the series by adding dummy variables, there is little evidence that the forecasts have improved substantially. Although there is a slight improvement for the Swedish and UK models, there is no improvement for Australia. Overall there is a lack of significance in most of the results, this could be due to the lack of any predictable overreaction or overshooting in these exchange rates over the recent past. Although it doesn't prove that there is no overshooting, it appears that if there is any it is not predictable using this approach. Similarly with regard to the contagion theory, if there are any adverse movements in the money markets, it doesn't appear to transfer to the foreign exchange markets in a predictable way based on our results.

Table 6.Estimation of Taylor rule exchange rate models for the Sweden.

Heterogeneous coefficient	*Model 1*	*Model 2*	*Model 5*	*Model 6*	*Model 9*	*Model 10*	*Model 13*	*Model 14*
R-squared	0.221	0.237	0.221	0.237	0.077	0.144	0.067	0.141
Adj. R-squared	0.137	0.139	0.144	0.147	0.010	0.071	0.008	0.076
$\hat{\sigma}$	0.052	0.055	0.052	0.055	0.056	0.057	0.056	0.057
Log likelihood	215.036	177.938	215.012	177.936	203.584	171.355	202.859	171.121
F-statistic	0.952	1.355	1.287	1.400	0.732	2.056	1.254	2.171**
Homogenous coefficient	*Model 3*	*Model 4*	*Model 7*	*Model 8*	*Model 11*	*Model 12*	*Model 15*	*Model 16*
R-squared	0.062	0.080	0.043	0.067	0.044	0.048	0.023	0.035
Adj. R-squared	0.026	0.038	0.013	0.033	0.015	0.014	0.001	0.009
$\hat{\sigma}$	0.055	0.058	0.056	0.058	0.056	0.059	0.056	0.059
Log likelihood	200.576	167.184	199.204	166.379	201.249	165.234	199.797	164.443
F-statistic	0.062	0.080	0.043	0.067	0.044	0.048	0.023	0.035

Table 7. Estimation of Taylor rule exchange rate models for the Australia.

Heterogeneous coefficient	*Model 1*	*Model 2*	*Model 5*	*Model 6*	*Model 9*	*Model 10*	*Model 13*	*Model 14*
R-squared	0.112	0.230	0.088	0.146	0.096	0.227	0.076	0.130
Adj. R-squared	0.048	0.164	0.030	0.082	0.047	0.176	0.032	0.082
$\hat{\sigma}$	0.0586	0.058	0.059	0.061	0.058	0.057	0.059	0.061
Log likelihood	195.283	169.545	193.488	163.634	196.059	169.324	194.523	162.569
F-statistic	1.073	5.423*	1.998**	3.254*	0.353	4.906*	1.735	2.240**
Homogenous coefficient	*Model 3*	*Model 4*	*Model 7*	*Model 8*	*Model 11*	*Model 12*	*Model 15*	*Model 16*
R-squared	0.090	0.039	0.059	0.004	0.089	0.038	0.058	0.004
Adj. R-squared	0.055	-0.005	0.030	-0.032	0.061	0.004	0.037	-0.022
$\hat{\sigma}$	0.058	0.064	0.059	0.064	0.058	0.063	0.059	0.064
Log likelihood	193.664	156.833	191.421	154.782	195.543	156.816	193.320	154.781
F-statistic	0.090	0.039	0.059	0.004	0.089	0.038	0.058	0.004

5. Conclusion

Following the success of the Taylor rule model of the exchange rate in out-of-sample forecasting based on the conventional forecast errors measures, we have used the PT test of directional accuracy to determine if this modelling approach produces forecasts that are equally accurate. However the results suggest there is mixed evidence of these models being able to consistently forecast directional change, which is in contrast to other studies using these models with the conventional forecasting approach. This suggests that the ability of a model to forecast future exchange rates doesn't imply it will be able to predict directional change, which can be a more practical way of assessing the profitability of investing in asset markets.

