Open Issues in Financial Economics

by

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Abstract

The breakdown of the Bretton Woods system and the adoption of generalized floating exchange rates ushered in a new era of exchange rate volatility and uncertainty. This increased volatility led economists to search for economic models able to describe observed exchange rate behaviour. In chapter 2 we propose more general STAR transition functions which encompass both threshold non-linearity and asymmetric effects. Our framework allows for a gradual adjustment from one regime to another, and considers threshold effects by encompassing other existing models, such as TAR models. We apply our methodology to three different exchange rate data-sets, one for developing countries, and official nominal exchange rates, the second emerging market economies using black market exchange rates and the third for OECD economies.

The large appreciation and depreciation of the dollar in the 1980s stimulate an exciting academic debate on using unit root tests for structural break. We propose a model which is the natural extension of the behavioural equilibrium exchange rate (BEER) model. We then propose more general smooth transition (STR) functions, which are able to capture structural changes along the equilibrium path, and are consistent with our economic model. Our framework allows for a gradual adjustment between regimes and considers under- and/or over-valued exchange rate adjustment. We apply our methodology to the monthly and quarterly nominal exchange rates for seventeen and twenty OECD economies and construct bilateral CPI-based real exchange rates against the U.S. dollar and the German mark.

The investigation of chapter 4 focuses on non-linear forecasts to testing exchange rate models by examining microstructure - order flow. The basic hypothesis is that if order flow includes heterogeneous beliefs and the information contained in them, heterogenous customer order flow can have forecasting power for exchange rates. Using statistical and economic evaluation, we quantify the role that, when the information is lagged or simultaneously released to all market participants, the key micro level price determinants - order flows is impounded into price. The results indicate: 1) order flow with non-linear consideration lead to considerable and statistically significant improvements compared to the random walk model; and 2) order flow is a powerful predictor of the exchange rate movement in an out-of-sample exercise, on the basis of economic value criteria such as Sharpe ratio and performance fees implied by utility calculations.

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But most of all, I appreciate the love and warmth of my family and Jaewhi for being there. I dedicate this work to the cherished memories of my father, and to my mother on her seventieth birthday.

Declaration

I declare that, except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow and any other institution.

Hyunsok Kim

Chapter 1

Reviews of Exchange Rate Model from Linear to Non-linear Specifications

1.1 Introduction

The investigation of exchange rate behaviour in both academic and practical terms has received considerable attention in the field of international market environments. A research paper by Meese and Rogoff (1983) and subsequent research have found random walk dominates exchange rate behaviour. The mainstream literature has widely investigated exchange rate dynamics from univariate to macro-fundamental relevance, but these studies have shown mixed results and still faced difficulty in forecasting exchange rates better than a simple random walk model. This stylized fact has been named an 'exchange rate disconnection puzzle' by Obstfeld and Taylor (1997) and is one of the major issues in open macroeconomics literature.

Based on the fact that pricing to market with nominal rigidities creates volatile deviations in real exchange rates several avenues of the most important theoretical contributions in non-linear approaches have been explored by Dumas (1992), Sercu, Uppal, and Hulle (1995) and Berka (2004) in the deviations of prices from parity and modelling the behaviour of the band of inaction regime. Those provide alternative non-linear specifications for the series depending on whether there is a price difference and deviation of price in excess of trade cost, which creates an arbitrage opportunity. Specifically, Dumas (1992) models the costs of arbitrage trade generating deviations from the law of one price. Sercu, Uppal, and Hulle (1995) investigate nominal exchange rate movement within a band around the nominal purchasing power parity (PPP) value. They explain the reason why below-unity slope coefficients exist, which increase toward unity under hyperinflation or with low-frequency data in regression tests of PPP. Alternatively, Berka (2004) explains persistence and deviations from PPP as a result of heterogeneous shipping costs in a dynamic general equilibrium framework with arbitrage trade.

Computational tractability as well as relative theoretical plausibility has helped widen application to non-linear issues and led to a sizeable investigation of reduced form-based analysis, which has concentrated on regime-switching non-linear models, such as threshold autoregressive (TAR) and smooth transition autoregressive (STAR). In particular, Obstfeld and Taylor (1997), Michael, Nobay, and Peel (1997), Taylor (2001), Peel, Sarno, and Taylor (2001), Sollis, Leybourne, and Newbold (2002), Kapetanios, Shin, and Snell (2003) and Sarno, Taylor, and Chowdhury (2004) have examined the evidence of non-linear adjustment in exchange rate deviation from the fundamental equilibrium level.

Another important source of non-linearity notes that, since forward looking agents forecast future time paths of fundamentals, the data generation process may be intrinsically non-linear. In particular, if agents expect that government reaction functions are subject to stochastic change or that authorities regulate the fundamentals driving the exchange rate, the appropriate functional form may be subject to structural changes. Dutta and Leon (2002) note that this finding is probably due to government intervention aimed at avoiding excessive appreciation or depreciation of a currency. Intuitively, monetary authorities may intervene in the foreign exchange market as a reaction to large depreciations or appreciations of a currency, which lead to different behaviour for moderate and large changes of the exchange rate. Similar behaviour may be observed for an exchange rate, which is constrained to lie within a prescribed band or target zone, as was the case in the Exchange Rate Mechanism (ERM) in Europe. In this case, the level of the exchange rate, rather than its change determines the regimes. In particular, Papell (2002) and Sollis (2005) empirically find evidence that exchange rates might show structure changes exhibiting much higher volatility than the target regime in the outer regimes.

Instead of macro fundamental-based analysis, the influential work of Lyons (1999) turned our attention to microstructure order flows as an alternative route. This effort helps to identify where the gaps in our knowledge may lie and suggest new avenues. Evans and Lyons (2002b) then provide empirical evidence that the behaviour of dealers and other market participants can influence equilibrium exchange rates. Specifically, the main conclusion of Evans and Lyons (2002b) is that the order flow is a significant determinant of two major bilateral exchange rates, obtaining coefficients of determination substantially larger than the ones usually found using standard macroeconomic models.

Hence, the Foreign Exchange (FX) market may act as an aggregator of information regarding the expectations and circumstances of the participants. The subsequent literature by Evans and Lyons (2005a) also supports these results and illustrates how gradual learning in the FX market can generate not only explanatory, but also forecasting power from order flow.

Although findings from microstructure consideration generally agree that order flows have explanatory power for exchange rate dynamics, the key results from Sager and Taylor (2008) reveal limitations in forecasting power with a lagged model setup, and point out the problem in out-of-sample performance using both inter-dealer and commercially available customer order flow data. They note the fact that the response is not always predictable; this makes it sometimes difficult to achieve the desired results, when macroeconomic information is lagged and released to all market participants.

This chapter critically reviews the most common empirical methodologies used in previous studies, with the focus being mainly on non-linear methods. However, in providing these exchange rate theories the chapter will also summarize some empirical works, which have made an important contribution to exchange rate modelling.

This chapter is organized as follows. Section 1.2 introduces the PPP debate and main findings. Section 1.3 summarizes exchange rate forecast models for our contribution. Our exchange rate modelling in the next chapters is briefly introduced and summarized in section 1.4. Section 1.5 concludes the chapter.

1.2 The purchasing power parity debate and real exchange rate

1.2.1 Textbook theory to testing the PPP hypothesis

The key concept of the purchasing power parity (PPP) hypothesis is the "law of one price" (LOP), which states that the purchasing power of a unit of one currency should be able to buy the same basket of goods in other country, so that there is parity in the purchasing power of the unit of currency across the two economies. In a two-country setup with homogenous traded goods, when there is no impediment to international trade, such as transportation costs and tariffs, the LOP for good i may be expressed as

$$P_t^i = S_t P_t^{i*},$$

where P^i denotes the price of the good i, S is the nominal exchange rate and the asterisk represents a foreign magnitude. One very simple way of gauging whether there may be discrepancies of PPP is to compare the prices from the basket in the two countries. Therefore the country's nominal exchange rate is determined as the ratio of the price levels at home and abroad. Assuming a measure for the price level, P_t and P_t^*, we can write,

$$S_t = \frac{P_t}{P_t^*}$$

PPP indicates the exchange rate between two currencies which would equate to the two relevant national price levels, so that the purchasing power of a unit of one currency would be the same in both economies. Therefore, the idea that PPP may hold because of international goods arbitrage is related to the LOP and, in the analysis, this is often termed ‘absolute PPP’.

Alternatively, when the rate of depreciation of one currency relative to another matches the difference in aggregate price inflation between the two countries concerned, it is termed ‘relative PPP’ and is defined as

$$\Delta S_t = \frac{\Delta P_t}{\Delta P_t^*}$$

which implies that changes in the exchange rates are equal to changes in the relative national prices.

Summing up, PPP holds that the nominal exchange rate between two currencies should be equal to the ratio of aggregate price levels between two countries so that a unit of one country’s currency will have the same purchasing power in a foreign country. This is a main building block in determining the equilibrium exchange rate.

Cointegration based tests

If the national price levels P_t and P_t^* are in logarithms, the early empirical studies on testing PPP are based on estimates of the following form

$$s_t = \alpha + \beta p_t + \beta^* p_t^* + \varepsilon_t \tag{1.1}$$

where ε_t is a disturbance term, s_t is the logarithm of nominal exchange rate (domestic price of foreign currency) and p_t and p_t^* are the logarithms of domestic and foreign price levels, respectively. A test of the restrictions $\beta = 1$, $\beta^* = -1$ would be interpreted as a test of absolute PPP, while a test of the same restrictions applied to the equation with the variables in first differences would be interpreted as a test of relative PPP. In particular, a distinction is often made between the test that β and β^* are equal and of opposite signs and the test that they are equal to unity and minus unity, respectively. Earlier empirical tests by Frenkel (1978) confirm that estimates of β and β^* are close to positive and negative unity on data for high inflation countries, suggesting that PPP represents an important benchmark in long-run exchange rate modelling. However, testing PPP based on estimates of equation (1.1) has an endogeneity problem of both nominal exchange rates and price levels. Furthermore, the most serious problem is 'spurious regression' suggested by Granger and Newbold (1974). That is, this kind of early study does not investigate the stationarity of the estimated variables and the stochastic properties of the residuals. Nowadays as we can recognize in time series analysis, if the residuals are non-stationary, part of shock impinging upon the real exchange rate will be permanent, which implies PPP violation. If the error term in equation (1.1) is stationary, a strong long-run linear relationship exists between exchange rates and relative prices, but the conventional statistical inference is still invalid because of the bias present in the estimated standard errors.

As originally developed by Engle and Granger (1987), an ideal approach for equation (1.1) seems to be the cointegration test. The fundamental concept is that, when a linear combination of the series exist, two non-stationary series are found to be integrated of the same order and cointegrated. That is, when both s_t and π_t are integrated of order d, $I(d)$, the linear combination of equation (1.1) can be compactly defined as

$$s_t + \kappa \pi_t = z_t$$

where π_t is $p_t - p_t^*$. When z_t is mean-reverting, we are confident that a strong long-run relationship exists between the two variables, s_t and π_t, since they share a common stochastic trend. Cointegration of a pair of variables is a necessary condition for them to have a stable long-run relationship. However, due to the fact that the Engle-Granger method suffers from several deficiencies such as poor small sample performance and asymptotic problems in the presence of endogeneity and serial correlation, earlier studies generally report the absence of significant mean-reversion of the exchange rate toward PPP for the floating period.

As an alternative approach to the Engle-Granger method, a number of studies has applied Johansen (1995)'s full information maximum likelihood method, which produces asymptotically better estimates. Using nine bilateral exchange rates of the floating periods from March 1973 to December 1992, MacDonald (1995a) compares both cointegration-based analyses. The results from the Engle-Granger method seem to be more appropriate with WPI rather than CPI. Most of the estimated coefficients are far from the hypothesized values and none of the test statistics are significant at the 5% or 10% levels, which is consistent with other studies. On the contrary, the results from Johansen's method provide evidence of a cointegrating vector for each country at the 5% significance level, except Sweden and Germany. Although the values are far from unity, most of the coefficients are correctly signed. Thus MacDonald (1995a) concludes that the evidence supports weak-form PPP rather than strong-form PPP.

Interestingly, when Deutsch mark based exchange rates are used, MacDonald and Moore (1996) provide strong-form PPP evidence. They note that the effect may be attributed to the following factors: 1) the existence of ERM has alleviated the volatility of Deutsch mark bilaterals relative to US dollar bilaterals; 2) the geographical proximity of European countries facilitates greater goods arbitrage and makes it more likely that PPP holds; and 3) in terms of trade, the greater the proportion of national output, the greater the opportunity for arbitrage, which forces the LOP.

The evidence from cointegration based analysis to the PPP hypothesis can be summarized as follows: weak-form PPP holds for dollar bilaterals and strong-form PPP holds for many Deutsch mark-based bilaterals. However, the implied mean reversion from the studies is still slow.

Unit root based tests

Based on the PPP definition (1.1), defining the logarithm of the real exchange rate, q_t, in the conventional way is shown as

$$q_t = s_t - p_t + p_t^*$$

The real exchange rate can be seen as a measure of deviations from PPP, which implies the nominal exchange rate is adjusted for relative national price level differences. Thus, the most common application for PPP investigation has been explicitly to address the issue of non-stationarity of the real exchange rate, which regresses the variable on a constant and lagged level,

$$q_t = \alpha + \beta q_{t-1} + \varepsilon_t \tag{1.2}$$

where q_t denotes a real exchange rate and α and β are assumed to be constant. Generally, a time trend is not included in equation (1.2) because such an inclusion would be theoretically inconsistent with long-run PPP.

We start with an analysis of whether the real exchange rate itself is stationary implying evidence of long-run PPP or whether it tends to follow a unit root process, implying the absence of any tendency to converge on a long-run equilibrium level. Early investigations using demeaned data q_t, under the assumption of constant α, do not consider possible effects of economic fundamentals which can be captured by shifts in the mean process. For example, using annual data for the dollar-sterling real exchange rate, Frankel (1986) estimates a first-order autoregressive process for the real exchange rate q_t of the form

$$(q_t - \bar{q}) = \phi\,(q_{t-1} - \bar{q}) + \varepsilon_t \tag{1.3}$$

where $\bar{q}$ is the assumed constant equilibrium level of q_t, ε_t is a random disturbance, and ϕ is the autocorrelation coefficient governing the speed of mean reversion. Note that a proportion of times will be part of the real exchange rate deviation at time t. In the present setting, we can say that the real exchange rate reverts toward its mean of $\bar{q}$ at the rate of $(1-\phi)$ per period because the random shock at time $t-1$ will be part of the real exchange rate deviation at time t. On the contrary, if the real exchange rate follows a random walk, $\phi = 1$, shocks would never disseminate. Frankel's estimate of ϕ is 0.86, and rejects the hypothesis of a random walk at the 5% level; the majority of earlier work generally concentrated on the use of the conventional Dickey-Fuller unit root tests and could not reject the unit root hypothesis implying the absence of PPP. To this 'first generation' empirical result, Frankel and Rose (1996) and Lothian and Taylor (1996) argue that the low power of standard Dickey-Fuller tests with smaller empirical samples may be responsible for the absence of rejections of the unit root null hypothesis in time series of real exchange rates, rather than the failure of the PPP hypothesis. These authors then extend the typical data sets to over 100 years and reject the null hypothesis of a unit root in real exchange rates. However, it has been argued that studies which extend data for real exchange rates back beyond 1973 are essentially reducing the relevance of their results to the question of verifying PPP, since they are combining data from fixed and floating exchange periods. Engel and Hakkio (1996) make this point, and go further by presenting evidence suggesting that with the long time series data sets used by some authors to test for PPP, combining periods of different exchange rate policy may be responsible for spurious rejections of the unit root hypothesis.

A second approach to testing for non-stationarity of the real exchange rate involves variance ratio tests, as proposed by Cochrane (1988). This method assesses the unit root characteristics of the data and captures autocorrelations that are unlikely to be captured in standard ADF tests. Under the null hypothesis the suggestion is that the real exchange rate follows a random walk; the persistence of the real exchange rate is measured following nonparametric tests as,

$$z(k) = \frac{1}{k} \frac{var(q_t - q_{t-k})}{var(q_t - q_{t-1})}$$

where k is a positive integer and var represents variance. This implies that the variance of the kth difference should equal k times the first difference. That is, if the real exchange rate follows a random walk, the ratio should equal to unity $z(k) = 1$, since the variance of a k-period change should be k times the variance of a one-period change. By contrast, if the real exchange rate exhibits mean-reversion, the ratio should be in the range, $0 < z(k) < 1$. This implies that, when the underlying process driving the real exchange rate is mean-reverting, the variance of the series would decrease as k increases. MacDonald (1995a) finds that the variance ratios of Swiss franc, pound sterling and Japanese yen show approximately 0.5 after 12 years. Although significant rejections of a unitary variance ratio are obtained, the extent of any mean reversion to PPP is still slow.

A third approach employs the fractional integration method. This method allows one to consider a broader range of stationary processes under the alternative hypothesis than do conventional unit root tests. By definition, the real exchange rate process may be represented as

$$\Phi(L)(1-L)^d q_t = \zeta(L) w_t$$

where $\Phi(L)$ and $\zeta(L)$ are polynomials of L with roots lying outside the unit circle, and w_t is a white-noise process. The parameter d is allowed to lie in the continuous interval between zero and unity. Fractionally integrated processes are more persistent than pure autoregressive moving-average (ARMA) processes, but are still stationary. If $d = 0$, then the real exchange rate simply follows an ARMA process. On the other hand, if d, $\Phi(L)$ and $\zeta(L)$ all equal unity, the real exchange rate follows a random walk. For example, Christopher F. Baum and Caglayan (1999) applied CPI-based rates to 17 countries and WPI-based rates to 12 countries, and demonstrated that the unit-root hypothesis is robust against fractional alternatives. Unfortunately, the evidence from long memory process does not support absolute long-run PPP during the post-Bretton Woods era.

Power of unit root tests and panel studies

To find supporting evidence of PPP, another group of studies uses more powerful panel data unit root tests. The tests with heterogeneous intercepts, which are equivalent to including country-specific dummy variables, involve estimating the following regressions

$$q_{jt} = \alpha_j + \beta_j q_{jt-1} + \sum_{i=1}^{k} \varphi_{jk} \Delta q_{jt-k} + \varepsilon_{jt}$$

where the subscript j indexes the countries. The disparity in the value of the coefficient α of the time series provides little support for such a restriction. However, the work of Levin and Lin (1992) showed that the addition of a small quantity of cross sectional evidence can substantially increase the power of unit root tests by imposing homogenous intercepts and indeed the application of panel unit root tests for mean reversion in real exchange rates has become very popular. For instance, MacDonald (1995b), Jorion and Sweeney (1996), Wu (1996) and Oh (1996) have used the methodology developed by Levin and Lin (1992) and find support for the validity of long-run PPP. In particular, Jorion and Sweeney (1996), using monthly data, employ panel unit root tests on real exchange rates for the G10 countries and show rejection of the unit root null at the 10% level. The rejection of a unit root is more significant for seven European currencies against the Deutschmark.

Wu (1996) tests dollar real exchange rates for a panel of 18 countries with various frequency such as annual, quarterly and monthly and finds strong rejection for both CPI (consumer price index) and WPI (wholesale price index) based rates. However, because of allowance for the trend in the model, it is hard to say that the rejection of the unit root null hypothesis provides evidence of PPP. Oh (1996) employs annual real exchange rates for the flexible exchange rate period constructed from the Summers and Heston data and is able to reject the null of a unit root at the 1% level of significance. This produces much stronger results than Frankel and Rose (1996) find with annual data or than previous studies with quarterly or monthly data.

However, O'Connell (1998) points out a problem with panel unit root tests, namely that they typically fail to control for cross-sectional dependence in the data, and shows that this may lead to considerable size distortion, raising the significance level of tests with a nominal size of 5% to as much as 50%. Furthermore, Taylor and Sarno (1998) additionally note that the conclusions suggested by panel studies may be misleading because of an incorrect interpretation of the null hypothesis of the panel unit root tests employed by Abauf and Jorion (1990) and appearing in subsequent literature. The null hypothesis in those studies is joint non-stationarity of the real exchange rates considered and, hence, rejection of the null hypothesis may occur even if only one of the series considered is stationary. Therefore, if rejection occurs when a group of real exchange rate is examined, this may not be very informative and certainly it cannot be concluded that this rejection implies evidence supporting PPP for all of the rates. For example, on the basis of a large number of Monte Carlo experiments calibrated on dollar real exchange rates among the five major currencies, Taylor and Sarno (1998) found that, for a sample size corresponding to the span of the recent float, the presence of a single stationary process together with three unit root processes led to rejection at the 5% level of the joint null hypothesis of non-stationarity in about 65% of simulations when the root of the stationary process was as large as 0.95 and more than 95% of occasions when the root of the single stationary process was 0.9 or less.

Overall, some empirical studies have used cointegration tests and claim that PPP holds in the long run. However, these approaches still show limitation that PPP mean reversions are approximately from three to five years. In contrast to the panel data method, time series analysis has concluded that PPP fails to hold at least in the short run. Rogoff (1996) describes the "purchasing power parity puzzle" as the difficulty of connecting high short-term volatility in exchange rate series with very slow adjustment to PPP.

1.2.2 Non-linearity under PPP hypothesis

With regard to the inconclusive evidence from linear approaches, one possible objection is the presence of trade impediments arising from transport costs, taxes, tariffs and nontariff barriers, which would induce a violation of the LOP. That is, when the same goods differ in price in different countries, it may not be worth arbitraging and therefore correcting the price difference unless the anticipated profit exceeds the cost of shipping goods between the two locations. The intuition of such frictions is that the lack of arbitrage arising from transaction costs such as shipping costs creates a 'band of inaction' within which price dynamics in the two locations are spatially disconnected. As an example of this, Giovannini (1988) initially provides a partial equilibrium model of the determination of domestic and export prices by a monopolistic competitive firm and shows that the stochastic properties of deviations from the LOP are strongly affected by the currency of denomination of export prices. In particular, Giovannini (1988) uses data on domestic and dollar export prices of Japanese goods and provides evidence that deviations from the LOP are mainly due to exchange rate movements; this is consistent with earlier relevant studies.

Engel (1993) notes that the consumer price of a good within a country tends to be much less variable than the price of a similar good in another country and suggests that models of real exchange rates are likely to have predictions regarding this relation, so this fact may provide a useful gauge for discriminating among models and uncovering empirical evidence. Engel and Hakkio (1996) empirically test the price differentials between similar goods in cities across the United States and Canada to provide evidence that the volatility of the price differential tends to be larger, the greater the distance between the cities concerned. That is, the price differentials increased substantially when prices in cities in different countries were compared, which proves the so-called 'border effect'. This implies that crossing national borders increases the volatility of price differentials by the same order of magnitude as would be generated by the addition of extra miles to the distance between the cities considered.

As shown in the above studies, possible explanations for the violation of the LOP are suggested by transportation costs, tariffs and non-tariff barriers. This insight began to be expressed more formally in the theoretical literature by Dumas (1992). This study considers the nature of the adjustment process in the presence of trade barriers that can prevent absolute PPP from holding and demonstrates transaction costs that induce non-linear adjustment towards equilibrium. Recently, Berka (2004) shows that, because of transaction costs imposed on international markets, non-linear adjustments better describe exchange rates dynamics.

These studies provide theoretical justification that there is an effect of transaction and distribution costs, which prevents the occurrence of LOP in all markets. That is, the proportional transportation costs create a band of deviation from LOP when the marginal cost of arbitrage exceeds the marginal benefit and the thresholds reflect the barriers.

Some recent studies based on investment theory under uncertainty show that the thresholds should be interpreted more broadly than simply reflecting shipping costs and trade barriers. Rather the thresholds should be seen as also resulting from the sunk costs of international arbitrage and the resulting tendency for traders to wait for sufficiently large arbitrage opportunities to open up before entering the market. Once beyond the upper and lower thresholds, the real exchange rate becomes increasingly mean-reverting with the distance from the threshold. Within the transaction costs band, when no trade takes place the process is divergent, so that the exchange rate is rarely close to parity.

In empirical work for the above implication, non-linearity can be examined through the estimation of models that allow different parameters between regimes. That is, transaction costs of arbitrage may lead to changes in the real exchange rate being purely random until a threshold equal to the transaction cost is breached, at which point arbitrage takes place and the real exchange rate reverts back toward the band through the influence of goods arbitrage. According to this view the real exchange rate dynamic should be seen as mean-reverting only when the price differentials are larger than the no arbitrage transaction band. This implies that the behaviour of an exchange rate depends on different states of the regimes. It is consistent with the non-linear argument that depends on the regime changes. That is, whole data generating processes can be globally mean-reverting, but this kind of non-linearity has a property that exhibits near unit root behaviour for deviations from equilibrium. Thus, this kind of model is known as the 'band of inaction' in theoretical modelling or 'regime switching' in empirical modelling.

To accommodate non-linearity, the mean reversion of real exchange rate equation (1.2) is re-defined as follows

$$\Delta y_t = \beta S(y_{t-d}, \theta) y_{t-1} + u_t, \tag{1.4}$$

where y_t represents demeaned q_t, and $S(y_{t-d}, \theta)$ denotes a transition function such as TAR and STAR-types in which θ is a set of parameters. These functions are summarized in Table (1.1). Equation (1.4) represents properties of economic time series which are dependent on the regime which reveals the economic and statistical properties of the series. In terms of regime change models, the deviation in the unit root regime is left uncorrected if it is not large enough to cover transaction costs or the sunk costs of international arbitrage.

These kinds of non-linear approaches were initiated by the work of Tong, who introduced the threshold autoregressive model (TAR) to statisticians and time series specialists in a long series of working papers, ultimately resulting in Tong and Lim (1980). In later work these models were extended and developed by Tong (1983), Priestley (1988) and Tong (1990). In TAR models a change in the autoregressive structure of the model occurs when the level of the series reaches a particular threshold value. The threshold and the length of time between the series reaching this threshold and the structure change occurring are unknown quantities to be estimated. Tong (1990) outlines a consistent estimation methodology.

As examples of the application to the exchange rate theory, Obstfeld and Taylor (1997) model price adjustment in various international cities in the post-1973 period and also find significant non-linearity. The implied transaction cost bands and adjustment speeds were also found to be of a reasonable size (consistent with direct shipping cost measures) and to vary systematically with impediments such as distance, tariffs, quotas and exchange rate volatility. Taylor (2001), O'Connell and Wei (2002), Sarno, Taylor, and Chowdhury (2004) and Bec, Salem, and MacDonald (2006) estimate using TAR models. In these TAR model-based studies, the non-linear nature of the adjustment process is investigated in terms of unit root regime relating to the costs caused by trade impediments. The TAR model allows for a transaction costs band within which

Model	Transition Function: $S(y_{t-d}, \theta)$	Parameter: θ
	Threshold - type	
TAR	$1\{y_{t-d} \leq c\}$	c
3-Regime SETAR	$1\{y_{t-d} \leq c_1\} + 1\{y_{t-d} \geq c_2\}$	c_1, c_2
	Smooth Transition - type	
LSTAR	$[1+\exp\{\gamma\,(y_{t-d} - c)\}]^{-1}$	γ, c
ESTAR	$1 - \exp(-\gamma y_{t-d}^2)$	γ
Asymmetric ESTAR	$[1 + \exp\{(-\gamma_1^2 y_{t-d}^2) I_t + (-\gamma_2^2 y_{t-d}^2)(1 - I_t)\}]^{-1} - \frac{1}{2}$	γ_1, γ_2

Table 1.1: TAR and STAR-type Transition Functions

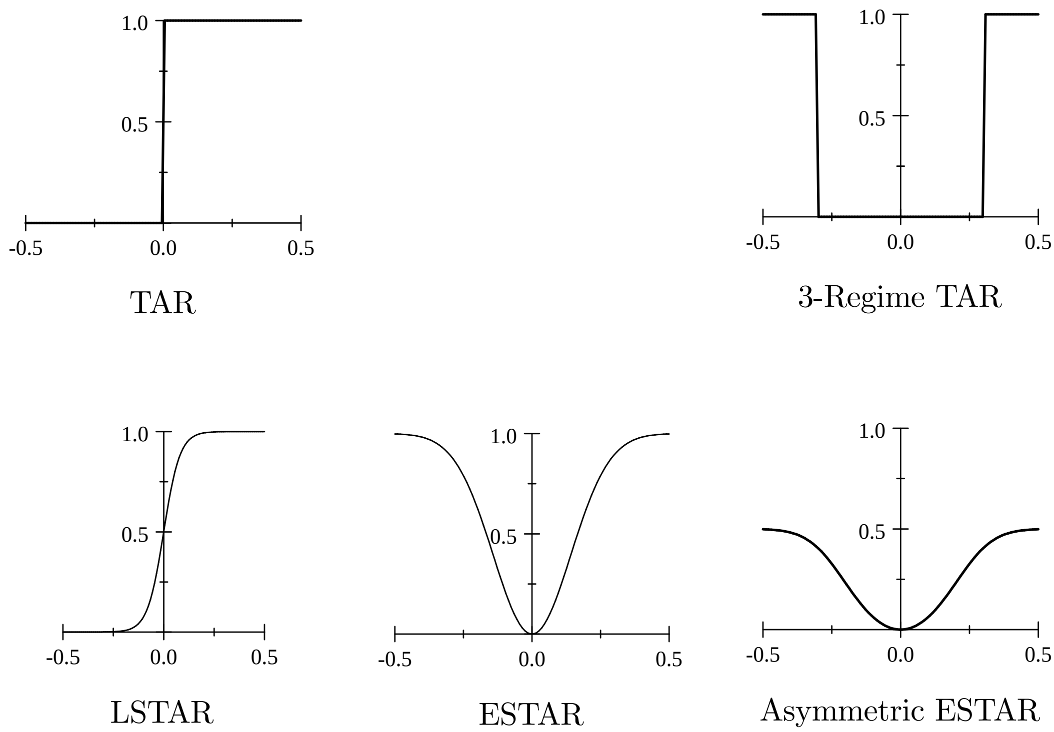

Figure 1.1: Simulation for TAR and STAR-type Transition Functions

no adjustment in deviation from the LOP take place so that deviations may exhibit unit root behaviour, while outside of the band, as goods arbitrage becomes profitable, the process switches abruptly to become stationary autoregressive.

However, a limitation of TAR models is that the change in the autoregressive structure is restricted to take place instantaneously, or not at all, which could make it conceptually difficult to accommodate economic intuition. For example, Dumas (1994) argues that time aggregation will tend to smooth transition between regimes. That is, if the real exchange rate is measured using price indices made up of goods prices, each with a different level of international arbitrage costs, one would expect adjustment of the overall real exchange rate to be smooth rather than discontinuous. Moreover, Cheung, Chinn, and Fujii (1999) point out the fact that transaction costs are likely to differ across goods, and so the speed at which price differentials are arbitraged may differ across goods. Furthermore, the aggregate real exchange rate is usually constructed as the nominal exchange rate multiplied by the ratio of national aggregate price level indices and so, instead of a single threshold barrier, a range of thresholds will be relevant, corresponding to the various transaction costs of the various goods whose prices are included in the indices. Some of these thresholds might be quite small, while others will be larger. As the real exchange rate moves further and further away from the level consistent with PPP, increasingly more of the transaction thresholds would be breached and so the effect of arbitrage would be more significantly felt.

An alternative way of modelling is to employ a well-developed class of econometric models that embody a kind of smooth but non-linear adjustment such that the speed of adjustment increases as the real exchange rate moves further away from the level consistent with PPP. For example, Michael, Nobay, and Peel (1997) and Taylor and Sarno (2001) note that given the use of highly aggregated data in calculating deviations from PPP, it is probable that smooth rather than sharp changes in the structure of the autoregressive representations of these deviations will occur. These groups of authors use a family of nonlinear autoregressive models that allow for smooth changes in the autoregressive structure of a times series, as discussed by Granger and Terasvirta (1993), and Terasvirta (1994). The STAR models extend TAR models by employing deterministic functions to allow any change in the autoregressive structure of the model to occur smoothly, while nesting the instantaneous and no change cases.

Specifically, Michael, Nobay, and Peel (1997) employ the STAR model to investigate the PPP hypothesis and take the approach of modelling the deviation from a cointegrating regression of the nominal exchange rate on the price indices of two countries. Taylor and Sarno (2001) test the PPP hypothesis in terms of the long-run mean reversion of real exchange rates. Both studies utilize the same exponential function for their applications. Peel, Sarno, and Taylor (2001) reject the hypothesis of a unit root in favour of the alternative hypothesis of non-linearly mean reverting real exchange rates using only the data for the post–Bretton Woods period. They also find that for modest real exchange shocks in the 1% to 5% range, the half-life of decay is under three years, while for larger shocks the half-life of adjustment is estimated to be much smaller - thus going some way toward solving the second PPP puzzle, half-lives. Kapetanios, Shin, and Snell (2003) also provide an exponential STAR model that is approximated in terms of scale parameter, which is efficient in estimation.

However, while transaction cost models have most often been advanced as possible sources of non-linear adjustment, the threshold and exponential functions used in these studies are restricted in symmetric adjustment. Thus other empirical arguments for the presence of non-linearity have also been advanced. For example, Sollis, Leybourne, and Newbold (2002) extend the symmetric function to asymmetric transition using the indicator function. In their investigation, asymmetric models empirically demonstrate that estimates show stronger mean reversion when the real exchange rate is below the mean than when it is positive. Taylor and Taylor (2004) argue that exchange rate non-linearity may also arise from the intervention operations of central banks. That is, intervention is more likely to occur and to be effective when the nominal and hence the real exchange rate has been driven a long distance away from its PPP or fundamental equilibrium. Nevertheless, all the STAR considerations are limited by their inability to represent a corridor regime that is able to capture the 'band of inaction'.

In general, both TAR and ESTAR-type models can capture the transition between the regimes but there still exist limitations in testing the economic implications. Specifically, while non-linear justification underpinning PPP suggests a 'neutral' band, the TAR model properly captures the inaction regime but also abrupt changes, which is problematic in the economic sense. Furthermore, the ESTAR model has only a narrow corridor regime and a limitation in representing the 'band of inaction' regime.

1.2.3 Structural changes under the PPP hypothesis

One reaction to the failure of PPP is a theory of exchange rate overshooting, while allowing for significant short-run deviations. In particular, despite the increased power of panel unit root tests, note that the null hypothesis is joint non-stationarity; there has been some criticism of this and other issues. For instance, Papell (1997) criticizes the regression on pooled real exchange rates for the free floating periods and shows several interesting results. The results of panel based methods for testing the unit root can be very sensitive to the size of the panel used and the frequency of the data analyzed. Furthermore, considering a heterogeneous intercept the evidence shows the PPP exhibits a faster rate of mean reversion when the Deutschmark rather than the US dollar is used as a base currency. His empirical results denote the fact that PPP is more likely to hold in the case of larger rather than smaller panels, for monthly rather than quarterly data and when the German mark rather than the US dollar is used as the base currency.

However, the most significant weakness of panel unit root tests is revealed by the work of O'Connell (1998). The study notes that all previous panel studies of PPP other than Abauf and Jorion (1990)'s do not take into account the presence of cross-sectional correlation between real exchange rates. Using the Monte Carlo method O'Connell (1998) shows that in the presence of cross-sectional correlation, panel unit root tests employing the critical values for Levin and Lin (1992) will be over sized, demonstrating the extent of this problem increasing with this size of the panel. Furthermore, even if the true distribution of the panel unit root tests statistic were available, the test would have less power to reject the unit root null hypothesis than its predecessors due to the reduced amount of information contained in the panel. The size distortion problem of panel unit root tests that do not take into account the effects of cross-sectional correlations explains why these studies find very strong rejections of the unit root null hypothesis whereas there is almost no evidence against this hypothesis from univariate tests. Therefore the results are sceptical of the conclusions from the studies that fail to compensate for these correlations. In particular, O'Connell (1998) finds no evidence in favour of PPP using a panel of 63 real exchange rates employing a pooled GLS-ADF test, which has the correct size in the presence of cross-sectional dependence.

The empirical evidence from panel data motivates some research considering alternative methods to test the international parity condition. For example, Kilian and Taylor (2003) argue that transaction costs could not provide a compelling explanation of long swings in nominal exchange rates, like the large and persistent overvaluation of the US dollar during the mid-1980s, nor do they explain the observed volatility in both real and nominal exchange rates. Hence they suggest a model in which uncertainty about the fundamental values of the exchange rate deters agents from speculating against small deviations from fundamentals. One possible explanation for the non-linear dynamics in exchange rate behaviour may be because small deviations may be considered unimportant by the market and policy makers but when the deviations become large enough the pressure from both market makers and policy makers will be strong enough to bring the exchange rate at least close to the fundamental equilibrium.

Instead of heterogeneous intercept of panel methods Papell (2002) demonstrates the failure of the unit root hypothesis caused by the large appreciation and depreciation of the US dollar in 1980, which can be explained by sudden changes in the mean. The study extends Perron (1989)'s model to develop panel unit root tests that allow for three breaks in the slope of the trend function, with the dates of the breaks determined endogenously. The dates of the breaks are first chosen by using the feasible GLS regressions. Once the break dates are chosen, the series are detrended as follows,

$$q_{jt} = \mu_j + \gamma_{j1}DT1_t + \gamma_{j2}DT2_t + \gamma_{j3}DT3_t + z_{jt}$$

where the coefficients on the dummy variables, DT are allowed to vary across countries. The test statistic is the t-statistic on β in the following regression,

$$z_{jt} = \beta_j z_{jt-1} + \sum_{i=1}^{k} \varphi_{jk} \Delta z_{jt-k} + \varepsilon_{jt}$$

The null hypothesis that all of the series have a unit root without structural change is rejected, against the alternative hypothesis that all of the series are stationary with PPP restricted structural change, if β_j is significantly different from zero. With this framework, Papell (2002) finds strong support for the PPP hypothesis. However, while the method offers an improvement over the panel unit root test, it is still limited in choosing the number of breaks and abrupt changes. Recently, Sollis (2005) employs structural changes that allow asymmetric and multiple adjustment in both intercept and trend. The test reveals statistically significant results for a number of series against the US dollar but the results of conservative PPP framework show rather weak results. That is, as shown in Wu (1996), investigation by Sollis (2005) has a problem with only being supportive when the models include the trend.

1.3 Exchange rate forecasting

Mundell (1961) and Fleming (1962) extend the exchange rate model by introducing capital flow into the analysis, which is capable of allowing for flexible or sticky prices but is adjustable in various ways. Dornbusch (1976) notes its poor empirical performance and develops sticky price or overshooting models. These have formed the basis of our understanding of exchange rate behaviour, but the influential work of Meese and Rogoff (1983) has been unable to produce statistically satisfactory results that are considered reliable and robust in out-of-sample performance.

