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ABSTRACT

We propose an empirical exchange rate model that follows a variant of the well-known risk-return relationship. The model relates the exchange rate return to its high-low price range, used as a proxy for volatility. Both statistical and economic value criteria are used to evaluate the out-of-sample performance of the proposed model. Despite the root-mean-squared-forecast-errors of the proposed model are less than those from a naïve random walk, the improvements are statistically insignificant. However, our results consistently show that the proposed model generates economic gains larger than those derived from a naïve random walk in a stylized international asset allocation exercise. The portfolio returns obtained using the proposed variant of the risk-return relationship, are sizable and only partially explained by the returns obtained by popular foreign exchange trading strategies.

Keywords: Exchange Rates, Economic Value, Volatility

JEL Codes: F31, F36, G11

1. Introduction

Foreign exchange forecasting is an important topic in international economics and finance. Meese and Rogoff (1983a, 1983b) forcefully demonstrate the difficulty of forecasting exchange rates – the forecasts from exchange rate models based on macroeconomic fundamentals do not outperform those from a naïve random walk (henceforth RW) model. Indeed, it is difficult to find an exchange rate model outperforming the RW model for all the sample periods, evaluation criteria, and currencies (see, *inter alia*, Cheung *et al.* (2005a, b) and the references therein).[1]

Nevertheless, a few studies have suggested that some empirical frameworks could outperform a naïve RW model out of sample, even at short horizons. Clarida and Taylor (1997) and Clarida *et al.* (2003), for example, show that the term structure of forward premia contains valuable information for forecasting exchange rates. Similarly, Evans and Lyons (2002, 2005) illustrates that the information embedded in foreign exchange order flows helps forecast exchange rates. These two approaches share a common element: they both advanced an 'agnostic' framework that links exchange rates and their predictive variables, namely forward premiums and spot exchange rate order flows, without imposing specific assumptions about risk premiums and/or expectations.

In this paper we propose a new empirical exchange rate model that relates the exchange rate return to its high-low price range, which is used as a measure of volatility. Similar to early studies that recorded some success in predicting out-of-sample exchange rates at short horizons, the proposed model does not impose specific assumptions about risk premiums and/or expectations. Further, it bears some implications for the well-known risk-return relationship, and could be used to generate conditional forecasts/expectations of both the exchange rate and its volatility, which are key ingredients of optimal portfolio choices.

The proposed model builds on two empirical stylized facts: 1) the large empirical evidence documenting that the risk-return relationship is characterized by important lead-lag interactions (Whitelaw, 1994; Brandt and Kang, 2004; Ludvigson and Ng, 2007 and the references therein), and 2) the univariate representation of the high-low range as measure of volatility is only efficient if certain common factor restrictions linking the dynamics of the highest and lowest spot exchange

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[1] A recent class of exchange rate models which incorporates monetary policy rules in modelling exchange rate dynamics may represent an exception; see, for example, Engle and West (2006), Mark (2007) and Engle *et al.* (2008) and Molodtsova *et al.* (2008). Rogoff and Starrakeva (2008) offer an alternative interpretation of the forecast results reported in these studies.

rates recorded over a certain time interval are satisfied (Kremers *et al.*, 1992; Sarno and Valente, 2006).

These two stylized facts suggest that the lagged conditional volatility can be used to forecast exchange rates since it may contain useful information that summarizes current and future market conditions. Furthermore, a more general model that does not impose common factor restrictions should result in an improvement upon the univariate empirical models based on volatility proposed in early studies (Domowitz and Hakkio, 1985; Fraser and Taylor, 1990; Chou, 2005).

In evaluating the predictive ability of the proposed model, we go beyond the usual practice of assessing its statistical performance. Most studies, including the seminal one by Meese and Rogoff (1983a), use statistical measures such as the root-mean-square-error or mean-absolute-error to compare an empirical model's exchange rate forecasting performance against a RW. Following the pioneering work of Leitcher and Tanner (1991) and West *et al.* (1993), a few recent contributions emphasize the importance of assessing the economic value of a forecast, which is more relevant than statistical performance to an economic agent (Abhyankar *et al*., 2005; Della Corte *et al.*, 2008a). In this paper, we evaluate the proposed model's forecast performance using both statistical criteria and economic value criteria, where the latter are based on the computation of utility-based measures within a dynamic asset allocation framework.

Furthermore, we note that although the RW model is the ubiquitous benchmark of exchange rate forecast evaluation, in the context of performance evaluation of asset allocation strategies, it does not necessarily represent a suitable comparator consistent with the one routinely used by market practitioners. Hence, it is of interest to compare the portfolio returns generated by the investment strategy implied by the forecasts obtained from the proposed model with those generated by popular trading strategies routinely adopted by market practitioners in the foreign exchange market (Pojarliev and Levich, 2008). Specifically, we assess the proposed model's performance against a benchmark that includes the returns from value trading based on the purchasing power parity (PPP), carry trade (based on deviations from uncovered interest parity, UIP), trend-following, and currency volatility. In doing so, we quantify the abnormal returns, or alpha returns relative to the selected trading strategies that represent a suitable measure of performance on a risk-adjusted basis in the context of the foreign exchange market.

This comparison is novel and useful for at least two reasons: first, it enables us to quantify the genuine incremental economic value associated with the proposed model over and above the economic gains accruing to agents using conventional foreign exchange rate strategies. Second, it allows us to compare the out-of-sample performance of the proposed model with the ones of well-known alternative exchange rate empirical models (e.g. modeling deviations from PPP or UIP) without the need of estimating the individual competing models. We only focus on the ability of these models to generate positive returns and, in turn, higher wealth and higher utility levels.

To anticipate our key results, we find some favourable in-sample and out-of-sample evidence for the proposed model estimated using 25 years of weekly data on five major US-dollar exchange rates. The model yields some useful information on the interactions between the foreign exchange rate return and its (lagged) volatility.

Although the forecasts from the proposed model are not statistically better than those from the RW, they offer substantially higher economic gains. Specifically, for a mean-variance investor who has a relative risk aversion (RRA) coefficient of 5, she would be willing to pay a monthly fee, on average across exchange rates, between 0.88% and 2.79% of the portfolio value. These results hold for different values of RRA coefficients, short-sales restrictions and after the introduction of transaction costs.

When compared to strategies routinely used by market practitioners in the foreign exchange market, the performance of the asset allocation method based on the proposed model is found to be related to the trend-following strategy and, to a lesser extent, to the value trading and currency volatility strategies. Nonetheless, there is a large proportion of the model's performance left unexplained by these trading strategies. In fact, the estimated alpha returns range between 37.2 percent (Japanese yen) and 5.2 percent (the euro), and, in most of the cases, are statistically significant at the conventional statistical level. The finding indicates that the proposed model contains information about exchange rates beyond what is embedded in these four foreign exchange trading strategies and it can be used in conjunction with existing strategies to enhance performance of international currency portfolios.

