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Fundamentals Based Exchange Rate Prediction Revisited*

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Abstract

This paper revisits the role of macroeconomic fundamentals as predictors for exchange rate movements at different horizons. It takes seriously the notion that these fundamentals are hard to measure and that the usual measures, such as monetary aggregates, price index and deflator series and GDP, are imperfect approximations of these fundamental movements. As an alternative measure of underlying fundamental movements of economies, we extract domestic and foreign dynamic $I(1)$ factors from large panels of economic data for the UK and abroad, and rotate these towards the exchange rate to get an estimate of the 'fundamental' or 'core' exchange rate level. Results for the US dollar/pound sterling exchange rate suggest that such a 'fundamental' exchange rate level serves as an attractor for the actual exchange rate, although significant and persistent deviations do occur. Using the current deviation between the two as a predictor of future movements for the US dollar/pound sterling exchange rate results in reasonably successful forecasts.

Keywords: Nominal exchange rates, forecasting, factor models, common stochastic trends.
JEL classification: C32, F30, F31, F47.

1 Introduction

Assessing future changes in exchange rates with current macroeconomic data has been of long interest to international economists as well as policy makers worldwide. Since the seminal Meese and Rogoff (1983) study, which showed the lack of predictive content of theoretical exchange rate models, the consensus has been that macroeconomic variables, such as interest rates, money aggregates, aggregate prices and real income, do not convey any information about future exchange rate movements over relatively short horizons.

A number of studies has tried to revive the use of macroeconomic variables, in particular those which are suggested by the monetary exchange rate model, in assessing *long-horizon*

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exchange rate changes. MacDonald and Taylor (1994), Mark (1995) and Chinn and Meese (1995) claim that current monetary model-based equilibrium errors can predict four-year ahead exchange rate changes and outperform the random walk model in an out-of-sample context in a 1973-1991 sample of US dollar exchange rates *vis-à-vis* Germany, Japan, Canada, and France. Notwithstanding these results, also the predictive accuracy of these monetary fundamentals at medium to long horizons has been shown to be weak, see eg Berkowitz and Giorgianni (2001) and Groen (1999). In fact, the long-run predictive power of monetary fundamentals for exchange rates seems only to be robustly present within the multi-country panel framework. Employing different techniques, Mark and Sul (2001) and Groen (2005) use panels of between 3 to 17 OECD countries to first test for cointegration between the exchange rate and monetary fundamentals, and secondly use this cointegrating relationship to successfully predict exchanges rates at horizons of three to four years.

Empirically, equilibrium errors based on theoretical models of floating exchange rate behaviour are known to be very persistent, and often are indistinguishable from unit root processes. In combination with the relatively short span of the data for the post-Bretton Woods flexible exchange rate era, this can result in standard time series-based tests of the predictive ability of fundamentals for exchange rates to fail to find any and *vice versa* for the multi-country panel-based tests.[1] This raises the question of why are these model-based equilibrium errors so persistent? One obvious answer could simply be that the set of macroeconomic variables that we economists think should eventually drive exchange rates is the wrong set of variables. On the other hand, it can also be the case that the input for our structural exchange rate relationships, ie the macroeconomic determinants, is itself measured imperfectly. For example, changes/revisions in the construction of macroeconomic time series can affect the quality of macroeconomic data. Faust *et al.* (2003) indeed show that the predictive performance of structural exchange rate models improves when original release data are used instead of fully-revised data.

We take this 'measurement error in fundamentals' argument further and relate it to the quality of the measurement of equilibrium movements in economies, as the current exchange rate level is in the literature assumed to be tied down by the present value of expected future economic activity in the home and foreign economies. Therefore, the observed breakdown on the empirical exchange rates-fundamentals link can occur because currently observed macro series provide a poor signal about the perceived equilibrium level of economic activity in an economy. At an heuristic level both Groen (2000, page 315) and Mark and Sul (2001, page 47) raised this possibility when they claim that their results indicate that monetary fundamentals are better measures of the equilibrium price levels of economies than currently observed aggregate price levels. Also, Engel and West (2005) argue that in the aforementioned present value relationship the observed fundamentals, such as money aggregates, are dominated by movements in unobservables, such as risk premia, real exchange rate shocks and money demand shocks. Hence, the current exchange rate level provides the best proxy for the perceived relative long-run development of two economies and thus should Granger-cause movements in observed macroeconomic fundamentals.

[1] See also the well known result in Shiller and Perron (1985) that the power of unit root tests to reject the null of non-stationarity critically depends on the span of the sample and not purely on the number of observations. Groen (2002) observes in Monte Carlo experiments that a panel-based cointegration testing framework has much better power to reject the null of no cointegration relative to a pure time series-based cointegration testing framework when this 'short span problem' occurs, and Berkowitz and Giorgianni (2001) show that the ability to find a cointegration relationship is crucial to find any predictive content in fundamentals.

In this paper, we attempt to show that a better measurement of the long-run determinants of economies, and hence of exchange rates, is the key to the predictive ability of fundamentals-based exchange rate relationships. Combining the different fundamentals-based forecasts into an aggregate one could be a convenient way to deal with this issue. Indeed, Wright (2003) applies Bayesian model averaging techniques to generate such an average forecast and he finds some mixed evidence that such a forecast combination can improve upon individual model-based forecasts. We, however, go a step further and claim that the determinants of economies themselves are unobserved and first have to be estimated in order to be able to end up with a fundamentals-based relationship that has predictive content for exchange rates. The dynamic factor models that recently have been introduced by Forni and Reichlin (1998), Forni *et al.* (2000) and Stock and Watson (2002a,b) for forecasting and leading indicator construction in macroeconomics, provide a means to estimate the fundamental drivers of economies. In these models, the informational content of large panels of macroeconomic and financial data are summarised in a relatively small number of (dynamic) principal components. Within such a framework, Giannone *et al.* (2005) show that fluctuations in the US economy are driven by two 'primitive shocks', one nominal and one real in nature, and that by tracking these two 'primitive shocks' one can track the fundamental dynamics of the US economy.

Building on insights from the dynamic factor literature, in particular Bai (2004), we estimate the 'primitive stochastic trends' of economies, which basically are I(1) equivalents of the Giannone *et al.* (2005) 'primitive shocks', to construct 'fundamental' exchange rate levels. On a quarterly 1975-2004 sample we show for the US dollar/pound sterling exchange rate that these 'fundamental' exchange rate levels do track the actual exchange rate pretty well. Also, we show that the current gap between the 'fundamental' and actual exchange rate is a superior forecaster for exchange rate changes *vis-à-vis* naive random walk and autoregressive forecasts, even at horizons of less then two years.

The plan for the remainder of this paper is as follows. In Section 2 we describe how one can link exchange rate levels to the present value of expected future values of macroeconomic fundamentals. By introducing measurement error in these fundamentals, this present value framework provides us with a motivation for our dynamic factor approach. The econometric framework is explained in Section 3 and this section we also estimate the 'primitive stochastic trends' for our economies. We assess in Section 4 whether 'fundamental' exchange rate levels based on these 'primitive stochastic trends' are linked to actual exchange rate movements. In Section 5 we test the predictive ability of the current 'fundamental'-actual exchange rate gap relative to the random walk model in an out-of-sample context. Finally, we end with concluding remarks in Section 6.

2 Exchange rates and macroeconomic fundamentals

One of the most clearest descriptions of the exchange rate being a product of asset price formation can be found in Mussa (1976), which centers on the notion that the exchange rate reflects the market expectation of the relative value of two national currencies, each of which can be seen as assets, now and in the future. And as the value of a currency is determined by its purchasing power, the exchange rate essentially equals the market perception about the long-run value of the relative price level for two economies. Each national price level in turn is driven by a *nominal factor* F_t^{Nominal} related to the demand side of an economy, which has a positive impact on the price level, and a *real factor* F_t^{Real} related to the supply side of the economy, which has a negative impact, and thus the exchange rate is based on the market estimate of the long-run values of these factors at home and abroad.

In the literature, one usually attempts to associate each of the home factors, F_t^{Nominal} and F_t^{Real}, and foreign factors, $F_t^{\text{Nominal}^*}$ and $F_t^{\text{Real}^*}$,[2] with observed variables in order to impose structure on the analysis. The monetary exchange rate model of, for example, Mussa (1976) is a widely used framework within one can do that. In this framework, the aggregate price level is related to other quantities is through a stable standard money demand function, which in logarithms reads like

$$m_t - p_t = \eta + \delta y_t - \omega i_t + \nu_t \tag{1}$$

where m_t, p_t and y_t are the logarithms of the quantity of money, the price level and real income in period t respectively, i_t is a nominal interest rate, ν_t is a zero-mean $I(0)$ disturbance, η is a constant, $\delta \geq 0$ and $0 \leq \omega \leq 1$. Assuming that an identical relationship as (1) holds abroad, one can combine these with purchasing power parity [PPP],

$$s_t = \mu + (p_t - p_t^*) + \varpi_t \tag{2}$$

where s_t is the logarithm of the nominal exchange rate and ϖ_t is a zero-mean $I(0)$ disturbance, as well as uncovered interest rate parity (UIP)

$$E_t(\Delta s_{t+1,t}) = (i_t - i_t^*) + \rho_t \tag{3}$$

In (3) $E_t(.)$ denotes the conditional expectation in period t, $\Delta s_{t+1,t} = s_{t+1} - s_t$ and ρ_t is a zero-mean $I(0)$ disturbance. All this combining results in:

$$s_t = \mu + \frac{1}{1+\omega}[\underbrace{(\eta + m_t - \delta y_t)}_{f_t} - \underbrace{(\eta^* + m_t^* - \delta^* y_t^*)}_{f_t^*} + (\varpi_t - \nu_t + \nu_t^*)] + \frac{\omega}{1+\omega}[E_t(s_{t+1}) + \rho_t] \tag{4}$$

Recursive forward substitution of (4) yields

$$s_t = \mu + \frac{1}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t[f_{t+j} - f_{t+j}^* + (\varpi_{t+j} - \nu_{t+j} + \nu_{t+j}^*)] + \frac{\omega}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(\rho_{t+j}) \tag{5}$$

When one subtracts $(f_t - f_t^*)$ from both the left hand right hand sides of (5), one gets after rearranging[3]

$$s_t - (f_t - f_t^*) = \mu + \sum_{j=1}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t[\Delta f_{t+j} - \Delta f_{t+j}^*] + \frac{1}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(\varpi_{t+j} - \nu_{t+j} + \nu_{t+j}^*) + \frac{\omega}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(\rho_{t+j}) \tag{6}$$

[2]In the following, a starred variable indicates the equivalent variable for the foreign economy.

[3]See eg Campbell *et al.* (1997, Chapter 7) for more details on how to derive this relationship.

It is a well documented fact that macroeconomic variables such as money aggregates and real income as well as nominal exchange rates are $I(1)$ series,[4] and thus (6) implies that the log exchange rate and the log monetary fundamentals are cointegrated, as the right hand side equals a combination of $I(0)$ variables. The resulting equilibrium error term $s_t - (f_t - f_t^*)$ can therefore be used to predict future changes in exchange rates and monetary fundamentals. From (5) and (6) it can be observed that within the structure of the monetary model F_t^{Nominal} ($F_t^{\text{Nominal}^*}$), ie the nominal drivers of the home and foreign price levels, is proxied by the domestic (foreign) money aggregate and F_t^{Real} ($F_t^{\text{Real}^*}$), ie the real drivers of the home and foreign price levels, by the domestic (foreign) real income.