In contrast to those macro-based models, Lyons (1999) and Evans and Lyons (2002b) suggest microstructure consideration that consistently outperforms both the random walk and the macro-based models. However, Sager and Taylor (2008) recently argue that applications using various datasets have shown different results in revealing evidence of the forecasting power of the microstructure model.

In this section we review a fundamental-based analysis to forecast nominal exchange rate which has become a workhorse in exchange rate literature. At the same time, we shall see, this builds on the PPP construct considered in the previous section.

1.3.1 Macro-fundamental based analysis

As a way of examining the empirical content of exchange rate models, the influential paper by Meese and Rogoff (1983) compares the out-of-sample forecasts produced by candidate structural models, including flexible-price (Frenkel - Bilson), sticky-price (Dornbusch - Frankel), and sticky-price current account (Hooper - Morton) models. The reduced form specifications of all three models are compactly defined as follows

$$s_t = \beta_0 \left(m_t - m_t^*\right) + \beta_1 \left(y_t - y_t^*\right) + \beta_2 \left(i_t - i_t^*\right) + \beta_3 \left(p_t - p_t^*\right) + \beta_4 \left(TB_t - TB_t^*\right) + \epsilon_t \tag{1.5}$$

where ϵ_t is a random disturbance term, s_t is the logarithm of the price of foreign currency, $m_t - m_t^*$ is the logarithm of the ratio of money supply to the foreign money supply, $y_t - y_t^*$ is the logarithm of the ratio of foreign real income, $i_t - i_t^*$ is the short-term interest rate differential and $p_t - p_t^*$ is the expected long-run inflation differential; TB_t and TB_t^* represent the cumulated trade balances.

All of the models exhibit first-degree homogeneity in the relative money supplies, $\beta_0 = 1$. The flexible-price model, which assumes purchasing power parity, constrains $\beta_3 = \beta_4 = 0$. The sticky-price model, which allows for slow domestic price adjustment and consequent deviations from purchasing power parity, sets as $\beta_4 = 0$. None of the coefficients is constrained to be zero in the Hooper-Morton model. This model extends the Dornbusch-Frankel model to allow for changes in the long-run real exchange rate. These long-run real exchange rate changes are assumed to be correlated with unanticipated shocks to the trade balance. Imposing the constraint that domestic and foreign variables (except for trade balances) enter equation (1.5) in differential form implicitly assumes that the parameters of the domestic and foreign money demand and price adjustment equations are equal.

Meese and Rogoff (1983) compare random walk forecasts with those produced by the flexible-price monetary model, Frankel's real interest rate differential variant of the monetary model and the synthesis of the monetary and portfolio balance models suggested by Hooper and Morton (1982). The variants of these models estimate for the dollar-mark, dollar-pound, dollar-yen and the traded weighted dollar for the sample period from March 1972 to November 1980, with the out-of-sample forecasts conducted over the sub-period December 1976 to November 1980. In particular, they use rolling regression to generate a succession of out-of-sample forecasts for each model at one to twelve month horizons.

The researchers base their forecasts on actual realized values of future explanatory variables but, when those analyses based on theoretical models are compared with a random walk model, the structural models perform poorly. In particular, the conclusion which emerges from this study is that upon comparison of root mean square errors, none of the asset market exchange rate models outperform the simple random walk, even though actual future values of the right-hand-side variables are allowed in the dynamic forecasts. The study also notes that the estimated models suffer from simultaneity bias. Alternatively, the variables in equation (1.5) can be defined by multivariate time series model as an vector autoregression (VAR),

$$X_t = \sum_{i=1}^{k-1} \Pi_i X_{t-1} + \Phi D_t + \epsilon_t, t = 1, \ldots, T \tag{1.6}$$

where $X_t = [s_t, m_t, m_t^*, y_t, y_t^*, i_t, i_t^*]$, D_t can contain a constant or a linear term and $\epsilon_t \sim i.i.d.$ with mean zero and covariance matrix Ξ. Imposing coefficient constraints taken from the empirical literature on money demand, they find that although the coefficient constrained asset-reduced forms still fail to outperform the random walk model for most horizons up to a year, combinations of parameter constraints can be found such that the models do outperform the random walk model for horizons beyond a year. In particular, the VAR model produced a ranking which is above the random walk at longer horizons but the models are unstable in the sense that the minimum root mean square error models have different coefficient values at different horizons. Thus Meese and Rogoff's findings have been interpreted as a particularly telling their approach has an unfair advantage by using actual data outcomes of the fundamentals rather than forecasting them simultaneously with the exchange rate.

However, Banerjee, Dolado, Galbraith, and Hendry (1986) note that, in finite sample, its biases can still be significant although endogeneity will have an asymptotically negligible effect on the coefficient estimates. To circumvent the problems in the presence of the issue of the non-stationarity of the data and simultaneous equation bias from the relationship between exchange rate and macro variables, Mark (1995) and Chinn and Meese (1995) suggest cointegration methods to test its long-run properties and find that predictability is at 'longer horizons', that is in horizons of 36 months and above.

The VAR representation of equation (1.6) may be reparameterized into the fully modified cointegration method suggested by Johansen (1995),

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i X_{t-i} + \Phi D_t + \epsilon_t, t = 1, \ldots, T \tag{1.7}$$

where $X_t \sim I(1)$, Δ represents the first difference operator, $\Gamma \left(\Gamma_i = -\sum_{i=1}^{k-1} \Pi_i \right)$ represents a $(n \times n)$ coefficient matrix, and $\Pi \left(\Pi = \sum_{i=1}^{k-1} \Pi_i - I \right)$ is a $(n \times n)$ matrix that determines the number of cointegrating vectors. In the present setting, when the Π is zero rank, there will be no cointegration amongst the elements in the long-run relationship. On the contrary, if Π is reduced rank, r there will exist $(n \times r)$ matrices α and β such that $\Pi = \alpha\beta'$ where β is the matrix whose columns are the linearly independent cointegrating vectors and the α matrix is interpreted as the adjustment matrix, indicating the speed with which the system responds to the last period's deviation from the equilibrium level of the exchange rate. Consequently, the VECM model depends on the existence of cointegration. For example, MacDonald and Taylor (1993) use VECM and are able to reject the null hypothesis where $X_t = [s_t, m_t, m_t^*, y_t, y_t^*, i_t, i_t^*]$. In particular, when the Johansen estimator or other estimators which include a correction for endogeneity and/or serial correlation of the error term are used, the null of no cointegration is rejected. Indeed, note that when the Johansen method is used there is clear evidence of multiple cointegrating vectors. A summary of a selection of the studies which have used these methods is contained in Table (1.2).

The idea of these approaches is to compare the volatility of the traditional set of monetary fundamentals typically employed in the literature to the volatility of

Source	Currencies	Period	m	m^*	y	y^*	i^s	i^{s*}	i^l	i^{l*}	Method	Results
Baillie-Selover (1987)	Jap/US	1973:3-1983:12	0.065		0.458		0.005		0.035		EG	No
Baillie-Selover (1987)	Can/US	1973:3-1983:12	-0.466		-0.047		0.010		-0.003		EG	No
Kearney-MacDonald (1990)	Aus/US	1984:1-1988:12	0.186		0.946		0.022		-0.012		EG	Yes
MacDonald-Taylor (1993)	DM/US	1976:1-1990:12	1		-1		0.049	-0.050			Johansen	Yes
MacDonald-Taylor (1994)	GBP/US	1976:1-1990:12	-0.471	1.06	-0.733	-0.284			-0.052	0.004	EG	No
MacDonald-Taylor (1993)	GBP/US	1976:1-1990:12	0.209	-0.49	-0.098	0.646			0.035	0.086	Johansen	Yes
Cushman et al (1997)	Turkish lira/US	1981Q3-1992Q4	0.21		-1.13		1.14				Johansen	Yes
Kouretas (1997)	Can/US	1970:6-1994:5	-0.12	-0.79	-0.32	0.32	0.08	-0.02			DOLS	Yes

Table 1.2: Cointegration Results for the Monetary Model [a]

[a] Source: MacDonald (2007)

the fundamentals that would be capable of explaining the volatility of foreign exchange rate returns. In particular, the economic fundamentals appear to be more important at longer horizons, but the short-run deviations from the fundamental level of exchange rate are attributed to excess speculation.

Recently, Cheung, Chinn, and Pascual (2004) examine exchange rate prediction by using a wide set of models that have been proposed in the last decades. In this study, they find that no model consistently outperforms a random walk in terms of the squared error measure. However, they note that some model specifications that work well in one period do not necessarily work well in another period.

1.3.2 Puzzle in forecasting

In financial markets, when the interest parity relationship holds,[1] equation (1.5) can be compactly redefined as

$$s_t = E_t f_t + \beta_2 E_t \left(\Delta s_{t+1}\right)$$

where $f_t = \beta_0 \left(m_t - m_t^*\right) + \beta_1 \left(y_t - y_t^*\right) + \beta_3 \left(p_t - p_t^*\right) + \beta_4 \left(TB_t - TB_t^*\right)$ represents the fundamentals at time t. In the present setting, $E_t f_{t+1}$ is the market-makers' expectation about future fundamentals conditional on information available at time t. This can be rearranged for the current exchange rate

[1] In a two-country, two money, two bonds and a single homogeneous traded good, bonds are assumed to be perfect substitutes, and so uncovered interest rate parity hold,

$$E_t \left(\Delta s_{t+k}\right) = \left(i_t - i_t^*\right)$$

as

$$s_t = (1-b) E_t f_t + b E_t (s_{t+1})$$

where $b = \beta_2 / (1+\beta_2)$ is the discount factor. By recursively substituting out the expected exchange rate for all future periods the forward extension of the monetary model may be obtained as

$$s_t = (1-b) \sum_{i=0}^{\infty} b^i E_t f_{t+i} \tag{1.8}$$

where the transversality or terminal condition, $\lim_{i \to \infty} b^i E_t s_{t+i} = 0$ is assumed to hold. The changes in current fundamentals can have more than a proportionate or magnified effect on s_t to the extent that they influence the future profile of expectations.

The present-value expression for the nominal exchange rate s_t can be rearranged as follows

$$\Delta s_{t+1} = \frac{(1-b)}{b} (s_t - E_t f_t) + \varepsilon_{t+1} \tag{1.9}$$

where $\Delta s_{t+1} = s_{t+1} - s_t$ and

$$\varepsilon_{t+1} \equiv (1-b) \sum\nolimits_{i=0}^{\infty} b^i (E_{t+1} f_{t+i+1} - E_t f_{t+i+1}) \tag{1.10}$$

Equation (1.9) decomposes the change in the log spot rate into two components, the expected change identified by the first term of $E_t \Delta s_{t+1}$ and the unexpected change, ε_{t+1}. Both terms contribute to the exchange rate dynamics in fundamental-based models. Equation (1.10) identifies how the new information impacts the FX price between the start of periods t and $t+1$, to the extent that it revises forecasts based on common information. Therefore, the future exchange rate change is a function of the gap between the current exchange rate and the expected current fundamentals, which are linked in a way that is broadly consistent with asset-pricing models of the exchange rate.

Concerning the weak results from macro-fundamental based analysis, Engel and West (2005) provide a valuable perspective on the forecastability of exchange rates when unobserved fundamentals follow a random walk or $I(1)$ process. They stress the properties of fundamentals and note the following: 1) when the fundamentals follow a random walk, equation (1.8) means $s_t = E_t f_t$ and the spot rate follows a random walk in terms of equation (1.9). In this case, the failure in forecasting is caused by a disconnection between fundamentals; and 2) when the fundamentals are $I(1)$, but do not follow a random walk process, forecasting will be difficult because the value of b implied by macro models is close to unity. As an example of this, Evans and Lyons (2005b) numerically show the underlying problems of forecasting models. Suppose that, when the fundamentals follow $I(1)$, the first differences of the fundamentals follow a first-order autoregression

$$\Delta f_t = \phi \Delta f_{t-1} + u_t$$

with $0 < \phi < 1$. Equation (1.8) implies that $s_t - f_t$ follows an $AR(1)$ process

$$s_t - f_t = \phi \left(s_{t-1} - f_{t-1}\right) + \frac{b\phi}{1 - b\phi} u_t$$

and

$$\varepsilon_{t+1} = \frac{1}{1 - b\phi} u_{t+1}$$

In the present setting, a theoretical R^2 is $(1-b)^2 \phi^2 / \left[(1-b)^2 \phi^2 + \left(1 - \phi^2\right)\right]$. The implied values for R^2 are below 0.01 when b is greater than 0.95 and ϕ is less than 0.8. That is, there is very little forecastability in Δs_t, when b is close to unity unless the changes in fundamentals are very strongly autocorrelated. Consequently, estimating (1.9) will produce poor results because bias from the measurement error pushes the coefficient on $s_t - f_t$ toward zero.

These demonstrations offer reasons why forecasting with fundamentals can be very hard and what causes the lack of forecasting power in most macro models. Nevertheless, these do not imply a rejection of conventional exchange rate determination theories because it tells us how the behaviour of fundamental affects the forecastability of exchange rates.

1.3.3 Microstructure consideration

As pointed out by Engel and West (2005) and Evans and Lyons (2005b), forecasting future spot rate changes with the fundamentals found in macro models is indeed a challenge, though some improvement has been achieved with the application of structural analysis. To overcome common macroeconomic fundamentals and/or empirical matters, recent studies have turned our attention towards the development of microstructure models of the foreign exchange (hereafter FX) market, which can help pinpoint when innovations in the exchange rate are highly correlated with news about fundamentals. As suggested by Engel and West (2005), the work of Lyons (1995) introduces testing the microstructure hypothesis in the foreign exchange market, and Lyons (1999) focuses microstructure on order flow. As a definition of the net of buyer-initiated and seller-initiated orders, while each transaction involves a buyer and a seller, the sign of the transaction is determined by the initiator of the transaction.

The initiator of a transaction is the trader (either buyer or seller) who acts based on new private information. He broadly introduces and summarizes how dealers and other market participants can influence equilibrium exchange rates. The microstructure we shall study identifies the role that order flow plays in conveying macro information to the FX market.

As the transmission mechanism links heterogeneous beliefs in the market with price discovery, Evans and Lyons (2002b) consider what they define as a 'hybrid model', namely a model which establishes a link between macro and micro models,

$$\Delta s_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \varepsilon_t \tag{1.11}$$

where $\Delta(i_t - i_t^*)$ represents the change in the domestic - foreign interest differential, X_t is the microstructure order flow and ε_t follows a white noise error term. The model also contains the elements found in the macro models and the spot exchange rate is determined as the foreign currency price quoted by dealers who have limited information about the current state of the economy. Specifically, dealers recognize interest rates, that is the policy instrument of a central bank that reacts to changes in the macroeconomy and, at the same time, understand the currency orders they receive from agents outside the FX market which are driven by portfolio choices that reflect macroeconomic conditions. The main conclusion of Evans and Lyons (2002b) is that the order flow is a significant determinant of two major bilateral exchange rates, obtaining coefficients of determination substantially larger than the ones usually found using standard macroeconomic models of nominal exchange rates. Hence, the FX market may act as an aggregator of information regarding the expectations and circumstances of the participants. Therefore, the consideration of microstructure order flow has shown successful performance in both explanation and prediction.

From a forecasting point of view, if there is no delay, this suggests market-makers can observe aggregate order flow contemporaneously; spot rates will be correlated contemporaneously with order flow as in equation (1.11). However, the forecasting power from order flow does not arise precisely because aggregation of the information would take time to be recognized across all market-makers. Evans and Lyons (2005b) illustrate how information in order flow may be delayed by relaying complete information offer and considering the transmission mechanism of nonpublic information.

Suppose that the market-maker i learns fully about aggregate order flow X_t with a lag following $AR(1)$ process

$$X_{t+1} = \lambda X_t + \nu_{t+1}$$

where $\nu_{t+1} \sim i.i.d.$ with mean 0 and variance σ_ν^2. Each market-maker i observes only part of the aggregate order flow in real time

$$X_{t+1}^i = X_{t+1} + \xi_t$$

where $\xi_t \sim i.i.d.$ with mean 0 idiosyncratic shock with variance σ_ξ^2. The unexpected order flow observed by market-maker i during period t trading can be defined as follows

$$X_{t+1}^i - E_t^i X_{t+1}^i = \nu_{t+1} + \lambda\psi\nu_t + \xi_t$$

where $\psi = \sigma_\xi^2 / \left(\sigma_\nu^2 + \sigma_\xi^2\right)$ and E_t^i denotes expectations conditioned on the information set. In the present setting, the order flow information received by market-maker i has an aggregate component ν_{t+1} that follows an $MA(1)$ and idiosyncratic component ξ_t. This means that the information received by individual market-maker's will be correlated with past innovations in aggregate order flow ν_t. This is inconsistent with a contemporaneous model (1.11).

To examine the properties from the information, Evans and Lyons (2005b) consider the following fundamental process

$$\Delta f_t = \phi \Delta f_{t-1} + u_t + \delta \nu_t \tag{1.12}$$

where u_t is a common knowledge component. This extends the fundamental process (1.12) and includes a common knowledge component u_t and a component correlated with the process in aggregate order flow, ν_t. In particular, while u_t is observed contemporaneously, ν_t is known to all market makers with a lag. Substituting for ν_t and combining (1.9) gives the following model

$$\Delta s_{t+1} = \frac{(1-b)}{b}\left(s_t - E_t f_t\right) + \frac{1}{1-b\phi} u_{t+1} + \frac{\left[1+\phi\left(1-b\right)\right]\delta}{1-b\phi}\left(X_{t+1} - \lambda X_t\right)$$

where $s_t = E_t f_t + \frac{b\phi}{1-b\phi} E_t \Delta f_t$ and $\varepsilon_{t+1} = \frac{1}{1-b\phi}\left(f_{t-1} - E_t \Delta f_{t+1}\right) - \frac{b\phi}{1-b\phi}\left(f_t - E_t \Delta f_t\right) - \frac{\delta}{1-b\phi}\nu_{t+1}$. This equation shows that lagged order flows can have forecasting power for spot rates even when the discount factor is very close to unity, $b \to 1$ because the coefficient on the last term has a limiting value of $\frac{\delta}{1-\phi}$.

Contrary to the contemporaneous model (1.11), Evans and Lyons (2005b) suggest following aggregate and disaggregate forecasting equations

$$\Delta s_{t+1} = \beta_0 + \beta_1 X_t^{AGG} + \varepsilon_{t+1}$$

and

$$\Delta s_{t+1} = \beta_0 + \sum_{j=1}^{6} \beta_j X_{j,t}^{DIS} + \varepsilon_{t+1}$$

Although the results provide a level of empirical validation as yet unattained, the above tests are qualitatively stronger than those of Meese and Rogoff with disaggregate order flows in lagged setup. However, using both inter-dealer and commercially available customer order flow data, Sager and Taylor (2008) find little evidence that the order flow data could predict exchange rate movements in out-of-sample exercise. Specifically, they compare the results from contemporaneous model, as used in Evans and Lyons (2002b), and the lagged model, as implied in the information mechanism. The contemporaneous model shows very good explanatory power and forecasting performance in statistical evaluation, but the lagged setup cannot outperform the random walk model and has no prediction ability.

Generally, in contrast to the structural approaches which rely on common macroeconomic fundamentals, analyses based on market microstructure considerations provide evidence that the behaviour of dealers and other market participants can influence equilibrium exchange rates and show significant explanatory power. Nevertheless, as shown in Sager and Taylor (2008), there is a limitation in out-of-sample exercises with lagged model; the response is not always predictable and makes it sometimes difficult to achieve the desired results.

1.3.4 Non-linearity in microstructure

As shown in the previous sections, microstructure investigation shows the behaviour of dealers and other market participants who are able to influence equilibrium exchange rates. The main results are drawn from the assumption that macroeconomic information is publicly and simultaneously released to all market participants and is largely impounded into prices via the micro-level price determinant, order flow. The conclusion of this research addresses the unanswered that, although information or news announcement with transmission lag sounds reasonable, the lagged model still shows no prediction power.

The fundamental based models provide intuitively appealing theory for economic forecasts, but empirically show poor forecasting power in the linear form. Recently, the lack of empirical evidence from the structural models has led researchers to propose considering non-linearity and/or microstructure in the relation of exchange rate and economic fundamentals. As Meese and Rose (1990) note, one important source of non-linearity is the data generation process itself. In order to investigate the robustness of non-linear forecast, Gradojevic and Yang (2006) employ the following artificial neural network (ANN) frameworks

$$\Delta q_{t+1} = f\left(\Delta(i_t - i_t^*), \Delta oil_t, X_t^{AGG}\right) + \varepsilon_{t+1}$$

and

$$\Delta q_{t+1} = f\left(\Delta(i_t - i_t^*), \Delta oil_t, X_t^{DIS}\right) + \varepsilon_{t+1}$$

where Δoil_t is the daily change in the logarithm of the crude oil price, over the sample January 1990 - June 2000. They conclude that the forecasting power of their model in terms of calculated root mean squared error (RMSE) and percentage of correctly predicted exchange rate changes 1 and 7 days ahead is significantly better than either a random walk or a linear specification that includes the same order flow and macro-economic variables. Although the empirical results are superior than a random walk model and any linear competing model for high-frequency exchange rate forecasting, those employ unclear economic framework as usually shown in the 'black box model'.

To specifically investigate whether the strength of the relationship between order flow and exchange rate is dependent upon prevailing market conditions or the announcement of macroeconomic news, a related but slightly different strand of studies have tried to address the relationship between macro news and order flow. Using transaction-level exchange rate return and trading data, Love and Payne (2003) test the relationship between the news contained in public information announcements and order flow illustrating how gradual learning in the FX market can generate explanatory and forecasting power through the order flow. The results show that information which is publicly and simultaneously released to all market participants is partially impounded into prices via the order flow. In particular, they conclude that the order flow played approximately one third of price-relevant information, which is incorporated via the trading process.

Instead of directly employing macro variables, Evans and Lyons (2005a) test the role of order flow from the published macro fundamentals. In particular, by examining the effects of news on subsequent trades by end-user participants such as hedge funds, mutual funds, and non-financial corporations, news arrivals induce subsequent changes in trading in all of the major end-user segments.

These induced changes remain significant for days and also have persistent effects on prices. Currency markets do not respond to news instantaneously. Summing up, the empirical results from Love and Payne (2003) and Evans and Lyons (2005a) show that even information that is contemporaneously released to all market participants is partially rather than fully impounded into prices via the microstructure order flow.

However, although the customer order flow represents the primary source of private information that is assumed to represent future innovations in fundamental exchange rate determinants, this only provides an intuitive explanation of the process of price discovery in the FX market. Bacchetta and Wincoop (2006) account for some important stylized facts on the relationship between exchange rates, fundamentals, and order flow: 1) fundamentals have little explanatory power for short- to medium-run exchange rate movements; 2) over long horizons the exchange rate is closely related to observed fundamentals; 3) exchange rate changes are a weak predictor of future fundamentals; and 4) the exchange rate is closely related to order flow. Therefore, they suggest considering alternative information structures, particularly when the information received by agents differs in quality or timing. There can also be heterogeneity about the knowledge of the underlying model, and the impact of observed variables on the exchange rate varies over time.

The body of empirical work on order flow increases our understanding of the nature of the information structure, providing guidance to this modelling. For example, Rime, Sarno, and Sojli (2010) investigate macroeconomic information in both direct and indirect ways and suggest considering the order flow transmission mechanism which facilitates the aggregation of dispersed price-relevant information such as heterogeneous interpretations of news, changes in expectations, and shocks to hedging and liquidity demands. Empirically, Rime, Sarno, and Sojli (2010) test the significance of the relationship between cumulative order flow and macroeconomic news with the following Probit model

$$I_{sumX_t} = \theta_0 + \theta_1 \mathbf{NEWS}_t + \varpi_t$$

where $I_{sumX_t} = 1$ if $sumX_t > 0$, and otherwise 0. With this framework, they find a statistically significant coefficient for the news and then suggest the following direct and indirect specifications

$$\Delta s_t = \alpha_1 + \sum_{n=1}^{N} \beta_n \mathbf{NEWS}_{n,t} + u_t$$

and

$$\Delta s_t = \alpha_1 + \sum_{n=1}^{N} \beta_n \mathbf{NEWS}_{n,t} + \gamma_1 \Delta X_t + u_t$$

in the present setting, they find that the addition of order flow significantly increases the explanatory power of the model.

The consideration of the above direct and indirect linkages clarifies the explanatory power of exchange rate fluctuations and provides an alternative explanation for the ambiguous specification between macroeconomic fundamentals and exchange rates examined by Bacchetta and Wincoop (2006). However, in practice it is hard to quantify macro variables when we consider high frequency data. It is necessary for the analysis when the macro fundamentals are omitted in the framework. Therefore, in consideration of outliers we are going to employ STAR, STR and time-varying parameter models in our analysis.

1.4 Main findings of the study

The main focus of this study is that by allowing for non-linearity in the form of exchange rate models we can consider an underlying data-generating process. In particular, we propose a model extension to properly capture the implications of the non-linear adjustment, which produces a statistically significant finding. In particular, this includes an extension of the relevant non-linear approaches by allowing asymmetric exchange rate dynamics. In this section, we briefly describe the main contributions and summarise the findings of each chapter.

1.4.1 3-Regime asymmetric STAR modelling and exchange rate reversion

The theoretical bases of our examination are Dumas (1992), Sercu, Uppal, and Hulle (1995) and Berka (2004). They show that the adjustment of the real exchange rate towards the purchasing power parity in the presence of market frictions is necessarily a non-linear process. There are market frictions that imply a band of inaction, within which the deviations from long-run equilibrium are left uncorrected. The key theoretical idea is that the deviations from the LOP will not be mean reverting as long as they are smaller than the band of arbitrage costs. However, when the deviations from the LOP cross the band of inaction, the real exchange rate series are mean reverting.

In this chapter the STAR methodology is employed to develop two extended DF specifications that under the alternative hypothesis, allow for symmetric and asymmetric non-linear mean reversion respectively. Both specifications, in the context of real exchange rates, are consistent with the literature on transaction costs in goods market arbitrage, in that they both allow for increasing mean reversion of the real exchange rate away from a non-stationary central regime. With symmetric and asymmetric non-linear mean reversion being the alternative hypothesis, as with standard DF tests, the specifications developed can be used to test the null hypothesis that the series being modelled is $I(1)$. An important aspect of the asymmetric specification developed is that it nests a symmetric form of non-linear mean reversion. In addition, both symmetric and asymmetric specifications nest the specification of the standard linear augmented DF test. Using these specifications, critical values for tests of a unit root against symmetric and asymmetric non-linear mean reversion respectively were simulated using Monte Carlo techniques for different empirical sample sizes, and the tests were applied to three data sets of monthly observations on the series of real exchange rates.

The results from our specifications reveal that the real exchange rate series have non-linear transitions between regimes, which can be characterized as undervalued and overvalued regimes. In particular, our symmetric and asymmetric STAR models can encompass previous threshold and smooth transition models and give additional insights into real exchange rate behaviour, while existing TAR or ESTAR models consider trade impediments but only provide symmetric adjustment.

1.4.2 Equilibrium exchange rate determination and multiple structural changes

To the large appreciation and depreciation of the dollar in the 1980s, the development of time series and panel unit root tests with a structural break empirically present both a challenge and an opportunity for researchers attempting to find strong evidence of long-run purchasing power parity. We will investigate the hypothesis that the failure to reject unit roots in real exchange rates with structural changes can be explained by the role of economic fundamentals in the Exchange Rate Mechanism (ERM). We extend Leybourne, Newbold, and Vougas (1998)'s model to develop univariate unit root tests and propose more general smooth transition (STR) functions, which are able to capture structural changes along the equilibrium path.

The STR methodology employed in this chapter develops three specifications with two transition functions that, under the alternative hypothesis, allow for symmetric and asymmetric structural changes, respectively. In the context of the conservative PPP hypothesis, structural changes in the intercept are consistent with the hypothesis on the economic fundamental based analysis, and allow for equilibrium reversion of the real exchange rate. With symmetric and asymmetric transition function being the alternative hypothesis, the specifications developed can be used to test the null hypothesis that the series being modelled is $I(1)$. Using these specifications, critical values for tests of a unit root against symmetric and asymmetric structural changes respectively were simulated using Monte Carlo techniques for different empirical sample sizes, and the tests were applied to the monthly and quarterly nominal exchange rates for seventeen and twenty OECD economies and we constructed bilateral CPI-based real exchange rates against the U.S. dollar and the Deutsch mark.

The results from our specifications provide a plausible economic interpretation by structural changes. In particular, exchange rates against the U.S. dollar during the 1980s can support the PPP hypothesis for quarterly, but not monthly data. This evidence appears to contradict the results from panel data that show stronger results for monthly rather than quarterly data.

1.4.3 Microstructure Order Flow: Statistical and economic evaluation of non-linear forecasts

A notable feature of existing analyses of exchange rates is the weakness between macro-fundamentals and empirical results. In particular, the poor explanatory power of macroeconomic fundamentals has been shown in the initial study by Meese and Rogoff (1983) and subsequent literature, which found that a random walk predicts exchange rates better than do macro-fundamental based models. As an alternative approach, Evans and Lyons (2002b), Evans and Lyons (2005b) and Sager and Taylor (2008) show explanatory power from the microstructure approach. However, in terms of forecasting performance, Sager and Taylor (2008) point out empirical problems from the microstructure approach and indicate the necessity of an intuitive explanation of the process of microstructure in the foreign exchange market.

The investigation of this chapter focuses on non-linear forecasts of testing exchange rate models by examining microstructure - order flow. As a modelling issue, the basic hypothesis is that if order flow includes heterogeneous beliefs and the information contained in them, heterogeneous customer order flow can have forecasting power for exchange rates. Using statistical and economic evaluation, we quantify the role that, when the information is lagged or simultaneously released to all market participants, the key micro level price determinants - order flows are impounded into price.

For statistical evaluation, two statistics are used to compare the models: root mean squared forecast error (RMSFE), and Diebold-Mariano (hereafter DM) test, which are the most common forecast accuracy measures used in the forecasting. However, since the statistical evidence in itself does not guarantee the power of predictability, using previous research by Fleming, Kirby, and Ostdiek (2001), Han (2006), della Corte, Sarno, and Tsiakas (2009) and Rime, Sarno, and Sojli (2010), we additionally assess the economic value of exchange rate predictability by evaluating the performance of dynamic asset allocation strategies. Specifically, to examine whether there are any economic gains from an order flow model relative to a naive random walk model, we employ mean-variance analysis as a standard measure of portfolio performance and apply quadratic utility, evaluated mainly by the performance fee that represents willingness to pay for switching from a portfolio strategy based on the random walk model to one conditioned on order flow. In addition, we calculate the break-even transaction cost that would remove any economic gain from a dynamic asset allocation strategy relative to a simple random walk strategy.

The results confirm that: 1) order flow with a non-linear consideration leads to considerable and statistically significant improvements compared to the random walk model; and 2) order flow is a powerful predictor of the exchange rate movement in an out-of-sample exercise, on the basis of economic value criteria such as Sharpe ratio and performance fees implied by utility calculations.

1.5 Conclusion

To clarify our contribution to non-linear exchange rate modelling, we summarize previous approaches through a review of selected literature. From critical reviews of major empirical tests used in the literature to test PPP hypothesis and exchange rate forecasts, we have tried to point out their limitations, STAR, STR and microstructure frameworks. In particular, we have presented 1) the necessity of asymmetric extension for the justification of existing trade impediment models; 2) the limitation of structural change in time series and panel unit root tests; and 3) problems in forecasting with microstructure consideration in the presence of different route of information mechanisms. One of the main limitations of this study is the difficulty in properly capturing theoretical implications.

Given that existing non-linear approaches are subject to the above drawback and the empirically mixed evidence supporting PPP, the issues of whether or not PPP holds and forecasts are not yet decisively settled. Thus we consider several theories in exchange rate economics and suggest a non-linear relationship between exchange rates and different macro/micro variables. However, different theories produce a different shape of non-linear functional forms. The problem in the non-linear econometrics is the large number of possible non-linear specifications. In this thesis three classes of non-linear models were briefly introduced to provide the econometric specifications for the empirical tests. The models introduced may be viewed as non-linear unit root tests and forecast frameworks. First, we will use the non-linear asymmetric STAR model, which extends ESTAR and TAR models. The motivation of the asymmetric STAR is to model asymmetric adjustment of the series. Second, we will use smooth transition (STR) models. The STR framework makes it possible to find and capture structural changes in equilibrium adjustment. In the previous literature the STR models have been applied in both time series and panel data but the model is over-specified in terms of the conservative PPP. We then propose a more general smooth transition (STR) function than has hitherto been employed, which is able to capture structural changes along the (long-run) equilibrium path, and show that this is consistent with our economic model. Finally, we consider microstructure order flows in exchange rate forecast. Instead of macro-fundamental based analysis we employ a time-varying parameter (TVP) model and provide both statistical and economic evaluations.

Issues concerning estimation, linearity tests and specifications will be extensively discussed in the following chapters.

Chapter 2

3-Regime Asymmetric STAR Modelling and Exchange Rate Reversion

2.1 Introduction

The breakdown of the Bretton Woods system and the adoption of generalised floating exchange rates ushered in a new era of exchange rate volatility and uncertainty. This increased volatility lead economists to search for economic models able to describe observed exchange rate behaviour. Purchasing Power Parity (hereafter PPP) is often the relationship economists first turn to when trying to explain longer run exchange rate behaviour and as a consequence it is probably one of the most investigated international parity conditions. Early empirical tests of PPP used linear models and were based on variants of the Dickey-Fuller (DF) regression. The empirical evidence from such "first generation" tests of PPP essentially failed to find much supportive evidence (see Meese and Rogoff (1988) and Mark (1990)). As an alternative, the empirical analysis of PPP shifted to testing for cointegration between nominal exchange rates and relative prices. For example, Lothian and Taylor (1996) argued that the lack of empirical evidence in favour of PPP was due to the low power of unit root tests in small samples. Following Lothian and Taylor (1996) researchers employed longer spans of data and found, in some cases, evidence supporting PPP. Engel (2000), however, criticised this approach since it involved using data spanning different exchange rates regimes and demonstrated that it can generate spurious rejection of the null hypothesis of a unit root.

"Second generation" tests of PPP advocated a different approach. Since the main problem with unit root tests is their lack of power in small samples, such second generation tests suggested pooling data together using both time series and cross sectional dimensions. The literature employing panel unit root and cointegration methods grew very rapidly producing consistent evidence in favour of PPP. However, O'Connell (1998) questioned this approach and showed that the empirical evidence of PPP from panel unit root and cointegration tests mainly arose from neglecting cross sectional dependence.

The econometric approaches noted above have considered PPP within a linear framework. However, there are now reasons to believe that the exchange rate is not in fact driven by a linear stochastic process. For example, Dumas (1992), Sercu, Uppal, and Hulle (1995) and Berka (2004) show that transaction costs can create a band of inaction when the marginal cost of arbitrage exceeds the marginal benefit. In this circumstance, the existence of transaction costs and other impediments to trade - such as transportation costs, tariffs and quotas in international trade - drives a wedge between prices in different locations. That is, when the marginal benefit is greater than the cost in absolute value, trade takes place to exploit evident profit opportunities and PPP deviations are corrected. On the other hand, when the marginal benefit is smaller than the marginal cost in absolute value, no trading takes place and PPP deviations are not corrected. In other words, in the presence of transactions costs, deviations from PPP will be non-equilibrium-reverting as long as they are smaller than the cost, and equilibrium reverting once they exceed costs. Based on this condition, the theoretical work cited above stresses the importance of these costs in modelling deviations from the equilibrium and provides a theoretical framework for non-linear models used in empirical work.

Following more or less the same theoretical argument, many empirical models have implemented non-linear adjustment for real exchange rates. For example, Obstfeld and Taylor (1997) and Sarno, Taylor, and Chowdhury (2004) employ a threshold autoregressive (hereafter TAR) model and Michael, Nobay, and Peel (1997), Sollis, Leybourne, and Newbold (2002), and Kapetanios, Shin, and Snell (2003) use smooth transition autoregressive (hereafter STAR) models. Within such frameworks, the non-linear dynamics of the adjustment process can capture the effect of transaction costs. In a TAR model, an inaction bound is considered within which the exchange rate follows a random walk process. Outside the threshold, a symmetric type of adjustment takes place. One of the few papers which takes a different approach is Sollis, Leybourne, and Newbold (2002), who allows for asymmetric mean reversion. However key main problem with the STAR models is that they only consider a narrow 'inner' regime, while assumptions underpinning PPP would suggest a 'neutral' band.

Michael, Nobay, and Peel (1997) argued that non-linear exchange rates models should consider a symmetric type of mean reversion because adjustments to deviations from PPP should be the same for both positive and negative deviations from equilibrium. However, Sollis, Leybourne, and Newbold (2002) demonstrate empirically that estimates show stronger mean reversion when the real exchange rate is below the mean than when it is positive. An explanation for this could run along the following lines. Persistent and large deviations from PPP can have important implications for a country's competitiveness and its net exports. In instances where a currency is overvalued governments are much more likely to intervene in foreign exchange markets and /or use interest rate changes to affect the potentially deleterious effect on competitiveness than they are when the currency is undervalued. These empirical results show the necessity of considering asymmetric effects together with an inaction band when modelling the non-linear dynamics of PPP.

The contributions of this chapter are threefold. First, we propose more general STAR transition functions which encompass both threshold non-linearity and asymmetric effects. Our framework allows for a gradual adjustment from one regime to another, and considers threshold effects by encompassing other existing models, such as TAR models. We allow the processes to follow a unit root in the band of inaction and test it against the alternative of a globally stationary STAR, by extending the infimum $t-$test recently suggested by Park and Shintani (2005). Second, we present some Monte Carlo simulations and show that the test has good size and power. Finally, we apply the proposed test to two different exchange rate data-sets, one for developing countries, and official nominal exchange rates, and the second for emerging market economies using black market exchange rates. Much of the extant testing of PPP has involved using data from developed industrial countries and little if any has been conducted using data from emerging market countries. The work that has been conducted uses official exchange rates and, as Reinhart and Rogoff (2002) note, such rates can be profoundly misleading as they are unlikely to be market determined. However, one of the unique features of emerging markets economies is that they have very well developed black markets for foreign exchange and the rates determined in these markets are fully market determined. Such black market exchange rates have a long tradition and in many cases have also been supported by governments. In fact, generally, the volume of transactions in black markets is even larger than that in the official market. Although black market exchange rates play such a major role in emerging market economies, it is surprising to note that very few papers use this major source of information to investigate real exchange rates dynamics. The present study attempts to fill the existing gap in the literature. Our results provide evidence suggesting that for several currencies, the asymmetric STAR model characterizes well deviations from PPP. In turn, these results are consistent with previous studies on transaction costs in international market arbitrage and the importance of considering asymmetric adjustment in deviations from PPP.

