Decision Making Tool to Hedge Exchange Rate Risk

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Abstract

New econometric and statistical techniques have been used in recent years to provide with exchange rates forecasting models that can statistically outperform a random walk. In particular, a model that uses the term structure of forward premia into a regime-switching vector error correction model has proven to be successful at such a task. In this paper, we propose that the exchange rate fluctuations are not solely influenced by the economic fundamentals of those countries involved in the exchange. Therefore, the accuracy of the aforementioned model can be improved by separately forecasting the average change in value of each of the currencies involved in the exchange rate, instead of forecasting the exchange rate itself. This is achieved by using a low volatility currency basket to transform the data before and after the modeling.

Keywords: Foreign Exchange; Forecasting; Currency Basket; Markov.

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1. Introduction

The break down of the Bretton Woods Agreement in 1973 spurred a vast amount of literature that tried to describe the nature of the foreign exchange fluctuations. Several different models and approaches arose but Meese and Rogoff (1983a) severely challenged their ability to accurately out-of-sample forecast. Their analysis of structural models based on fundamentals yielded statistically robust evidence against their predictive ability. Specifically, they showed that those models could not outperform a simple random walk.

These results were indeed very discouraging since their implication on a wide array of empirical applications such as investment portfolio choice, risk analysis, international trade, macroeconomic policy, etc. However, significant progress has been made during the last 10 years. McCracken and Sapp (2005) revised the literature and proposed that sometimes the inability of the models to outperform a random walk lies not on the models per se, but on the statistical techniques used to test them. Certainly, Abhyankar, Sarno, and Valente (2005) did not test the performance of a monetary-fundamentals model against a random walk. Instead, they evaluated the economic value of predictability by designing two different investment portfolios, one which was optimized under the monetary-fundamentals model while the other assumed a random walk. They did find that the portfolio's optimal allocations are different as well as the end-of-period wealth, which was substantially lower for the portfolio designed with the random walk in mind.

In their attempt to outperform the random walk, Clarida and Taylor (1997) proposed that the term structure of forward exchange premiums contains valuable information for this task in the short run. They designed an empirical framework flexible enough to accommodate deviations from rational expectations and the simple efficiency hypothesis, which permits the use of non-optimal predictors (i.e. forward contracts prices) into a Vector Error Correction Model *(VECM)*. Later, Clarida, Sarno, Taylor, and Valente (2003) included into this context the presence of nonlinearities displayed by exchange rates via augmenting the previous model with the use of a regime-switching VECM, increasing the accuracy of the out-of-sample forecasts. Finally, Sarno and Valente (2005) evaluated the ability of the model to provide a satisfactory density forecast with the use of a generalized version of Clarida et al.'s Markov Switching – VECM.

In this paper, we propose that a country's currency has an intrinsic value which is determined by its total demand (i.e. imports, exports, foreign investment, tourism, etc.) Thereafter, the exchange rate among two countries should be determined by contrasting the total value of one currency versus the total value of the other instead of just accounting for the flow of capital between the two parties. Such value should be dependent upon the ability of a country to generate demand for its currency, which can be elicited through its monetary, political, and trade policies.[†] Here, we circumvent this task by estimating the change in value of a currency as compared to the average

[†] Groen (2005) argued that exchange rates are consistent with rational expectations-based monetary models with a common long-run relationship, where deviations from them should last for short periods of time. His analysis relates to ours by using a panel of VECMs across their selected exchange rates. This framework was developed by Groen and Kleibergen (2003). Groen concludes that the exchange rates used in his study should be modeled simultaneously within a panel structure, in order to find consistent results independent of the choice of *numeraire*. See section 3 of this paper.

change of value of all the conforming currencies in the basket of minimum variance created by Hovanov, Kolari, and Sokolov (2002). Thereafter, Sarno and Valente's Markov Switching – VECM is used to out-of-sample forecast the value of several different currencies which are later matched to generate the expected exchange rates. This model fits our purposes perfectly, since monetary-fundamentals models render fluctuations too wide to be practical. Finally, the results are tested both against the random walk and Sarno and Valente's original set up with McCracken and Sapp's methodology. We found that the accuracy of the model is increased.

