High Frequency Exchange Rate Forecasting

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Abstract

Most technical analysis studies are concerned with the profitability of technical trading rules and they almost exclusively focus on trend following patterns. In this paper we examine a different kind of technical indicator which suggests a structural relationship between High, Low and Close prices of daily exchange rates. Since, for a given exchange rate, it can be shown that these prices have different time series properties, it is possible to explore the structural relationships between them using multivariate cointegration methods. This methodology facilitates the construction of dynamic structural econometric models and these are used to derive dynamic out-of-sample forecasts over different time horizons. Compared to standard benchmarks, it turns out that these models have extremely good forecasting properties, even when allowance has been made for transactions costs and risk premia.

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Although Technical Analysis[1] is often dismissed by academic time series analysts because of its lack of theoretical underpinnings, its popularity has always been high amongst practitioners. For example, in a recent survey of foreign exchange market participants, Menkhoff (1995) showed that there is widespread use of technical analysis by traders and institutional investors for short to medium-term forecasts. These findings support the results of an earlier survey by Taylor and Allen (1992) of the London foreign exchange market who find that over 90% of dealers use some form of technical analysis in order to derive a short-term forecast. Recent studies also indicate the profitability of technical trading on the basis of simple filter rules (see, for example, Dooley and Shafer (1983), Sweeny (1986) and, more recently, Levich and Thomas (1993)[2], where profitability is assessed by outperforming a transactions costs adjusted buy-and-hold strategy.[3]

In this paper we seek to take recent academic work on technical analysis one step further. In particular, a common feature of extant studies is that the trend-following indicators are normally calculated on a close of price basis. However, a different class of technical indicators, widely used among foreign exchange traders, exploits the fact that certain values for a price series appear to have a higher informational content than others. On a daily basis, these correspond to the two extremes: the highest and lowest prices of the day, and the opening and closing price of the market.[4,5] The difference between High and Low represents the trading range and gives information about the trading activity of a certain period. Given a specific High and Low, the Close price supposedly contains information about the further price

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[1] That is, the use of a broad class of prediction rules for forecasting financial prices.

[2] Schulmeister (1987), Leoni (1989) and Menkhoff and Schlumberger (1995) additionally take moving average based indicators and momentums into consideration.

[3] However, Cheung and Wong (1997) and Menkhoff and Schlumberger (1995) show that profits derived from technical trading can diminish substantially if a risk premium is accounted for.

[4] Since foreign exchange is traded around the world and around the clock, there exists, unlike for stock markets or futures markets, a closing or an opening price. On a daily basis, the Close price therefore corresponds to 5 pm New York time when trading in NY ceases and Sydney prepares to start its currency trading. On weekdays closing prices are identical to the opening prices, since they are recorded at the same point in time, Open and Close prices differ only on weekends and holidays when there is a considerable length of nontrading in the currency market, i.e. that is for weekend: 5 pm NY time on Friday to 8 am Sydney time on Monday.

[5] Recently Parkinson (1980) and Garman and Klass (1980) have shown that the efficiency of estimators of price volatility can be increased up to eight times if the classical Close priced based estimators are augmented with information embodied in High and Low prices. An additional motivation for this study lies therefore in the fact that the same might hold for point forecasts.

development. So-called Candlestick charts are a graphical way of displaying the different constellations between High, Low, Open and Close prices, where each constellation implies a different forecast (see e.g. Feeny, 1989).[6] While individual candles provide the chartist with information about the trading activity of a certain time period, combinations of consecutive candles form the basis of specific trading signals. Feeny (1989) distinguishes between 24 different types of individual candles and 34 different candlestick formations; however, non-academic sources claim the existence of more than 100 different candlestick formations.

Since it can be shown that High, Low and Close prices of the same exchange rate series have different time series properties, we propose exploring the structural relationships between these prices using multivariate cointegration methods. We find that by restricting the cointegration space it is possible to empirically identify 'long-run' relationships in the data that coincide with the underlying structure of this class of technical analysis. Further, using dynamic modelling techniques we are able to use the identified structural relationships to derive dynamic out-of-sample forecasts over different time horizons. These models produce a creditable out-of-sample forecasting performance in terms of beating a martingale, and also in terms of their ability to generate significant directional ability. Perhaps most pleasingly our forecasting performance does not disappear when risk and transaction costs are allowed for.

The outline of the remainder of this paper is as follows. In the next section we briefly outline the concept of a stochastic, which is a technical indicator that ties down the relationship between High, Low and Close. In section 3 the data set used in this study is discussed and some preliminary statistics presented. The econometric methodology is presented in section 4 along with our estimated results. The forecasting performance of our models is assessed in section 5 in terms of beating a random walk and directional ability, while in Section 6 the implied profitability of the different exchange rate models is compared to a buy-and-hold strategy. A conclusion is presented in Section 7.

[6] Candlestick charts were already used by Japanese rice traders in the 17th century in order to derive profitable trading rules from a special graphical plot of High, Low, Open and Close prices per time unit, which has a certain similarity to candles.

2. The Stochastics

Rather than just displaying the relationship in a graphical way, so-called contra-trend indicators try to quantify the relationship between High, Low and Close prices in order to generate a clear trading signal.[7] The Stochastics, introduced by William Lane (1991), is a good example of such an indicator. It derives a trading signal using the following formula:

$$\%K = 100\left(\frac{C_t - L_t^{min}}{H_t^{max} - L_t^{min}}\right)$$

$$\%D = \frac{1}{n}\sum_{i=1}^{n} \%K_{t-i+1} \tag{1}$$

where C_t is today's close, H_t^{max} biggest high of a certain moving period, n, and L_t^{min} is corresponding lowest low for the same period. Having established these values, %K generates a signal which can take on values between 0 and 100. A common practice among technical analysts is to calculate H_t^{max} and L_t^{min} over the last 14 periods and H_t^{max} - L_t^{min} denotes the so-called trading range or spread of a given period and can be interpreted as a basic measure of volatility. Crucio and Goodhard (1992) define trading range as "(...) the price range within which an asset has traded in the past and (which) can be characterised by the maximum and minimum of the series (of various length) of latest prices." The term C_t - L_t^{min} defines the upward potential of a given trading range. The Stochastics thus weight the upward potential of a given period with the volatility of that period. %D represents a smoothed version of %K, where the smoothing factor used is normally 3 periods.

The Stochastics can be traded in many different ways.[8] Since the actual trading techniques used are not of interest in this study the reader is referred to the literature on Technical Analysis. (e.g. Murphy 1986). For our purposes it is simple worth noting that the Stochastics is commonly interpreted as a so-called overbought-undersold

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[7] Since the trading algorithm of the Stochastics can be quantified, and its predictive power can be investigated using formal statistical method, the signals generated by the Stochastics qualify as Markov times and thus represent well defined forecasts in the sense of Neftci (1991).

[8] A more complex way to trade Stochastics is to apply the same technique as described for a moving average cross-over (see e.g. Schulmeister 1987). The intersects between %K and %D are then consequently interpreted as buy and sell signals. A trading signals is considered most powerful, when

indicator. The idea behind overbought-undersold indicators is closely linked to the concept of the trading range. The boundaries of the trading range, given by the maximum and minimum of that period, represent temporary support and resistance levels[9]. For example, DeGrauwe and Decupere (1992) use 11 years of daily exchange rate data for USDDEM and USDJPY to show that certain price levels which coincide with round numbers, such as 1.500 for USDDEM or 100.00 for USDJPY, represent psychological barriers that might initiate buying or selling activity and hence act as substantial support and resistance levels.[10]

Since the Stochastics measure the trading range over a moving period, it should be possible to capture the trading activity over time fairly well. The implication of the overbought / undersold indicators is once the exchange rate comes close to the extremes of the range, a reversion to the centre of the trading range is expected. Stochastic values between 70 and 100 are considered as indicating an overbought situation; that is, currency A has appreciated rather sharply against currency B and now a correction of this "exaggerated" price movement is expected. Stochastic values below 30 are considered as undersold. Both regions have the implication of the expectation of a change in the direction of the price movement. Due to the set up of the Stochastics, values between 30 and 70 correspond to an exchange rate movement close to the middle of the range and therefore no change in the exchange rate is expected. When trading the Stochastics as an overbought-undersold indicator, the exchange rate can be seen as a form of mean-reverting process. However, the mean does not correspond to the absolute sample mean but to the average of the periodic extremes, thus taking the concept of temporary support and resistance levels into consideration.

