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Economic Modelling 19 (2002) 353–374

Economic Modelling

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Towards the fundamentals of technical analysis: analysing the information content of High, Low and Close prices ☆

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Accepted 27 February 2001

Abstract

Technical analysis assigns a special importance to the Open, High, Low and Close prices in forecasting the mean and volatility of exchange rates. In this paper we propose to investigate the time series properties and the informational content of these different prices, using range and cointegration methods. The application of these methods to a high frequency data set indicates the existence of stable structural relationships and asymmetric information flows, which is supportive of certain predictions of market microstructure models of the foreign exchange market. In sum, we argue that a technical analysis of High, Low and Close prices is a useful way of learning about latent Granger causality in high frequency exchange rates. © 2002 Elsevier Science B.V. All rights reserved.

JEL classification: F31

Keywords: Technical analysis; Exchange rates; Volatility; Extreme value; Estimators; Candlestick analysis

☆ The authors are grateful to an anonymous referee for helpful comments on an earlier draft of this paper. The views in this paper are those of the authors and should not be interpreted as those of the World Bank or any of its affiliates.

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PII: S0264-9993(01)00067-0

1. Introduction

Technical analysis (TA) assigns a special importance to the Open, High, Low and Close prices in forecasting the mean and volatility of exchange rates. Candlestick analysis is a popular form of TA that combines Open, High, Low and Close prices for the purpose of charting and forecasting and represents probably the most exhaustive attempt to classify price forecasts according to High–Low–Close constellations.[1] Within Candlestick analysis, as well as in other forms of TA, the difference between Open and Close prices serves as a measure of the direction and the extent of intradaily trends. The difference between High and Low prices marks the intradaily trading range and represents a measure of volatility. For many forms of TA, it is the interaction between trend and volatility that is assumed to be informative about future price developments.

While TA is often perceived as an example of trading on information unrelated to underlying fundamental rationalisation (Shleifer and Summers, 1990), we argue that this is not the full story: the underlying fundamental rationalisation, at least in part, is provided by the market microstructure of the foreign exchange market. Furthermore, there appears to be a direct link between TA and the favourable statistical properties of the extreme value estimators of Parkinson (1980), Garman and Klass (1980) and Kunitomo (1992).[2] Blume et al. (1994) have recently shown that TA is valuable when information is costly. In particular, they demonstrate how sequences of volume and prices can be informative and how TA of market data arises as natural components of an agent's learning process.

We argue that similar hypotheses can be formulated for the analysis of High and Low prices once we realise that: (1) High and Low prices reveal information about shifts in the demand and supply structure; and (2) changing order flows play an important part in determining market prices. The academic work on support and resistance levels (Curcio and Goodhart, 1992; DeGrauwe and Decupere, 1992) seems to support the first point. The recent empirical evidence for the latter point is provided by Menkhoff (1998) in a survey of the German foreign exchange market. Menkhoff's results strongly underline the role of order flow analysis in the expectation formation process of foreign exchange market participants. Given that the order flow is unobservable to the uninformed trader, a TA of directly observable High and Low prices allows traders to learn about the underlying market mechanism that drives these order flows.

[1] Candlestick charts were introduced by Japanese rice traders in the 17th century as 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).

[2] Parkinson (1980) and Garman and Klass (1980) have recently demonstrated that the efficiency of traditional return-based volatility estimators can be greatly increased by additionally incorporating the extremes of a range — the High and Low prices — into the information set of a volatility forecasting function. Kunitomo (1992) has shown that the efficiency of extreme value estimators can be increased further once a drift term is accounted for.

Rather than providing a formal model at this stage, it is the intention of this paper to investigate the informational content of Open, High, Low and Close prices and their value in forecasting volatility, as well as future levels of daily exchange rates. An important feature of our analysis is to realise that High, Low and Close prices, even though derived from the same time series, do not share the same time series characteristics. Although this concept may seem somewhat unusual, the theoretical justification is provided by the time delay concept of Takens (1981).

Once we have identified High, Low and Close prices of the *same* exchange rate as *different* time series, we then open the possibility of applying a wide range of multivariate modelling techniques to explore the dynamic and structural relationships between High, Low and Close prices. In particular, we are able to show that High, Low and Close prices carry useful information for forecasting the volatility as well as the level of future exchange rates. Since the relevance of High and Low prices in forecasting speculative prices has been recognised by technical analysts for some time, our analysis also raises the question of whether TA (possibly in an intuitive way) exploits latent Granger causality.

The remainder of this paper is organised as follows: Section 1 tries to explore the determinants of High, Low and Close prices. Attention is drawn to concepts related to TA, as well as to more general features of the foreign exchange market microstructure. Section 2 investigates the time series properties of High, Low and Close prices for the US dollar bilateral of the German mark (USDDEM), Japanese yen (USDJPY) and British pound (GBPUSD), and provides conclusive evidence in favour of different time series characteristics. Section 3 reveals an information asymmetry between extreme value and return-based volatility measures and shows that a simple High–Low volatility estimator compares favourably to more sophisticated forecasting techniques, including GARCH models. Section 4 reports the results of a multivariate cointegration analysis of High, Low and Close prices and presents evidence from Granger causality tests that point towards the possibility that TA might indeed exploit latent structural relationships in high frequency exchange rate data. The main conclusions are presented in Section 5.

2. Determinants of High, Low and Close prices

Exchange rates are recorded on a daily basis in the form of Open, High, Low and Close prices. This convention reflects the belief that these four prices have a higher informational content than other intradaily prices. While Open and Close refer to the price at the opening and closing of the market, respectively, High and Low prices correspond to the two extremes: the highest and lowest prices of the day.[3] High and Low prices indicate market turning points and confine the daily trading range. Highs and Lows therefore represent *intradaily* support and resistance levels, which can also transform into *interdaily* support and resistance levels when not breached during the course of the next trading day.

Edwards and Magee (1966, p. 211) provide a definition of support and resistance that links support and resistance levels to supply and demand, and thus, to the selling and buying activity of speculative assets.