The remainder of this chapter is organized as follows. In the next section we provide an overview of the existing analysis of real exchange rate behaviour, from the basic theory to non-linear empirics. We also present a theoretical justification for using the information conveyed by non-linear and multi-regime approaches. Section 2.3 summarizes previous empirical work using non-linear unit root tests and then proposes our models along with the estimation method and the properties of our proposed models. The empirical results of our real exchange rate modelling using black market exchange rates are contained in section 2.5. Section 2.6 concludes the chapter.

2.2 Testing for PPP

The fundamental basis of PPP is the LOP. The real exchange rate, $q_t = s_t - p_t + p_t^*$ can be seen as a measure of deviations from PPP. In practice, empirical applications of PPP use the real exchange rate according to the above definition and aggregate national price indices. The real exchange rate can be driven away from its PPP equilibrium value due to, for example, exchange rate market intervention or non-zero interest differentials. One way of capturing this idea is to use the real exchange rate model below and test for a unit root:

$$q_t = \rho q_{t-1} + \beta + \varepsilon_t, \tag{2.1}$$

where $0 < \rho < 1$ is the parameter of mean reversion, the random error term, ε_t, is normally and independently distributed over time and β is constant. In terms of unit root tests, the idea is to search for the stationarity of the real exchange rate. That is, since the real exchange rate can be interpreted as a deviation from PPP, a necessary condition for PPP to hold is that the real exchange rate is stationary over time and not driven by permanent shocks.

Recently, PPP researchers have attempted to incorporate non-linearities into real exchange rate behaviour. For example, in the presence of transaction costs and trade barriers, Dumas (1992) and Berka (2004) a non-linear adjustment process better describes exchange rates dynamics. In this context, traditional PPP is then defined as:

$$s_t = \pi + p_t - p_t^*,$$

where π is the symmetric transportation costs or other impediments between the home and foreign country trade. Since the relative price fluctuates in a range $-\pi < \frac{p_t}{p_t^*} < \pi$, deviations from PPP are permissible as in:

$$-\pi < q_t < \pi.$$

To this argument Berka (2004) recently shows that if transportation costs depend on distance, the range of variation in the relative price will also depend on that distance. However, sunk costs may widen the band above and below that associated with simple trade restrictions. In this context, it is argued that deviations from PPP should follow a non-linear mean-reverting process with the speed of mean reversion depending on the magnitude of the deviation from PPP.

Figure (2.1) graphically describes the properties of the band of inaction when p is the relative price of goods. In terms of the LOP, p can be then viewed as the real exchange rate. Figure (2.1) shows several important features of non-linear exchange rates adjustment. As a function of current price, the expected change in prices is: (i) negative when the deviation from parity is positive and vice versa; (ii) a curvature near the edge suggests that larger deviations from parity imply faster adjustments; (iii) the shape of the function depends crucially on the relative risk aversion parameter. In fact, the lower the risk aversion, the less sensitive ex-ante benefits of diversification achieved by shipping. A low degree of risk aversion consequently makes rebalancing of physical capital less desirable, which implies a slower mean reversion.

Thus non-linear models better describe exchange rates dynamics and a substantial amount of empirical research has now employed them and found evidence

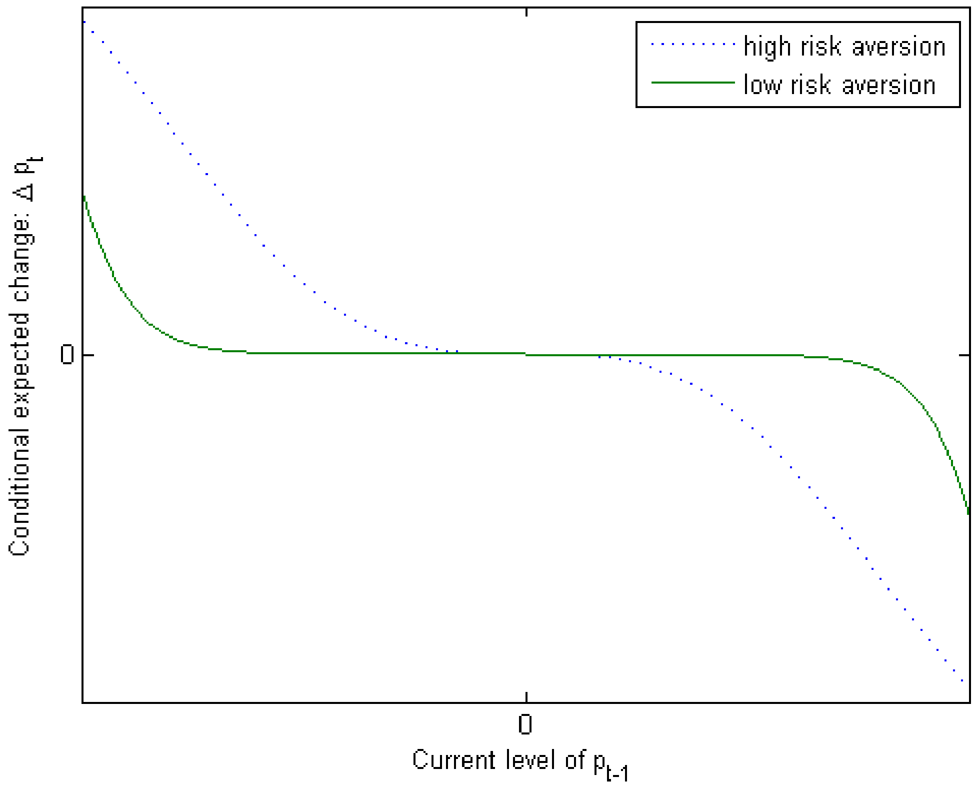

Figure 2.1: Conditional Expected Change of the Real Exchange Rate

supporting PPP. For example, Obstfeld and Taylor (1997), and Sarno, Taylor, and Chowdhury (2004) used TAR models. These models capture the effects of transaction costs on exchange rates dynamics. Michael, Nobay, and Peel (1997), Sollis, Leybourne, and Newbold (2002), and Kapetanios, Shin, and Snell (2003) use instead STAR models to capture non-mean-reverting regime. TAR and STAR models have been largely used in empirical applications and provided encouraging results supportive of PPP. However, and as already pointed out, most of these models only consider symmetric adjustments except Sollis, Leybourne, and Newbold (2002). Furthermore, STAR models only assume a narrow 'inaction' bound.

In the next sections we shall present a more general econometric framework which encompasses both the theoretical and empirical arguments mentioned above. We suggest a transition function which allows for threshold effects and asymmetrical adjustments when the real exchange rate is away from equilibrium.

2.3 Non-linear unit root tests

2.3.1 The model

Consider the following Dickey-Fuller (DF) regression

$$\Delta y_t = \beta y_{t-1} + u_t,$$

where y_t is mean corrected series and $u_t \sim i.i.d.$.

To accommodate non-linearity the following transition function $S(y_{t-d}, \theta)$ is introduced. Here, y_{t-d} is the transition variable with lag delay $d \geq 1$, θ is a parameter set that has to be estimated and $S(y_{t-d}, \theta)$ is then a real value function that takes values between zero and one. The DF regression can be written as

$$\Delta y_t = \beta S(y_{t-d}, \theta) y_{t-1} + u_t, \tag{2.2}$$

where $u_t \sim i.i.d.$.[1]

Using the DF regression above one can then test the unit root null hypothesis

$$H_0 : \beta = 0,$$

against the alternative

$$H_1 : \beta < 0.$$

The transition functions $S(y_{t-d}, \theta)$ considered in the literature are given in Table (2.1). The unit root test with exponential smooth transition autoregressive (hereafter ESTAR) was suggested by Michael, Nobay, and Peel (1997) and Kapetanios, Shin, and Snell (2003). In their framework, the function is bounded between 0 and 1, and its value depends on the value of the parameter γ. Transition between the central and outer regimes occurs with deviations of

[1] In Dickey-Fuller framework, $y_t = \lambda y_{t-1} + \varepsilon_t$. When we consider a transition function, $S(\cdot)$, the model is reparameterized as

$$\Delta y_t = \phi y_{t-1} + \beta S(\cdot) y_{t-1} + \varepsilon_t$$

where $\phi = \lambda - 1$. Imposing $\phi = 0$ our specification is given

$$\Delta y_t = \beta S(\cdot) y_{t-1} + \varepsilon_t$$

Model	Transition Function: $S(y_{t-d}, \theta)$	Parameter: θ
ESTAR	$1 - \exp(-\gamma y_{t-d}^2)$	γ
Asymmetric STAR	$[1 + \exp\{(-\gamma_1^2 y_{t-d}^2) I_t + (-\gamma_2^2 y_{t-d}^2)(1 - I_t)\}]^{-1} - \frac{1}{2}$	γ_1, γ_2
3-Regime SETAR	$1\{y_{t-d} \leq c_1\} + 1\{y_{t-d} \geq c_2\}$	c_1, c_2

Table 2.1: Transition Functions

y_{t-d} from the mean, μ, and the speed of transition increases with the value of γ. Specifically, when $y_{t-d} = \mu$, the transition function $S(y_{t-d}, \theta)$ takes the value zero and the specification (2.2) follows an $I(1)$ process. With the ESTAR the unit root regime is therefore an inner regime and mean-reversion an outer regime. This model collapses to a linear model with scale parameter, γ.

The asymmetric STAR was introduced in Sollis, Leybourne, and Newbold (2002). The model has similar properties to the ESTAR but it allows asymmetric scale parameters, γ_1 and γ_2. In addition, the transition function $S(y_{t-d}, \theta)$ is bounded from 0 to 0.5 when the γ_1 and γ_2 have sufficiently large values. The fundamental properties of the asymmetric STAR movement between regimes are the same as the ESTAR function and, obviously, for $\gamma_1 = \gamma_2$ it encompasses the symmetric model.

In a TAR model, initially proposed by Tong (1983), a change in the autoregressive structure occurs when the level of the series reaches a particular threshold value. Since the introduction of TAR models there have been several variations of them, such as the 3-regime self-excited TAR (hereafter SETAR) introduced in Kapetanios and Shin (2003). The threshold variable considered in such a model is taken to be the lagged value of the time series itself, y_{t-d}. In the central state, when $-c_1 < y_{t-d} < c_2$, $S(y_{t-d}, \theta) = 0$, and in the limiting outer states, when $y_{t-d} \leq c_1$ and $y_{t-d} \geq c_2$, $S(y_{t-d}, \theta) = 1$.

2.3.2 Symmetric transition function

We propose a transition function that should bridge the gap between the PPP theory and the existing empirical evidence. We specify a transition function $S(y_{t-d}, \theta)$ with a middle-regime value of θ that occurs when $-c < y_{t-d} < c$. Crucially, this middle-regime is the infimum of the function, so that the process is less persistent either side of its equilibrium threshold rather than just one side. We add an indicator function to the logistic function to allow it to take certain values either sides of the threshold. Consider, for example, the Heavyside indicator function $\mathbf{I}_t$,[2]

$$\mathbf{I}_t = \begin{cases} 1 & \\ & , \text{ if } \\ 0 & \end{cases} \begin{matrix} y_{t-1} < 0 \\ \\ y_{t-1} \geq 0 \end{matrix}$$

with the logistic function

$$S(y_{t-d}, \theta) = [1 + \exp\{\gamma(y_{t-d} - c)\mathbf{I}_t - \gamma(y_{t-d} + c)(1 - \mathbf{I}_t)\}]^{-1} \tag{2.3}$$

where the parameter set θ includes the scale parameter γ and the threshold c.

The function (2.3) should allow for both threshold effects and smooth transition movements of y_{t-d}. In the central regime, when $-c < y_{t-d} < c$, $S(y_{t-d}, \theta) = 0$, the random variable considered follows an $I(1)$ process. In the limiting outer regimes, when $y_{t-d} < -c$ and $c < y_{t-d}$, $S(y_{t-d}, \theta) = 1$ it follows an $I(0)$ mean reverting process. The specification given by (2.3) allows for a random walk in the central regime and the limiting outer regime of the model is a stationary

[2] The Heavyside indicator has been used by Enders and Granger (1997) who introduced TAR methodology into Dickey-Fuller test, in which the change in autoregressive structure under the alternative hypothesis takes place instantaneously as the lagged level of the series in a standard Dickey-Fuller specification reaches a particular threshold, or not at all.

autoregression. Note that this type of approach is also consistent with a 3-regime SETAR.

2.3.3 Asymmetric transition function

We now consider asymmetric effects and change the transition function as follows

$$S(y_{t-d}, \theta) = [1 + \exp\{\gamma_1(y_{t-d} - c_1)\mathbf{I}_t - \gamma_2(y_{t-d} - c_2)(1 - \mathbf{I}_t)\}]^{-1} \tag{2.4}$$

where the parameter set, θ includes the scale parameter γ_i and threshold c_i when $i = 1, 2$.

The desired neutral band, implied by the PPP theory, occurs when $c_1 < y_{t-d} < c_2$. This function is also consistent with a symmetric transition. However, if $\gamma_1 \neq \gamma_2$ and $c_1 \neq c_2$, then with changes in y_{t-d}, the transition function $S(y_{t-d}, \theta)$ is asymmetric.

To illustrate and compare the nature of our proposed models (2.3) and (2.4) with other STAR models, we perform a simulation with our CMK-STAR, ESTAR and asymmetric ESTAR. Since the parameters of an asymmetric function include that of symmetric, the functions in Figure (2.2) are simply plotted for the same symmetric threshold values of y_{t-d}, where $d = 1$ with six different scale parameters γ. We consider a sequence of $y_{t-1} \in [-0.5, 0.5]$, threshold parameter $c = 0.4$ and various values of the speed parameter γ ranging from 0.1 to 100. Figure (2.2) shows the results. When the function moves between 0 and -1 as y_{t-1} changes, the shape is determined by the size of γ. As expected

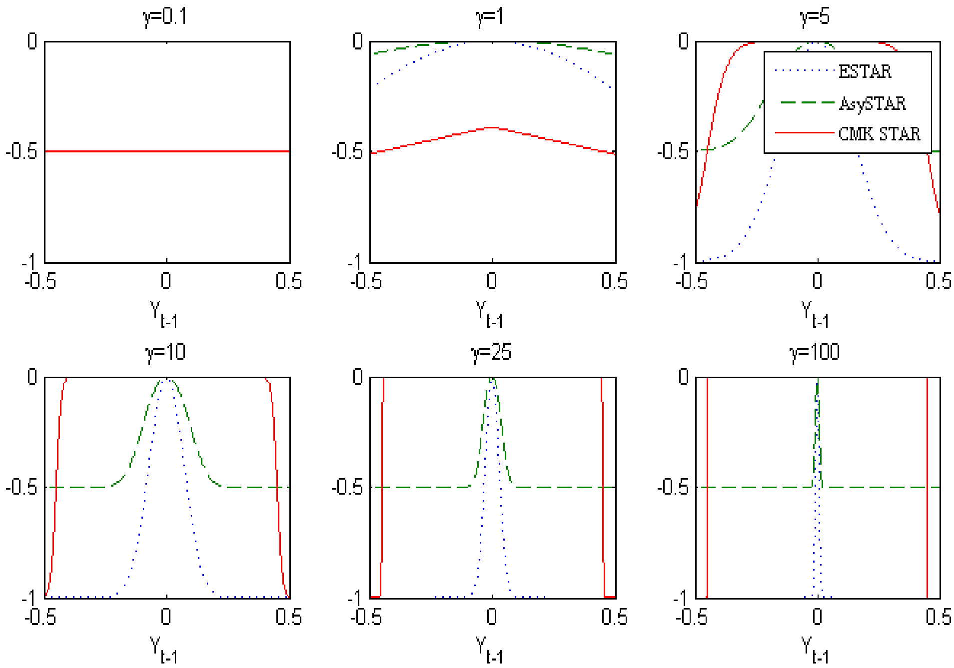

Figure 2.2: Properties of ESTAR, Asymmetric STAR, CMK-STAR Functions

small values of γ, for example, $\gamma = 0.1$ generate slow transitions (near unit root), whereas large values, say $\gamma = 100$, generate rapid transitions. While all the functions tend to become flat as the scale parameter goes to zero, the exponential and CMK-STAR are close in the medium scale parameter such as 5 or 25. On the other hand, as the value of the scale parameter, γ, increases, the shape of the transition function become different and the CMK-STAR, as expected, tend to become discontinuous. Thus we are able to trace many observations in the immediate neighbourhood of the threshold value c.

2.3.4 Estimation method

With non-linear models, consistent estimation of parameters can be obtained by ordinary least squares or, equivalently, maximum likelihood under the Gaussian assumption. The estimation technique begins by setting a proper grid over the parameters and at each point in the grid minimizing the residual sum of squares with respect to the remaining parameters in the model. In the presence of autocorrelation we suggest using the following modified Dickey and Fuller (1979) regression:

$$\Delta y_t = \beta S(y_{t-d}, \theta) y_{t-1} + \sum_{i=1}^{p} \rho_i \Delta y_{t-i} + \varepsilon_t, \tag{2.5}$$

where $\varepsilon_t \sim i.i.d.$ and $S(y_{t-d}, \theta)$ the symmetric or asymmetric function described above.

Consider for simplicity the case when $p = 0$ in the equation above. In the central regime the model follows an $I(1)$ process, since $S(y_{t-d}, \theta) = 0$. On the other hand, outside the inner regime, the model becomes $\Delta y_t = \beta y_{t-1} + \varepsilon_t$ since $S(y_{t-d}, \theta) = 1$. This specification therefore allows for an $I(1)$ central regime and the limiting outer case of the model is a stationary autoregression. The appropriate parameters to be estimated are β, ρ_i and the parameter set of transition function, θ.[3] We estimate these parameters considering various values for d in descending order and choose the value of d obtained in the model with the smallest residual sum of squares. This approach was also used in Peel, Sarno, and Taylor (2001). The coefficient, p is determined using a general-to-specific approach at the 10% level of significance.

[3] Apart from d and p

To overcome the problem of unidentified parameters raised in Davies (1987), Leybourne, Newbold, and Vougas (1998) suggested calculating the test statistics over a grid set of possible values with summary statistics. The estimation of β in equation (2.5) can be obtained by using OLS as

$$\hat{\beta}(\theta) = \left(\sum_{t=1}^{T} x_t(\theta) x_t(\theta)' \right)^{-1} \left(\sum_{t=1}^{T} x_t(\theta) \Delta y_t \right),$$

with residuals $\varepsilon_t = y_t - \hat{\beta}(\theta)' x_t(\theta)$ where $x_t(\theta) = [S(y_{t-d}, \theta) y_{t-1}, \Delta y_{t-1}, ..., \Delta y_{t-p}]$.

Note that under the assumption that ε_t is normally distributed, the resulting estimates are equivalent to the maximum likelihood estimates. Finally, the parameters of interest can be estimated by the following conditional least squares,

$$\tilde{\theta} = \arg\min_{\theta} \sum_{t=1}^{T} (y_t - \hat{\beta}(\theta)' x_t(\theta))^2 = \arg\min_{\theta} \hat{\sigma}^2(\theta), \tag{2.6}$$

Leybourne, Newbold, and Vougas (1998) argue that this method reduces the dimensionality of the non-linear least square estimation problem considerably. However, from the simulation experiments undertaken using the GAUSS OPTIMUM library, convergence was found to be difficult to achieve because of the initial value problem and parameter dimensionality in asymmetric specifications.

To circumvent the above problems, we propose to estimate our non-linear STAR models using the inf-t estimator $\hat{\theta}$ recently proposed in Park and Shintani (2005) as opposed to non-linear least squares (NLLS). Although both the estimators are consistent, the inf-t estimator is more efficient when $\beta < 0$. In fact, the NLLS estimator corresponds to the sup-Wald estimator which maximizes

$W(\theta) = \frac{\beta(\theta)'(X(\theta)'X(\theta))\beta(\theta)}{\hat{\sigma}(\theta)^2} = \frac{y'(I-M(\theta))y}{y'M(\theta)y}$, where I is an identity matrix, M an idempotent matrix and $\hat{\sigma}_i = \sum_{t=1}^{T} \varepsilon_t^2/(T-p-1)$, that is

$$\tilde{\theta} = \arg\max\{T_n^2(\theta)|\theta \in \Theta_n\}$$

On the other hand, the inf-t estimator can be written as

$$\begin{aligned} \hat{\theta}_n &= \arg\inf_{\theta\in\Theta} T_n(\theta) \\ &= \arg\max\{T_n^2(\theta)|\beta_n(\theta) < 0, \hat{\theta} \in \Theta_n\} \end{aligned}$$

The relevant infimum $t-$statistic is then given by

$$\text{inf-}t(\hat{\beta}) = \frac{\hat{\beta}(\theta)}{s(\hat{\beta}(\theta))},$$

where $s(\hat{\beta}(\theta))$ is the standard error of the estimate $\hat{\beta}(\theta)$. Choi and Moh (2007) show that this test has better small sample properties than other non-linear tests.

In the presence of unidentified parameters, the parameter values for the optimization are obtained by grid search over c and γ. A meaningful set of values for the threshold parameter c is then defined as sample percentiles of the transition variable as suggested by Caner and Hansen (2001). For the threshold parameter c of the model, we therefore set the parameter space as

$$[Q(15), Q(85)], \tag{2.7}$$

where $Q(15)$, $Q(85)$ are the 15th and 85th percentiles of y_{t-d} respectively.

At the same time, to determine a useful set of scale parameter γ, van Dijk, Terasvirta, and Fransesvan (2002) suggested re-scaling the transition function with the sample standard deviation, which makes γ approximately scale-free. That is, the transition parameter was standardized through by its sample variance. We therefore estimate the scale parameter γ over the interval given by:

$$[10^{-1}P_n, 10^3 P_n], \tag{2.8}$$

where $P_n = (\sum_{t=1}^{n} \frac{y_t^2}{n})^{-\frac{1}{2}}$.

However, the estimate of γ may be rather imprecise and often appears to be insignificant because of the fact that even large changes in γ_i only have a small effect on the shape of the transition function. As shown in the Figure (2.2), we need to trace many observations in the immediate neighbourhood of c. Therefore, at each step, the parameters set were estimated so as to maximize the sup-Wald test statistics. The combination of parameters, c and γ values that provide the overall maximum of the sup-Wald test statistics were then chosen as the estimated parameters for the model.

2.4 Monte Carlo experiments

In order to clarify the advantage of our model with respect to alternatives we perform an additional simulation and compare the proposed model with representative regime switching models, such as, ESTAR and 3-regime SETAR, using a sequence of $y_{t-1} \in [-0.5, 0.5]$, $\beta = -0.3$ and, for simplicity, symmetric value of threshold parameter, $c = 0.5$ and scale parameter, $\gamma = 5$.

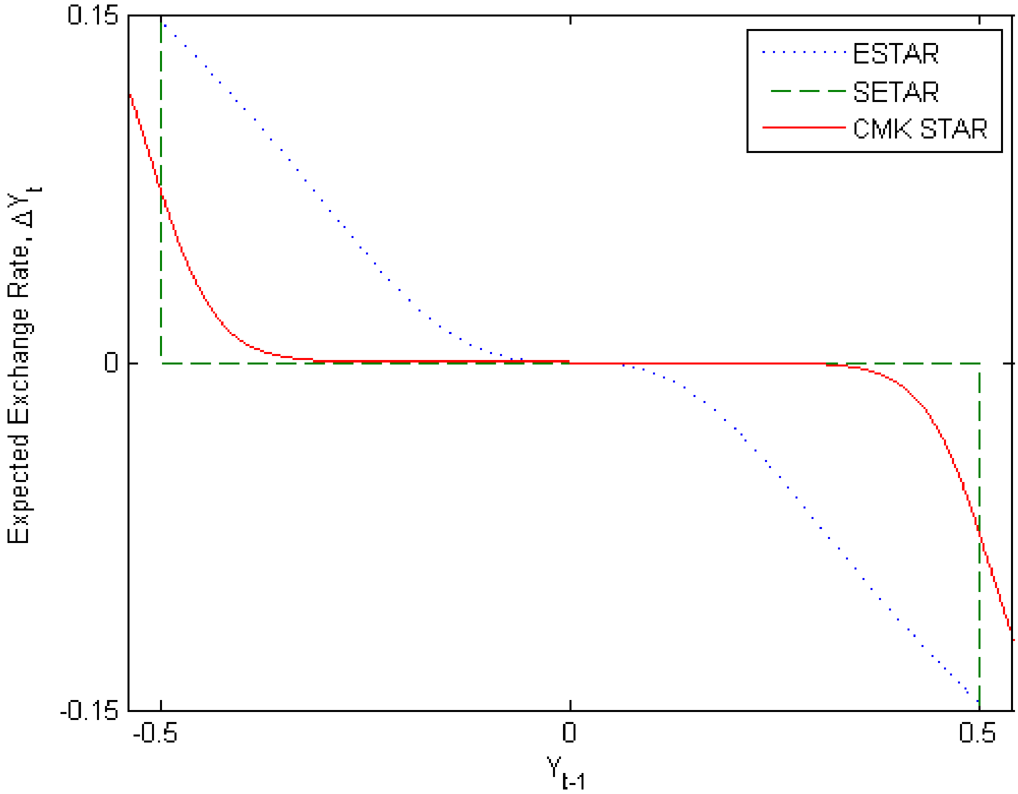

Figure 2.3: Simulated Conditional Expected Change Functions

Transition Function	Asymptotic Critical Values					
	1%	5%	10%	90%	95%	99%
Symmetric STAR	-3.89	-3.30	-3.02	-0.92	-0.48	0.24
Asymmetric STAR	-3.81	-3.23	-2.94	-1.02	-0.69	-0.11

Table 2.2: Asymptotic Critical Values

In terms of theoretical implications, Figure (2.3) shows that our proposed model, CMK-STAR, most closely mimics the behaviour of the real exchange rate movement predicted by Dumas (1992) and Berka (2004) when the level of relative risk aversion is low. On the other hand, the ESTAR is not able to capture these dynamics (i.e. the inaction bound) under any parameterization. The main limitation with 3-regime SETAR models is that the change is restricted to take place instantaneously, or not at all. That is, while the 3-regime SETAR offers an improvement over the ESTAR by considering a neutral band, it is still misspecified if the transition is gradual rather than instantaneous.

The critical values associated with our symmetric and asymmetric CMK-STAR models can be calculated using the same estimation procedure, as suggested above. The null distribution of the test was therefore simulated using Monte Carlo simulation methods under the random walk assumption. Therefore, a driftless random walk with standard normal error term, $u_t\tilde{}i.i.d$ was chosen as data generating process (hereafter DGP) with $d = 1$. A sample size of $1,000$ observations and $10,000$ replications were considered. Critical values at 1%, 5% and 10% significant levels are given in Table (2.2). The critical values for all of the symmetric and asymmetric tests are, in general, more negative than those for the corresponding standard Dickey-Fuller test.

We now report size and power analysis and compare our test with the DF test. For the size all results are empirical rejection frequencies from $10,000$ replications when the underlying DGP is a random walk process with serially correlated errors. Since the tests are based on demeaned data, we employ the same process here. To examine the power of the tests, we follow Park and Shintani (2005) and use the following DGP,

$$\Delta y_t = \beta S(y_{t-d}, \theta) y_{t-1} + \rho \Delta y_{t-1} + \varepsilon_t, \tag{2.9}$$

where u_t follows the standard normal distribution. We consider how the size is affected by the parameter ρ and consider the sample sizes 100, 200, and 300, where $\beta = 0$ and $\rho = \{-0.5, 0, 0.5\}$ respectively. For comparison we also report the size for the DF statistics t_{DF}. The inf-t^{AS} test is generally close to its nominal level at 5%. It is important to note what also reported in Sollis (2005), that is, under-fitting the number of lags lead to size distortions, while overfitting leads to smaller size distortions.

We now turn to the power analysis where use the GDP above in conjunction with the following equation

$$\Delta y_t = \phi y_{t-1} + \beta S(y_{t-d}, \theta) y_{t-1} + \varepsilon_t \tag{2.10}$$

where $\phi = 0.1$ and $\beta = -0.3$ with asymmetric parameters for c and γ. Overall the power of our t_{NL}^{AS} is good, and it is generally superior to the ADF test. On the other hand the ADF test has a higher power when the time series are highly persistent.

	ρ = -0.5			0			0.5		
	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
$k = 0$									
T =100	0.4571	0.4306	0.3829	0.0643	0.0554	0.0556	0.0359	0.0359	0.0328
200	0.4660	0.4621	0.3977	0.0591	0.0509	0.0495	0.0336	0.0353	0.0324
300	0.4886	0.4660	0.3925	0.0622	0.0495	0.0512	0.0330	0.0307	0.0324
$k = 1$									
T =100	0.0622	0.0491	0.0528	0.0625	0.0522	0.0552	0.0659	0.0543	0.0503
200	0.0536	0.0495	0.0508	0.0603	0.0510	0.0530	0.0608	0.0533	0.0520
300	0.0531	0.0499	0.0555	0.0547	0.0550	0.0548	0.0611	0.0492	0.0514
$k = 4$									
T =100	0.0539	0.0462	0.0443	0.0556	0.0484	0.0457	0.0592	0.0494	0.0461
200	0.0516	0.0501	0.0533	0.0594	0.0464	0.0460	0.0591	0.0493	0.0437
300	0.0571	0.0452	0.0490	0.0588	0.0467	0.0461	0.0583	0.0519	0.0487

Table 2.3: Size of Symmetric and Asymmetric CMK-STAR

Asymmetric DGP				T =100			200			300		
c_1	c_2	γ_1	γ_2	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
-3.5	0.5	20	0.001	0.4340	0.5689	0.3074	0.8001	0.8803	0.5620	0.9571	0.9815	0.8502
	1.5			0.4337	0.5735	0.3141	0.7992	0.8835	0.5640	0.9554	0.9821	0.8499
	2..5			0.4359	0.5669	0.3114	0.8014	0.8831	0.5722	0.9566	0.9803	0.8401
	0.5	0.1		0.1262	0.1268	0.1404	0.3271	0.3317	0.3754	0.6075	0.6447	0.7036
	1.5			0.1272	0.1348	0.1483	0.3153	0.3428	0.3806	0.6055	0.6357	0.6944
	2..5			0.1298	0.1256	0.1386	0.3178	0.3427	0.3792	0.6074	0.6495	0.7061

Table 2.4: Power of Symmetric and Asymmetric CMK-STAR

2.5 Empirical results

2.5.1 Linearity test

The first step in estimating our proposed model involves testing for linearity against STAR non-linearity. Testing linearity against STAR-type non-linearity implies testing the null hypothesis, $H_0 : \beta = 0$ in equation (2.2). However, under the null, the parameter set, θ is not identified. Alternatively, we could choose $H_0' : \gamma = 0$ as our null hypothesis in which case neither c nor β would be identified. A solution proposed by Luukkonen, Saikkonen, and Terasvirta (1988) and adopted by Terasvirta (1994) is to replace the transition function $S(y_{t-d}, \theta)$ by the second order Taylor series approximation around $\gamma = 0$. With this linearized model, Harvey and Leybourne (2007) recently suggest a standard Wald test, denoted by W_T, which is shown to possess the usual $\chi^2(2)$ distribution asymptotically. In this case testing for linearity is then performed by an auxiliary regression,

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-1}^2 + \beta_3 y_{t-1}^3 + \sum_{j=1}^{p} \beta_j \Delta y_{t-i} + \varepsilon_t, \qquad (2.11)$$

which allow $AR(p)$ structures.

Under the null hypothesis linearity is tested as

$$H_0 : \beta_2, \beta_3 = 0.$$

The alternative hypothesis of non-linearity is then defined as

$$H_1 : \text{at least one of } \beta_2, \beta_3 \neq 0.$$

The test statistic is computed using the following procedure. First, estimate (2.11) under the null hypothesis by OLS and calculate the residual sum of squares, RSS_0. Second, using the residuals from the previous step, estimate a model that contains the regressors of (2.11) to compute the residual sum of squares RSS_1. The test of H_0 against H_1 can be then carried out using the W_T,

$$W_T = \frac{RSS_1 - RSS_0}{RSS_0/T} \sim \chi^2(2)$$

The W_T will have an asymptotic χ^2 distribution with degree of freedom given by the number of parameter restrictions under the null hypothesis.

2.5.2 Data and preliminary tests

In this empirical application we use monthly data on black market nominal exchange rates and official nominal exchange rates for twenty-five and thirty-eight emerging market economies respectively. The former series are obtained from recent Cerrato and Sarantis (2007), which covers 1973:01-1998:10. The nominal exchange rate data set is retrieved from the International Monetary Fund's International Financial Statistics (IFS) over the free floating period 1980:1-2007:12. The data used are monthly nominal and black market exchange rate against US dollar and CPIs (Consumer's Price Index) for both series. We work with demeaned data measured in logs.

We begin with the official real exchange rates of thirty-eight emerging market economies, and use the standard DF test t_{DF}. The number of lags, p was determined using the general-to-specific testing strategy at the 10% level of significance, starting with $p = 12$. The results from the standard t_{DF} and the linearity test W_T for the real exchange rates are given in Table (2.5), along with the values of p for each series. The t_{DF} statistics in Table (2.5), suggests that the null hypothesis of a unit root is rejected only in seven out of thirty-eight countries, thus providing evidence against mean reversion.

To apply the linearity test, W_T, we select the AR order in the regression (2.11) using a general-to-specific methodology and a 10%-significance level, (4.605), with a maximum permitted AR order of four and a minimum order of two. We find evidence of non-linearity for nineteen real exchange rates. Therefore half of the series analyzed exhibit evidence of non-linearity and would suggest that non-linear models may be appropriate.

Let us turn now to the black market exchange rate series. The results of the standard t_{DF} and the linearity test W_T are shown in Table (2.6). The standard t_{DF} rejects the null in eight series out of twenty-five countries. Furthermore the linearity test W_T shows the same results as in the previous case. Thus more than half of the series will be considered in the next section.

Note that hereafter, *,**,*** denote the 10%, 5% and 1% significance levels, respectively, T is the number of observations and p is the order of the autoregressive terms included to account for additional serial correlation in the data.

Country	Duration	T	p	t_{DF}	W_T
Asian emerging market					
India	1980:01-2007:10	334	2	-1.3941	$16.355^{\dagger}$
Indonesia	1980:01-2007:10	334	1	-1.7208	$16.931^{\dagger}$
Korea	1980:01-2007:10	334	2	-2.4181	$38.366^{\dagger}$
Malaysia	1980:01-2007:10	334	1	-0.8961	$6.472^{\dagger}$
Pakistan	1980:01-2007:10	334	2	-1.5478	3.445
Philippines	1980:01-2007:10	334	2	-1.7855	0.384
Singapore	1980:01-2007:10	334	12	-1.8375	0.199
Thailand	1980:01-2007:10	334	2	-1.3420	$25.595^{\dagger}$
Other emerging market					
Algeria	1980:01-2007:10	334	4	-1.1741	$31.469^{\dagger}$
Argentina	1980:01-2007:10	334	2	-2.7553^{*}	$37.773^{\dagger}$
Bolivia	1980:01-2007:10	334	0	-4.1298^{***}	$127.924^{\dagger}$
Botswana	1980:01-2007:10	334	2	-2.1014	3.457
Brazil	1980:01-2007:10	334	2	-2.2828	2.426
Burundi	1980:01-2007:10	334	0	-0.9976	$16.158^{\dagger}$
Chile	1980:01-2007:10	334	2	-1.7540	0.642
Columbia	1980:01-2007:10	334	2	-1.7773	$4.743^{\dagger}$
Costa Rica	1980:01-2007:10	334	2	-4.0042^{***}	3.579
Dominica Rep.	1980:01-2007:10	334	0	-2.3475	$68.035^{\dagger}$
Egypt	1980:01-2007:10	334	12	-1.9443	1.696
El Salvador	1980:01-2007:10	334	1	-3.1679^{***}	$27.660^{\dagger}$
Ethiopia	1980:01-2007:10	334	2	-1.1152	2.934
Guatemala	1980:01-2007:10	334	0	-2.0960	$47.866^{\dagger}$
Haiti	1980:01-2007:10	334	0	-1.5733	3.171
Honduras	1980:01-2007:10	334	0	-2.5212	$506.488^{\dagger}$
Jamaica	1980:01-2007:10	334	4	-2.0329	$13.569^{\dagger}$
Jordan	1980:01-2007:10	334	1	-1.4372	1.812
Kenya	1980:01-2007:10	334	2	-2.3725	0.966
Madagascar	1980:01-2007:10	334	1	-1.9043	$8.045^{\dagger}$
Malawi	1980:01-2007:10	334	2	-1.3723	3.857
Mauritius	1980:01-2007:10	334	12	-2.5105	1.741
Mexico	1980:01-2007:10	334	12	-3.6830^{***}	$22.716^{\dagger}$
Morocco	1980:01-2007:10	334	1	-4.4510^{***}	0.236
Paraguay	1980:01-2007:10	334	1	-1.5376	0.096
Peru	1980:01-2007:10	334	0	-2.6784^{*}	$40.029^{\dagger}$
South Africa	1980:01-2007:10	334	11	-2.1588	1.030
Turkey	1980:01-2007:10	334	2	-2.3503	$8.755^{\dagger}$
Uruguay	1980:01-2007:10	334	12	-2.3618	1.616
Venezuela	1980:01-2007:10	334	0	-2.4544	3.066

Table 2.5: Estimated DF and Linearity Test Statistics for RER against the US Dollar

Country	Duration	T	p	t_{DF}	W_T
Asian emerging market					
India	1973:01-1998:10	307	3	-1.1732	1.057
Indonesia	1973:01-1998:10	307	5	-0.1700	$17.322^{\dagger}$
Malaysia	1973:01-1998:10	307	0	1.3233	$5.261^{\dagger}$
Pakistan	1973:01-1998:10	307	0	-0.9783	1.231
Philippines	1973:01-1998:10	307	0	-2.8242^{*}	$26.798^{\dagger}$
Thailand	1973:01-1998:10	307	0	-1.8190	$9.072^{\dagger}$
Other emerging market					
Argentina	1973:01-1998:10	307	0	-2.4285	$69.890^{\dagger}$
Bolivia	1973:01-1998:10	307	0	-3.6346^{***}	$49.978^{\dagger}$
Chile	1973:01-1998:10	307	2	-4.9681^{***}	$36.599^{\dagger}$
Columbia	1973:01-1998:10	307	3	-1.1646	1.063
Cyprus	1973:01-1998:10	307	2	-2.6874^{*}	2.044
Dominica Rep.	1973:01-1998:10	307	1	-1.9126	2.633
Equador	1973:01-1998:10	307	1	-1.4390	$4.652^{\dagger}$
Egypt	1973:01-1998:10	307	6	-4.9040^{***}	$5.028^{\dagger}$
El Salvador	1973:01-1998:10	307	0	-1.6569	$42.853^{\dagger}$
Ethiopia	1973:01-1998:10	307	0	-2.3821	0.271
Kenya	1973:01-1998:10	307	1	-2.5974^{*}	1.190
Mexico	1973:01-1998:10	307	0	-2.7611^{*}	$14.028^{\dagger}$
Morocco	1973:01-1998:10	307	0	-1.4907	$9.165^{\dagger}$
Paraguay	1973:01-1998:10	307	1	-1.3271	1.490
Peru	1973:01-1998:10	307	0	-1.6184	3.394
South Africa	1973:01-1998:10	307	0	-3.6084^{***}	$14.228^{\dagger}$
Turkey	1973:01-1998:10	307	0	-2.2894	$16.049^{\dagger}$
Uruguay	1973:01-1998:10	307	0	-1.8358	$5.226^{\dagger}$
Venezuela	1973:01-1998:10	307	3	-1.6902	1.466

Table 2.6: Estimated DF and Linearity Test Statistics for BER against the US Dollar

2.5.3 Application to the real exchange rate

In this section we apply the symmetric and asymmetric non-linear tests to the two data sets of exchange rates analyzed above. Table (2.7) reports the empirical results.