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is corresponds with the overbought-undersold indication of the Stochastics, i.e. when a sell signal occurs in the overbought region and a buy signal in the oversold area.

[9] Edwards and Magee (1966, p.211) provide a definition of support and resistance that link support and resistance to supply and demand and thus selling and buying activity of speculative assets.

[10] Many other ways to determine support and resistance levels can be found in the technical analysis literature. However, all have the common property that, once established, they coincide with local maxima and minima and thus confine the trading until enough buying or selling interest is gathered in order to break through the upper or lower boundary of the present trading range and then consequently establish a new trading range, where - in the case of a break-out through the top of the trading range - former top levels (resistance levels) will now become new bottom levels (support levels). (see Edwards and Megee, 1966, p.213)

By setting %K =50 in (1) and re-arranging yields:

$$H_t^{max} - L_t^{min} = 2(C_t - L_t^{min}). \qquad (2)$$

Adding L_t^{min} twice to both sides of the equation and re-arranging yields:

$$C_t = 0.5(H_t^{max} + L_t^{min}) = 0.5\ H_t^{max} + 0.5\ L_t^{min},$$

or

$$C_t - 0.5\ H_t^{min} - 0.5\ L_t^{min} = 0, \qquad (3)$$

which translates into vector form as:

$$(1,-0.5,-0.5,0). \qquad (3')$$

The Stochastics thus establish a structural relationship between today's Close and the Maximum and Minimum price of a moving period, measured as the highest High and lowest Low. This structural relationship represents a testable hypothesis and we demonstrate in the next section that it is possible to identify a long-run relationship in the exchange rate data that comes close to the empirical counterpart. By incorporating this cointegrating relationship into short-run dynamic models we are then able to present out-of sample forecasts based on the dynamic representation of the exchange rate system. We take a good forecasting performance of our model as an indication that Technical Analysis methods can be thought of as capturing any latent Granger causality that exists in the data.

3. Data Sources and Preliminary Statistics.

Daily data for the High, Low, Open and Close prices for the US Dollar/German Mark (USDDEM), US Dollar/Japanese Yen (USDJPY) and Pound Sterling/US Dollar (GBPUSD) were used. The period studied was from August 1986 to August 1996 for USDDEM and USDJPY, yielding 2770 observations for each series. For GBPUSD only data from August 1989 to August 1986 was available, producing 1890 observations. The data was log-transformed and checked for outliers and missing observations. Obvious outliers were removed and missing observations in the series were closed by linear interpolation. The data set was obtained from Knight Ridder Financial Ltd.

The currency pairs selected for this study comprise the three most actively traded currencies. The average daily turnover for these three currency pairs in April 1995 comprised more than half (50.4%) of the total foreign exchange market turnover.[11] According to the Bank of International Settlements, the daily average of foreign exchange market turnover in April 1995, net of local and cross-border inter-dealer double counting, totalled for all currency pairs to 1136.9 billions US dollar. Trading in USDDEM had a percentage share of 22.3%, USDJPY of 21.3% and GBPUSD of 6.8%.

Since non-stationarity is a pre-condition of cointegration, the daily data for the three exchange rate series on High, Low, Open and Close prices was tested for unit roots using an Augmented Dickey Fuller (ADF) and Phillips Perron tests. USDJPY and GBPUSD appeared to be I(1) since the null hypothesis of a unit root could not be rejected for either of the eight series at the 5% level, and the first differences proved to be stationary. The results of the ADF test are presented in the appendix, in Tables 1 to 6. However, USDDEM appeared to be borderline stationary under the conventional ADF test and the Phillips Perron test. When considering heteroskedasticity-consistent standard errors in the ADF test, the null hypothesis for a unit root could not be rejected for USDDEM.[12] All three currencies therefore proved to be I(1) and

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[11] Bank of International Settlements (BIS), 1996, table F-4.

[12] The borderline nonstationarity of USDDEM could be due to heteroskedasticity in the residuals and/or due to additive outliers. Since heteroskedasticity in the residuals of an otherwise properly specified linear model leads to inconsistent covariance matrix estimates, and thus faulty statistical inference (White, 1980), and since the presence of additive outliers move standard inference towards stationarity (Hoeck, 1995), the unit root hypothesis could be wrongly rejected. An easy remedy for these problems is the combination of the OLS-based ADF with heteroskedasticity-consistent standard errors (robusterrors), a procedure proposed by Lucas (1995) in order to yield more robust standard DF t-statistics and also to provide protection against the distortive effect of additive outliers.[12] The inclusion of heteroskedasticity consistent standard errors yields different critical values for the DF test statistics, however, since these values converge with increasing sample size towards the standard DF test statistics, these values did not prove critical for our sample. An alternative approach is to use maximum likelihood estimators which have, in general, a higher robustness than OLS estimators; see Lucas(1995), Hoeck(1995).

integrated of the same order and thus satisfy an important precondition of cointegration.

Clearly, a cointegration analysis is only meaningful if the time series properties of the variables under consideration have different time series properties. Since High, Low and Close prices are drawn from the same time series, one might argue that these would share the same (indeed identical) time series properties and hence finding a cointegrating vector is an expected feature. It is, however, exactly this point that presents the motivation of our analysis: High, Low and Close prices of the same time series have different time series properties. Looking at daily exchange rate data, then according to Takens' delay time concept (Takens 1981), the Open series represents an embedding of the Close series since Open and Close are always recorded at the same points in time; i.e. the opening and closing time of the corresponding market.[13] Low and High prices, however, carry different information - they do not coincide with a certain times of the day but with the extreme prices of the trading day. Since Low and High prices do not occur at specific time of the day, neither Low nor High series can therefore be expressed as an embedding of the Close series. Thus, High, Low and Close should not have the same dynamic characteristics and it should be possible to treat them as three different discrete time series.

One way to illustrate the different dynamics of the High, Low and Close is to look at the difference between the autocorrelation function (ACF) of the differences of these series. If High, Low and Close had the same time series properties, the difference between the series should follow a white noise process: the ACF between the differences of High and Close, High and Close and Close and Low should therefore decay immediately to zero. However, this is not the case as Figure 1, which represents the plot of the ACF of the difference between the High and the Close prices for the first 500 lags of GBPUSD, demonstrates. The slow decay of the ACF is significant and hence the difference between the three series are structural and not random in

[13] Takens theorem states (Takens 1981) that if x(t) is a discrete representation of a continuous time series, by applying delay time co-ordinates, a different discrete time series $y_t = g(x_t)$ can be constructed that has the same dynamic characteristics as x(t). $y_t^m = (y_t, y_{t+m},...,y_{t+m-1})$ is then called an m-embedding of x(t).

nature. It takes roughly around 100 lags for both series before the ACF becomes zero for the first time.[14]

Another indication for the different time series properties can be derived from the results of the Augmented Dickey Fuller unit root test for the different time series. The results of the ADF test, presented in the appendix, show that different lag lengths have to be included in order to yield zero correlation in the residuals. The different lag lengths for High, Low and Close and the same lag lengths of Close and Open series reflect the different degree of serial correlation in the residuals and hence support the different time series properties hypothesis.[15]