The reminder of the paper is as follows: in Section 2 we introduce and discuss the empirical model. Section 3 describes the data and reports the preliminary statistical results. Section 4 evaluates the economic value of the exchange rate forecasts generated by the proposed model. Section 5 concludes.

2. The Empirical Framework

The variables used in the empirical exercise are the highest exchange rate (s_t^H), the lowest exchange rate (s_t^L), the high-low range ($R_t = s_t^H - s_t^L$), and the average exchange rate $s_t^A = (s_t^H + s_t^L)/2$ recorded during a predetermined trading period. In the current exercise, the period is a trading week, the average return is given by Δs_t^A, where Δ is the differencing operator, and its variability is given by R$_t$.[2] The variables s_t^H and s_t^H are expressed in logarithmic form.

To construct an empirical specification that exploits the interaction between s_t^A and R$_t$, we note that, as reported in most studies, exchange rates are realizations of non-stationary, or I(1), processes. However, the range usually follows a stationary process that has a non-zero mean. The stationarity property is quite intuitive – exchange rate variability is not expected to drift around without bounds under normal circumstances.

If both s_t^H and s_t^L have a stationary and invertible ARMA representation after first differencing, the stationarity of the range R$_t$ implies that s_t^H and s_t^L move together in the long run and exhibit a common stochastic trend; that is, they are cointegrated with the cointegrating vector [1 -1]. The relationship between s_t^H and s_t^L can be described by a cointegrating VAR, which, by means of the Granger Representation Theorem (Engle and Granger, 1987), must possess a vector error correction model (VECM) representation where the range R$_t$ plays the part of an equilibrium error:

$$(1) \qquad \Delta\mathbf{X}_t = \Gamma(L)\Delta\mathbf{X}_t + \Pi\mathbf{X}_{t-1} + \varepsilon_t = \Gamma(L)\Delta\mathbf{X}_t + \alpha R_{t-1} + \varepsilon_t ,$$

where $\mathbf{X}_t \equiv (s_t^H, s_t^L)'$, $\Gamma(L)$ is a lag polynomial of order p containing 2 × 2 coefficient matrices, p is a choice parameter, $\Pi = \alpha\beta'$ where α and β are 2 × 1 vectors, and $\varepsilon_t \sim iid(0,\Sigma)$.[3] The vector $\alpha = [\alpha^H \;\; \alpha^L]'$ contains the adjustment coefficients that capture the effects of shocks to the range on Δs_t^H, Δs_t^L and, hence, s_t^H, s_t^L.

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[2] Indeed, the expression $R_t^2/(4ln2)$ is an efficient volatility estimator under certain conditions. See, Parkinson (1980) and Alizadeh *et al.* (2002).

[3] As discussed in Section 3, our data affirm that the range variable is stationary and, thus, the cointegrating vector β is set to [1 -1].

The VECM specification given by Equation (1) offers some useful and under-exploited insights into the well-known risk-return relationship. For instance, the interaction between the exchange rate returns and their volatility can be derived as follows. Let Λ = [½ ½] and pre-multiply both sides of (1) by Λ:

(2) $$\Lambda\Delta\mathbf{X}_t = \Lambda\Gamma(L)\Delta\mathbf{X}_t + \Lambda\alpha R_{t-1} + \Lambda\varepsilon_t .$$

Taking the stationarity properties of Δs_t^A and R_t into consideration, we re-arrange terms in (2) and obtain an expression for the weekly average return:

(3) $$\Delta s_t^A = \gamma R_{t-1} + \psi_t ,$$

where $\psi_t = \Lambda\Gamma(L)\Delta\mathbf{X}_t + \Lambda\varepsilon_t$ and $\gamma = \Lambda\alpha$.

A few remarks are in order. First, the relationship between the exchange rate return Δs_t^A and its lagged volatility R_{t-1} given in (3) directly follows from the empirical high-low model of exchange rates. Hence the VECM specification (1), which captures the interaction between the high and low exchange rates, offers an alternative way of deriving a relationship between risk and return.

Second, a variant of Equation (3) has been employed by many researchers in testing for the relationship between security returns and risk (Ludvigson and Ng, 2007; Lettau and Ludvigson, forthcoming and the references therein). It is noted that if $\Lambda\Gamma(L)\Delta\mathbf{X}_t = 0$ or, equivalently $\psi_t = \Lambda\varepsilon_t$, then the return depends on volatility and not on changes in the highest and lowest exchange rates. Since the dynamics of $\Lambda\Gamma(L)\Delta\mathbf{X}_t$ is likely to violate the zero restriction, past values of Δs_t^H and Δs_t^L contain valuable information about future average returns (Kremers *et al.*, 1992; Sarno and Valente, 2006). This also implies that the study of the relationship of returns and volatility using Equation (3) with ψ_t being treated as a standard error term could result in information loss, which, in turn, may lead to the reported difficulty in revealing the empirical link between returns and their (lagged) volatility.

Third, there is no clear consensus in the empirical literature on whether the lagged volatility is positively or negatively related to returns.[4] Equations (1) and (3) provide an alternative insight on risk-return interactions. The VECM specification (1) requires that a) $\alpha^H < 0$ and $\alpha^L > 0$ such that

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[4] See, among others, Campbell (1987), Bollerslev *et al.* (1988), Harvey (1989), Whitelaw (1994), Brandt and Kang (2004), Ghysels *et al.* (2005), Lettau and Ludvigson (forthcoming) and Ludvigson and Ng (2007).

the responses of high and low exchange rates to ranges are consistent with the stationarity of the range variable, and b) at least one of the two adjustment coefficients is statistically significant. The sign and magnitude of the coefficient γ is not relevant *per se.* In fact it just reflects the relative magnitude of the adjustment coefficients α^H and α^L – that is the relative response rate of the high and the low to the range variable. Specifically, the coefficient γ is positive if $|\alpha^H| < \alpha^L$, is negative if $|\alpha^H| > \alpha^L$, and is zero if $|\alpha^H| = \alpha^L$.

Thus, in the current setting, the adjustment coefficients α^H and α^L bear direct implications for the sign of the risk-return relationship. The observed coefficient γ depends on the degree of asymmetric adjustment of the highest and the lowest exchange rates to shocks to the volatility measure R_t.