Our results are important for several reasons. In particular there's extensive research (Adler and Dumas, 1984; Adler, 1994; Bodnar and Marston, 2002; Bartram, Dufey, Frenkel, 2005; Dominguez and Tesar, 2004) that support the belief that firms are still exposed to foreign exchange risk, especially small firms (Dominguez and Tesar, 2004) and firms in the short- and medium- term (Bartram, Dufey, Frenkel, 2005). Such exposure can be efficiently hedged with the use of financial instruments, which according to Bartram, Dufey and Frenkel, carry high risks for the unsophisticated user. As suggested by Sarno and Valente (2005), accurate forecasts are also necessary in optimal investment portfolio design and more reliable measures of risk exposure such as *Value at Risk*.[‡]

This paper is organized as follows. In section 2, we describe how the chosen currency basket is formulated, its properties and its economic meaning as well. In section 3, we briefly review the evolution of Clarida and Taylor (1997)'s forecasting VECM to its final stage as a MSIAH-VECM, advanced by Sarno and Valente (2005). In section 4, we explain the methodology used to test our results. In section 5, we describe the data and provide preliminary statistics as well as our final results. We conclude in section 6.

2. Value of a currency

The base of choice plays a major role when examining the relationship between two currencies. For instance, the dynamics observed between Swiss francs and sterling pounds is different when the base chosen is changed from Euros to US dollars. This was observed by Hovanov, Kolari, and Sokolov (2002) and thereby constructed an index that is independent of the base currency choice. Their *invariant currency value index (ICVI)* can then be used to account for the intrinsic value of a currency as compared to the value of the constituting currencies. Thereafter, Hovanov et al. use the ICVI weights to build a stable aggregate currency basket *(SAC)* that inherits those desirable properties. Also, the SAC is found to be stable over time and has little or no correlation with the individual currencies in the basket. Therefore, using SAC as the base of analysis, helps to focus on the average change in value of that currency relative to the rest currencies in the basket, instead of analyzing the rate of appreciation or depreciation versus another currency. The methodology to build the SAC follows:

Let c_{ij} be the exchange rate of currency i in currency j units (the base) at time t.[§] Then, the normalized value in exchange $(NVal_i)$ for a given currency is:

[‡] Value at Risk measures the probability of a catastrophic loss. See Jorion (2001).

[§] Notice that in the notation provided by Hovanov et al., c_{ij} is the exchange rate where j refers to the currency on the numerator. For instance, for the Euro/U.S. dollar exchange rate, j refers to the Euro, while i refers to the United States dollar.

$$NVal_i = \frac{c_{ij}}{\sqrt[n]{\prod_{r=1}^{n} c_{rj}}}, \tag{1}$$

where n is the total number of currencies chosen to be in the index[**]. Then, this value is normalized to an arbitrary time t_0:

$$RNVal_i(t/t_0) = \frac{NVal_i(t)}{NVal_i(t_0)}. \tag{2}$$

The *index of value in exchange* is computed as

$$Ind(w;t) = \sum_{i=1}^{n} w_i RNVal_i(t/t_0), \tag{3}$$

where w_i are weights found by minimizing the variance of the index (Var*(Ind(w;t))*) subject to the unit additive, $\sum_{i=1}^{n} w_i = 1$, and non-negativity constraints $w_i \geq 0$ as well . Then, the optimal weights are finally used to generate each currency's quantities that constitute the *stable aggregate currency (SAC)* :

$$q_i^* = \frac{w_i^*}{c_{ij}(t_0)} \cdot \left(\sum_{r=1}^{n} \frac{w_r^*}{c_{rj}(t_0)} \right)^{-1}. \tag{4}$$

3. Evolution review of the term structure forecasting models

Clarida and Taylor (1997) discussed that the existing literature tested the risk-neutral efficient markets hypothesis (RNEMH) by projecting the rate of depreciation of the spot exchange onto the lagged forward premiums. The results contradicted the theoretical framework but did generate significant coefficients. The authors noted that such findings suggested that important information could be extracted from the term structure. After a thorough review of the RNEMH, they concluded that while market participants may be risk averse and do not precisely conform to the rational expectations hypothesis, the markets do convey relevant information into the forward rates. They suggest that deviations of the simple efficient markets hypothesis are realizations of a stationary stochastic process. Thereafter, they developed a theoretical framework that implies that forward and spot exchange rates are unit root processes that share a common stochastic trend with a cointegrated relationship captured in a [1,-1] cointegrating vector. Using the spot and forward rates of contracts with 4-, 13-, 26-, and 52-week maturities, they investigated a VECM (through the methodologies provided by Engle and Granger, 1987, and Johansen, 1991). They finally specified a vector error correction model with four unique cointegrating relationships

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[**] n does include the currency used as a base.

given by a β' = [**1**, -I] matrix, where **1** is a 4 element vector of ones and I is a 4 x 4 identity matrix.