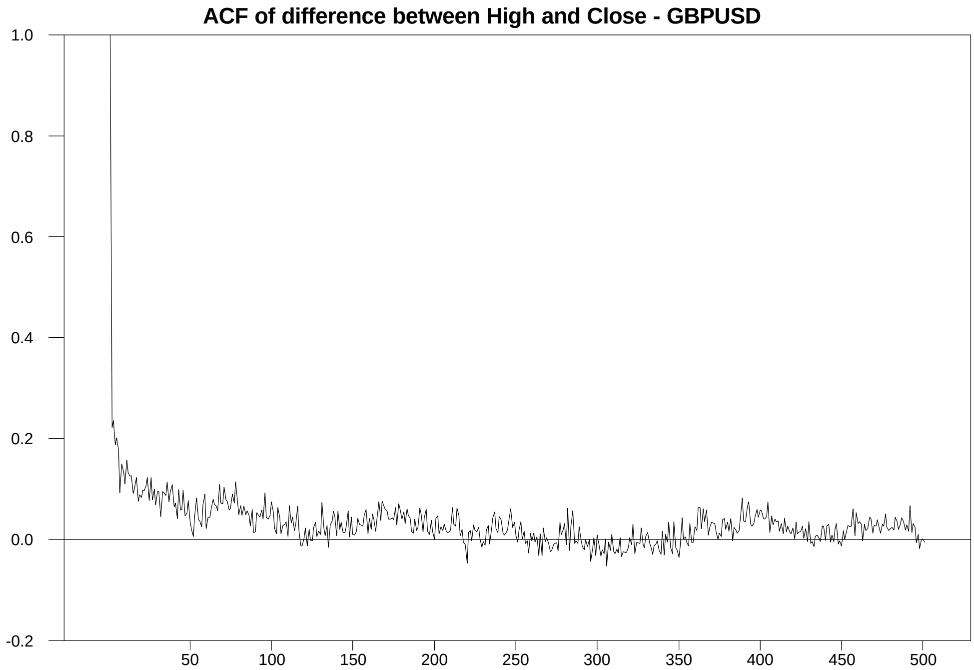

Figure 1

[14] The ACF for the differences between the High, Low and Close series show similar results for USDDEM and USDJPY and are therefore not presented here in order to save space.

[15] The ACF of the difference between High and Low (figure 3) shows a particularly slow decay and thus reflects a high degree of structural relationship between these two series. This, however, is not surprising since the absolute difference between High and Low denotes a simple measurement of daily volatility and a slowly decaying ACF therefore indicates the presence of autoregressive conditional heteroskedasticity (ARCH), a feature of daily exchange rates widely accepted within the foreign exchange market microstructure theory. See, for example, Baillie and Bollerslev (1989) and the references therein.

4. Econometric Methods and Results

4.1 Structural Econometric Modelling.

The modelling strategy applied follows recent developments in the econometric literature, in particular the work of Clements and Mizon (1991), Hendry and Mizon (1993) and Johansen (1988), and we label it structural econometric modelling (SEM).[16] Via a series of testable restrictions and reductions, this modelling strategy transforms an initial VAR in levels into a set of linear structural equations that incorporate both long and short-run dynamics.[17]

Starting from an unrestricted vector autoregressive model (VAR), the hypothesis of cointegration is formulated as a hypothesis of reduced rank of the long-run impact matrix Π. The VAR is generated by the vector z_t, which defines the potential endogenous variables of the model. Taking first differences the VAR can be transformed into

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_{k-1} \Delta z_{t-k=1} + \Pi z_{t-k} + \psi D_t + \varepsilon_t, \qquad \varepsilon_t \sim IN(0, \Sigma) \tag{4}$$

where the estimates of $\Gamma_i = -(I - A_1 - \ldots - A_i), (i = 1, \ldots, k-1)$ describe the short-run dynamics to changes in z_t and $\Pi = -(I - A_1 - \ldots - A_i)$ captures the long-run adjustments, and *D* contains deterministic terms.

This modelling strategy involves the transformation of the initial VAR into a constrained VAR (CVAR) by placing restrictions on the cointegration space. Secondly, the CVAR is then made more parsimonious (PVAR) by successively removing insignificant short-term variables, based on F-tests, until all remaining variables are significant at the 5% level. This PVAR is then transformed into a simultaneous equation model (SEM) by determining the short-term causality amongst the system variables. In order to reduce the dimensionality of the system further, by increasing robustness to changes, the individual equations are then finally estimated

[16] A recent application of this modelling technique in the field of exchange rate economics is MacDonald and Marsh (1996).

[17] While Clement and Mizon (1991) and Hendry and Mizon (1993) do not suggest a particular stratgey to identify the short-run dynamics, Johansen and Juselius (1994) identify the short-run independently from the long-run following an exploartive identification processs. Hsiao (1997) stresses, however, the necessity of identifying the long and short-run structure simultaneously. Since no consensus about the identification problem of the short and long run dynamics has been reached as yet, we decided to follow the first two approaches.

with Full Information Maximum Likelihood estimation (FIML). Considering the data-driven nature of the identification procedure, an important test statistic is the ability of the SEM to parsimoniously encompass the PVAR (see Clements and Mizon (1991)). A specific set of equations represents an acceptable parameterisation of the original VAR, if it contains roughly the same information as the PVAR from which it was derived given the restrictions imposed

4.2. Cointegration and the Stochastics

The Stochastics establishes a structural relationship between the Close of today and the Maximum and Minimum price of a moving period, measured as the highest High and the lowest Low. Specifying a VAR with the data vector $z_t = (C_t, H_t^{max}, L_t^{min})$ for USDDEM, USDJPY and GBPUSD and testing for cointegration between the three variables should reveal if the Stochastics intuitively exploits Granger causality between these three series. Each VAR included a constant in the cointegration space and 15 lags of each of the variables, which was sufficient to produce random errors.[18, 19]

The estimates of λ_{max} and λ_{trace} for the three currencies, reported in Table 2, indicate up to two significant cointegration vectors for USDJPY and GBPUSD and up to three for USDEM. However, based on a graphical inspection of the cointegration relationships, and on an analysis of the companion matrix, we used only the first two vectors for USDDEM.

USDDEM.

Table 2.

Null Hypothesis	Alternative Hypothesis	USDDEM	USDJPY	GPBUSD	95% Critical Value	90% Critical Value
λ_{trace} test		λ_{trace} value	λ_{trace} value	λ_{trace} value		
r = 0	r > 0	274.15	285.44	208.63	35.10	31.88
r ó 1	r > 1	60.24	59.75	39.92	20.17	17.79
r ó 2	r > 2	9.30	6.52	5.03	9.10	7.50
λ_{max} test		λ_{max} value	λ_{max} value	λ_{max} value		

[18] The deterministic components of the VAR were defined according to the rank test suggested in Johansen (1992). The rank test facilitates defining the deterministic components of the model together with the rank of the cointegration matrix using the so-called Pantula principle. The rank test suggests the inclusion of a constant in the cointegration space for all three currencies and gave evidence for three cointegration vectors in the case of USDDEM and two for USDJPY and GBPUSD.

[19] The model specifications for the three models are presented in the appendix in table 7.

r = 0	r = 1	213.91	225.69	168.71	21.90	14.09
r = 1	r = 2	50.94	53.23	34.89	15.25	10.29
r = 2	r = 3	9.30	6.52	5.03	9.10	7.50

Normalising the first vector on the first element and the second on the third yields the following estimates for β (Table 3) and a (Table 4):

Table 3:

	USDDEM		USDJPY		GBPUSD	
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
Close	1.000	0.652	1.000	0.042	1.000	0.794
Maximum	-0.481	-1.609	-0.508	1.000	-0.488	1.000
Minimum	-0.518	1.000	-0.491	-1.041	-0.519	-1.929
Constant	-0.001	0.031	-0.006	-0.043	0.002	0.013

Table 4:

	USDDEM		USDJPY		GBPUSD	
	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_1$	$\hat{\alpha}_2$
Close	-0.112	-0.016	-0.077	0.003	-0.124	-0.009
	(-2.462)	(-2.129)	(-1.70)	(0.35)	(-2.11)	(-1.06)
Maximum	0.134	0.016	0.183	-0.020	0.250	-0.014
	(9.251)	(4.708)	(9.28)	(-5.06)	(9.94))	(-3.73)
Minimum	0.183	-0.018	0.169	0.025	0.250	0.019
	(9.251)	(-5.430)	(7.81)	(5.61)	(3.50)	(4.07)

t-values in brackets

The results for USDDEM give evidence for two cointegration relationships in the data set comprising C_t , H_t^{max} and L_t^{min}. In the presence of multiple cointegrating vectors, it is now common practice to try to interpret these vectors in an economically and statistically meaningful way. In order to test if these theoretical values are indeed identifying we performed several hypothesis tests. According to Johansen (1992) and Johansen and Juselius (1994) a system is exactly, or just, identified if k = r-1 restrictions are placed on each cointegration vector and the rank condition for generic identification is satisfied. Generic identification requires in the case of two cointegration vectors that the rank condition rank ($R_i' H_j$) $\geq$ 1 for i, j = 1,2 and i $\neq$ j is fulfilled. Where R_i is the orthogonal complement of H_i, thus that R_i and H_i are both of full rank and satisfy the conditions $R_i' H_i = 0$, $R_i' b_i = 0$ and $b_i = H_i \varphi_i$. R_i are p$*$k matrices and H_i are p$*$s matrices with k + s = p. If more than k = r - 1 restrictions are placed on each cointegration vector then it is possible to test with a LR test whether these overidentifying restrictions are valid and thus restrict the variation of the parameters. If the overidentifying restrictions satisfy the rank condition and the LR test is passed successfully than each cointegration vector is said to be uniquely identified.