There are, however, several reasons to believe that linking up these long-run drivers of the exchange rate with observables like money aggregates and real income can be unwise. Both on the nominal as well as the real sides of the economy there are examples of issues like 'what is the correct measure of liquidity/money used in transactions?', 'what is the correct measure of the aggregate price level?', 'what is the correct measure of the real consumption level?' or 'how to measure production technology?'. Issues like this result in a set of fundamentals that is measured with error, and this affects the present value relationship that prices the exchange rate in the sense that not only money demand, PPP and UIP deviations are unobserved, but also F_t^{Nominal}, $F_t^{\text{Nominal}^*}$, F_t^{Real} and $F_t^{\text{Real}^*}$; see Engel and West (2005) who partially impose that. Therefore, instead of (5) there is in reality a pricing relationship like

$$s_t = \mu + \frac{1}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t[(f_{t+j}+z_{t+j}) - (f_{t+j}^* + z_{t+j}^*) + (\varpi_{t+j} - \nu_{t+j} + \nu_{t+j}^*)] + \frac{\omega}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(\rho_{t+j}) \quad (7)$$

where z_t and z_t^* are the (unobserved) measurement errors of the home and foreign monetary fundamentals relative to the 'true' nominal and real long-run drivers of the home and foreign price levels, ie F_t^{Nominal}, $F_t^{\text{Nominal}^*}$, F_t^{Real} and $F_t^{\text{Real}^*}$. To make (7) an empirically viable relationship, we assume that for each economy there are a large number of macroeconomic and financial series that contain at least partially information about F_t^{Nominal} and F_t^{Real} as well as the measurement errors relative to these long-run determinants of the aggregate price level, both in the present and at leads and lags. From these series we extract two dynamic factors $(\hat{F}_{1t} \quad \hat{F}_{2t})'$ that represent the current long-run prediction for F_t^{Nominal} and F_t^{Real}, and these basically serve as proxies for the present value of the fundamentals plus their error in (7), ie

$$\frac{1}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(f_{t+j}+z_{t+j}) \approx H\begin{pmatrix}\hat{F}_{1t}\\ \hat{F}_{2t}\end{pmatrix}$$

and

$$\frac{1}{1+\omega}\sum_{j=0}^{\infty}\left(\frac{\omega}{1+\omega}\right)^j E_t(f_{t+j}^*+z_{t+j}^*) \approx H^*\begin{pmatrix}\hat{F}_{1t}^*\\ \hat{F}_{2t}^*\end{pmatrix}$$

where H and H^* are 2×2 rotation matrices. In the next section we shall discuss how one can estimate these dynamic factors $(\hat{F}_{1t} \quad \hat{F}_{2t})'$ and $(\hat{F}_{1t}^* \quad \hat{F}_{2t}^*)'$.

[4]See, for example, de Vries (1994).

3 A generalised dynamic $I(1)$ factor framework for our economies

In the previous section we argued that in practice it is unlikely that we can explicitly link the long-run nominal and real determinants of an economy's aggregate price level to a particular set of variables. Instead, pieces of information about these long-term determinants can be 'spread out' over a large number of series, and one needs to find a way to synthesise all this information in order to get an estimate of the nominal and real fundamental drivers of the economy. A convenient way to do that is to employ factor models, which have been shown to be efficient in aggregating information across a large number of series. In the remainder of this section we explain the framework through which we extract factors for each of our economies in Section 3.1, the underlying data for each of the economies' dynamic factor models are briefly discussed in Section 3.2 and this subsection also describes the fundamental factors that drive each economy.

3.1 Methodology

For a certain economy we have N $I(1)$ data series: $X_{it};\ i = 1, \ldots, N,\ t = 1, \ldots, T$, and these N series are driven by r factors $F_t = (F_{1t} \cdots F_{rt})'$ with $r < N$. One can assume that the relationship between the X_{it}'s and F_t is static, ie purely contemporaneous, or dynamic where F_t also affect the X_{it}'s with leads and lags. We follow Forni *et al.* (2000) and assume the latter, ie

$$X_{it} = \lambda'_{i0} F_t + \lambda'_{i1} F_{t-1} + \cdots + \lambda'_{ip} F_{t-p} + e_{it}; \quad e_{it} \sim I(0),\ E(e_{it}) = 0 \tag{8}$$

where

$$F_t = F_{t-1} + u_t; \qquad u_t \sim I(0),\ E(u_t) = 0$$

The structure of the dynamic factor model in (8) obeys the Chamberlain and Rothschild (1983) approximate factor structure, which allows for weak cross-section correlation across the e_{it}'s, and (8) also allows for the possibility of heteroskedasticity in the e_{it}'s both over the cross-section dimension $i = 1, \ldots, N$ as well as the time series dimension $t = 1, \ldots, T$.

The dynamic structure in (8) is convenient as it allows for primitive shocks to affect different sectors of the economy at different times and it allows for transmission effects, and therefore estimates of F_t characterise the long-run dynamics of the economy. Applying the standard principal components approach as in Stock and Watson (2002a,b), ie first difference the X_{it}'s and then extracting the principal components, will not yield the r dynamic factors, but rather it results in $r + rp$ principal components that summarise both the contemporaneous and lagged impact of the dynamic factors F_t on the X_{it}'s in (8). Alternatively, one can use the Forni and Reichlin (1998) and Forni *et al.* (2000) dynamic principal components approach on the ΔX_{it}'s, where the lead/lag effects are essentially filtered out before principal components is applied. However, our preference is to preserve the data in levels, as our economic understanding more often than not relates to the fundamental level of the exchange rate. Hence, we follow Bai (2004) and extract the dynamic factors in an $I(1)$ context.

In estimating the r dynamic factors F_t, we rewrite (8) in error correction form:

$$X_{it} = \gamma'_{i0} F_t - \gamma'_{i1} \Delta F_{t-1} - \cdots - \gamma'_{ip} \Delta F_{t-p} + e_{it}, \tag{9}$$

where $\gamma_{ik} = \lambda_{ik} + \lambda_{i,k+1} + \cdots + \lambda_{ip}$. A super-consistent estimate of the r dynamic factors F_t equals the r eigenvectors that corresponds with the first r largest eigenvalues of

$$\frac{XX'}{T^2 N} \tag{10}$$

where $X = (X_1 \cdots X_N)$ and $X_i = (X_{i1} \cdots X_{iT})'$ for $i = 1, \ldots, N$, and we denote the corresponding $T \times r$ matrix of the estimated dynamic factors with $\tilde{F}$. The corresponding $N \times r$ matrix of loading factors equals $\boldsymbol{\gamma}_0 = X'\tilde{F}diag(T^{-2})$, and both the estimated dynamic factor $\tilde{F}$ and $\boldsymbol{\gamma}_0$ are mixed normal distributed.[5] Consistent estimates of $\Delta F_{t-1} \cdots \Delta F_{t-p}$ equal the rp eigenvectors that correspond with the $r+1, \ldots, r+rp$ largest eigenvalues of

$$\frac{XX'}{TN} \tag{11}$$

and these are assembled in a $T \times rp$ matrix $\tilde{G}$. An estimate of *all* the loading factors in (9) $\boldsymbol{\gamma} = X'(\tilde{F} \quad \tilde{G})diag(T^{-2},\ T^{-1})$, where loading factor matrix $\boldsymbol{\gamma}$ has the dimension $N \times (r + rp)$.

Up to now we have outlined the way through which we will estimate the dynamic factors that determine the long-run behaviour of our economies. The utilised approach, however, assumes that one knows the correct number of dynamic factors r. We shall now discuss a method through which one can determine r in a super-consistent way.

In the case of determining the number of factors extracted from $I(0)$ series, Bai and Ng (2002) provide a set of information criteria, ie

$$\begin{aligned} PC1 &= \ln(V(k)) + \alpha(T)k\left(\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right)\right) \\ PC2 &= \ln(V(k)) + \alpha(T)k\left(\left(\frac{N+T}{NT}\right)\ln C_{NT}^2\right) \\ PC3 &= \ln(V(k)) + \alpha(T)k\left(\frac{\ln(C_{NT}^2)}{C_{NT}^2}\right) \end{aligned} \tag{12}$$

In (12) k is a given number of factors, $C_{NT}^2 = min(N, T)$, a consistent estimate of the variance of the idiosyncratic components of the individual series based on k factors equals $V(k) = (\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{e}_{it})/NT$ and $\alpha(T) = 1$. Starting with a given upper bound for k, k_{max}, for each of the criteria in (12) a consistent estimate of the number of factors is the one that minimises the value of the criterion over $k = 1, \ldots, k_{max}$. As mentioned in the previous subsection, applying the criteria in (12) on first differences of our N $I(1)$ series, ie ΔX_{it} for $i = 1, \ldots, N$, will not provide a consistent estimate of the number of dynamic $I(1)$ factors r but rather the number of dynamic factors and their lag order $r + rp$. However, Bai (2004) shows that criteria like (12) applied on the $I(1)$ in levels in the context of (9) and with $\alpha(T) = T/(4\ln\ln(T))$ in stead of $\alpha(T) = 1$ will provide a (super-)consistent estimate of the number of dynamic factors r; we will denoted these adjusted versions of the criteria in (12) with $IC1$, $IC2$ and $IC3$ respectively.

3.2 The data and results

In this draft we focus on the US dollar/pound sterling exchange rates, and thus we will have to estimate the fundamental drivers of both the UK and US economies. We use quarterly data starting in the first quarter of 1975 and ending in the last quarter of 2004, and this sample covers a major part of the post-Bretton Woods era of floating exchange rates.

For both economies we use series that represent the broad spectrum of aggregate economic activity, ranging from components of GDP, industrial production and consumer price indices to

[5] That is, conditional on the correct number of dynamic factors r, $\tilde{F}$ and $\boldsymbol{\gamma}_0$ have a standard asymptotic distribution; see Bai (2004, Theorem 6).

components of nominal aggregates like M3 and banking loans. We have chosen the series such that in levels they are inherently $I(1)$, which rules out most survey data as well as unemployment data. Despite the fact that short-term and long-term interest rates are also $I(0)$, we do not exclude these from the sample as they contain important forward-looking information about agent's perceptions of future real and nominal trends. We therefore convert the interest rate series to quarterly frequencies and accumulate them to get $I(1)$ series.

In case of the United Kingdom we use in total 86 time series to estimate the dynamic factors that drives the UK economy. Without going into specific details these series comprise several components of the industrial production index, components of producer price, consumer price and retail price indices, components of export and import volumes, terms of trade, retail sales, components of M0 and M4 money aggregates (including lending), accumulated interest rates at maturities of 3 months, 1 year, 3 years, 5 years and 10 years, as well as several stock price indices ranging from the overall FTSE-250 to sub-indices that represent different sectors of the economy. With the exception of the interest rate data and stock price data, which we acquired from *Global Financial Data*, these data are from the data that underlies the analysis in Kapetanios *et al.* (2005), and the reader can find more details regarding the sources of the data in that paper. The US dynamic factors are extracted from data set of 91 series, which contains series comparable to those used for the UK plus in addition to that data on components of more money aggregates (in total we look for the US at the components of M1, M2, M3 and MZM as well as base money), outstanding bank loans to different sectors and employment surveys. These data, again with the exception of the interest rate and stock price data which we got from *Global Financial Data*, were obtained from the FRED® database at the Federal Reserve Bank of St. Louis. A more complete outline of the data used to estimate the dynamic factors of the respective economies can be found in Appendix A.

We are now able to apply the procedure as outlined in Section 3.1 on the data described in Section 3.2 to estimate the fundamentals drivers of the UK and US economies. In doing so, we first apply the Bai and Ng (2002) $PC1$, $PC2$ and $PC3$ criteria on the first differences of the series in order to determine the total number of dynamic factors and their lags $r + rp$, where we start with an upper bound of 12 principal components. Secondly, having determined $r + rp$ through the $PC1$, $PC2$ and $PC3$ criteria, we use the Bai (2004) $IC1$, $IC2$ and $IC3$ criteria on the levels of the series, with the estimated $r + rp$ as an upper bound, to determine the number of dynamic factors r. To avoid scale effects that can contaminate the estimation of the principal components, we follow Stock and Watson (2002a,b) and both demean and standardised the log first differences of the series to determine $r + rp$ via the $PC1$, $PC2$ and $PC3$ criteria. Complimentary to that, we use detrended, standardised logs of the levels of the series to determine r via the $IC1$, $IC2$ and $IC3$ criteria.