The framework provided by Clarida and Taylor was efficient enough to outperform the random walk in out-of-sample forecasting. But there was still room for improvement given that exchange rate returns are non-linear.[††] Hamilton (1994) explains how Markov chains can be used to specify a broad class of different probability densities which are not even restricted to be symmetric. Clarida et al. (2003) extended the model to a nonlinear three regime Markov-Switching VECM that allows shifts in the intercept and variance-covariance structure of the error terms. They found that this model specification strongly outperforms the random walk and the linear VECM. Finally, Sarno and Valente (2005) evaluated the performance of such models in terms of density forecasting. They provided a more general model that allows shifts in the autoregressive parameters. This formulation is named a Markov-Switching-Intercept-Autoregressive-Heteroskedastic VECM with one lag and three regimes (MSIAH(3)-VECM(1)):

$$\Delta y_t = v(z_t) + \prod(z_t) y_{t-1} + \sum_{d=1}^{p-1} \Gamma_d(z_t) \Delta y_{t-d} + \varepsilon_t , \qquad (5)$$

where $y_t = [s_t, f_t^4, f_t^{13}, f_t^{26}, f_t^{52}]'$; s_t is the spot rate while f_t denotes the forward rate. The superscripts specify the maturity of the forward contract in weeks. $z_t \in \{1,2,3\}$ denotes the current regime, $\Pi=\alpha(z_t)\beta'$ is the state dependent long-run impact matrix whose rank determines the number of spot and forward rates cointegrating vectors. $\alpha(z_t)$ is the state dependent adjustment coefficients while β' remains fixed and is as specified above. $v(z_t) = [v_1(z_t), v_2(z_t), v_3(z_t)]'$ is the vector of regime dependent intercept terms. $\Gamma_d(z_t)$ is the regime dependent autoregressive matrix with d as the number of lags included in the model. The error structure is denoted by the error vector ε_t which is i.d. Normal with 0 expected value and state dependent Variance-Covariance matrix $\Sigma_\varepsilon(z_t)$ *i.e.* $\varepsilon_t \sim N(0,\Sigma_\varepsilon(z_t))$. The regime-generating process is assumed to be an ergodic Markov chain with three states denoted by the state variable z_t that takes on values 1,2, and 3 governed by the transition probabilities $p_{ij} = Pr[z_{t+1}=j|z_t=i]$ with $\sum_{j=1}^{3} \mathrm{p_{ij}} = 1$ for all i. This is the model used in this text.

4. Model testing

We test our results after the estimation of the model explained above. McCracken and Sapp (2005) revised the literature on foreign exchange forecasting and concluded that the testing of the models is usually not accurate. They argue that usual inference (Meese and Rogoff, 1988; Diebold and Mariano, 1995; Cheung, Chinn, and Pascual, 2005) treats the test statistics as asymptotically normal, which is inappropriate when comparing two nested models. Structural models usually nest the random walk model. In other words, $u_{1,s}= u_{2,s}$ where $u_{i,s}$ refers to model i's forecasting error in the step s. Therefore, McCracken and Sapp build on the findings of West (1996), Kilian (1999), McCracken (2000), Clark and McCracken (2001) , Chao, Corradi, Swanson (2001), and Clark and McCracken (2003) to derive the tests described below. Then,

[††] Nonlinearity and non-normality of foreign exchange returns are widely reported. Clarida et al. (2003) refer this discussion to Boothe and Glassman (1987).

they re-evaluate the predictive ability of some models including the monetary model (Frenkel, 1976; Mussa, 1976; Bilson, 1978). They found that their tests show evidence of a higher predictive ability than previously thought.

The heart of this methodology relies on constructing asymptotically valid estimates of p-values along with q-values - a procedure that is frequently applied in the statistical genetics literature. Then, the p-values are interpreted as usual while the q-values are used to evaluate the probability of a null hypothesis being/not being rejected correctly.