3. Estimation Results

3.1 Data and preliminary analyses

Our data set comprises daily spot exchange rates of five major currencies; namely German mark, the euro, Japanese yen, British sterling and Swiss franc, *vis-à-vis* the US dollar for the period January 1979 to August 2007, with the exceptions of the German mark which ends on December 1998 and the euro that starts on January 1999. These daily rates are the 4 pm central European time fixings provided by the Bank for International Settlements (BIS).[5] The daily observations from a trading week are used to derive the weekly high and low exchange rates $\mathbf{X}_t \equiv (s_t^H, s_t^L)'$.[6]

As a preliminary exercise we test for unit root behavior of the high and low exchange rate series. The standard augmented Dickey-Fuller (ADF) tests with the lag length selected by conventional information criteria show that these exchange rate series are nonstationary I(1) processes and their first differences are stationary. The unit root results are consistent the existing empirical literature.[7] Further, the individual range series are found to be stationary.

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[5] We use the data provided by the BIS because they contains interest rates data that are recorded simultaneously with the exchange rate data. The Eurocurrency interest rate data are used in Section 4.

[6] Strictly speaking, these high and low values are not necessarily the actual weekly highest and lowest levels, which require information of, say, intradaily data. To the best of our knowledge, intradaily data are not available over the long sample period examined in this study.

[7] The Johansen likelihood ratio tests, which are not reported to save space but are available from the authors upon request, give the same result.

The Johansen (1991) maximum likelihood test is used to examine the cointegrating relationship of s_t^H and s_t^L. For each exchange rate considered, the test strongly rejects the null hypothesis of no cointegration against the alternative of the presence of one cointegrating vector. We also cannot reject the hypothesis that the cointegrating vector is given by [1, -1]. Thus, in the subsequent analyses, the range $R_t = s_t^H - s_t^L$ is used as the stationary equilibrium residual (i.e. the error correction term) in the VECM specification (1).

Based on the cointegration results, we fitted the data to the VECM specification (1). The lag parameter *p* was set to one according to conventional information criteria. Table 1 presents the estimates of the adjustment coefficients α^H and α^L with their respective standard errors in parentheses. In all cases both α^H and α^L estimates are correctly signed and statistically significant at conventional levels. That is, when the range variable is off from its equilibrium value, both the high and the low of the exchange rate adjust to restore the equilibrium.

The last column of Table 1 gives the estimates of the coefficient γ derived from the α^H and α^L estimates according to $\gamma = \Lambda\alpha$. With the exception of the British sterling case, the γ estimates are negative in sign; that is $|\alpha^H| > \alpha^L$ and shocks to the volatility measure are restored by a larger extent by changes in the high exchange rates, s_t^H. Three of the four negative γ estimates are statistically significant. As discussed in Section 2, the insignificant γ estimates do not necessarily imply that the estimated VECM specifications yield insignificant evidence on risk and return interactions. Indeed, in the next two Sections, it is illustrated that the VECM specification could generates for all exchange rates out-of-sample forecasts that allow a real-world investor benefit from volatility and expected return timing.

3.2 Out-of-sample forecasting: A statistical assessment

Before evaluating its economic value, we present evidence pertaining to the statistical performance of the proposed model. Following the common practice, forecasts generated from the VECM specification (1) are compared against those from the RW specification.[8] The first five years of data are used to obtain the first set of VECM coefficient estimates, which are used to construct the

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[8] The weekly forecasts of the RW are set to $\Delta s_{t+1}^A = 0$ for the conditional mean and $R_{t+1} = R_t$ for the conditional variance. In the pilot study, we experimented with alternative specifications of conditional variance under the RW model including a rolling variance estimator with different moving windows and GARCH(1,1). The results are qualitatively similar to those reported in Sections 3 and 4.

one week ahead forecasts of Δs^{H}_{t+1} and Δs^{L}_{t+1}. The one-week ahead forecasts, $\widetilde{\Delta s}^{H}_{t+1}$ and $\widetilde{\Delta s}^{L}_{t+1}$, are used to derive the forecasts of the next week highest and lowest exchange rates $\tilde{s}^{H}_{t+1}$ and $\tilde{s}^{L}_{t+1}$, which are then used to construct the forecast of the average rate $\tilde{s}^{A}_{t+1}$ (and its return $\widetilde{\Delta s}^{A}_{t+1}$) and the forecast of the volatility measure $\tilde{R}_{t+1} = \tilde{s}^{H}_{t+1} - \tilde{s}^{L}_{t+1}$.[9] The series of recursive forecasts are obtained by updating the sample, re-estimating the VECM coefficient estimates, and repeating the forecasting procedure forward.[10]

The forecast accuracies of the proposed model and RW model are compared using the squared error criterion. Following Welch and Goyal (2008), Campbell and Thomson (2008) and Della Corte *et al.* (2008b), we consider two forecast performance measures: the difference in root mean square errors given by $\Delta RMSE = (MSE_{RW})^{1/2} - (MSE_{VECM})^{1/2}$, and the out-of-sample R^2 given by $\text{oos}R^2 = 1 - (MSE_{VECM}/MSE_{RW})$; where MSE_{RW} and MSE_{VECM} are the mean square errors computed for the forecasts of the RW model and the VECM specification (1), respectively.

These two measures are reported in the second and third columns in Table 2. For the five exchange rate series, both the exchange rate and volatility forecasts generated from the VECM specification (1) yield a smaller root mean square error than those from the RW. The out-of-sample R^2 measure also indicates the proposed model delivers a superior forecasting performance. Specifically, the exchange rate forecasts from the proposed model yield a mean squared forecast error that is 3.8% to 12.5% less than the RW. In the case of volatility forecast, the reduction in mean squared forecast error is in the range of 0.5% to 3.3%.

To assess the statistical significance of the forecast improvement, we report the *p*-values of the *MSE-F* test statistic of equal forecast accuracy (McCraken, 2007) and the encompassing (*ENC*) test statistic (Clark and McCracken, 2001) in the last two columns of Table 2. The two tests are formulated as follows:

$$MSEF - F = \frac{MSE_{RW} - MSE_{VECM}}{MSE_{VECM}} \tag{4}$$

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[9] The forecasts of the measure of volatility, for both the VECM and the RW, have also been computed as $\Upsilon_{t+1} = 0.361 R^{2}_{t+1} / n$, where $n = 0.2$ to generate forecasts consistent with the range-based estimator of the weekly integrated variance (Parkinson, 1980; Brandt and Diebold, 2006). The results, not reported to save space, are quantitatively and qualitatively similar to the ones reported and discussed in Sections 3 and 4.

[10] Note that the forecasting periods for the German mark and the euro, because of the introduction of the euro in January 1999, are shorter than those for the remaining exchange rates. There are 782 and 346 forecasts generated for the German mark and the euro, respectively.