The main policy implications of these findings relate to both the asset management sector and macroeconomic policy makers. For asset managers being able to predict directional change can be essential for active asset management strategies involving the use of technical trading rules. This in turn is important for the efficient allocation of resources by financial markets. Similarly for macroeconomists attempting to forecast future economic events, these results indicate it is difficult to predict directional changes to the economy, such as following a sudden financial crises.

However there is evidence that the results are sensitive to the specification of the models used, in particular the measure of wealth used. Some specifications of these models can produce reasonably accurate forecasts and therefore the potential to make a profit by using these forecasts. For instance for Australia and the UK exchange rates, the symmetric model, with no smoothing, homogenous coefficients and stock prices as the wealth effect appears to do better than simple chance, perhaps reflecting the importance of the stock markets in these two countries and the role of capital flows between the UK, Australian and the US asset markets. This suggests that future research could concentrate more on the asset market aspects of these models as well as related issues in terms of global liquidity, current account imbalances and productivity shocks if these forecasts are to be improved.

Conflict of interest

The authors declare no conflict of interest in this paper.

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Appendices

Table A1. UK Summary Statistics.

UK	Δs_t	π_t	y_t	$w_t(s)$	$w_t(h)$	$\tilde{q}_t$	i_t	$\pi_t - \tilde{\pi}_t$	$y_t - \tilde{y}_t$	$w_t - \tilde{w}_t(S)$	$w_t - \tilde{w}_t(H)$	$i_t - \tilde{i}_t$
Mean	-0.0020	0.0554	0.0014	-0.0007	0.0000	0.5448	7.8901	0.0121	0.0017	0.0000	0.0000	1.5363
Median	0.0001	0.0355	0.0011	0.0022	-0.0058	0.5429	6.4800	0.0017	0.0019	0.0075	-0.0021	1.3450
Maximum	0.1499	0.2356	0.0365	0.3119	0.1457	0.8202	17.1300	0.1556	0.0444	0.2094	0.1275	6.9000
Minimum	-0.1626	0.0061	-0.0397	-0.3682	-0.1123	0.1632	0.3100	-0.0266	-0.0424	-0.3730	-0.0743	-6.8600
Std. Dev.	0.0515	0.0525	0.0142	0.1062	0.0435	0.1174	3.6526	0.0338	0.0164	0.0719	0.0408	2.5450
Skewness	-0.2441	1.5869	0.0770	-0.6472	1.0424	-0.2988	0.5610	2.2832	0.0011	-0.8096	0.6467	-0.2014
Kurtosis	3.4479	4.8300	3.3284	4.6535	5.1522	3.5694	2.2842	8.6585	3.1107	8.1023	3.7967	3.7781
Jarque-Bera	2.4872	76.0590	0.7452	24.9882	43.3969	3.8611	10.0363	299.5962	0.0695	162.3822	11.1519	4.3498
Probability	0.2883	0.0000	0.6889	0.0000	0.0000	0.1451	0.0066	0.0000	0.9659	0.0000	0.0038	0.1136
Observations	136	136	136	136	116	136	136	136	136	136	116	136

Note: The descriptive statistics are the log form of the USD/UK exchange rate change, inflation, output gap, stock price index, house price index, real USD/UK exchange rate, interest rate, inflation difference, output gap difference, stock price difference, house price difference and interest rate difference between the US and UK, respectively. All statistics are constructed from quarterly observations running from 1975 to 2008 with definitions listed above. All differentials are measured as the US minus the foreign data.

Table A2. Swedish Summary Statistics.