We note that now in addition to the seven rejections obtained by the t_{DF}, there are two additional rejection obtained by the t_{NL}^{S} test. All these rejections occur at the 1% level of significance. In particular, while for countries like Argentina and Peru rejections were at 10% level now all rejections are at the 1% significance level.

Looking at the empirical results when an asymmetric adjustment is considered, we note that there are now nine rejections. That is, there are two additional rejections that occur at the 10% significance level for Indonesia and Turkey. Thus this extension of the inf-t^S reveals evidence that supports long-run PPP that would not have been detected by the application of the inf-t^S alone.

For all emerging market countries that we have considered, Table (2.7) shows that the threshold range, c_1, is wider in absolute value and the speed of adjustment, γ_1, is greater the lower the threshold. For example, Argentina shows lower and upper thresholds of -0.4663 and 0.1180 respectively. This indicates a higher threshold tolerance for depreciations. The speed of adjustment is 0.2283 between the middle and upper regimes and 9.0874 from the lower to the middle regime. This indicates a quicker move between the corridor and the depreciation regimes than between the appreciation regime and the corridor. This is consistent with previous results in (e.g. Sollis, Leybourne, and Newbold

Country	Symmetric			Asymmetric				
	$\lvert c \rvert$	$\lvert \gamma \rvert$	inf-t^S	c_1	c_2	γ_1	γ_2	inf-t^{AS}
Asian emerging market								
India	0.2701	2886.3238	-1.7981	-0.3062	0.1498	457.4515	0.2886	-2.4539
Indonesia	0.4780	3.8123	-2.4427	-0.4780	0.1927	8.2800	0.2079	-3.0289*
Korea	0.1960	19.2553	-4.0005***	-0.1960	0.0519	25.7552	0.6469	-4.0325***
Malaysia	0.3470	3325.0853	-1.7474	-0.3470	0.1235	3325.0853	0.3325	-2.6176
Thailand	0.2998	11.8491	-1.9643	-0.2998	0.0959	15.8489	0.3981	-2.3189
Other emerging market								
Algeria	0.7045	872.9211	-2.5138	-0.2580	0.2048	1417.4289	0.1417	-1.7449
Argentina	0.4663	4.1841	-3.9073***	-0.4663	0.1180	9.0874	0.2283	-4.0130***
Bolivia	0.4265	1.6055	-6.0403***	-0.4265	0.1326	1.4571	1.4571	-5.6817***
Burundi	0.4826	4.4667	-1.5385	-0.4826	0.1568	9.7013	0.2437	-1.6170
Columbia	0.1551	3349.2495	-1.9954	-0.1615	0.1353	3349.2495	0.3349	-2.1558
Dominica Rep.	0.2264	2.1225	-2.9368	-0.1940	0.1377	3053.0825	1.9264	-2.8523
El Salvador	0.2131	3504.9674	-4.1643***	-0.2174	0.0484	0.5691	3.5909	-3.5780**
Guatemala	0.2304	4.1607	-2.7993	-0.2304	0.1129	14.6734	2.3256	-2.7500
Honduras	0.4188	5.7462	-5.0870***	-0.4188	0.0965	0.3134	1.9779	-3.9627***
Jamaica	0.2759	4.2589	-2.3892	-0.2759	0.0537	15.0197	2.3804	-2.3531
Madagascar	0.1595	558.9409	-1.9542	-0.1585	0.1936	379.2669	0.2393	–2.1119
Mexico	0.1913	5.8825	-4.2063***	-0.1913	0.0526	3.2880	3.2880	-4.1477***
Peru	0.5254	34.2456	-3.8879***	-0.5254	0.0971	10.6989	1.6956	-3.1809**
Turkey	0.1726	6.5206	-2.6542	-0.1482	0.0564	5776.4174	0.5776	-3.0397*

Table 2.7: Estimated Results for RER against the US Dollar

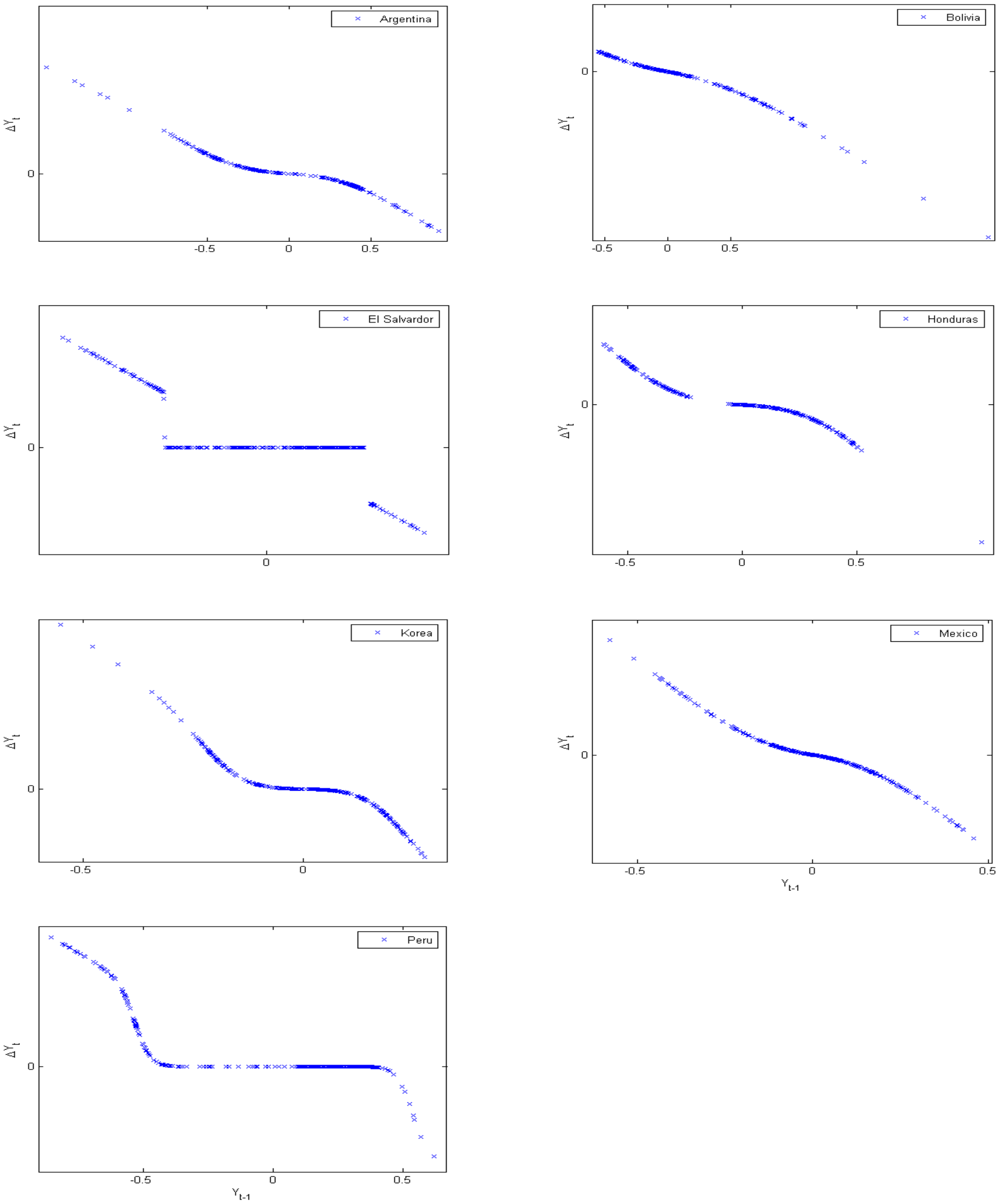

Figure 2.4: Symmetric CMK-STAR for RER

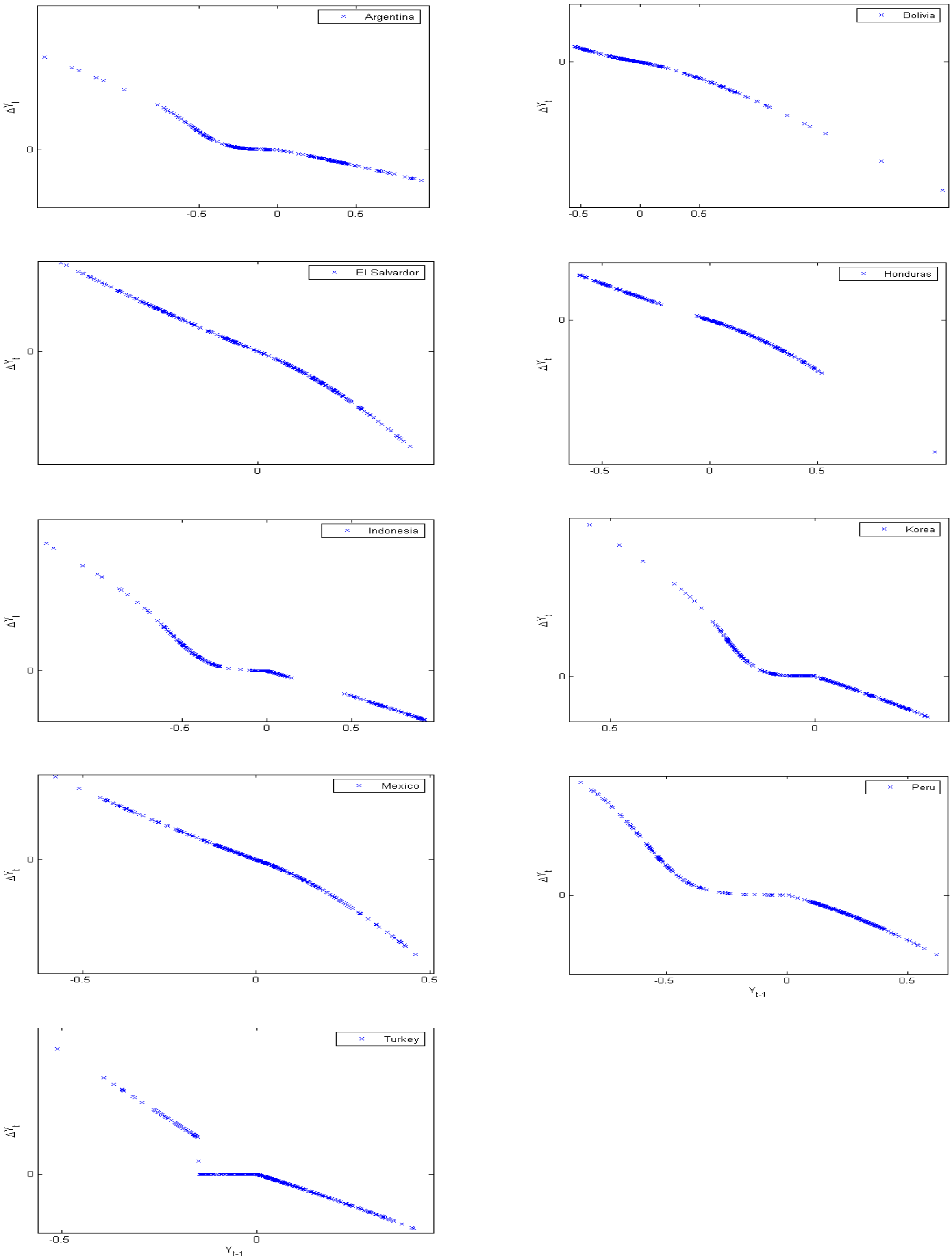

Figure 2.5: Asymmetric CMK-STAR for RER

(2002)).

As shown in Figure (2.4) and Figure (2.5), the nature of symmetry and asymmetry from estimated results can be best illustrated by plotting the values y_{t-1} against Δy_t for the symmetric and asymmetric models respectively. In particular, all figures consistently show that when the rate is below the mean it shows rather faster mean reversion than when the rate is above the mean.

2.5.4 Application to black market exchange rates

To further investigate non-linearity and asymmetry in exchange rate dynamics, we now use the black market exchange rate data set. Since non-linearity was detected in six out of eight series, in this application we have also included them. We now, additionally, reject the unit root null hypothesis in two countries, Argentina and Turkey.

We turn now to the asymmetric test. We note that in addition to the eight rejections obtained by the inf-t^S test, there is one additional rejection obtained by the inf-t^{AS}. This rejection occurs at the 1% level of significance (El Salvador). Thus this extension of the inf-t^S test reveals evidence that support long-run PPP that would not have been revealed by the application of the inf-t^S test alone.

Table (2.8) shows that the threshold range c_1 is wider in absolute value and the speed of adjustment γ_1 is greater in the lower threshold. As an example of this, El Salvador has lower and upper thresholds of -0.3575 and 0.1195, respectively. This result implies a higher threshold tolerance for depreciations. The speed of

Country	Symmetric			Asymmetric				
	$\|c\|$	$\|\gamma\|$	inf-t^S	c_1	c_2	γ_1	γ_2	inf-t^{AS}
Asian emerging market								
Indonesia	0.4097	1.5251	-0.7438	-0.4098	0.4117	1.3841	1.3841	-0.7286
Malaysia	0.0968	5202.3604	-1.2444	-0.1849	0.0598	0.5202	130.6773	0.5316
Philippines	0.1596	7.3134	-3.9706***	-0.1595	0.0454	4.0877	0.6478	-3.8151***
Thailand	0.0754	7534.9477	-2.0549	-0.0785	0.0388	1194.2087	29.9972	-2.1116
Other emerging market								
Argentina	0.6033	5.0994	-4.2822***	-0.6033	0.1836	1713.3364	0.1713	-4.3831***
Bolivia	0.2722	3.4464	-4.6984***	-0.2721	0.0865	1.9264	0.3053	-4.6503***
Chile	0.3280	4.3052	-5.8482***	-0.3280	0.1243	2348.7630	0.2349	-6.3066***
Equador	0.3505	1105.9413	-1.9414	-0.3575	0.1195	11.6087	0.2916	-2.0263
Egypt	0.1335	3.4743	-5.8779***	-0.1335	0.0499	125.5331	0.4998	-6.4986***
El Salvador	0.3772	134.2111	-2.8114	-0.3772	0.1397	61.7940	0.2460	-3.7975***
Mexico	0.3262	10.8116	-3.5277**	-0.3262	0.0814	14.4614	2.2919	-3.1889**
Morocco	0.2092	22.3533	-2.2342	-0.1493	0.0782	733.0452	2.9183	-2.1309
South Africa	0.1249	5968.2076	-4.2752***	-0.1449	0.0478	3.7656	3.7656	-4.0822***
Turkey	0.2407	4282.1032	-3.4631**	-0.2238	0.0883	4282.1032	0.4282	-3.4306**
Uruguay	0.2153	3285.5944	-2.1868	-0.2241	0.1178	82.5304	0.3286	-2.5256

Table 2.8: Estimated Results for BER against the US Dollar

adjustment is 0.2916 between the middle and upper regimes, and 11.6087 from the lower to the middle regime. This indicates a quicker movement between the corridor and the depreciation regimes than between the appreciation regime and the corridor. These results are consistent with the RER models suggested in the literature.

Figure (2.6) and (2.7) confirm that when exchange rates are below their mean, the value of Δy_t is higher than when they are above their mean. Interestingly, the applications of asymmetric models to both the data sets consistently supports the argument that when the exchange rate is depreciated tend to defend the currency more vigorously.

2.5.5 Application to OECD data

To compare emerging market with developed countries, we now test the OECD countries data set. In this application, there are four rejections obtained by the inf-t^S test.[4] We note that there are only one additional rejection obtained by the inf-t^S test. All these rejections occur at the 5% level of significance.

In the asymmetric test, we note that in addition to the four rejections obtained by the inf-t^S test, there are seven additional rejections obtained by the inf-t^{AS} test. Most of these rejections occur at the 5% level of significance and only Netherland rejects the hypothesis at the 10% level. The additional seven countries would not have been shown by the application of the linear test, t_{DF}

[4]We use quarterly data for twenty OECD economies, which covers 1973:1-1998:2. In a preliminarily test, three rejections obtained by the Dickey-Fuller test.

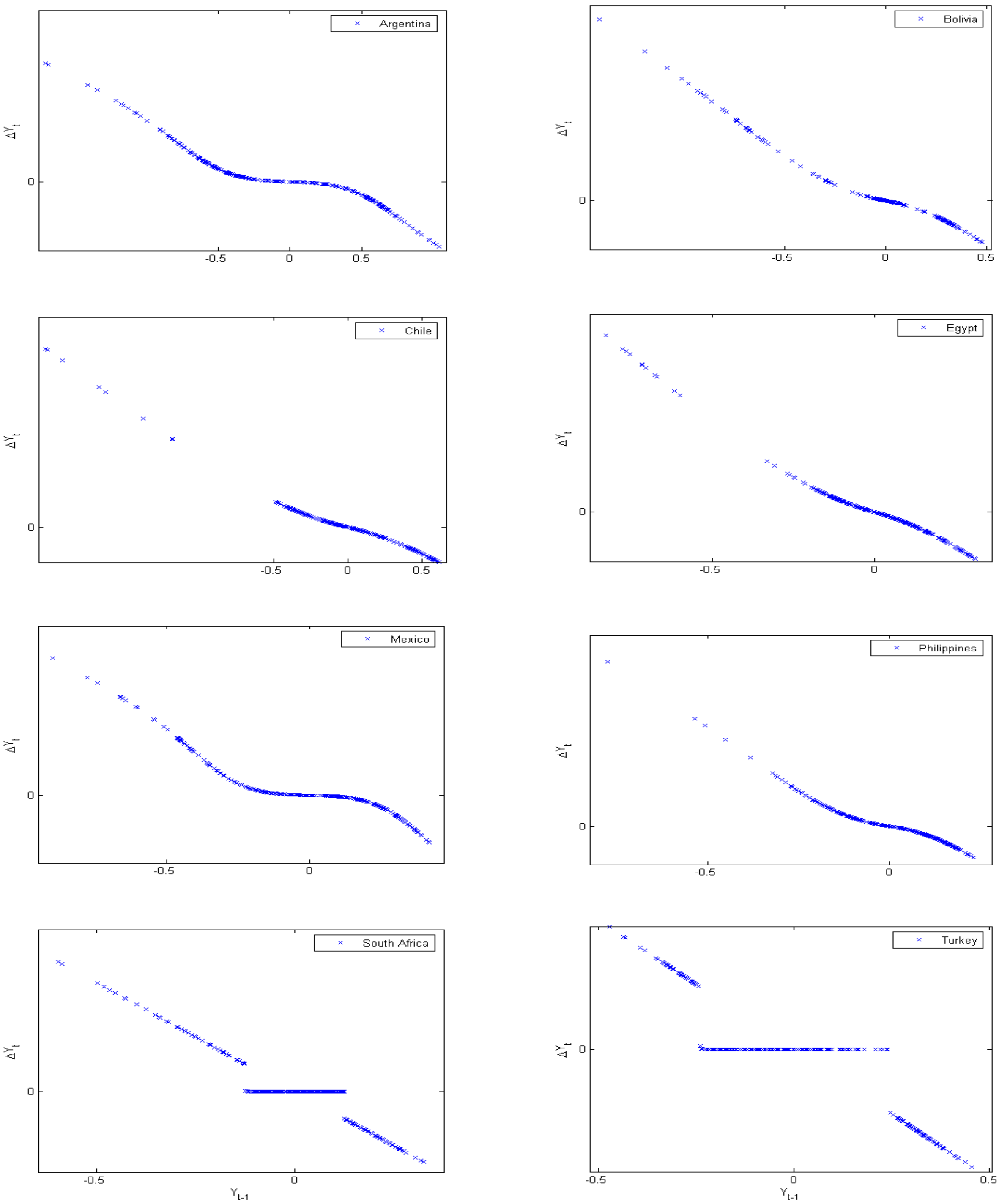

Figure 2.6: Symmetric CMK-STAR for PER

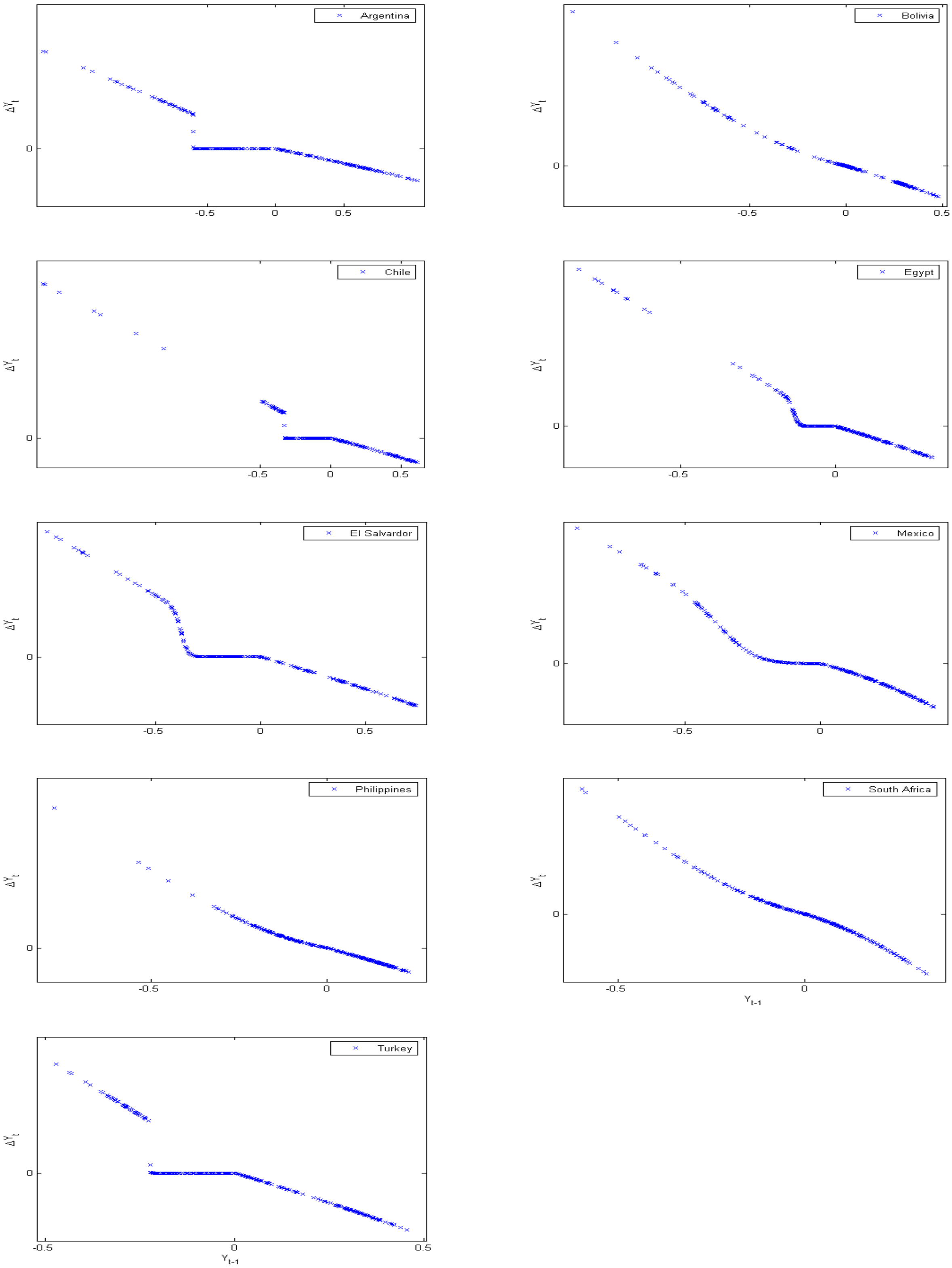

Figure 2.7: Asymmetric CMK-STAR for PER

or symmetric test, inf-t^S. In particular, this extension of the inf-t^{AS} test reveals evidence that supports long-run PPP more than half of the data set.

Looking at the Table (2.9) when asymmetric test is considered, as shown in previous tests, the results show that the threshold range c_1 is generally wider in absolute value except Finland and the speed of adjustment γ_1 is consistently greater in the lower threshold. For example, while only Finland has lower and upper thresholds of -0.0539 and 0.0912, respectively and upper threshold c_2 is slightly wider in absolute value, other results are consistently wider in lower threshold, which implies higher tolerance for depreciations and quicker movement between the corridor and the depreciation regimes. These results are the same as the RER and BER for emerging market provided in previous tests.

In Figure (2.8) and Figure (2.9), the properties of symmetry and asymmetry are graphically shown when exchange rates are appreciated or depreciated. Particularly, as shown in emerging market cases, all figures in Figure (2.9) except Finland show that when the rates of OECD countries are below the mean it shows rather faster mean reversion than the rate is above mean. This implies that the "dread of depreciation" is also applicable in OECD countries and not just in emerging market economies.

2.6 Conclusion

In this chapter we have re-examined the PPP hypothesis using non-linear modelling methods. Although such modelling has become increasingly popular of

Country	Symmetric			Asymmetric				
	$\|c\|$	$\|\gamma\|$	inf-t^S	c_1	c_2	γ_1	γ_2	inf-t^{AS}
Australia	0.1393	7665.5241	-2.1256	-0.1393	0.0331	192.5492	0.7665	-2.0108
Austria	0.1009	5916.4187	-2.8744	-0.1185	0.0552	5916.4187	0.5916	-3.3511**
Belgium	0.1033	5319.4397	-2.4927	-0.1212	0.0686	5319.4397	0.5319	-2.7931
Canada	0.0379	10418.4460	-1.7350	-0.0511	0.0303	1651.2124	1.0418	-1.7691
Denmark	0.0463	5909.9979	-2.4605	-0.0482	0.0589	936.6715	0.5910	-2.9252
Finland	0.0591	7013.7319	-3.3056**	-0.0539	0.0912	7013.7319	4.4253	-3.2300**
France	0.1389	6467.9852	-2.6823	-0.1416	0.0382	6467.9852	0.6467	-3.3699**
Germany	0.0348	6092.5821	-2.7250	-0.1133	0.0509	965.6091	0.6092	-3.2510**
Greece	0.0882	6287.4421	-2.5335	-0.1246	0.0453	6287.4421	0.6287	-2.8086
Ireland	0.0987	7806.6516	-3.0078	-0.1323	0.0386	31.0788	0.7806	-3.3801**
Italy	0.1331	7.6023	-2.6402	-0.1142	0.0465	6734.6729	0.6734	-2.8704
Japan	0.1531	4237.2333	-2.4163	-0.1439	0.1175	106.4344	2.6735	-2.2747
Netherland	0.0283	6222.7671	-2.7111	-0.0896	0.0424	6222.7671	0.6222	-3.0821*
New Zealand	0.1451	1.8134	-3.3679**	-0.0423	0.0392	1090.0543	4.3395	-3.4825**
Norway	0.0898	5096.0317	-2.6771	-0.0934	0.0322	207.8540	0.8275	-3.3408**
Portugal	0.1961	3142.2792	-2.1374	-0.2001	0.0642	5102.3599	0.5102	-2.5451
Spain	0.0508	5328.2922	-2.5063	-0.1837	0.0488	21.2123	0.5328	-2.7186
Sweden	0.1731	846.2946	-2.9879	-0.1731	0.0444	147.7838	0.5883	-3.6004**
Swiss	0.1684	5244.4175	-3.6096**	-0.1909	0.0620	131.7338	3.3090	-3.4299**
U.K.	0.0873	7315.9827	-3.5523**	-0.1356	0.0395	29.1254	0.7315	-3.7958**

Table 2.9: Estimated Results for OECD RER against the US Dollar

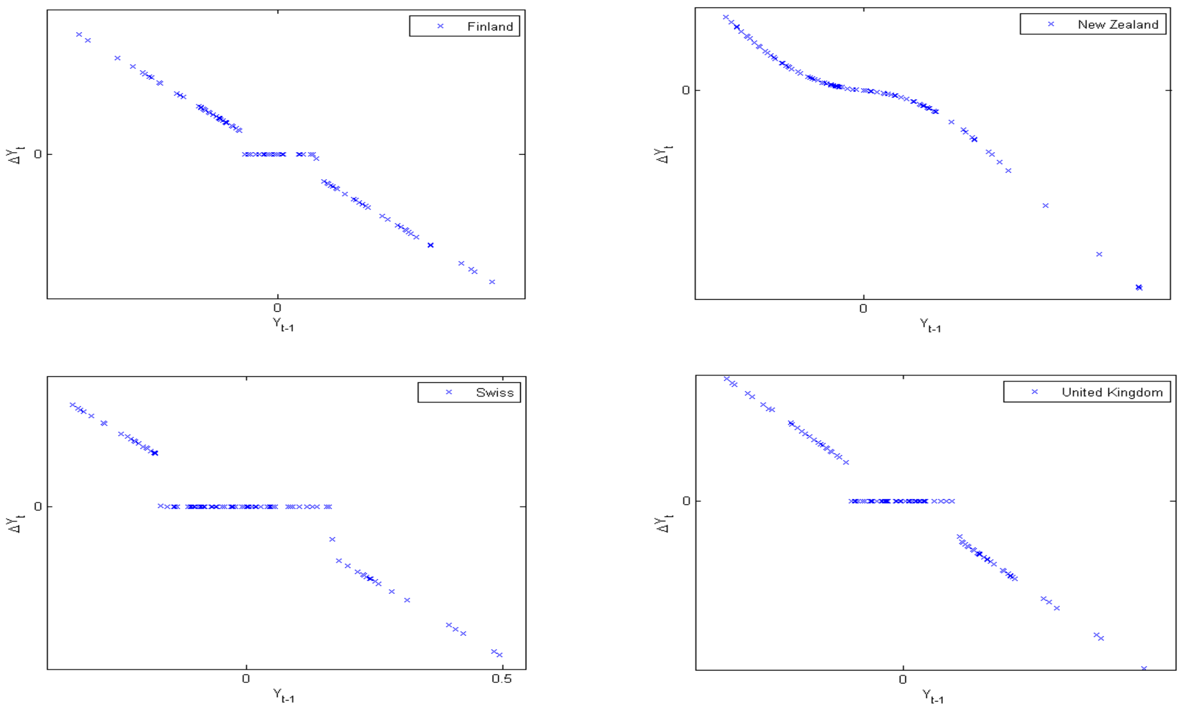

Figure 2.8: Symmetric CMK-STAR for OECD RER

late, we offer a number of novel features in our own work. First, we use more general STAR transition functions than have been used hitherto in the literature and these functions encompass both threshold non-linearity and asymmetric effects. Our framework allows for a gradual adjustment from one regime to another, and considers threshold effects by encompassing other existing models, such as TAR models. Second, we present Monte Carlo simulations which show that our test has good size and power properties. Finally, we apply the proposed test to three different exchange rate data-sets, one for developing countries, using official nominal exchange rates, the second consisting of a unique data set of emerging market economies using black market exchange rates, and the third one consisting of twenty quarterly OECD exchange rates.

Our results provide evidence suggesting that for the majority of currencies,

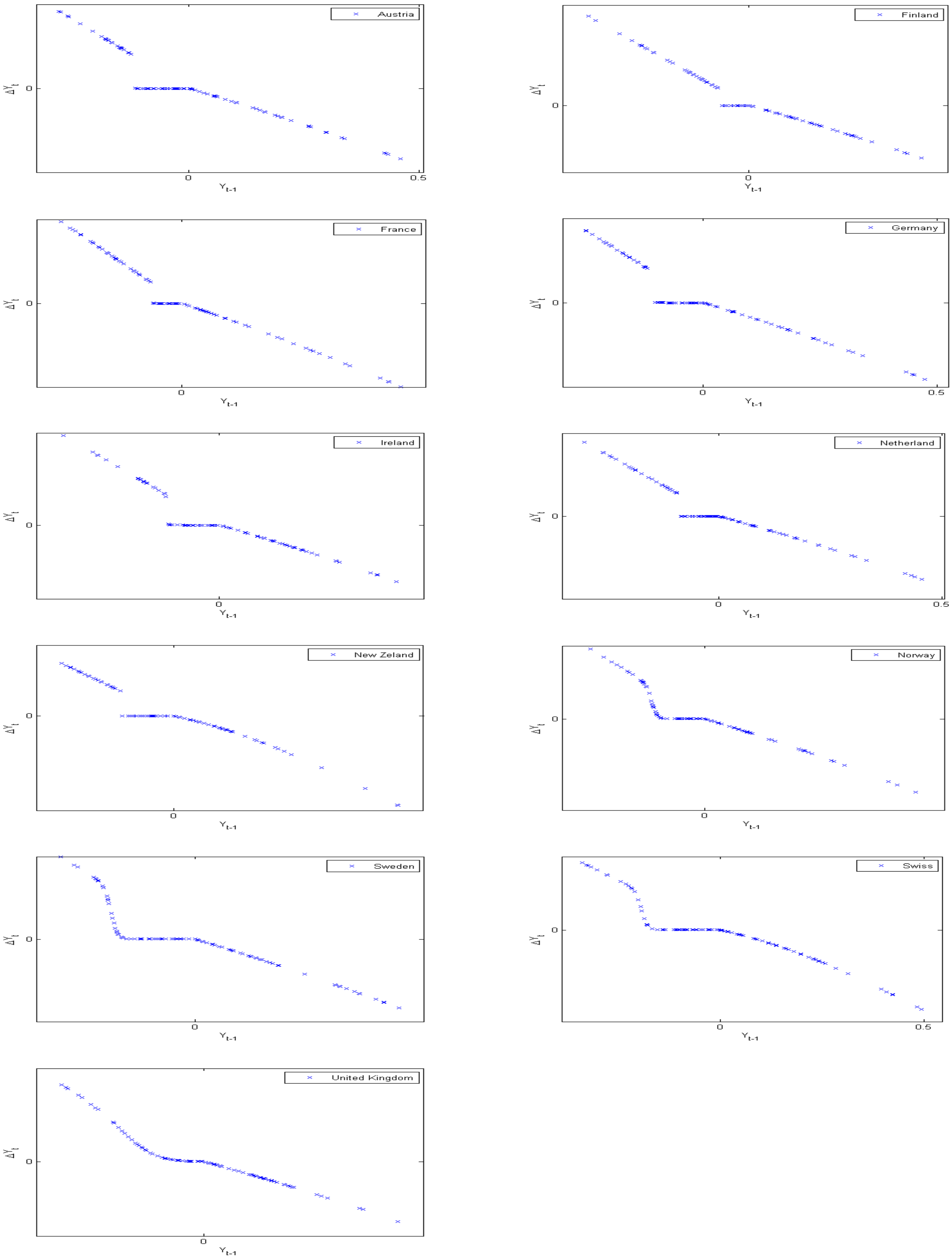

Figure 2.9: Asymmetric CMK-STAR for OECD RER

the asymmetric STAR model characterizes well deviations from PPP. Also our empirical results support what Dutta and Leon (2002) call the "dread of depreciation" in emerging markets. Our results are consistent with previous studies that consider the role of transaction costs in international market arbitrage, although we have used a less restrictive framework than other researchers to obtain our results.

Appendix 2.A

Stationary DGP,

$$\Delta y_t = \beta S(\cdot) y_{t-1} + \varepsilon_t$$

where $\beta = -0.3$.

Symmetric DGP				T =100			200			300		
$\mid c \mid$		$\mid \gamma \mid$		inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
0.1		20		0.2882	0.2966	0.3508	0.7779	0.7980	0.8783	0.9824	0.9835	0.9979
		1		0.2671	0.2752	0.3195	0.7441	0.7610	0.8454	0.9764	0.9813	0.9955
		0.01		0.1231	0.1238	0.1372	0.2891	0.3020	0.3536	0.5407	0.5641	0.6548
0.3		20		0.2979	0.3085	0.3578	0.7803	0.7963	0.8761	0.9806	0.9835	0.9967
		1		0.2665	0.2695	0.3096	0.7412	0.7560	0.8325	0.9740	0.9785	0.9945
		0.01		0.1199	0.1209	0.1377	0.2881	0.3042	0.3525	0.5402	0.5731	0.6579
0.5		20		0.2957	0.3062	0.3562	0.7759	0.7969	0.8782	0.9837	0.9816	0.9971
		1		0.2565	0.2607	0.2973	0.7394	0.7567	0.8294	0.9715	0.9733	0.9911
		0.01		0.1193	0.1231	0.1383	0.2850	0.2967	0.3521	0.5375	0.5612	0.6511
Asymmetric DGP				T =100			200			300		
c_1	c_2	γ_1	γ_2	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
-0.1	0.3	20	0.01	0.1808	0.1913	0.2114	0.4814	0.5254	0.5826	0.8083	0.8502	0.8860
		1		0.1685	0.1777	0.1958	0.4608	0.5092	0.5488	0.7833	0.8368	0.8736
	0.5	20		0.1755	0.1874	0.2023	0.4677	0.5176	0.5674	0.7986	0.8433	0.8812
		1		0.1812	0.1855	0.2074	0.4617	0.5142	0.5486	0.7864	0.8294	0.8712
-0.3	0.1	20		0.1776	0.1880	0.2129	0.4864	0.5354	0.5860	0.8031	0.8497	0.8886
		1		0.1749	0.1836	0.2019	0.4776	0.5170	0.5540	0.7822	0.8326	0.8675
	0.5	20		0.1787	0.1938	0.2094	0.4896	0.5300	0.5780	0.7928	0.8402	0.8797
		1		0.1689	0.1801	0.1962	0.4552	0.4986	0.5404	0.7920	0.8380	0.8714
-0.5	0.1	20		0.1773	0.1927	0.2112	0.4784	0.5281	0.5664	0.7995	0.8436	0.8841
		1		0.1779	0.1878	0.2024	0.4586	0.5016	0.5441	0.7871	0.8365	0.8696
	0.3	20		0.1845	0.1957	0.2169	0.4832	0.5303	0.5711	0.8033	0.8524	0.8906
		1		0.1684	0.1736	0.1922	0.4702	0.5145	0.5567	0.7913	0.8395	0.8708

Table 2.10: Estimated Power of Alternative Tests with Non-lienar DGP

Appendix 2.B

As we discussed near unit root process, in terms of globally stationary process of equation (2.10), we ensure $\mid \phi + \beta \mid < 1$ for stationary 3-regime STAR models. The condition, which has unit root regime in the model of transition, allows for locally unit root ($\phi = 1$) or even explosive ($\phi > 1$) behaviour, while maintaining global stationarity. Thus, as a meaningful experiment, we consider a DGP,

$$y_t = \phi y_{t-1} + \beta S(\cdot) y_{t-1} + \varepsilon_t$$

where $\phi = 0.1$ and $\beta = -0.3$ with same values for c and γ in previous experiments.

