On the Short-Term Predictability of Exchange Rates: A BVAR Time-Varying Parameters Approach

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ABSTRACT

In this paper we set out a Bayesian vector autoregressive model with time-varying parameters (BVAR-TVP) to examine the predictability of exchange rates over short horizons that is novel in this context. An important contribution of the paper is the application of the BVAR-TVP model, for the first time, to daily data using information from financial markets. Another contribution is the production of forecasts in real time at the very short horizons of 1-day up to 5-trading days ahead typically used by traders and investors in financial markets. We employ both statistical and financial criteria to assess the exchange rate predictability. The out-of-sample forecasting performance of the BVAR-TVP model is quite impressive and dominates significantly the random walk model at all horizons and for all exchange rates. The model's forecast errors are also statistically smaller than those from a VAR model for all forecast horizons and exchange rates, thus supporting the view that time variation of coefficients is a crucial factor in exchange rate forecasting. We show that international investors could have made statistically significant excess profits in currency markets during the 1990s if they had followed an inter-day trading strategy based on the interest rate parity and the buy/sell signals generated by the model's 1-day ahead exchange rate forecasts, even after allowing for transaction costs and risk factors.

Keywords: Exchange rate forecasting; Short horizons; BVAR model; Time-varying parameters; Profitability of forecasts

JEL Classification: F31, C51, C53

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1. Introduction

The poor out-of-sample forecasting performance of empirical exchange rate models has been a longstanding puzzle in international finance. Although some authors (e.g. Chinn and Meese, 1995; Sarantis and Stewart, 1995b, Mark, 1995; MacDonald and Marsh, 1997; Mark and Sul, 2001) show that greater attention to long-run properties and the dynamics of exchange rate models can improve predictability at longer horizons, the general conclusion of the literature is that empirical exchange rate models drawn from economic theory fail to improve upon the forecasting performance of the random walk at short horizons. In a recent comprehensive investigation of the out-of-sample forecasting performance of a large number of exchange rate models, Cheung et al (2003) conclude that no model consistently outperforms a random walk at short horizons and that the question of exchange rate predictability remains unresolved, thus confirming the general conclusion of Meese and Rogoff's (1983a,b) pioneering study. Qi and Wu (2003) report similar results for 1-, 6- and 12-month forecast horizons from the application of a nonlinear model with monetary fundamentals at. But even the evidence on long-horizon exchange rate predictability based on fundamentals has been called into question by some authors (e.g. Kilian, 1999; Berkowitz and Giorgianni, 2001; Faust et al, 2003).

Even if one was to accept the favourable evidence of long-horizon exchange rate predictability, this is of little practical use. Given that over 90 per cent of the daily turnover in foreign exchange markets consists of trading in financial assets (Lyons, 2001) and that investors and FX traders have very short horizons, forecasts for horizons of one up to four years are hardly of any use to practitioners. Consequently, if the research programme on exchange rate forecasting is to be of any value to practitioners in foreign exchange markets, we should focus on the short-term predictability of exchange rates.

This is the challenge taken up by this paper. Given that risk hedgers, speculators, and other investors have very short horizons (typically 1-day or 1-week ahead)\(^1\), we employ daily data for

\(^1\) One may argue that fund managers tend to revise their portfolios once every month, which necessitates 1-month out forecasts. But Dunis et al (2000, 2001) argue that even portfolio management has moved towards more 'high frequency' trading over the recent years.
the four most heavily traded exchange rates and produce forecasts in real time for one to five
days ahead. Although daily data on macroeconomic variables are not available, there are daily
data on financial variables that reflect both current economic performance and the markets' expectations about future economic performance. Hence, this is the first study that examines the out-of-sample forecasting performance of exchange rate models at such short horizons using daily data.

The empirical literature has highlighted a number of potential factors for the poor forecasting performance of exchange rate models: (i) parameter instability, (ii) simultaneity problems, (iii) failure of the rational expectations hypothesis, and (iv) failure to account for nonlinearities in exchange rates. Therefore, any modelling framework employed for forecasting exchange rates should address all these issues rather than one at a time as tends to be the practice. Such a framework is the Bayesian vector autoregressive model with time-varying parameters (hereafter, BVAR-TVP). This model introduces complex nonlinear dependencies in the moments of the time series through the time variation of coefficients, thus addressing the problems of parameter instability and potential nonlinearities, and treats all the variables as endogenous. Furthermore, given that the forecasting model evolves over time, the predictions generated by the model imply the existence of adaptive learning rules and bounded rationality in financial markets (see Sargent, 1993). Although this model has been applied to macroeconomic forecasting, surprisingly it has not been used in foreign exchange rate forecasting. The only exception is a paper by Canova (1993) who used weekly data and demonstrated that it is possible to improve upon the

2 The real world is characterized by policy shifts, structural changes in the national economy and currency markets, varying investment horizons, asymmetric information, and diversity of expectations. As a result, the forecasting models used by economic agents in financial markets are evolving over time to reflect the learning process of investors, the changing structure of the economic model, and the latest information available. As Pesaran and Timmermann (1995) point out, in practice it is difficult to disentangle these two effects on the evolutionary process of the forecasting model. But the important implication is that the parameters of the BVAR model are likely to vary over time.

forecasting performance of the random walk\textsuperscript{4}.

Our paper extends Canova's (1993) work in four fundamental ways. First, we use daily data. As far as we are aware, this is the first study to apply the BVAR model to daily data. Second, we introduce long-term interest rates, stock returns and currency volatility (measured by implied volatility) into the model - Canova (1993) used only short-term interest rates. The introduction of long-term interest rates allows for varying asset maturities and inflation premium. The use of stock returns captures the interaction between currency and stock markets, while the introduction of currency volatility captures the influence of time-varying risk premium. Third, we examine the statistical significance of the model's forecasts by employing an ARCH-modified version of the Diebold-Mariano test (see Harvey et al, 1997b). Fourth, we examine the economic significance of exchange rate predictability, by calculating the daily excess profits that an investor could have made in the currency markets from an inter-day trading strategy based on the one-day-ahead exchange rate forecasts that allows for transaction costs, and by employing a wide range of trading performance measures. Neither Canova (1993) nor any of the other studies mentioned above have investigated the potential profitability of exchange rate forecasts\textsuperscript{5}. Third, our study extends the sample period to cover the 1990s.