(5) $$ENC = \frac{\sum_{t=1}^{T}\left(\tilde{e}_{RW,t}^{2} - \tilde{e}_{RW,t}\tilde{e}_{VECM,t}\right)}{MSE_{VECM}}$$

where $\tilde{e}_{VECM,t}$ and $\tilde{e}_{RW,t}$ denote the out-of-sample forecast errors from the VECM specification (1) and the RW respectively, and T is the out-of-sample number of observations. The reported p-values are generated via parametric bootstrapping.[11] Echoing the difficulty reported in the literature, we found that the mean squared forecast errors of these models are not statistically different from each other. Thus, the proposed model does not beat the RW model by offering a statistically better forecast performance.[12]

In sum, the proposed model yields forecasts that have a smaller mean squared error than those from the RW model but the improvement is deemed not statistically significant. Nevertheless, an investor may be more interested in the economic gain, rather than the statistical significance, offered by a model (Leitch and Tanner, 1991; West *et al.*, 1993; Abhyankar *et al.*, 2005; Della Corte *et al.* 2008a, b). In the next section, we conduct an economic assessment of the proposed model.

4. Economic Assessment

4.1 The framework

In this section we describe our framework for measuring the economic value of exchange rate forecasts. The approach is based on a utility-based measure for ranking the performance of competing models (West *et al.*, 1993; Fleming *et al.,* 2001; Della Corte *et al.*, 2008a, b). Specifically, consider the standard portfolio choice problem of which an investor has to decide how to allocate her wealth between nominally safe domestic and foreign bonds. These two bonds yield continuously compounded returns i and i^* and are denominated in their respective local currencies.[13] The foreign bond's yield in domestic currency is risky because of foreign exchange uncertainty, which is the only source of risk in this setup.

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[11] See McCracken (2007), Clark and McCracken (2001), and Della Corte *et al.* (2008b) for detailed discussions of the tests. The bootstrap procedure is described in the Appendix of this paper.

[12] The Diebold and Mariano (1995) test results, which were not reported for brevity, gave the same inference that these forecasts are not statistically different from each other.

[13] The interest rates used in our empirical exercise are one-month Eurocurrencies rates obtained from the BIS.

In a mean-variance framework, the portfolio weight on the foreign bond that solves this portfolio choice problem is given by[14]

$$(6) \qquad \omega_t = \frac{E_t\left(i_t^* + \Delta s_{t+1}^A - i_t\right)}{\lambda \operatorname{var}_t\left(i_t^* + \Delta s_{t+1}^A - i_t\right)} = \frac{\left(i_t^* - i_t\right) + E_t\left(\Delta s_{t+1}^A\right)}{\lambda \operatorname{var}_t\left(\Delta s_{t+1}^A\right)} = \frac{\left(i_t^* - i_t\right) + \widetilde{\Delta s}_{t+1}^A}{\lambda \widetilde{R}_{t+1}},$$

where E_t and var_t denote the conditional expectations and conditional variance operators respectively, and λ is the relative risk aversion (RRA) coefficient. The weight on the domestic bond is equal to $1 - \omega_t$. Both forecasts of the conditional mean and the conditional variance are required to implement the investment strategy implied by these portfolio weights.[15]

One measure of investment performance is the Sharpe ratio

$$(7) \qquad SR = \frac{E\left(r_{t+1} - i_t\right)}{\operatorname{var}\left(r_{t+1}\right)},$$

where E and var denote unconditional expectations and variance respectively, and $r_{t+1} = \left(1 - \omega_t\right) i_t + \omega_t \left(i_t^* + \Delta s_{t+1}^A\right)$ is the return, expressed in domestic currency, from holding the optimally constructed portfolio comprising both domestic and foreign bonds. However, the Sharpe ratio, which depend on unconditional expectations and variance, could severely under-estimate the performance of dynamic strategies (Marquering and Verbeek, 2004; Han, 2006; Della Corte *et al.*, 2008a).

In addition to the Sharpe ratio, we adopt a performance fee approach to assess the economic value of the proposed VECM specification (1). The idea is that when comparing alternative portfolio strategies, the one that offers an investor a larger economic value (in terms of higher wealth or higher utility) should command a high performance fee. Obviously an investor's utility function has direct implications for the performance fee she is willing to pay to switch from one strategy to another. In the current exercise, we quantify the (maximum) amount that a mean-variance investor is willing to pay for switching from a portfolio strategy based on the RW model to a portfolio strategy based on the proposed VECM specification (1). Specifically, we determine the

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[14] For further details, see Campbell and Viceira (2002), Campbell and Thomson (2008) and the references therein.

[15] It is important to note that a portfolio based on the future average exchange rate, $\tilde{s}_{t+1}^A$, which is not a tradable price, it is unlikely to be a realistic portfolio managed by US traders or desk managers. However, our objective is not to design a tradable asset allocation strategy – which can be done by adding some specific assumptions on the dynamics of the daily exchange rate and their relationship with the average weekly exchange rate $\tilde{s}_{t+1}^A$ – but to measure the economic significance of the information embedded in the lagged measure of volatility.

performance fee that can be deduced from the proposed strategy's returns such that the portfolio strategies based on the RW model and the proposed model offer the same average utility.

Following West *et al.* (1993) and Della Corte *et al.* (2008a, b), the average realized utility $\bar{U}$ is given by:

$$\bar{U} = \frac{W_0}{T}\sum_{t=0}^{T-1}\{(1+r_{t+1}) - \frac{\lambda}{2(1+\lambda)}(1+r_{t+1})^2\} \tag{8}$$

where W_0 is the initial wealth and T is the time period over which the portfolio strategies are compared. Without loss of generality, W_0 is set to one. The performance fee, denoted by Φ, that equates the average utilities generated by the two portfolio strategies can be determined from the equality:

$$\sum_{t=0}^{T-1}\{[(1+r_{t+1}^{VECM}) - \Phi] - \frac{\lambda}{2(1+\lambda)}[(1+r_{t+1}^{VECM}) - \Phi]^2\} = \sum_{t=0}^{T-1}\{(1+r_{t+1}^{RW}) - \frac{\lambda}{2(1+\lambda)}(1+r_{t+1}^{RW})^2\} \tag{9}$$

where r_{t+1}^{VECM} and r_{t+1}^{RW} are realized returns from currency portfolios whose weights are constructed from forecasts generated by the VECM specification (1) and the RW model respectively. The performance fee Φ is positive if the proposed model offers forecasts that are better than the ones generated by a naïve RW.[16]

4.2 Economic Value

We assess the economic value of one-week ahead exchange rate predictability by analyzing the performance of the dynamically rebalanced portfolios constructed using the forecasts derived from either the VECM specification (1) or the RW. For the asset allocation strategy based on the proposed model, the procedure described in Section 3.2 is used to generate the forecasts $\widetilde{\Delta s}_{t+1}^{A}$ and $\widetilde{R}_{t+1}$, which are then used to compute the portfolio weight according to equation (6). To assess the sensitivity to the risk preference, four different values of the RRA coefficient λ (2, 5, 10, and 20) are we used to compute the portfolio weight.