Applying the Bai and Ng (2002) $PC1$, $PC2$ and $PC3$ criteria on the first differences of the series for the United Kingdom, starting with an upper bound equal to 12 principal components, results in a selection of 6 principal components using the $PC1$ and $PC2$ criteria and 5 based on the $PC3$ criterion. In case of the United States, the $PC1$ and $PC2$ criteria also select 6 principal components for the first differenced data, whereas the $PC3$ criterion selects in this case 8 principal components. Bai and Ng (2002) argue that their $PC3$ criterion has poorer finite sample properties than $PC1$ and $PC2$, and thus we conclude that for both the United Kingdom and the United States the dynamics of the first differences of the series can be described by 6 principal components. Hence, for both economies we have $r + rp = 6$, ie the total number of dynamic factors and their lags equals six.

Using the Bai (2004) $IC1$, $IC2$ and $IC3$ criteria on the levels of the series in the UK and US panels respectively, starting with an upper bound equal to 6, we select for both economies the appropriate number of dynamic factors r. For the United Kingdom, this procedure results in $r = 2$ based on $IC1$ and $IC2$, and $r = 1$ using $IC3$. The criteria $IC1$, $IC2$ and $IC3$ unanimously select $r = 2$ for the United States. Therefore, we set for each economy the number of dynamic $I(1)$ factors equal to 2.

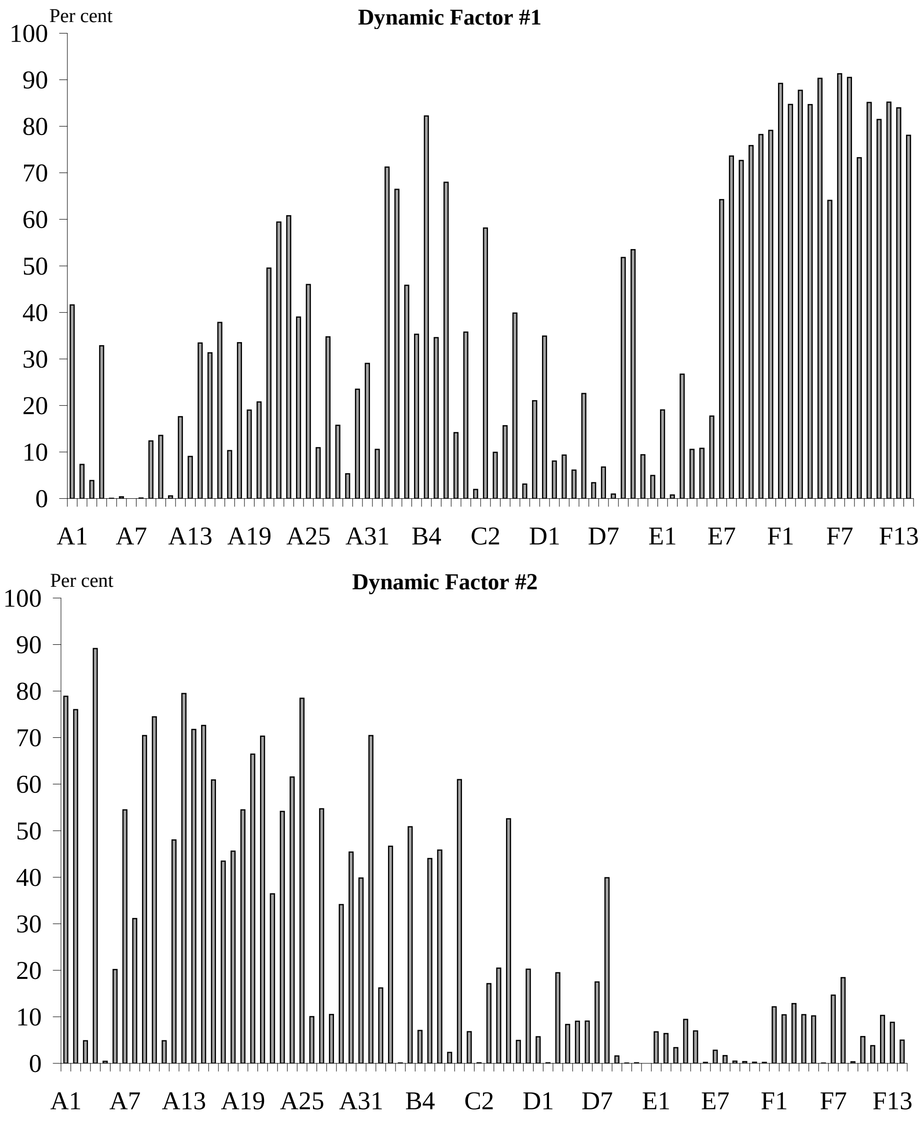
Although we now have established that the UK and US economies are fundamentally driven by two dynamic $I(1)$ factors, it would also be useful to give some kind of economic meaning to each of these factors. In order to be able to do that we approximate the faction of variability in each component of an economy's data panel that is explained by each of the factors by computing the squared long-run correlation between the relative change in an individual series with the first difference of each of the dynamic factors. This long-run correlation is determined through the long-run covariance matrix between demeaned ΔX_{it} (ΔX^*_{it}) and respectively ΔF_{1t} (ΔF^*_{1t}) and ΔF_{2t} (ΔF^*_{2t}) for each $i = 1, \ldots, N(N^*)$, which is estimated with the approach of Newey and West (1987, 1994). The resulting squared long-run correlations can be found in Chart 1 for the United Kingdom and in Chart 2 for the United States. From these charts it becomes clear that for both economies the first dynamic factor mainly explains the variation in price and interest rate series, whereas the second dynamic mainly explains the variation in GDP components, other real series and labour market series and not at all with the price and interest rate series. This leads us to interpret the first dynamic $I(1)$ factor as a nominal long-term factor that in essence measures the accumulation of core inflation, and the second dynamic (1) factor as a real long-term factor.

In summary, our sequential selection procedure, applied on both the first differences as well as the levels of the series in the UK and US panels, suggests that the dynamics of both the UK and US economies can be approximated by 2 dynamic $I(1)$ factors, which influence the individual series up to a lag order equal to 2. Looking at the co-movement of these dynamic factors with the individual series for each economy, we interpret these dynamic factors as proxies for equilibrium nominal and real trends of each economy. This result is in compliance with the analysis in Giannone *et al.* (2005), where it is shown for the United States that the dynamics of large panel of US macroeconomic data is related to the dynamics in two 'primitive shocks', one real and one nominal, which are extracted from that panel with dynamic factor techniques. Hence, we believe that for both the United Kingdom and the United States our two dynamic $I(1)$ factors are good approximations for the long-run real and nominal dynamics of both economies, and as such they can be considered as the 'primitive stochastic trends' of the respective economies.

4 Approximating 'fundamental' exchange rates

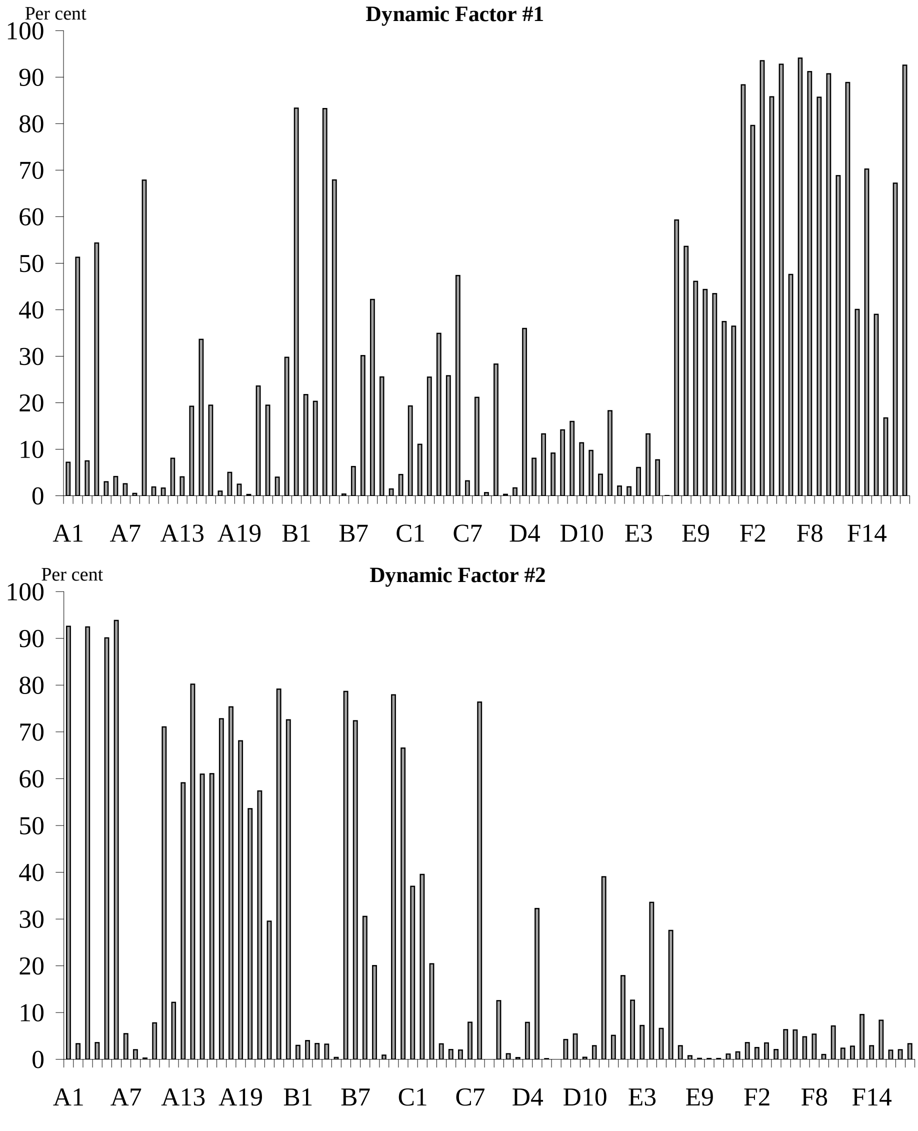
Having shown in the previous section that the fundamental movements of the UK and US economies can be approximated by two dynamic factors, which are estimated from a multitude of macroeconomic and financial series, we now have to show whether these proxies for the long-term fundamentals can be successfully mapped into the observed exchange rate movements. The methodology through which we attempt to do that is outlined in Section 4.1, whereas the results for the US dollar/pound sterling exchange rate can be found in Section 4.2.

Figure 1: Squared long-run correlations of the individual UK detrended series with the estimated dynamic factors



The upper (lower) graph depicts the squared long-run correlations between the first differenced individual series and the first difference of the first (second) dynamic $I(1)$ factor, where the long-run correlation is computed using the procedures from Newey and West (1987, 1994). The series are categorised in six groups, ie A: real/GDP components, B: labour market, C: international, D: money and credit, E: financial prices and F: prices; see Appendix A for more details on these series.

Figure 2: Squared long-run correlations of the individual US detrended series with the estimated dynamic factors



The upper (lower) graph depicts the squared long-run correlations between the first differenced individual series and the first difference of the first (second) dynamic $I(1)$ factor, where the long-run correlation is computed using the procedures from Newey and West (1987, 1994). The series are categorised in six groups, ie A: real/GDP components, B: labour market, C: international, D: money and credit, E: financial prices and F: prices; see Appendix A for more details on these series.

4.1 Methodology

Along the lines of the framework outlined in Section 2, we use the two estimated dynamic factors for both the home and foreign economies to approximate the current exchange rate as the present value of the currently expected future nominal and real dynamics of the respective economies, which represents the current 'fundamental' exchange rate level. We can achieve this approximation by rotating the estimated home dynamic factors, $\hat{F}_t = (\hat{F}_{1t}\ \hat{F}_{2t})$, as well as the estimated foreign dynamic factors, $\hat{F}_t^* = (\hat{F}_{1t}^*\ \hat{F}_{2t}^*)$, towards the log spot exchange rate s_t, ie

$$s_t = \alpha + \delta' \begin{pmatrix} \hat{F}_t \\ \hat{F}_t^* \end{pmatrix} + error \tag{13}$$

suggesting a 'fundamental' or 'core' exchange rate level equal to

$$s_t^c = \hat{\alpha} + \hat{\delta}' \begin{pmatrix} \hat{F}_t \\ \hat{F}_t^* \end{pmatrix} \tag{14}$$

Inference on the parameter estimates in (14) is in itself not very informative, as the dynamic factors themselves are estimated up to a rotation.[6] But one can construct confidence intervals around our approximated 'fundamental' exchange rate levels, which reflect both the uncertainty about the fit between realised log exchange rate s_t and its 'fundamental' approximation s_t^c as well as the uncertainty about the accuracy of our estimated dynamic factors for the respective economies. In constructing these confidence intervals, we adapt the framework from Bai and Ng (2006) for $I(1)$ factors.