Sweden	Δs_t	π_t	y_t	$w_t(s)$	$w_t(h)$	$\tilde{q}_t$	i_t	$\pi_t - \tilde{\pi}_t$	$y_t - \tilde{y}_t$	$w_t - \tilde{w}_t(s)$	$w_t - \tilde{w}_t(h)$	$i_t - \tilde{i}_t$
Mean	0.0043	0.0498	0.0007	-0.0002	0.0000	1.8920	8.0796	0.0064	0.0010	0.0004	0.0000	1.7257
Median	0.0022	0.0413	-0.0015	-0.0180	-0.0035	1.9678	8.2550	0.0027	-0.0018	0.0092	-0.0005	1.8650
Maximum	0.2490	0.1375	0.0491	0.6046	0.1300	2.4230	35.7800	0.0633	0.0560	0.4044	0.1318	32.5200
Minimum	-0.1055	-0.0112	-0.0420	-0.4976	-0.0898	1.1252	1.6200	-0.0427	-0.0361	-0.4953	-0.0839	-4.4000
Std. Dev.	0.0562	0.0391	0.0162	0.1999	0.0436	0.3349	4.5750	0.0259	0.0188	0.1593	0.0446	3.9932
Skewness	1.2818	0.4132	0.2540	0.2179	0.6526	-0.7995	1.6046	0.3224	0.6230	-0.0914	0.6087	3.4469
Kurtosis	6.3521	1.9314	3.8248	3.5877	3.8156	2.5857	10.9428	2.1512	3.3564	3.4175	3.6219	27.2233
Jarque-Bera	100.9125	10.3420	5.3173	3.0336	11.4499	15.4609	415.8643	6.4377	9.5161	1.1767	9.0322	3594.3290
Observations	136	136	136	136	116	136	136	136	136	136	116	136

Table A3. Australian Summary Statistics.

Australia	Δs_t	π_t	y_t	$w_t(s)$	$w_t(h)$	$\tilde{q}_t$	i_t	$\pi_t - \tilde{\pi}_t$	$y_t - \tilde{y}_t$	$w_t - \tilde{w}_t(s)$	$w_t - \tilde{w}_t(h)$	$i_t - \tilde{i}_t$
Mean	-0.0051	0.0556	0.0008	-0.0029	0.0000	-0.3016	8.9820	0.0123	0.0011	-0.0023	0.0000	2.6282
Median	0.0024	0.0457	-0.0004	-0.0056	-0.0075	-0.2749	7.5050	0.0040	-0.0024	-0.0067	-0.0042	2.2800
Maximum	0.1144	0.1628	0.0488	0.4281	0.1361	-0.0447	18.3600	0.0840	0.0484	0.2754	0.1258	10.5200
Minimum	-0.3592	-0.0045	-0.0356	-0.3826	-0.0997	-0.6883	4.2400	-0.0344	-0.0421	-0.2396	-0.1115	-5.5500
Std. Dev.	0.0596	0.0378	0.0172	0.1221	0.0422	0.1589	4.1228	0.0286	0.0194	0.0969	0.0467	3.1550
Skewness	-2.2882	0.5642	0.6566	0.4991	0.7792	-0.5996	0.8022	0.7524	0.4066	0.2575	0.1587	0.2839
Kurtosis	13.0328	2.4558	3.7480	4.5702	4.2203	2.7014	2.4002	2.5980	2.6956	2.9113	3.2920	3.6431
Jarque-Bera	689.0707	8.8940	12.9435	19.6176	18.9364	8.6541	16.6250	13.7460	4.2716	1.5475	0.8989	4.1699
Observations	136	136	136	136	116	136	136	136	136	136	116	136

Table A4. U.S. Summary Statistics.

US	π_t	y_t	$w_t(s)$	$w_t(h)$	i_t
Mean	0.0434	-0.0003	-0.0007	0.0000	6.3538
Median	0.0335	-0.0015	-0.0004	-0.0029	5.5600
Maximum	0.1355	0.0343	0.2216	0.0558	17.7800
Minimum	0.0124	-0.0457	-0.3279	-0.1150	0.5100
Std. Dev.	0.0273	0.0127	0.0989	0.0224	3.5188
Skewness	1.5636	-0.2275	-0.4570	-0.9688	1.0157
Kurtosis	4.9019	3.5774	3.7532	9.8068	4.2784
Jarque-Bera	75.9163	3.0623	7.9491	242.0905	32.6464
Probability	0.0000	0.2163	0.0188	0.0000	0.0000
Observations	136	136	136	116	136