The paper is organised as follows: Section 2 describes the specification of the BVAR-TVP model. Section 3 discusses the economic information used in the model, the measurement of variables, and data sources. Section 4 outlines the estimation methodology and forecasting strategy employed in the paper. Section 5 analyses the out-of-sample forecasting results. Section

\textsuperscript{4} Sarantis and Stewart (1995b) also applied the BVAR model to exchange rate forecasting, but with fixed parameters. That study shows that the BVAR model can improve upon the forecasting performance of the random walk at horizons of one to eight quarters ahead.

\textsuperscript{5} In contrast to studies employing empirical exchange rate models, a number of authors (e.g. Levich and Thomas, 1993; LeBaron, 1996; Neely \textit{et al}, 1997; Qi and Wu, 2002, Neely and Weller, 2003) have investigated the potential profitability of technical rules in currency markets. To our knowledge, the only study that investigates the economic value of exchange rate forecasts based on fundamentals is a recent paper by Abhyankar \textit{et al} (2003), although the authors adopt a different methodology and focus on long-term horizons which is not particularly relevant to practitioners who have very short-term forecast horizons.
6 examines the daily profitability of exchange rate forecasts via a simulated trading strategy. The final section provides a discussion of the main findings.

2. Specification of the BVAR Time-Varying Parameters Model

Based upon the work of Doan *et al* (1984) and Canova (1993), we specify the BVAR-TVP model as follows:

\[
Y_t = B_t Y_{t-1} + u_t, \quad u_t \sim N(0, V) \quad (1)
\]

\[
B_t = D_t B_{t-1} + (I-D_t)E(B_0) + A_t \varepsilon_t, \quad \varepsilon_t \sim (0, \Sigma_t) \quad (2)
\]

\[
D_t = \delta_t I \quad (3)
\]

\[
A_t = I \quad (4)
\]

\[
B_0 \sim N(E(B_0), \Sigma_0) \quad (5)
\]

\[
E(B_{0,i}) = \delta_{i2}, \text{ if } i=1, \text{ and } 0 \text{ otherwise, } i=1,....n \quad (6)
\]

\[
\Sigma_t = \delta_3 \Sigma_0 \quad (7)
\]

\[
\Sigma_0 = h(\sigma_{0i}) \quad (8)
\]

\[
\sigma_{0i} = \delta_4 g(l) f(i,j)(s_i/s_j) \quad (9)
\]

where \(Y_t\) is an (nx1) vector of all variables in the model, \(B_t\) is an nxn(l+1) matrix of time-varying coefficients; \(i, j\) and \(l\) denote equation, variable and lag, respectively; \(I\) is the identity matrix; and \((u_t, \varepsilon_t)\) are vectors of error terms with covariances \(V\) and \(\Sigma_t\), respectively.

A major feature of this model is that the matrices \(D\), \(A\) and \(\Sigma\) (describing the law of motion of the coefficients), \(E(B_0)\) and \(\Sigma_0\) (describing the initial conditions), depend on a small set of unknown parameters, \(\delta\). This extension, proposed by Doan *et al* (1984), reduces drastically the large number of parameters to be estimated, as well as the high variability of forecasts typically associated with large systems with time-varying coefficients.
Equation (2) is part of the prior and $B_0$ is therefore assumed to have a prior distribution with mean $E(B_0)$ and a covariance matrix $\Sigma_0$ (see eq. 5). The law of motion of the coefficients, described by equations (3)-(5), is assumed to follow a first-order Markov process that decays towards zero. The speed of decay of this process is measured by $\delta_1$: when $\delta_1=1$, the coefficients are random walks; when $\delta_1=0$, they are random around $B_0$. The parameter $\delta_{i2}$ is the mean of the prior distribution on each coefficient, $\beta_{i2}$. Following Doan et al (1984), Doan (1990) and Canova (1993), we assume that each coefficient has an independent and normal prior distribution with small standard deviations (with decreasing standard deviations on longer lags) and zero mean, except for the coefficient on the first lag of the own variable which has a mean of unity. Equations (7)-(9) describe the time evolution of the covariance matrix of the coefficients, $\Sigma_t$. The covariance matrix of the prior, $\Sigma_0$, is a function of a vector of prior parameters (see eq. 9), with parameter $\delta_3$ measuring the relative tightness of time variation. On the basis of previous studies, we consider values in the range of 0.001-0.0000007.

Equation (9) gives the standard deviations of the prior distribution for lag 1 of variable $j$ in equation $i$ for all $i, j$ and $l$. $s_i$ and $s_j$ are the standard errors of variables $i$ and $j$ respectively. The parameter $\delta_4$ is the overall tightness of the prior; it is the standard deviation of the prior on the first own lag in each equation. Following Doan's (1990) recommendation, we consider both 'loose' values of 0.2 and 0.3, and a 'tighter' value of 0.1. Function $g(l)$ describes the lag pattern (the tightness of lag 1 relative to lag 1) and is assumed to be harmonic: $g(l) = l^{-\delta_5}$. We consider two alternative values for the decay parameter $\delta_5$: a 'looser' value of 1, and a relatively 'tight' value of 2.0.

The tightness function $f(i,j)$ measures the weight attached to the coefficients on other variables, $j$, floating the number in the bracket. The prior on the first own lag is measured by $\delta_4$. Following Doan's recommendation, we consider values of 0.2 and 0.3, and a 'tighter' value of 0.1. Function $g(l)$ describes the lag pattern (the tightness of lag 1 relative to lag 1) and is assumed to be harmonic: $g(l) = l^{-\delta_5}$. We consider two alternative values for the decay parameter $\delta_5$: a 'looser' value of 1, and a relatively 'tight' value of 2.0.

6 This is referred to as the 'Minnesota' prior and is a standard assumption in all applications of the BVAR model. See, for example, Artis and Zhang (1990), Sarantis and Stewart (1995b), Dua and Ray (1995), Sarantis and Lin (1999), Robertson and Tallman (1999). Dua and Ray (1995) provide a good discussion of the appropriateness of the Minnesota prior even when the variables are cointegrated.

7 The range of values for the parameters $\delta_4$ and $\delta_5$ are those recommended by Doan (1990), and have been used successfully by previous studies on BVAR applications (see footnotes 3 and 4), in that they produce the more accurate forecasts.
relative to that on the own lags, in forecasting variable $i$. This function can be symmetric or
gen-eral. With a symmetric prior, $f(i,j) = \delta_6$, so there is only one free hyper-parameter to
determine. The parameter $\delta_6$ takes values between zero and one. When $\delta_6=1$, all variables in each
equation have equal weight when forecasting the own variable $i$. At the other extreme, as $\delta_6$
approaches zero, the model approaches a set of univariate autoregressions with time-varying
coefficients.