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. Support and resistance levels have the characteristic that, once established, they coincide with local maxima and minima, and thus, confine trading until enough buying or selling interest is gathered to break through the upper or lower boundary of the present trading range. This subsequently establishes 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 Magee, 1966, p. 213)

The importance of trading ranges and their direct link to support and resistance levels has not only been widely acknowledged within the literature on TA, but the evidence of the profitability of trading rules derived from local support and resistance levels has also been recently provided by Curcio and Goodhart (1992), Curcio et al. (1997) and Mills (1997).

We do not have to rely exclusively on TA to find explanations for the determinants of High and Low prices. High and Low prices represent market turning points and thus indicate selling and buying activity. Market participants with overnight positions place stop-loss orders generally near the recent Highs or Lows — large stop-loss orders can trigger a price reversal and as a result confirm recent High and Low levels. Also, institutional changes like the recent increase in derivative trading — especially that of path-dependent options such as double knock-outs or double knock-ins — might offer a further explanation why markets turn at certain points. Recent surveys of foreign exchange markets (Menkhoff, 1998) show that market participants see flow analysis as an important instrument for forecasting future price movements. Since flows are only known to informed traders, the knowledge of order flows presents insider information that can be profitably exploited even under strong-form market efficiency. Given that High and Low prices represent observable components of large order flows that are unobservable by uninformed traders, there is a rational incentive to study High and

[3]Since foreign exchange is traded around the world and around the clock, the foreign exchange market, unlike stock markets or futures markets, never really closes. It is nevertheless conventional to report an opening and closing price. On a daily basis, the Close price corresponds to 17.00 h New York time when trading in NY ceases and Sydney prepares to start its currency trading. On weekdays closing prices are identical to 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 non-trading in the currency market. For a weekend the closing and opening prices are, respectively, 17.00 h New York time on Friday, and 08.00 h Sydney time on Monday.

Low prices in order to recover information about the underlying unobservable flow.

Candlestick chart analysis, which enjoys a growing popularity amongst practitioners could be interpreted as such an attempt. Candlestick charts derived their name from a special graphical plot of Open, High, Low and Close prices, which has a certain similarity to a candle with its wick and shadow. Candlesticks are comprised of a vertical line that represents the difference between the High and the Low, and a rectangle that measures the difference between the Open and the Close. The rectangle is drawn with the same width, but its length and colour depends on the absolute difference between the Open and the Close. If the market closes on a higher level than the opening price (rising prices), the rectangle is filled in white (white body). If the Close price lies below the Open (falling prices) the rectangle is filled in black (black body). The rectangle is reduced to a horizontal line if the market opens and closes at the same price level (Doji). The difference between the Open and the Close prices thus serves as a measure of the direction and the extent of intradaily trends. The difference between High and Low prices marks the intradaily trading range and measures volatility. It is the interaction between trend and volatility that is believed to be informative about future price developments.

While individual candles provide the chartist with information about the trading activity of a certain time period, combinations of 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.[4]

Since Candlestick charts represent an attempt to combine the information of intradaily price trends (Open−Close) with intraday volatility (High−Low) for the purpose of forecasting, we propose an analysis of the time series properties of these different prices.

3. Time series properties of High, Low and Close prices

According to Takens' delay time concept (Takens, 1981) with daily exchange rate data, 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.[5,6] Low and High prices, however, carry different information — they do not coincide with certain times of the day but with the extreme prices of the trading day. Since Low and High prices do not occur at a

[4] Table 6 gives an example of three candlestick formations and their interpretations

[5] Takens (1981) theorem states 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 $x(t)$. $y_t^m = (y_t,\ y_{t+m,\dots,}y_{t+m-1})$ is then called an m-embedding of $x(t)$.

[6] Viewing the Open series as an embedding of the Close series is more relevant for stock markets, since for the foreign exchange market we can approximate: $\text{Open}_t = \text{Close}_{t-1}$ (see footnote 4).

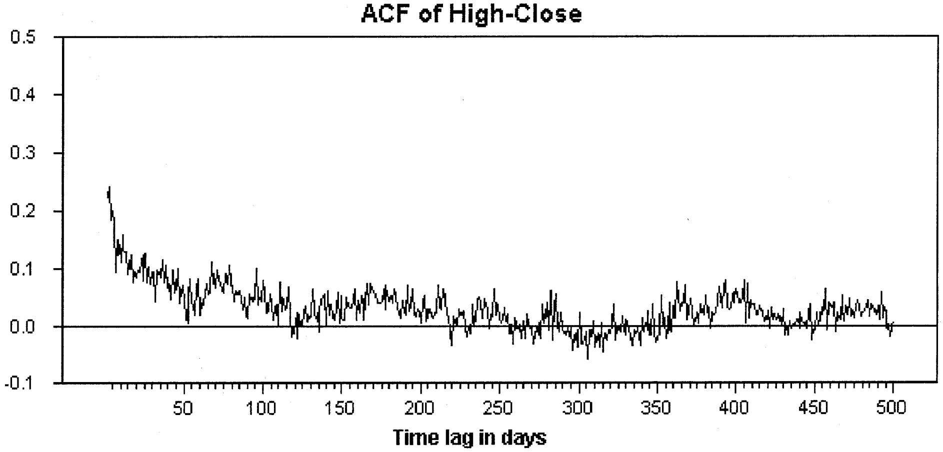


Fig. 1. ACF of the difference between the High and Close series (lag zero omitted) — GBPUSD.

specific time of the day, neither can be expressed as an embedding of the Close series.

Thus, even though High, Low and Close prices are realisations of the same exchange rate, the three series are in fact random drawings. It is therefore possible to apply a wide range of multivariate time series analysis to investigate the dynamics between these different prices. Before we investigate the dynamics between the series, we propose analysing the time series properties of the individual series in order to highlight the difference between them.

One way to illustrate the different dynamics of the High, Low and Close price series is to look at the autocorrelation function (ACF) of the differences between these series.[7] If High, Low and Close had the same time series properties, the difference between the series should be random: the autocorrelation functions of the differences of High and Close, High and Low and Close and Low should contain no significant autocorrelations. However, this is not the case, as demonstrated by Fig. 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. The slow decay of the ACF is significant and, hence, the differences between the two series are

[7]Another indication for the different time series properties can be derived from the results of the Augmented Dickey Fuller (ADF) unit root test for the different time series. While all series were found to be I(1) in levels and I(0) in first differences, the ADF tests 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 reflect different degrees of serial correlation in the residuals, while the same lag lengths for the Close and Open series indicate similar degrees of serial correlation in the residuals (see Chapter 2 in Fiess, 1999, for a detailed listing of the unit root tests). Our sample consists of daily observations of Open, High, Low and Close prices and covers the period from January 2, 1986 to August 30, 1996 for USDDEM and USDJPY (2775 observations), and a period from August 21, 1989 to August 30, 1996 for GBPUSD (1860 observations).

