Obtaining Directional Signals on Future Exchange Rate Movements

Collette Wheeler

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Advisor : Professor Suhas Ketkar

Abstract: This paper uses a market based approach to assess whether exchange rates follow a random walk pattern. A risk-adjusted yield differential (RAYD) model is used to obtain directional signals on exchange rate movements. These signals are then compared to the signals obtained by the random walk model. The results indicate that the RAYD performs significantly better than the random walk model for obtaining directional signals on exchange rate movements. Furthermore, when the RAYD model focuses only upon significant signals as well as different threshold levels, the results further improve. These results strengthen the argument that the theoretical signals obtained from the RAYD model are not validated due to chance alone.

1. Introduction

Do exchange rates follow a random walk? Economists have sought economic models in order to describe nominal exchange rate determination. Such models include, but are not limited to, the purchasing power parity (PPP) model, the flexible price model, and the sticky price model. The seminal work of Meese and Rogoff (1983) however, finds that the random walk model performs as well as any estimated model of forecasting short-run exchange rate movements. Their results imply that there is no relationship between the exchange rate and the fundamentals of an economy. As a result, economists have largely abandoned their quest to develop alternative models that forecast exchange rate movements in the short-run.

Despite the decrease in economic literature on forecasting exchange rates, economists, such as Rossi (2005), have found that exchange rates do not follow random walks for certain currencies. In fact, as Rossi's nested models indicate, the problem with past economic models was not that the fundamentals were unrelated to exchange rates, but rather that the previous models failed to recognize the unstable nature of the parameters of such relationships. Her research yielded the following insight: that there is a relationship between the exchange rate and the fundamentals of an economy, but that it is not stable over time. Interestingly, Rossi also finds that the proposed optimal tests reject the conclusion that a random walk model is the best specification—even when the out of sample tests do not reject the hypothesis that the random walk model performs better. Essentially, her research highlights the possibility of constructing an economic model that is better than the random walk model at forecasting future exchange rate movements.

Although economic models have been far from successful in predicting exchange rates, it may be possible to construct models that generate directional signals on exchange rates. The present paper explores one such possible approach—the use of risk-adjusted yield differentials (RAYD). The unique feature of this RAYD model is the inclusion of certain market risk variables—namely, volatility risk, sovereign default risk, and liquidity risk. While other models have included a risk component, such as volatility, their explanatory power is limited due to their narrow view on risk. The primary goal of this paper is to demonstrate the possibility of obtaining short term directional signals on currencies by relating implied yields[1] to these risk elements. Such signals are based on the premise that currencies that offer significantly higher yields that are commensurate with their risk characteristics will tend to appreciate, and vice versa. Furthermore, this paper tests the performance of the RAYD model against the random walk model, which is considered the benchmark model for forecasting exchange rates.

2. Theoretical Background

2.1 Fundamental Approaches to Exchange Rate Determination

The exchange rate is essential for international trade because it allows individuals to compare the relative prices between foreign and domestic goods and services. The foreign exchange market is considered to be in equilibrium when the uncovered interest parity (UIP) condition is satisfied. The UIP condition arises when the deposits of all currencies offer the same expected rate of return. If the expected rates of returns are not equalized, then individuals will move their liquid assets into currencies that offer the highest yield (the highest interest rate).

[1] Formal treatment of this term will be presented in section 4.1

Generally, the higher the interest rate, or yield, the stronger the currency will be due to the fact that more individuals will prefer to hold deposits in the stronger currency. What happens if the foreign exchange market is out of equilibrium? Let's assume that the imbalance is caused by the yield differential between the U.S. Dollar (USD) and the Euro (EUR) where the expected yield for the USD is higher than the expected yield for the EUR. Anyone who holds the euro will want to sell their euro deposits for the more enticing dollar deposits. The individuals holding euro deposits will attempt to sell their euros for dollars, but individuals with dollars are not willing to sell their dollar deposits for euros at the prevailing rate. Individuals holding euros will attempt to entice dollar holders by offering a higher bid premium for those dollars, which will cause the euro to become cheaper relative to the dollar. If the dollar still offers a higher yield, capital will continue to flow into dollar deposits until there is no longer an incentive for the holders of the euro deposits to offer a premium. This process will continue until the yield differential disappears, or when euro and dollar deposits have equal returns. To formalize this process, the expected rates of return between two currencies are equal when:

$$R_i = R_j + \frac{(E^e_{i/j} - E_{i/j})}{E_{i/j}}$$

$$i = USD$$

$$j = EUR$$

$$R_i = \textit{Today's interest rate on one-year "i" deposits}$$

$$R_j = \textit{Today's interest rate on one-year "j" deposits}$$

$$E_{i/j} = \textit{The spot } i/j \textit{ exchange rate}$$

$$E^e_{i/j} = \textit{The one-year future expected } i/j \textit{ exchange rate}$$

In the short-run there is a link between the money market, the interest rate, and the exchange rate. In the foreign exchange market, equilibrium is established by given interest rates and expectations about future exchange rates—the interest rate is determined by the money market (if there is an expansion of the money supply this will lower interest rates by injecting more liquidity in the market, enabling banks to lend more). The money market establishes an interest rate, which in turn influences the equilibrium exchange rate. Interest rates affect the exchange rate in the following manner: a rise in the domestic interest rate will attract individuals due to the increase of the rate of return yielded by domestic assets, individuals will move into domestic assets and demand domestic currency to purchase these assets. This process will bid up the value of the domestic currency and cause an appreciation relative to the foreign currency. Conversely, a fall in the domestic interest rate will persuade individuals to convert out of domestic assets for foreign assets. This process will bid down the value of the domestic currency and cause its depreciation relative to the foreign currency.[2]

Returning to the process of exchange rate adjustment, asset re-allocations will eventually restore equilibrium and investors will be indifferent between holding domestic versus foreign assets. This relation between the money market, the interest rate, and the exchange rate is displayed in the graph below using the Yuan/US Dollar exchange rate:

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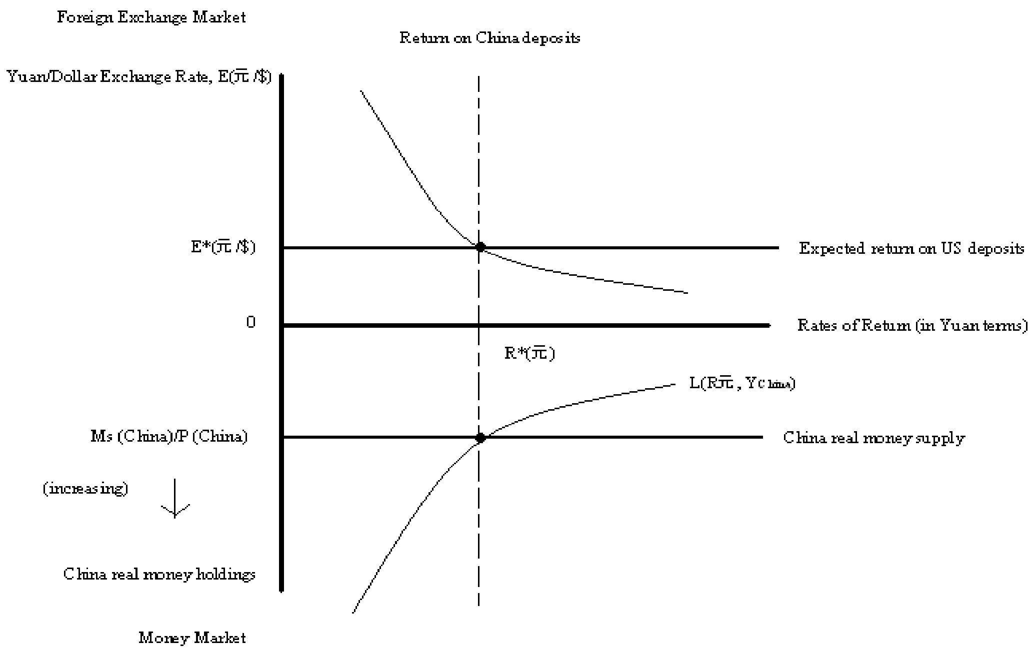
[2] There are exceptions to this rule. For example, the current global economic crisis has quenched global risk appetite. This behavior directs capital flows into "safe-havens". Despite the 0% interest rate, investors still prefer to hold US deposits over foreign deposits—"flight to safety".



Although the UIP condition is useful for the elementary understanding of short-run exchange rate movements, it has a degree of uncertainty because it uses expected exchange rates rather than forward exchange rates. Forward exchange rate contracts hedge against the uncertainty of the expected exchange rate by allowing the buyer to secure a quoted future exchange rate to avoid unexpected exchange rate movements. When individuals cover their exposure to exchange rate risk by using the forward exchange rate rather than the future spot rate, the covered interest parity (CIP) condition arises. John Maynard Keynes (1923) was the first to examine the CIP condition. He found that the equilibrium CIP condition occurs when the rates of return on domestic deposits is equal to the rates of return on “covered” foreign deposits; alternatively, when the interest rate on domestic deposits is equal to the interest rate on foreign deposits plus the forward premium. This can be formalized as:

$$R_i = R_j + \frac{(F_{i/j} - E_{i/j})}{E_{i/j}}$$

$i = USD$

$j = EUR$

$R_i = \text{Today's interest rate on one - year "i" deposits}$

$R_j = \text{Today's interest rate on one - year "j" deposits}$

$E_{i/j} = \text{The spot } i/j \text{ exchange rate}$

$F_{i/j} = \text{The one - year forward price of } j \text{ in term}$

Theoretically, if the foreign exchange market is out of equilibrium due to yield differentials then arbitrage funds should restore the CIP condition by equalizing the rates of return across different currencies. For instance, if the USD is offering higher yields than the EUR, then individuals should move into dollar deposits and therefore increase its bid price, causing an appreciation of USD relative to the euro. As shown above with UIP, this appreciation of the dollar will continue until the rates of return for both currencies are equal again. The CIP relationship is held when deposit holders are able to convert between currencies and move capital abroad instantaneously; however this requires a highly liquid market and perfect capital mobility. In order to eliminate the yield differential between different currencies, the supply of arbitrage funds must be infinitely elastic according to Keynes' theory of CIP. As previously discussed, yield differentials will continue to exist outside the Keynesian framework because arbitrage funds are limited due to risks associated with trading foreign currencies. Such risks will be incorporated into the RAYD model in order to compare the relationship between certain risk variables and actual currency yields.

3. Background Literature

3.1 The Random Walk Model

Before discussing the seminal work of Meese and Rogoff (1983), it is useful to examine the theoretical context of the random walk model and to consider its application to exchange rate theory. Traditionally, random walk models postulate that upward or downward movements will have equal probability for every time interval. The basic version of a random walk is a discrete, non-stationary, time-series model with Gaussian independent increments. The model posits that the trend of the underlying variable is barely predictable, or in other words, the model follows a stochastic trend. In its economic context, the random walk model concludes that the exchange rate today is equal to the exchange rate yesterday plus a random shock. The random walk model can be formalized by the following (solved by iteration):

y_t is said to be random walk when,

$$y_t = y_{t-1} + \varepsilon_1$$

Where ε_t is independent and identically distributed, $(0, \sigma^2)$

A consequence of the random walk model is that any shock to the initial position or price is permanent, as follows:

$$y_1 = y_0 + \varepsilon_1$$
$$y_2 = y_1 + \varepsilon_2 = (y_0 + \varepsilon_1) + \varepsilon_2$$
$$y_3 = y_2 + \varepsilon_3 = \left[(y_0 + \varepsilon_1) + \varepsilon_2\right] + \varepsilon_3$$

y_0 = initial position or price
y_1 = position or price for time period one
ε_t = random shock

Repeating this process yields the following:

$$y_t = y_0 + \sum_{i=1}^{t} \varepsilon_i$$

The random walk model is a useful tool for analyzing fully efficient markets, where the possibility of speculation does not exist. Within the exchange rate framework however, economists, including Froot and Rogoff (1995), argue that real and nominal exchange rates should not be subject to the fully efficient market assumption. They contend that there is little reason to expect real and nominal exchange rates to be random walks because both real and nominal exchange rates are subject to arbitrage activity due to yield differentials. While there are other examples of random walk models with different trends, they are not within the scope of this paper.

3.2 The Random Walk Model & Exchange Rate Determination

Meese and Rogoff's random walk model (1983) is considered the benchmark for other exchange rate models due to its ability to predict exchange rates better than previously theorized economic models. The goal of their research was to compare the out of sample accuracy of various exchange rate models. Out of sample tests are appealing for research purposes because they forecast outcomes that are still unknown. The economic models of concern for Meese and Rogoff include the flexible price monetary model (Frenkel-Bilson, 1976), the sticky price monetary model (Dornbusch-Frankel, 1976), and the sticky price model with the current account (Hooper-Morton, 1982).