The BVAR-TVP model described by equations (1)-(9) involves complex nonlinear
dependencies, generated from the time-variation of the coefficients, in the conditional moments
of all variables in the system. Canova (1993) shows that this model encompasses a number of
familiar parametric models employed to characterize nonlinearities in the first and second
moments of financial time series: ARMA-ARCH, ARCH-M, Hamilton's (1989) Markov regime-
switching model, and the bilinear model. It is also interesting to notice that the predictions
generated by the BVAR-TVP model in effect imply that economic agents use adaptable learning
rules, and hence provide support for the presence of bounded rationality in financial markets (see
Sargent, 1993).

3. Economic Information and Data

Conclusions on the forecasting performance of the BVAR-TVP model may well depend on the
information contained in the vector $Y_t$. Theoretical exchange rate models suggest a number of
macroeconomic variables as determinants of exchange rates. But as various surveys of traders
and investors in currency markets indicate (e.g. Cheung and Chinn, 1999; Cheung et al, 2000),
these factors play no role in short term exchange rate forecasting. Furthermore, there are no daily
data available on macroeconomic variables, so they cannot be included in our analysis. Instead,
we have to rely on financial variables that are available on a daily basis. To provide a theoretical
framework, the variables included in the analysis are drawn from an extended version of the
uncovered interest rate parity hypothesis (UIP). The standard UIP model suggests that exchange
rate changes depend only on short-term interest rate differentials ($r_s - r_s^*$).

We introduce three extensions to the standard UIP model. First, Sarantis (1995) and Boughton
show that differentials among interest rates in the large industrial countries during the post-Bretton Woods period have behaved differently across the maturity spectrum. They therefore argue that it is theoretically ambiguous whether short-term or long-term interest rates matter most for exchange rate determination. In view of this ambiguity, the authors advocate the introduction of both short-term and long-term interest rates in the UIP model. Sarantis (1995) and Sarantis and Stewart (1995a) find strong evidence for the presence of long-term interest rates \((r_l^l, r_l^*)\) in sterling exchange rate equations. Justification for the introduction of the long-term interest rate differential is also provided by Frankel's (1979) real interest rate model where this variable captures the expected inflation differential.

Second, Gavin (1989), Chiang (1991) and Morley (1997) show that there are important interactions between currency and stock markets. The transmission mechanism for this interaction differs, with some studies stressing stock market effects on aggregate demand, others stock market effects on the demand for money, and others the influence of risk premia across financial markets. Empirical evidence by Morley (1997) and Zhu (1998) provides significant empirical support for the importance of stock market effects on exchange rates. Evidence from studies of the demand for money also supports the interdependence between money and stock markets (see Choudhry, 1996). Consequently, we believe that the stock return differential \((q-q^*)\) might contain useful information for exchange rate predictions.

Third, we introduce currency volatility. One of the reasons often cited for the empirical failure of the UIP relationship is the presence of a time-varying risk premium (see, MacDonald, 2000). Theoretical studies (i.e. Engel, 1996) show that a fundamental determinant of the risk premium is the expected variability of the future exchange rate. In this paper we use actual data on implied volatility, \(IV\), to measure expected currency volatility.

Hence, the vector of variables (asterisks denote foreign variables) in the BVAR-TVP model is represented by

\[
Y_t = [\Delta s_t, r_t^s - r_t^*, r_t^l - r_t^*, q_t - q_t^*, IV]'
\] (10)

All data, with the exception of implied volatility, were obtained from Datastream. Exchange rate changes are measured as $\Delta s_t = (\ln S_t - \ln S_{t-1}) \cdot 100$, where $S$ is the spot exchange rate at closing London time, defined as domestic currency price of foreign currency. The short-term interest rates are 1-month market rates. The long-term interest rates are the yields on long-term (10-year) government bonds. Both interest rates are measured in percentages. The rate of return in the stock market is measured by $(\ln P_t - \ln P_{t-1}) \cdot 100$, where $P$ is the stock price. The stock price indices are: USA: SP500; Germany: DAX; Japan: NIKKEY; UK: FTSE 100.

We use data on 1-month implied volatility to measure expectations about the future volatility of the exchange rate. Currency volatility has now become a traded quantity in financial markets and is therefore directly observable on the marketplace. The volatility time series we use are at-the-money forward, market-quoted volatilities at the close of business in London. We use at-the-money rather than in-the-money or out-of-the-money straddles, since the last two would introduce biases due to the 'smile effect'. According to the market practice, quoted volatilities are annualised and expressed in percentages. Since these data are directly quoted from brokers, they avoid the potential biases associated with the 'backing out' of implied volatilities from a specific option pricing model. Our approach is further warranted by current practice in financial markets where market makers and brokers in currency options deal directly in volatility terms and not in option premium terms. Reuters obtain the data on market quoted volatilities from brokers on a daily basis at the close of business in London. The databank for the 1-month and 3-month implied volatilities for all the exchange rates covered in our study is maintained by the Centre for International Banking, Economics and Finance (CIBEF) at Liverpool Business School, and is updated regularly from Reuters 'Ric' codes.

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8 These data on implied volatility have been used only in a few studies on forecasting currency volatility. See Dunis et al (2000, 2001). We are grateful to Christian Dunis from CIBEF for making these data available to us.
4. Estimation and Forecasting Strategy

The estimation of the model and generation of out-of-sample forecasts are carried out with the Kalman filter algorithm, once the prior vector of hyper-parameters, $\delta$, is specified. We use data for the period 1.1.1991-31.12.1992 to obtain initial parameter estimates, while the period 1.1.1993-16.3.2001 is used for analysing the model's out-of-sample forecasting performance. This long forecasting period provides 2141 observations and covers varying episodes of exchange rate fluctuations and currency volatility, thus providing a very stringent test of the model's forecasting performance.

The prior parameters can take a range of values. Given the large number of variables and long lags, we restrict the parameters $\delta_1-\delta_6$ to be common in all equations. Zellner and Hog (1989) show that this restriction improves the forecasting performance of BVAR models with a large number of parameters. We also set $\delta_1=1$, which assumes that coefficients are random walks. Canova (1993) and Doan et al (1984) adopted a similar approach. But this still leaves us with determining the priors $\delta_3-\delta_6$.