4.1 Test Statistics

We only present the results here, since these statistics are discussed in detail in McCracken and Sapp (2005). The first statistic is designed to test for equal MSE. Both models have equal MSE under the null while the MSE provided by the second model is significantly smaller under the alternative. That is, this is a test of equal forecasting accuracy. This statistic has a non standard distribution which is dependent on nuisance parameters. Therefore, McCracken and Sapp build the asymptotically valid p-values and critical values by using the bootstrap procedures motivated by Clark and McCracken(2003). Here, we use Richardson's (2005) methodology with the Simetar © simulation software which is based on Latin Hypercube sampling instead of Montecarlo.[‡‡]

$$MSE - F = (P - \tau + 1)\frac{MSE_1 - MSE_2}{MSE_2}. \tag{6}$$

McCracken and Sapp enumerate the sample from *1* to *R*. The out-of-sample observations span $R + \tau$ through $R + P$. $(P - \tau + 1)$ are the number of step ahead forecasts.

The following statistic is designed to test for model encompassing. The forecast from model 1 encompasses the one from model 2 under the null. Under the alternative, the second model contains more information. The limiting distribution for equation (7) is also obtained by bootstrapping due to the same arguments we explained before.

$$ENC - F = (P - \tau + 1)\frac{\bar{c}}{MSE_2}, \tag{7}$$

where

$$\bar{c} = (P - \tau + 1)^{-1}\sum_{t=R}^{P+R-\tau}\hat{u}_{1,t+\tau}(\hat{u}_{1,t+\tau} - \hat{u}_{2,t+\tau}). \tag{8}$$

[‡‡] Simetar© by Simetar, Inc. is a simulation language programmed as an add-in to Microsoft Excel©. http://www.simetar.com

4.2 Inference

An adjustment must be made when multiple hypotheses are tested simultaneously. The famous Bonferroni correction suggests reducing the rejection rule by dividing the significance level over the number of tests: α/m, but this correction is found to be too conservative. Here, McCracken and Sapp methodology is used. It is first proposed by Benjamini and Hochberg (1995) and results in a higher power test than Bonferroni's by trying to ensure that the number of false rejections is small. Building in that concept, Storey (2003) defines a *q-value* as the minimum possible false discovery ratio for which the null can be rejected. Then, the *p-values* are used to categorize a rejected or non-rejected hypothesis, and the *q-values* are later used to categorize them into true or false rejections. McCracken and Sapp's modifications allow testing for longer forecasting horizons. Under the assumptions of (1) asymptotically valid *p-values*, (2) the p-values satisfy certain weak conditions, and (3) the number of tests m is large, their algorithm follows:

1. Let $p_{(1)} \leq p_{(2)} \leq \ldots \leq p_{(m)}$ be the ordered *p-values* from the m tests.
2. For $\lambda \in [0.01, 0.99]$ estimate the rate of true hypothesis rejections over the total number of tests with $\hat{\pi}_0(\lambda) = \dfrac{\#(p_j > \lambda)}{m(1-\lambda)}$.
3. Fit a cubic spline $f^*(\cdot)$ of $\hat{\pi}_0(\lambda)$ on λ.
4. Set $\hat{\pi}_0 = f^*(1)$.
5. Calculate $\hat{q}(p_{(m)} = \min\limits_{t \geq p_{(m)}} \dfrac{\hat{\pi}_0 mt}{\#(p_j \leq t)} = \hat{\pi}_0 p_{(m)}$.
6. For $i = m-1, m-2, \ldots, 1$ calculate
$$\hat{q}(p_{(i)}) = \min_{t \geq p_{(i)}} \frac{\hat{\pi}_0 mt}{\#(p_j \leq t)} = \min_{t \geq p_{(i)}} \left(\frac{\hat{\pi}_0 m p_{(i)}}{i}, \hat{q}(p_{(i+1)}) \right).$$
7. The estimated *q-value* for the i^{th} most significant test is $\hat{q}(p_{(i)})$.