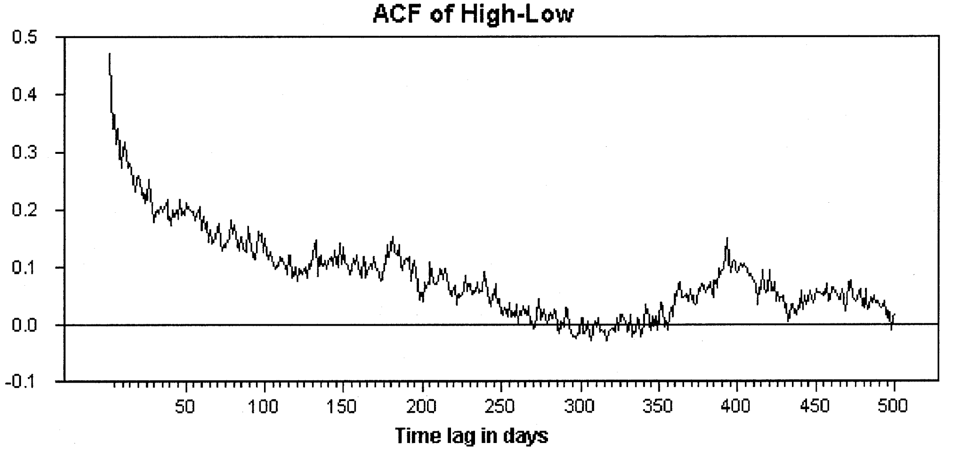


Fig. 2. ACF of the difference between the High and the Low series (lag zero omitted) — GBPUSD.

structural and not random in nature. It takes approximately 100 lags before the ACF becomes zero for the first time.[8]

The ACF of the difference between High and Low (Fig. 2) shows a particularly slow decay and thus reflects a high degree of structure between these two series. This is expected since the absolute difference between High and Low denotes a

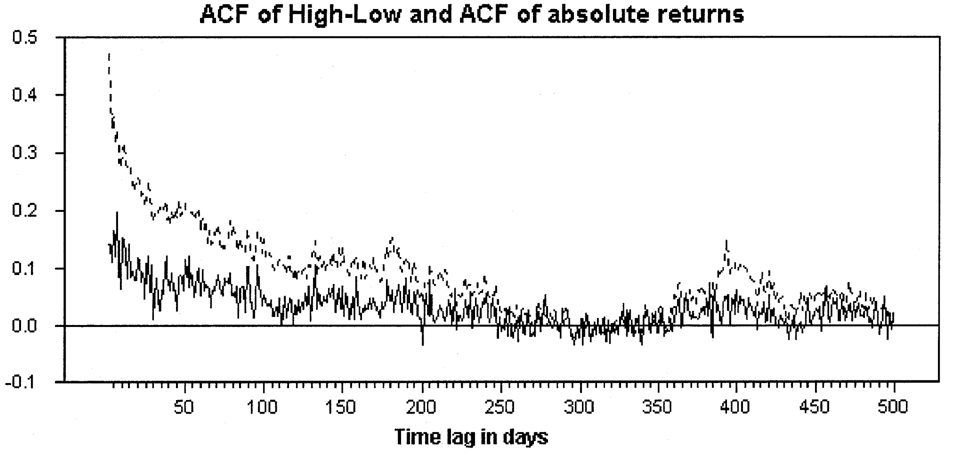


Fig. 3. Autocorrelation function of absolute returns with ACF of difference between High and Low superimposed (dashed line) — lag zero omitted.

[8]The ACFs for the High, Low and Close for USDDEM and USDJPY show similar results and are not presented here in order to save space.

simple measurement of daily volatility and a slowly decaying ACF therefore indicates the presence of autoregressive conditional heteroscedasticity (ARCH), a widely noted feature of daily exchange rates. Thus, like return-based GARCH models, range-based extreme value estimators seem to have the potential of capturing serial dependencies in the conditional volatility of exchange rates. Our empirical results suggest that extreme value estimators do an even better job.

Fig. 3 compares the ACF of absolute returns, with the ACF of the difference between Highs and Lows, and thus allows a direct comparison of extreme value and Close–to–Close volatility estimators. Interestingly, it takes about the same number of lags for both ACFs to become zero. However, the ACF of the difference of Highs and Lows decays at a much slower rate. This reflects a higher degree of persistence and requires explanation. One possible explanation could be that High and Low prices do not only determine the intradaily trading range, but also often coincide with interdaily support and resistance levels and are therefore less likely to change as frequently as Close prices.

Since support and resistance points that are not breached during the course of a trading day retain their importance, they provide a proxy for the next day's volatility. This volatility proxy stands a fair chance of being superior to a return based volatility estimate if support and resistance levels are not breached during the next trading day either. Even when support and resistance levels have been breached, the extremes of the new (intradaily) trading range manifest themselves immediately in new market Highs and/or Lows. This interpretation assigns an inherent forward-looking element to a volatility measure which is based on the (previous day's) trading range, and also assumes that information is more rapidly incorporated into trading range based volatility estimators than into return-based volatility estimators. Does our data set provide empirical support for this hypothesis?

Since lagged correlation reveals the presence of causal relations and information flow structures, an analysis of the difference between the correlation of the trading range and absolute returns, at positive lags and corresponding negative lags, should reveal any asymmetry in the information flow and causality (see e.g. Müller et al., 1995).[9]

Strong correlation of time series 1 with time series 2 at a positive lag, indicates information flow from time series 1 to time series 2 where the information manifests itself with a positive lag. Since it is very likely that there might be a third common cause influencing the behaviour of both series 1 and 2, we cannot always

[9] Müller et al. (1995) analyse different volatility measures defined over different time intervals and find that 'coarse' volatility helps predict 'fine' volatility. Müller et al. (1995) base their hypothesis on the finding of asymmetry in the lagged correlation between coarse and fine volatility measures, which seems to suggest that coarsely defined volatility systematically predicts fine volatility. Müller et al. (1995) present evidence from intradaily as well as daily volatility measures. For intradaily data, coarse volatility is defined as the absolute return over a 3-h interval and fine volatility as the mean absolute return within 3 h. For daily data, coarse volatility is defined as the absolute weekly return and fine volatility as the mean of five daily returns.