We can view (13) as a 'in-sample prediction' relationship, and therefore we can follow Bai and Ng (2006) and write the asymptotic 90% confidence interval for s_t^c as

$$(s_t^c - 1.65C_t, \quad s_t^c + 1.65C_t) \tag{15}$$

where

$$C_t^2 = \hat{\sigma}_\varepsilon^2 \hat{z}_t'(\hat{z}'\hat{z})^{-1}\hat{z}_t + \frac{1}{N}(\hat{\delta}_1\ \hat{\delta}_2)Var(F_t)(\hat{\delta}_1\ \hat{\delta}_2)' + \frac{1}{N^*}(\hat{\delta}_1^*\ \hat{\delta}_2^*)Var(F_t^*)(\hat{\delta}_1^*\ \hat{\delta}_2^*)' \tag{16}$$

In (16) $\hat{z}_t = (1 \quad \hat{F}_t' \quad \hat{F}_t^{*'})'$, $\hat{z} = (\hat{z}_1 \cdots \hat{z}_T)$ and N (N^*) is the number of series in the panel of macroeconomic data for the home (foreign) economy. Also, $\hat{\sigma}_\varepsilon^2$ measures the variance of the rotation of the home and foreign factors F_t and F_t^* towards the log exchange rate s_t. Note that in (13) both s_t as well as the dynamic factors are $I(1)$ variables, which implies that (13) can be interpreted as a cointegrating relationship. This complicates the estimation of $\hat{\sigma}_\varepsilon^2$ and it cannot be simply estimated as the variance of the residuals of an OLS estimate of (13), as the dynamic misspecification of (13) assures that this particular variance estimator is inconsistent due to potential endogeneity between s_t, F_t and F_t^* as well as residual serial correlation. Instead we estimate $\hat{\sigma}_\varepsilon^2$ as

$$\hat{\sigma}_\varepsilon^2 = \hat{\sigma}_\nu^2/(1 - \sum_{j=1}^{p} \rho_i)^2 \tag{17}$$

[6] Generally that always is the case for dynamic factor models, see eg Bai (2003).

from

$$\hat{\varepsilon}_t = \sum_{j=1}^{p} \rho_j \hat{\varepsilon}_{t-j} + \nu_t \tag{18}$$

which corrects for any residual correlation in (13) due to dynamic misspecification. In (18) the $\hat{\varepsilon}_t$ variable results from a Stock and Watson (1993) dynamic OLS (DOLS) version of (13)

$$s_t = \hat{\alpha} + \hat{\delta}'(\hat{F}_t \quad \hat{F}_t^*)' + \sum_{j=-q}^{q} \hat{\chi}_j'(\Delta \hat{F}_{t-j} \quad \Delta \hat{F}_{t-j}^*)' + \hat{\varepsilon}_t \tag{19}$$

and this specification deals with potential endogeneity.

The confidence interval (15) also reflect the uncertainty with which the home and foreign dynamic factors are estimated, ie $Var(F_t)$ and $Var(F_t^*)$. We adapt the CS-HAC variance estimator outlined in Bai and Ng (2006):[7]

$$Var(F_t) = \hat{V}^{-1}\hat{\Gamma}\hat{V}^{-1}; \quad \hat{\Gamma} = \frac{1}{\sqrt{N}} \left(\sum_{i=1}^{\sqrt{N}} \hat{\Gamma}_i \right) \tag{20}$$

with $\hat{V}^{-1}$ is a $r \times r$ diagonal matrix with the inverted r largest eigenvalues of $X'X/(T^2N)$, see (9) and (10), on its diagonal and

$$\hat{\Gamma}_i = \frac{1}{\sqrt{N}} \sum_{i=1}^{\sqrt{N}} \sum_{j=1}^{\sqrt{N}} \hat{\gamma}_{0i}\hat{\gamma}_{0j}' \frac{1}{T} \sum_{t=1}^{T} \hat{e}_{i,t}\hat{e}_{j,t} \tag{21}$$

where $\hat{e}_{i,t}$ and $\gamma_{0i} = \lambda_{0i} + \lambda_{1i} + \cdots + \lambda_{pi}$ results from an estimate of (9). Estimator (21) is the CS-HAC variance estimator, which is robust to heteroskedasticity and weak cross-correlation, and because of the weak correlation assumption underlying the factor model, this estimator computes the variance over a random subset, consisting of $\sqrt{N}$ series, of the N residuals $\hat{e}_{1,t}, \ldots, \hat{e}_{N,t}$ from (9). In order to decrease the impact of the random nature with which the subset of residuals are selected, we repeat the computation of (21) $\sqrt{N}$ times and take the average; see (20).

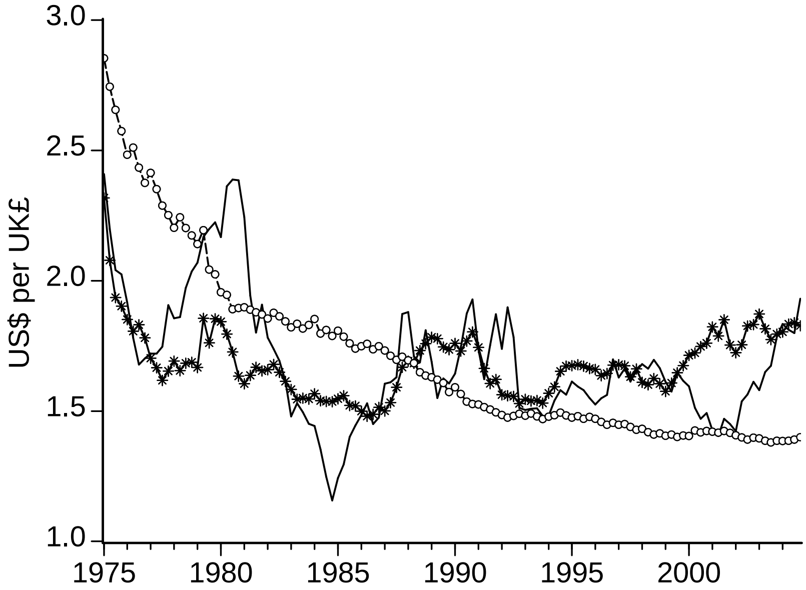
4.2 Results

We are now able to investigate whether our measure of the 'fundamental' exchange rate tracks actual exchange rate movements well. We focus in this draft on the US dollar/pound sterling exchange rate[8] over a quarterly 1975-2004 sample, and this sample spans a representative part of the post-Bretton Woods era of floating exchange rates. As outlined in more detail in the previous section, our measure of the 'fundamental' exchange rate is constructed by rotating the two dynamic $I(1)$ factors for each of the UK and US economies, as estimated in Section 3.2, towards the corresponding bilateral exchange rate through 13.

[7] Obviously, the same estimator is used for F_t^* but for notational convenience we only discuss it below for the F_t case.

[8] In the following, the United States is considered as the home country, whereas the United Kingdom is considered as the foreign country. Therefore, an increase in this exchange rate indicates that pound sterling has appreciated *vis-à-vis* the US dollar, and *vice versa*.

Figure 3: Actual, 'fundamental' and PPP-based levels of US dollar/pound sterling exchange rate; 1975.I-2004.IV



The solid line represents the actual US dollar/pound sterling exchange rate, the line with stars is 'fundamental' level of this exchange rate, constructed by rotating the two estimated US dynamic factors and the two estimated UK dynamic factors towards the exchange rate, and the line of with circles is the exchange rate level consistent with PPP, constructed using US and UK GDP deflators.

In Chart 3 we have plotted for the US dollar/pound sterling exchange rate the log of the realised spot exchange rate s_t, the 'fundamental' level that results from rotating s_t towards the four UK and US dynamic factors, ie s_t^c, as well as an alternative to s_t^c in the form of an exchange rate level consistent with purchasing power parity (PPP), which is constructed using US and UK GDP deflators as proxies for the respective aggregate price levels. A striking feature of this chart is that, at least at first sight, the actual exchange rate seems to track our factor-based 'fundamental' measure s_t^c better than more traditional measures of fundamental exchange rate movements such as the PPP measure. In fact, despite some large deviations between the two, the low frequency movements in the actual exchange rate appears to be approximated pretty well by s_t^c. This warrants a more thorough analysis to the fit of s_t^c for the actual US dollar/pound sterling exchange rate.

As pointed out in Section 4.1, when there is a significant fit between the log exchange rate s_t and the dynamic factor rotation-based s_t^c measure, this implies that the two variables are cointegrated. More precisely, for the s_t^c confidence intervals based on (16) to be valid the existence of cointegration between s_t and s_t^c is imperative. An indication for this can be obtained by testing for cointegration between s_t and s_t^c within the Johansen (1991) vector error correction

(VEC) model framework, ie

$$\Delta Z_t = \boldsymbol{\alpha} \left(\boldsymbol{\beta}' \quad -\boldsymbol{\beta_0}'\right) \tilde{Z}_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t \tag{22}$$

In (22), the 2×1 vector Z_t is given by:

$$Z_t = (s_t \quad s_t^c)'$$

$\Delta Z_t = Z_t - Z_{t-1}$, $\tilde{Z}_{t-1} = (Z_{t-1}' \ 1)'$ and ε_{it} is a 2×1 vector of white noise disturbances. The $1 \times q$ vector $\boldsymbol{\beta_0}$ is a vector of intercept terms, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $2 \times q$ matrices of adjustment parameters and cointegrating vectors, respectively, and q is the cointegrating rank value of VEC model (22). In this context testing for cointegration is done through likelihood ratio tests for $H_0 : q = 0$ (ie absence of error correction terms in (22)) versus $H_0 : q = 2$ as well as for $H_0 : q = 1$ (ie one cointegrating relationship in (22)) versus $H_0 : q = 2$. The results of this analysis can be found in Table 1 and these suggest that s_t and s_t^c are cointegrated and also that they are proportional to each other in the long-run. Interestingly, the results in the lower panel of Table 1 also suggests that the actual exchange rate does all the adjustment to close the gap between s_t and s_t^c.

At this stage, it is useful to take a more detailed look at the fit between s_t and s_t^c in Chart 4. This chart plots the actual and dynamic factor rotation-based 'fundamental' exchange rate levels as well as the asymptotic 90% confidence intervals around the latter, which are computed through (16). From it we can conclude that over the 1975-2004 sample the bulk of the US dollar/pound sterling movements were most likely in line with the underlying macroeconomic fundamentals although we do observe occasionally significant under- and overvaluation of pound sterling *vis-à-vis* the US dollar, such around 1985 as well as during the dollar appreciation over the 2000-2002 period.

Finally, it is of interest to assess the importance of the respective nominal and real factors in driving the dynamics of the factors-based 'fundamental' exchange rate. We show this decomposition in Chart 5 for the 'fundamental' US dollar/UK pound sterling exchange rate. What becomes clear from this chart is that the UK and US nominal factors have been the principal driving forces behind the movements in s_t^c as shown in Chart 4.

5 Out-of-sample evaluation

Since the seminal paper of Meese and Rogoff (1983) on out-of-sample evaluation of structural models for nominal exchange rate behaviour, it has become an accepted norm that random walk forecasts dominate fundamentals-based forecasts. A description of our out-of-sample evaluation methodology can be found in Section 5.1. The results are reported in Section 5.2.