Symmetric DGP				T =100			200			300		
$\mid c \mid$		$\mid \gamma \mid$		inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
0.1		20		0.8047	0.8156	0.8976	0.9997	0.9992	1.0	1.0	1.0	1.0
		1		0.7035	0.7166	0.7897	0.9990	0.9983	0.9997	1.0	1.0	1.0
		0.01		0.1294	0.1284	0.1461	0.3052	0.3174	0.3716	0.5877	0.6137	0.7052
0.3		20		0.8084	0.8206	0.8940	0.9999	0.9994	1.0	1.0	1.0	1.0
		1		0.6936	0.7071	0.7653	0.9994	0.9985	0.9996	1.0	1.0	1.0
		0.01		0.1235	0.1277	0.1436	0.2999	0.3229	0.3730	0.5799	0.6017	0.6927
0.5		20		0.8085	0.8189	0.8950	0.9999	0.9994	1.0	1.0	1.0	1.0
		1		0.6785	0.6850	0.7444	0.9988	0.9990	0.9998	1.0	1.0	1.0
		0.01		0.1286	0.1295	0.1476	0.3097	0.3265	0.3837	0.5846	0.6085	0.6948
Asymmetric DGP				T =100			200			300		
c_1	c_2	γ_1	γ_2	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}	inf-t^S	inf-t^{AS}	t_{DF}
-0.1	0.3	20	0.01	0.2947	0.3276	0.3333	0.7292	0.8078	0.7965	0.9589	0.9843	0.9801
		1		0.2743	0.3096	0.3079	0.7032	0.7830	0.7585	0.9465	0.9797	0.9715
	0.5	20		0.2984	0.3322	0.3312	0.7359	0.8099	0.7957	0.9542	0.9860	0.9779
		1		0.2691	0.3047	0.3011	0.6937	0.7804	0.7489	0.9431	0.9778	0.9702
-0.3	0.1	20		0.2966	0.3350	0.3307	0.7341	0.8186	0.7956	0.9561	0.9869	0.9783
		1		0.2660	0.2999	0.2924	0.6894	0.7773	0.7489	0.9398	0.9790	0.9676
	0.5	20		0.2957	0.3325	0.3369	0.7271	0.8093	0.7833	0.9584	0.9851	0.9804
		1		0.2747	0.3080	0.2991	0.6913	0.7791	0.7471	0.9401	0.9757	0.9702
-0.5	0.1	20		0.3005	0.3405	0.3411	0.7355	0.8173	0.7880	0.9603	0.9856	0.9770
		1		0.2672	0.3020	0.2885	0.6881	0.7752	0.7436	0.9417	0.9758	0.9662
	0.3	20		0.2901	0.3323	0.3222	0.7340	0.8176	0.7863	0.9603	0.9863	0.9774
		1		0.2709	0.3016	0.3012	0.6792	0.7656	0.7375	0.9413	0.9755	0.9675

Table 2.11: Estimated Power of Alternative Tests with Near Unit Root Non-linear DGP

Chapter 3

Equilibrium Exchange Rate Determination and Unit Root Test with Multiple Structural Changes

3.1 Introduction

The strong overvaluation of the U.S. dollar during the early to mid 1980s led the industrialized nations to agree with coordinated intervention to stabilize the U.S. dollar within a 'target zone'. The intervention together with macro policy has played an important role in the Exchange Rate Mechanism (ERM). Sarno and Taylor (2002) pointed out that intervention was rather effective in the very short run. However, the difference between the empirical analysis and the policy effectiveness is still unclear.

Jorion and Sweeney (1996), Oh (1996), Wu (1996) and Papell (1997) used pooled ADF regressions and were able to find evidence supporting Purchasing Power Parity (PPP) with the base currency chosen at monthly or quarterly observations. In particular, Papell (1997) concludes strongly in favour of stationarity, with a faster rate of mean reversion when the Deutschmark rather than the US dollar is used as the base currency (with an estimated half-life of 2 years in the former case and 2.5 years in the latter). However, O'Connell (1998) criticizes these studies, asserting that the rejections of the unit root hypothesis are caused by the tests being badly over-sized in the presence of cross-sectional dependence. This evidence has stimulated a reopening of the discussion.

Papell (2002) and Sollis (2005) empirically showed that the lack of evidence favouring PPP might be due to structural breaks. However, their results show rather weak evidence when the U.S. dollar is assumed to be the basis currency. Furthermore, these approaches do not consider economic fundamentals and mainly focus on the power of the unit root test.

One of the important things what those have missed relationship between changes in macroeconomic variables and changes in exchange rates is that exchange rates often exhibit much greater variability than do macroeconomic time series in the short run. Therefore the present chapter firstly stresses on the economic fundamentals, which should be considered to explain systematic exchange rate movements. To address the issue of the determination around the equilibrium path, we extend the behavioural equilibrium exchange rate (hereafter BEER) approach as in Clark and MacDonald (1998) by using the setup discussed in Dutta and Leon (2002). In particular, differently from previous studies using a multivariate approach, we rely upon a univariate approach that also includes structural changes. Furthermore, we try to identify the effect caused by the risk premium and present justification for the equilibrium variations.

Additionally to the cited novel contribution, we also make an econometric contribution by suggesting a novel transition function, which is able to describe our economic model. Based on our transition function, we propose two structural break tests and report their size and power. Some final empirical applications to different exchange rates data are provided.

The chapter is organized as follows. In the next section we overview existing analyses of the exchange rate determination and also present equilibrium exchange rate models for our theoretical arguments. The empirical specification and the simulation results are presented in section 3.3 and section 3.4 respectively. The results of the tests are contained in section 3.5. Finally, section 3.6 contains conclusion.

3.2 Literature overview and theoretical modelling

3.2.1 Unit root based analysis

Unit root tests have been the most common methodology to investigate PPP. The most common test for PPP is the univariate ADF test, which regresses the variable on a constant, its lagged level and p lagged first differences,

$$q_t = \alpha + \beta q_{t-1} + \sum_{i=1}^{p} \phi_i \Delta q_{t-i} + \varepsilon_t \tag{3.1}$$

where q_t denotes a real exchange rate and α and β are assumed to be constant.[1] To find evidence supporting PPP, the analysis of equilibrium reversion generally employ demeaned q_t under the assumption of constant α. The often non-linear models such as TAR or STAR-type characterize mean reversion better than most conventional linear approaches regarding the trade cost. Indeed, recent investigation indicates that the asymmetric transition to the equilibrium is empirically shown by policy intervention or short run factors. However, since the constant α is subsumed in those approaches, the chaotic behaviour in the reversion is still unclear.

Alternatively, researchers have turned to panel data methods. Abauf and Jorion (1990) and Jorion and Sweeney (1996), using monthly data, conduct panel unit root tests on real exchange rates for the G10 countries and show rejection of the unit root null at the 10% level. In particular, Jorion and Sweeney (1996) employ six more years of monthly data from 1973 to 1993 for 10 currencies against the US dollar and reject the unit root hypothesis at the 5% significance level, using no lags of the differenced dependent variable in the ADF regression. For seven European currencies against the Deutschmark, the rejection of a unit root is even stronger, with a $p-$value of 0.002.

Wu (1996) tests annual, quarterly and monthly dollar real exchange rates for a panel of 18 countries from January 1974 to April 1993 and strongly rejects the unit root hypothesis for both CPI (consumer price index) and WPI (wholesale price index) - based rates. In particular, he is able to reject the null at the 1% level in both cases, and estimates an autoregressive parameter of 0.98 for

[1] Generally, a time trend is not included in the equation (3.1) because such an inclusion would be theoretically inconsistent with long-run PPP.

monthly data. However, since Wu (1996) allows for a time trend, which makes the alternative hypothesis trend stationary rather than level, it is hard to say that the rejection of the unit root null provide evidence of PPP.

Oh (1996) employs annual real exchange rates for the flexible exchange rate period constructed from the Summers and Heston data and shows rejection of the unit root hypothesis. This result shows much stronger results than Frankel and Rose (1996) find with annual data or than previous studies with quarterly or monthly data.

Papell (1997) criticizes the regression on pooled real exchange rates for the free floating periods and suggests considering a heterogeneous intercept in the regression, which is equivalent to including country-specific dummy variables. He shows evidence of PPP and a faster rate of mean reversion when the Deutschmark rather than the US dollar is used as a base currency. In particular, the estimated half-life is 2 years in the former case and 2.5 years in the latter. Finally, his empirical results show that PPP is more likely to hold in the case of larger than smaller panels, for monthly rather than quarterly data and when the German mark rather than the US dollar is used as the base currency. However, O'Connell (1998) points out that the empirical evidence favouring PPP is mainly due to tests being badly over-sized when the unit root null is true and provides convincing Monte Carlo evidence to support this assertion. Specifically, employing a pooled GLS-ADF test, which has the correct size in the presence of cross-sectional dependence, he finds no evidence in favour of PPP using a panel of 63 real exchange rates (and smaller regional subpanels), using quarterly data from 1973:2 to 1995:4.

The mixed empirical evidence on PPP led some researchers to find alternative routes to investigate this international parity condition. For example, based on the large appreciation and depreciation of the dollar in the 1980s, Papell (2002) suggests structural change. Using panel methods, the test strongly rejects the unit root null for those countries that adhere to the typical pattern of the dollar's rise and fall. Christopher F. Baum and Caglayan (1999) consider fractional integration and mean shift in single currency. In their study, they use both CPI- and WPI-based rates and demonstrate that the unit root hypothesis is robust against both fractional alternatives and structural breaks. This evidence suggests rejection of the unit root during the floating period and structural changes. However, Bleaney and Leybourne (2003) point out that the rejection of the unit root hypothesis is not necessarily correct because these tests strongly over-reject the null in certain circumstances, particularly when the series have a stochastic unit root. Sollis (2005) recently suggests univariate smooth transition models, which allow under the alternative hypothesis for stationarity around a gradually changing deterministic trend function. The test reveals statistically significant evidence against the null hypothesis of a unit root for the real exchange rates of a number of countries against the US dollar. However, the tests include a time trend and the results are rather weak within a conservative PPP framework.

3.2.2 Modelling the equilibrium exchange rate

In contrast to the overwhelming body of multivariate models, in this section we present a univariate model with structural break that should help to shed some light on PPP hypothesis. Indeed, this section introduces a simple model of the real exchange rate. We propose that the exchange rate dynamics for the real exchange rate, q_t, are determined by the lagged real exchange rate, q_{t-1}, a fundamental term $z_{t-1} = r_{t-1} - r^*_{t-1}$, which is the difference between home and foreign real interest rates, and s_t, which we interpret as the stationary part of the real exchange rate and is driven by non-fundamentals, such as the many kind of trading rules described in the technical analysis literature:

$$q_t = \beta q_{t-1} + m z_{t-1} + s_t + \varepsilon_t,$$

where $0 < \beta < 1$, and $\varepsilon_t \tilde{} i.i.d.$ Taking expectations we have

$$E_{t-1}(q_t) = \beta q_{t-1} + m z_{t-1}, \tag{3.2}$$

where $E_{t-1} q_t|_{s_t=0} = \bar{q}_t$.[2] In this model the parameter m is important and captures the persistence of monetary policy. Thus, a negative value of this parameter would suggest reversion to the equilibrium. Note that, in this context, if $m = 0$, the model is consistent with a traditional interpretation of PPP.

We now introduce the risk adjusted real interest parity condition which can be derived by a manipulatiomn of the the uncovered interest parity (UIP) condition, $q_t = q_{t-1} + r^*_{t-1} - r_{t-1}$ with rational expectations imposed, as suggested by Clark and MacDonald (1998),[3]

$$E_{t-1}(q_t) = q_{t-1} + r^*_{t-1} - r_{t-1} + \pi_{t-1}, \tag{3.3}$$

[2] Survey studies find that FX market participants tend to have extrapolative expectations over short-term horizons and mean-reverting over longer horizons.

[3] Dutta and Leon (2002) employ uncovered interest parity condition, $E_{t-1}(q_t) = q_{t-1} + r^*_{t-1} - r_{t-1}$

where π_{t-1} is a wedge and is normally interpreted as a risk premium although it could equally reflect an expectational error that represents deviations from uncovered interest parity (or indeed both).

As an example we solve the model for the inner regime case. The other cases can be solved in a similar way. From the two orthogonal relationships, (3.2) and (3.3), we can obtain an explicit reduced form for z_{t-1} in the inner regime (i.e. equilibrium state)

$$z_{t-1} = \frac{1}{m+1}\pi_{t-1} + \frac{1-\beta}{m+1}q_{t-1}. \tag{3.4}$$

We assume that $s_t = \lambda(\bar{q}_t)$:

$$s_t = \begin{cases} \lambda_L(q_L - \bar{q}_t) & \bar{q}_t < q_L \\ 0 & \text{if} \quad q_L < \bar{q}_t < q_H \\ \lambda_H(q_H - \bar{q}_t) & q_H < \bar{q}_t \end{cases},$$

where $0 \leq \lambda_i \leq 1$ and $i = L, H$. Thus, when $s_t = 0$ (i.e. the inner regime), equation (3.4) is satisfied. If we additionally substitute (3.4) into (3.3), we have the equation for the inner regime showed below

$$q_t = \begin{cases} a_{L,t-1} + b_L q_{t-1} & \bar{q}_t < q_L \\ a_{0,t-1} + b_0 q_{t-1} & \text{if} \quad q_L < \bar{q}_t < q_H \\ a_{H,t-1} + b_H q_{t-1} & q_H < \bar{q}_t \end{cases}. \tag{3.5}$$

Thus, in the inner regime the real exchange rate is given by $q_t = a_0 + b_0 q_{t-1}$. The equations for the exchange rate outside the inner regime can be obtained in a similar way and we only report the solutions below:

$$\begin{array}{lll} a_{L,t-1} = \frac{\lambda_L q_L}{1+m(1-\lambda_L)} + \frac{m(1-\lambda_L)}{1+m(1-\lambda_L)}\pi_{t-1} & & b_L = \frac{(1-\lambda_L)(m-\beta)}{1+m(1-\lambda_L)} \\ a_{0,t-1} = \frac{m}{1+m}\pi_{t-1} & \text{and} & b_0 = \frac{(m-\beta)}{1+m} \\ a_{H,t-1} = \frac{\lambda_H q_H}{1+m(1-\lambda_H)} + \frac{m(1-\lambda_H)}{1+m(1-\lambda_H)}\pi_{t-1} & & b_H = \frac{(1-\lambda_H)(m-\beta)}{1+m(1-\lambda_H)} \end{array} . \tag{3.6}$$

In the present setting, when the expected value, $\bar{q}_t$ is $q_L < \bar{q}_t < q_H$, $s_t = 0$, the exchange rate is at its equilibrium level and $\lambda = 0$. On the other hand, when $\bar{q}_t$ falls below q_L or rises above q_H, market participants will trade according to the following strategy: $s_t = \lambda_L (q_L - \bar{q}_t)$ and $s_t = \lambda_H (q_H - \bar{q}_t)$.

A similar approach can be used to determine the exchange rate dynamics when the exchange rate drifts away from its long-run equilibrium value. In this case, the stationary part of the exchange rate will play an important role. The structural parameters (m, β) are not identified but equation (3.5) provides a testable implication where the stationarity of q_t depends on the sign of parameter b_0.

In contrast to Dutta and Leon (2002)[4] the intercept, a_0 varies now in the range $[q_L, q_H]$. The shift of the intercept in the cited range allows us to capture the response of investors to shift in risk premium π_{t-1} along the equilibrium path. The inclusion of a non-zero intercept in this case has some noticeable advantages. If for simplicity we assume a constant π_{t-1}, when the monetary

[4]The coefficients a_i and b_i in the Dutta and Leon (2002) framework are derived

$$\begin{array}{ccc} a_L = \frac{\lambda_L q_L}{1+m(1-\lambda_L)} & & b_L = \frac{(1-\lambda_L)(m+\beta)}{1+m(1-\lambda_L)} \\ a_0 = 0 & \text{and} & b_0 = \frac{(m+\beta)}{1+\beta} \\ a_H = \frac{\lambda_H q_H}{1+m(1-\lambda_H)} & & b_H = \frac{(1-\lambda_H)(m+\beta)}{1+m(1-\lambda_H)} \end{array}$$

and there is no constant in non-intervention regime $[q_L, q_H]$ where the uncovered interest parity holds.

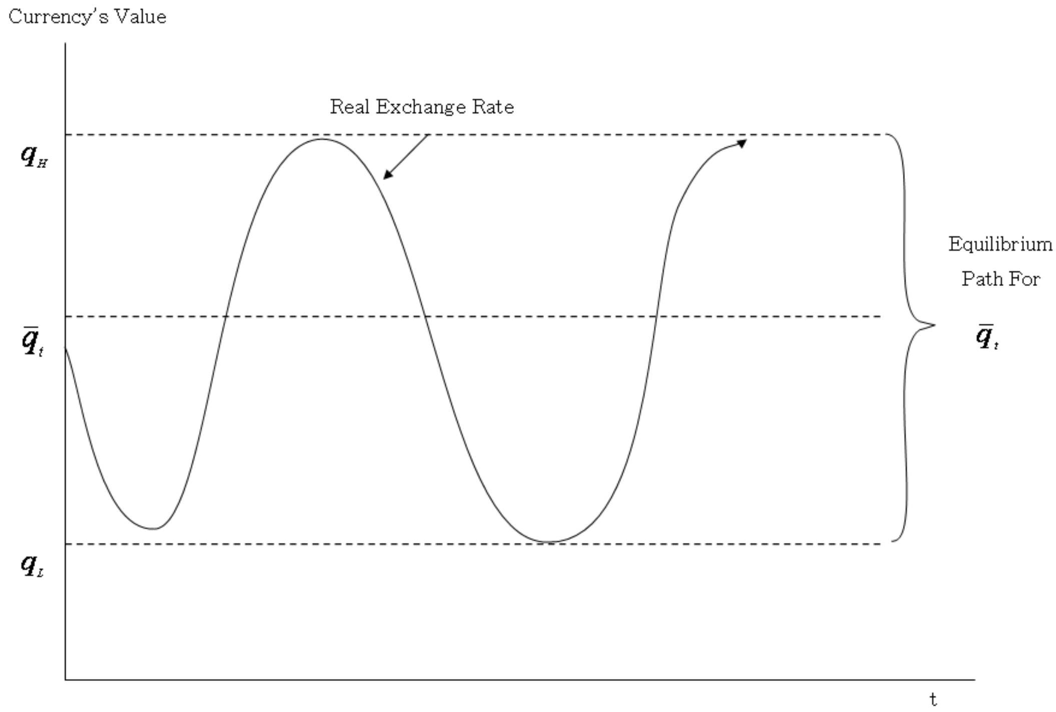

Figure 3.1: Equilibrium Exchange Rate Path

policy is effective $\mid m \mid < 1$, the equilibrium exchange rate $\bar{q}_t$ moves upward when $0 < m < 1$, and downward when $-1 < m < 0$. Monetary policy in the present setting shows the changes to a certain equilibrium level even in the intervention regime $[q_L, q_H]$.[5]

Figure (3.1) describes how the equilibrium path is determined and why considering structural instability along the equilibrium path (rather than assuming a fixed mean) is important. An example of this was the European Monetary System (EMS) where intervention by central banks was supposed to take place at $\pm 2.25\%$ around the central parity in most of the member countries. In these cases, although the official band is set at $\pm 2.25\%$ around the central parity, it is likely that intervention begins before the rate actually hits $\pm 2.25\%$ points. As empirically pointed out by Sollis (2005), the mean have shifted over time in some instances and the description of exchange rate data have varied substantially around the mean but not away from it for extended period time.

In the next sections we propose an econometric model which should be able to characterize the exchange rate dynamics described in this section [6].

[5] If a significant number of investors engaged in extrapolative trading strategies, exchange rates might tend to overshoot on both the upside and downside, which could further obscure the relationship between macroeconomic fundamentals and the short term movement of exchange rate. In the present setting, we provide the policy effectiveness in the equilibrium determination.

[6] Lyons (1999) argues that portfolio shifts in the foreign exchange market will be gradual rather than abrupt.

3.3 Model specification

3.3.1 Overviews of unit root tests with structural change

Unit root tests have been largely criticized since the issue of a correctly specification of the intercept has noticeable implications. Perron (1989) argues that if the deterministic intercept and/or trend exhibit structural change, the tests will lead to a misleading conclusion that there is a unit root, when in fact there is not. We present in this section a selective survey on unit roots and structural breaks.

Tests assuming a known break

The earliest test for structural change in the economic literature was suggested by Chow (1960). This test considers stationary variables and a single break only. Perron (1989) proposes a modified Dickey-Fuller (hereafter DF) test for a unit root with three different types of deterministic trend functions, given a known structural break which is assumed to be given exogenously. Perron (1989) presents Monte Carlo results with trend-stationary process and shows the effect that a shift in the level of the series, or a shift in the slope would have on the standard unit root test. Perron (1989) finds that tests of the unit root are not consistent against trend-stationary alternatives when the trend function contains a shift in slope or a shift in the intercept. In these cases the power of unit root tests is substantially reduced.

On the basis of these results, Perron (1989) develops a testing procedure involving ADF regressions modified with dummy variables to ensure consistent tests for stationarity in the presence of structural breaks at time $1 < T_B < T$. He considers the following three models,

$$\text{Model (I):} \quad DT_t = a_0 + a_1 DU_t + b_t \text{ where } DU_t = \begin{cases} 1 & \text{if} \quad t > T_B \\ 0 & \phantom{\text{if}} \quad t \leq T_B \end{cases}$$

$$\text{Model (II):} \quad DT_t = a + b_0 t + b_1 DT_t \text{ where } DT_t = \begin{cases} t - T_B & \text{if} \quad t > T_B \\ 0 & \phantom{\text{if}} \quad t \leq T_B \end{cases}$$

$$\text{Model (III):} \quad DT_t = a_0 + a_1 DU_t + b_0 t + b_1 DT_t \text{ where } DT_t = \begin{cases} t & \text{if} \quad t > T_B \\ 0 & \phantom{\text{if}} \quad t \leq T_B \end{cases}$$

where Model (I) permits an exogenous change in the level of the series, Model (II) allows an exogenous change in the rate of growth, and Model (III) admits both changes.

Perron (1989) applies the tests to the U.S. data first examined by Nelson and Plosser (1982) and consisting of annual observations on fourteen indices of various economic time series. The results contradicted the original finding of Nelson and Plosser (1982) that thirteen out of the fourteen series could be characterized as $I(1)$ processes. Perron's results suggested that rather than being $I(1)$, many macroeconomic time series were in fact stationary around a deterministic trend with a structural break.

Tests assuming an unknown break

The model suggested by Perron (1989) has been criticized on the ground that it assumes the break point to be known. Zivot and Andrews (1992) argue that if the break is treated as endogenous, then Perron's conclusions are reversed. Zivot and Andrews (1992) argue that, while Perron (1989) assumes events such as the 1929 Great Depression and 1973 oil crisis to be exogenous, the effects of such events could be interpreted as a realization from the tail of the underlying data generating process. Furthermore if structural change is caused by an event endogenous to the domestic economy such as financial deregulation, then the correct unit root test procedure should account for the fact that the break points in the regressions might be data dependent. Zivot and Andrews (1992) develop a unit root test where the time of the structural break, under the alternative hypothesis, is indeed determined by the data.

Zivot and Andrews (1992) are concerned with the estimation of the break point that gives most weight to the trend stationary alternative hypothesis. Hence, the time of the break is selected by sequentially modelling a structural break in ADF regressions, and then choosing the break for which the DF $t-$statistic is minimized. For all of the models, Zivot and Andrews (1992) derive the asymptotic null distribution of their test statistics and tabulate asymptotic null critical values.

Zivot and Andrews (1992) apply their tests to the same Nelson and Plosser data series but the overall results are weaker than the ones obtained in Perron (1989).

Tests based on smooth transition functions

Leybourne, Newbold, and Vougas (1998) argue that while the Zivot-Andrews test offers an improvement over the Perron's test by endogenising the structural break, it is still limited since it can be misspecified when the structural break is gradual rather than instantaneous. With economic time series generally dependent on the behaviour of individual agents with different amounts of information and ability, gradual adjustment from one regime into another seems a more attractive proposition than the instantaneous break imposed in the Zivot-Andrews procedure. Thus, a smooth transition function is considered in order to account for stationarity around an endogenously determined intercept and/or trend. Leybourne, Newbold, and Vougas (1998) suggest the following three regression models,

$$\begin{aligned}
&\text{Model (A):} \quad y_t = a_0 + a_1 S_t(\theta) + u_t \\
&\text{Model (B):} \quad y_t = a_0 + a_1 S_t(\theta) + b_0 t + u_t \\
&\text{Model (C):} \quad y_t = a_0 + a_1 S_t(\theta) + b_0 t + b_1 t S_t(\theta) + u_t
\end{aligned}$$

where u_t is a zero-mean $I(0)$ process and $S(\theta)$ is a smooth transition function based on sample of size T and the parameter set θ.

The transition functions $S_t(\theta)$ considered in previous studies are given in Table (3.1). These are all variations of the modified exponential transition. Nelder (1971)

$$S_t(\theta) = \frac{1}{\left[1 + \exp\left\{-\frac{\gamma(t-cT)}{\delta}\right\}\right]^{\delta}} \tag{3.7}$$

where $\delta = 1$ is consistent with the logistic function. The function traverses the interval $(0, 1)$, where $t = cT$ is the inflexion point of the function.

The structural change with logistic smooth transition (hereafter LSTR) is the one considered in Leybourne, Newbold, and Vougas (1998). The function is bounded between 0 and 1, and the time of the transition is determined by c.

Model	Transition Function: $S_t(\theta)$	Parameter: θ
LSTR	$[1+\exp\{-\gamma\,(t-cT)\}]^{-1}$	γ, c
ESTR	$1-\exp\left[-\gamma^2\,(t-cT)^2\right]$	γ, c
Asymmetric ESTR	$1-\exp\left[-I_t\gamma_1^2\,(t-cT)^2-(1-I_t)\gamma_2^2\,(t-cT)^2\right]$	γ_1, γ_2, c

Table 3.1: Functions for Structural Change

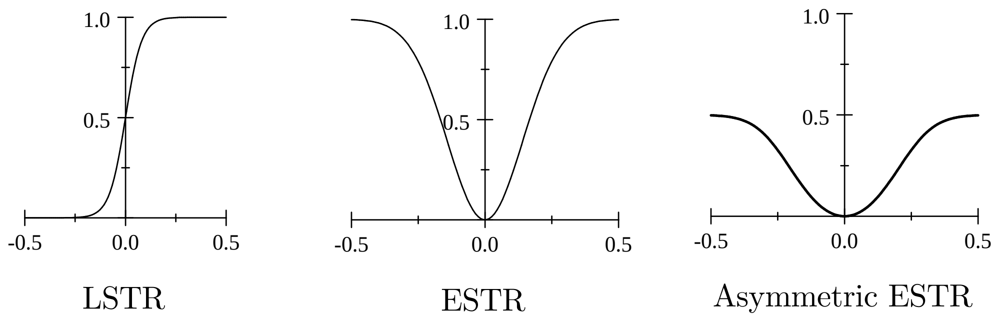

Figure 3.2: Simulation for LSTR and ESTR

For $\gamma > 0$, we have that $S_{-\infty}(\theta) = 0$, $S_{+\infty}(\theta) = 1$ and $S_{cT}(\theta) = 0.5$. This corresponds to the point of inflexion of the logistic function occurring when $t = cT$. The speed of the transition is determined by the parameter γ.

Since the logistic function-based models are unable to capture more than one break, Sollis (2005) extends it by considering an exponential smooth transition (hereafter ESTR) and asymmetric exponential smooth transition (hereafter Asymmetric ESTR). This function traverses the interval $(0, 1)$ as $(t - cT) \to \pm\infty$, and is symmetric or asymmetric around the time of the transition cT. The value of $S_t(\theta)$ depends on the value of the parameter γ and when $t = cT$, transition function $S(y_{t-d}, \theta)$ takes converges to zero.

To illustrate the nature of the transition functions mentioned above, Figure (3.2) graphically compares their characteristics. The LSTR function only considers a single break whereas the ESTR function considers multiple breaks. In Figure (3.2) we plot the function considering $\gamma = 5$. Thus, with the ESTR function, the structural change is an inner regime.

The asymmetric ESTR suggested by Sollis, Leybourne, and Newbold (2002) has similar properties as the ESTR but it allows asymmetric scale parameters, γ_1 and γ_2 where $I_t = 1$ if $(t - cT) \leq 0$ and 0 otherwise. The transition function $S_t(\theta)$ is also bounded from 0 to 1 when the γ_1 and γ_2 are sufficiently large values and if $\gamma_1 \neq \gamma_2$ the speed of transition is asymmetric either side of the mid-point cT.

3.3.2 The econometric model

Thus, the functions employed by Leybourne, Newbold, and Vougas (1998) and by Sollis (2005) to estimate deviation from equilibrium were the logistic and the exponential function respectively. In this section we shall propose a more flexible transition function which considers multiple structural changes and allows the estimation of the model described above.

The symmetric smooth transition

We consider the following transition function

$$\left[1 + \exp\left\{-\gamma^2 \left(t - c_1 T\right)^2\right\}\right] \left[1 - \exp\left\{-\gamma^2 \left(t - c_2 T\right)^2\right\}\right] - 1 \qquad (3.8)$$

This modification allows for symmetric movement from zero and inflexion point of the function defined by structural changes along the equilibrium path.

The function (3.8) is plotted in Figure (3.3) for the same positive and negative values with the same scale parameter γ. As showed in the left-hand-side panel of Figure (3.3), $1 + \exp\left\{-\gamma_1^2 \left(t - c_1 T\right)^2\right\}$ moves between 0 and 2, and $1 -$

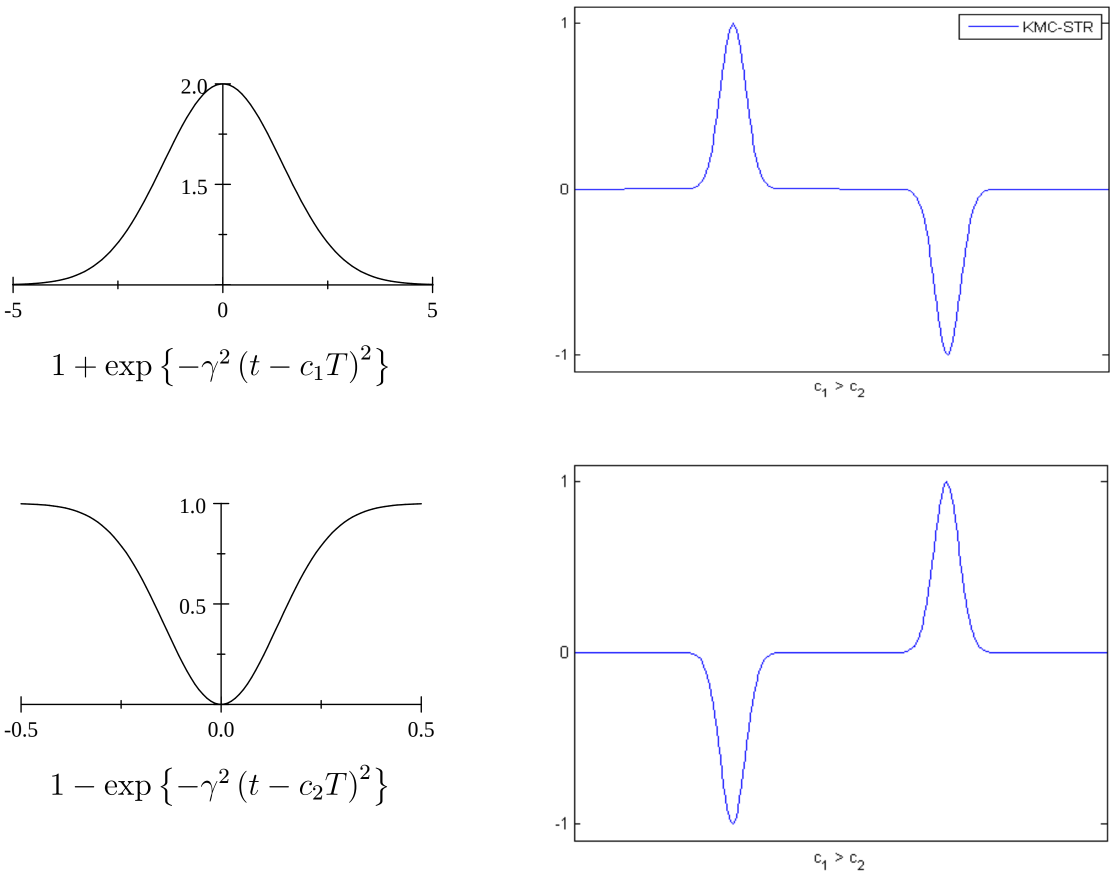

Figure 3.3: Simulation for KMC-STR

$\exp\left\{-\gamma_1^2 (t - c_2 T)^2\right\}$ between 0 and 1. Thus, our transition function ranges between 0 and 2. In our empirical applications we have normalized the function between -1 and 1.

The speed at which the function moves between -1 and 1 changes with γ. As showed in Figure (3.3), this model is able to capture structural changes taking place in the overvaluation regime as well as the undervaluation regime regardless which of these takes place first. If $c_1 < c_2$, $0 < S_t(\theta) < 1$ when $t = c_1 T$, and $-1 < S_t(\theta) < 0$ when $t = c_2 T$. In the limiting state $S_t(\theta) = 0$ the Model (A) collapses to $y_t = a_0 + u_t$, and a_0 is consistent with the (economic) model proposed above.

Thus, in contrast to the existing smooth transition functions, LSTR and ESTR, our proposed function $KMC - STR$ is able to capture the adjustment process along the equilibrium path due to monetary policy m, and risk π_{t-1} in the BEER modelling.

The asymmetric smooth transition

We now consider an extension of the symmetric specification presented above to incorporate asymmetry. Consider for example, the different scale parameter, γ_1^2 and γ_2^2. In this case the transition function above can be re-written as

$$\left[1 + \exp\left\{-\gamma_1^2 (t - c_1 T)^2\right\}\right] \left[1 - \exp\left\{-\gamma_2^2 (t - c_2 T)^2\right\}\right] - 1 \qquad (3.9)$$

The fundamental properties of equation (3.9) are the same as the symmetric case. However, since $\gamma_1^2 \neq \gamma_2^2$, the function $S_t(\theta)$ is asymmetric around zero

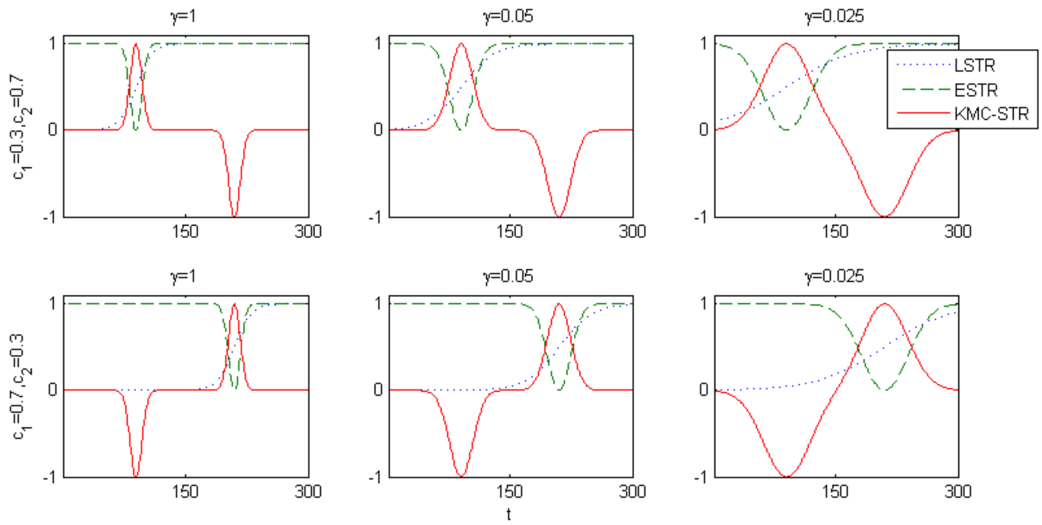

Figure 3.4: Properties of LSTR, ESTR, and KMC-STR

from its limiting values, 1 or -1.

Simulation Results

In order to show the properties of our model, we perform another simulation and compare proposed model with representative transition functions, LSTR and ESTR in a sequence of $t \in [1, 300]$, $c_i = 0.3$ and 0.7 and, for simplicity, symmetric scale parameter, $\gamma = \{1, 05, 0.025\}$ respectively.

The Figure (3.4) shows the nature of the transition function. As pointed out above our proposed model is more flexible than other existing ones. For example, the LSTR is only able to capture the transition from $I(0)$ to $I(1)$ process- thereby it only considers one structural change. The ESTR, by considering multiple changes, provides an improvement over the LSTR. However, with these two models (i.e. LSTR and ESTR) the change is restricted to take place in a certain region, for example above zero and reverse to the equilibrium. When the break takes place around the equilibrium, the previous models are rather restrictive. It is clear that the proposed $KMC - STR$ function (3.4) can flexibly capture structural changes around the equilibrium path regardless of which one takes place first.

3.3.3 Estimation method

Models (A-C) consider different types of structural changes. Assuming that u_t is an $I(0)$ process then in Model (A) y_t is stationary around a mean which changes from the initial value a_0 to final value $a_0 + a_1$. In Model (B) the intercept changes from a_0 to $a_0 + a_1$, but the model contains a fixed slope term. Finally, in Model (C) both the intercept and the slope change simultaneously, from a_0 to $a_0 + a_1$, b_0 to $b_0 + b_1$ respectively.