Estimates of the 'optimal' vector of the priors are obtained through maximisation of the likelihood function over the estimation period as in Canova (1993), thus ensuring that the specification of the 'priors' is based entirely on in-sample criteria. Given the high computation cost involved, the search procedure for the optimal vector of hyper-parameters was repeated at the end of each month rather than daily. We adopted the following strategy: first, given the grid of values for the hyper-parameters, we used the Kalman filter algorithm to estimate the model and compute the likelihood function for each combination of the prior parameters over the initial sample period 1.1.1991-31.12.1992. Second, we chose the 'optimal' prior parameters on the basis of the largest likelihood function. Third, having obtained the values of the hyper-parameters, the BVAR-TVP model was estimated with the Kalman filter algorithm over the initial period 1.1.1991-31.12.1992, and these estimates were used to generate forecasts at horizons of one to

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9 The results we obtained for the hyper-parameters (see Table 1) justifies this strategy. All estimations of the BVAR-TVP model and computation of out-of-sample forecasts were done on the econometric software RATS.
five days. Fourth, data for 1.1.1993 were added to the sample, the model was re-estimated (using the same hyper-parameters) and new forecasts were generated for one through five days ahead. This rolling-over procedure continued until the last day of the month (January 1993). Fifth, at the end of January 1993 we repeated our optimisation procedure for choosing the vector of hyper-parameters as in stages one and two. These hyper-parameters were then used for generating one to five days ahead forecasts for February 2003 employing the rolling procedure described in stages three and four. This rolling strategy of estimation and generation of out-of-sample forecasts continued until the end of our forecasting period. Hence our forecasts for 1993-2001 are produced in real time, using only past information and in-sample criteria for choosing the parameter estimates.

### 4.1 Forecast Accuracy Criteria

To evaluate the accuracy of each k-step-ahead forecast, we use a number of alternative criteria. The first error measure is the standard Root Mean Square Error ($RMSE = \sqrt{\sum(A_t - F_t)^2/n}$), where $A_t$ is the actual value, $F_t$ is the forecast value and $n$ is the number of observations). Our second criterion is the Theil $U$ statistic. This is the ratio of the $RMSE$ for the estimated model to the $RMSE$ of the random walk model that is used as a benchmark. Hence if $U<1$, the model performs better than the random walk; if $U>1$, the random walk outperforms the estimated model.

Neither the $RMSE$ nor the $U$ forecast error measures tell us whether the differences between the forecast errors of competing models are statistically significant. We employ the Diebold-Mariano (1995) approach to conduct a statistical comparison of the predictions produced by our model and those produced by the random walk. Denote by $e_1t$ the forecast errors of our model, and by $e_2t$ the forecast errors of the random walk model. To test whether the differences between the forecasts from the two competing models are statistically significant, we define the loss function$^{10}$, $d_t = e_1t^2 - e_2t^2$, $t=1,...,n$, and then test the null hypothesis $E(d_t) = 0$. The Diebold-Mariano test is based on the statistic

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$^{10}$ A similar loss function was used by Diebold and Mariano (1995) and Harvey et al (1997a, 1997b) in their simulation tests, as well as in Mark (1995).
\[ S = [V(d)]^{1/2} \]  

(11)

where \( d \) is the sample mean of \( d_t \), and \( V(d) \) is the consistent estimator of the variance of \( d \),

\[ V(d) = n^{-1} [\gamma_0 + 2 \sum_{k=1}^{h-1} \gamma_k] \]  

(12)

where \( \gamma_k \) is the \( k^{th} \) autocovariance of \( d_t \), and \( h \) is the \( h \)-step ahead forecast error. The \( S \) statistic has an asymptotic standard normal distribution under the null hypothesis.

Harvey et al (1977a) argue that the Diebold-Mariano test tends to be seriously over-sized, particularly for small and moderate samples, when the forecast errors are generated by heavy-tailed distributions. The authors propose a modification to the Diebold-Mariano test to overcome these problems. The modified test statistic, \( S^* \), which is compared with critical values from the Student's t-distribution and is shown to have substantially better size properties than the Diebold-Mariano test \( (S) \) in small and moderate samples, is given by

\[ S^* = n^{-1/2} \left[ n + 1 - 2h + n^{-1}h(h-1) \right]^{1/2} S \]  

(13)

Harvey et al (1997b) show that the presence of autoregressive conditional heteroscedasticity (ARCH) effects in forecast errors can induce size distortions in the Diebold-Mariano test. For practical purposes, they suggest the replacement of \( h \) in (13) by \( [0.5n^{1/3}] + h \) whenever ARCH effects in the forecast errors are suspected. The authors' simulation evidence demonstrates that the ARCH-modified Diebold-Mariano test, \( LS^* \), performs better than other competing test statistics, exhibits satisfactory behaviour for all sample sizes, and, hence, provides considerable protection against spurious rejection of the null hypothesis of equality of forecast mean squared errors in the presence of heavy-tailed distributions, moderate sample sizes and ARCH effects.
5. Forecasting Results

The hyper-parameters chosen by our estimation strategy for each exchange rate are shown in Table 1. It is interesting to observe that the hyper-parameters for each exchange rate changed only once during the forecasting period and that the estimates of these priors are quite similar across exchange rates. We also notice that three of the exchange rates have a relatively tight prior.

The out-of-sample forecasting performance of the model is reported in Table 2. We show the RMSE and U criteria at 1- to 5-days ahead horizons for each exchange rate. For each of these statistics we also report the average value over one to three and one to five steps in order to make a general assessment of the model's forecasting performance over varying horizons.

The accuracy of the forecasts is quite impressive at all forecast horizons and for all exchange rates, with the dollar/pound and D-mark/pound rates displaying the lowest RMSEs. The U statistics suggest a major improvement over the random walk at all horizons. The average values for 1- to 5-steps ahead imply forecast gains of 29% for the D-mark/dollar, 29.50% for the yen/dollar, 29.2% for the dollar/pound, and 29.4% for the D-mark/pound. These forecast gains over the random walk are much greater than those reported in Canova (1993).

But are the out-of-sample forecast errors of the BVAR-TVP model statistically smaller than those of the random walk? To answer this question we have applied the Diebold-Mariano test methodology. Table 3 indicates the presence of highly significant ARCH effects in the forecasts errors for all exchange rates and forecast horizons. As Harvey et al (1997a, 1997b) have demonstrated, the appropriate statistic in this case is the ARCH-modified Diebold-Mariano statistic. The results, reported in Table 4, are quite striking. All the statistics are highly significant at the one percent level of significance for all exchange rates and forecast horizons. These findings provide overwhelming evidence for the superior forecasting performance of the BVAR-TVP model over the random walk at horizons as short as one to five days ahead11.