The flexible price model holds the following key assumptions: prices are perfectly flexible, UIP is maintained, and real output is at its natural level. One implication produced by this model is that movements in exchange rates are directly proportional to movements in prices on a continuous basis. Furthermore, this implies that the purchasing power parity (PPP) must always hold and that prices will instantly adjust in the presence of excess demand.[3] The sticky price model has similar assumptions as the flexible price model except that the PPP condition is expected to hold only in the long-run. The main difference between the flexible price model and sticky price model is that prices are allowed to *gradually* adjust to excess demand rather than

[3] The PPP maintains that the exchange rate between two currencies is equal to the ratio of the two countries' price level of a fixed basket of goods and services.

changing instantaneously. The sticky price model with the current account approach is an extension of the sticky price model that permits changes in the real exchange rate in the long-run. These changes in the real exchange rate are thought to be associated with trade balance shocks.

The general specification for the reduced form of all three models is as follows (Meese and Rogoff):

$$s = a_0 + a_1(m - \dot{m}) + a_2(y - \dot{y}) + a_3(r_s - \dot{r}_s) + a_4(\pi^e - \dot{\pi}^e) + a_5 TB + a_6 \overline{\dot{TB}} + u, \tag{1}$$

$s = log(dollar\ price\ of\ foreign\ currency),$

$(m - \dot{m}) = log(ratio\ of\ the\ US\ money\ supply\ to\ the\ foreign\ money\ supply),$

$(y - \dot{y}) = log(ratio\ of\ US\ to\ the\ foreign\ real\ income),$

$(r_s - \dot{r}_s) = Short\text{-}term\ interest\ rate\ differential,$

$(\pi^e - \dot{\pi}^e) = Expected\ long\text{-}run\ inflation\ differential,$

$TB\ and\ \overline{\dot{TB}} = Cumulated\ US\ and\ foreign\ trade\ balances,$

$u = disturbance\ term\ (may\ be\ serially\ correlated)$

All three structural models assume first-degree homogeneity in relative money supplies, or where $a_1 = 1$. The flexible price model continuously holds purchasing power parity, which is satisfied when $a_4 = a_5 = a_6 = 0$. The sticky price model allows for gradual domestic price adjustment and deviations from the PPP, which is satisfied when $a_5 = a_6 = 0$. For the sticky price model with current account included, none of the coefficients are constrained in the equation due to the unanticipated shocks to the trade balance.

Meese and Rogoff employed a few varieties of the random walk model. The first model they consider is a basic random walk model, which uses the spot exchange rate as a predictor of future spot exchange rates. This stochastic method was discussed earlier:

$$s_t = s_{t-1} + u_{it} \qquad (2)$$
$$s_t = \textit{Exchange rate for time period "t"}$$
$$s_{t-1} = \textit{Lagged exchange rate, time period "t - 1"}$$
$$u_{it} = \textit{Disturbance term for time period "t"}$$

The other method employed in their paper is a random walk model with an estimated drift parameter. They found the estimate of the drift parameter by taking the logarithmic of the mean monthly exchange rate change. Using the variables from equation (1) and the mean monthly exchange rate change, they ran an unconstrained vector autoregression (VAR). The unconstrained model differs from the flexible price model and the sticky price model estimation in that the coefficients previously restricted to zero are no longer restrained. Including the VAR is crucial for their forecasting measures because it does not expose their model to some of the estimation problems caused by the restrained variables found in structural models. Each variable is regressed against its lagged values and against the other variables through the following exchange rate equation:

$$s_t = a_{i1}s_{t-1} + a_{i2}s_{t-2} + \ldots a_{in}s_{t-n} + B'_{i1}X_{t-1} + B'_{i2}X_{t-2} + \ldots B'_{in}X_{t-n} + u_{it}, \qquad (3)$$
$$X_{t-j} = \textit{a vector of the explanatory variables in equation (1), lagged "j" periods,}$$
$$X_{t-n} = \textit{a vector of the explanatory variables in equation (1), for a uniformly lagged length, "n",}$$

Meese and Rogoff estimated the structural models using the ordinary least squares method, the generalized least squares method, and Fair's instrumental variable technique (1970). Furthermore, they re-estimated the parameters of each model in every period by using rolling regressions, which is a procedure that estimates the same linear equation many times by using a growing sample or overlapping partial sections of a larger sample.

Despite their efforts to account for the statistical difficulties in structural models, Meese and Rogoff discovered that the random walk model still had smaller forecast errors than the structural models. The resulting conclusion was that economic models of exchange rates did not outperform the random walk model in a significant way. An implication that followed from this result is that the fundamentals do not matter in the short-run determination of exchange rates.

Is there an explanation for this poor model performance, or is a random walk model currently the best explanation for exchange rate movements? Further exchange rate literature has illuminated more problems with forecasting economic models—not only do these models require regular revisions to their model specifications and parameter estimates but their success is highly dependent on the sample period (Meese, 1990). Despite these problems however, there are possible explanations for the poor model performance. Some suggested reasons include the presence of simultaneous equation bias, sampling error, stochastic movements in the true data generating variables, model misspecification, and possible non-linearities that were not considered (Meese and Rogoff, 1983).

3.3 Explanation for the Meese-Rogoff Puzzle

As alluded to earlier, there has been a resurgence in economic literature on exchange rate determination and on the Meese-Rogoff puzzle (the random walk). In particular, there is evidence that rejects the null hypothesis that exchange rates follow a random walk. A possible explanation for the Meese-Rogoff puzzle is that the random walk model did not account for parameter instability (Rossi, 2005). Parameter instability implies that the relationship between exchange rates and the fundamentals of economy are highly unstable over time. Parameter instability does not necessarily imply that there is no relationship at all, but rather the relationship may not remain constant over time, largely due to exogenous shocks. Left unaccounted for, parameter instability will produce asymptotically biased forecasts due to the estimation error in the parameter that measures the persistence of exchange rates and fundamentals. Furthermore, when this bias overshadows the benefits of utilizing economic information, the random walk model will appear to forecast exchange rate movement better than economic models. Rossi proposes a test to account for the presence of highly persistent variables using nested models.