Since the data in this model was constructed imposing the relationship $C_t = 0.5(H_t^{max} + L_t^{min})$, the estimated coefficients of the normalised first cointegration vector should be close to their theoretical values (1, -0.5, -0.5, 0). We attempt to interpret the second vector as a structural relationship of the form $H_t^{max} - L_t^{min}$ = constant, i.e. a stationary spread between the periodic High and Low prices. In vector form, the second cointegration vector should be of the form (0,1,-1,*).

A test of the first cointegration being equal to (1,-0.5, -0.5,0) entails three restrictions on the first cointegration space. A test of the second cointegration being described by (0,1,-1,*) places two restrictions on the second cointegration vector. A joint test of these restrictions is implemented as follows:

$$H_1' = \begin{vmatrix} 1 & -0.5 & -0.5 & 0 \end{vmatrix} \quad \text{and} \quad H_2' = \begin{vmatrix} 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 \end{vmatrix} \qquad (5)$$

$$\text{with } R_1' = \begin{vmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 \end{vmatrix} \quad \text{and} \quad R_2' = \begin{vmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{vmatrix}$$

The LR test of this model specification has a χ^2 distribution with 3 degrees of freedom. For USDDEM the calculated value of $\chi^2 = 4.24$ has a p-value of 0.24. Since the rank condition of generic identification is satisfied the statistical model specified by these restrictions is uniquely identifying[20]. The estimated value of the coefficient of the

[20] Rank Verification of the Rank Condition of Generic Identification of the Long Run Structure:

	rank ($R_1'H_2$)	rank ($R_2'H_1$)

constant in the second cointegration vector, which is the only freely estimated parameter in the cointegration space, is - 0.041. This parameter value suggests that the spread between H_t^{max} and L_t^{min} equals 0.041, or 4.1% since log transformed values of the levels were used. The actual average spread between H_t^{max} and L_t^{min} over the period August 1989 - August 1996 was 70 basis points, which translates into 3.8% in log terms. Since the coefficient of the constant has an associated standard error of 0.002, a Wald test of the form

$$\left(\frac{-0.041-(-0.038)}{0.002}\right)^2 = 2.25$$

can be used to test the hypothesis that the estimated value equals its empirical counterparts. The Wald statistic, which is asymptotically distributed as χ^2, does not reject this hypothesis since $\chi^2_{0.95} = 3.84$.

The results of the tests for USDJPY indicate the existence of a similar structural relationship to USDDEM, since the null hypothesis of the first vector being given by (1,-0.5,-0.5,0) and the second being equal to (0,1,-1,*) could not be rejected ($\chi^2(2)$ =1.25, p-value = 0.53). While the normalised estimates of the cointegration vectors for GBPUSD also seem to suggest a similar structural specification to the cointegration vectors of USDDEM and USDJPY, the LR tests for GBPUSD failed to accept the hypothesis that the first cointegration vector can be identified by (1,-0.5,-0.5,0). However, the less restrictive test of (1,-0.5, -0.5,*) being part of the first cointegration vector was accepted. The Likelihood Ratio test of this hypothesis is $\chi^2(1)$ and the calculated value of χ^2=3.70 has a p-value of 0.05 and is significant at conventional levels. Since the second cointegration vector of GBPUSD could not be identified as (0,1,-1,*), no evidence for a constant spread between the periodic Highs and Lows could be found for the period. We interpret this as reflective of the sharp depreciation of the Pound against the Dollar after the UK's decision to leave the ERM in August 1992.

Test VI :	1	1
Test VII:	2	1

The cointegration space for our three exchange rate models is therefore, in the terminology of Johansen and Juselius (1994), not only empirically but also economically identified in the sense that the estimated coefficients can be interpreted from an economical point of view[21].

4.3 Structural Econometric Forecasting Models

We now use our identified cointegration relationships to derive short-run dynamic forecasting models for USDDEM and USDJPY using the SEM method discussed above. Using the identified long-run relationship from the previous section, we generated a CVAR and then a PVAR. Compared to the CVAR, the latter systems, have 43 less variables for USDDEM and 42 less for USDJPY. Given the data-driven nature of the identifiaction procedure, an important test statistic is the ability of the SEM to parsimoniously encompass the PVAR (see Clements and Mizon (1991)). A specific set of equations is taken to represent an acceptable parameterisation of the original VAR, if it contains roughly the same information as the PVAR from which it was derived, given the restrictions imposed. As can be seen in Tables 5 to 6, each of our models easily passes the Clement-Mizon LR test of over-identifying restrictions.

The identified model structures reveals that $\Delta\,\text{max}$ and $\Delta\,\text{min}$ have an immediate impact on $\Delta\,\text{cl}$, while $\Delta\,\text{max}$ and $\Delta\,\text{min}$ can be identified as AR(1) processes. This model structure is in line with the identified theoretical relationship embodied in the first cointegration vector which assumes that today's Close is affected by today's periodic Maximum and Minimum. Since the Maximum and Minimum series correspond to local Maxima and Minima of the High price and Low price series, it is not surprising that $\Delta\,\text{cl}$ does not enter either $\Delta\,\text{max}$ or $\Delta\,\text{min}$.

Since the error correction components are highly significant in almost all system equations, it is clear that a single equation reduced form modelling strategy would not have been appropriate. An additional advantage of using a structural

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[21] It is interesting to note that the structural relationships that were identified in the data constructed from the Close and the periodic High and Low series (C_t, H_t^{max}, L_t^{min}) could not be identified in a data set constructed from daily Close, High and Low series. The Johansen cointegration method revealed also two cointegration vectors for this data set. But even though the cointegration vectors in the data had coefficients quite similar to the two cointegration vectors for USDDEM in the C_t, H_t^{max}, L_t^{min} model, the data for C_t , H_t , L_t failed to accept the hypothesis of vector (1,-0.5, -0.5,*) being part of the cointegration space for all three currencies. This suggests that the relationship C = 0.5(H + L) only holds for periodic High and Low prices of the currencies studied and not for daily High and Low prices and that the cointegration relations between daily data of High, Low and Close seem to follow more complicated dynamics.

equation approach, rather than a single equation reduced form modelling strategy, is that only the first provides us with a closed system that faciliates computation of fully dynamic multi-step ahead forecasts. The forecasted values of each variable are in this case fed back into the system to provide the basis for the forecasts of subsequent periods. As such, no unfair advantage is given to the model over the random walk.

Table 5: SEM estimates for USDDEM

	Δ cl	Δ max	Δ min	Δ cl_{t-1}	Δ max_{t-1}	Δ min_{t-1}	$Ecm1_{t-1}$	$Ecm2_{t-1}$
Δ cl	-1	0.7976	1.0035				-0.1977	
		(4.4)	(6.2)				(-6.8)	
Δ max		-1			0.1895		0.0874	-0.0277
					(9.7)		(17.5)	(6.9)
Δ min			-1			0.2432	0.0802	0.0224
						(12.5)	(16.6)	(5.8)

LR Test of over-identifying restrictions $Chi^2(9) = 10.6$ [0.30]

Residual Correlation: $R = \begin{bmatrix} 1 & & \\ -0.087 & 1 & \\ -0.1586 & -0.004 & 1 \end{bmatrix}$

Table 6: FIML Estimation for USDJPY

	Δ cl	Δ max	Δ min	Δ cl_{t-1}	Δ max_{t-1}	Δ min_{t-1}	$Ecm1_{t-1}$	$Ecm2_{t-1}$
Δ cl	-1	0.4234	0.9968				-0.1700	-0.0189
		(2.6)	(5.6)				(-5.8)	(-2.2)
Δ max		-1			0.229		0.0822	-0.0252
					(11.9)		(-6.7)	(15.5)
Δ min			-1			0.2030	0.0994	0.0271
						(10.22)	(17.3)	(5.7)

LR test of over-identifying restrictions $Chi^2(8) = 14.39$ [0.072]

Residual Correrlcation: $R = \begin{bmatrix} 1 & & \\ 0.0743 & 1 & \\ 0.0116 & -0.1268 & 1 \end{bmatrix}$

5. Out-of-Sample Forecasting Results.

The forecasting models were estimated over the first 2500 data observations and their forecasting ability compared to a random walk (with and without drift) over the remaining sample, thus sparing roughly 10% of the total sample for forecasting. The drift component for the random walk model was estimated as the mean of the absolute changes of the Close series. Even though our model is able to forecast the Close, the periodic High (Max) and the periodic Low (Min) prices *n*-steps into the future, only forecasts of the Close series were considered. Only these forecasts represent a “true” forecasts in that they assign a certain value to a specific point in time, i.e. a forecast of tomorrow’s Close represents a forecast of tomorrow’s spot rate at 1700 hours. A forecast of the Max or Min, however, does not reveal any information at which time of day this value is to be expected and thus is of little use under market timing considerations.