11 Clarida et al (2003) report that the term structure of forward exchange rates contains useful information for forecasting exchange rates, though they do not provide any economic rationale for such a model. Using a Markov regime-switching vector error correction framework to model the term structure, they show that the out-of-sample forecasts are significantly superior to the random walk forecasts. However, Clarida et al (2003) only report multi-step forecasts with the
To assess the importance of time-variation in the coefficients, we have also produced 1-to 5-days ahead forecasts using the traditional VAR model and the same sequential methodology described in Section 3. The ARCH-modified Diebold-Mariano statistics, shown in Table 4, suggest that the forecast errors of the BVAR-TVP model are statistically smaller than those from the VAR model for all exchange rates and forecast horizons, with the largest improvement occurring in the case of the D-mark/dollar and the dollar/pound rates. These findings support the view that failure to account for parameter instability in the exchange rate models is likely to reduce the out-of-sample forecasting performance of these models.

6. The Profitability of Exchange Rate Forecasts

Predictability of exchange rates, as measured by the traditional RMSE and U criteria, does not necessarily imply that an investor can make profits from a trading strategy based on such forecasts. First, these measures may not be reliable in terms of signalling profit opportunities. Second, net trading profits can be eroded by transaction costs.

To assess the economic significance of the exchange rate forecasts, we use an inter-day trading strategy typically employed in markets and the academic literature (see Levich and Thomas, 1993; LeBaron, 1996, Neely et al, 1997) to examine whether an investor could have made excess profits by using the one-day-ahead predictions of exchange rate changes and the uncovered interest rate parity. Assume that an investor has an initial stock of wealth that provides him with the necessary credit to trade foreign exchange contracts with a commercial bank. The one-day-ahead predictions of exchange rate changes lead to the following trading strategy:

12 Scinasi and Swamy (1989) and Wolf (1987), using single regressions, also demonstrated that by allowing for time-varying coefficients it is possible to produce out-of-sample forecasts that beat the random walk.

13 As in Neely et al (1997) and other studies, the trading strategy is formulated from the perspective of investors in the domestic currency. That is, German investors for the D-
a. When the predicted exchange rate change is positive (i.e. the domestic currency, DC, is expected to depreciate and foreign currency, FC, to appreciate), borrow domestic currency and convert to FC at the spot rate to earn the foreign daily interest rate: *Long position in FC: z = +1.*

b. When the predicted exchange rate change is negative (i.e. the domestic currency is expected to appreciate and FC to depreciate), sell any long FC position and take a short position in FC by borrowing FC and convert to domestic currency at the spot rate to earn the domestic daily interest rate: *Short position in FC: z = -1.*

The daily excess returns over the period (t, t+1), $i_t$, from this trading strategy are obtained as follows:

\[
 i_t = z_t \{ (\ln S_{t+1} - \ln S_t) + [\ln(1+r^*_t) - \ln(1+r_t)] \} \tag{14}
\]

where $z_t = +1$ for long (buy) FC position, and $z_t = -1$ for short (sell) FC position, and the right-hand side of (14) denotes the actual exchange rate change one day-ahead adjusted for the interest rate differential.

The above excess returns are gross, in that they do not allow for transaction costs. Following previous practice (see LeBaron, 1996; Neely *et al*, 1997; Dunis and Williams, 2002; Qi and Wu, 2002), net excess returns are obtained by subtracting a transaction cost, $c$, from the gross return every time a trade is made (i.e. whenever there is a change in the sign of the signal variable, $z_t$).

In the literature, authors tend to use a transaction cost in the range of 0.01 percent to 0.05 percent (e.g. LeBaron, 1996; Neely *et al*, 1997; Qi and Wu, 2002). Dunis and Williams (2002) argue that a cost of 3 pips (0.0003 EURO/USD) per trade (one way) between market makers is normal in practice. This implies a transaction cost of 0.033 percent that is well above the middle point of the range typically used in other studies, and this is the value for $c$ that we use in our paper.

---

14 Note that the interest rates used in eq. (14) are the 1-month rates converted into daily rates, and measured in decimals.
Summary statistics for the distribution of daily excess returns (without transaction costs) for the D-mark/dollar, yen/dollar, dollar/pound and D-mark/pound over the period 1.1.1993-16.3.2001 (a total of 2140 observations) are shown in Table 5. All series display slight skewness and high kurtosis, with the Jarque-Bera statistic strongly rejecting the null hypothesis of normality for all series. The Q statistics show evidence of autocorrelation for the daily returns on the mark/dollar and yen/dollar, but not for the other series \(^{15}\).

In Table 6, we present a wide range of statistical and financial measures for analysing the inter-day trading performance results on the daily excess returns (without and with transaction costs). The overall findings are quite impressive. The first important observation is that the BVAR-TVP forecasts generate positive excess returns on all currencies. Even allowing for transaction costs, the annualised mean excess return is positive and significant at the 1 percent level in all cases, with the largest profit made on the yen/dollar rate (30.4%), followed by the mark/dollar (11.7%). These findings provide support for the economic significance of the BVAR-TVP out-of-sample forecasts \(^{16}\). The cumulative daily excess return is also impressive, ranging from 26.4% on the dollar/pound rate to 243.8% for the yen/dollar rate.

These returns compare favourably with those reported by a number of studies based on technical trading rules. Using various technical trading rules for a number of currencies, Levich and Thomas (1993) report annual excess returns in the order of 1.8%-8.1% (with zero transaction cost), LeBaron's (1996) zero cost returns range from 7% to 10%, Neely et al (1997) show annual returns in the order of 1%-6.5% (with 0.01 transaction cost), while Qi and Wu (2002) report mean returns from the application of 2127 trading rules for seven currencies ranging from 4.8% to 13% (with 0.025 percent transaction cost). Our results also contrast sharply with Lee and Marthur (1996) and Neely and Weller (2003) who failed to find evidence of significant excess returns.

\(^{15}\) See, for example, Gencay (1999) and Qi and Wu (2002) for similar evidence on normality and autocorrelation in daily returns.