Table 3 reports the Sharpe ratios for individual exchange rates over the forecasting period. These ratios are computed under two different assumptions about short-selling restrictions. When there is no short-selling restriction, the portfolio weights ω_t is not constrained and the resulting Sharpe

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[16] Besides the performance fee, we also assess the transaction costs associated with the portfolio strategy based on the proposed model in the next sub-section.

ratios are presented in Panel (A). Panel (B) considers the case of restricted degree of short-selling with $-1 < \omega_t < 2$ (Abhyankar *et al.*, 2005).

Our results suggest that the asset allocation strategy derived from the proposed high-low exchange rate model offers a higher risk-adjusted return, as measured by the Sharpe ratio, than the one derived from the RW. The inference holds for all the exchange rates under consideration and is independent of whether the portfolio weight constrained or unconstrained. Indeed, the results are quite striking – all the Sharpe ratios of the asset allocation strategy based on the forecasts of the RW model are well below unity while those ratios generated from the strategy based on the VECM specification (1) are higher than one and in some cases close to two. This pattern is consistent across different values of the RRA coefficient for all exchange rates.

It is worthwhile noting that market practitioners in the foreign exchange market are not interested in a currency investment strategy that yields a Sharpe ratio less than unity (Lyons, 2001 p. 215; Sarno *et al.*, 2006). The anecdotal evidence on the view on the Sharpe ratio is corroborated by interviews with several proprietary traders and desk managers, who indicated that large shifts in speculative capital, obtained by means of extremely large amounts of order flow, only occur when traders or desk managers conceive Sharpe ratios of at least unity.

The estimates of the performance fee are presented in Table 4. The fee an investor is willing to pay for adopting the asset allocation strategy based on the proposed model varies across exchange rates and risk preferences. Nonetheless, these performance fee estimates show that the proposed model offer a considerable amount of economic gains over and above the RW.

When the portfolio weight ω_t is unconstrained and risk preference is equal to 2, an investor would be willing to pay a monthly fee of more than 5 percent, on average across exchange rates, to switch from the portfolio strategy based on the RW model to the one based on the VECM specification (1). A larger than 5 percent fee is a very strong piece of evidence for the proposed model. The superior performance is, however, likely to be driven by the lack of short-selling restrictions. In fact, when the restrictions are imposed on ω_t, the monthly fee, again averaged across the five exchange rates, is shrunk to the level of 0.96 percent. Arguably, a monthly fee of slightly less than one percent compares quite favourably with performance fees generally charged by actively managed international portfolios. Pojarliev and Levich (2008) indicate that management fees charged by currency managers are typically 2 percent per year (or about 0.16% per month).

When an investor has a RRA coefficient λ of 20 (that is, a very low level of risk appetite), the monthly fee she is willing to pay to switch is, on the average, 0.37 percent when no short-selling restrictions are imposed. It is noted that the fee estimates in Panel (B) are in general smaller than the corresponding ones in Panel (A) and exhibit a lower level of variability across the RRA coefficients (between 0.43 and 1.05 percent on average across exchange rates). Conceivably, the restriction on ω_t reduces the variability of the portfolio performance, which, in turn, alleviates the effect of risk preference on the fee for switching.

Transaction costs are an important issue in assessing the economic value of an asset allocation strategy. In the current exercise, the portfolio is re-balanced every week based on forecasts of the average exchange rate and its variability. If transaction costs are sufficiently high, the performance reported in Tables 3 and 4 may be over-stated. Making an accurate determination of the size of transaction costs is difficult because it involves several factors including the type of investor, the transaction size, …, etc. The difficulty is reflected in the wide range of transaction cost estimates used in empirical studies.

We address this issue by computing break-even transaction costs. Following Han (2006) and Della Corte *et al.* (2008a,b), we assume that transaction costs equal a fixed proportion of the value traded in each bond and the break-even transaction cost is the amount that renders the portfolio return zero. If an investor faces transaction costs that are lower than the estimated break-even transaction cost, she will prefer the asset allocation strategy.

The estimates of the break-even transaction cost, expressed in weekly basis points, to match the weekly re-balancing schedule, are reported in Table 5. Overall, the break-even transaction cost is between 8 and 29 basis points when there is no restriction on the portfolio weight and is between 17 and 27 basis points there are restrictions. Transaction costs in foreign exchange markets are fairly small when compared to other large financial markets. For instance, Akram *et al.* (2008) document that transaction costs incurred by arbitrageurs to carry out round-trip arbitrage strategies on Reuters D3000 are equal to $1/10^{\text{th}}$ of a pip (or, alternatively, 1/1000th of a basis point). The break-even estimates in Table 5 represent convincing evidence that transaction costs associated with rebalancing the portfolio according to the asset allocation strategy implied by the proposed VECM specification (1) are unlikely to offset the large economic gains reported in Tables 3 and 4.

These results based on the analysis of Sharpe ratios, performance fees, and break-even transaction costs corroborate with each other and deliver the same message: the proposed model yields considerable economic gains over the RW model. Furthermore, the evidence of proposed model's economic value is established using weekly forecasts derived from non-proprietary data. Thus, these results are relevant because 1) only a few recent studies have documented the ability of some exchange rate models to outperform the RW model on an economic ground (see, *inter alia*, Abhyankar *et al*., 2005; Della Corte *et al.*, 2008a), 2) beating the RW model at short-horizons is known to be quite challenging, and 3) the few studies which report superior forecasting results are based on proprietary data; for example, customer order flow data that are not publicly available (Evans and Lyons, 2005; Sager and Taylor, 2008).

4.3 An alternative benchmark

Since the seminal study by Meese and Rogoff (1983a), the RW model is routinely used as the benchmark for evaluating foreign exchange forecasts. The RW benchmark is employed not just in studies that focus on the statistical properties but also in studies that investigate the economic value of exchange rate forecasts. Despite the RW specification offers an intuitive and simple framework to assess statistical forecast performance, the economic value assessment could benefit from an alternative benchmark.

In this sub-section, we examine the relationship between the performance of the asset allocation strategy based on the proposed model and a few styles of currency trading, which are intended to represent an alternative benchmark for evaluating exchange rate forecasts. Recently, Pojarliev and Levich (2008) propose a factor model to assess the performance of hedge fund and mutual fund currency managers. In essence, the factor model determines the portion of returns attributable to a currency manager's skill (i.e. alpha returns or abnormal returns) and the portion correlated to returns generated by well-known trading strategies.