Thus under Models A-C we have

H_0: $y_t = u_t$, $u_t = u_{t-1} + \varepsilon_t$, $u_0 = \psi$

H_1: Model (A), Model (B), Model (C)

and

H_0: $y_t = u_t$, $u_t = \kappa + u_{t-1} + \varepsilon_t$, $u_0 = \psi$

H_1: Model (B), Model (C)

where ε_t is assumed to be a stationary process with zero mean.

The test statistics can be computed using a two-step procedure. Firstly, we estimate the deterministic component of the model using a non-linear least square (hereafter NLS) algorithm and compute the residuals

$$\begin{aligned}
\text{Model (A):} \quad & \hat{u}_t = y_t - \hat{a}_0 - \hat{a}_1 S_t(\hat{\theta}) \\
\text{Model (B):} \quad & \hat{u}_t = y_t - \hat{a}_0 - \hat{a}_1 S_t(\hat{\theta}) - \hat{b}_0 t \\
\text{Model (C):} \quad & \hat{u}_t = y_t - \hat{a}_0 - \hat{a}_1 S_t(\hat{\theta}) - \hat{b}_0 t - \hat{b}_1 t S_t(\hat{\theta})
\end{aligned}$$

The model parameters to be estimated are $\hat{a}$, $\hat{b}$ and the parameter set, θ of the transition function. The parameter set of interest suffers from unidentified parameter problem introduced by Davies (1987). For the models A-C, Leybourne, Newbold, and Vougas (1998) suggest a way of simplifying the non-linear computation problem. That is, they note that the NLS can be concentrated with respect to the estimates, $\hat{a}$ and $\hat{b}$ when the fixed values of the parameter set in transition function are given. Taking Model (C) as an example, the estimated parameters of Model (C) can be obtained by OLS

$$\hat{\theta} = \arg\min_{\theta} \sum_{t=1}^{T} (y_t - \hat{\beta}(\theta)' x_t(\theta))^2 = \arg\min_{\theta} \hat{\sigma}^2(\theta)$$

where $x_t(\theta) = [1, t, S_t(\hat{\theta}), S_t(\hat{\theta})t]$ and $\hat{\beta}(\theta) = \left(\sum_{t=1}^{T} x_t(\theta) x_t(\theta)'\right)^{-1} \left(\sum_{t=1}^{T} x_t(\theta) y_t\right)$.

To circumvent the initial value problem, we first determine sensible initial values, which are obtained by grid search over c_i and γ_i. A meaningful set of values for the parameters, c_i are defined as sample percentiles as suggested by Caner and Hansen (2001). We therefore set c_i as

$$[Q(15), Q(85)] \tag{3.10}$$

where $Q(15)$ and $Q(85)$ are the 15th and 85th percentiles of T.

At the same time, to determine a useful set of scale parameter γ_i, van Dijk, Terasvirta, and Fransesvan (2002) suggest rescaling the transition function with the sample standard deviation, which makes γ_i approximately scale-free. The transition parameters were then standardized through division by its sample variance. We estimate the scale parameter γ_i over the interval given by

$$[10^{-1}P_n, 10^3 P_n] \tag{3.11}$$

where $P_n = (\sum_{t=1}^{n} \frac{y_t^2}{n})^{-\frac{1}{2}}$.

At each step in the grids, the parameters set θ were estimated so as to minimize the residual sum of squares. When the combination of parameters c_i and γ_i provided the overall minimum of the residual sum of squares, NLS estimation was used using the Broyden, Fletcher, Goldfarb and Shanno (BFGS) optimization algorithm in MATLAB 2008.

We then compute the ADF $t-$statistic associated with ρ in the ordinary least squares (OLS) regression

$$\Delta\hat{u}_t = \rho\hat{u}_{t-1} + \sum_{i=1}^{k}\phi_i\Delta\hat{u}_{t-i} + \hat{\varepsilon}_t$$

where the lagged difference terms are included to account for residual autocorrelation. The statistics associated with models A, B, and C are denoted t^A , t^B and t^C respectively.

3.4 Monte Carlo experiment

3.4.1 Critical values

With NLS estimation closed-form solutions are generally difficult to obtain. Leybourne, Newbold, and Vougas (1998) estimate the null distribution of the test using Monte Carlo simulation. The critical values of the test statistics associated with models A, B, and C can be computed using the same two-step procedures as in Leybourne, Newbold, and Vougas (1998) and Sollis (2005), but replacing the transition function with the $KMC - STR$. The null DGP was specified as a random walk with standard normal error terms,

$$\begin{aligned} y_t &= u_t \\ u_t &= u_{t-1} + \varepsilon_t \ \varepsilon_t \sim NID(0,1) \\ u_0 &= \psi \end{aligned}$$

and $\psi = 0$. We set k equal to zero. The null distribution of the test was estimated using Monte Carlo simulation and based on 10,000 replications. For the symmetric and asymmetric $KMC - STR$ tests, the critical values of the null distributions of the tests at 1%, 5% and 10% significance levels are given in Table (3.2). As expected given the extra parameters being estimated, the critical values for this test are bigger in absolute value than the ones for the DF-GLS tests.

	Null Critical Values								
T	t_S^A			t_S^B			t_S^C		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
100	-4.581	-3.951	-3.626	-4.984	-4.330	-4.004	-5.183	-4.563	-4.248
200	-4.450	-3.885	-3.574	-4.783	-4.226	-3.940	-5.000	-4.453	-4.143
300	-4.412	-3.854	-3.564	-4.760	-4.210	-3.920	-4.958	-4.432	-4.140
1000	-4.403	-3.839	-3.543	-4.758	-4.203	-3.915	-4.938	-4.413	-4.139
	t_{AS}^A			t_{AS}^B			t_{AS}^C		
100	-5.005	-4.388	-4.058	-5.177	-4.571	-4.258	-5.559	-4.973	-4.662
200	-4.887	-4.281	-3.973	-5.060	-4.485	-4.172	-5.459	-4.852	-4.555
300	-4.824	-4.272	-3.971	-5.015	-4.476	-4.162	-5.335	-4.802	-4.519
1000	-4.808	-4.224	-3.924	-4.987	-4.457	-4.160	-5.329	-4.762	-4.496

Table 3.2: Critical Values for Symmetric and Asymmetric KMC-STR

3.4.2 The size of the test

In this section, we perform a Monte Carlo investigation of the test above and compare it with the Dickey-Fuller test, using the 5% asymptotic critical values provided in Table (3.2). All results are empirical rejection frequencies from $1,000$ replications when the underlying DGP is the random walk process.

In these experiments, we follow Leybourne, Newbold, and Vougas (1998) and Sollis (2005) and use the following ARIMA$(1,1,0)$,

$$\begin{aligned} y_t &= u_t \\ \Delta u_t &= \phi \Delta u_{t-1} + \varepsilon_t,\, \varepsilon_t \sim NID(0,1) \end{aligned}$$

where ε_t follows the standard normal distribution.

We consider how the size is affected by the parameter ϕ, k and consider the sample sizes 100, 200, and 300 where $\phi = \{-0.4, 0, 0.4\}$ and $k = \{0, 1, 4\}$ respectively. Table (3.3) reports the actual rejection rate of the symmetric and asymmetric $KMC-STR$ tests, t_S^A and t_{AS}^A, and compares them with those of the standard Dickey-Fuller test t_{DF}. The tests are close to the nominal level of 5% with well acceptable size in the absence of serially correlated errors, even when the number of observations is small. When the error is serially correlated, however, the size distortion could become a problem. In this case, it seems desirable to make the finite sample adjustments based on the fitted AR models and use the size corrected critical values based on the fitted AR model.

	ϕ = -0.4			0			0.4		
	t_S^A	t_{AS}^A	t_{DF}	t_S^A	t_{AS}^A	t_{DF}	t_S^A	t_{AS}^A	t_{DF}
$k = 0$									
T =100	0.415	0.639	0.000	0.054	0.060	0.042	0.005	0.004	0.032
200	0.406	0.579	0.000	0.054	0.053	0.061	0.003	0.003	0.030
300	0.386	0.516	0.000	0.050	0.050	0.064	0.001	0.003	0.033
$k = 1$									
T =100	0.052	0.074	0.004	0.042	0.069	0.004	0.053	0.058	0.004
200	0.043	0.050	0.004	0.029	0.053	0.003	0.041	0.074	0.004
300	0.038	0.067	0.004	0.031	0.060	0.004	0.028	0.054	0.002
$k = 4$									
T =100	0.018	0.052	0.004	0.028	0.050	0.005	0.033	0.056	0.010
200	0.034	0.033	0.005	0.042	0.045	0.002	0.018	0.035	0.005
300	0.032	0.048	0.005	0.028	0.038	0.004	0.023	0.040	0.001

Table 3.3: Size of Symmetric and Asymmetric KMC-STR

3.4.3 The power of the test

In this section we assess the power of the $KMC - STR$ tests. We employ the following DGP,

$$\begin{aligned} y_t &= \begin{cases} a_0 + a_1 S_t(\theta) + u_t \\ a_0 + a_1 S_t(\theta) + b_0 t + u_t \\ a_0 + a_1 S_t(\theta) + b_0 t + b_1 t S_t(\theta) + u_t \end{cases} \\ S_t(\theta) &= \left[1 + \exp\left\{-\gamma_1^2 (t - c_1 T)^2\right\}\right]\left[1 - \exp\left\{-\gamma_2^2 (t - c_2 T)^2\right\}\right] - 1 \\ u_t &= \phi u_{t-1} + \varepsilon_t,\, \varepsilon_t \sim NID(0,1) \end{aligned}$$

A similar DGP was also used in Leybourne, Newbold, and Vougas (1998). The impact of different transition speeds and inflexion points are considered where a sample size $T = \{100, 200\}$. We consider series with $\phi = 0.8$ and allow for slow transitions ($\gamma = 0.01$), medium speed transition ($\gamma = 0.1$) and fast transition ($\gamma = 1$).

Leybourne, Newbold, and Vougas (1998) compare the power of the tests with an t_{DF} for a stationary $AR(1)$ generating process, finding it to be unbiased and consistent. We do not report the power results for the t_{DF} test here. However, as expected, the power of symmetric and asymmetric $KMC - STR$ tests are very close to the t_{DF} due to the fact that the symmetric and asymmetric $KMC - STR$ require the estimation of more parameters than the t_{DF}. Sollis (2005) compares the model with other structural break models suggested by Papell (2002) and argues that the instantaneous-break test can suffer from a significant loss in power when trend-break are gradual. Our investigation therefore involves comparing the power of the asymmetric $KMC - STR$ test with the ESTR (e_a) for a stationary generating process around a smooth transition in mean. The model considered are Model (A-C) respectively, where $\varepsilon_t \sim NID(0,1)$.

For each of the 1000 simulated series the tests t_{AS}^{A}, t_{AS}^{B}, t_{AS}^{C}, e_{α}, $e_{\alpha(\beta)}$ and $e_{\alpha\beta}$ were calculated to the empirical power of the tests at the 5% and 10% nominal sizes respectively. The results are given in Table (3.4). The $KMC-STR$ has good power overall. While it appears to have similar power as the ESTR when the number of observations is larger, it appears slightly more power than the ESTR when the number of observations are smaller. The tests show higher power than ESTR when persistence is high.

3.5 Empirical results

In our empirical application we use monthly and quarterly nominal exchange rates for seventeen and twenty OECD economies respectively and construct bilateral CPI-based real exchange rates against the U.S. dollar and the mark. The series are obtained from the International Monetary Fund's International Financial Statistics (IFS), which covers 1973:01-1998:12 and 1973:Q1-1998:Q4. Due to the fact that EMU (Economic and Monetary Union) clearly constituted a major break not only for the participating economies but potentially also for the parities between other currencies, we consider two sample periods: the first, our full sample, starts from 1973 to 1998 and sub-sample considers the period during 1980 to 1998. The data used are nominal rate against US dollar and CPIs (Consumer's Price Index) for both series.

Model A: $y_t = a_0 + a_1 S_t(\theta) + u_t$											
$u_t = \phi u_{t-1} + \varepsilon_t$, $\varepsilon_t \sim NID\,(0,1)$ where $a_0 = 1$, $a_1 = 0.2$											
				t_{AS}^{A}				e_{α}			
$\phi = 0.8$				$T = 100$		200		100		200	
γ_1	γ_2	c_1	c_2	5%	10%	5%	10%	5%	10%	5%	10%
5	1	0.5	0.95	0.3680	0.5680	0.9590	0.9940	0.2540	0.4130	0.9460	0.9890
		0.25	0.75	0.3710	0.5510	0.9520	0.9880	0.2440	0.4170	0.9390	0.9870
		0.45	0.55	0.3620	0.5490	0.9470	0.9840	0.2360	0.4050	0.9250	0.9810
	0.1	0.5	0.95	0.3710	0.5700	0.9550	0.9890	0.2230	0.4190	0.9390	0.9880
		0.25	0.75	0.3400	0.5460	0.9470	0.9930	0.2150	0.4130	0.9220	0.9880
		0.45	0.55	0.3570	0.5510	0.9440	0.9850	0.2410	0.4290	0.9370	0.9870
	0.01	0.5	0.95	0.3410	0.5420	0.9520	0.9870	0.2090	0.3930	0.9420	0.9850
		0.25	0.75	0.3670	0.5750	0.9510	0.9880	0.2490	0.4310	0.9380	0.9870
		0.45	0.55	0.3970	0.5640	0.9510	0.9880	0.2470	0.4220	0.9360	0.9820
Model B: $y_t = a_0 + a_1 S_t(\theta) + b_0 t + u_t$											
$u_t = \phi u_{t-1} + \varepsilon_t$, $\varepsilon_t \sim NID\,(0,1)$ where $a_0 = 1$, $a_1 = 0.2$, $b_0 = 1$											
				t_{AS}^{B}				$e_{\alpha(\beta)}$			
5	1	0.5	0.95	0.4030	0.5650	0.9380	0.9820	0.1310	0.2610	0.8250	0.9390
		0.25	0.75	0.3740	0.5420	0.9360	0.9820	0.1300	0.2720	0.8220	0.9370
		0.45	0.55	0.3900	0.5570	0.9180	0.9660	0.1250	0.2600	0.8150	0.9140
	0.1	0.5	0.95	0.3780	0.5490	0.9350	0.9830	0.1340	0.2690	0.8210	0.9280
		0.25	0.75	0.3880	0.5520	0.9390	0.9860	0.1320	0.2620	0.8260	0.9170
		0.45	0.55	0.4160	0.5730	0.9360	0.9820	0.1410	0.2860	0.8160	0.9240
	0.01	0.5	0.95	0.4070	0.5840	0.9380	0.9790	0.1200	0.2670	0.8230	0.9360
		0.25	0.75	0.3740	0.5460	0.9360	0.9770	0.1280	0.2530	0.8040	0.9260
		0.45	0.55	0.3870	0.5430	0.9300	0.9760	0.1260	0.2750	0.8180	0.9140
Model C: $y_t = a_0 + a_1 S_t(\theta) + b_0 t + b_1 t S_t(\theta) + u_t$											
$u_t = \phi u_{t-1} + \varepsilon_t$, $\varepsilon_t \sim NID\,(0,1)$ where $a_0 = 1$, $a_1 = 0.2$, $b_0 = 1$, $b_1 = -0.25$											
				t_{AS}^{C}				$e_{\alpha\beta}$			
5	1	0.5	0.95	0.3120	0.4500	0.8880	0.9640	0.1230	0.2220	0.6980	0.8880
		0.25	0.75	0.3080	0.4500	0.8920	0.9640	0.1280	0.2140	0.7080	0.8900
		0.45	0.55	0.2980	0.4500	0.8690	0.9470	0.1080	0.2070	0.7180	0.8690
	0.1	0.5	0.95	0.3090	0.4410	0.8740	0.9560	0.1140	0.2050	0.7250	0.8740
		0.25	0.75	0.2940	0.4620	0.8890	0.9610	0.1090	0.2110	0.7220	0.8820
		0.45	0.55	0.3200	0.4810	0.8700	0.9550	0.1370	0.2340	0.7270	0.8630
	0.01	0.5	0.95	0.3090	0.4460	0.8940	0.9600	0.1160	0.2100	0.7130	0.8920
		0.25	0.75	0.3060	0.4290	0.8710	0.9590	0.1330	0.2100	0.6880	0.8680
		0.45	0.55	0.3100	0.4650	0.8790	0.9600	0.1280	0.2280	0.7110	0.8710

Table 3.4: Power of Symmetric and Asymmetric KMC-STR for Model A, B and C

We begin with the official real exchange rates and the number of lags, k were determined using the general-to-specific testing strategy at the 10% level of significance, starting with $k = 12$.

3.5.1 OECD RER against US dollar

If we consider the full sample period-see Table (3.5), the results of the tests for models, t_{LSTR}, t_{ESTR}, t_S^A, and t_{AS}^A provide little evidence against the unit root hypothesis. With quarterly data, the unit root tests, t_S^A and t_{AS}^A reject the null hypothesis at 10% level for only two countries, Japan and New Zealand respectively. With monthly data, the null cannot be rejected for any country. These findings are consistent with other empirical works of other researchers, and consistent with a unit root in the real exchange rates.

We then consider sub-samples during the period 1980 to 1998. This sample length corresponds to a homogeneous regime of the recent floating period. Indeed, by dropping the data before 1980, we exclude the initial turbulent year of the ERM. Also by ending the sample in 1998, we aim to avoid any contamination in the run up to EMU.

Table (3.6) shows that the t_{ESTR} cannot reject the unit root null with quarterly data, while the t_{LSTR} rejects the unit root null at the 10% level for several countries. In contrast to the previous non-linear tests, the t_{AS}^A rejects the null hypothesis in more than half of the countries. Figure (3.5) shows the (quarterly data fitted) smooth transition for t_{AS}^A, over the sample period 1980:Q1-1998:Q4. It is evident that the asymmetric models fit the data well. Finally, the results

	Monthly (1973:M1-1998:M12)								Quarterly (1973:Q1-1998:Q4)							
	LSTR		ESTR		Sym KMC-STR		Asym KMC-STR		LSTR		ESTR		Sym KMC-STR		Asym KMC-STR	
Country	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A
Australia									6	-3.2221	11	-3.0679	11	-3.2218	11	-3.2301
Austria	11	-2.6173	11	-2.4417	11	-2.2446	11	-2.2493	4	-2.6820	4	-2.5704	4	-2.3963	5	-2.1969
Belgium	11	-2.5644	11	-2.4971	11	-2.3289	11	-2.3885	4	-2.5885	11	-2.6546	8	-2.6402	8	-2.6416
Canada	11	-2.4285	11	-2.3629	11	-2.1707	11	-2.1706	12	-2.5364	3	-2.2119	7	-1.4732	8	-2.1811
Denmark	11	-2.4431	11	-2.3597	11	-2.3485	11	-2.3477	4	-2.4100	4	-2.4954	4	-2.3530	4	-2.4202
Finland	11	-2.8142	11	-2.7734	11	-2.7449	11	-2.7655	4	-2.8917	4	-2.9167	7	-2.9624	7	-3.0012
France	11	-2.4860	12	-2.5475	11	-2.4029	11	-2.4029	4	-2.7542	4	-2.7647	4	-2.7957	8	-3.2074
Germany	11	-2.3004	11	-2.2814	11	-2.4330	11	-3.0331	4	-2.4990	4	-2.4722	4	-2.6347	4	-3.3573
Greece	12	-2.4870	12	-2.4538	12	-1.9785	12	-1.9792	4	-2.9215	4	-2.9330	4	-2.2237	4	-3.5576
Ireland									1	-3.4960	4	-3.1963	4	-3.2237	4	-3.2014
Italy	11	-2.7689	3	-2.7790	11	-2.5617	11	-2.5617	1	-2.8622	1	-2.8850	4	-2.9164	4	-2.6173
Japan	12	-3.1266	12	-3.0532	12	-3.0881	12	-3.0532	11	-3.8521	11	-3.5180	11	-3.6757*	11	-3.5180
Netherlands	11	-2.6317	12	-2.5202	11	-2.4085	11	-2.4081	0	-2.4440	4	-2.8348	8	-2.4155	8	-2.4155
New Zealand									7	-3.1597	6	-3.3545	8	-3.4254	8	-4.0755*
Norway	2	-2.2621	2	-2.2413	2	-2.2664	2	-2.3954	11	-2.4332	11	-2.3255	8	-2.7248	8	-2.6446
Portugal	12	-2.4010	12	-2.2124	12	-1.7521	12	-1.7505	8	-2.6938	4	-2.6284	8	-1.7653	8	-1.7629
Spain	9	-2.6652	12	-2.8888	9	-2.2644	9	-2.3889	8	-2.9073	4	-3.0040	8	-2.6499	8	-2.8924
Sweden	10	-2.4249	10	-2.3641	11	-2.3291	10	-2.4195	8	-2.8090	8	-3.0422	8	-3.3210	8	-3.4888
Swiss	11	-2.9647	11	-2.8962	11	-2.4651	11	-2.8367	4	-3.0688	4	-2.7983	4	-2.7116	4	-2.7138
U.K.	12	-2.9122	11	-2.8516	11	-2.7748	11	-2.7735	8	-3.6859	8	-3.7083	8	-3.2557	12	-3.6774

Table 3.5: Estimated Results for OECD RER against the US Dollar

Country	Monthly (1980:M1-1998:M12)								Quarterly (1980:Q1-1998:Q4)							
	LSTR		ESTR		Sym KMC-STR		Asym KMC-STR		LSTR		ESTR		Sym KMC-STR		Asym KMC-STR	
	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A
Australia									6	-2.6945	11	-2.8867	8	-2.7584	8	-2.8146
Austria	5	-3.8097	5	-2.8750	11	-1.7192	11	-2.7131	1	-4.0403*	1	-2.9679	4	-4.4926***	4	-4.9023**
Belgium	5	-3.7434	7	-3.7497	11	-1.8967	0	-3.5942	1	-4.0325*	1	-3.0764	4	-4.1823**	4	-4.2631*
Canada	11	-2.4342	12	-2.0125	11	-1.1348	11	-1.1238	8	-2.2666	6	-2.1208	8	-1.1321	8	-1.1321
Denmark	5	-3.8637	5	-2.8144	11	-1.8155	0	-3.7123	1	-4.2201*	1	-2.9583	4	-4.0208**	4	-4.3188**
Finland	11	-2.6676	11	-2.5317	11	-2.3031	11	-2.5593	7	-2.6839	4	-2.6160	4	-2.9355	4	-2.9548
France	7	-3.6759	7	-3.6699	11	-1.8589	11	-3.4428	1	-3.9841*	1	-3.0171	4	-3.9147*	4	-3.9764*
Germany	4	-3.6707	7	-3.6818	11	-1.8114	11	-2.8028	1	-3.8858	1	-3.0334	4	-4.5271***	4	-4.5965*
Greece	0	-3.2147	0	-3.0924	0	-1.4884	0	-1.4880	6	-3.2944	0	-3.0760	1	-2.7340	4	-4.3716**
Ireland									1	-4.2520**	1	-3.1079	4	-3.7348	4	-3.8043
Italy	5	-3.3239	5	-2.5778	11	-1.9400	11	-2.8517	1	-3.6563	1	-2.7532	4	-2.9631	4	-3.5756
Japan	3	-2.9084	12	-2.9794	12	-2.9691	12	-3.0409	4	-2.9446	11	-3.5580	11	-4.4925***	11	-3.8217
Netherlands	7	-3.9025*	7	-3.8337	11	-2.0205	12	-3.7353	1	-4.1522*	1	-3.2297	4	-4.6651***	4	-4.7355**
New Zealand									10	-3.9993*	8	-3.4158	8	-3.4170	8	-4.1938*
Norway	7	-3.0144	7	-2.3416	2	-1.9384	11	-2.6121	1	-3.1448	1	-2.3841	8	-2.0817	0	-2.7365
Portugal	7	-3.3224	5	-2.8393	12	-1.3670	12	-1.3701	6	-3.5946	7	-3.3632	4	-3.9609**	4	-5.0715***
Spain	8	-3.1576	8	-2.3930	9	-1.6434	9	-1.6434	1	-3.2318	8	-2.5207	4	-2.8527	4	-4.2389*
Sweden	10	-3.1175	10	-2.0908	10	-2.0175	10	-2.3981	3	-3.4782	3	-2.2164	3	-2.2164	3	-2.8770
Swiss	4	-3.6014	4	-2.8790	11	-1.1985	11	-1.9176	1	-3.6518	6	-3.0995	4	-4.4163**	4	-4.6383**
U.K.	11	-3.4971	8	-3.4887	1	-3.6594*	4	-3.4506	1	-3.6126	8	-3.6441	8	-1.9868	1	-3.6639

Table 3.6: Estimated Results for OECD RER against the US Dollar

from the sub-sample period support the PPP hypothesis for quarterly, but not monthly data. This evidence appears to contradict the results of Papell (1997). In fact, he argues that using panel data tests the evidence favouring PPP is stronger with monthly than quarterly data.

One possible reason for this might be the relationship between frequency and data. On the other hand, the relative strength of the results for quarterly data mostly comes from accounting for structural changes.

3.5.2 OECD RER against DM

By focusing on currencies that are less volatile relative to each other, Jorion and Sweeney (1996) pointed out that PPP works better among European countries than these countries and the U.S. Indeed panel methods find more evidence of long-run PPP when the German mark, instead of the U.S. dollar, is used as the base currency. With the same method and data spanning as those described above, we construct from nominal exchange rates, domestic consumer price indexes against the German CPI.

The monthly and quarterly full samples between 1973 and 1998 are presented in Table (3.7). It is clear that there is more evidence of long-run PPP for German than for the U.S. With quarterly data, the unit root null of t^{A}_{AS} is rejected for 4, 10, 12 out of the 20 countries considered, at the 1, 5, 10% levels respectively. With monthly data, the null is rejected for 3, 5, and 7 countries out of the 17 considered at the 1, 5, 10% levels respectively. These results contrast with the empirical evidence on PPP when the U.S. dollar is assumed as a base

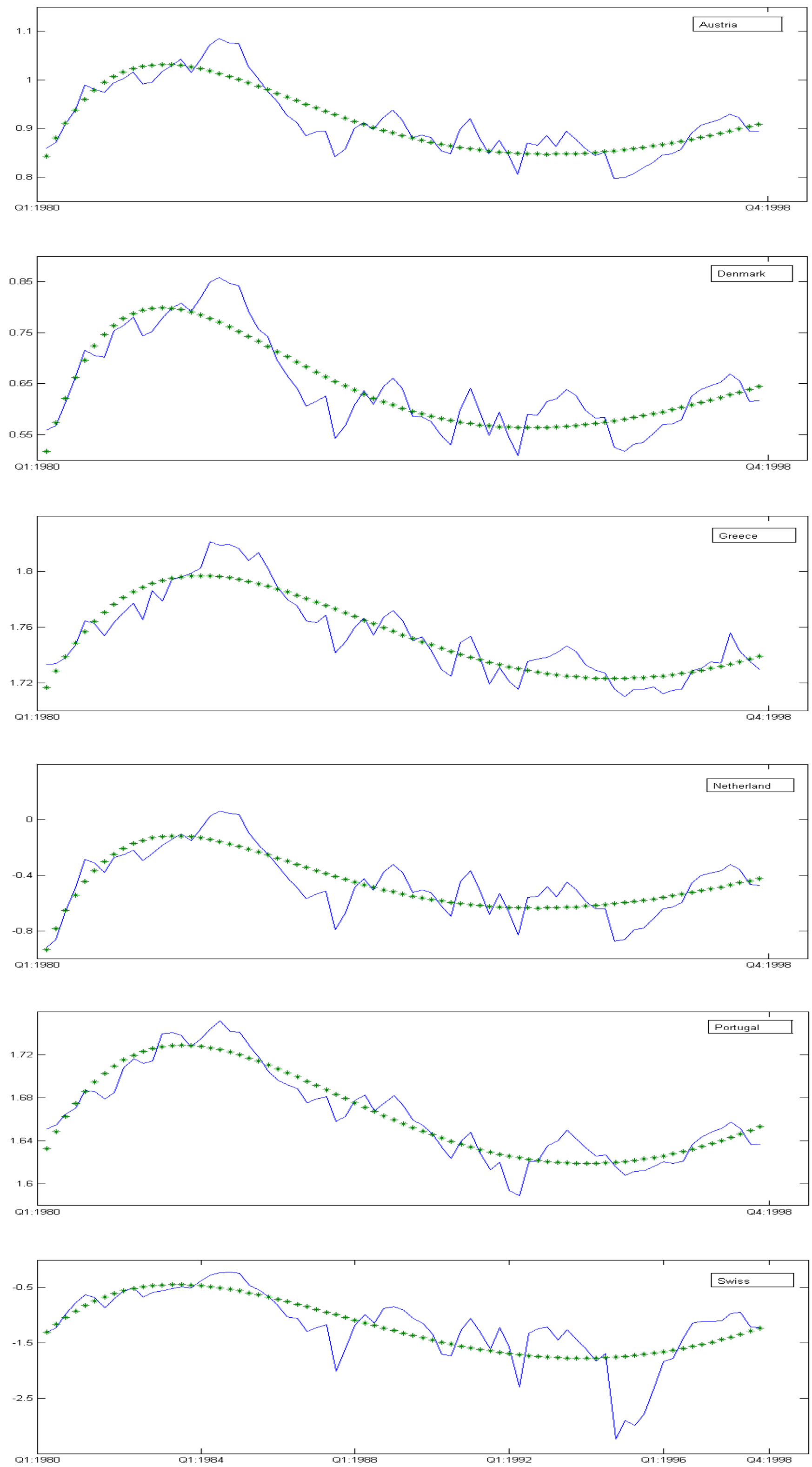

Figure 3.5: Asymmetric KMC-STR for Quarterly RER against the US dollar

Country	Monthly (1973:M1-1998:M12)								Quarterly (1973:Q1-1998:Q4)							
	LSTR		ESTR		Sym KMC-STR		Asym KMC-STR		LSTR		ESTR		Sym KMC-STR		Asym KMC-STR	
	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A
Australia									11	-3.1372	4	-3.5243	4	-3.2763	11	-4.4435**
Austria	12	-4.2966**	12	-4.2966**	12	-4.5129***	12	-4.7357**	4	-3.7440	4	-3.7440	2	-3.3914	0	-5.0685***
Belgium	9	-4.7321**	9	-5.0058***	10	-2.6216	0	-5.3002***	3	-4.4660**	3	-4.4671***	7	-3.4288	7	-2.0365
Canada	12	-3.1216	12	-3.0696	12	-2.1442	11	-2.5542	4	-3.2972	4	-3.2860	4	-2.2707	4	-4.2598*
Denmark	0	-2.9797	0	-2.9797	0	-2.9667	1	-2.8984	10	-2.8554	10	-2.8554	10	-2.9161	10	-2.8554
Finland	12	-2.8174	12	-2.8220	12	-2.4095	12	-2.4171	5	-2.8940	5	-2.8849	5	-2.9181	5	-4.3024**
France	9	-4.1364*	9	-4.1022*	9	-3.2904	9	-3.9801*	6	-4.3646**	6	-4.3081***	8	-3.1556	8	-5.0549***
Greece	1	-3.9692*	1	-3.8945*	1	-3.1866	1	-3.5019	0	-4.0600*	0	-3.7170	0	-2.9529	0	-2.9511
Ireland									1	-2.3201	7	-2.3665	12	-3.3266	8	-3.9859*
Italy	0	-2.4290	0	-2.2546	11	-1.8872	11	-1.8922	10	-2.8875	10	-2.8316	11	-2.6352	11	-4.5799**
Japan	10	-4.8470**	10	-4.0687*	8	-4.1574**	10	-4.7001**	3	-4.7929***	3	-4.2836***	3	-4.4458**	3	-4.4789**
Netherlands	6	-6.7152***	6	-5.8668***	0	-3.5745*	6	-8.9939***	0	-7.9740***	0	-7.3494***	0	-1.9767	0	-9.2612***
New Zealand									4	-3.5541	4	-3.2704	4	-2.9002	4	-2.8988
Norway	12	-3.2076	12	-3.2019	12	-3.5751*	12	-2.2215	6	-3.3094	6	-3.2545	5	-2.4051	5	-4.4560**
Portugal	12	-4.4026**	12	-4.3574**	12	-2.7793	12	-4.1804*	4	-4.8866***	4	-4.6313***	4	-2.7802	4	-4.5792**
Spain	10	-2.5385	10	-2.7610	10	-3.0623	10	-2.7610	6	-2.8182	11	-2.9839	6	-3.0300	6	-2.9800
Sweden	12	-4.1471*	12	-3.9254*	12	-3.2984	12	-3.2986	5	-4.5879**	5	-4.5348***	5	-3.5110	5	-3.4983
Swiss	12	-5.8196***	12	-5.5610***	12	-5.7601***	12	-5.6879***	4	-5.9572***	4	-5.8337***	4	-5.9074***	4	-5.8153***
U.K.	3	-2.9049	3	-2.6499	3	-2.7308	12	-3.0020	7	-2.7940	7	-2.9757	7	-3.1416	7	-3.9076
U.S.	11	-2.3004	11	-2.2814	11	-2.4330	11	-3.0331	4	-2.4990	4	-2.4722	4	-2.6347	4	-3.3573

Table 3.7: Estimated Results for OECD RER against the DM

currency. The result is also consistent with previous studies. In particular, the unit root null (using t^A_{AS}) is rejected at the 5% level for more than half of the countries with quarterly data. Jorion and Sweeney (1996), Papell (1997) and Papell (2002) argue that, while the large appreciation and depreciation in 1980s generate the higher volatility in real exchange rates against the U.S. dollar, less (exchange rate) volatility and geographic proximity provide more information for the mark real exchange rates.

As before we now consider sub-samples. The t_{LSTR} (see Table (3.8)), provides stronger support than other multiple structural change tests for both monthly and quarterly data. The test rejects the null in 6 out of 17 and 20 countries at the 5% level for monthly and quarterly data respectively. Sollis (2005) argues that the smaller number of rejections from a test-the t^A_{AS} test in this case- should not be taken as evidence that the additional rejections from t_{LSTR} reported in Table (3.8) are due to a misspecified model. In fact, there is a trade-off between flexibility of the model under the alternative hypothesis and the power of the test.

In contrast with the U.S., the results in this case show one interesting aspect. The test with full-sample period shows more supportive evidence favouring PPP than when a sub-sample period is used.