\(^{16}\) It is interesting to note that Abhyanka et al (2003) fail to find significant economic value for the monetary exchange rate model forecasts over horizons of one year. Though they report increasing gains over longer horizons (particularly over a 10-year horizon), these findings are of limited use to practitioners who have short horizons (see Section 1).
returns using various technical trading rules. Only Dunis and Williams (2002) report a better performance for trading the EURO/USD rate using signals generated from a neural network model based on daily financial variables as inputs, though that study covers only a short period of trading (May 2000-June 2001). The predictability of exchange rates can also be assessed in terms of risk-adjusted trading profits as measured by the Sharpe ratio, which weights the series of returns by their volatility. Even with the high transaction cost of 0.033 percent, Sharpe ratios above 1.0 are attained for three rates, with the highest for the yen/dollar (2.56). The only exception is the Sharpe ratio for the dollar/pound (0.4), though it still compares well with other studies. Overall, our Sharpe ratios are well above Qi and Wu's (2002) findings of 0.053-0.075 (without transaction cost), LeBaron's (1996) estimates of 0.629-0.981 (for c=0.01) and 0.155-0.694 (for c=0.05), and Neely's et al (1997) findings of 0.101-0.500 (for c=0.01), which are based on technical trading rules. They also compare well with the Sharpe ratios reported by Dunis and Williams (2002) for a number of statistical models.

Another important indicator of trade performance is the downside risk as measured by the probability of a 10% loss. The downside risk is extremely low in all cases, ranging from

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17 It should be noted that Dunis and Williams (2002), Qi and Wu (2002) and Lee and Marthur (1996) ignore the interest rate differential, so the return is measured simply by the exchange rate change.

18 The annualised volatility implies that excess returns display considerable inter-day volatility. It is interesting to note, however, that this is lower than the implied volatility of each currency (i.e. 10.82 for the mark/dollar; 12.0 for the yen/dollar; 9.0 for the dollar/pound; 8.44 for the mark/pound).

19 This financial criterion was developed by Dunis and Williams (2002) and has not been employed by any of the previous studies mentioned above. The probability of loss, $PoL$, is given by

$$PoL = \left[\frac{1-P}{P}\right]^{(MaxRisk/A)}$$

where,

$$P = 0.5*(1+(Z/A)),$$

$$Z = (ProbWin*AvgGain) + (ProbLoss*AvgLoss).$$
0.018% for the yen/dollar to 2.49% for the dollar/pound. Even after allowing for transaction costs, the downside risk remains very low for the yen/dollar, mark/dollar and mark/pound rates (0.028%-1.23%), though it jumps a bit higher for the dollar/pound (12.1%). This performance for the yen and mark rates is superior to that reported by Dunis and Williams for the EURO/USD rate (0.09% downside risk for their preferred neural network model, without transaction cost). The low downside risk reflects the fact that the trading strategy based on the model's forecasts has generated a much larger percentage of winning trades than losing trades in all cases, and has also produced an average gain/loss ratio greater than one for all currencies even after allowing for transaction costs.

As a comparison, we also report trading results obtained from the benchmark 'buy-and hold' strategy. The excess returns from this strategy are given by the actual exchange rate change adjusted by the interest rate differential, which in effect implies no switching of currency (that is, \( z = 1 \)). The deterioration in trading performance is very striking. Although it continues to remain positive, the annualised mean excess return is reduced dramatically in all cases (by -67.6% for the mark/dollar, -87.7% for the yen/dollar, -95.8% for the dollar/pound, and by -57.3% for the mark/pound), and becomes entirely insignificant for the dollar/pound rate. The poor performance of this trading strategy is also reflected in the large drop of the Sharpe ratios and, more critical, in the dramatic increase of the downside risk. The latter is particularly pronounced, and unacceptable from a trader's perspective, in the cases of the dollar/pound rate (rising to 89.2%), yen/dollar (32.6%) and the mark/dollar (18.8%).

\[ A = \left( \frac{\text{ProbWin} \times \text{AvgGain}^2 + (\text{ProbLoss} \times \text{AvgLoss}^2)^{1/2}}{\text{MaxRisk}} \right) \]

and \( \text{MaxRisk} \) is the risk level determined by the user (following Dunis and Williams, we set it at 10%)
7. Conclusions

In this paper we have proposed a Bayesian vector autoregressive model with time-varying parameters (BVAR-TVP) to examine the predictability of exchange rates over very short horizons in four large industrial countries, which is novel in this context. This modelling framework has the advantage of addressing simultaneously the problems of parameter instability, endogeneity, information structure, and bounded rational expectations.

An important contribution of the paper is the application of the BVAR-TVP model to daily data and its use to produce forecasts at the very short horizons of 1-day up to 5-days (trading) ahead typically used by traders and investors in financial markets. Another contribution is the production of out-of-sample forecasts in real time using economic and financial information from the money, bonds, equities and derivatives markets. The forecasting period covers 2140 trading days over the 1993-2001 period which was characterised by many turbulent episodes in currency markets, thus providing a stringent test of the model's forecasting performance.

The out-of-sample forecasting results are very impressive. The BVAR-TVP forecasts strongly dominate the random walk forecasts at all horizons and for all exchange rates. On the basis of the $RMSE$s, the average forecast gains over the 1- to 5-days ahead horizon are around 30%. Using an ARCH-modified Diebold-Mariano test, we find that the forecasts errors of the model are significantly smaller than those of the random walk at the 1% significance level at all forecast horizons. This provides strong evidence for the superior out-of-sample forecasting performance of the BVAR-TVP model over the random walk at horizons as short as one to five trading days ahead. The test also shows that the models' forecast errors are statistically smaller than those from a VAR model for all forecast horizons and exchange rates. These findings support the view that failure to account for time variation of coefficients is likely to reduce the out-of-sample forecasting performance of empirical exchange rate models. Another important factor is the informational content of economic and financial variables from different financial markets, which can be exploited for exchange rate forecasting.

From the perspective of investors, an important criterion of forecasts is whether they are successful in signalling profit opportunities. We show that international investors could have
made statistically significant excess profits in currency markets during the 1990s if they had followed an inter-day trading strategy based on the uncovered interest rate parity and the buy/sell signals generated by the model's 1-day ahead exchange rate forecasts, even after allowing for transaction costs and risk factors. The profitability of the exchange rate predictions compares very favourably with that of technical trading rules reported by previous studies, both in terms of overall profitability and in terms of risk-adjusted performance, with high Sharpe ratios and very small downside risk. This evidence on significant excess profits in currency markets presents a serious challenge to the efficient market hypothesis, and it is difficult to see how any rational expectations model could possibly explain it. Our interpretation is that the results are indicative of market inefficiency, the existence of bounded rationality and the presence of a time-varying currency risk premium.