Using this framework, we could offer an alternative characterization of the portfolio returns derived from the VECM specification (1) forecasts. Specifically, the estimated alpha return will represent the economic gains generated by the proposed model that are beyond those offered by common currency strategies. To this end, we estimate the following four-factor model:

$$(10) \qquad (r_t^{VECM} - i_t) = \varphi_0 + \sum_{q=1}^{4} \varphi_q F_t^q + \varepsilon_t ,$$

where $(r_t^{VECM} - i_t)$ is the excess return of the portfolio that is constructed from forecasts generated by the VECM specification (1) over the forecasting period, φ_0 quantifies the alpha return, F_t^q is the factor representing the excess return associated with the *q*-th currency strategy, φ_q is a coefficient measuring the sensitivity between excess returns generated by the *q*-th currency strategy and the ones of the VECM forecasts, and ε_t is the regression error term. It is instructive to note that the term $\sum_{q=1}^{4} \varphi_q F_t^q$ is intended to represent an alternative benchmark to the RW model for evaluating exchange rate forecasts.

The four currency strategies examined are carry trade, trend following, value, and volatility trading. The carry trading factor is approximated by returns on the Citibank Beta1 G10 carry index (Citibank, 2007) measuring portfolio returns obtained by investing in deviation from UIP in the G10 countries. The value (or fundamental) factor is approximated by returns on the Citibank Beta1 G10 Purchasing Power Parity index (Citibank, 2007) measuring portfolio returns obtained by investing in deviations from PPP in the G10 countries. The volatility factor is approximated by a 5-year rolling volatility of trade-weighted exchange index of major currencies (DTWEXM) compiled by the Federal Reserve Bank (H.10 Foreign Exchange Rates).[17] The trend following index is approximated by the returns of an equally-weighted portfolio of three moving average rules (26, 61, and 117 days) on the five currencies investigated in this paper (Lequeux and Acar, 1998).[18]

Because the data on these factors are available on a monthly basis and only from January 1990, we converted the weekly returns into monthly returns before estimating Equation (10) over the sample period 1990-2007. Table 6 reports the individual and combined effects of these factors with the portfolio weight ω_t constrained and unconstrained. For brevity, we present the results pertaining to the case of the RRA coefficient λ equals 2.[19]

A few observations are in order. First, for all the exchange rates, regardless of the use of constrained or unconstrained portfolio weights, the estimates of the alpha return φ_0 are positive and, in most cases, statistically significant at the one percent level. The average alpha return computed across individual exchange rates equals18 percent on the annual basis when ω_t is left unconstrained, and 5 percent when ω_t is constrained. For individual exchange rates, the Japanese yen case garners the largest gains – an annual alpha return of 37.2 percent with the unconstrained portfolio and of

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[17] The volatility factor used Pojarliev and Levich (2008) is based on the implied volatilities of the US dollar exchange rates of the Euro and the Japanese yen. In the pilot study, we found that the results derived from this volatility factor, not reported to save space, are qualitatively similar to the ones reported in Table 6.

[18] See Pojarliev and Levich (2008, pp.19-20) for a detailed discussion of these four factors.

[19] Results from the pilot study showed that the results for the cases of λ=5, 10, 20 are qualitatively and quantitatively similar to those in Table 6.

6.4 percent with a constrained one. Among unconstrained portfolios, the euro case has the smallest estimated annualized alpha return of 5.2 percent. The German mark case gives the smallest alpha return of 4.2 percent per annum among the constrained portfolios.

The evidence of positive and significant alpha returns reinforces the results reported in Tables 3 and 4. Specifically, the significant alpha returns suggest that the proposed model is not only able to outperform the RW model, but also to generate excess returns which are beyond those generated by common currency strategies.

Second, for all the exchange rates under consideration, the trend-following factor is positively correlated to the performance of the asset allocation strategy based on the VECM specification (1). Indeed, it is the only factor that consistently exhibits a loading parameter (φ_3) that is statistically significant at the 1 percent level across specifications and it can explain more than 20% of the variation of the excess returns implied by the proposed model.[20] The result suggests that the excess returns of the asset allocating strategy based on the forecasts from the VECM specification (1) are correlated to the returns of moving average trading rules.

It is important to emphasize that the linkages between the returns generated by currency portfolios based on the VECM specification (1) and the four factors vary across exchange rates. Even when these linkages are statistically significant, their respective explanatory powers, as indicated by the adjusted R-squares estimates, are quite meager. That is, the economic gains generated by the proposed model are somewhat correlated with returns from popular currency trading strategies but they are certainly not a mere proxy for their returns. The result suggests that the proposed model contains information about exchange rates beyond what is embedded in these four foreign exchange trading strategies and it can be used in conjunction with existing strategies to enhance performance of international currency portfolios.

5. Conclusions

Since the publication of Meese and Rogoff (1983a, b), numerous studies has shown that, especially at short horizons, most exchange rate models do not forecast better than a naïve RW specification. The result, to a large extent, holds up quite well even when a RW model is compared

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[20] Pojarliev and Levich's (2008) also find that the trend-following factor could explain a large portion of currency manager's returns.

with elaborated exchange rate models estimated with sophisticated econometric techniques. In line with a few exceptions that document an agnostic model with appropriate information could outperform a naïve RW model even at short horizons,[21] we propose an empirical high-low model of exchange rates. The model offers an interesting perspective on the empirical risk-return relationship where risk is approximated by the high-low price range.

Data on five major dollar exchange rate series are used to establish the in-sample validity of the proposed model. Even though the proposed framework generates forecasts that yield smaller mean-squared-forecast-errors than those from a RW specification, the forecast improvement is deemed to be insignificant under the usual statistical criteria; a result that is largely consistent with the extant literature.

The proposed model fares much better when we go beyond statistical criteria. Using several recently developed metrics, it is found that the proposed model, relative to the RW model, offers investors discernable economic values. First, the Sharpe ratios of the portfolios based on the proposed model are consistently higher than one and are substantially larger than the corresponding ratios of the portfolios based on the RW model. Second, the estimates of the maximum performance fee and the break-even transaction cost suggest that the proposal model offers a sizeable economic value to investors. Third, it is demonstrated that the proposed model yields significant alpha returns relative to four common currency trading rules – that is, its ability to generate economic gains cannot be replicated by these trading rules.

The high-low model's intrinsic link to the well-known risk-return relationship offers an interesting way to interpret the results: volatility helps predict exchange rates. Arguably, the proposed framework is quite simple to implement and operate. An added advantage is that the data for the analysis are typically non-proprietary and readily available. It is also noted that the proposed model is not specific to a particular asset or a particular data frequency. In fact it could be fitted to high and low prices of any reasonably liquid financial instrument. In our exercise, we use weekly data and focus on weekly forecasts. However the model is able to provide forecasts at any frequency, even intradaily, as long as high and low data for the selected time interval are available.