Since the classic paper of Meese and Rogoff (1983), the crucial factor in determining the worth of an exchange rate model is how well it forecasts in an out-of-sample context relative to a random walk, using the metric of root mean square errors (RMSEs). In Table 4, the Theil statistics are calculated as the ratio of the RMSE of the forecasting model over the RMSE of a driftless random walk[22]; a value equal to one indicates equal forecasting accuracy, a value smaller than one indicates that the forecasting model outperforms the random walk and a value bigger than one indicates that the model does worse than the random walk in respect of root mean square error minimisation. The significance of the Theil statistics are tested using the Diebold-Mariano procedure (1995). This tests the null hypothesis of equal forecasting accuracy of two alternative forecasting models by regressing the difference of the RMSE of the two alternative forecasts on a constant. The Newey and West correction for heteroscedasticity and serial correlation (induced by overlapping observations with multi-step forecasts) is used to adjust the standard errors.

From an investor’s point of view a forecast that correctly predicts the direction of change is more useful than RMSE minimisation and so we also present a test of directional forecasting ability. The significance of the directional forecasts were tested using the regression-based Cumby-Modest (1987) statistics, which are robust to moving average errors. According to the Cumby-Modest approach a model provides value if it correctly predicts the sign of subsequent large changes, even if it gets the direction wrong on average.

As can be seen from Table 4, the USDDEM model performs very well, compared to the random walk forecast. Even though the Theil statistics indicate more accurate forecasts of the naive model for USDDEM over a horizon of 3 days, this does not prove significant using the Diebold-Mariano statistics. The USDDEM model outperforms the random walk forecast in a time horizon of more than 4 days, however, since the Theil statistics are again not significant, these results should only be taken as indicative. Table 5 reports the proportion of exchange rate changes for which the model gets the direction of change correct. The USDDEM model clearly outperforms the forecast based on a random walk with drift. The USDDEM model gets the direction right in all but one case, with percentages lying between 51.3% and 55.8%. The one-day ahead forecast is significant at the 10% level according to the Cumby-Modest statistics. This indicates that a forecast based on a model derived from considerations common to Technical Analysis is able to outperform a random walk on a time horizon as short as a day. The declining forecasting ability over time of the Technical Analysis models seems to be consistent with the view that Chartists tend to revise their forecasts on a daily basis. It also corresponds to the relative importance given to Technical Analysis as a means of forecasting by respondents in a survey of the London foreign exchange market by Talyor and Allan (1994).

According to Taylor and Allan, Chart Analysis appears to exercise its greatest influence when market participants are formulating forecasts or trading decisions for the short-term horizon. Around 90% of their respondents reported using Technical Analysis in a time span of less than one week, while the weight given to Technical Analysis in the longer term sharply declines in favour of Fundamental Analysis.[23]

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[22]Since the random walk model with drift had a bigger RMSE than the driftless random walk over all time horizons, it was decided to use the latter as a benchmark for our model forecasts.

[23] However, Menkhoff (1995) fails to reproduce the same results in a survey of the German Foreign exchange market. The number of respondents relying on Technical Analysis in a time horizon of less than a week (40%) lies far below the figure quoted by Taylor and Allan. Menkhoff also fails to find evidence that the weight given to technical analysis when formulating trading decisions is declining over time. Only from a time horizon of 6 month onwards does fundamental analysis gain the upperhand. Menkhoff claims that the discrepancy between the two surveys could be partly due to the fact that his respondents could allocate their preferences between three alternatives (Flow Analysis, Technical Analysis and Fundamental Analysis) and not just between two (Technical Analysis and Fundamental Analysis) as in the Taylor and Allan survey, where respondents might have classified Flow analysis as a form of Technical analysis. However, the discrepancy between the two surveys could also indicate a difference in the market microstructure of the London and Frankfurt foreign exchange market.

Table 4: RMSE of driftless Random Walk and Theil statistics

	USDDEM	USDJPY
USDDEM	Model 1	Model 1
1	1.012	0.995
2	1.008	0.985
3	1.003	0.985
4	0.999	0.985*
5	0.999	0.995**
6	0.991	0.986
7	0.997	0.986
8	0.999	0.991
9	0.996	0.989
10	0.995*	0.993

Significance according to the Diebold Mariano procedure is indicated by * for the 10% level and by ** for the 5% level.

Table 5: Directional Forecasting Performance

	USDDEM		USDJPY	
	Model	Random Walk	Model	Random Walk
1	0.558*	0.478	0.573**	0.419
2	0.538	0.478	0.560*	0.419
3	0.528	0.467	0.547	0.405
4	0.533	0.484	0.561	0.459
5	0.527	0.461	0.545	0.361
6	0.516	0.467	0.547	0.370
7	0.519	0.481	0.545	0.355
8	0.490	0.490	0.570	0.372
9	0.513	0.496	0.554	0.400
10	0.550	0.504	0.531	0.377

Directional forecasts that are significant according to the Cumby Modest statistics is indicated with * for the 10% level and with * * for the 5% level.

The results for USDJPY, also reported in Table 4 and 5, are even more encouraging. The Theil statistics indicate a more accurate forecast performance of the USDJPY model over the random walk alternative for all time horizons: however, only the Theil statistics for the 3, 4 and 5 day ahead forecast are significant according to the Diebold-Mariano procedure. The USDJPY model also shows good directional forecasting ability, correctly predicting the direction of change between 53.1% and

57.3% over all time horizons. Again, as for USDDEM, the one-day ahead forecast yields the best result with a 57.3% strike, which is significant at the 5% level according to the Cumby-Modest statistics.[24]

It is interesting to compare the forecasting performance of the two empirically identified cointegration vectors to the non-identified cointegration vectors, since restricting the cointegration space changes the short-run dynamics of the system.[25] Considering the fact that exactly identifying cointegration vectors entail more restrictions on the cointegration space than just simply determining the cointegration rank, one would expect that a forecasting model based on non-identified cointegration vectors is less robust to changes and hence is more affected if the exchange rate has different features during the estimation period as in an out-of sample forecasting period. This is the case in our forecasting experiment where the beginning of the out-of sample forecasting period coincides with a change in the long-term trend of the dollar. Table 6 shows that the identified cointegration vectors yield the better forecasts for USDDEM as well as USDJPY. The model based on the non-identified cointegration relationships still gets the direction right in more than 50% of all cases and clearly does better than the model without error correction parts. However, it cannot match the results of the identified cointegration vectors. According to both test statistics of directional forecasting, it can clearly be seen that only the models with the identified *ecms* are able to significicantly outperform the random walk. These results are encouraging since the good out-of sample performance of these models might also persist in an out-of sample experiment that does not directly succeed the in-sample estimation period.

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[24] While the directional forecasts of model 3 are with exception of the 2 and 5 day ahead forecasts, all significant according to the test statistics proposed by Dacorogna et al., only the one day ahead forecast is significant according to the Cumby-Modest statistics. Since not correcting the Cumby-Modest statistics for serial correlation yielded that same results as the test proposed by Dacorogna et al. , the importance of correcting for serial correlation can clearly be seen.