Overall, our findings imply that it is possible to develop empirical exchange rate models that beat the random walk, even at the very short term horizons of one day or one week ahead, and generate signals for profitable opportunities for investors, provided that we employ a modelling framework that addresses a number of crucial modelling issues and exploits all the information available in financial markets. As with all empirical papers, our findings are subject to the caveat that they are sample specific. A logical extension would be to test the robustness of our results using other sample periods and exchange rates. Another extension is to consider a larger set of daily financial indicators from the financial markets (even commodities markets). From an econometric perspective, there are two important challenges for future research: one is to replace the Minnesota prior in the BVAR-TVP model with the Normal-Wishart prior distribution\textsuperscript{20}. The other is to introduce into the BVAR-TVP model some of the other types of nonlinearities used in the nonlinear literature (for example, markov switching or STAR processes), though it is recognised that these two approaches represent quite different econometric methodologies.

\textsuperscript{20} It should be noted, however, that that the BVAR models that have used the Normal-Wishart prior (e.g. Sims and Zha, 1998; Robertson and Tallman, 1999) assume constant coefficients.
REFERENCES


Table 1

Hyper-parameters

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<td>2.2.98-16.3.01</td>
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<td>1.1.93-30.9.99</td>
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<td>0.00001</td>
<td>0.00001</td>
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<tr>
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<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>δ6</td>
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<td>0.3</td>
<td>0.3</td>
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### Table 2

Statistics on Out-of-Sample Forecast Accuracy: BVAR-TVP Model

<table>
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<tr>
<th>Step (days)</th>
<th>N.Obs</th>
<th>RMSE</th>
<th>Theil U</th>
<th>RMSE</th>
<th>Theil U</th>
<th>RMSE</th>
<th>Theil U</th>
<th>RMSE</th>
<th>Theil U</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>2141</td>
<td>0.617214</td>
<td>0.705193</td>
<td>0.745510</td>
<td>0.7091590.</td>
<td>0.504608</td>
<td>0.705912</td>
<td>0.500921</td>
<td>0.702867</td>
</tr>
<tr>
<td>D2</td>
<td>2140</td>
<td>0.624621</td>
<td>0.711047</td>
<td>0.760731</td>
<td>7113870.6</td>
<td>0.507765</td>
<td>0.717782</td>
<td>0.508207</td>
<td>0.706813</td>
</tr>
<tr>
<td>D3</td>
<td>2139</td>
<td>0.623647</td>
<td>0.702422</td>
<td>0.760985</td>
<td>979780.70</td>
<td>0.507577</td>
<td>0.693037</td>
<td>0.507916</td>
<td>0.714287</td>
</tr>
<tr>
<td>D4</td>
<td>2138</td>
<td>0.623579</td>
<td>0.723094</td>
<td>0.761290</td>
<td>16430.704</td>
<td>0.504178</td>
<td>0.716112</td>
<td>0.506064</td>
<td>0.702287</td>
</tr>
<tr>
<td>D5</td>
<td>2137</td>
<td>0.623550</td>
<td>0.708326</td>
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<td>905</td>
<td>0.504133</td>
<td>0.704543</td>
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<td>0.701835</td>
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<tr>
<td>AV 1-3</td>
<td></td>
<td>0.621827</td>
<td>0.706221</td>
<td>0.755742</td>
<td>0.7061750.</td>
<td>0.506650</td>
<td>0.705577</td>
<td>0.505681</td>
<td>0.707989</td>
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<td>AV 1-5</td>
<td></td>
<td>0.622522</td>
<td>0.710016</td>
<td>0.757897</td>
<td>705014</td>
<td>0.505652</td>
<td>0.707477</td>
<td>0.505817</td>
<td>0.705618</td>
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Table 3

ARCH Effects in Forecast Errors

<table>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>52.6808 (10)</td>
<td>173.8712 (9)</td>
<td>81.5383 (12)</td>
<td>107.6547 (9)</td>
</tr>
<tr>
<td>D2</td>
<td>53.4523 (10)</td>
<td>180.0304 (9)</td>
<td>84.7252 (12)</td>
<td>101.3137 (9)</td>
</tr>
<tr>
<td>D3</td>
<td>54.1077 (10)</td>
<td>178.0038 (9)</td>
<td>73.2154 (9)</td>
<td>112.1320 (9)</td>
</tr>
<tr>
<td>D4</td>
<td>54.7866 (10)</td>
<td>179.2644 (9)</td>
<td>73.1509 (9)</td>
<td>110.8394 (9)</td>
</tr>
<tr>
<td>D5</td>
<td>54.8038 (10)</td>
<td>184.1585 (12)</td>
<td>73.0519 (9)</td>
<td>110.7534 (9)</td>
</tr>
</tbody>
</table>

*Note:* Reported statistics are for Engle's Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH) up to order $q$. This test statistic is distributed as a $\chi^2(q)$. Numbers in parentheses are for the lag order $q$. 
Table 4

Tests for Forecast Equality: BVAR-TVP vs Random Walk and VAR

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>$L_{RW}$</td>
<td>$L_{VAR}$</td>
<td>$L_{RW}$</td>
<td>$L_{VAR}$</td>
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<tr>
<td>D1</td>
<td>2141</td>
<td>-15.0608</td>
<td>-2.0523</td>
<td>-10.9554</td>
<td>-2.2289</td>
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<tr>
<td>D2</td>
<td>2140</td>
<td>-14.0299</td>
<td>-3.9662</td>
<td>-10.4496</td>
<td>-2.3345</td>
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<tr>
<td>D4</td>
<td>2138</td>
<td>-14.3718</td>
<td>-3.5695</td>
<td>-8.2200</td>
<td>-2.2214</td>
</tr>
<tr>
<td>D5</td>
<td>2137</td>
<td>-12.8672</td>
<td>-4.0373</td>
<td>-9.3812</td>
<td>-2.0340</td>
</tr>
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</table>

Note: $L_{RW}$ is the ARCH-modified Diebold-Mariano statistic (Harvey et al, 1997a, 1997b), which follows Student's t-distribution. $L_{RW}$ and $L_{VAR}$ test the forecasts errors of the BVAR-TVP model against those from the random walk and the VAR models, respectively.
Table 5