3.5.3 Robustness Checks

In this section we extend the sample period for some of the currencies investigated in the previous section. The span of the dataset runs from 1973 to

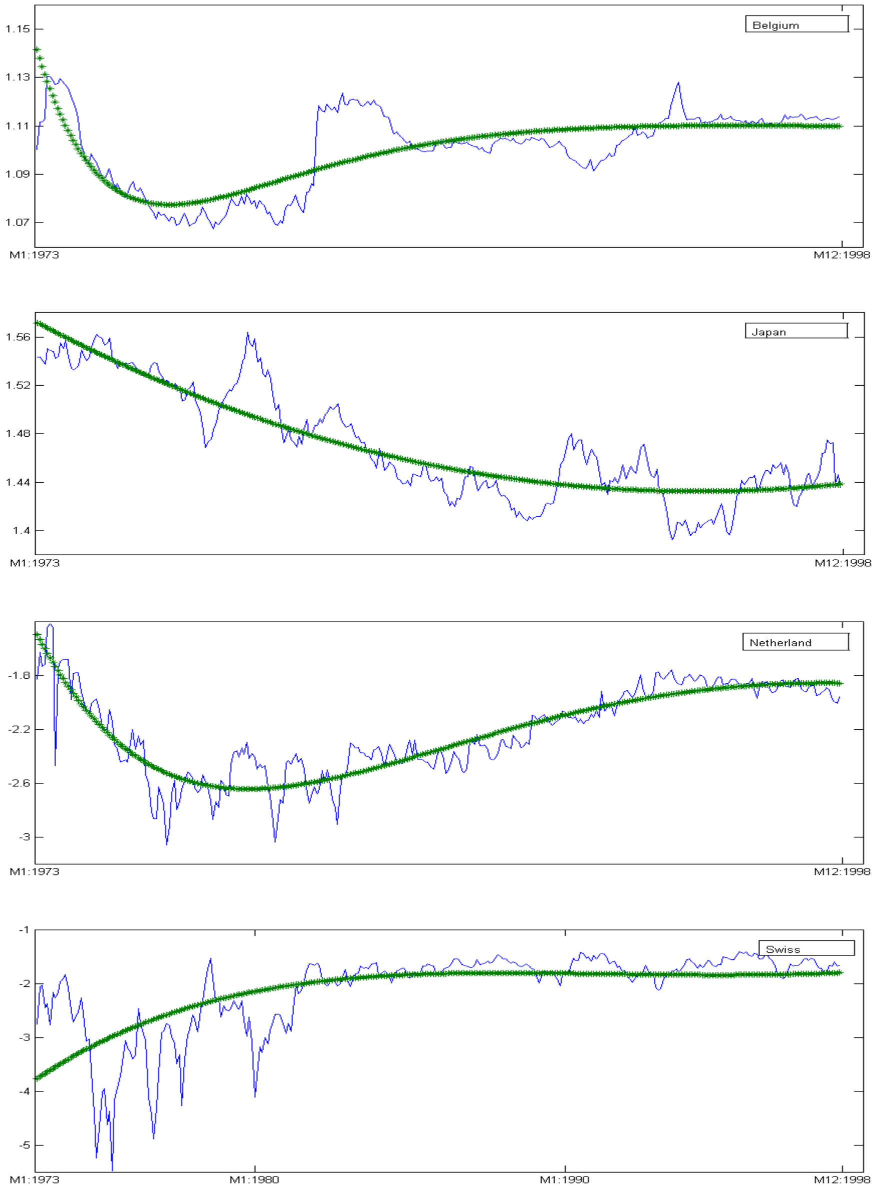

Figure 3.6: Asymmetric KMC-STR for Monthly RER against the DM for M1:1973 - M12:1998

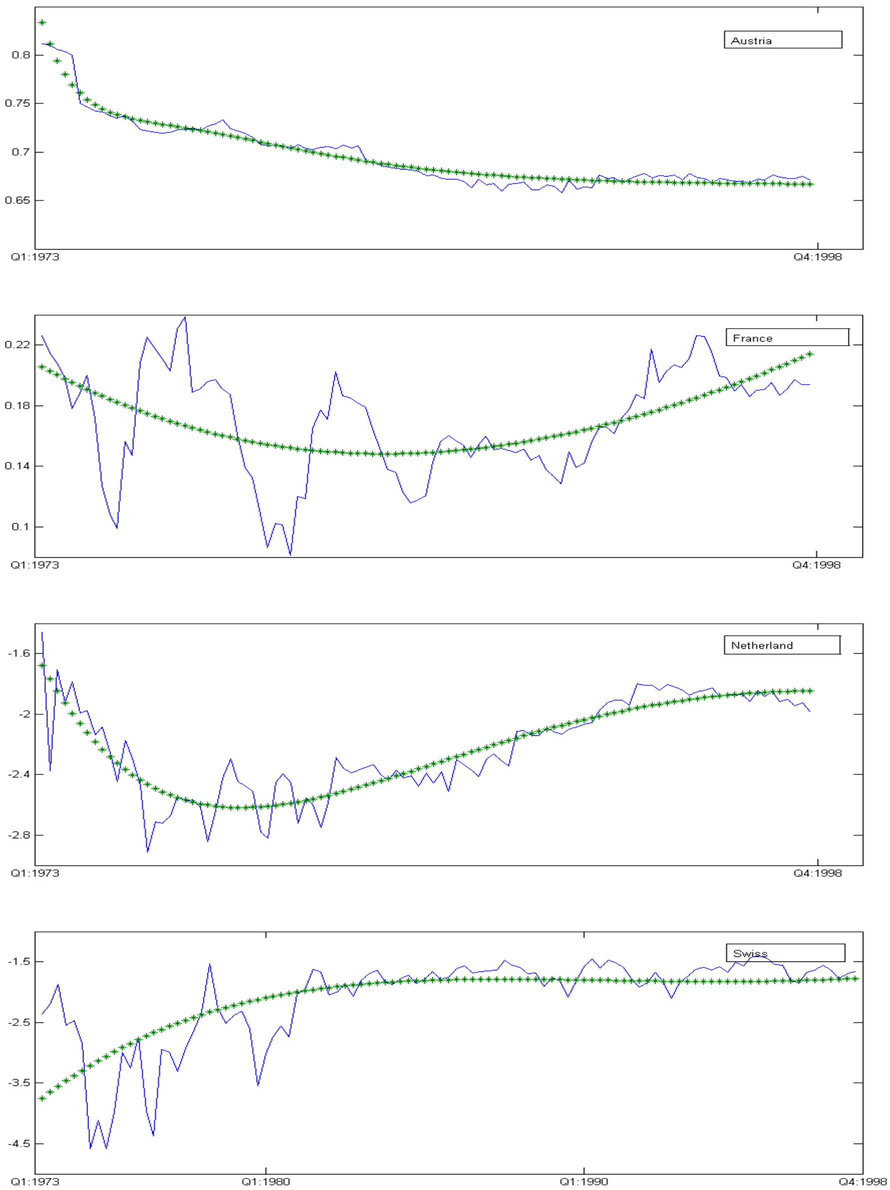

Figure 3.7: Asymmetric KMC-STR for Quarterly RER against the DM for Q1:1973 - Q4:1998

	Monthly (1980:M1-1998:M12)								Quarterly (1980:Q1-1998:Q4)							
	LSTR		ESTR		Sym KMC-STR		Asym KMC-STR		LSTR		ESTR		Sym KMC-STR		Asym KMC-STR	
Country	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A
Australia									0	-3.3266	11	-4.2328**	6	-3.6686*	4	-3.8564
Austria	0	-4.9051***	0	-3.1510	0	-3.2571	0	-3.1510	0	-5.2148***	0	-3.1033	0	-3.6131*	0	-3.1034
Belgium	8	-2.2754	4	-3.1749	1	-2.8041	1	-4.2152*	7	-2.6802	4	-3.1867	7	-3.0680	7	-3.0492
Canada	5	-3.2932	5	-3.8004	12	-1.3642	12	-3.4420	1	-3.4334	1	-4.1257*	4	-3.7911*	4	-3.9123
Denmark	0	-2.2691	12	-2.2326	12	-2.3941	12	-2.2326	9	-2.8895	9	-2.9658	9	-3.3442	9	-2.9685
Finland	0	-3.7005	0	-3.6065	2	-1.2175	2	-1.2152	0	-3.6728	1	-3.4030	5	-3.7948*	5	-2.9764
France	12	-4.8072***	0	-4.3818**	12	-3.7419*	12	-4.0757*	5	-5.7108***	4	-3.8952*	3	-3.6897*	3	-3.6987
Greece	0	-3.4111	0	-3.4497	1	-3.1525	0	-2.8178	0	-3.3189	0	-3.3395	0	-2.3824	0	-4.2136*
Ireland									4	-3.5721	0	-3.3650	2	-1.6581	2	-1.6547
Italy	2	-2.5265	2	-2.6511	11	-1.7845	11	-2.4166	0	-2.7588	0	-2.9633	10	-2.3486	10	-4.0992*
Japan	10	-3.9936*	10	-3.9316*	10	-3.9021**	10	-3.9916*	1	-3.8376	4	-3.8066	4	-3.8163*	4	-3.8066
Netherlands	1	-5.4636***	0	-4.0363*	0	-4.0367**	0	-4.0363*	0	-4.5791***	0	-3.0608	0	-3.0611	0	-2.7873
New Zealand									0	-3.6875	0	-3.6783	4	-2.8838	4	-2.8838
Norway	0	-4.1791**	0	-4.2794**	4	-1.2561	4	-2.8428	1	-4.3968***	1	-4.2286**	4	-1.4329	4	-2.8276
Portugal	12	-4.6532**	12	-4.6746**	12	-3.5779*	12	-3.5778	4	-5.6187***	4	-5.2255***	4	-2.1610	4	-4.1929*
Spain	10	-2.0693	10	-2.0697	10	-2.1979	10	-2.9926	11	-2.5404	5	-2.3790	5	-2.2689	5	-2.1862
Sweden	12	-3.5608	1	-3.1384	3	-2.6030	3	-2.5306	4	-3.5816	5	-3.5097	5	-1.9227	6	-2.9215
Swiss	1	-4.5990**	1	-4.5900**	1	-4.1643**	1	-4.6058**	1	-4.5487***	1	-4.5487**	1	-4.5487***	1	-4.5474**
U.K.	12	-2.7831	7	-2.7902	12	-2.5790	12	-2.5790	6	-2.8355	7	-2.8617	4	-2.9810	4	-3.1237
U.S.	4	-3.6707	7	-3.6818	11	-1.8114	11	-2.8028	1	-3.8858	1	-3.0334	4	-4.5271	4	-4.5965**

Table 3.8: Estimated Results for OECD RER against the DM

2009.

Table (3.9) shows the empirical results. These remain qualitatively the same as the ones reported previously. The t_{LSTR} and t_{ESTR} can reject the unit root null at a 5% level with quarterly data for the Swiss Franc, while the t_{AS}^{A} rejects the unit root null at the 1 or 5% level for the Australian Dollar, the, Japanese Yen and the British Pound. On the other hand, there is only a single rejection (at the 5% level) when monthly data are used. Using our proposed asymmetric model, we find evidence supporting PPP in almost 50% of cases both with monthly and quarterly data.

The model we propose therefore seems flexible enough to fit the large spike in the US Dollar in the 1980s and indeed it provides more empirical evidence for PPP than other studies such as, for example, Papell (2002).

3.6 Conclusion

The present chapter examined the determination of the equilibrium real exchange rate in the presence of structural changes. In particular, we propose an equilibrium exchange rate model with a risk premium and a stationary component, resulting from non-fundamental trading behaviour, to motivate structural changes. Additionally, the chapter proposed a novel transition function which is capable to mimic the behaviour of our simple exchange rate model. As benchmark cases, it compared logistic and exponential transition functions with the multiple structural change models proposed.

	Monthly (1973:M1-2009:M12)								Quarterly (1973:Q1-2009:Q4)							
	LSTR		ESTR		Sym KMC-STR		Asym KMC-STR		LSTR		ESTR		Sym KMC-STR		Asym KMC-STR	
Country	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A	k	t_{LSTR}	k	t_{ESTR}	k	t_S^A	k	t_{AS}^A
Australia									1	-3.1021	11	-2.9725	11	-2.3892	11	-4.8859***
Canada	12	-3.4479	12	-2.7911	12	-2.4705	12	-3.7431	11	-4.0036*	8	-3.1119	8	-2.6667	9	-3.0382
Denmark	11	-3.4523	11	-3.2236	11	-2.9097	11	-3.0734	3	-3.0673	10	-3.1521	10	-2.8594	4	-2.9367
Japan	11	-3.2627	12	-2.6157	11	-2.5305	12	-4.4635**	10	-3.1371	4	-2.5851	4	-2.5587	11	-4.6853**
New Zealand									8	-3.5281	12	-4.0071*	12	-3.8790	0	-3.5350
Sweden	10	-3.2152	0	-3.8880	11	-3.1192	10	-3.1257	8	-3.5294	3	-3.1477	8	-2.9795	8	-3.8303
Swiss	11	-4.3663**	11	-4.3080**	11	-3.3843	11	-3.4742	4	-4.3841**	4	-4.2348**	4	-3.2715	5	-3.6149
U.K.	12	-3.6166	12	-3.4993	12	-3.2974	12	-3.9050*	12	-3.9535*	12	-4.1769*	12	-3.6283	12	-4.3183**

Table 3.9: Estimated Results of RER against the US Dollar for 1973 - 2009

We provide an empirical application based on monthly and quarterly real exchange rate data and two numeraire currencies, the US dollar and the German mark, and show that once we incorporate structural breaks, evidence of stationarity in real exchange rates increases. The empirical results show that, while there is weak evidence supporting PPP for the U.S. dollar-based real exchange rates, monthly and quarterly over the period from 1973, for more than half of the quarterly series for the sub-sample period post-1980 the evidence in favour of PPP is more clear. In particular, we show that evidence in favour of a stationary real exchange rate is much stronger when quarterly rather than monthly data are used.

The chapter also considered German mark-based real exchange rates and the empirical results are in line with the literature and show that there is stronger evidence in favour of stationarity across the range of tests considered in this paper, although the new tests proposed here work best for the US dollar.

Appendix 3.A

Derivation of the Model Parameters

The solutions (3.6) can be obtained by solving for equilibrium conditions in each state, H, inner regime and L, which correspond to the intervals (q_H, ∞), (q_L, q_H) and $(-\infty, q_L)$ respectively.

Suppose that $s_t = 0$ and $E_{t-1}(q_t) = \bar{q}_t$. Consider the following exchange rates dynamics with and without the risk-adjusted interest parity condition

$$\bar{q}_t = \beta q_{t-1} + m z_{t-1} \tag{3.12}$$

and

$$\bar{q}_t = q_{t-1} - z_{t-1} + \pi_{t-1}$$

where $z_{t-1} = r_{t-1} - r^*_{t-1}$ and m represents the persistence of the monetary policy.

If we consider, as an example, the inner regime and rational expectations, we have

$$E_{t-1}(q_t) = \bar{q}_t + \lambda(\bar{q}_t) = \bar{q}_t \tag{3.13}$$

On the other hand, if $\bar{q}_t$ is below H or above L, we have respectively $E_{t-1}(q_t) = \bar{q}_t + \lambda_H(q_H - \bar{q}_t)$ or $E_{t-1}(q_t) = \bar{q}_t + \lambda_L(q_L - \bar{q}_t)$.

By the definition of (3.12) and (3.13) in the inner regime we have

$$\begin{aligned} E_{t-1}(q_t) &= \bar{q}_t + \lambda(\bar{q}_t) \\ &= \bar{q}_t \\ &= \beta q_{t-1} + m z_{t-1} \\ &= q_{t-1} - z_{t-1} + \pi_{t-1} \end{aligned}$$

where $\bar{q}_t = \beta q_{t-1} + m z_{t-1}$ and thus

$$z_{t-1} = \frac{1}{m+1}\pi_{t-1} + \frac{m+\beta}{m+1} q_{t-1} \tag{3.14}$$

Substituting (3.14) into equation $\bar{q}_t = q_{t-1} - z_{t-1} + \pi_{t-1}$ results

$$\bar{q}_t = a_0 + b_0 q_{t-1}$$

where $a_0 = \frac{m}{1+m}\pi_{t-1}$ and $b_0 = \frac{(m+\beta)}{1+\beta}$.

A similar approach can be used to obtain $\bar{q}_t$ in the region of H and L.

Chapter 4

Microstructure Order Flow: Statistical and Economic Evaluation of Non-linear Forecasts

4.1 Introduction

There is something of a consensus in the exchange rate literature that macro based models of the exchange rate fail to outperform a simple random walk model in an out-of- sample forecasting context (see, for example, Meese and Rogoff (1983)). Given this, many researchers have turned to a market microstructure approach to provide alternative insights into the forecasting behaviour of exchange rates. For example, Evans and Lyons (2002b), Evans and Lyons (2005b) and Sager and Taylor (2008) use such an approach and provide mixed evidence that microstructure models (i.e. order flow models) can do better than a simple random walk in out of sample forecasts. The main conclusion of Evans and Lyons (2002b) is that order flow is a significant determinant of exchange rates and can be also used to forecast exchange rates out of sample. However, Sager and Taylor (2008) finds little empirical evidence supporting these conclusions after employing interdealer and commercially available order flow data.

A related but slightly different strand of the market microstructure literature investigates the issue of whether the strength of the relationship between order flow and exchange rates is dependent upon prevailing market conditions or the announcement of macroeconomic news. For example, Love and Payne (2003) examines the role of order flow in the transmission of news regarding published macro fundamentals and finds that information that is contemporaneously released to all market participants is partially impounded into prices via the microstructure order flow. However, this is clearly at odds with rational expectations. Bacchetta and Wincoop (2006) and Rime, Sarno, and Sojli (2010) argue that macroeconomic information impacts on exchange rates both directly, as in a standard macro model, but also indirectly via order flow. Thus, order flow can be viewed as a random variable which maps disperse information in the market in to price discovery. In particular, since the order flow of the FX market consists of different participants, displaying significant heterogeneity in terms of risk-return expectations and informational asymmetries, the customer order flow represents the primary source of private information that is assumed to represent future innovations in fundamental exchange rate determinants.

The above microstructure models provide some useful insights into the foreign exchange market, but there are still several unanswered questions. For example, the success of microstructure models in out of sample forecasts has primarily been achieved when the information is publicly and simultaneously released to all market participants contemporaneously. However, since the information of the state of the economy available at a given point may takes some time before it affects the exchange rate, it is probably preferable to consider a lagged order flow model as in Sager and Taylor (2008). Additionally, since different market participants trade using private as well as public information, expectations about the new equilibrium exchange rate are formed based on a combination of macroeconomic fundamentals and market microstructure variables.

In this chapter we try to shed some light on some of the issues raised above. Firstly, we propose a modelling approach which should accommodate model instability. Indeed, if order flow does reflect heterogeneous beliefs about the current and future state of the economy, and if currency markets do not discover order flow in real time but only through a gradual learning process, the heterogeneity in the market can cause model instability. This important point has been largely neglected in the literature. Rime, Sarno, and Sojli (2010) recognize the importance of heterogeneity and employ a Probit model and show that order flow may be linked to macroeconomic fundamentals both via a direct link, as in classical exchange rate theory, and via order flow, as in the microstructure approach to FX. We attempt to capture this effect using time-varying parameter (TVP), structural change (STR) and smooth transition (STAR) models. This is also in line with Gradojevic and Yang (2006).

Also, and as pointed out by Sarno and Valente (2009), parameter instability caused by instabilities in macro fundamentals, and agents' heterogeneity, or swings in expectations about future values of the exchange rate, make it difficult to select a predictive model. We show that our model specifications can address this issue. In particular, our study suggests the inclusion of microstructure variables and non-linear models produces out-of-sample forecasts which are superior to those from a random walk model.

Finally, we evaluate our out of sample forecasts using statistical tests, such as the root mean squared forecast error (hereafter RMSFE), and the Diebold-Mariano (hereafter DM) tests, as well as mean-variance analysis as a standard measure of portfolio performance, as in Fleming, Kirby, and Ostdiek (2001), Han (2006), della Corte, Sarno, and Tsiakas (2009) and Rime, Sarno, and Sojli (2010).

The remainder of this chapter is organized as follows. In the next section, we provide a brief literature review. Section 4.3 describes the link between order flow and exchange rates and statistical evaluation method. The forecasting setup and the investor's asset allocation problem are described in Section 4.4, and the results on the statistic and economic evaluation of forecasting models that condition on order flow are reported in Section 4.5. The final section concludes the chapter and recommends further research.

4.2 Reviews of the literature on exchange rate predictability

4.2.1 Macro puzzle and micro consideration

The feature of the macro fundamentals-based approach to modelling the nominal exchange rate introduces the possibility of excessive exchange rate movements relative to fundamentals. The nominal exchange rate is given by forward-looking expectations of the following form

$$s_t = (1 - b) \sum_{i=0}^{\infty} b^i E_t f_{t+1} \tag{4.1}$$

where s_t is the log nominal spot rate, b is the discount factor, and f_t represents fundamentals at time t. In the monetary context, f_t can be a parsimonious set of fundamentals, comprising the money supply and output, but it can also include a broader set of fundamentals such as net foreign assets or trade balance. The $E_t f_{t+1}$ can be viewed as the market-makers' expectation about future fundamentals conditional on information available at time t. By iterating (4.1) we have

$$\Delta s_{t+1} = \frac{(1 - b)}{b} (s_t - E_t f_t) + \varepsilon_{t+1} \tag{4.2}$$

where $\varepsilon_{t+1} \equiv (1 - b) \sum_{i=0}^{\infty} b^i (E_{t+1} f_{t+i+1} - E_t f_{t+i+1})$. Therefore future exchange rate changes are a function of the gap between the current exchange rate and the expected current fundamentals.

A large part of the literature has investigated the relationship between exchange rates and economic fundamentals focusing on deviations of the nominal exchange rate from its fundamental value. Researchers have mainly used the models to investigate exchange rate predictability, after re-formulating as

$$\Delta s_{t+k} = c + \beta u_t + \varepsilon_{t+k}$$

where k represents the k-difference operator and $u_t = s_t - f_t$.

Meese and Rogoff (1983) pioneered this strand of the exchange rate literature and found empirical evidence representing that most structural or statistical exchange rate models cannot outperform a simple random walk model in out-of-sample forecast. Recently, Engel and West (2005) demonstrate that if the fundamentals are random walk or follow $I(1)$, the discounting factor is near unity. This means that the fundamental based analysis cannot outforecast the random walk model of exchange rates. In particular, they find little evidence that the exchange rate is explained by the 'observable' fundamentals and also agree with other investigations that there is a role for 'unobserved' fundamentals such as real shocks and risk premium. It seems, at least in part, explaining why forecasting with fundamentals can be troublesome.

As shown in equation (4.2), Engel and West (2005) note that innovations in the exchange rate must be highly correlated with news about future fundamentals, which is consistent with the study of market microstructure. In the presence of heterogeneous information in the market and typical macro variables, considered in the structural exchange rates models, macro fundamentals fail to act as aggregators of this information into price discovery. Microstructure models view order flow as a random variable which maps heterogeneous disperse information into price discovery. Thus, relative to macro based exchange rate models, order flow in the microstructural approach represents the missing link between exchange rates changes and changes in economic conditions. Consider the following (contemporaneous) order flow model,

$$\Delta s_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \varepsilon_t \tag{4.3}$$

where Δs_t is the change of the (log) nominal exchange rate, $\Delta(i_t - i_t^*)$ represents the change in the domestic - foreign interest differential, X_t is the order flow in t, and $\varepsilon_t\tilde{}i.i.d.$ random variable.

Using the above model, Evans and Lyons (2002b) report significant explanatory power for the order flow when the mark–dollar and the yen–dollar exchange rates are considered. The empirical analysis of Evans and Lyons (2002a) is extended to an additional seven exchange rates and report explanatory power ranging from 0.00% to 68%. They also report a high out of sample power of the order flow model when compared to a simple random walk model. Killeen, Lyons, and Moore (2006) also report significant explanatory power of the order flow model which is consistent with the results of Evans and Lyons (2002b).

Payne and Vitale (2003) point out that the model above is not very relevant in practice as it assumes perfect foresight. Indeed, using central bank order flow for Swiss franc–dollar over the sample period 1986–95, they show that, although inter-dealer order flow has significant contemporaneous correlation with exchange rate returns, its predictive power is minimal. Recently Sager and Taylor (2008) investigate this issue further in a large empirical study. They argue that the announcement of public information is impounded in prices with a delay. Thus, they suggest the following so called "publication lag" model,

$$\Delta s_t = \beta_1 \Delta(i_{t-1} - i^*_{t-1}) + \beta_2 X_{t-1} + \varepsilon_t \tag{4.4}$$

After undertaking a large empirical analysis, they show that the (lagged) order flow model has very little (in sample) explanatory power and cannot outperform a simple random walk model in forecasting exchange rates at different horizons. Additionally, they show widespread evidence of a Granger-causal relationship that runs from exchange rate returns to customer order flow. This result is consistent with the empirical evidence of Engel and West (2005), which have found some support for the link between fundamentals and exchange rate in the other direction: exchange rates can help forecast the fundamentals.

More recently, Cerrato, Sarantis, and Saunders (2009) uses weekly customer order flow for nine of the most liquid currencies and investigates the in-sample and out-of-sample forecasting power of the order flow models. While empirical results using aggregate data are in line with Sager and Taylor (2008)[1], using disaggregate data seems to increase the in-sample and out-of-sample forecasting power of the order flow model.

4.2.2 Model instability

In the presence of the role of macro fundamentals, a consequence of both microstructure approaches (4.3) and (4.4) is that macro variable contains relevant common knowledge, which is impounded into a currency with any microstructure role. As a similar but slightly different approach, Evans and Lyons (2005a), Evans and Lyons (2008), and Love and Payne (2008) have tried to clarify the relationship between the release of economic news and the order flow, and provide empirical evidence that macro news triggers trading that reveals dispersed information, which in turn affects currency prices. In this context, the order flow is linked to macroeconomic news, but the explanatory power is either not reported or documented to be lower than the model describes.

[1] However, the in-sample results, using the contemporaneous order flow model, strongly support such a model. In effect, with weekly data, the lagged model might be too restrictive.

The hypothesis suggested by Rime, Sarno, and Sojli (2010) is that the heterogeneous interpretation of macroeconomic news may lead market makers to make inferences differently and that the order flow incorporate this information gradually. They estimate the following regression

$$\Delta X_t = \phi_0 + \sum_{n=1}^{N} \phi_n \mathbf{NEWS}_{n,t} + u_t$$

where $\mathbf{NEWS}_{n,t}$ is measured as the standardized difference between the actual and the expected value of the macroeconomic fundamentals. The results from estimated coefficients are statistically significant at the 10% level implying that news are an important determinants of order flow. However, they note that the sign of the relation between news and order flow is ambiguous since it depends on the extent to which the exchange rate adjusts directly in response to the news. Thus, they empirically investigate the significance of the relation between cumulative order flow and macroeconomic news using a Probit model,

$$I_{sumX_t} = \theta_0 + \theta_1 \mathbf{NEWS}_t + \varpi_t$$

where $I_{sumX_t} = 1$ if $sumX_t > 0$, and otherwise 0. Using this model, they find a correctly signed and statistically significant coefficient for macroeconomic news. Note that while the order flow reflects the heterogeneous interpretations of the news for the new equilibrium price, the common knowledge part of the news directly affects the exchange rate by shifting the equilibrium price.

Based on this observation, Rime, Sarno, and Sojli (2010) propose the following direct (4.5) and indirect (4.6) specifications,

$$\Delta s_t = \alpha_1 + \sum_{n=1}^{N} \beta_n \mathbf{NEWS}_{n,t} + u_t \tag{4.5}$$

and

$$\Delta s_t = \alpha_1 + \sum_{n=1}^{N} \beta_n \mathbf{NEWS}_{n,t} + \gamma_1 \Delta X_t + u_t \tag{4.6}$$

Both of the above two models show evidence that exchange rate fluctuation are linked to macroeconomic fundamentals via a direct link, as in traditional exchange rate theory, and order flow via an indirect link, as in the microstructure approach to the foreign exchange rate. The equation (4.5) implies that the heterogeneous interpretation of market information directly affects the asset price if order flows fully contain macroeconomic news as implied by typical microstructure approaches. However, as shown in the studies of Love and Payne (2008), if the order flows partly reflect heterogeneous interpretation of macroeconomic news, the equation (4.6) specifies the effects between news and order flows.

This modelling approach can provide some explanation for the link between macroeconomic fundamentals and exchange rates examined in Bacchetta and Wincoop (2006) and Evans and Lyons (2008). Note that the finding of significant explanatory power for macroeconomic news on the exchange rate does not automatically imply that order flow information is redundant. (e.g. Rime, Sarno, and Sojli (2010)). The addition of order flow significantly increases the explanatory power of the model. Rime, Sarno, and Sojli (2010) demonstrates that macroeconomic news can explain exchange rates changes to the same extent that they explain order flow.

Overall, the empirical literature in this area seems to have produced conflicting results and we believe a key reason for this could lie in the way the models are estimated. For example, for the news models mentioned above, news is constructed using monthly macroeconomic data. However, with high frequency data that approach is not feasible and so an alternative specification is required, which can properly capture shifts in expectations. The aim of the present study is to shed some light on these issues and address some problems that in our view have been neglected when modelling exchange rates dynamics. In particular, most of the studies cited above have mainly focused on linear models and a direct relationship between the exchange rate and the order flow. We believe these models are very restrictive with high frequency data sets. In this chapter we propose a novel approach which we believe clarifies the role of heterogeneous information and relaxes the linearity assumption.

4.3 Empirical models and evaluation

The models introduced in the previous section suggest that shifts in expectations can cause model instability. Very few papers have considered this an important issue (see for example Rime, Sarno, and Sojli (2010))[2]. We propose three different models which address this important issue and test them in out of sample exercises.

[2] As we shall discuss in the next sections there is a clear advantage in using our modelling approach instead of the approach as in Rime, Sarno, and Sojli (2010).

4.3.1 Time-varying parameter model

The first model we consider is a variation of the standard model considered in the literature. The idea is that if an economic announcement affects the order flow, this will cause a change in the parameters governing the exchange rate forecasts. Thus, we suggest the following time varying parameter model.

In a time-varying parameter model the dynamic for exchange rate returns is driven by the following regression

$$\Delta s_{t+k} = \alpha + \beta_t X_{t-1} + \varepsilon_{t+k}$$

The parameters of the model are estimated in the usual way, using the first n observations. The estimates are then updated in each subsequent observation, $s_{n+1}, s_{n+2}...s_T$. The main difference with the approach used in the literature is that, this model uses a different recursive filter.[3] That is, once the tth observation becomes available, β_t may be obtained from β_{t-1} without the matrix inversion implied by OLS (ordinary least squares).

[3] Given the basic setup

$$y_t = X_t \beta_t + \varepsilon_t$$

The relevant formulae are given by

$$\beta_t = \beta_{t-1} + \left(X'_{t-1} X_{t-1}\right)^{-1} x_t \left(y_t - X_t \beta_{t-1}\right) / f_t$$

where $f_t = 1 + x'_t \left(X'_{t-1} X_{t-1}\right)^{-1} x_t$ and $X_t = (x_1, x_2, ..., x_t)$

4.3.2 Smooth transition model

The second specification we use is completely new in the literature. We propose a non-linear model which allows for slow exchange rates adjustment to the equilibrium.[4] As shown in Rime, Sarno, and Sojli (2010) macro news can cause changes in expectations. We try to capture the effect of changes in expectations (on the exchange rate) by employing the smooth transition function, $CMK-STAR$ of chapter 2

$$\Delta s_{t+k} = \alpha + \beta S(\theta) X_{t-1} + \varepsilon_{t+k}$$

where

$$S(\theta) = [1 + \exp\{\gamma_1 (X_{t-1} - c_1)\mathbf{I}_t - \gamma_2 (X_{t-1} - c_2)(1 - \mathbf{I}_t)\}]^{-1}$$

and θ represents parameter set to be estimated. The function $S(\theta)$ allows for both threshold effects and smooth transition movements of X_{t-1}. In the central regime, when $-c < X_{t-d} < c$, $S(X_{t-d}, \theta) = 0$. In the limiting outer regimes, when $X_{t-d} < -c$ and $c < X_{t-d}$, $S(X_{t-d}, \theta) = 1$. The specification given by $S(\theta)$ allows the transition depending on X_{t-1}. Thus, if the news directly affects order flow and expectations are heterogeneous, the transition depending on the order flow, X_{t-1} should be able to capture this effect. We use the above model in our forecasting exercises.

[4] The slow adjustment may be due to, for example, a low risk aversion.

4.3.3 Structural change model

The models above suggest a direct link between macroeconomic news and exchange rates. In contrast to the direct specification, when order flow is partly reflecting macroeconomic news and expectations, we suggest an alternative model. This modelling approach is very convenient when using high frequency data or unobservable fundamentals. The model we consider incorporates structural breaks due to shifts in expectations by allowing a shift in the mean process

$$\Delta s_{t+k} = \alpha_1 + \alpha_2 S(\theta) + \beta X_{t-1} + \varepsilon_{t+k},$$

where

$$S(\theta) = \left[1 + \exp\left\{-\gamma_1^2 (t - c_1 T)^2\right\}\right] \left[1 - \exp\left\{-\gamma_2^2 (t - c_2 T)^2\right\}\right] - 1.$$

The transition function $S(\theta)$ traverses the interval $(-1, 1)$ and the timing of the transition is determined by c_i. The speed at which the function moves between -1 and 1 changes with γ. As discussed in chapter 3, this model is able to capture structural changes taking place in different regimes. If $c_1 < c_2$, $0 < S_t(\theta) < 1$ when $t = c_1 T$, and $-1 < S_t(\theta) < 0$ when $t = c_2 T$. In the limiting or no structural change state $S_t(\theta) = 0$, the model collapses to $\Delta s_{t+k} = a_1 + \beta X_{t-1} + \varepsilon_{t+k}$, and is consistent with the linear model proposed in previous studies. On the contrary, when the structural changes take place because of omitted economic fundamentals such as macro news, or a different interpretation of them, the model becomes $\Delta s_{t+k} = a_1 + \alpha_2 S(\cdot) + \beta X_{t-1} + \varepsilon_{t+k},$. The mean process is determined by the value $S_t(\theta)$. Thus, this structural change model might be viewed as a reasonable approximation of model instability caused by omitted variables, when fundamentals have an indirect link to order flows.

4.3.4 Forecast evaluation

We assess the out of sample forecasts produced by the three models above in different ways. Firstly, we use the root mean squared forecast error (RMSFE)

$$RMSFE = \sqrt{\frac{\varepsilon'_{t+k}\varepsilon_{t+k}}{T}}$$

Additionally, we also construct a test statistic for comparing the forecasting performance of the models relative to a simple random walk (RW). Given two forecasts, the RW forecast and the forecast provided by the alternative models (hereafter AM), the ratio of RMSFE against RW can be used to evaluate the out of sample forecasts. We also support this test using the Diebold and Mariano (1995) test. This test allows us to compare the forecasting accuracy of two competing models. Defining $d_t = g(\varepsilon_{1,t}) - g(\varepsilon_{2,t})$ where $t = 1, ..., n$, the Diebold-Mariano test statistic is

$$DM = \frac{\bar{d}}{\left[var\left(\bar{d}\right)\right]^{\frac{1}{2}}}$$

where $\bar{d} = n^{-1}\sum_{t=1}^{n} d_t$ and $var\left(\bar{d}\right)$ represents the asymptotic (long-run) variance of $\sqrt{T}\bar{d}$.

Diebold and Mariano (1995) show that under the null of equal predictive accuracy, $DM \sim N(0,1)$, and we can reject the null of equal predictive accuracy at the 5% level if

$$|DM| > 1.96$$

We use the Diebold-Mariano test to assess the out of sample forecasts of our models with respect to a simple Random Walk model RW.

4.4 Economic value of exchange rate predictability

Most of the previous studies have focused on evaluating the statistical performance rather than the economic significance of non-linear approach. Here we also examine the latter and specifically examine the economic value of non-linear models to risk-averse investors. To measure the economic value of the out of sample forecasts, we address the issue of whether our three models can be used practically by assessing the forecasts where a portfolio of assets is rebalanced according to a trading rule at each time t.

4.4.1 Portfolio weights of a mean-variance framework

In order to measure the economic performance of a portfolio it is standard to use Sharpe ratios. However, as Marquering and Verbeek (2004) and Han (2006) note, Sharpe ratios can underestimate the performance of dynamically managed portfolios. This happens because Sharpe ratios are calculated using the average standard deviation of the realized returns, which overestimates the conditional risk (standard deviation) faced by an investor at each point in time.

Consequently, Sharpe ratios cannot properly quantify the economic gains of a dynamic strategy.

As an alternative measure of forecasting performance, we use a mean-variance framework and calculate the performance fee to quantify the economic gain from using the exchange rate models introduced above with respect to a simple random walk model. The framework for our analysis is straightforward. We consider an investor who uses a mean-variance optimization rule to allocate funds across assets. The investor's objective is to maximize the expected return matching a target expected volatility.

Allowing for weekly rebalancing, the solution to the investor's portfolio problem is a dynamic trading strategy that specifies the optimal asset weights. Implementing this strategy requires estimates of both the conditional expected returns and the conditional covariance matrix. If the conditional expected return and covariance are constant, the optimal portfolio weights w will be constant over time. However, when the conditional expected return and covariance are defined as recursive estimates, investors will rebalance their portfolio weights and change strategies. Thus, in terms of one-step ahead forecasts, we treat the expected returns as the conditional mean, $\mu_{t+1|t} = E_t \left[r_{t+1} \mid \mathcal{F}_t \right]$ and let the variation in the portfolio weights be driven purely by changes in the conditional covariance matrix, $\sum_{t+1|t} = E_t \left[\left(r_{t+1} - \mu_{t+1|t} \right) \left(r_{t+1} - \mu_{t+1|t} \right)' \mid \mathcal{F}_t \right]$ where $\mathcal{F}_t$ represents the current information set.

To maximize the conditional expected return, $\mu_{t+1|t}$ subject to a given level of conditional volatility σ_p^*, investors solve the following problem at time t,

$$\max_{w_t} \left\{ \mu_{p,t+1} = w_t' \mu_{t+1|t} + (1 - w_t' \mathbf{1}) \, r_f \right\}$$
$$\text{s.t.} \ \ \left(\sigma_p^*\right)^2 = w_t' \sum\nolimits_{t+1|t} w_t$$

where $\mu_{p,t+1}$ and σ_p^* denote the conditional mean and variance of the portfolio return, $r_{p,t+1}$ of risky assets. In the present setting, w_t is the portfolio weights on the risky assets, and r_f is the return on the riskless asset. Among the trading strategies such as the minimum variance and maximum return, the above mean-variance analysis solves for the weight that maximizes the conditional return where the portfolio variance equal to a fixed target.

After constructing the covariance matrix of the portfolio, we determine the weights by maximizing the conditional mean of the portfolio return. The solution to this problem yields the following risky asset weights,

$$w_t = \frac{\sigma_p^*}{\sqrt{C_t}} \sum\nolimits_{t+1|t}^{-1} \left(\mu_{t+1|t} - \mathbf{1} r_f \right)$$

where $C_t = \left(\mu_{t+1|t} - \mathbf{1} r_f \right)' \sum_{t+1|t}^{-1} \left(\mu_{t+1|t} - \mathbf{1} r_f \right)$. The optimal weights will vary across the models depending on the conditional mean and volatility. That is, the trading strategy identifies the rebalanced portfolio that optimizes maximum conditional expected return subject to the conditional variance-covariance.

In our analysis, the benchmark against which we compare the model specifications is a simple RW. In other words, our objective is to evaluate whether there is any economic value in conditioning on microstructure order flow and non-linear models and, if so, which of the four specifications including RW has superior forecasting power.

4.4.2 Performance measures under quadratic utility

To measure the performance of a trading strategy, using a generalization of West, Edison, and Cho (1993)'s method, Fleming, Kirby, and Ostdiek (2001) suggest comparing the performance of the dynamic strategies to that of the unconditional mean-variance efficient static strategy. The latter is based on the relation between mean-variance analysis and quadratic utility. Using a second-order approximation to the investor's true utility function, the investor's realized utility is defined as

$$U(W_{t+1}) = W_{t+1} - \frac{\lambda}{2} W_{t+1}^2 = W_t R_{p,t+1} - \frac{\lambda}{2} W_t^2 R_{p,t+1}^2,$$

where W_{t+1} is the investor's wealth at $t+1$, $R_{p,t+1}$ is the gross portfolio return, equal to $1 + r_{p,t+1}$ and λ represents absolute risk preference.

In our empirical exercise we fixed the value of relative risk aversion (RRA) as $\delta = \frac{\lambda W_t}{1-\lambda W_t}$. Given the level of initial wealth W_0, the average realized utility is then defined as

$$\bar{U}(\cdot) = W_0 \sum_{t=0}^{T-1} \left\{ R_{p,t+1} - \frac{\delta}{2(1+\delta)} R_{p,t+1}^2 \right\},$$

where δ is constant. The average realized utility ($\bar{U}$) can be used to consistently estimate the expected utility generated at the given level of initial wealth, W_0, and value of relative risk aversion (RRA), δ. If the value of RRA is assumed to be $\delta = \{2, 6\}$ and the initial wealth is fixed at $W_0 = 1$, we can standardize the investor problem of maximum conditional expected return and assess the economic value of our FX strategies in the context of asset allocation.

To measure the economic value of our FX strategies, we use the average utility and compute the performance fee as suggested in Fleming, Kirby, and Ostdiek (2001). The selected pairs of portfolios, RW against alternatives are evaluated by equating the average utilities. That is, if an investor is indifferent between holding a portfolio where the optimal weights have been computed using a simple RW and an alternative portfolio using a more "sophisticated" approach, then the value of Φ can be interpreted as the performance fee that the investor would be willing to pay to switch from the RW to the alternative model, such as TVP, STAR and STR. The performance fee, Φ, is defined as:

$$\sum_{t=0}^{T-1}\left\{\left(R_{p,t+1}^{AM}-\Phi\right)-\frac{\delta}{2\left(1+\delta\right)}\left(R_{p,t+1}^{AM}-\Phi\right)^{2}\right\}=\sum_{t=0}^{T-1}\left\{R_{p,t+1}^{RW}-\frac{\delta}{2\left(1+\delta\right)}\left(R_{p,t+1}^{RW}\right)^{2}\right\},$$

where $R_{p,t+1}^{RW}$ is the gross portfolio return obtained using forecasts from the benchmark RW model, and $R_{p,t+1}^{AM}$ is the gross portfolio return constructed using the forecasts from the alternative models. Thus, the utility-based criterion measures how much the investor is willing to pay for conditioning on order flow as in the AM strategy for the purpose of forecasting exchange rate returns. In the context of this maximum return dynamic strategy, we can compute both the in-sample and the out-of-sample performance fee, Φ.