5.1 Methodology

Meese and Rogoff (1983) compared post-sample predictions for monetary exchange rate model specifications with those of a random walk or 'no change' model at forecasting horizons up to one year. Chinn and Meese (1995) and Mark (1995) conduct a similar exercise in which they compare the out-of-sample exchange rate change predictions of current error-correction terms, based on monetary exchange rate model specifications, with those of the random walk

Table 1: Cointegration tests between s_t and s_t^c (14) for the US dollar/pound sterling exchange rate; 1975.I-2004.IV

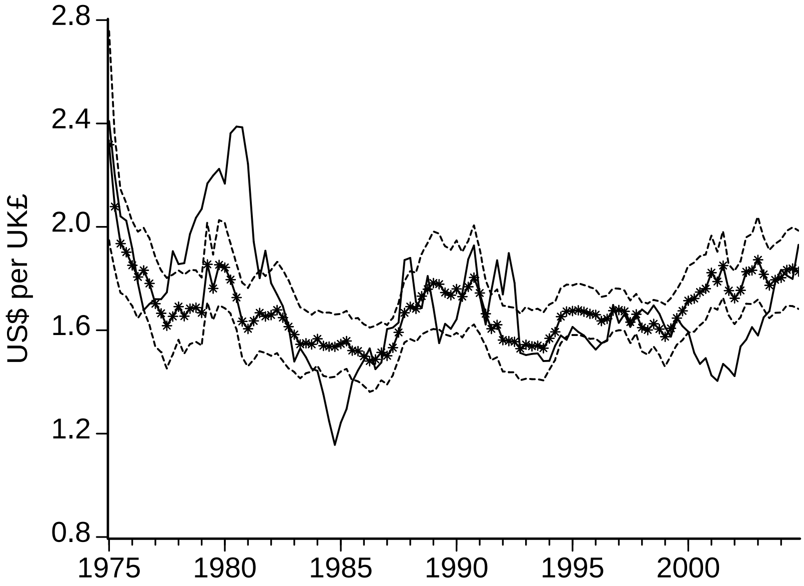
p	q	LR(q|2)	90%	95%	99%
8	0	21.23**	17.79	19.99	24.74
	1	6.74	7.50	9.13	12.73

$$\hat{\beta} = (1 \quad -1.27^{**} \quad 0.42)'$$
$$se(\beta_{s^c}) = 0.56 \qquad se(\beta_c) = 0.94$$
$$[0.68]$$

$$\hat{\alpha} = (-0.17^{***} \quad -0.01)'$$
$$se(\alpha_{\Delta s}) = 0.05 \qquad se(\alpha_{\Delta s^c}) = 0.02$$

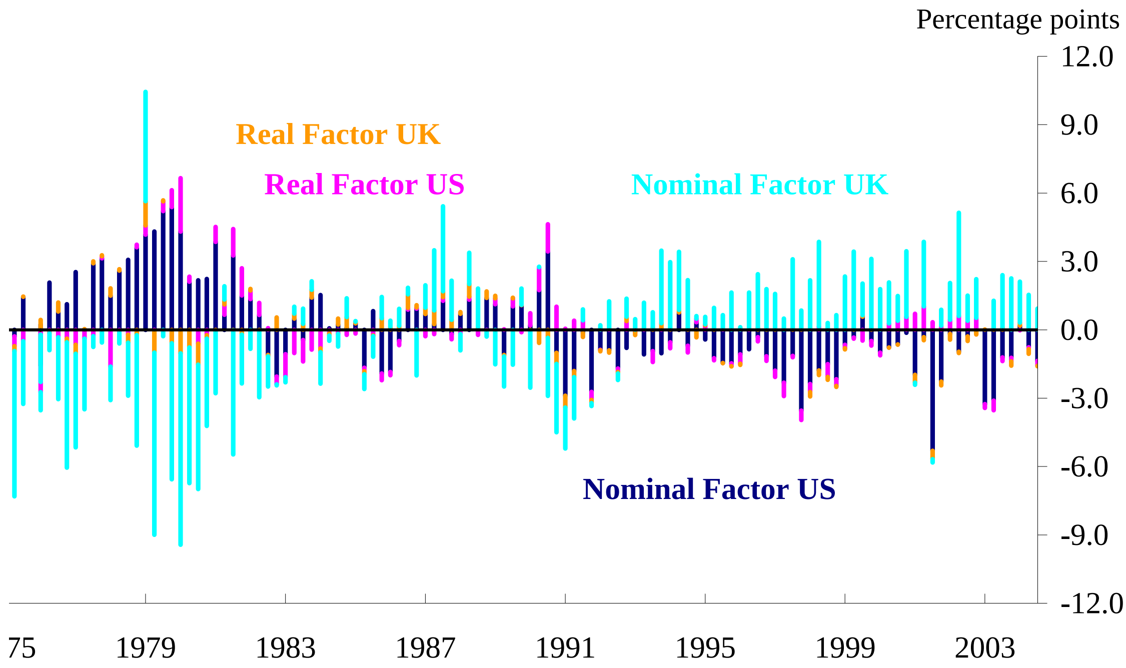
Notes: The column denoted with 'p' contains the order of first differences in (22). LR(q|2) denotes the values of the Johansen (1991) likelihood ratio test statistic for H_0: rank($\boldsymbol{\alpha\beta'}$) = q versus H_1: rank($\boldsymbol{\alpha\beta'}$) = 2 in (22). The row '90%' ('95%') ['99%'] contains the asymptotic 90% (95%) [99%] quantile for LR(r|2) under the null, see Johansen (1996, Table 15.2). The symbol * (**) [***] indicates rejection of these H_0's at the corresponding 10% (5%) [1%] significance level. Estimates for the cointegrating vector normalised on s_t and the vector of error adjustment parameters under $q = 1$ are indicated by $\hat{beta}$ and $\hat{\alpha}$ respectively, whereas standard errors for the individual parameter estimates are indicated by a '$se(.)$'. The value in squared brackets is the p-value for a t-test for $H_0 : \beta_{s^c} = -1$ in $\hat{\beta}$. In all other cases the symbol * (**) [***] indicates rejection of a $H_0 = 0$ at the corresponding 10% (5%) [1%] significance level.

Figure 4: Actual and 'fundamental' levels of US dollar/pound sterling exchange rate; 1975.I-2004.IV



The solid line represents the actual US dollar/pound sterling exchange rate, the line with stars is 'fundamental' level of this exchange rate, constructed by rotating the two estimated US dynamic factors and the two estimated UK dynamic factors towards the exchange rate, whereas the dashed lines represents the asymptotic 90% confidence interval for the 'fundamental' exchange rate estimated based on (16).

Figure 5: Decomposing relative changes in the factors-based US$/UK£'fundamental' exchange rate level; 1975.I-2004.IV



In this chart we decompose the quarter-to-quarter relative change in s_t^C in terms of the relative quarter-to-quarter changes in each of the home and foreign dynamic factors using $\Delta s_t^C = \hat{\delta}_1 \Delta \hat{F}_{1t} + \hat{\delta}_2 \Delta \hat{F}_{2t} + \hat{\delta}_1^* \Delta \hat{F}_{1t}^* + \hat{\delta}_2^* \Delta \hat{F}_{2t}^*$.

model at horizons up to four years. As this has become standard in empirical exchange rate analysis, we also follow this approach and compare the out-of-sample exchange rate change forecasts with naive no-change forecast over a horizon of h quarters. However, Meese and Rogoff (1983) also considered *ad hoc* autoregressive (AR) specifications as well AR models with moving average errors, whereas in the macroeconomic forecasting literature the AR specification is a more common benchmark than no change forecasts, see eg Stock and Watson (2003).

We therefore use as benchmarks for our fundamentals-based forecasts an AR model

$$\Delta s_{t+h,t} = \alpha^h + \sum_{i=1}^{p} \varrho_i \Delta s_{t-i+1,t-i} + \epsilon_{t+h,t} \tag{23}$$

where the number of lagged first difference $\Delta s_{t-i+1,t-i}$ is determined by sequentially applying Schwarz (1978)'s Information Criterion (SIC) starting with a maximum lag order of $p_{max} = 8$ down to zero, as well as random walk-based no change predictions

$$\Delta s_{t+h,t} = 0 \tag{24}$$

The fundamentals-based forecasts of h quarters-ahead exchange rate change are generated using a model that adds the current gap between the factor-based fundamental and actual exchange levels to (23), ie

$$\Delta s_{t+h,t} = \alpha^h + \beta^h(s_t^{\mathrm{F}} - s_t) + \sum_{i=1}^{p} \tilde{\varrho}_i \Delta s_{t-i+1,t-i} + \epsilon_{t+h,t} \tag{25}$$

where s_t^{F} is the 'fundamental' exchange rate level that results from rotating our two estimated UK dynamic factors and two estimated US dynamic factors towards s_t as in (14), and the lag order p is determined by applying the SIC sequentially starting from $p_{max} = 8$ downwards.

For the forecast evaluation we split our quarterly 1975-2004 sample in two, where the latter half, ie 1989.IV-2004.IV, is used for the out-of-sample evaluation. We generate our forecasts using a recursive update of (25), where the first h-period ahead forecast is generated at observation t_0 ($t_0 < T$), ie 1989.IV. In the first stage, we first estimate for each economy the dynamic factor model (9) under $r = 2$ and $p = 2$ on a sample that runs up to $t_0 - h$, resulting in two dynamic $I(1)$ factor for each of the home and foreign economies. We then rotate these four dynamic factors towards the corresponding spot exchange rate as in (14), again using data up to $t_0 - h$. All of this facilitates the estimation of (25) on a sample which runs up to $t_0 - h$.[9] As a second stage, we again extract the aforementioned four dynamic factors as well as compute the rotation to get the 'fundamental' exchange rate level, but now with data up to t_0. Using the estimate of (25) up to $t_0 - h$ with as inputs s_{t_0}, $\Delta s_{t_0,t_0-1}, \ldots, \Delta s_{t_0-p+1,t_0-p}$ (if at all) and the $s_{t_0}^{\mathrm{F}}$ computed with the four dynamic factors estimated up to t_0, we can generate forecasts for the relative exchange rate change at all forecasting horizons h. These two stages are repeated for the observations $t_0+1, t_0+2, \ldots, T-h$. An identical procedure, without the dynamic factor estimation, is applied to generate the (23) based benchmark forecasts.

We base our assessment the forecasting performance of (25) relative to random walk-based forecasts on the mean of the squared forecast errors [MSE]

$$\mathrm{MSE} = \frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} e_{s,s+h}^2, \tag{26}$$

[9] For each t_0 and h we separately apply SIC to select lag order p.

where $e_{s,t+h}$ is the forecast error of the model-generated prediction of the exchange rate change, based on the previously described recursive updating scheme, relative to the *observed* exchange rate change over h quarters. In order to evaluate the behaviour of our recursive fundamentals-based forecasts, we follow the tradition in this literature and compare its MSE to that of the random walk model, and obviously for our fundamentals-based exchange rate change predictions to be valid its MSE should be significantly smaller than that of the benchmark prediction (either AR based or random walk based). Following Diebold and Mariano (1995) and West (1996), we can test whether the difference between the MSE corresponding to a benchmark forecast and that corresponding to a fundamentals-based forecast is significantly different from zero through:

$$z_{\mathrm{MSE}} = \sqrt{T - t_0 - h}\left(\frac{\mathrm{MSE_B} - \mathrm{MSE_F}}{\sqrt{Var(u_{t+h} - (\mathrm{MSE_B} - \mathrm{MSE_{F)}})}}\right) \tag{27}$$

with B = AR or RW, and

$$u_{t+h} = e^2_{\mathrm{B},s,s+h} - e^2_{\mathrm{F}s,s+h}; \quad s = t_0, \ldots, T - h$$

In (27) $\mathrm{MSE_B}$ and $\mathrm{MSE_F}$ are the MSE corresponding to the benchmark prediction, based on either (23) or (24), and the fundamentals-based exchange rate prediction respectively, u_{t+h} is the difference in the squared prediction error from the benchmark and fundamentals-based forecasts, and $Var(u_{t+h} - (\mathrm{MSE_B} - \mathrm{MSE_F}))$ is an estimate of the variance of the demeaned u_{t+h}'s, which in case of $h > 1$ is computed using the Newey and West (1987) estimator with a bandwidth equal to $2(h - 1)$. In case of non-nested models (27) has an asymptotically normal distribution, see eg West (1996), but for our case of nested prediction models Clark and McCracken (2001) have shown that the limiting behaviour of (27) equals a Brownian motion functional and for $h > 1$ this Brownian motion functional also includes nuisance parameters (see Clark and McCracken (2005)). We therefore bootstrap the distribution of (27) to test $H_0 : \mathrm{MSE_{RW}} - \mathrm{MSE_F} = 0$ versus $H_1 : \mathrm{MSE_{RW}} - \mathrm{MSE_F} > 0$.