[25] FIML estimation of the system containing the non-identified cointegration vectors is not given here, since the same set of linear equation, even though with slightly different coefficients, was found for both pairs of cointegration vectors. The coefficients for the two pairs of the error correction parts varied slightly as expected.

Table 6:

	Model (without ecms)	*Model (unidentified ecms)*	*Model*	*RW with drift*
USDDEM				
Direction	0.481	0.548	0.558	0.478
RMSE	0.00509	0.00506	0.00506	0.00501
MAE	0.00367	0.00363	0.00362	0.00357
USDJPY				
Direction	0.526	0.536	0.573	0.419
RMSE	0.00643	0.00639	0.00636	0.00641
MAE	0.00450	0.00448	0.00446	0.00446

By relaxing the independence assumption of subsequent returns of the Hendriksson-Merton (1981) test, the Cumby-Modest statistics evaluate the probability of profitable directional forecasts rather than the probability of correct directional forecasts. The Cumby-Modest statistics take not only the sign, but also the amplitude of the forecasting signal into consideration. A forecasting signal that is significant according to these statistics should, on average, predict large enough changes in the exchange rate that allow the accommodation of transaction costs and risk premia. In the last section of this paper we therefore present a profitability analysis of our forecasting models.

6. Assessing the profitability of the forecasting models

In this section we test the profitability of our forecasting model. Since the stochastics is a trading rule, rather than a forecasting model, we view this as a more appropriate method of assessment than the acadmic industry's benchmark, the random walk.[26]In order to construct profitability estimates, our forecasting model has to be transformed into a trading model by defining a vector that issues exactly defined trading signals. Since our models work most successfully at the one-day ahead horizon, a Buy signal (Long position) is issued if the one-day ahead forecast exceeds the current Close c_t and a Sell signal (Short position) is given if tomorrow's forecast lies below the current Close c_t.

$$p_{Long} = F(\hat{c}_t | \hat{c}_t > c_t)$$

$$p_{Short} = F(\hat{c}_t | \hat{c}_t < c_t)$$

The Stochastics, on the other hand, can be traded in many different ways. However, since all of these strategies are effectively variations of the following two strategies, we focus on them here. (1) Concentrating on %K alone, the Stochastics can be treated as a so-called Overbought-Undersold Indicator, where a Buy signal is given if the Stochastics fall below values of 30 and a Sell signal arises if the Stochastics rise above 70 (Stochastics 70/30). (2) Alternatively, many traders use the intersection between %K with its smoothed version %D as a trading system (Stochastics Crossover). In this case, a Long signal is given, if %K rises above %D and a Short signal corresponds to a fall of %K below %D.

Since the Stochastics belong to the family of contra-trend indicators and the majority of studies about technical analysis focus on trend-following trading systems, a simple trend-following trading model based on a 10 and a 20 day Moving Average was additionally taken into consideration. This trading model issues a Long signal if the 10 day Moving Average rises above the 20 day Moving Average. A Short signal occurs if the shorter term Moving Average falls below the longer term Moving Average.

Since we did not choose the 10/20 day specification of the MA nor the 14 day specification of the Stochastics on grounds of profitable *ex post* optimisation, the *ex ante* application of these two specific technical trading rules comes close to a real world experiment. We assess the profitability of the 4 different trading models starting from the simple profitability of following the trading signals and then add further aspects to the analysis, by including a Buy & Hold benchmark and considering various aspects of risk.

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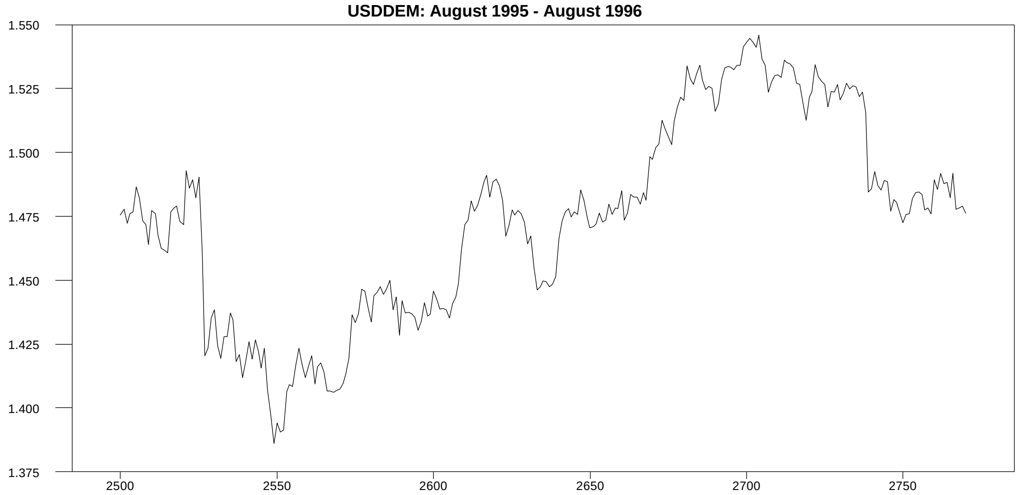
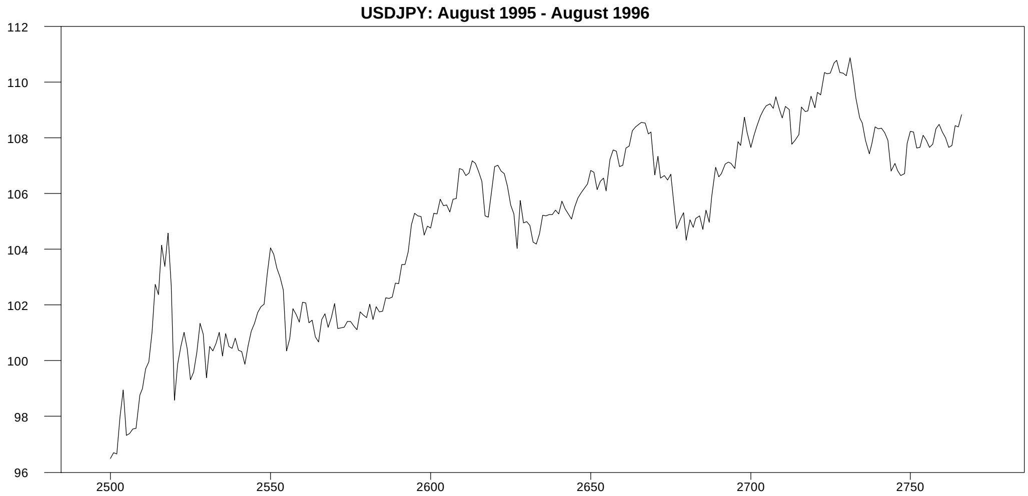
[26] As explained earlier, the Stochastics calculates an indicator that reveals over-bought and undersold situations. The Stochastics formula does not allow derivation of a point forecast.





6.i Profitability

Assuming a 1 US$ investment per trading signal and excluding the reinvestment of speculative profits, our profitability calculations take three components into consideration: the absolute return, the interest rate differential and transaction costs.

1) The absolute return is calculated as the cumulative sum of single returns, p_i, where single returns are measured as the log-ratio of the exchange rate between opening, s_{t0}, and closing, s_{t1}, a foreign currency position:[27]

$p_i = \ln(s_{t1} / s_{t0})$

[27] We follow the traditional practice in the field and measure returns in log-forms.

Since the trading models are active for different time spans, the absolute returns are made comparable by calculating an annualised rate of return:

$$R_i = 100 \frac{1\ \text{Year}}{D_i} \Sigma r_i \ ,$$

where a year is taken to comprise 262 business days and D_i denotes the cumulative duration of all open positions in days;

2) The net interest rate effect accounts for the fact that a dollar Long position earns dollar interest, pays DM interest in the case of USDDEM, and pays Yen interest in the case of USDJPY. The net interest effect of opening in a dollar Long position in USDDEM consists of the interest rate differential (r_{usd}-r_{dem}). The net interest effect of a Short position is given by -(r_{usd}-r_{dem}). Following Schulmeister (1986), the overall interest effect i_i of holding currency positions in USDDEM can be approximated as:[28]

$$i_i = \frac{(r_{usd} - r_{dem})(D_L - D_S)}{D_{L+S}}$$

Using 3 month Eurocurrency market rates, the interest differential for USDDEM averaged 1.93 % over the out-of sample period and 5.01% for USDJPY, thus resulting in a discount to the total annual rate of return for trading models with more Short than Long positions and in a premium in the opposite case.