Table 1
Asymmetry in the lagged ACFs

Differences	USDDEM	USDJPY	GBPUSD
$\rho_1 - \rho_{-1}$	0.017	−0.014	−0.093[b]
$\rho_2 - \rho_{-2}$	−0.046[b]	−0.065[b]	−0.060[b]
$\rho_3 - \rho_{-3}$	−0.057[b]	−0.068[b]	−0.043[c]
$\rho_4 - \rho_{-4}$	−0.046[b]	−0.063[b]	0.008
$\rho_5 - \rho_{-5}$	−0.020[c]	−0.026[c]	−0.032[c]
BS[a]	0.0189	0.0189	0.0229

[a] Bartlett S.E.
[b] Significant at the 95% level.
[c] Significant at the 90% level.

assume direct causality. However, even in the case of a third common cause, we have to accept that the information flow to series 2 is slower than that to series 1. If two time series are generated on the basis of a synchronous information flow, they have a symmetric lagged correlation function, $\rho_\tau = \rho_{-\tau}$; the symmetry will only be violated by insignificantly small, purely Stochastic deviations. A significant deviation of ρ_τ and $\rho_{-\tau}$ indicates an asymmetric information flow and a causal relation.

Fig. 4 shows a significant asymmetry in the difference between positive and corresponding negative lags of the two volatility series for USDJPY. As can be seen from Table 1, a similar asymmetry can be found for USDDEM and GBPUSD. This points to the fact that information flows slower to a volatility measure consisting of absolute daily return and indicates that a volatility measure based on the trading range systematically predicts Close−to−Close volatility, at least within an intra-weekly time frame.

4. Forecasting volatility

Parkinson (1980) and Garman and Klass (1980) have demonstrated, on purely statistical grounds, that volatility measures which incorporate High and Low prices are more efficient than return-based volatility estimators. Under the assumption that the logarithm of speculative prices follows a continuous time random walk with a constant diffusion constant, the exact distribution of the range — the difference of interperiod Highs and Lows — follows from the theory of range statistics (see, e.g. Hurst, 1950; Feller, 1951). Parkinson (1980) is able to show that the moments of this High/Low price distribution are directly related to the underlying variance of the process and suggests an alternative variance estimator based on this relationship. Garman and Klass (1980) show that by combining functions of daily ranges — closed-market returns and open-market returns — it is possible to construct extreme value estimators which are up to 8.4 times more efficient than estimators based on daily closing prices.

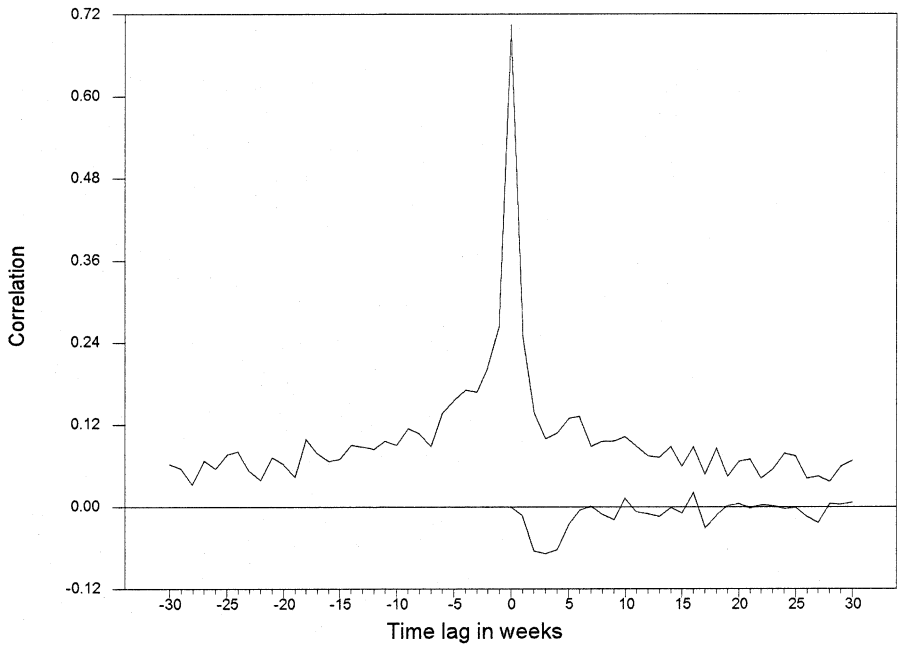


Fig. 4. Lagged correlation function between daily trading range and daily returns. The lower line shows the difference between positive and negative lags, and indicates asymmetry in the information flow.

Beckers (1983) and Wiggins (1993) present empirical support that extreme value estimators help predict future Close–to–Close variance estimates for individual stocks. The improvements in both studies are, however, are not as large as suggested by the Garman–Klass analysis.[10] The reason for this might be that the higher efficiency of extreme value estimators is derived within the context of a time-invariant conditional variance and, as Bollerslev et al. (1992) point out, the generalisation to Stochastic processes with time-varying variances is not straightforward. While true, our analysis in the last section showed that a volatility measure based on the daily trading range has an information advantage over volatility measures based on absolute daily returns. This seems to suggest that the superiority of extreme value estimators rests not only on better statistical properties, but also on the ability to capture important features of the market microstructure of

[10] Schwert (1990), in an alternative approach to ARCH modelling, applies a two-stage estimation procedure where ARMA type models are estimated for the conditional standard deviation, as measured by the absolute error from a first stage regression of the conditional mean of the return series. Schwert (1990) finds that including the logarithmic ratio of High and Low prices does not help to predict stock returns, but adds significant information in predicting volatility.