4.4.3 Transaction costs

In the literature, transaction costs are generally assumed given and not estimated. For example, Marquering and Verbeek (2004) consider three levels of transaction costs, 0.1%, 0.5%, and 1%, representing low, medium, and high costs, respectively. Our empirical models use dynamic strategies and in this context transaction costs can play a significant role in determining returns and comparative utility gains where individuals rebalance their portfolios. Thus, instead of assuming a given cost, we follow the method introduced by Han (2006), della Corte, Sarno, and Tsiakas (2009) and Rime, Sarno, and Sojli (2010), and calculate the break-even transaction costs,

$$\tau \sum_{j=0}^{9} \left| w_t^j - w_{t-1}^j \frac{1 + r_{t+1}^j}{R_{p,t+1}} \right|,$$

which make the investors indifferent between the dynamic and buy-and-hold strategies in terms of utility. In the present setting, the break-even transaction cost, τ, is the minimum proportional cost that cancels out the utility advantage of a given strategy.

Using the above mean-variance quadratic-utility framework, we design a global strategy consisting of a US investor holding a portfolio of 10 currencies: one domestic (United States), and nine foreign currencies. The investor is exposed to currency risk. We employ each of the 4 models to forecast the one step ahead period of the exchange rate returns. Thereafter, we dynamically rebalance our portfolio by computing the new optimal weights for the maximum return strategy conditioned on the forecasts of each model. In the analysis, the yields of the riskless bonds are proxied by the LIBOR rates.

We report the performance fees for the combinations corresponding to the following cases: (1) three sets of target annualized portfolio volatilities $\sigma_p^* = \{8\%, 10\%, 12\%\}$; (2) all pairs of 3 models against RW; and (3) degrees of RRA $\delta = \{2, 6\}$. We report our estimates of Φ and break-even transaction cost τ as annualized fees expressed in basis points.

4.5 Estimation and empirical results

4.5.1 Data and preliminary test

In this study we use two different datasets. The first dataset is the customer order flow dataset used in Cerrato, Sarantis, and Saunders (2009). The dataset consists of customer weekly frequency order flows from UBS and covers the period November, 02 2001 - November, 23 2007 for nine of the most liquid currencies. This is the largest dataset ever used in the literature. The dataset is aggregated across currency pairs with customers split into 4 classifications: asset managers, hedge funds, corporate and private clients. The currencies considered are the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the Australian Dollar (AUD), the New Zealand Dollar (NZD), the UK Pound (GBP), the Japanese Yen (JPY), the Norwegian Krone (NOK) and the Swedish Krone (SEK). We use three month LIBOR rate collected from Bloomberg to approximate the risk-free rate. Since all rates are foreign currency per US dollar, a positive coefficient indicates dollar buying (foreign currency selling), the rate will increase as the foreign currency weakens. On the contrary, a decline in this rate represents a strengthening of the foreign currency relative to the US dollar. Descriptive statistics for this dataset are reported in Cerrato, Sarantis, and Saunders (2009).[5] Since exchange rates are found to be $I(1)$, we employ log differenced rates. We have used this dataset to assess the in sample predictive power of the three models introduced above. The results were not different to that already reported in Cerrato, Sarantis, and Saunders (2009) and therefore are not reported in this study to save space.

[5] See appendix A and B

Linearity test for the STAR					
	aggregate	disaggregate			
		AM	CO	HF	PC
EUR/dollar	10.198†	4.022	1.713	4.794†	0.161
JPY/dollar	4.393	2.022	1.002	10.517†	11.476†
GBP/dollar	13.046†	32.893†	6.698†	1.518	3.789
CHF/dollar	10.885†	5.943†	17.234†	5.669†	0.073
AUD/dollar	3.725	9.074†	64.932†	2.875	23.236†
CAD/dollar	3.939	13.249†	1.689	4.705†	5.471†
NOK/dollar	22.766†	1.818	2.147	0.645	17.980†
SEK/dollar	15.545†	8.687†	13.278†	0.083	3.802
NZD/dollar	36.289†	7.843†	32.099†	18.601†	3.631

Table 4.1: Linearity test to the aggregate and disaggregate order flows

Linearity tests against STAR non-linearity for the order flow are reported in Table (4.1). We use the approach as suggested in Harvey and Leybourne (2007). To implement this test, we select the AR order in the regression using a general-to-specific methodology and a 10%-significance level, (4.605), with a maximum permitted AR order of four and a minimum order of two. We find evidence of non-linearity for six aggregate order flows and more than half disaggregate order flows. Thus, more than half of the series analyzed exhibit evidence of non-linearity and would suggest that non-linear models may be appropriate.

4.5.2 The Evans and Lyons' dataset: out of sample forecasts

The second dataset considered in this study is the one used in Evans and Lyons (2002b). It contains 80 daily observations on inter-dealer order flow for mark–dollar and yen–dollar during the period May 1–August 29, 1996. These data were originally collected from the Reuters D2000-1 inter-dealer service and are defined as the difference between the number of buyer-initiated and seller-initiated trades. Thus, unlike the previous dataset, this dataset consists of interdealer order flow

We start with the out-of-sample forecasts and compare these using the order flow model as in Evans and Lyons (2002b) and thereafter using the methodologies for model instability as discussed in the previous sections.

Table (4.2) shows the empirical results. We use a recursive approach to compute forecasts and root mean squares errors. At the 1 and 2-week horizons, the Evans–Lyons model, which considers publication lag, does not outperform the random walk. Our models show a significant predictive power for weekly exchange rates returns at any horizon.

4.5.3 Customer order flow data: out of sample forecasts

Aggregate order flow

We now turn to the UBS customer order flow data and do the forecasting exercise as in the previous section. The out-of-sample predictions are reported in Table (4.3). As in the previous section, the out-of-sample exercise involves two steps: (1) initial parameter estimation for the first 267 observations, and (2) sequential weekly updating of the parameter estimates for the rest of out-of-sample period. In other words, the forecasts at any given week are constructed according to a recursive procedure that is conditional only upon information up to the date of the forecast. The model is then successively re-estimated as

Out of sample prediction results: forecasts of lagged models using Evans and Lyons Dataset

		RW	E&L	E&L/RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
DEM/dollar	k =1	0.4332	0.5213	1.2075	0.3966	0.9155	0.3123	0.4184	0.9657	1.3353	0.4078	0.9412	1.0868
	5	0.9700	1.8073	1.8631	0.9212	0.9497		0.9321	0.9610		0.8537	0.8801	
	10	1.5162	2.7752	1.8303	1.3593	0.8965		1.3323	0.8787		1.2175	0.8030	
JPN/dollar	k =1	0.4019	0.4191	1.0430	0.3815	0.9494	0.2777	0.3655	0.9094	1.7169	0.3834	0.9540	0.7069
	5	0.9513	1.8123	1.9050	0.9342	0.9820		0.8287	0.8711		0.9288	0.9763	
	10	1.383	3.2625	2.3499	1.1595	0.8835		0.7786	0.5932		1.0154	0.7737	

[a]

Table 4.2: Estimated Results for TVP, STAR and STR with Evans and Lyons Dataset

[a]Note: The table reports the ratio of RMSFE for exchange rate forecasts at various horizons against RW with TVP: $\Delta y_{t+k} = \alpha + \beta_{1t}\Delta(i_t - i_t^*) + \beta_{2t}X_t$, STAR: $\Delta y_{t+k} = \alpha + \beta_1\Delta(i_t - i_t^*) + \beta_2 S(.)X_t$ and STR: $\Delta y_{t+k} = \alpha_1 + \alpha_2 S(.) + \beta_1\Delta(i_t - i_t^*) + \beta_2 X_t$ respectively.

the date on which forecasts are conditioned moves through the data set. Hence the design of the out-of-sample exercise is computationally intensive.

At all the horizons, except for GBP, the RMSFE statistics computed using the TVP, STAR and STR are slightly lower than those associated with the random walk forecasts. The Diebold-Mariano test statistic shows that only NZD is significant at 5% level.

The empirical results in this section are in line with Cerrato, Sarantis, and Saunders (2009) and show very little evidence of forecasting power for the order flow model.

Disaggregate order flow

Evans and Lyons (2005b) argue that the lack of success in generating results generally supportive of the core hypotheses of the market microstructure literature may be due to using aggregate customer order flow data. However, the heterogeneities in the customer segment of the foreign exchange market imply that different customers may react to news in different ways. Sager and Taylor (2008) points out that knowledge of the types of customers prevalent in the market at any given time and of the ways in which they trade and interact with the wider market should help understand the behaviour of an exchange rate at that time.

In this section, following Evans and Lyons (2005b), Sager and Taylor (2008) and Cerrato, Sarantis, and Saunders (2009), we test whether the predictive performance of the order flow model can be improved using disaggregate customer

Out of sample prediction results: forecasts of lagged models using aggregate order flow											
			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$			$y_{t+k} - y_t = \alpha_1 + \alpha_2 S(.) + \beta X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
EUR/dollar	k =1	0.8165	0.8041	0.9848	0.13	0.7767	0.9512	0.97	0.7652	0.9372	1.40
	2	1.1761	1.0704	0.9101		1.0805	0.9187		1.0750	0.9141	
	3	1.5422	1.3282	0.8612		1.3218	0.8571		1.3422	0.8703	
	4	1.8963	1.6106	0.8493		1.6318	0.8606		1.6585	0.8746	
GBP/dollar	k =1	0.8980	0.9055	1.0084	-0.06	0.8899	0.9910	0.30	1.0812	1.2040	0.15
	2	1.1837	1.2522	1.0579		1.2263	1.0360		1.1933	1.0081	
	3	1.2362	1.3032	1.0542		1.2955	1.0479		1.3208	1.0684	
	4	1.4269	1.4714	1.0312		1.4209	0.9958		1.4644	1.0263	
CHF/dollar	k =1	0.9651	0.9258	0.9592	0.26	0.9434	0.9775	0.67	0.9539	0.9884	0.60
	2	1.3064	1.2197	0.9336		1.2553	0.9609		1.2917	0.9888	
	3	1.7263	1.5029	0.8706		1.6169	0.9366		1.6856	0.9764	
	4	1.9992	1.7050	0.8529		1.8457	0.9232		1.9965	0.9987	
NOK/dollar	k =1	1.2806	1.2360	0.9651	0.27	1.2522	0.9778	1.15	1.2666	0.9891	1.18
	2	1.8348	1.7370	0.9467		1.7796	0.9699		1.8198	0.9918	
	3	2.3171	2.2241	0.9599		2.2263	0.9608		2.3030	0.9939	
	4	2.8380	2.6468	0.9326		2.5912	0.9130		2.7728	0.9770	
SEK/dollar	k =1	1.0853	1.0806	0.9956	0.03	1.0784	0.9936	0.26	1.0836	0.9984	0.11
	2	1.6874	1.6256	0.9633		1.6406	0.9722		1.6537	0.9800	
	3	2.2432	2.1364	0.9524		2.1391	0.9536		2.1845	0.9738	
	4	2.6823	2.5523	0.9516		2.5498	0.9506		2.6035	0.9706	
NZD/dollar	k =1	2.0665	1.9246	0.9313	0.42	2.0291	0.9819	1.34	2.0411	0.9877	2.43**
	2	2.9120	2.8220	0.9691		2.8729	0.9866		2.8926	0.9933	
	3	3.5876	3.4556	0.9632		3.4894	0.9726		3.5264	0.9830	
	4	4.3568	4.1361	0.9493		4.1954	0.9630		4.2819	0.9828	

Table 4.3: Estimated Results for STAR and STR with Aggregate Order Flow

data.

The results of asset managers, with TVP, STAR and STR are reported in Table (4.4). All the series that have non-linearity show less than 1 in the ratio of $RMSFE$. The most striking contrast between the results reported in Tables (4.3) and (4.4) is the additional rejection of AUD and CAD in Diebold-Mariano test. This is slightly better than the results of estimated aggregate order flows and can at least partly be explained by multiple structural changes that have been manipulated to ensure customer heterogeneity.

Table (4.5) and (4.6) report the forecasts from the TVP, STAR and STR models for corporate clients and hedge funds respectively. Except for the CHF with the STR model (see hedge fund), in all the cases the RMSFE ratios are less than 1. However, only for CAD (see hedge funds) can the hypothesis that the RMSFE ratios is less than one be rejected at the 10% level with the Diebold-Mariano statistic.

Summing up, the empirical evidence from the previous sections is in line with Cerrato, Sarantis, and Saunders (2009) and shows weak empirical evidence that the order flow model can overcome a simple random walk model in out of sample forecasts.

Out of sample prediction results: forecasts of lagged models using disaggregate data (AM asset manager)											
			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$			$y_{t+k} - y_t = \alpha_1 + \alpha_2 S(.) + \beta X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
GBP/dollar	k =1	0.8980	0.8687	0.9674	0.26	0.8840	0.9844	0.49	0.8825	0.9827	0.60
	2	1.1837	1.2255	1.0353		1.2279	1.0374		1.0421	0.8803	
	3	1.2362	1.2881	1.0420		1.2915	1.0447		1.3013	1.0526	
	4	1.4269	1.4602	1.0234		1.4782	1.0359		1.4663	1.0276	
CHF/dollar	k =1	0.9651	0.9086	0.9414	0.39	0.9496	0.9839	0.93	0.9622	0.9970	0.78
	2	1.3064	1.2310	0.9423		1.2556	0.9611		1.2994	0.9946	
	3	1.7263	1.5312	0.8869		1.6370	0.9482		1.7070	0.9888	
	4	1.9992	1.7171	0.8589		1.8469	0.9238		1.9815	0.9911	
AUD/dollar	k =1	1.6960	1.6276	0.9597	0.25	1.6725	0.9861	0.96	1.6699	0.9846	1.97**
	2	2.4159	2.3195	0.9601		2.3450	0.9707		2.3496	0.9726	
	3	2.9776	2.7620	0.9276		2.8687	0.9634		2.8806	0.9674	
	4	3.5769	3.3396	0.9337		3.4226	0.9569		3.4723	0.9708	
CAD/dollar	k =1	1.1611	1.0798	0.9300	0.45	1.1096	0.9557	2.18**	1.1197	0.9643	1.64*
	2	1.9189	1.6888	0.8801		1.7990	0.9375		1.8172	0.9470	
	3	2.4335	2.0534	0.8438		2.1779	0.8949		2.2029	0.9052	
	4	2.8512	2.4694	0.8661		2.5104	0.8805		2.5438	0.8922	
SEK/dollar	k =1	1.0853	1.0467	0.9645	0.30	1.0685	0.9846	0.70	1.0753	0.9907	0.97
	2	1.6874	1.5712	0.9311		1.6314	0.9668		1.6467	0.9759	
	3	2.2432	2.1195	0.9448		2.1350	0.9518		2.1849	0.9740	
	4	2.6823	2.5499	0.9507		2.5389	0.9466		2.6106	0.9733	
NZD/dollar	k =1	2.0665	1.9985	0.9671	0.21	2.0513	0.9926	0.63	2.0469	0.9905	1.09
	2	2.9120	2.8519	0.9794		2.8737	0.9868		2.8757	0.9875	
	3	3.5876	3.5244	0.9824		3.5221	0.9818		3.5038	0.9766	
	4	4.3568	4.2676	0.9795		4.2477	0.9750		4.2368	0.9725	

Table 4.4: Estimated Results for STAR and STR with Disaggregate Order Flow - AM asset managers

Out of sample prediction results: forecasts of lagged models using disaggregate order flow (CO corporate clients)											
			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$			$y_{t+k} - y_t = \alpha_1 + \alpha_2 S(.) + \beta X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
GBP/dollar	k =1	0.8980	0.8907	0.9918	0.07	0.8697	0.9685	1.28	0.8729	0.9721	1.49
	2	1.1837	1.1463	0.9684		1.1804	0.9972		1.1696	0.9881	
	3	1.2362	1.1552	0.9344		1.1429	0.9245		1.1471	0.9279	
	4	1.4269	1.3278	0.9305		1.3480	0.9447		1.3184	0.9239	
CHF/dollar	k =1	0.9651	0.9466	0.9808	0.13	0.9305	0.9641	1.21	0.9429	0.9770	0.96
	2	1.3064	1.2386	0.9481		1.1932	0.9134		1.2554	0.9609	
	3	1.7263	1.5057	0.8722		1.5890	0.9204		1.6619	0.9627	
	4	1.9992	1.7356	0.8681		1.8184	0.9095		1.9371	0.9689	
AUD/dollar	k =1	1.6960	1.6580	0.9776	0.14	1.6845	0.9932	0.43	1.6859	0.9940	0.80
	2	2.4159	2.2956	0.9502		2.3681	0.9802		2.3951	0.9914	
	3	2.9776	2.7520	0.9242		2.8693	0.9636		2.9285	0.9835	
	4	3.5769	3.3033	0.9235		3.3779	0.9443		3.4927	0.9765	
SEK/dollar	k =1	1.0853	1.0179	0.9379	0.51	1.0609	0.9775	0.44	1.0593	0.9761	0.58
	2	1.6874	1.5810	0.9369		1.7233	1.0213		1.7086	1.0125	
	3	2.2432	2.1529	0.9597		2.3326	1.0398		2.3292	1.0383	
	4	2.6823	2.6715	0.9960		2.7673	1.0317		2.7947	1.0419	
NZD/dollar	k =1	2.0665	2.0193	0.9772	0.14	2.0627	0.9981	0.10	2.0534	0.9936	0.63
	2	2.9120	2.8764	0.9878		2.8859	0.9910		2.8733	0.9867	
	3	3.5876	3.4798	0.9700		3.5010	0.9759		3.5495	0.9894	
	4	4.3568	4.2384	0.9728		4.2293	0.9707		4.3062	0.9884	

Table 4.5: Estimated Results for STAR and STR with Disaggregate Order Flow - CO corporate clients

Out of sample prediction results: forecasts of lagged models using disaggregate order flow (HF hedge funds)											
			$y_{t+k}-y_t=\alpha+\beta_t X_t$			$y_{t+k}-y_t=\alpha+\beta S(.)X_t$			$y_{t+k}-y_t=\alpha_1+\alpha_2 S(.)+\beta X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
EUR/dollar	k =1	0.8165	0.7879	0.9650	0.29	0.7768	0.9514	1.36	0.7967	0.9757	0.95
	2	1.1761	1.0823	0.9203		1.0862	0.9236		1.1338	0.9641	
	3	1.5422	1.3557	0.8790		1.3751	0.8916		1.4531	0.9422	
	4	1.8963	1.6279	0.8585		1.6495	0.8699		1.7927	0.9454	
JPY/dollar	k =1	1.4010	1.3240	0.9450	0.31	1.3851	0.9886	0.94	1.3843	0.9881	1.40
	2	1.6165	1.5253	0.9436		1.5939	0.9860		1.5789	0.9767	
	3	2.0704	1.8661	0.9013		2.0355	0.9832		2.0203	0.9758	
	4	2.5014	2.4427	0.9765		2.5473	1.0183		2.5178	1.0065	
CHF/dollar	k =1	0.9651	0.9273	0.9608	0.25	0.9605	0.9952	0.25	0.9652	1.0001	-0.01
	2	1.3064	1.2534	0.9594		1.2842	0.9830		1.3062	0.9998	
	3	1.7263	1.4976	0.8675		1.6429	0.9517		1.7084	0.9896	
	4	1.9992	1.7300	0.8653		1.8762	0.9385		2.0033	1.0021	
CAD/dollar	k =1	1.1611	1.0909	0.9396	0.38	1.1272	0.9708	1.67*	1.1323	0.9752	1.25
	2	1.9189	1.7343	0.9038		1.8458	0.9619		1.8614	0.9700	
	3	2.4335	2.0981	0.8622		2.2649	0.9307		2.2984	0.9445	
	4	2.8512	2.5219	0.8845		2.5657	0.8999		2.6051	0.9137	
NZD/dollar	k =1	2.0665	1.9743	0.9554	0.28	2.0482	0.9911	0.64	2.0497	0.9918	1.52
	2	2.9120	2.8301	0.9719		2.8852	0.9908		2.8999	0.9959	
	3	3.5876	3.4154	0.9520		3.4868	0.9719		3.5118	0.9789	
	4	4.3568	4.0425	0.9279		4.2441	0.9741		4.3012	0.9873	

Table 4.6: Estimated Results for STAR and STR with Disaggregate Order Flow - HF hedge funds

Out of sample prediction results: forecasts of lagged models using disaggregate order flow (PC private client)											
			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$			$y_{t+k} - y_t = \alpha_1 + \alpha_2 S(.) + \beta X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM	STR	STR/RW	DM
JPY/dollar	k =1	1.4010	1.2933	0.9231	0.43	1.3714	0.9789	1.54	1.3929	0.9942	0.47
	2	1.6165	1.5917	0.9847		1.6050	0.9929		1.6501	1.0208	
	3	2.0704	1.8900	0.9128		2.0600	0.9950		2.1359	1.0316	
	4	2.5014	2.4764	0.9900		2.5534	1.0208		2.6537	1.0609	
AUD/dollar	k =1	1.6960	1.5726	0.9272	0.45	1.6500	0.9729	1.83*	1.6658	0.9822	2.51**
	2	2.4159	2.2930	0.9491		2.3531	0.9740		2.3754	0.9833	
	3	2.9776	2.7927	0.9379		2.8409	0.9541		2.9092	0.9770	
	4	3.5769	3.3276	0.9303		3.4057	0.9521		3.4924	0.9764	
CAD/dollar	k =1	1.1611	1.0204	0.8788	0.76	1.0808	0.9309	2.89***	1.0949	0.9430	2.88***
	2	1.9189	1.5745	0.8205		1.7286	0.9008		1.7760	0.9255	
	3	2.4335	1.9758	0.8119		2.2099	0.9081		2.2706	0.9330	
	4	2.8512	2.4414	0.8563		2.5118	0.8810		2.5974	0.9110	
NOK/dollar	k =1	1.2806	1.2387	0.9673	0.25	1.2576	0.9820	0.95	1.2576	0.9820	1.38
	2	1.8348	1.7319	0.9439		1.7573	0.9578		1.7746	0.9672	
	3	2.3171	2.1881	0.9444		2.1477	0.9269		2.1990	0.9491	
	4	2.8380	2.6614	0.9378		2.6303	0.9268		2.7076	0.9541	

Table 4.7: Estimated Results for STAR and STR with Disaggregate Order Flow - HF hedge funds

4.5.4 Economic evaluation

Evans and Lyons' dataset

In this and the following sections we use a different approach to evaluate our forecasts. Indeed, we build a portfolio of currencies and measure the out of sample forecasting performance using the mean variance approach introduced above. We start with the Evans and Lyons data set. Results are presented in Table (4.8). Panel A of Table (4.8) contains the out-of-sample annualized Sharpe Ratios for the non-linear models. We build an efficient portfolio by investing in the daily return of two currencies, the German DM and Japanese Yen, and using the two exchange rates to convert the portfolio return in US dollars. The maximum return strategies are evaluated at three target portfolio return volatilities, 8%, 10%, and 12%. For instance, at $\sigma_p^* = 10\%$, the out-of-sample Sharpe Ratios are 0.41 for TVP, 1.86 for STAR, and 2.43 for STR. Thus, we can conclude that in terms of economic value the models perform better than a RW.

Panel B of Table (4.8) contains the out-of-sample performance fees, Φ, and the break-even transaction costs τ^{BE}. The fees denote the amount an investor with quadratic utility and a degree of relative risk aversion equal to 2 and 6 is willing to pay for switching from the RW model to an alternative model. The target portfolio volatilities are set at 8%, 10%, and 12%. τ^{BE} is defined as the minimum proportional cost that cancels out the utility advantage of a strategy. The fees are expressed in annual basis points. As an example, setting $\sigma_p^* = 10\%$ and $\delta = 2$ the results indicate the out-of-sample fees for switching

Panel A: Sharpe Ratios for Out of Sample Forecasts

σ_p^*	TVP	STAR	STR
8%	0.5146	2.3324	3.0456
10%	0.4117	1.8659	2.4365
12%	0.3431	1.5549	2.0304

Panel B: Performance fee for in-sample forecasts against RW

	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	110.3	20.1	110.9	20.2	97.7	8.5	98.4	8.6	90.2	65.0	90.9	65.5
10%	116.3	16.9	116.9	17.0	100.8	7.0	101.4	7.1	91.5	52.7	92.1	53.1
12%	122.2	14.8	122.8	14.9	103.9	6.0	104.5	6.0	92.7	44.5	93.3	44.8

Table 4.8: Economic Evaluations for the TVP, STAR and STR Forecasts with Order Flows

from the RW model to the non-linear models are 116 bps for TVP, 100 bps for STAR and 91 bps for STR. Both economic evaluations using the Sharpe Ratio and performance fees confirm that our TVP, STAR, and STR models consistently outperform a RW in out-of-sample forecasts.

Aggregate and disaggregate customer order flows

The empirical results for the UBS dataset are reported in Table (4.9). We calculate the performance fee and this is reported in the Table (4.9). We estimate the fees assuming different degrees of relative risk aversion, specifically $\delta = 2$ and $\delta = 6$.

The out-of-sample performance fees are displayed in Table (4.9) and suggest that there is still high economic value in non-linear specifications. This is a new and important result, which is in contrast with the seminal contribution of Meese and Rogoff (1983). Specifically, at $\sigma_p^* = 10\%$ and $\delta = 2$, the performance fees for switching from RW to an alternative model are 1793 bps for TVP, 1951 bps for $STAR$ and 1149 bps for STR , when aggregate order flow is used. We can therefore conclude that there is a substantial economic value out-of-sample against the naive random walk model and in favour of conditioning on the order flows with nonlinearity. Thus, there is clear out-of-sample economic value relative to the naive random walk benchmark.

If transaction costs are sufficiently high, the period-by-period fluctuations in the dynamic weights of an optimal strategy will render the strategy too costly to implement relative to the static random walk model. We address this concern by computing the break-even transaction cost, τ, as the minimum proportional

	Performance fee for out-of-sample forecasts against RW											
	Aggregate											
	TVP				STAR				STR			
σ_p^*	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1556.7	104.6	1557.2	104.6	1686.1	172.9	1686.6	172.9	1040.4	48.4	1041.0	48.4
10%	1793.6	96.4	1794.1	96.4	1951.8	159.9	1952.2	160.0	1149.3	42.8	1149.9	42.8
12%	2030.3	90.9	2030.8	90.9	2216.8	151.2	2217.3	151.2	1258.3	39.0	1258.9	39.1
	AM(Asset Manager)											
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	2031.2	9.1	2031.7	9.1	1619.1	18.5	1619.7	18.5	1348.8	30.6	1349.3	30.6
10%	2387.9	8.5	2388.4	8.5	1872.8	17.1	1873.3	17.1	1534.9	27.9	1535.4	27.9
12%	2744.6	8.2	2745.1	8.2	2126.5	16.2	2127.0	16.2	1721.0	26.0	1721.5	26.1
	CO(Corporate Client)											
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1525.7	50.7	1526.2	50.8	1345.8	84.1	1346.3	84.2	1536.6	43.0	1537.1	43.1
10%	1756.0	46.7	1756.5	46.7	1531.1	76.6	1531.6	76.6	1769.7	39.7	1770.2	39.7
12%	1986.4	44.0	1986.9	44.0	1716.5	71.5	1717.0	71.6	2002.7	37.4	2003.2	37.4
	HF(Hedge Fund)											
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1409.9	34.1	1410.4	34.1	1250.7	22.2	1251.2	22.3	1557.5	76.5	1558.0	76.6
10%	1611.3	31.1	1611.8	31.1	1412.3	20.1	1412.8	20.1	1795.7	70.6	1796.1	70.6
12%	1812.6	29.2	1813.1	29.2	1573.8	18.6	1574.3	18.7	2033.8	66.6	2034.3	66.7
	PC (Private Client)											
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1324.8	33.7	1325.3	33.7	1293.3	27.5	1293.8	27.5	1233.1	56.7	1233.6	56.8
10%	1504.9	30.6	1505.4	30.6	1465.4	24.9	1465.9	24.9	1390.2	51.2	1390.8	51.2
12%	1684.9	28.5	1685.4	28.6	1637.5	23.2	1638.0	23.2	1547.4	47.5	1547.9	47.5

Table 4.9: Economic Value for the TVP, STAR and STR Forecasts with Order Flows

cost that cancels out the utility advantage of a given strategy. In comparing a dynamic strategy with the static random walk strategy, an investor who pays a transaction cost lower than τ will prefer the dynamic strategy. All the statistics in the tables are expressed in annual basis points.

The out-of-sample break-even transaction costs are reported in Table (4.9). It is clear from this that for the TVP, $STAR$ and STR models the values of τ^{BE} are positive and high. They tend to be higher than 50 bps and can be as high as 1000 bps. For instance, at $\sigma_p^* = 10\%$ and $\delta = 2$, the investor will switch back to the RW benchmark model if he is subject to a proportional transaction cost of at least 1504 bps for TVP, 1465 bps for $STAR$, and 1390 bps for STR with PC order flows. Furthermore, the τ^{BE} for $STAR$ versus RW shows a very large bps. Marquering and Verbeek (2004) argue that, at the reasonably high transaction cost of 50 bps, there is still significant out-of-sample economic value in empirical models that condition on the microstructure order flows, especially under non-linear specifications.

Table (4.9) shows that the out-of-sample τ^{BE} values for combined forecasts are generally high. In short, as the τ^{BE} values are generally positive and reasonably high, we conclude that the out-of-sample economic value we have reported is robust to reasonably high transaction costs.

4.5.5 Summary of results

Thus, the empirical results presented above can be summarized as follows: (1) the non-linear models consistently outperform a random walk model when

RMSFEs are considered; (2) When a portfolio of currencies is considered, after conditioning on the microstructure order flow models introduced above, there is clear empirical evidence that these models have a higher economic value than a simple random walk model; (3) The economic value of the forecasts increases after conditioning on the non-linear models.

4.6 Robustness

In this section we conduct some robustness tests to check that our results are not driven by a specific model specification. Table (4.10) presents Sharpe Ratios of the out-of-sample performance for the aggregate and disaggregate order flow models. Conditioning on non-linear models generally outperform the benchmark RW under various scenarios. Overall these empirical results are in line with the ones reported in the previous section.

The order flow models we have used above did not contain the interest rates differential. As an additional check, we have also repeated all the empirical applications as above using the same approaches but using the interest rates differential as an additional regressor. The empirical results are in line with what is already reported and therefore not given here to save space[6].

[6] These empirical results are available upon request.

Sharpe Ratios for Out of Sample Forecasts				
		Aggregate		
	σ_p^*	TVP	STAR	STR
Aggregate	8%	0.9230	1.2809	0.6902
	10%	0.7384	1.0248	0.5522
	12%	0.6153	0.8540	0.4601
		Disaggregate		
AM(Asset Manager)	8%	0.7232	0.9621	0.7186
	10%	0.5786	0.7696	0.5749
	12%	0.4821	0.6414	0.4791
CO(Corporate Client)	8%	0.6272	1.0383	0.7000
	10%	0.5018	0.8306	0.5600
	12%	0.4181	0.6922	0.4667
HF(Hedge Fund)	8%	0.8504	0.7337	0.4633
	10%	0.6803	0.5870	0.3707
	12%	0.5669	0.4892	0.3089
PC (Private Client)	8%	0.5201	1.0096	0.6626
	10%	0.4161	0.8077	0.5301
	12%	0.3467	0.6731	0.4417

Table 4.10: Sharpe Ratios for the TVP, STAR and STR Forecasts with Order Flows

4.7 Conclusion

This chapter makes several contributions to the literature on exchange rates forecasting. We focus on the initiating customer trades and consider non-linearity. In a microstructure context, Gradojevic and Yang (2006) highlights the necessity of embodying information in a non-linear way. Our empirical results show that, in line with the large part of the literature, using a statistical approach to evaluate the forecasting power of the empirical exchange rates models, there is little forecasting power (in a statistical sense) when using our models.

However, the assessment of the economic value of exchange rate forecasts indicates that the predictive ability of the microstructure order flow has substantial economic value in a dynamic portfolio allocation context and that non-linear models outperform the naive RW model. We believe these are new and important results which have not been previously documented.

Appendix 4.A

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
Mean	0.277	-0.239	-0.129	-0.005	-0.0007	0.014	-0.016	-0.007	0.0097
Median	0.195	-0.212	-0.062	0.028	-0.011	0.004	-0.013	-0.0156	0.0018
Std.Dev.	1.466	0.826	0.752	0.808	0.303	0.115	0.252	0.146	0.1104
Skewness	0.946	0.801	-0.357	-3.974	0.877	1.319	0.918	1.5908	0.891
Kurtosis	11.14	10.83	2.833	34.51	6.053	13.304	9.407	8.429	7.226
Jarque-Bera	4.52	11.12	2.41	5.34	22.31	59.21	78.2	101.1	30.23
Probability	0.16	0	0.17	0.051	0	0	0	0	0
Observations	317	317	317	317	317	317	317	317	317
Source: Cerrato, Sarantis, and Saunders (2009)									

Table 4.11: Summary Statistics for Order Flow

Appendix 4.B

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
Mean	-0.001	-0.047	-5E-04	-0.0017	-0.0026	-0.0018	-0.01	-0.0129	-0.004
Median	-0.002	-0.01	-9E-04	-0.002	-0.0045	-0.0028	-0.018	-0.021	-0.007
Std.Dev.	0.011	1.518	0.0065	0.0176	0.0197	0.0131	0.1023	0.1082	0.0264
Skewness	-0.39	0.248	0.1608	0.5822	0.3058	0.4319	0.2056	0.6441	0.633
Kurtosis	-0.02	0.419	-0.052	-0.2702	0.4518	0.0509	0.2919	-0.0383	-0.036
Jarque-Bera	0.892	1.832	1.201	0.0671	18.45	1.331	1.451	20.11	1.233
Probability	0.551	0.455	0.551	0.962	0.0011	0.541	0.481	0.0002	0.541
Observations	316	316	316	316	316	316	316	316	316
Source: Cerrato, Sarantis, and Saunders (2009)									

Table 4.12: Summary Statistics for Exchange Rate Changes

7

Chapter 5

Summary and Conclusions

5.1 Summary

In the past decades a number of non-linear models have been analysed and applied in an attempt to explain a variety of financial phenomena. The introduction of ideas related to exchange rate theories and its study in other disciplines, in economics and econometrics, has given rise to a large body of applications but has failed so far to produce conclusive results. This has necessitated the examination of two important areas of research. Firstly, we have needed to develop a framework within which justification of non-linearity subject to economic constraints, and subsequent test of these constraints, may be carried out. Secondly, at the empirical level, it has required the development of tests of coefficient instability in the non-linear regression model. This study has been concerned with the estimation and testing of models under the assumption of parameter variability in the underlying theory and tailored towards the analysis of exchange rate models but of course is applicable with other areas.

Chapter 2 of this thesis focused on extending augmented Dickey-Fuller specifications to develop new tests for a unit root which allow for symmetric and asymmetric non-linear mean reversion as the alternative hypothesis. In particular, one of the basic aims of this work has been to develop a justification for model extension in the context of asymmetry, and in general non-linear models given that the need for the extension of non-linearity is established. In particular, this research has concentrated on providing extensions to econometric models and efficient estimation in the context of non-linear approaches. The applications of these tests to time series of real exchange rates against the dollar revealed significant evidence of non-linear and asymmetric mean reversion for some series, although for others the unit root null hypothesis could not be rejected. Note in addition that employing the inf-t test statistic proposed and simulated critical values presented, Monte Carlo experiments suggest that in the presence of non-linear mean reversion the tests developed in this chapter are sufficiently powerful to justify a role as general alternatives to the augmented Dickey-Fuller test.

Chapter 3 concentrated on testing the unit root null hypothesis against an alternative hypothesis of stationarity around a smooth transition in the mean. The test suggested by Leybourne, Newbold, and Vougas (1998) and Sollis (2005) was generalized to incorporate potential asymmetry in the transition. Simulation and empirical analysis revealed gains in power by employing this generalization. In the investigation K-STR was used to allow autoregressive models to capture the changes in the stochastic behaviour of exchange rates equilibrium path. A test with this type of structural change as the alternative hypothesis and a fixed unit root under the null hypothesis was developed and applied to the real exchange rates against the dollar and Deutschmark. Despite a structural change from I(0) to I(1) in these series having been an issue that has previously been widely researched, this new test reveals substantial differences not previously recognized among real exchange rates over the periods regarding a structural change of this nature.

Chapter 4 of this thesis turned to a practical application of microstructure, which is based on heterogeneity of beliefs in the forex market. For the model specifications a considerable amount of attention was directed toward a non-linear modelling methodology in outperforming a simple random walk model. The application of these tests shows that the statistical evaluation methods produce mixed results. While, when the RMSFE is used for the suggested models, the non-linear specifications are better compared to the RW model, the results of the Diebold and Mariano test show insignificant statistics. In contrast to the statistical evaluation, it is straightforward to conclude that the economic evaluation based on mean-variance portfolio optimization shows significant and non-linear application should be preferred. In support of these claims it is worth pointing out that, for a microstructure consideration, the non-linear approaches are favoured over the linear models by all information criteria used.

5.2 Conclusions

The attempts have been made to link the underlying structure of theoretical ideas to empirical models. In these investigations, extended non-linear models have been considered. In particular, we move the focus of our study away from linear models towards non-linear and asymmetric alternatives. In the course of this shift, empirical evidence has accumulated, indicating that asymmetric extension is a flexible and powerful tool capable of providing insights into and superior approximations for a number of applications. The ability of those specifications to deal with asymmetric adjustments to the equilibrium path, both in terms of direction and magnitude of the deviation from the equilibrium, provide a significant generalization over the existing non-linear specifications.

In terms of both practical and theoretical perspectives, since autoregressive models can be criticised by economists who prefer using structural time series models, it is more sensible to employ a structural time series model to explicitly allow the data to include the nature of the economic structure, rather than pretesting for the presence of a stochastic autoregressive approximation. The empirical applications undertaken for this thesis suggest that microstructure has a valuable role to play in the analysis of exchange rates, both in the general sense of offering better approximations of unknown data generation processes and allowing for more accurate forecasts, but also for their ability to reveal heterogeneous information about the impact on economic times series of specific economic policies and market imperfections.

The work here carried out introduced a variety of possible avenues for further research. Firstly, a number of extensions and modifications to the models proposed are possible. Secondly, the issues concerning efficient estimation method should be considered to minimize the computational burden. Finally, more extensive investigation of empirical model selection could be undertaken, possibly including other classes of models, such as stochastic volatility models. The incorporation of these ideas, underlying our models, in a structural time series framework would be worth investigating. The idea of specifying the model so as to allow its underlying parameters to be estimated along with the rest of the model is an issue to be investigated on its own, irrespectively of the use of a structural time series model. Additionally, the application of the econometric models to other economic series could be considered. Further, the extension of the models to a multivariate framework, where additional variables could be considered, should be fruitful. In such a framework, ideas from stochastic analysis could be coupled with volatility effects to produce more realistic exchange rate mechanisms.

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