5. Empirical results[§§]

Our objective is to assess if there is a gain in the prediction accuracy of the model when the data is first transformed into *SAC* units. Three different exchange rates are estimated for this purpose. All three are estimated with, and later without, our proposed methodology in SAC units. In this section, we apply the procedures explained above to accomplish our goal. First, we describe the data used. Then, we express the data in terms of the currency basket, i.e. *SAC* units. Thereafter, the data is fed into the model which is estimated to provide with the out-of-sample forecasts (still in *SAC* units). We proceed to transform the data back again into exchange rates, and we finalize by testing the results against those obtained without the *SAC* transformation, and those obtained

[§§] Many of the results mentioned here are not reported in this text. All of the results are available upon request and will be included in the final version of this paper.

by the random walk[***]. Detailed description of each of these stages and preliminary results follow.[†††]

5.1 Data description

The sample period covers from January 6, 1999 to August 30, 2006 (400 observations) in order to have all the Euro's history into our analysis. All the series have a weekly frequency on Wednesdays (mid week trading day) and were obtained from *Datastream*. The series used to create the currency basket are the Japanese Yen, Euro, Swiss frank, Australian dollar, Canadian dollar, New Zealand dollar, and the United States dollar. All these currencies are considered as "stable" and include major trading countries. All the series are based on the British sterling pound. Also, in British sterling pound units, Forward contract series with maturities in 4, 13, 26, and 52 weeks were collected for the Euro, U.S. dollar, and Australian dollar.

5.2 SAC conversion

We begin by applying equations (1) through (4) to generate the SAC series with the use of all the spot series. In order to do so, equation (3) is solved by using the Newton Forward algorithm programmed in Microsoft Office Excel 2003. Figure 1 presents charts of the analyzed exchange rates as well as those particular currencies in SAC units. Notice how the EUR/SAC fluctuations parallels the EUR/GBP movement, but they are not identical. This shows seasons where the Euro was appreciating/depreciating on its own when compared to the rest currencies in the basket. The SAC used to transform the spot data is also used to transform all the forward contracts.

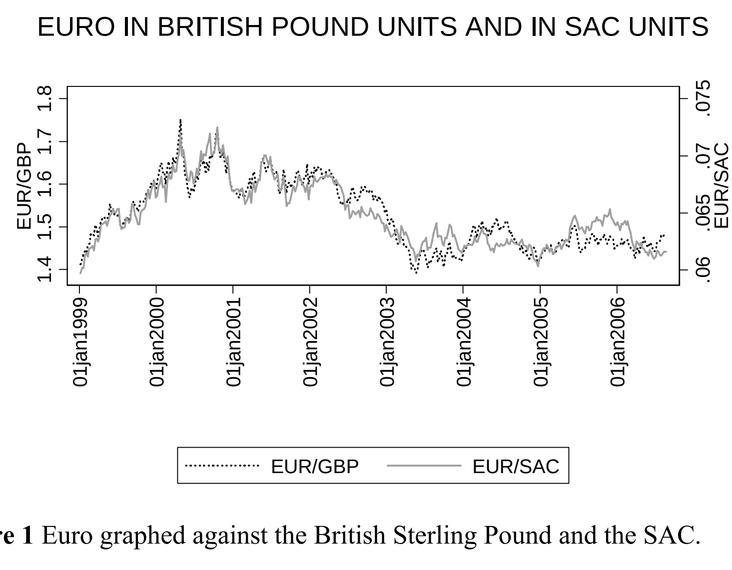

Figure 1 Euro graphed against the British Sterling Pound and the SAC.

[***] Forthcoming. These are the tests suggested by McCracken and Sapp (2005).
[†††] The corresponding statistics are available from the authors upon request. This working paper shows preliminary results.

5.2 Model estimation

We proceed to obtain out-of-sample dynamic forecasts using the SAC based data obtained from the step above. We start by estimating the MSIAH-VECM using the two stages methodology described by Krolzig (1997). Essentially, we implement the Johansen's (1988, 1991) procedure to specify a linear VECM in the first stage. Then, we proceed to include the Markovian shifts in to the model with the use of the maximum likelihood Expectaion-Maximization (EM) algorithm.

5.2.1 Stage 1: Unit root tests and cointegration analysis

Following Johansen's methodology, we test for stationarity on each of the series (i.e. s_t, f_t^4, f_t^{13}, f_t^{26}, f_t^{52} both as exchange rates and in SAC units). Using the Augmented Dickey-Fuller test, we found that they are all integrated of order one. Then we proceeded to test for cointegration between the vector $y_t = [s_t, f_t^4, f_t^{13}, f_t^{26}, f_t^{52}]'$. We found evidence that support the existence of exactly four cointegrating relationships by rejecting the hypothesis of just three versus the alternative of four, but being unable to reject the hypothesis of four cointegration vectors versus the alternative of five relationships.