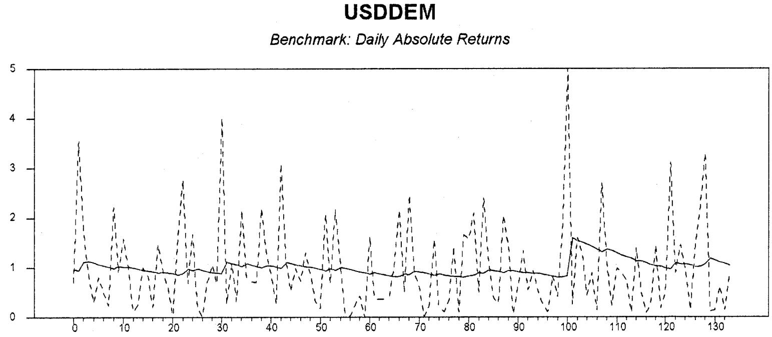


Fig. 5. Daily GARCH(1,1) volatility forecast vs. daily returns (dotted line).

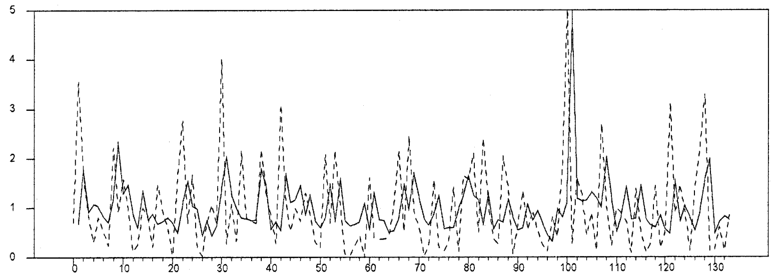


Fig. 6. Daily trading range volatility forecast vs. daily returns (dotted line).

the foreign exchange market, which are related to the information embodied in market turning points.

Since it is common practice to compare different volatility estimators by their forecasting performance, we evaluate the explanatory power of a simple volatility estimator based on the trading range of the previous period as a predictor of one-step-ahead volatility. Competing volatility forecasts are provided by a GARCH(1,1) forecast a forecast derived from the Garman and Klass estimator and a naïve forecast based on the previous day's return.[11,12]

When evaluating the predictive power of the different volatility estimators, we take ex post realised absolute returns as well as a recent volatility measure suggested by Andersen and Bollerslev (1998) as a benchmark. Andersen and Bollerslev (1998) present a volatility measure based on the cumulated sum of

[11] We also used an MA-GARCH(1,1) specification as in Andersen and Bollerslev (1998), however, the results from the GARCH (1,1) and the MA-GARCH(1,1) did not differ much.

[12] The Garman and Klass estimator is calculated as follows:

$$\sigma = 0.5(High_t - Low_t)^2 - 0.3863(Close_t - Close_{t-1})^2$$

Table 2
Competing volatility forecasts

	Daily absolute returns[14] [a]	Cumulated absolute 15-min returns[b]
USDDEM		
GARCH(1,1)	0.1902	0.3088
(HILO){1}	0.2417	0.4053
Garman/Klass{1}	0.1890	0.4114
CLCL{1}	0.0780	0.2676
USDJPY		
GARCH(1,1)	0.1749	0.1579
(HILO){1}	0.2527	0.4484
Garman/Klass{1}	0.2013	0.4531
CLCL{1}	0.1194	0.3041
GBPUSD		
GARCH(1,1)	0.2956	0.2132
(HILO){1}	0.2380	0.3776
Garman/Klass{1}	0.2577	0.3501
CLCL{1}	0.1434	0.2899

[a] Benchmark for volatility forecasts: ex post realised absolute returns.
[b] Benchmark for volatility forecasts: ex post realised cumulated 15-min returns.

intraday 5-min returns as a more efficient and less noisy volatility estimator than absolute daily returns. In addition, Andersen and Bollerslev (1998) show that a GARCH process tracks volatility far better when ex post volatility is measured on an intradaily basis than on a daily basis.

To allow comparison with the Andersen and Bollerslev (1998) study, we follow their approach and report the ex post correlation between different volatility forecasts with alternative measures of ex post volatility.[13]

As can be seen from the first column in Table 2, the Correlation Coefficient identifies the High–Low estimator, based on the previous day's trading range, as a superior volatility forecast for Close–to–Close volatility for USDDEM and USDJPY. The Garman–Klass estimator comes second, followed by the GARCH fore-

[13] Since we have only access to 15-min return data, our results are, however, not directly comparable to Andersen and Bollerslev (1998), who use 5-min returns.

[14] Our forecasting experiment is limited by our sample size. Our sample of daily Open, High, Low and Close prices covers the period from January 2, 1986 to August 30, 1996 for USDDEM and USDJPY, and a period from August 21, 1989 to August 30, 1996 for GBPUSD. Our sample of 15-min intradaily returns (12 960 observations per currency) covers, however, only the period from February 1996 to August 1996. The forecasting experiment involving daily absolute returns is therefore based on a sample size of 1860 for GBPUSD and 2770 for USDDEM and USDJPY. For the forecasting experiment involving intradaily returns (column 2), we have only 136 days for observation.

USDDEM

Benchmark: Daily Absolute Cumulated Returns

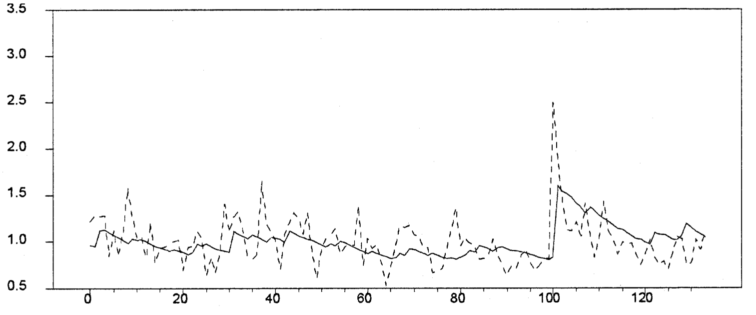


Fig. 7. Daily GARCH(1,1) volatility forecast vs. cumulated intradaily returns (dotted line).

cast. The naïve forecast based on the previous day's return performs worst for all three currencies. Only for GBPUSD, are extreme value estimators outperformed by a GARCH forecast.