The null hypothesis in our forecast evaluation is that a fundamentals-based forecasting model like (25) cannot provide more accurate exchange rate change predictions than those based on a more parsimonious model like (23) or (24), and thus (25) overfits the data. Given this null hypothesis it is therefore questionable whether one should compare the 'raw' MSE of the fundamentals-based predictions, as defined in (26), with the MSE of random walk predictions. Indeed, Clark and West (2005b) show both asymptotically as well as in Monte Carlo simulations that the point estimate of $\mathrm{MSE_{RW}} - \mathrm{MSE_F}$ is biased downwards as $\mathrm{MSE_F}$ is inflated by spurious noise that is the result of inappropriately fitting a larger model on the data. In the limit this spurious noise in $\mathrm{MSE_F}$ will disappear, but it can be quite pervasive in finite samples, especially in the case of (25) where s^{F} first has to be estimated before a forecast can be constructed. As a consequence, one can observe that for sample sizes comparable to those used in practice the distribution of (27) is skewed such that the test for $H_0 : \mathrm{MSE_B} - \mathrm{MSE_F} = 0$ versus $H_1 : \mathrm{MSE_B} - \mathrm{MSE_F} > 0$ is severely undersized, see Clark and West (2005a,b), which makes it harder to find any evidence against the benchmark forecast.

Clark and West (2005a,b) suggest to correct the MSE of the larger, alternative prediction model for the aforementioned spurious fitting noise. In the case of (25) this corrected MSE equals

$$\mathrm{MSE}_{\mathrm{F}}^{adj} = \mathrm{MSE}_{\mathrm{F}} - \left(\frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} \left(\Delta \hat{s}_{s,s+h}^{\mathrm{B}} - \Delta \hat{s}_{s,s+h}^{\mathrm{F}} \right)^2 \right); \quad \mathrm{B} = \mathrm{AR} \text{ or } \mathrm{RW} \tag{28}$$

with $\Delta \hat{s}_{s,s+h}^{\mathrm{RW}} = 0$, the recursive fit of (23) for each prediction in the forecast sample

$$\Delta \hat{s}_{s,s+h}^{\mathrm{AR}} = \hat{\alpha}_{s,s-h}^{h} + \sum_{i=1}^{p} \hat{\varrho}_{i,s,s-h} \Delta s_{s-i+1,s-i}$$

as well as the recursive fit of (25)

$$\Delta \hat{s}_{s,s+h}^{\mathrm{F}} = \hat{\alpha}_{s,s-h}^{h} + \hat{\beta}_{s,s-h}^{h} (s_s^c - s_s) + \sum_{i=1}^{p} \hat{\hat{\varrho}}_{i,s,s-h} \Delta s_{s-i+1,s-i}$$

Given (28) we can formulate a corrected version of test statistic (27)

$$z_{\mathrm{MSE}}^{adj} = \sqrt{T - t_0 - h} \left(\frac{\mathrm{MSE}_{\mathrm{B}} - \mathrm{MSE}_{\mathrm{F}}^{adj}}{\sqrt{Var(u_{t+h}^{adj} - (\mathrm{MSE}_{\mathrm{B}} - \mathrm{MSE}_{\mathrm{F)}}^{adj})}} \right); \quad \mathrm{B} = \mathrm{AR} \text{ or } \mathrm{RW} \tag{29}$$

with

$$u_{t+h}^{adj} = e_{\mathrm{B},s,s+h}^{2} - (e_{\mathrm{F}s,s+h}^{2} - \Delta \hat{s}_{s,s+h}^{2}); \quad s = t_0, \ldots, T - h$$

Although Clark and West (2005b) show that when nested forecasts are based on *rolling* updating (29) will be asymptotically distributed according to a standard normal distribution, in our recursive updating setting (29) will have a non-standard limiting distribution, with nuisance parameters if $h > 1$, following the line of reasoning in Clark and McCracken (2001, 2005).[10] Hence, as in the case of (27), we will bootstrap the distribution of (29) to test the null that predictions based on either (23) or (24) and those based on (25) have equal forecasting accuracy.

5.2 Results

We use the quarterly 1975-2004 sample of the US dollar/pound sterling exchange rate. The last half of the sample, 1989.IV-2004.IV, is used for the out-of-sample evaluation, we recursively generate forecasts from (25), as described in the previous subsection, and we use as forecasting horizons h = 1, 2, 3, 4, 8, 12 and 16 quarters. This out-of-sample evaluation period contains a number of turning points that could potentially be challenging for our fundamentals-based models, ie the ERM crisis in 1992 as well as the appreciation-depreciation cycle of the US dollar relative over 2000-2004. We use in the forecasting evaluation both the AR specification (23) and the no-change forecast of the random walk model (24) as a benchmark for the exchange rate predictions based on (25), and we evaluate the performance of the forecasts in terms of the corresponding MSE (26) as well as the MSE adjusted for spurious noise (28) in case of the (25) based forecasts. Significance of the MSE differences is tested using test statistics (27) and (29), where we bootstrap their distributions under the null of equal forecasting accuracy; see Appendix B for details on these bootstrap procedures.

[10]Note that Clark and West (2005a) show that under certain circumstances doing prediction inference with a corrected statistic like (29) based on the standard normal distribution will not bias the results too much.

Table 2: Forecast evaluation US dollar/pound sterling exchange rate (AR model (23) as benchmark); 1989.IV-2004.IV

h	$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{F}})$	$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{F}}^{adj})$	$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{M}})$	$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{M}}^{adj})$
1	0.01	0.03	−0.00	0.01
	(1.04)	(2.29)	(−0.41)	(0.78)
	0.15	*0.01*	*0.66*	*0.22*
2	0.05	0.12	−0.03	0.02
	(1.00)	(2.64)	(−0.70)	(0.51)
	0.16	*0.00*	*0.78*	*0.30*
3	0.09	0.25	−0.06	0.04
	(0.91)	(2.50)	(−0.76)	(0.42)
	0.18	*0.01*	*0.78*	*0.34*
4	0.12	0.44	−0.15	0.05
	(0.69)	(2.23)	(−0.97)	(0.29)
	0.25	*0.01*	*0.83*	*0.39*
8	0.33	1.55	−0.61	0.33
	(1.22)	(1.88)	(−1.44)	(0.67)
	0.11	*0.03*	*0.93*	*0.25*
12	0.34	2.06	−1.83	0.68
	(1.12)	(1.78)	(−3.86)	(0.86)
	0.13	*0.04*	*1.00*	*0.20*
16	0.08	1.35	−2.95	1.16
	(0.34)	(4.16)	(−6.29)	(1.03)
	0.37	*0.00*	*1.00*	*0.15*

Notes: The forecasting horizons (in quarters) can be found under the heading "h". Columns headed with '$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{F}})$' and '$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{F}}^{adj})$' is the MSE difference between AR model (23) based and (25) based forecasts without and with the Clark and West (2005a,b) spurious noise adjustment for the MSE of 25 (see (28)). The columns headed with '$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{M}})$' and '$(\text{MSE}_{\text{AR}}\text{-MSE}_{\text{M}}^{adj})$' report comparable MSE differences between AR model (23) based and (31) based forecasts. In parentheses we report the corresponding test statistics (27) and (29) for the null that the different forecasts are of equal accuracy versus the alternative that (25) based forecast are more accurate. The values in italics are the p-values of test statistics (27) and (29), based on bootstrapping their distributions under the null hypothesis; for more details see Appendix B.

As our fundamentals-based exchange rate forecasting model (25) 'borrows' its specification from the AR forecast model (23) by adding the current gap between the factors-based fundamental and actual exchange rate levels, it is a natural starting point to asses the out-of-sample performance of (25) *vis-à-vis* (23). Table 2 reports the corresponding MSE-based forecasting evaluation results. When we focus on comparing the 'raw' MSE of (25) based exchange rate predictions with the MSE of AR based predictions in the first column, then it indicates that our 'fundamental'-actual gap measure only marginally outperforms the *ad hoc* autoregressive forecasts and the corresponding test statistic never indicates that the MSE difference is significantly greater than zero. As an alternative, one can compare the random walk based MSE with an *adjusted* MSE for the (25) based forecasts, where the adjustment corrects for spurious noise under a true null of equal prediction accuracy. When we use these correction factors to adjust the MSE of the fundamentals based predictions, it becomes apparent that the improvement in forecasting performance of (25) over the pure autoregressive specification becomes more pronounced, see the second column of Table 2, especially at large forecasting horizons. Indeed, the corresponding test statistic (29) suggests that at all forecasting horizons exchange rate predictions from the 'fundamental'-actual gap model are significantly more accurate than the pure autoregressive forecasts.

In order to be able to gauge the empirical performance of our factor-based 'fundamental' exchange rate measure against other fundamental measures used in the literature, we re-run the out-of-sample prediction exercise using a standard monetary exchange rate model based measure. We basically use (6) with $\eta = \eta^* = \alpha$ and $\delta = \delta^* = 1$ to construct an alternative fundamentals based exchange rate measure[11]

$$s_t^{\mathrm{M}} = \hat{\alpha} + (m_t - m_t^*) - (y_t - y_t^*) \tag{30}$$

$$\Delta s_{t+h,t} = \alpha^h + \beta^h(s_t^{\mathrm{M}} - s_t) + \sum_{i=1}^{p} \tilde{\varrho}_i \Delta s_{t-i+1,t-i} + \epsilon_{t+h,t} \tag{31}$$

The exchange rate predictive regression (31) based on (30) is the specification used by Mark (1995) to assess the predictive performance of macroeconomic fundamentals for future exchange rate dynamics, which was shown in his study to be successful at explaining long-horizon exchange rate returns, only now with lagged first differences of the exchange rate return added to it. The results *vis-à-vis* pure autoregressive exchange rate change forecasts are reported in the last two columns of Table 2, and at none of the horizons these monetary fundamentals based forecasts can significantly outperform *ad hoc* AR forecasts.

Since Meese and Rogoff (1983)'s contribution, the random walk specification has become the ultimate benchmark in the literature against which one assesses the predictive power of fundamentals-based models. We therefore also evaluate the predictive performance of our factors-based 'fundamental' measure relative to the random walk-based no-change prediction (24), and the results for this evaluation can be found in the first two columns of Table 3. Once we correct for spurious noise in the (25) based MSE under the null, the superiority of exchange rate predictions that utilise the information in the current gap between the factors-based 'fundamental' exchange rate measure and the actual exchange rate becomes significant, and this

[11]In (30) we use for the United Kingdom the logarithm of the M0 money aggregate and for the United States the log of the M1 money aggregate to pin down movements in $(m_t - m_t^*)$, whereas we use for both economies the log of GDP in volume terms to approximate $(y_t - y_t^*)$. The data were taken from the data bases that underlies our analysis in Section 3.2.

result holds irrespective of the forecasting horizon although the magnitude of the improvement is the largest at the larger horizons. Again, we compare this result with those based on the monetary model based fundamental exchange rate measure, as in Mark (1995), see the last two columns of Table 3. These results are similar as when we use the pure autoregressive exchange rate change predictions as a benchmark, and for horizons smaller than three years this is to be expected, as Mark (1995) already showed that (31) cannot outperform the random walk at these horizons. But in contrast to Mark (1995), (31) based forecasts also have difficulty to significantly outperform the random walk specification at long horizons, even when we correct for spurious noise in the (31) based MSE under the null.