It is worth noting that the proposed model can be extended in several directions. For instance, it can be modified to incorporate additional stylized features of the price data, including

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[21] For example, see Clarida and Taylor (1997), Clarida *et al.* (2003) and Evans and Lyons (2002, 2005).

nonlinearities, regime switching behavior and asymmetric responses.[22] Further, a panel version of the model can be devised to accommodate the joint estimation of multiple exchange rates to allow for a more realistic international asset allocation setting (Della Corte *et al.*, 2008a). We leave these possible extensions as topics for future research.

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[22] See, for example, Clarida *et al.* (2003, 2006), Sarno and Valente (2006) and Sarno *et al.* (2006).

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Appendix: Bootstrapped p-values for Out-of-Sample Tests

To evaluate the out-of-sample forecast accuracy of the VECM specification (1), we rely on two statistical tests. The first is the McCracken (2007) *MSE-F* test for the null hypothesis of equal MSE between the RW and the VECM specification (1). The second is the *ENC* test proposed by Clark and McCracken (2001) for the null hypothesis that the RW model encompasses the VECM specification (1).

As in Goyal and Welch (2008), Campbell and Thomson (2008) and Della Corte *et al.* (2008b) we rely on parametric bootstrapping to determine the statistical significance of the out-of-sample results reported in Table 2.[23]

In our case, the bootstrapping exercise computes how often an exchange rate which follows a driftless RW would produce the level of predictability found in actual data. For each exchange rate, we impose a data generating process of no predictability in the daily exchange rate; that is $\Delta s_{t+1} = \eta_{t+1}$ and construct bootstrapped p-values for the test statistics as follows:

1. Draw with replacement 5,000 error η_{t+1} samples of size T compatible with the daily sample of each exchange rate from the null DGP.
2. Use the series obtained in the previous step to construct 5,000 series of weekly s_t^H, s_t^L.
3. Estimate Equation (1) using the simulated weekly high and low exchange rates to obtain 5,000 out-of-sample *MSE*s from the VECM specification (1) and from the benchmark driftless random walk and compute the *MSE-F* and the *ENC* tests.
4. Determine the bootstrapped *p*-values of the two tests using the times the test statistic under the null DGP is greater than the corresponding test statistic computed from the actual data.

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[23] See Kilian and Berkowitz (2000) for further details.

Table 1

VECM Estimation

The table reports some key results from estimating the VECM model given by Equation (1) in the main text. α^H and α^L denote the components of the 2 × 1 adjustment coefficient vector α, that determines the rates at which the high and low adjust to changes in the price range. Values in parenthesis are asymptotic autocorrelation-and-heteroskedasticity-consistent standard errors (Newey and West, 1987). The last column denotes the implied coefficient γ (=$\Lambda\alpha$) as in Equation (3) of the main text.

	α^H	α^L	$\gamma = \left(\frac{\alpha^H + \alpha^L}{2}\right)$
DEM	-0.384	0.177	-0.104
	(0.059)	(0.060)	(0.042)
EUR	-0.381	0.361	-0.010
	(0.098)	(0.094)	(0.068)
JPY	-0.394	0.226	-0.084
	(0.044)	(0.051)	(0.034)
GBP	-0.285	0.285	–
	(0.047)	(0.050)	(–)
CHF	-0.400	0.258	-0.071
	(0.050)	(0.052)	(0.036)

Table 2

Forecasting Assessment: Statistical Significance

The table reports the out-of-sample forecasting performance of the VECM specification (1) compared to the naïve random walk (RW) model. Panel A shows the results pertaining to the forecasts of the conditional mean s_{t+1}^{A} while Panel B shows the results for the forecasts of the conditional variance that is proxied by the range. ΔRMSE denotes the root mean square error differential between the conditional forecasts of the RW model and the VECM specification (1) computed as in Welch and Goyal (2008). oosR^2 denotes the out-of-sample R^2 (Campbell and Thomson, 2008). *MSF-F* and *ENC* are, respectively, the test statistics for equal predictive accuracy proposed by McCracken (2007) and Clark and McCraken (2007). One-sided *p*-values generated via nonparametric boostrapping based on 10,000 iterations are given in brackets.

Panel A) Forecasts of the conditional mean

	ΔRMSE	oosR^2	*MSF-F*	*ENC*
DEM	0.0004	0.059	[0.356]	[0.367]
EUR	0.0002	0.038	[0.368]	[0.379]
JPY	0.0008	0.125	[0.353]	[0.364]
GBP	0.0005	0.082	[0.356]	[0.367]
CHF	0.0006	0.087	[0.345]	[0.355]

Panel B) Forecasts of the conditional variance (values x 100)

	ΔRMSE	oosR^2	*MSF-F*	*ENC*
DEM	0.0011	0.033	[0.394]	[0.406]
EUR	0.0002	0.012	[0.426]	[0.439]
JPY	0.0003	0.005	[0.415]	[0.427]
GBP	0.0004	0.012	[0.413]	[0.425]
CHF	0.0007	0.020	[0.398]	[0.410]

Table 3

Economic Performance: Annualized Sharpe ratios

The table reports the annualized Sharpe ratios given by Equation (7). For each currency pair the asset allocation strategy builds an efficient portfolio by investing in the weekly returns of two deposit rates (US and each one of the foreign currencies) and using the relevant exchange rate to convert the returns back in US dollar. Panel A reports the results when the portfolio weight ω_t (computed using Equation (6) in the text) is unconstrained. Panel B reports the results when the weight ω_t is bounded between −1 and 2. The weekly Sharpe ratios are scaled by $\sqrt{52}$ to give the annualized figures. λ denotes the coefficient of relative risk aversion. RW and VECM indicate, respectively, the random walk model and the VECM specification (1).