The good performance of the GARCH forecast for GBPUSD is a finding worthy of mention since most studies which report a poor performance for GARCH forecasts generally base their verdict on an analysis of USDDEM.

If the intraday volatility measure (cumulated 15-min absolute returns) is taken as a benchmark instead of the Close–to–Close volatility estimator (CLCL), the picture does not change that dramatically. While the trading range estimator (HILO) and the Garman–Klass estimator change places, extreme value estimators as a group still present superior volatility forecasts. GARCH forecasts prove inferior, and are even outperformed by the naïve forecast for USDJPY and GBPUSD if ex post correlation is taken as a criterion for prediction quality.

Furthermore, we can confirm the findings of Andersen and Bollerslev (1998), for USDDEM, that GARCH models fit intraday volatility better than Close–to–Close

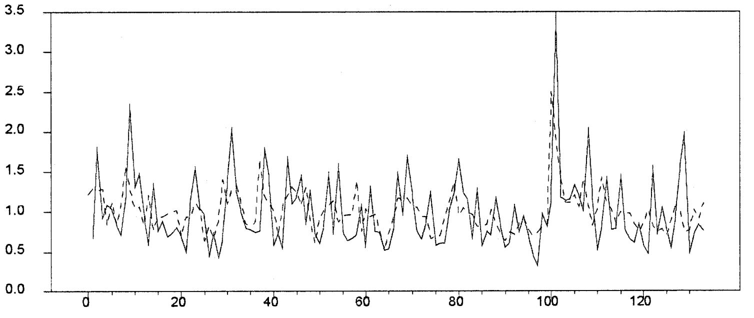


Fig. 8. Daily trading range volatility forecast vs. cumulated intradaily returns (dotted line).

volatility. But, as Figs. 5–8 show, GARCH forecasts provide only a second best strategy when extreme value estimators are considered.[15]

5. A multivariate cointegration analysis between High, Low and Close prices

While our results so far show that High and Low prices play an important role in forecasting volatility, it is also interesting to address the question of whether technical indicators which combine High, Low and Close prices contain useful information for point forecasts. After all, foreign exchange traders make profits by correctly anticipating upward or downward trends and opening Long or Short positions accordingly. While a number of extant studies explore the possible profitability of technical trading rules, only a few investigate if the persistent profitability could have an explanation in the underlying structure of high frequency data.[16]

Since Candlestick charts derive a forecast from different constellations of High, Low and Close prices it seems an appropriate starting point to investigate if High, Low and Close prices are linked by a structural relationship. A structural relationship between High, Low and Close prices could then point to useful information for forecasting future prices. Since High, Low and Open prices are all I(1) variables, cointegration analysis seems to be an appropriate means of exploring possible structural relationships between these prices. We intend to interpret cointegration as evidence that the use of TA (intuitively) exploits latent Granger causality and, hence, presents a useful instrument for forecasting daily exchange rates.

While the empirical evidence in favour of cointegration between different exchange rates is modest, and does not suggest a stable structural relationship, our approach differs since we propose to test for cointegration between different observations, i.e. the High, Low and Close prices of the same exchange rate.

The existence of potential cointegrating vectors was explored using the multivariate methods of Johansen (1988). In summary form, this involves taking an unrestricted vector autoregressive model (VAR):

$$z_t = A_1 z_{t-1} + \ldots + A_k z_{t-k} + \psi D_t + \varepsilon_t, \quad \varepsilon_t \sim IN(0,\Sigma)$$

[15] Figs. 5–8 plot volatility estimates for USDDEM from a GARCH(1,1) model and volatility estimates derived from a 1-day lagged trading range against ex post realised absolute daily returns (top figures) as well as ex post cumulated intradaily returns (bottom figures). As can be seen from Figs. 5–8 the simple trading range-based volatility estimate tracks volatility much better than the GARCH(1,1) model. Since the findings for USDJPY and GBPUSD were very similar, they were omitted to save space.

[16] An exception is Clyde and Osler (1997). Clyde and Osler (1997) explore the link between technical analysis and Chaos theory and find evidence that certain chart formations like the Head and Shoulder constellation represent some form of non-linear analysis.

where z_t, defines the potential endogenous variables of the model and D contains deterministic terms. Taking first differences of the variables, the VAR can be transformed into a vector error correction representation of the following form:

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \dots + \Gamma_{k-1} \Delta z_{t-k=1} + \Pi z_{t-1} + \psi D_t + \varepsilon_t$$

where the estimates of $\Gamma_i = -(I - A_1 - \dots - A_i)$, $(i = 1,\dots, k-1)$ describe the short run dynamics to changes in z_t and $\Pi = -(I - A_1 - \dots - A_i)$ captures the long run adjustments. Cointegration occurs in the case of reduced rank of the long-run impact matrix, Π. Only if the rank is reduced $(r < n)$ is it possible to factorise Π into Π $(= \alpha\beta')$ where α denotes the adjustment coefficients and β the cointegration vectors. The cointegration vectors β have the property that $\beta\ z_t$ is stationary, even though z_t itself is non-stationary.

If the rank is reduced, it is possible to interpret the VAR in first differences as a vector error correction model and to obtain estimates of α and β via the reduced rank regression. Since the rank of Π is equal to the number of independent cointegration vectors and the rank of Π is also equal to the number of non-zero eigenvalues, the test of cointegration thus amounts to a test for the number of non-zero eigenvalues. The trace statistics, λ_{trace}, is a non-standard distributed likelihood-ratio test, which is commonly used to determine the number of cointegration vectors (Johansen, 1988). The trace statistic tests the null hypothesis that there are at most r cointegration vectors:

$$H_0 : \lambda_i = 0, \text{ for } i = r + 1,..n$$

where only the first r eigenvalues, λ, are non-zero against the unrestricted hypothesis that $r = n$.[17]

The modelling approach involved the inclusion of 3 lags for USDDEM and USDJPY based VARs and 6 lags for the GBPUSD VAR (these lag lengths were sufficient to produce random residuals). For all three models a constant was introduced into the cointegration space. The modelling of a constant in the cointegration space was indicated by the rank test based on the Pantula principle, and also conforms to the recommended specification of Diebold et al. (1994).