We then tested for the validity of the cointegration vectors of the form $\beta' = [\mathbf{1}, -\mathrm{I}]$. As Clarida et al. (2003) and Sarno and Valente (2005), we too find evidence against this hypotheses. When we analyzed the magnitudes of the departures, we also found them too small to be economically significant as explained by Clarida et al. and Sarno and Valente. Further, Sarno and Valente suggested to continue the analysis with the imposition of such restrictions since deviations from them imply a unit root in international interest rate differentials. We do so.

Finally, we estimated the linear VECM. Clarida et al. found the optimal number of lags to be 1, whereas Sarno and Valente found them to be 3. Here, we also used both the Akaike Information Criterion and the Schwartz Information Criterion to find that only one lag is required.

5.2.2 Stage 2: Estimation of the Markov Switching model

We now tested for nonlinearities with the use of the model shown in equation (5). Following the "bottom up" procedure described by Krolzig's (1997), we determined that there is evidence that supports the use of the model that incorporates Markovian shifts, i.e. the MSIAH-VECM with one lag and three regimes. We refer to Sarno and Valente (2005) for a discussion on the economic meaning of the model. The estimation was generated using Ox version 4.00 (see Doornik, 2005) and the Arfima package version 1.00 (Doornik and Ooms, 2003) .Figure 2 shows the gains in accuracy from forecasting the value of a currency instead of the exchange rate per se. The graph shows the out-of-sample forecasting errors in percent absolute deviations. Notice how the MSIAH-VEC model explodes after the15th step ahead when is fed with the untransformed data. The change in the out-of-sample forecasting MAPE is from 19% to 13%.

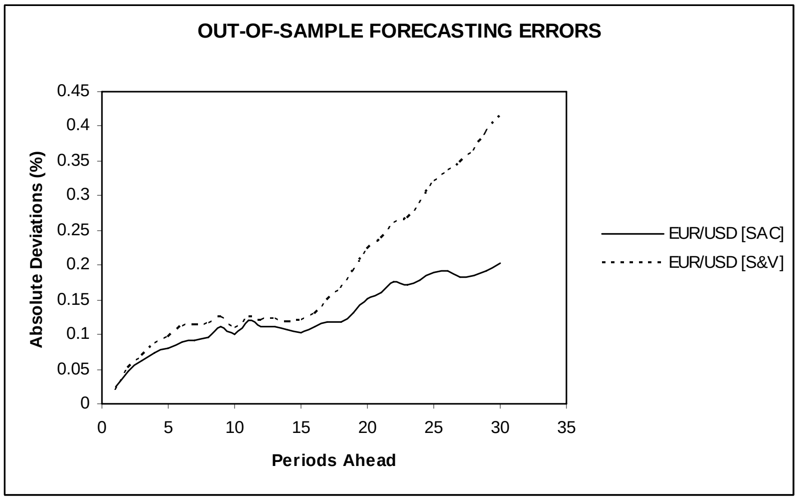

Figure 2 Out-of-sample forecasting errors for the Euro/U.S. dolar exchange rate.

6. Conclusion

It is evident that foreign exchange fluctuations cause volatility on expected cash flows that might affect firms either in a positive or negative way resulting in major implications on firm behavior. But forecasting the exchange rate yields fluctuations too wide when using monetary-fundamentals models, rendering them unpractical. In this paper, we proposed that the exchange rate fluctuations are dependent upon the currencies own intrinsic value, given by their own total demand by other countries. Therefore, we used a currency basket to determine such intrinsic value and thereafter out-of-sample exchange rate forecasts were produced. When a Markov-Switching Vector Error Correction Model is used, the accuracy of the forecasts was found to be improved. Caution must be taken when using the model specification in this paper as it relies on non optimal predictors. Yet, the model successfully produces an exchange rate density description useful to generate an effective tool for business strategic decision making. Since the manager (investor) is no longer required to assume random walks in foreign exchange, discretionary hedging (risk assessment) can be successfully developed.

Provided that the exchange rate between two countries is determined by the total value of each of the currencies involved in the exchange, given their own total demand, opens a new area of research. Our methodology should be extended with the use of a more complete macroeconomic model to analyze the effects of different policies upon a country's currency value and its implications on trade and international transactions. Furthermore, the model can also be used to evaluate domestic economic shocks isolated from noise produced from foreign countries.

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