6 Concluding remarks

This paper tries to take seriously the notion that the macroeconomic determinants of the exchange rate themselves are unobserved, and that market participants have to estimate these determinants first in order for them to be able to price exchange rates. This suggests that the common finding in the literature that fundamentals-based forecasts, using observed series such as money aggregates as the macroeconomic determinants, cannot outperform naive random walk forecasts of the exchange rate, could be due to mismeasurement of the macroeconomic fundamentals of exchange rate movements.

Instead of equaling the exchange rate fundamentals with observed macroeconomic variables, such as aggregate price indices, real GDP, money aggregates and so on, we estimate the fundamental drivers of an economy first by extracting the dynamic $I(1)$ factors of a large panel of macroeconomic and financial data for such an economy. Subsequently, we rotate these home and foreign dynamic factor towards the corresponding exchange rate to get a measure of 'fundamental' exchange movements. This in turn, can then be used to forecast future exchange rate movements.

In a preliminary exercise, we do this for the US dollar/pound sterling exchange rate over a quarterly sample starting in 1975 and ending in 2004. For each economy we find that the fundamental dynamics can be approximated by two dynamic factors, which is in line with findings of Giannone *et al.* (2005). When we rotate these four dynamic factors towards the spot exchange rate, we obtain a 'fundamental' exchange rate measure which tracks the low frequency movements in the actual US dollar/pound sterling exchange rate very well. This suggests that this rotation would have been useful over this period to assess whether pound sterling was significantly over- or undervalued relative to the US dollar. We also use the current gap between the estimated 'fundamental' US dollar/pound sterling exchange rate level and the actual level to predict future relative changes in this exchange rate for horizons up to two years. In contrast to the literature, our results for the US dollar/pound sterling exchange rate seem to suggest that for the 1975-2004 sample the current gap relative to a dynamic factor-based measure can outperform naive random walk forecasts.

The current analysis is at an early stage and there are a number of steps that can be taken to robustify our conclusions. Firstly, we could look at other exchange rates, in particular *vis-à-vis* the Euro area. Next, one could test whether our 'primitive stochastic trends' also track movements in observed relative macroeconomic fundamentals, underscoring the aforementioned Engel and West (2005) notion that exchange rates should Granger-cause relative fundamentals.

Table 3: Forecast evaluation US dollar/pound sterling exchange rate (random walk based no-change forecasts (24) as benchmark); 1989.IV-2004.IV

h	($\mathrm{MSE_{RW}}$-$\mathrm{MSE_F}$)	($\mathrm{MSE_{RW}}$-$\mathrm{MSE_F^{adj}}$)	($\mathrm{MSE_{RW}}$-$\mathrm{MSE_M}$)	($\mathrm{MSE_{RW}}$-$\mathrm{MSE_M^{adj}}$)
1	0.00	0.02	−0.02	0.00
	(0.04)	(1.09)	(−1.09)	(0.07)
	0.48	*0.14*	*0.86*	*0.47*
2	0.01	0.06	−0.06	−0.01
	(0.32)	(1.57)	(−1.61)	(−0.38)
	0.38	*0.06*	*0.95*	*0.65*
3	0.01	0.15	−0.14	−0.04
	(0.14)	(1.55)	(−1.69)	(−0.47)
	0.45	*0.06*	*0.95*	*0.68*
4	−0.00	0.27	−0.27	−0.07
	(−0.03)	(1.52)	(−1.66)	(−0.43)
	0.51	*0.06*	*0.95*	*0.67*
8	0.11	1.19	−0.83	0.08
	(0.51)	(1.66)	(−1.75)	(0.20)
	0.31	*0.05*	*0.96*	*0.42*
12	0.23	1.62	−1.94	0.36
	(0.91)	(1.62)	(−3.74)	(0.56)
	0.18	*0.05*	*1.00*	*0.29*
16	0.26	1.32	−2.78	1.00
	(0.93)	(3.36)	(−5.41)	(1.25)
	0.18	*0.00*	*1.00*	*0.10*

Notes: The forecasting horizons (in quarters) can be found under the heading "h". Columns headed with '($\mathrm{MSE_{RW}}$-$\mathrm{MSE_F}$)' and '($\mathrm{MSE_{RW}}$-$\mathrm{MSE_F^{adj}}$)' is the MSE difference between random walk-based and (25) based forecasts without and with the Clark and West (2005a,a) spurious noise adjustment for the MSE of (25) (see (28)). The columns headed with '($\mathrm{MSE_{RW}}$-$\mathrm{MSE_M}$)' and '($\mathrm{MSE_{RW}}$-$\mathrm{MSE_M^{adj}}$)' report comparable MSE differences between random walk-based and (31) based forecasts. In parentheses we report the corresponding test statistics (27) and (29) for the null that the different forecasts are of equal accuracy versus the alternative that (25) based forecast are more accurate. The values in italics are the p-values of test statistics (27) and (29), based on bootstrapping their distributions under the null hypothesis; for more details see Appendix B.

A Data for the dynamic factor estimation

The data used in this paper to estimate the dynamic factors, which are described in more detail below, were taken from the following sources: for the United Kingdom, with the exception of the financial prices, the data are an updated version of the data that underlies the analysis in Kapetanios *et al.* (2005) (denoted with KLP hereafter), and more details about the sources can be found in that paper, whereas for the United States, again except the financial prices, the data are extracted from the Federal Reserve Bank of St. Louis' FRED® database (denoted with FRED hereafter). Also, for the United Kingdom, we retrieved data on components of the retail price index (RPI) from the OECD's Main Economic Indicators through Datastream (denoted with OECD hereafter). The bulk of the financial data for both economies are acquired from the *Global Financial Data* website: http://www.globalfinancialdate.com (denoted with GFD hereafter).

United Kingdom

A: Real/GDP component series

A1: GDP Chained Volume Measure;	source: KLP
A2: Index of Production: All Production Industries;	source: KLP
A3: Index of Production: Mining & Quarrying;	source: KLP
A4: Index of Production: Manufacturing;	source: KLP
A5: Index of Production: Electricity, Gas & Water Supply;	source: KLP
A6: Index of Production: Food, Drink & Tobacco;	source: KLP
A7: Index of Production: Textile & Textile Products;	source: KLP
A8: Index of Production: Leather & Leather Products;	source: KLP
A9: Index of Production: Wood & Wood Products;	source: KLP
A10: Index of Production: Pulp/Paper/Publishing Industries;	source: KLP
A11: Index of Production: Petroleum Products & Nuclear Fuels;	source: KLP
A12: Index of Production: Chemicals & Man-made Fibres;	source: KLP
A13: Index of Production: Rubber & Plastic Products;	source: KLP
A14: Index of Production: Non-metallic Mineral Products;	source: KLP
A15: Index of Production: Basic Metals & Fabricated Products;	source: KLP
A16: Index of Production: Machinery & Equipment;	source: KLP
A17: Index of Production: Electrical & Optical Equipment;	source: KLP
A18: Index of Production: Transport Equipment;	source: KLP
A19: Inventories to Output Index: Manufacturing;	source: KLP
A20: Output Index: Construction;	source: KLP
A21: Output Index: Distribution, Hotels, Catering & Repairs;	source: KLP
A22: Output Index: Transport, Storage & Communication;	source: KLP
A23: Output Index: Total;	source: KLP
A24: Total Fixed Capital Formation;	source: KLP
A25: Gross Domestic Product (Factor Costs);	source: KLP
A26: General Government: Final Expenditure;	source: KLP
A27: Household Final Consumption Expenditure;	source: KLP
A28: Real Households Disposable Income;	source: KLP
A29: Purchase of Vehicles;	source: KLP
A30: Total Durable Goods Consumption	source: KLP
A31: Total Non-Durable Goods Consumption	source: KLP
A32: Total Services Consumption	source: KLP
A33: Total Semi-Durable Goods Consumption	source: KLP

B: Labour market

B1:	Unemployment Rate (%)	source: KLP
B2:	Total Wages & Salaries	source: KLP
B3:	Total UK Workforce Jobs (1000s)	source: KLP
B4:	Whole Economy Labour Earnings Including Bonusses	source: KLP
B5:	Number of Employed (16yrs and older - 1000s)	source: KLP
B6:	Number of Unemployed (16yrs and older - 1000s)	source: KLP
B7:	Population (16yrs and older - 1000s)	source: KLP
B8:	Total Actually Weekly Hours Worked (millions)	source: KLP

C: International

C1:	Effective Real Exchange Rate	source: KLP
C2:	Import Price Index Finished Manufacturers	source: KLP
C3:	Total Imports Goods & Services	source: KLP
C4:	Total Exports Goods & Services	source: KLP
C5:	Total Trade in Goods & Services	source: KLP
C6:	Trade-weighted Nominal Exchange Rate Index Relative to G7 Economies	source: IFS/IMF
C7:	Terms-of-Trade (Ratio Export Price Index/Import Price Index)	source: IFS

D: Money and credit

D1:	M4 Money Stock;	source: KLP
D2:	M0 Money Stock;	source: KLP
D3:	Sectoral M4 Money Stock: Private Non-Financial Corporations (PNFCs) (break adjusted);	source: KLP
D4:	Sectoral M4 Money Lending Component: PNFCs (break adjusted);	source: KLP
D5:	Monetary Financial Institutions' (MFIs) Sterling Net Lending to Private Sector;	source: KLP
D6:	MFIs' Sterling Net Lending to PNFCs;	source: KLP
D7:	MFIs' Sterling M4 Liabilities to PNFCs;	source: KLP
D8:	MFIs' Sterling M4 Liabilities to Other Financial Corporations;	source: KLP
D9:	MFIs' Sterling Net Lending to Households;	source: KLP
D10:	MFIs' Sterling Liabilities to Households;	source: KLP
D11:	Notes & Coins in Circulation;	source: KLP
D12:	M0-wide Monetary Base;	source: KLP

E: Financial Prices

E1:	Financial Times (FT) All-Share Stock Price Index;	source: GFD
E2:	FT Stock Price Index - Financials;	source: GFD
E3:	FT Stock Price Index - Industrials;	source: GFD
E4:	FT Stock Price Index - Non-Cyclical Consumer Goods;	source: GFD
E5:	FT Stock Price Index - Building Materials;	source: GFD
E6:	FT Stock Price Index - Retail Sector;	source: GFD
E7:	3-month Interbank Interest Rate;	source: KLP
E8:	12-month Interbank Interest Rate;	source: GFD
E9:	3-year Treasury Bond Yield;	source: GFD
E10:	5-year Treasury Bond Yield;	source: GFD
E11:	10-year Treasury Bond Yield;	source: GFD
E12:	FT Corporate Bond Yield;	source: GFD

F: Prices

F1:	Long-Run Consumer Price Index (CPI);	source: KLP
F2:	Gross Domestic Product (GDP) Deflator (Market Prices);	source: KLP
F3:	Retail Price Index (RPI) Excl. Mortgage Interest Rate Payments;	source: KLP
F4:	GDP (Expenditure) Deflator (Market Prices);	source: KLP
F5:	Household Final Consumption Expenditure Deflator;	source: KLP
F6:	Total Durable Goods Consumption Deflator;	source: KLP
F7:	Total Non-Durable Goods Consumption Deflator;	source: KLP
F8:	Total Services Consumption Deflator;	source: KLP
F9:	Total Semi-Durable Goods Consumption Deflator;	source: KLP
F10:	Producer Price Index (PPI): Output of Manufactured Products;	source: KLP
F11:	PPI: All Manufacturing Excl. Duty;	source: KLP
F12:	RPI: All Items;	source: OECD
F13:	RPI: Excluding Energy & Food;	source: OECD
F14:	RPI: Food;	source: OECD