3) The level of the transaction costs is estimated in line with other studies as the percentage bid-ask spread of interbank quotes. The interbank quotation of bid and ask rates for USDDEM and USDJPY shows a usual spread of 3 base points (BP), i.e. 1.5560-1.5563 DM or 104.30 to 104.33 YEN per US$. Given an exchange rate of 1.50 DM and 100 Yen per 1 US$, estimated transaction costs per round trip, and thus per trading signal, are 0.02% for USDDEM and 0.03% of USDJPY.[29]

The level of transaction costs assumed here are slightly lower than the figures used by Sweeny (1986), Schulmeister (1987) and Menkhoff (1995), reflecting the

[28] The overall interest effect of holding currency positions in USDJPY is likewise calculated as

$$i_i = \frac{(r_{usd} - r_{yen})(D_L - D_S)}{D_{L+S}}$$

[29] According to Demsetz (1968) the bid-ask spread corresponds to the costs of two transactions. Since the trading strategies investigated here involve switching from Short to Long position or vice versa, i.e. a neutral positions are excluded. Each trading signal involves the closing of the starting position

declining spread in foreign exchange markets. However, they are still higher than figures quoted by bankers who told us in interviews that transactions costs average around 100 DM per spot transaction and around 200 DM per forward transaction for USDDEM as well as USDJPY.[30, 31]

6.ii Buy & Hold

The profits from technical analysis are generally compared to a Buy & Hold strategy, where Buy & Hold is considered an investment in a particular currency. The profits of Buy & Hold for USDDEM and USDJPY are calculated as the difference in the exchange rate at the beginning and end of the forecasting period, acknowledging the net interest rate effect of investing in foreign rather than domestic money. As can be seen from Figure 1 and 2, following a Buy & Hold strategy for USDDEM does not result in a substantial profit, in effect the exchange rate increased by only 90 basis points over the sample. Only higher US interest rates left the investor with an annualised return rate of 2.05%. The appreciation of the dollar against the Yen in the forecasting period from 96.50 Yen to 108.25 Yen per US$ makes Buy & Hold more profitable for USDJPY. The resulting annualised rate of return of 16.25% establishes a difficult test criterion for our technical trading rules.

On pure profitability considerations, our model yields by far the highest annualised return rates with 9.52% for USDDEM and 20.20% for USDJPY. While the Stochastics 70/30 also leaves the investor with a substantial annualised rate of return of 6.18% for USDDEM and 5.56% for USDJPY, the Stochastics Crossover and the Moving Average 10/20 trading model have a pure performance in comparison. While the MA 10/20 fails to provide any profits for USDDEM (-5.29%), it seems, however, to be quite profitable for USDJPY (6.75%). Following the trading signals of the Stochastics Crossover results in effect in a loss for USDDEM (-4.44%) as well as USDJPY (-10.25%).

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and the opening of the opposite at the same point in time. Thus each trading signal requires tow transactions.

[30] Assuming transaction costs of 100 DM, selling or buying of 5 bn US $ thus amounts to 0.0014% , i.e. not even 1 BP. This might explain the custom of foreign exchange dealers to quote sometimes a zero spread to good customers. Since the level of transaction costs can be crucial for the profitability of a trading model, the returns of the different trading models are calculated inclusive and exclusive of transaction costs.

When the profitability of the different models is compared to a simple Buy&Hold stratgey, the picture changes. While our models have no problem beating Buy&Hold for USDDEM as well as USDJPY, Stochastics 70/30 and MA10/20, that seemed to be doing well for USDJPY on pure profitability considerations both fail to outperform the Buy&Hold benchmark of 16.25%.

Taking the returns of Buy&Hold as a measure of the underlying trend rates in the data (Poole, 1967), it can be see that the high excess returns of our models cannot be explained by a positive trend alone. In fact, the profitability of our models seems to be unrelated to the underlying trend in the currency, since our model yields a high rate of profitability in a trending (as in the case of USDDEM) as well as in trendless (as in the case of USDJPY) markets. The profitability of the trendfollowing MA 10/20 is, however, clearly linked to the underlying trend in the sample. MA10/20 profits in a market with a strong trend (USDJPY) and does appallingly in a trendless market (USDDEM).

Table 8: Profitability Profile of USDDEM and USDJPY trading models

	Model	Stochastics (70/30)	Stochastics Crossover	Ma 10/20
USDDEM:				
days long	139 (53%)	137 (53%)	119 (49%)	121 (49%)
days short	123 (47%)	122 (47%)	125 (51%)	116 (51%)
annual rate	11.4%	6.70%	-1.81%	-0.20%
- incl. transaction costs	9.4%	6.33%	-4.39%	-5.55%
- incl. trans & net interest	9.52%	6.18%	-4.44%	-5.29%
USDJPY:				
days long	137 (52%)	86 (35%)	118 (49%)	138 (61%)
days short	125 (48%)	161 (65%)	122 (51%)	87 (39%)
annual rate	22.3%	7.63%	-3.86%	5.83%
- incl. transaction costs	20.0%	7.17%	-10.15%	5.43%
- incl. trans & net interest	20.2%	5.56%	-10.25%	6.75%

[31] Thiessen (1995) reports similar figures. According to Thiessen, the transaction costs lie between 80-120 DM per transaction, if a broker is involved, additionally 20DM per 1bn US$ have to be paid.

6.iii Risk Adjustment

Since the persisting profitability of our models could be explained by a risk premium, we go one step further and adjust the profits of the different trading rules for risk. Levich and Thomas (1993) show that the total return from following a trading strategy will overstate the true excess return, if a risk premium is present, especially if currencies exhibit prolonged trends. In order to derive the true excess return, we follow the methodology proposed by Sweeny (1986) and Levich and Thomas (1993), and estimate the risk premium as a constant over the sample period and equal to the returns from a Buy&Hold strategy. Adjusting the risk premium further for the fraction of days we are long in foreign currency (1-*f*) and short in foreign currency (*f*), the expected excess return of following a specific trading rule is calculated as:

$R^* = (1-f)\ RP - f\ RP$.

Levich and Thomas (1993) find that if the percentage of days Long and Short are in a 45-55% range and/ or the Risk Premium is close to zero, a constant risk premium has a negligible effect on the total return. While the estimated risk premium for USDDEM is small with only 0.0205 and not significant (t-value: 0.25), the risk premium for USDJPY is quite high with 0.1625 and borderline significant at the 10% level (t-value:1.60). The fraction of days Long and Short is close to 50% for our model forecast and for the Stochastics Crossover for both currencies. The expected return of these two trading strategies is therefore close to zero and our earlier results are thus almost unaffected by including a risk premium. However, in the case of USDJPY, matters are quite different for the Stochastics 70/30 and the MA 10/20 model. The clear discrepancy between Long and Short positions demand an adjustment of the total return in these cases. The expected rate of return of the MA 10/20 is 0.036 (annualised: 4.14%), adjusting the annualised rate of return of 6.75% accordingly yields a far lower true rate of return of only 2.61%. Since, according to Thomas and Levich, the trading models accumulate the risk premium over the fraction of days long and release the risk premium over the days short, the higher fraction of days short (61%) for the Stochastics 70/30 results therefore in an the expected negative rate of return of -0.049 (annualised: -5.2%). The effectively realised rate of return of 5.56% must be viewed within this context.

The expected negative return of the Stochastics 70/30 might actually be explained by a known weakpoint of the Stochastics. By construction, this indicator tends to give the wrong signals in a market situation with a pronounced trend. LeBeau and Lucas (1992) advise therefore not to use this indicator in such a market situation. If the exchange rate exhibits a strong upward trend, as in the case of USDJPY in the out-of sample forecasting period, the Stochastics 70/30 will frequenlty wrongly indicate an overbought situation and thus a Short position. It is interesting to note that our model does not seem to share this weakpoint with the Stochastics. The reason for this is that the Stochastics derives a trading signal based on the assumption that the exchange rate exhibits mean reverting tendencies within the actual trading range, marked by Max and Min prices. The Stochastic does not provide a point forecast of the Close series. Our modelling strategy differs in the respect that we incorporated the mean-reverting tendency of high freqeuncy exchange rates (*ecm1*) within a trading range (*ecm2*) into structural simultaneous equations for the Close, Max and Min series in order to derive a point forecast for the Close series and then, in a next step, to generate a trading signal.