The nested models are of particular interest due to their ability to detect the presence of parameter instability and to test the null hypothesis on the parameters. Furthermore, Rossi's proposed optimal tests also estimate whether the explanatory variables are statistically significant given the observed data and can determine whether this relationship is stable over time. She notes that rather than specifying the economic model as the following:

$$Y_{1,t} = Y_{2,t-1}\beta + \varepsilon_t$$

The economic model should instead be specified as the following equation:

$$Y_{1,t} = Y_{2,t-1}\beta_t + \varepsilon_t$$

where $Y_{1,t}$ is the rate of growth of the real exchange rate, where $Y_{2,t}$ is the rate of growth of the interest rate differential lagged one period, and where ε_t is not forecastable. The variable β_t expresses the time varying component of the parameter, which was not accounted for in the original random walk puzzle (Meese and Rogoff, 1983). The time variable reflects the unstable relationship between the real exchange rate and the fundamentals over time. Without its inclusion, the tests comparing the random walk model to the structural models may not be as robust to parameter instability. Two autoregressed models were analyzed using the likelihood ratio test. One model looked at the growth rate of the nominal exchange rate while the other model examined the relationship between the growth rate of the exchange rate and the growth rate of its lagged fundamentals. The more interesting conclusion resulting from the first model found that the random walk model is not a good description of the data even in cases where the random walk model is not rejected—this situation tended to occur in the presence of parameter instability. The results of the second autoregressed model found that there is a relationship between the fundamentals and the exchange rate, but that the relationship is not stable over time. Essentially, the literature indicates that in the presence of parameter instability there is not enough evidence to conclude that the random walk model is a good description of the data. Most importantly, these autoregressed models indicate a link between the fundamentals and the exchange rate, which provides a direction for future research endeavors.

Although Rossi provides theoretical evidence against the random walk model, she does not propose an empirical model that is a better fit for exchange rate determination. The goal of this paper is to fill in this gap with empirical evidence, and to provide an explanatory model for exchange rate signals. While the proposed risk differential model does not forecast future exchange rate levels, it does provide signals for future exchange rate movements.

4. An Risk-Adjusted Yield Differential Model for Generating Exchange Rate Signals

4.1 A Market Based Approach to Exchange Rate Determination

Before the removal of the gold standard in 1971, the Bretton Woods Agreement mandated that each currency have a fixed price relative to gold. Under the gold standard, independent monetary policy is nearly impossible because the key monetary tool, the interest rate, is used for holding the value of the currency against its gold parity rather than for managing inflation and the money supply. Once the gold standard collapsed and the central banks instituted a floating exchange rate system, however, the policy focus shifted to open market operations and to targeting interest rates. Similar to other policy options, a floating exchange rate system can expose market participants to certain risk elements. While there are quite a few risk factors associated with the foreign exchange market, the central approach of this paper is to relate three risk elements to implied yields on several currencies. The implied yields used in this study are the 30-day US dollar denominated yields derived from the actual 30-day yields in other currencies, adjusted with the 30-day forward market exchange rates. Thus, the actual 30-day yield on a currency such as the Argentine peso (ARS) is adjusted with its 30-day forward exchange rate to obtain the implied yield on ARS. The three risk variables help explain the persistence of implied yield differentials. The selected risks that this paper seeks to analyze include the sovereign default risk, liquidity risk, and volatility risk; all three will be formally discussed later in this section.

Although the trade and current account imbalances drive exchange rates in the long run, capital flows via currency markets are crucial determinants of exchange rates in the short run. The process is initiated by the presence of an implied yield differential, where differences in local currency yields emerge in different countries. These implied yield differentials can be accounted for by gaps in the actual inflation rate versus the targeted inflation rate and by a country's position on monetary policy. Furthermore, the divergence of yields across countries exists in the forward exchange rate markets rather than being eliminated by arbitrage. As one should expect from an open market instrument, currencies that offer significant differences in implied yields ought to either appreciate or depreciate given the direction of the yield differential. Currencies that offer higher implied yields relative to other currencies ought to attract foreign capital while the converse is true for currencies that offer lower implied yields. The currency offering a higher yield ought to appreciate relative to other currencies on the spot market, while the currency offering a lower yield should depreciate relative to other currencies. The implied yield differentials ought to be eliminated with arbitrage funds through shifts in the direction of capital flows. But these yield discrepancies continue to exist because the different risks associated with trading foreign currencies limit the supply of arbitrage funds. The three risk elements mentioned earlier, Sovereign Default risk (SR), Liquidity risk (LR), and Volatility risk (VR), are analyzed in this paper due to their influence on the availability of arbitrage funds.

4.2 Three Market Risk Variables: SR, VR, & LR

As previously mentioned, there are three market risk variables that influence the availability of arbitrage funds: Sovereign Default Risk (SR), Volatility Risk (VR), and Liquidity Risk (LR). Sovereign Default Risk attempts to capture the economic, financial, and political factors that impact a country's ability or likeliness to repay foreign currency obligations. Generally, developing countries have a lower capacity to repay foreign currency obligations compared to obligations in its local currency. Sovereign Default Risk is obtained from Standard & Poor's short-term foreign currency credit ratings, where each currency is given a letter rating to denote its creditworthiness. For the purpose of this model, these letter ratings have been converted into numerical risk scores from 1 (least risky) to 7 (most risky). Each numerical risk score is then placed into a bin—if a currency is assigned "1" or "2" then it is considered "low risk", if it is assigned "3" or "4" then it is considered "medium risk", if it is assigned "5", "6", or "7" then it is considered "high risk". Countries that are assigned to high risk tend to face more restricted availability of arbitrage funds and also tend to have less diversified sources of funding. For countries associated with higher risk, investors will demand higher implied yields on currency investments. Furthermore, arbitrage funds will move from currencies offering lower implied yields than commensurate with their risk to currencies offering higher implied yields than commensurate with their risk.

In general, volatility attempts to measure the market risk associated with major fluctuations in exchange rates. Implied volatility risk, rather than historic volatility, will be used for this model because it is a forward looking measure of expected exchange rate volatility. Implied volatility generally rises if there are indicators of a looming currency crisis. Some possible reflections of rising implied volatility risk include a decline in trading liquidity, the sum total of USD call and put options, and the excess of USD calls over puts ("flight to safety"). Whenever traders perceive a potential for rise in volatility, they write up the implied volatility. When there is a rise in a currency's Implied Volatility Risk, the availability of arbitrage funds will decrease due to the potential risk involved with investing in that currency. One month implied volatility risk will be considered in the ensuing empirical investigation for obtaining signals for short-run exchange rate movements.