The test statistics (Table 3) clearly indicate cointegration between the High, Low and Close prices for USDDEM, USDJPY and GBPUSD. The trace statistics, λ_{trace}, identify two cointegration vectors for USDDEM, USDJPY and GBPUSD. The existence of two cointegration vectors was further supported by a graphical plot (not shown) of the first three cointegration relationships for the three currencies. The estimates of the cointegration vectors, β_i, and the adjustment parameters, α_i, for USDDEM, USDJPY and GBPUSD are presented in Tables 4

[17] The null hypothesis of most r cointegration vectors implies that there are n-r unit roots and, theoretically, n-r zero eigenvalues. This is because the hypothesis of cointegration is formulated as the reduced rank of $\Pi = \alpha\beta'$ and the full rank of $\alpha_\perp{}'\Gamma\beta_\perp$, where α and β are $n \times r$ matrices and $\alpha_\perp$ and $\beta_\perp$ are $n \times (n\text{-}r)$ matrices orthogonal to α and β. This then allows us then to distinguish between r cointegrating I(0) relations and n-r non-cointegrating I(1) relations.

Table 3
Results of multivariate cointegration tests

Null hypothesis H_0: rank $= r$	Alternative hypothesis	USDDEM	USDJPY	GBPUSD	95% critical value	90% critical value
λ_{trace} test		λ_{trace} value	λ_{trace} value	λ_{trace} value		
$r = 0$	$r > 0$	598.98	1229.68	432.64	35.10	31.88
$r \leq 1$	$r > 1$	163.49	388.27	118.43	20.17	17.79
$r \leq 2$	$r > 2$	11.11	8.41	5.73	9.10	7.50

Table 4
Estimates of the cointegration vectors

	USDDEM		USDJPY		GBPUSD	
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
Close	1.000	0.028	1.000	0.222	1.000	0.018
High	−0.526	1.000	−0.559	1.000	−0.498	1.000
Low	−0.476	−1.029	−0.443	−1.220	−0.502	−1.030
Constant	0.002	−0.010	0.008	−0.022	−0.000	−0.003

and 5. The first cointegration vectors were normalised on the first element and the second vectors on the second element, respectively.

The t-values for the adjustment coefficients for USDDEM, USDJPY and GBPUSD show that all rows of the adjustment coefficient matrix contain elements that are significantly different from zero. Thus no evidence of weak exogeneity is given and none of the variables can be excluded from the cointegration space.

An attempt to empirically identify an existing structural relationship in the data requires a hypothesis about a relationship which might govern High, Low and Close prices. The empirical estimates of the cointegration vectors suggest the following relationships. The second cointegration vector reduces to:

$$\mathrm{ecm}_2 = H_t - L_t - \mathrm{Constant} \tag{1}$$

Table 5
Estimates of adjustment coefficients

	USDDEM		USDJPY		GBPUSD	
	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_1$	$\hat{\alpha}_2$
ΔClose	−0.526	−0.034	−0.566	−0.008	0.024	−0.128
	(−4.95)	(−0.89)	(−8.02)	(−1.35)	(0.12)	(−2.84)
ΔHigh	0.552	−0.185	0.509	−0.045	0.918	−0.218
	(6.60)	(−6.20)	(9.50)	(−9.66)	(6.60)	(−6.94)
ΔLow	0.488	0.145	0.396	0.046	1.036	0.062
	(6.05)	(5.03)	(6.87)	(9.24)	(7.30)	(1.94)

where ecm denotes error correction mechanism. Eq. (1) therefore gives us a measure of the (stationary) daily trading range.

If we denote the two non-normalised elements of the first cointegrating vectors as β_{11} and β_{12}, so that we have:

$$\mathrm{ecm}_1 = C_t - \beta_{11} H_t - \beta_{12} L_t$$

then we see that for all three data sets, the restriction $\beta_{11} + \beta_{12} = 1$ is strongly implied. In other words, we have:

$$\mathrm{ecm}_1 = (C_t - L_t) - \beta_{12}(H_t - L_t) \tag{2}$$

which is a linear combination of two of the differences analysed in Section 3 and which can be identified in a class of technical indicators known as the Stochastics, which try to capture mean reversion within a trading range (Fiess and MacDonald, 1999).

The Stochastics (Lane, 1984) is popularly used by foreign exchange traders as an indicator of overbought/oversold market situations.[18] The Stochastics quantifies the relationship between daily Close prices and periodic High and Low prices and derives a trading signal using the following formula:

$$\%K = 100\left(\frac{C_t - L_t^{\min}}{H_t^{\max} - L_t^{\min}}\right) \tag{3}$$

where $H_t^{\max}$ and $L_t^{\min}$ are defined as the highest High and the lowest Low over a given time period, $H_t^{\max} - L_t^{\min}$ denotes the trading range of that period and $C_t - L_t^{\min}$ defines the upward potential of the trading range. In common with our interpretation of the second cointegrating vector, the Stochastics weight the upward potential of a given period with the trading range of that period.

Fiess and MacDonald (1999) are able to identify cointegration vectors Eqs. (1) and (2) in a data set consisting of daily Close prices and periodic High and Low prices. They then use this information to construct dynamic structural econometric models for dynamic out-of-sample forecasting over different time horizons. It turns out that even when allowance has been made for transactions costs and risk premia, these models have extremely good forecasting properties and are able to out-perform a random walk forecast on a time horizon as short as 1 day.

[18] The idea behind overbought–oversold 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. The implication of the overbought–oversold indicators is that 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 strongly 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 strongly oversold. 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, a value of 50 indicates the middle of the range and therefore no change in the exchange rate is expected.

Even though our estimated cointegration vectors come close to Eqs. (1) and (2), we are unable to identify them jointly in a data set consisting of daily High, Low and Close prices.[19] The positive evidence of Fiess and MacDonald (1999) therefore seems to suggests that Eq. (1) only holds for periodic High and Low prices, but not for daily High and Low prices. The cointegration relationships between daily data of High, Low and Close prices seem to follow more complicated dynamics and may be an attempt to quantify Candlestick analysis which, as stated earlier, claims to be able to distinguish between more than 100 different Candlestick formations (Table 6) and which matches these different constellations of C_t, H_t and L_t with different forecasts, might provide an insight into the structural specification of the daily data.