Panel A) Unconstrained weigths ω_t

	model	DEM	EUR	JPY	GBP	CHF
λ=2	RW	0.633	0.446	0.372	0.529	0.425
	VECM	*1.460*	*1.586*	*1.868*	*1.768*	*1.670*
λ=5	RW	0.633	0.446	0.372	0.529	0.425
	VECM	*1.460*	*1.586*	*1.868*	*1.768*	*1.670*
λ=10	RW	0.634	0.447	0.372	0.529	0.425
	VECM	*1.460*	*1.587*	*1.868*	*1.768*	*1.671*
λ=20	RW	0.634	0.447	0.372	0.530	0.426
	VECM	*1.461*	*1.587*	*1.869*	*1.769*	*1.671*

Panel B) Constrained weights ω_t

	model	DEM	EUR	JPY	GBP	CHF
λ=2	RW	0.526	0.998	0.724	0.941	0.656
	VECM	*1.492*	*1.595*	*1.801*	*1.758*	*1.559*
λ=5	RW	0.645	0.706	0.879	0.918	0.749
	VECM	*1.662*	*1.638*	*1.867*	*1.832*	*1.836*
λ=10	RW	0.732	0.618	0.920	0.804	0.741
	VECM	*1.704*	*1.761*	*1.930*	*1.830*	*1.860*
λ=20	RW	0.739	0.482	0.823	0.670	0.732
	VECM	*1.558*	*1.617*	*1.884*	*1.838*	*1.712*

Table 4

Economic Performance: Monthly Performance Fees Φ (%)

The table reports the estimated (maximum) performance fee, Φ, that an investor, endowed with quadratic utility and a degree of risk aversion λ, is willing to pay on a monthly basis to switch from the strategy that is based on the random walk model to the strategy based on the VECM specification (1). See notes to Table 3.

Panel A) Unconstrained weigths ω_t

	DEM	EUR	JPY	GBP	CHF
λ=2	4.51	5.68	7.86	5.09	3.94
λ=5	1.53	1.21	2.79	1.81	1.49
λ=10	0.72	0.40	1.33	0.84	0.72
λ=20	0.32	0.16	0.64	0.40	0.36

Panel B) Constrained weights ω_t

	DEM	EUR	JPY	GBP	CHF
λ=2	0.52	0.76	1.08	1.17	1.25
λ=5	1.17	0.88	1.00	1.12	1.12
λ=10	0.84	0.68	0.80	0.88	0.76
λ=20	0.44	0.32	0.52	0.48	0.40

Table 5

Economic Performance: Weekly Break-even Transaction Costs (bps)

The table reports the estimated break-even transaction costs in weekly basis points of the portfolio strategy based on the VECM specification (1) against the RW model. The break-even transaction costs are the minimum proportional cost which cancels out the utility advantage of the VECM specification (1) against the RW. See notes to Table 3.

Panel A) Unconstrained weigths ω_t

	DEM	EUR	JPY	GBP	CHF
λ=2	17	29	29	24	21
λ=5	16	15	26	21	21
λ=10	15	11	25	20	20
λ=20	14	8	25	20	20

Panel B) Constrained weights ω_t

	DEM	EUR	JPY	GBP	CHF
λ=2	24	16	22	23	23
λ=5	27	19	21	24	24
λ=10	25	20	22	25	25
λ=20	23	17	21	25	25

Table 6

Pojarliev and Levich's (2008) Regressions

The table reports the results of the Pojarliev and Levich (2008) regression discussed in Section 4.3. φ_0 denotes monthly alpha returns obtained over the period 1990-2007. Value, Carry, Trend and Volatility denote exposures of the excess returns obtained from using the VECM (1) towards the excess returns generated by the four popular foreign exchange strategies discussed in Section 4.3. R^2 is the adjusted coefficient of determination. All results are reported for both constrained and unconstrained portfolio choices with a coefficient of relative risk aversion equal to 2. ***, ** and * denote estimates statistically significant at 1%, 5% and 10% significance level.

Panel A) DEM

	φ_0	Value	Carry	Trend	Volatility	R^2
Unconstrained	0.0154***	0.536				0.027
Constrained	0.0045***	-0.021				0.001
Unconstrained	0.0160***		-0.411			0.002
Constrained	0.0045***		-0.066			0.001
Unconstrained	0.0132***			3.284***		0.217
Constrained	0.0041***			0.611***		0.151
Unconstrained	0.0091				0.001	0.001
Constrained	0.0041***				0.001	0.001
Unconstrained	0.0059	0.801	-0.625	3.432***	0.001	0.258
Constrained	0.0035***	0.008	-0.006	0.614***	0.001	0.119

Panel B) EUR

	φ_0	Value	Carry	Trend	Volatility	R^2
Unconstrained	0.0130***	-0.924*				0.035
Constrained	0.0040***	-0.383**				0.060
Unconstrained	0.0055		1.358			0.012
Constrained	0.0039*		-0.104			0.001
Unconstrained	0.0110***			2.554***		0.143
Constrained	0.0036***			1.838***		0.253
Unconstrained	0.0080**				0.003	0.001
Constrained	0.0034***				0.001	0.001
Unconstrained	0.0043	-0.547	1.532	2.412***	0.001	0.129
Constrained	0.0040**	-0.211	-0.009	1.014***	0.001	0.232

(continued)

(Table 6 continued)

Panel C) JPY

	φ_0	Value	Carry	Trend	Volatility	R^2
Unconstrained	0.0230***	-0.346				0.005
Constrained	0.0048***	-0.241***				0.064
Unconstrained	0.0262***		-1.388			0.013
Constrained	0.0051***		0.210			0.001
Unconstrained	0.0217***			2.912***		0.079
Constrained	0.0043***			0.634***		0.098
Unconstrained	0.0297***				-0.001*	0.010
Constrained	0.0054***				-0.001	0.004
Unconstrained	0.0310***	-0.049	-1.021	2.784***	-0.001*	0.079
Constrained	0.0053***	-0.204**	-0.003	0.576***	-0.001	0.131

Panel D) GBP

	φ_0	Value	Carry	Trend	Volatility	R^2
Unconstrained	0.0187***	-0.012				0.001
Constrained	0.0050***	-0.037				0.002
Unconstrained	0.0236***		-1.938*			0.045
Constrained	0.0052***		-0.114			0.003
Unconstrained	0.0176***			3.074***		0.152
Constrained	0.0047***			0.644***		0.132
Unconstrained	0.0151***				0.001	0.001
Constrained	0.0044***				0.001	0.002
Unconstrained	0.0181***	0.364	-1.814*	3.021***	0.001	0.181
Constrained	0.0043***	0.005	-0.039	0.644***	0.001	0.118

Panel E) CHF

	φ_0	Value	Carry	Trend	Volatility	R^2
Unconstrained	0.0146***	0.199				0.003
Constrained	0.0044***	-0.007				0.001
Unconstrained	0.0164***		-0.617			0.005
Constrained	0.0043***		0.022			0.001
Unconstrained	0.0138***			3.115***		0.187
Constrained	0.0041***			0.830***		0.174
Unconstrained	0.0161***				-0.001	0.001
Constrained	0.0055***				-0.001	0.007
Unconstrained	0.0157***	0.454*	-0.537	3.187***	-0.001	0.189
Constrained	0.0048***	0.034	0.101	0.845***	-0.001	0.168