United States

A: Real/GDP component series

A1:	Output Business Sector;	source: FRED
A2:	Output per Hour, Business Sector;	source: FRED
A3:	Output Non-Farm Business Sector;	source: FRED
A4:	Output per Hour, Non-Farm Business Sector;	source: FRED
A5:	Final Sales of Domestic Product;	source: FRED
A6:	Real Gross Domestic Product (GDP);	source: FRED
A7:	Real Potential GDP;	source: FRED
A8:	Real Government Consumption & Expenditure;	source: FRED
A9:	Corporate Sector: Consumption of Fixed Capital;	source: FRED
A10:	Corporate Profits with Inventory Valuation and Capital Consumption Adjustment (IVCCA);	source: FRED
A11:	Proprietors' Profits with IVCCA;	source: FRED
A12:	Rental Income with IVCCA;	source: FRED
A13:	Real Disposable Personal Income;	source: FRED
A14:	Real Personal Consumption Expenditures;	source: FRED
A15:	Real Personal Consumption Expenditures: Durable Goods;	source: FRED
A16:	Real Personal Consumption Expenditures: Non-Durable Goods;	source: FRED
A17:	Real Personal Consumption Expenditures: Services;	source: FRED
A18:	Real Gross Private Domestic Investment;	source: FRED
A19:	Real Non-Residential Investment: Equipment & Software;	source: FRED
A20:	Real Private Non-Residential Fixed Investment;	source: FRED
A21:	Real Private Residential Fixed Investment;	source: FRED
A22:	New Privately Owned Housing Units Started;	source: FRED
A23:	Industrial Production;	source: FRED
A24:	Real Retail Sales;	source: FRED

B: Labour market

B1:	Unit Labour Costs, Business Sector;	source: FRED
B2:	Real Compensation per Hour, Business Sector;	source: FRED
B3:	Real Compensation per Hour, Non-Farm Business Sector;	source: FRED
B4:	Unit Labour Costs, Non-Farm Business Sector;	source: FRED
B5:	Average Hourly Earnings: Total Private Industries;	source: FRED
B6:	Aggregate Weekly Hours Index: Total Private Industries;	source: FRED

B7:	Civilian Employment: 16yrs and over;	source: FRED
B8:	Civilian Participation Rate;	source: FRED
B9:	Civilian Labour Force;	source: FRED
B10:	Civilian Non-Institutional Population;	source: FRED
B11:	Civilian Employment Population Ratio;	source: FRED
B12:	Total Non-Farm Payrolls: All Employees;	source: FRED

C: International

C1:	Imports: Goods, Services & Income;	source: FRED
C2:	Imports: Goods;	source: FRED
C3:	Imports: Services;	source: FRED
C4:	Exports: Goods, Services & Income;	source: FRED
C5:	Exports: Goods;	source: FRED
C6:	Exports: Services;	source: FRED
C7:	Real exports: Goods & Services;	source: FRED
C8:	Real imports: Goods & Services;	source: FRED
C9:	Broad Trade-Weighted Exchange Rate Index;	source: FRED

D: Money and credit

D1:	Outstanding Household Credit Market Debt;	source: FRED
D2:	St. Louis Adjusted Reserves Measure;	source: FRED
D3:	St. Louis Adjusted Monetary Base Measure;	source: FRED
D4:	Commercial & Industrial Loans at all Commercial Banks;	source: FRED
D5:	Consumer Loans at all Commercial Banks;	source: FRED
D6:	Currency Component of M1 Money Stock;	source: FRED
D7:	M1 Money Stock;	source: FRED
D8:	M2 Money Stock;	source: FRED
D9:	M3 Money Stock;	source: FRED
D10:	MZM Money Stock;	source: FRED
D11:	Other Securities at all Commercial Banks;	source: FRED
D12:	Total Consumer Credit Outstanding;	source: FRED
D13:	Real Estate Loans at all Commercial Banks;	source: FRED

E: Financial prices

E1:	S&P 500 Stock Price Index;	source: GFD
E2:	S&P 500 Stock Price Index: Industrials;	source: GFD
E3:	S&P 500 Stock Price Index: Consumer Sector;	source: GFD
E4:	S&P 500 Stock Price Index: Automobiles;	source: GFD
E5:	S&P 500 Stock Price Index: Financials;	source: GFD
E6:	S&P 500 Stock Price Index: Telecommunications;	source: GFD
E7:	3-month Treasury Bill Rate: Secondary Market;	source: FRED
E8:	12-month Interbank Interest Rate;	source: GFD
E9:	3-year Treasury Bond Yield;	source: GFD
E10:	5-year Treasury Bond Yield;	source: GFD
E11:	10-year Treasury Bond Yield;	source: GFD
E12:	Moody's AAA Grade Corporate Bond Yield;	source: GFD
E13:	Moody's BAA Grade Corporate Bond Yield;	source: GFD

F: Prices

F1:	Implicit Gross Domestic Product (GDP) Deflator;	source: FRED
F2:	GDP: Chain-type Price Index;	source: FRED
F3:	Personal Consumption Expenditures: Chain-type Price Index;	source: FRED
F4:	Personal Consumption Expenditures: Chain-type Price Index Less Food and Energy;	source: FRED
F5:	Consumer Price Index (CPI) for All Urban Consumers: All Items;	source: FRED
F6:	CPI for All Urban Consumers: Energy;	source: FRED
F7:	CPI for All Urban Consumers: All Items Less Energy;	source: FRED
F8:	CPI for All Urban Consumers: All Items Less Food & Energy;	source: FRED
F9:	CPI for All Urban Consumers: Food;	source: FRED
F10:	CPI for All Urban Consumers: All Items Less Food;	source: FRED
F11:	Producer Price Index (PPI): All Commodities;	source: FRED
F12:	PPI Finished Goods: Capital Equipment;	source: FRED
F13:	PPI: Finished Energy Goods;	source: FRED
F14:	PPI: Industrial Commodities;	source: FRED
F15:	PPI: Intermediate Energy Goods;	source: FRED
F16:	PPI: Intermediate Foods & Feeds;	source: FRED
F17:	PPI: Intermediate Materials - Supplies & Commodities;	source: FRED
F18:	PPI: Finished Goods Less Food & Energy;	source: FRED

B Bootstrap algorithm for the out-of-sample forecasting evaluation

Given the non-standard limiting behaviour of our forecast evaluation statistics, due to the comparison of nested models as well as the use of multi-period forecasting horizons, we use a parametric bootstrap procedure to approximate the distribution of our test statistics under the null hypothesis that the benchmark model is the true model. The building blocs for this bootstrap procedure are the following data generating processes (DGPs):

DGP Benchmark Model:

$$AR: \quad \Delta s_t = c + \sum_{j=1}^{p} \varrho_j \Delta s_{t-j} + \epsilon_t \tag{B.1}$$

or

$$RW: \quad \Delta s_t = c + \epsilon_t \tag{B.2}$$

DGPs Home and Foreign Dynamic Factors:

$$\begin{aligned} \Delta \hat{F}_t &= \sum_{j=1}^{p^F} \boldsymbol{\chi}_j \Delta \hat{F}_{t-j} + u_t \\ \Delta \hat{F}_t^* &= \sum_{j=1}^{p^{F^*}} \boldsymbol{\chi}_j^* \Delta \hat{F}_{t-j}^* + u_t^* \end{aligned} \tag{B.3}$$

In the two VAR models in (B.3) $\Delta \hat{F}_t = (\Delta \hat{F}_{1t} \ \Delta \hat{F}_{2t})'$ and $\Delta \hat{F}_t^* = (\Delta \hat{F}_{1t}^* \ \Delta \hat{F}_{2t}^*)'$ are the first differences of the two estimated dynamic $I(1)$ factors for the home and foreign economies respectively, $\boldsymbol{\chi}_j$ and $\boldsymbol{\chi}_j^*$ are 2×2 parameter matrices, and the lag orders p^F and p^{F^*} are selected using the SIC criterion based on an upper bound of eight lags.

DGPs Individual Macro Data:
Home:

$$\begin{aligned}
X_{it} =& \hat{\gamma}_{i0}'\hat{F}_t - \hat{\gamma}_{i1}'\Delta\hat{F}_{t-1} - \cdots - \hat{\gamma}_{ip}'\Delta\hat{F}_{t-\bar{p}} + \hat{e}_{it} \\
\hat{e}_{it} =& \sum_{j=1}^{p^i} \zeta_j \hat{e}_{i,t-j} + u_{it}^e \\
\text{for each} \quad & i = 1, \ldots, N
\end{aligned} \tag{B.4}$$

Abroad:

$$\begin{aligned}
X_{it}^* =& \hat{\gamma}_{i0}^{*\prime}\hat{F}_t^* - \hat{\gamma}_{i1}^{*\prime}\Delta\hat{F}_{t-1}^* - \cdots - \hat{\gamma}_{ip}^{*\prime}\Delta\hat{F}_{t-\bar{p}^*}^* + \hat{e}_{it}^* \\
\hat{e}_{it}^* =& \sum_{j=1}^{p^{i*}} \zeta_j^* \hat{e}_{i,t-j}^* + u_{it}^{e*} \\
\text{for each} \quad & i = 1, \ldots, N^*
\end{aligned} \tag{B.5}$$

In (B.4) and (B.5), the $\hat{e}_{it}$ ($\hat{e}_{it}^*$) represent the estimated idiosyncratic component of each individual series in the home (foreign) panel of data; see (9) for more details.

The DGPs (B.1)-(B.5) are estimated on the data and these estimated DGPs are then used in the following steps:

1. We generate $T + 50$ pseudo-residuals for (B.1)-(B.5) by randomly drawing from the estimated residuals of (B.1)-(B.5), ie $\hat{\epsilon}_t$, $\hat{\epsilon}_t^*$, $\hat{u}_t$, $\hat{u}_t^*$, the N $\hat{u}_{it}^e$'s and the N^* $\hat{u}_{it}^{e*}$'s, such that the cross-sectional structure is preserved. These $T + 50$ pseudo residuals are then used to generate artificial data through (B.1)-(B.5): $\tilde{s}_t, \tilde{X}_{1t}, \ldots, \tilde{X}_{Nt}, \tilde{X}_{1t}^*, \ldots, \tilde{X}_{Nt}^*$. Only the last T observations on $\tilde{s}_t, \tilde{X}_{1t}, \ldots, \tilde{X}_{Nt}, \tilde{X}_{1t}^*, \ldots, \tilde{X}_{Nt}^*$ are retained, in order to circumvent initial observation bias.

2. Extract the 2 home dynamic factors from $\tilde{X}_{1t}, \ldots, \tilde{X}_{Nt}$ and the 2 foreign dynamic factors from $\tilde{X}_{1t}^*, \ldots, \tilde{X}_{N^*t}^*$. Following that, we rotate the pseudo log exchange rate $\tilde{s}_t$ on these 4 factors to construct the pseudo factors-based 'fundamental' exchange rate level $\tilde{s}_t^c$.

3. Run the forecast evaluation exercise on the pseudo data for forecast horizons $h = 1, \ldots, 4, 8, 12, 16$, construct the z_{MSE} and z_{MSE}^{adj} test statistics, and save these test statistics.

4. Repeat 10,000 times and compute the p-value of empirical z_{MSE} and z_{MSE}^{adj} test statistics using the 10,000 simulated corresponding test statistics.

In case of the Mark (1995) specification we follow the same steps as outlined above, except we replace the DGPs (B.1)-(B.5) with one single DGP:

$$\begin{pmatrix} \Delta s_t \\ (\Delta m_t - \Delta m_t^*) \\ (\Delta y_t - \Delta y_t^*) \end{pmatrix} = \begin{pmatrix} c_s \\ c_{(m-m^*)} \\ c_{(y-y^*)} \end{pmatrix} + \sum_{j=1}^{p} \boldsymbol{\chi}_j \begin{pmatrix} \Delta s_t \\ (\Delta m_t - \Delta m_t^*) \\ (\Delta y_t - \Delta y_t^*) \end{pmatrix} + \begin{pmatrix} u_{s,t} \\ u_{(m-m^*),t} \\ u_{(y-y^*),t} \end{pmatrix} \tag{B.6}$$

where for the random walk-based benchmark we impose:

$$\boldsymbol{\chi}_j = \begin{pmatrix} 0 & 0 & 0 \\ \chi_{21,j} & \chi_{22,j} & \chi_{23,j} \\ \chi_{31,j} & \chi_{32,j} & \chi_{33,j} \end{pmatrix} \quad \text{for } j = 1, \ldots, p$$

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