Liquidity Risk provides an indication of the cost to enter and exit from a currency. The Liquidity Risk is determined by the bid-offer spreads on currencies and is calculated as:

$$\frac{(\text{Ask Price} - \text{Bid Price})}{((\text{Ask Price} + \text{Bid Price})/2)}$$

When a currency's ask-bid spreads are low, it implies abundant liquidity and lower liquidity risk because it is cheaper to buy and sell that currency. Conversely, if a currency's ask-bid spreads are high, it implies less liquidity and higher liquidity risk because it is more expensive to buy and sell that currency. Investors will typically demand higher implied yields to invest in currencies associated with higher liquidity risk. Unfortunately, the available data records only the last transaction of the day, which makes the process of measuring liquidity risk more difficult. Essentially, this allows the size of the last transaction of the day to skew the measure of risk, which creates measurement error for liquidity risk. Although the measurement error for liquidity risk is of concern, it will not cause the explanatory power of the model to be overestimated. In fact, liquidity risk does not tend to be significant in the results anyway. Furthermore, the worst case scenario is that it reduces the explanatory power of the model. Liquidity risk should not be dropped however, because the results indicate that it is significant at the 10% level in some cases. Also, the exclusion of liquidity risk could induce the problem of an omitted variable bias, which provides another reason for its inclusion in the model estimation.

4.3 The Data, Model Motivation, and Model Specification

The RAYD model seeks to relate implied yields (IY) on currencies to their respective SR, VR, and LR elements.[4] The relationship between IY and the three independent risk variables is estimated on the first business day of each month by using public and proprietary data on 27 currencies (the list of selected currencies can be found in the appendix) from January 2005 to December 2006. Originally, this investigation was to also cover 2007. Due to the generalized appreciation of the dollar during the first six months and then to the sudden depreciation of the dollar during the last six months, however, the results for 2007 are dropped. This will be further addressed in forthcoming sections. There are 18 emerging market and 9 developed currencies,

[4] While sovereign credit risk is obtained from Standard and Poor's short-term foreign currency credit ratings, the data on the other variables are proprietary. They are obtained from the Royal Bank of Scotland (RBS). The assistance of David Simmonds in making the proprietary data available is gratefully acknowledged.

all paired against the US Dollar (USD). Using this relationship, the goal is to identify on a given day outlier currencies that offer either significantly higher or lower implied yields relative to their risk. *Ceteris paribus*, subsequently these outlier currencies can be expected to appreciate or depreciate until they are no longer outliers. Once the implied yield differential has been arbitraged away, outlier currencies will cease to be outliers. A paneled, cross-section database is used, which pools three months (81 observations) for each linear regression. Although the model is regressed over three months, a dummy structure distinguishes every month which preserves the short-term relationship. Preserving the one month time horizon within the paneled database is crucial in order to reflect the short positions held in the foreign exchange rate market—although exchange rate adjustments can occur instantaneously, implied yields are frequently derived as one-month horizons. Furthermore, using a one-month implied yield horizon does not necessarily imply that traders will take a 30-day position on a certain currency. High sovereign risk and the slope intercept term are both suppressed in order to prevent perfect multi-collinearity between the slope intercept, the time dummy, and the sovereign risk dummy. The model will then assume the Sovereign Risk variable is high risk unless denoted otherwise by the low risk or medium risk dummy. Furthermore, the three independent variables are lagged by one day, which avoids the simultaneity problem.

The RAYD model can be specified as the following equation:

$$IY_{it} = \beta_t \delta_t + \rho_0 LR_{i(t\text{-}1)} + \rho_1 d_{1i(t\text{-}1)} + \rho_2 d_{2i(t\text{-}1)} + \rho_3 VR_{i(t\text{-}1)}$$

$t = \textit{First business day of the month,}$

$t - 1 = \textit{Last business day of the previous month,}$

$IY_{it} = \textit{Implied yield for currency i at time t,}$

$\delta_t = \textit{Time dummy variable,}$

$LR_{i(t-1)} = \textit{Liquidity Risk for currency i at time t - 1,}$

$d_{1i(t-1)} = \{1 \textit{ if } SR_{i(t-1)} = 1 \textit{ or } 2\}, \textit{or} = \{0 \textit{ if otherwise}\}, \textit{for Sovereign Risk of currency i}$
$\quad \textit{at time t - 1. "Low Risk",}$

$d_{2i(t-1)} = \{1 \textit{ if } SR_{i(t-1)} = 3 \textit{ or } 4\}, \textit{or} = \{0 \textit{ if otherwise}\}, \textit{for Sovereign Risk of currency i}$
$\quad \textit{at time t - 1. "Medium Risk",}$

$VR_{i(t-1)} = \textit{Volatility Risk for currency i at time t - 1}$

If roughly 50% of the variation in implied yields is explained by SR, LR, and VR, then the RAYD model performs well in explaining the variation in IY across many currencies. This is especially true since interest rates are determined by domestic monetary policies that are directed for managing inflation. It is expected that higher levels of composite risk ought to have a positive impact on IY due to the risk premium. Although LR ought to significantly impact IY theoretically, due to the measurement error found in reporting LR, it is not likely to show up as significant. As mentioned above, the measure of liquidity is skewed by transaction size, which erodes the link between the bid-offer spread and liquidity. The variation in implied yields explained by these three independent risk variables will provide a guide to the direction of flows in arbitrage funds. The direction of arbitrage funds will indicate which currencies can be expected to appreciate or depreciate.

4.4 Reported Regression Results

Regressions on the panel cross-section database for 2005 and 2006 with the three independent risk variables, SR, VR, LR, accounted for about 73% of the variation in IY. The adjusted R^2 value averaged 0.71 for the same dataset for years 2005 and 2006—recall that each year had four sets of paneled data, where each set accounts for three months of data. All R^2 and adjusted R^2 values are reported in the Appendix. As expected, LR is only significant three out of the eight sets (37.5%) of regressions at the .01% to 1% significance level. This low figure is most likely due to the erosion of the relationship between the bid-offer spread and liquidity, as previously mentioned. SR and VR are both found to be significant: reflecting "low risk" is significant six out of the eight sets (75%) while reflecting "medium risk" is significant seven out of the eight sets (87.5%) of regressions. SR is found to have a strong, positive influence on IY, which is not surprising given that currencies with larger composite risks tend to offer higher risk premiums to compensate investors. VR is significant six out of the eight sets (75%) of regressions, and has a strong, positive influence on IY. Both the SR and VR variables were significant at levels of .01% to 1%. To provide an illustrative example, the results for April 2006 – June 2006 are reported and analyzed here:

Estimating the Determinants of Implied Yields April 2005 – June 2005	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.843 *** (1.093)
β_2	5.813 *** (1.130)
β_3	4.907 ***

	(1.243)
Liquidity Risk	276.362 (287.561)
Low Risk	-3.820 *** (0.849)
Medium Risk	-4.181 *** (0.941)
Volatility Risk	0.294 *** (0.075)
Observations R-squared Adjusted R-Squared	81 0.828 0.810

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The results for April 2006 – June 2006 indicate that about 80% of the variation in implied yields is explained by these three independent risk elements. Also, the results agree with *a priori* expectations—LR is not found to be significant (perhaps due to the measurement error), and both SR and VR are found to exert a significant, positive impact on IY at the .01% level. The model assumes that the currency's SR characteristic is "high risk" unless denoted otherwise by the "medium risk" $\langle 0,1 \rangle$ or "low risk" $\langle 1,0 \rangle$ dummy variable, which is why IY is expected to decrease if a currency reflects low or medium risk. As it was noted earlier, currencies with higher risk must compensate investors with a risk premium; in other words, by offering a higher implied yield. Thus currencies that have higher SR characteristics tend to offer a risk premium, or higher implied yields. This is evident in the regression results—IY is reduced when a currency reflects low or medium risk characteristics. In the regression example above however, it is interesting to find that reflecting medium risk characteristics reduces IY more than reflecting low risk characteristics but that reflecting high risk increases IY. This discrepancy might be due to higher levels of risk that are not offset by a risk premium. Furthermore, because SR is a measure of a country's economic fundamentals, it can be said that the fundamentals do contribute to the variation in implied yields. VR also has a positive impact on IY, which may also be related to the risk premium. For instance, if a currency has high levels of VR, investors will demand yields that are commensurate with risk. Although the explanatory power of the RAYD model provides some insight for the variation of implied yields across many countries, the main focus of this paper is to obtain directional signals. The methodology for obtaining these signals will be further explained in the forthcoming section.

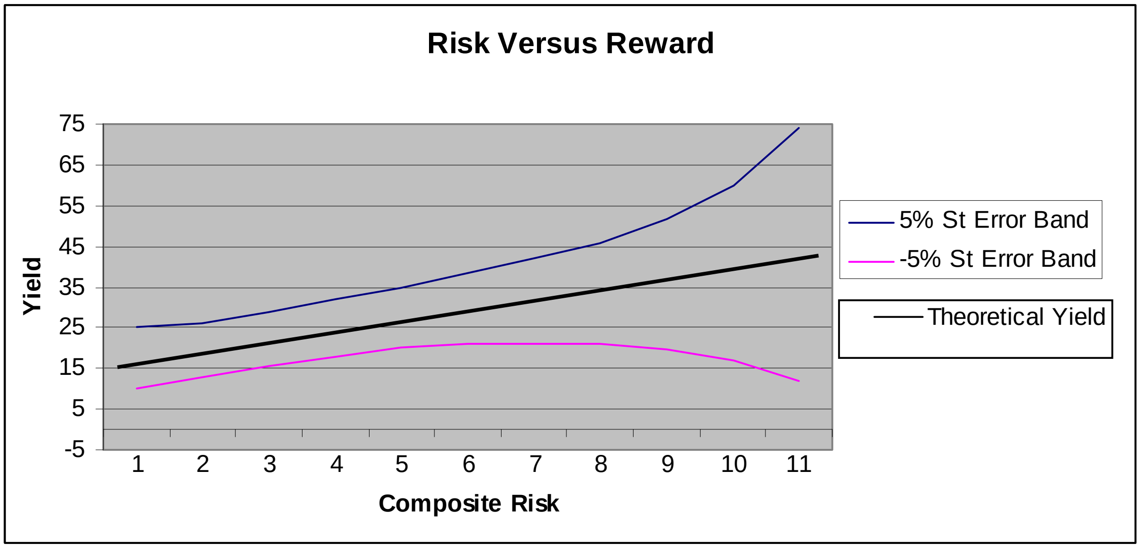
5. Obtaining Directional Signals with RAYD Model

5.1 Method for Obtaining Directional Signals

Conceptually, the fitted regression line is used to derive predicted IY values that are adjusted for the SR, VR, and LR characteristics of each currency. Any currency that deviates substantially from this fitted line will offer yields that are not commensurate with their risks. These currency outliers that offer substantially higher yields relative to their composite risk characteristics can be expected to appreciate, while the currency outliers that offer substantially lower yields relative to their composite risks depreciate. Identifying these currency outliers will allow the model to generate directional signals on future short-run currency movements.

In order to identify outliers, a standard error band is imposed with a 90% confidence interval around the fitted regression line[5]. The positive and negative standard error bands are plotted exponentially and logarithmically (respectively), rather than linearly, in order to represent the different levels of risk in a given sample of currencies. Generally, developing currencies will have higher levels of composite risk relative to developed currencies. For instance, the composite risk of the Argentinean Peso (ARS) is higher than the composite risk of the Euro (EUR) due to a variety of political and economic reasons. Hence, IY on ARS would exceed IY on EUR. But that doesn't imply that investors would purchase ARS exposure. For instance, if ARS fails to provide IY that significantly exceeds the level commensurate with its risks, then investors would instead opt for the safer EUR contract. The point here is that riskier currencies will need to offer an excess risk premium in order to entice investors to hold their currency. Meanwhile, developed currencies are not as likely to experience this restriction of capital flows due to their low risk profile, even in light of smaller actual yields. Given this behavior, a linear band does not adequately reflect the risk premium because it holds constant the level of risk relative to yield. This more likely exponential and logarithmic relationship can be demonstrated graphically as follows:

[5] A 90% confidence interval is chosen because it allows the RAYD Model to capture more outliers when compared to higher confidence intervals.