Since Parkinson (1980) and Garman and Klass (1980) have shown that the efficiency of estimators of price volatility can be substantially increased if the classical Close priced based estimators are augmented with information embodied in High and Low prices, our results seem to suggest that the same holds for point forecasts.

7. Conclusion

In this paper we have taken the relationship suggested by the technical indicator known as a stochastic to establish cointegration relationships in daily exchange rate data consisting of Close, periodic High and periodic Low prices. Using the dynamic modelling strategy of Clement and Mizon (1991) and Hendry and Mizon (1993) and Johansen (1988) we were able to derive fully dynamic forecasting models for USDDEM and USDJPY, which proved to significantly outperform a random walk, in an out-of sample forecasting experiment, at a time horizon as short as one day, and the models were also demonstrated to have directional forecasting ability.

By transforming our forecasting model into a trading model we were further able to investigate the model’s profitability. The results were compared to a Buy&Hold benchmark, as well as to three different trading strategies commonly used by Technical Analysts. Two of these technical indicators represented variations of the Stochastics and thus allowed us to directly compare the forecasting performance of our model to its generic root. The third trading system was an arbitrarily chosen moving average system, which represents the class of trend-following trading models widely used by technical analysts.

The results of our profitability study showed that while the arbitrarily chosen technical indicators had problems in beating the Buy&Hold strategy, our models had no difficulties in passing this criterion for both currencies. Adjusting for risk, using the methodology proposed by Thomas and Levich (1993), also had no substantial effect on the profitability of our models. Even though the trading strategy of the traditional stochastics and moving average models resulted in a quite high annualised rate of return, they could not match the performance of our models. The dynamic modelling strategy utilised in this paper must therefore possess an important informational advantage over such models and, indeed, our forecasting analysis revealed that the good forecasting performance of our models is directly linked to the inclusion of error correction components.

We of course appreciate that our relatively small sample size means that we have to be extremely careful in interpreting our results. However, although this might be a serious short-coming for the persistent profitability analysis of the three Technical Trading Models, the high dealing frequency of our models meant that we were able to analyse 250 trading signals, which is in fact similar to the number of trading signals studied in the 'long-term' studies of Schulmeister (1987) and Menkhoff (1995). Since the profitability of our models persisted in two completely different market situations, we assign a certain statistical meaningfulness to our results.

Appendix

Table A1: Test for Unit Roots - USDDEM

	Coefficient	ADF Statistics (with Constant) Number of lags in brackets without robusterrors	ADF Statistics (with Constant) Number of lags in brackets with robusterrors	Phillips Perron Test (with Constant)	
Close	-0.0033	-2.88 (0)	-2.59 (0)	-2.92	I(1)
Δ Close	-1.007	-53.54 (0)			I(0)
Open	-0.0034	-2.89 (0)	-2.55 (0)	-2.87	I(1)
Δ Open	-1.0170	-29.65 (0)			I(0)
High	-0.0031	-2.93 (3)	-2.66 (2)	-2.93	I(1)
Δ High	-0.9280	-29.71 (2)			I(0)
Low	-0.0031	-3.04 (1)	-2.80 (1)	-2.90	I(1)
Δ Low	-0.8650	-45.97 (0)			I(0)

Critical DF-value at the 5% level: -2.87

Critical DF-value at the 2.25% level -3.12

Table A2: Test for Unit Roots - USDJPY

	Coefficient	ADF Statistics (with Constant) Number of lags in brackets without robusterrors	ADF Statistics (with Constant) Number of lags in brackets with robusterrors	Phillips Perron Test (with Constant)	
Close	-0.0015	-2.59 (10)	-2.32 (10)	-2.48	I(1)
Δ Close	-0.9258	-15.00 (9)			I(0)
Open	-0.0015	-2.58 (9)	-2.33 (9)	-2.48	I(1)
Δ Open	-0.958	-15.01 (9)			I(0)
High	-0.0015	-2.53 (2)	-2.26 (2)	-2.50	I(1)
Δ High	-0.9185	-16.13 (8)			I(0)
Low	-0.0015	-2.62 (1)	-2.17 (1)	-2.51	I(1)
Δ Low	-0.947	-15.37 (9)			I(0)

Critical DF-value at the 5% level: -2.87

Critical DF-value at the 2.25% level -3.12

Table A3: Test for Unit Roots - GBPUSD

	Coefficient	ADF Statistics (with Constant) Number of lags in brackets without robusterrors	ADF Statistics (with Constant) Number of lags in brackets with robusterrors	Phillips Perron Test (with Constant)	
Close	-0.0038	-1.93 (6)	-1.86 (6)	-2.06	I(1)
Δ Close	-0.9900	-17.86 (5)			I(0)
Open	-0.0034	-2.07 (0)	-2.05 (0)	-2.06	I(1)
Δ Open	-0.1017	-43.89 (0)			I(0)
High	-0.0036	-2.00 (2)	-2.00 (1)	-2.06	I(1)
Δ High	-0.8670	-37.75 (0)			I(0)
Low	-0.0036	-2.07 (1)	-2.03 (1)	-2.00	I(1)
Δ Low	-0.8670	-37.75 (0)			I(0)

Critical DF-value at the 5% level: -2.87, Critical DF-value at the 2.25% level -3.12

Table A4: Unit root tests for time series modified according to Stochastics - USDDEM

	Coefficient	*ADF statistics (with constant)*	*lags*	
H_t^{max}	-0.00161	-2.91	6	I(1)
ΔH_t^{max}	-0.507	-16.33	5	I(0)
L_t^{min}	-0.00163	-2.92	6	I(1)
ΔL_t^{min}	-0.415	-11.95	9	I(0)
$C_t - L_t^{min}$	-0.0965	-9.26	13	I(0)
$H_t^{max} - L_t^{min}$	-0.0347	-7.88	16	I(0)

Critical ADF t-value at 5% level: -2.87

Table A5: Unit root tests for time series modified according to Stochastics - USDJPY

	Coefficient	*ADF statistics (with constant)*	*lags*	
H_t^{max}	-0.00082	-2.19	16	I(1)
ΔH_t^{max}	-0.4519	-11.38	15	I(0)
L_t^{min}	-0.00087	-2.19	15	I(1)
ΔL_t^{min}	-0.4178	-10.81	14	I(0)
$C_t - L_t^{min}$	-0.1009	-8.62	14	I(0)
$H_t^{max} - L_t^{min}$	-0.0453	-7.33	14	I(0)

Critical ADF t-value at 5% level: -2.87

Table A6: Unit root tests for time series modified according to Stochastics - GBPUSD

	Coefficient	*ADF statistics (with constant)*	*lags*	
H_t^{max}	-0.0018	-1.64	3	I(1)
ΔH_t^{max}	-0.6411	-19.75	2	I(0)
L_t^{min}	-0.0022	-1.89	3	I(1)
ΔL_t^{min}	-0.6229	-19.13	2	I(0)
$C_t - L_t^{min}$	-0.1127	-7.23	14	I(0)
$H_t^{max} - L_t^{min}$	0.1180	5.31	14	I(0)

Critical ADF t-value at 5% level: -2.87

Table A7: Johansen approach: model specification

	Lags	*LB*	*L(1)*	*L(4)*	*Trace*	*Log*	*SC*	*HC*	*ARCH*	R^2
USDDEM	15	6118.02	30.96	9.24	0.21	-33.30	-33.90	-33.09	90.24	0.04
		chisq(6030)	chisq(9)	chisq(9)					65.94	0.30
		0.21	0.00	0.42					27.52	0.30
USDJPY	15	5799.1	33.9	7.93	0.22	-33.30	-33.90	-33.10	70.43	0.04
		chisq(6021)	chisq(9)	chisq(9)					72.59	0.33
		0.98	0.00	0.54					28.43	0.27
GBPUSD	15	4147.31	12.47	20.97	0.27	-32.96	-32.26	-32.66	116.9	0.05
		chisq(3996)	chisq(9)	chisq(9)					31.0	0.49
		0.05	0.19	0.01					228.7	0.22

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