Summary Statistics for the Daily Excess Returns

<table>
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<tr>
<td>Skewness</td>
<td>-0.0436</td>
<td>0.6317</td>
<td>-0.1741</td>
<td>0.0095</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.7611</td>
<td>7.7680</td>
<td>5.4742</td>
<td>4.0017</td>
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<tr>
<td>Jarque-Bera</td>
<td>277.236</td>
<td>2169.44</td>
<td>556.638</td>
<td>89.5161</td>
</tr>
<tr>
<td>$\rho(1)$ [Q(1)]</td>
<td>-0.055 [0.010]</td>
<td>-0.038 [0.079]</td>
<td>-0.019 [0.387]</td>
<td>-0.022 [0.308]</td>
</tr>
<tr>
<td>$\rho(2)$ [Q(2)]</td>
<td>-0.003 [0.036]</td>
<td>-0.002 [0.212]</td>
<td>0.008 [0.638]</td>
<td>-0.004 [0.586]</td>
</tr>
<tr>
<td>$\rho(3)$ [Q(3)]</td>
<td>-0.018 [0.062]</td>
<td>-0.083 [0.001]</td>
<td>-0.027 [0.476]</td>
<td>-0.010 [0.735]</td>
</tr>
<tr>
<td>$\rho(4)$ [Q(4)]</td>
<td>0.016 [0.096]</td>
<td>-0.008 [0.001]</td>
<td>0.005 [0.637]</td>
<td>-0.002 [0.864]</td>
</tr>
<tr>
<td>$\rho(5)$ [Q(5)]</td>
<td>-0.023 [0.109]</td>
<td>0.010 [0.003]</td>
<td>-0.013 [0.712]</td>
<td>-0.023 [0.788]</td>
</tr>
<tr>
<td>$\rho(6)$ [Q(6)]</td>
<td>-0.013 [0.155]</td>
<td>0.004 [0.006]</td>
<td>-0.019 [0.714]</td>
<td>0.027 [0.682]</td>
</tr>
<tr>
<td>$\rho(10)$ [Q(10)]</td>
<td>-0.036 [0.201]</td>
<td>0.001 [0.008]</td>
<td>-0.043 [0.204]</td>
<td>0.011 [0.904]</td>
</tr>
</tbody>
</table>

Note: The Jarque-Bera statistic tests for normality in the series and is distributed as $\chi^2(2)$ under the null. $\rho(1)\ldots\rho(15)$ are the first 15 autocorrelations of each series, while $Q(k)$ are the $p$-values for the Ljung-Box Q-statistic for the null hypothesis that there is no autocorrelation up to order $k$. 

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Table 6
Inter-day Trading Performance Results (2140 trading days)

<table>
<thead>
<tr>
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<th>D-Mark/US Dollar</th>
<th>Yen/US Dollar</th>
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<td></td>
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<td>With</td>
<td>Buy-and-hold</td>
<td>Without</td>
<td>With</td>
<td>Buy-and-hold</td>
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<td>strategy</td>
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<td>strategy</td>
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<tr>
<td>(t-statistic)</td>
<td>(65.46)</td>
<td>(54.84)</td>
<td>(21.14)</td>
<td>(118.2)</td>
<td>(111.7)</td>
<td>(15.22)</td>
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<tr>
<td>Cummulative Return(%)</td>
<td>118.277</td>
<td>99.005</td>
<td>38.329</td>
<td>258.159</td>
<td>243.771</td>
<td>33.674</td>
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<tr>
<td>Sharpe Ratio</td>
<td>1.415</td>
<td>1.185</td>
<td>0.457</td>
<td>2.555</td>
<td>2.416</td>
<td>0.329</td>
</tr>
<tr>
<td>Maximum Daily Profit(%)</td>
<td>2.869</td>
<td>2.869</td>
<td>3.009</td>
<td>5.475</td>
<td>5.475</td>
<td>3.259</td>
</tr>
<tr>
<td>% Winning Trades(%)</td>
<td>54.486</td>
<td>53.318</td>
<td>53.224</td>
<td>56.028</td>
<td>55.187</td>
<td>54.159</td>
</tr>
<tr>
<td>% Losing Trades(%)</td>
<td>45.514</td>
<td>46.682</td>
<td>46.776</td>
<td>43.972</td>
<td>44.813</td>
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<td>Number of Up Periods</td>
<td>1166</td>
<td>1141</td>
<td>1139</td>
<td>1199</td>
<td>1181</td>
<td>1159</td>
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<tr>
<td>Number of Down Periods</td>
<td>974</td>
<td>999</td>
<td>1001</td>
<td>941</td>
<td>959</td>
<td>981</td>
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<td>Number of Trades</td>
<td>584</td>
<td>584</td>
<td>436</td>
<td>436</td>
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<tr>
<td>Avg Gain in Up Periods(%)</td>
<td>0.473</td>
<td>0.475</td>
<td>0.449</td>
<td>0.581</td>
<td>0.583</td>
<td>0.504</td>
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<tr>
<td>Avg Loss in Down Periods(%)</td>
<td>-0.445</td>
<td>-0.443</td>
<td>-0.473</td>
<td>-0.466</td>
<td>-0.463</td>
<td>-0.561</td>
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<tr>
<td>Avg Gain/Loss Ratio</td>
<td>1.063</td>
<td>1.072</td>
<td>0.949</td>
<td>1.247</td>
<td>1.259</td>
<td>0.898</td>
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<td>Probability of 10% Loss(%)</td>
<td>0.535</td>
<td>1.228</td>
<td>18.761</td>
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<td>0.028</td>
<td>32.594</td>
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Table 6 continued

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<tr>
<td>Annualised Return(%)</td>
<td>5.718</td>
</tr>
<tr>
<td>(t-statistic)</td>
<td>(33.0)</td>
</tr>
<tr>
<td>Annualised Volatility(%)</td>
<td>8.015</td>
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<tr>
<td>Cummulative Return(%)</td>
<td>48.561</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.713</td>
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<tr>
<td>Maximum Daily Profit(%)</td>
<td>2.231</td>
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<tr>
<td>% Winning Trades(%)</td>
<td>52.991</td>
</tr>
<tr>
<td>% Losing Trades(%)</td>
<td>47.009</td>
</tr>
<tr>
<td>Number of Up Periods</td>
<td>1130</td>
</tr>
<tr>
<td>Number of Down Periods</td>
<td>1010</td>
</tr>
<tr>
<td>Number of Trades</td>
<td>673</td>
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<tr>
<td>Avg Gain in Up Periods(%)</td>
<td>0.364</td>
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<tr>
<td>Avg Loss in Down Periods(%)</td>
<td>-0.359</td>
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<tr>
<td>Avg Gain/Loss Ratio</td>
<td>1.014</td>
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<tr>
<td>Probability of 10% Loss(%)</td>
<td>2.486</td>
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