A possible explanation as to why it is easier to identify Eqs. (1) and (2) in data consisting of daily Close prices and periodic High and Low prices may be that the cointegration relationships between daily data of High, Low and Close prices follow more complicated dynamics and may be an attempt to quantify Candlestick analysis which, as stated earlier, claims to be able to distinguish between more than 100 different Candlestick formations which matches these different constellations of C_t, H_t and L_t with different forecasts, might provide an insight into the structural specification of the daily data.

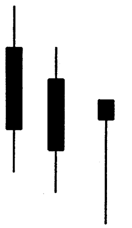
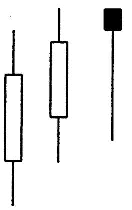
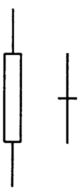
Nevertheless, Granger causality tests within a Vector Error Correction (VEC) framework (see Table 7) further indicate that past values of High, Low and Close prices, together with the error correction terms as defined in Table 4, are significant in the short-run equation for the Close series. We therefore cannot disregard the possibility that TA of High, Low and Close prices exploits latent Granger causality (in an intuitive way, perhaps) in high frequency exchange rates.

6. Conclusion

Technical analysis assigns a special role to High, Low and Close prices in forecasting volatility and future levels of exchange rates. The difference between High and Low prices corresponds to the so-called trading range. The trading range is supposed to give information about the trading activity during the course of the day and serves as a simple measure of volatility. Given a specific trading range, the Close price supposedly contains information about the future price development. Different constellations between High, Low, Open and Close prices are considered to imply different forecasts, and Candlestick analysis represents maybe the most comprehensive attempt to classify price forecasts according to High–Low–Close constellations. Many forms of TA try to combine an intradaily trend measure (Open–Close) with an intradaily volatility measure (High–Low) when generating a

[19]A test if $\beta_{11} + \beta_{12} = 1$ holds in the first cointegration relationship is only not rejected for GBPUSD [$\chi^2(1) = 2.21$, $P = 0.14$]. A test if the second cointegration can be interpreted as a stationary trading range (High-Low) cannot be rejected for USDDEM [$\chi^2(1) = 0.84$, $P = 0.36$] and USDJPY [$\chi^2(1) = 3.98$, $P = 0.05$].

Table 6
Different candlestick formations

Formation	Interpretation
Hammer: 	The hammer refers to a day with high volatility where the market opens at a relatively high level, drops drastically during the course of the day, but then recovers to Close in the neighbourhood of the open. It is said to be at its most powerful after a long lasting downtrend and establishes a 'bullish' signal.
Hanging Man: 	The candlestick formation with this dramatic name is considered to be the equivalent of the hammer formation in the case of a pronounced uptrend. Its implication is 'bearish'.
Hamari Cross: 	This formation describes a long black or white candle followed by so-called Doji candle (a Doji forms when the market opens and closes at the same price — *douji* in Japanese means no change). The Hamari Cross is said to lead the way to a change in trend direction.

forecasting signal. This paper represents a first attempt to analyse the informational content of Open, High, Low and Close prices in order to identify a rationale for the use of TA in time series analysis.

The theoretical work of Parkinson (1980), Garman and Klass (1980) and Kunitomo (1992) on extreme value estimators, indicates the superior statistical properties of range-based volatility estimators over return-based estimates. Our analysis shows that a range-based volatility measure has a further informational advantage over a return-based volatility measure. In particular, it allows the former to capture important features of the market microstructure of the foreign exchange market, which are related to the information embodied in market turning points. We believe that the superior statistical properties of range-based estimators, together with their ability to exploit asymmetric information flows, provides a reasonable

Table 7
Granger causality tests[a]

Dependent variable	Lags (F-tests)			Error correction terms (t-tests)	
	$\sum_{i=1}^{j} \varphi_i \Delta \text{Close}_{t-i}$	$\sum_{i=1}^{j} \gamma_i \Delta \text{High}_{t-i}$	$\sum_{i=1}^{j} \kappa_i \Delta \text{Low}_{t-i}$	ecm_{1t-1} (unidentified)	ecm2_{t-1} (unidentified)
USDDEM ΔClose	$\chi^2(2) = 17.48$*	$\chi^2(2) = 18.56$*	$\chi^2(2) = 10.78$*	t-test $= -5.96$*	t-test $= 0.96$
USDJPY ΔClose	$\chi^2(2) = 19.52$*	$\chi^2(2) = 6.64$*	$\chi^2(2) = 8.06$*	t-test $= -6.69$*	t-test $= -1.24$
GBPUSD ΔClose	$\chi^2(5) = 1.85$**	$\chi^2(5) = 2.92$*	$\chi^2(5) = 0.23$	t-test $= -0.13$	t-test $= -2.99$*

[a] The lag length for the first difference terms was set according to the model specification in the cointegration analysis, i.e. 2 lags for USDDEM and USDJPY and 5 lags for GBPUSD. For the summation operators in Table 7, we have therefore $j = 2$ for USDDEM and USDJPY, and $j = 5$ for GBPUSD. Cointegration implies Granger causality, and Granger causality indicates that one cointegrated time series can help to predict another. In order to investigate if the unidentified cointegration relationships in the data consisting of daily High, Low and Close prices (Table 4) do indeed carry information useful to forecasting, the derived long-run relationships were incorporated into short-run dynamic equations for the Close series. Granger causality tests were only conducted for the Close series, since from a forecasting point of view only forecasts of Close series represent ‘true’ forecasts in the sense 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 17.00 h. A forecast of the periodic High or Low, however, does not reveal any information about the time of day that this value is to be expected and thus is of little use under market timing considerations.

The * and ** indicate 5% and 10% significance levels respectively.

justification for their use in TA. There is, therefore, no reason why range-based estimators should only feature in the forecasting toolbox of a technical analyst. The existence of a stable structural relationship between High, Low and Close prices and the evidence of Granger causality shows that by following a modelling strategy that combines High, Low and Close prices it is indeed possible to generate superior forecasts of volatility as well as future levels of exchange rates. A technical analysis of High, Low and Close prices might therefore present a crude but useful way of exploiting any latent Granger causality which exists in high frequency exchange rates.

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