The currencies that lie on or beyond the standard error band are generating significant directional signals and are considered outliers. Currencies that offer higher yields relative to risk are above the +5% standard error band, and generate an "appreciation" signal. Currencies that offer lower yields relative to risk are below the -5% standard error band, and generate a "depreciation" signal. The standard errors that are adjusted for individual variances are derived from the matrix of the theoretical yield.[6]

After identifying outliers and their respective signals, the following step is to compare the currency signals generated from the theoretical RAYD model against the actual currency movements of the spot exchange rate. In order to compare the theoretical signals against the actual outcome, the theoretical signals are derived from the 90% confidence interval for the

[6] The standard error adjusted for individual variance is derived from the theoretical yield:
Theoretical Yield = $X\beta$
Recall, $Var(X\beta) = X'Var(\beta)X$
Where $X' = Transpose\ of\ X$
It follows that the standard error = $\sqrt{X'Var(\beta)X}$

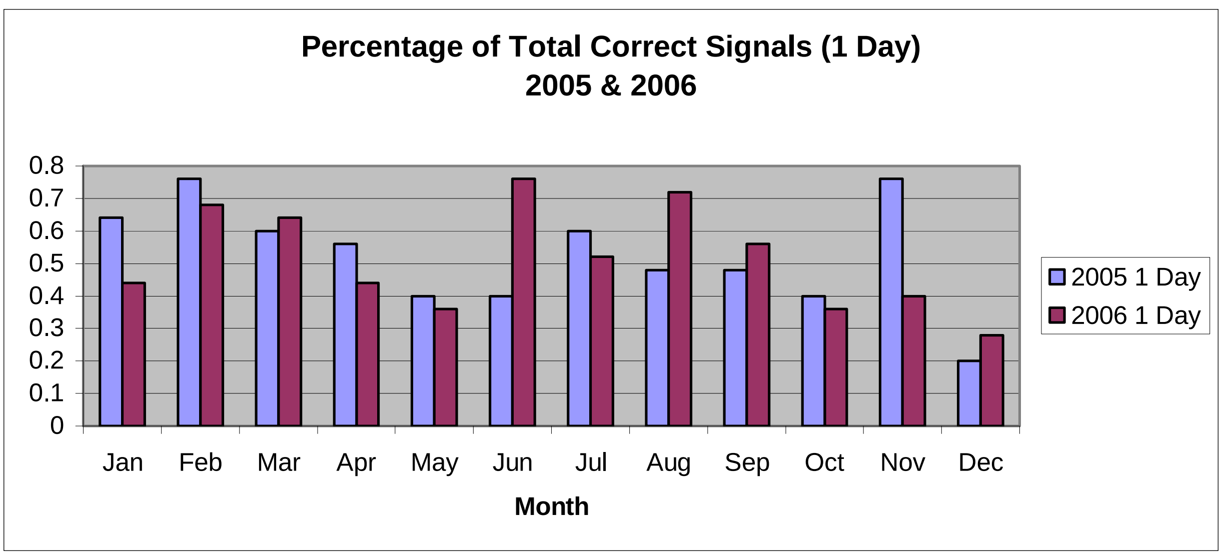
For the purposes of this paper, the standard error function was calculated using the "predict" function in the statistical program, R-Project.

standard error band. If actual yield is above the upper band, then the currency is expected to appreciate relative to the U.S. Dollar (USD). If actual yield is below the lower band, then the currency is expected to depreciate relative to USD (recall USD is the base currency of the RAYD model). It is important to note here that outlier currencies are presumably generating stronger signals compared to the currencies generating weaker signals near the theoretical line. For the purpose of this paper, outlier currencies will be said to offer significant directional signals for future exchange rate movement. Hypothetically, if the RAYD model predicts that the actual yield for ARS is well below the -5% standard error band, then ARS is denoted as an outlier and is said to generate a significant signal for depreciation relative to USD. After obtaining these significant signals, the goal is to compare these against the actual exchange rate movements. Determining the actual direction is done by comparing the exchange rate on the first business day of the month, for which the RAYD model is estimated, to the exchange rate at either the next, fifteenth, or last business day of the month. For example, if the exchange rate between currency ARS and USD (ARS/USD) is 2.5 on the first day of the month and is 2.75 on the last day of the month, then ARS is said to have depreciated against USD (it takes more ARS to buy one unit of USD). In this hypothetical example, the RAYD model correctly predicted ARS to depreciate relative to the USD. In the forthcoming results section, it will be useful to not only calculate the number of significant signals that were correct but to also calculate the total number of correct signals for any given year. If the theoretical model is correct in its directional forecasts more than it is incorrect, then the RAYD model is a decent approximation of future exchange rate directions relative to other models (which will be demonstrated in future sections).

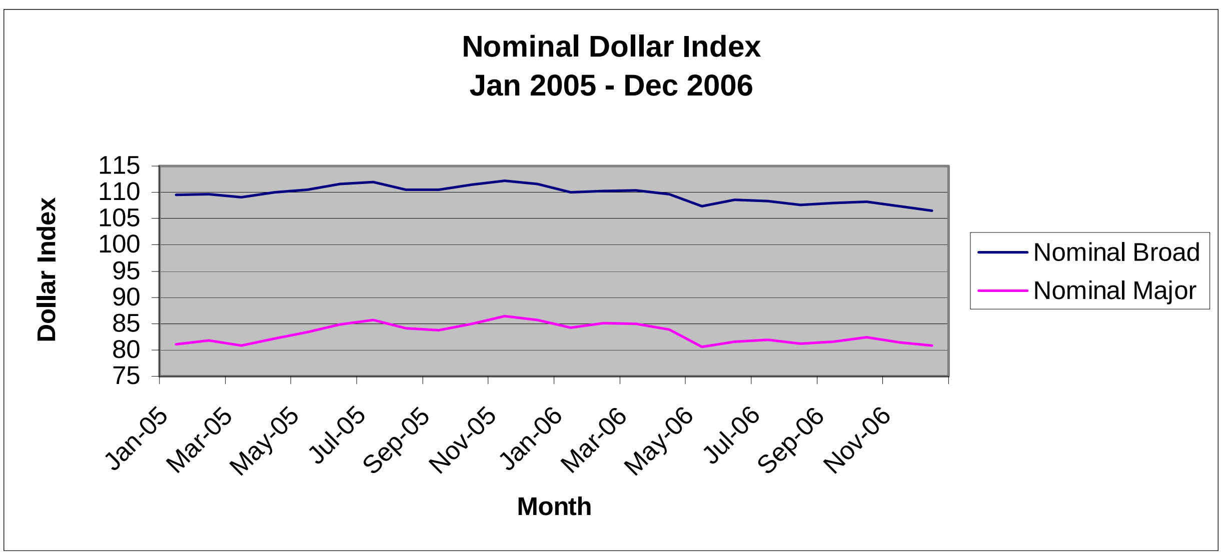
5.2 Directional Signals: General Results & Outliers

Reported Results for 2005 & 2006:

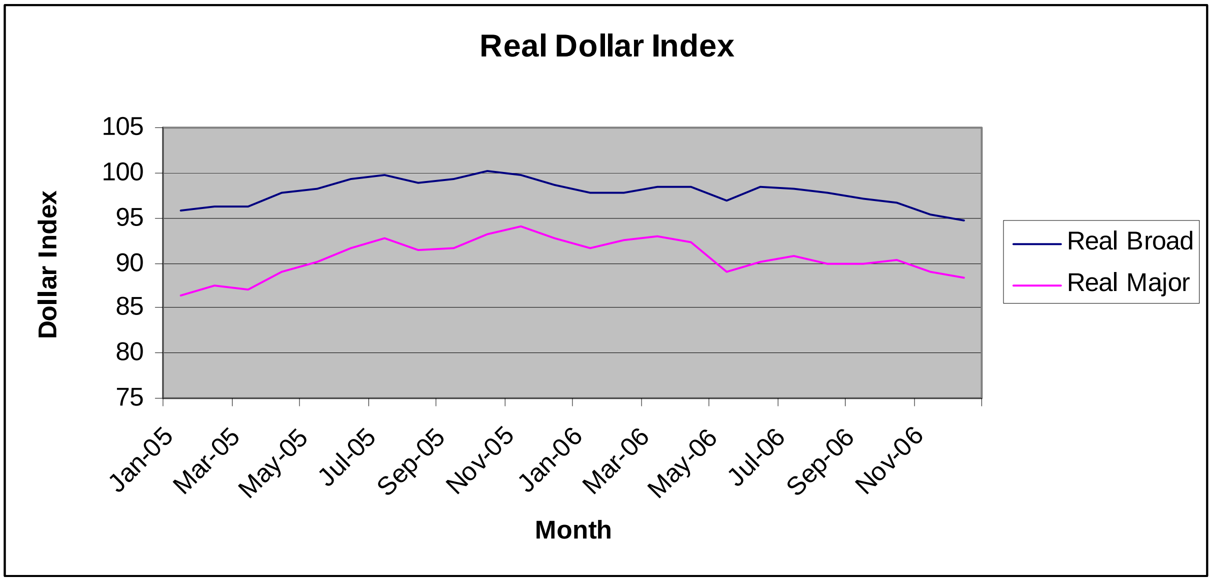
The purpose of this section is to present the general results for 2005 and 2006; however, further discussion of these figures will be addressed in future sections when analyzing different approaches to obtaining directional signals. Using the theoretical signals produced by the RAYD model, the percentage of total signals that are correct is 54.5% (2005) and 51.3% (2006) for a time horizon of 1 day (future exchange rate, e_{t+1}, is observed one day after the initial exchange rate, e_t). Furthermore, the percentages of total outlier signals that are correct are 50.3% (2005) and 55.3% (2006) for a time horizon of 1 day. Although the total signals for 2006 and the outlier signals for 2005 don't appear to be very impressive, they do improve greatly when other considerations are taken into account. This is addressed in future sections. The following graph summarizes these results by breaking the signals up according to month:



Although there are clearly some months that perform better than others, the reasoning behind these results is not entirely clear. However, looking at the second half of 2006, these results are not entirely surprising in viewing the generalized direction of the US dollar. In 2006 the US dollar was strengthening in real and nominal terms relative to both the broad index and the major index of currencies[7]. It is difficult to identify appreciating currencies when the US dollar is undergoing generalized appreciation because the RAYD model uses USD as the base currency. For exchange rate models, it is best to use stable currencies for the base (denominator) currency because the goal is to examine changes in the numerator. It becomes difficult to determine appreciating signals when the base currency is also appreciating. Although the numerator currency may indeed be appreciating relative to many other currencies, the model would not be able to detect this because it is paired against USD. Along the same line of reasoning, it is also difficult to identify depreciating currencies when the US dollar is undergoing generalized depreciation. The graphs below demonstrate the generalized appreciation of the US dollar during the time frame of interest:



[7] Both indices are produced by the Federal Reserve Bank and measure the generalized direction of the USD. The broad index uses a weighted average of the foreign exchange values of the USD against the currency of a large group of major US trading partners. The major index uses a weighted average of the foreign exchange values of the USD against a subset of currencies in the broad index that circulate widely outside the country of issue.



5.2 Directional Signals: Time Horizons & Discrete Thresholds

Although the RAYD model offers a strong explanation of the variation in IY, there are a couple of unknowns determining the successful short-run directional signals. The first unknown is the speed with which observed exchange rates can be expected to change in response to the RAYD signals. Having estimated the model on the first business day of the month, that day's exchange rate provides the starting point. But it is not as obvious to determine the "end" rate, which should be used to determine the exchange rate move. The end rate would depend upon how quickly exchange rates adjust, or in other words, how quickly do arbitrage funds eliminate the excess discernible yield differentials? The second unknown is whether this adjustment process takes the same amount of time for all currencies or whether it is longer for specific currencies (such as developing currencies) compared to others? Due to these unknowns, the validity of all, as well as significant, directional signals obtained from the RAYD model is examined against the actual exchange rate changes 1-day, 15-days, and 30-days following the first business day of the month.

In light of the generalized appreciation of USD in 2006, it will be useful to account for other considerations when obtaining directional signals from the RAYD model. In addition to identifying currency outliers and different adjustment times, the successful hits (i.e. actual currency moves in synchronization with the signals) are also calculated at four discrete thresholds for changes in exchange rates, of 0.5%, 1.0%, 1.5%, and 2.5% and reported separately for each currency as well as for groups of currencies from developing versus developed countries. This is done so for the purpose of filtering out noise that occurs due to small fluctuations in exchange rates. The goal is to determine how many currency signals generated by the RAYD model are correct and are synchronized with sizeable changes in exchange rates.

Reported Results for 2005:

In 2005, by using the theoretical signals of the RAYD model, the percentages of total signals that are correct (regardless of outliers) are 54.5% for 1-day, 50.3% for 15-days, and 52% for 30-day horizons. Furthermore, the percentage of total outlier signals that are correct follow: 50.3% for 1 day, 50.0% for 15 days, 50.7% for 30 days. All results are reported in Appendix. As previously noted, the four discrete thresholds of 0.5%, 1.0%, 1.5%, and 2.5% are used to filter out noise and to focus on sizable changes in actual exchange rates. Using the 0.5% threshold, the actual currency moves over 1-day, 15-day, and 30-day horizons are found to have been consistent with the RAYD signals for all currencies, 64.3%, 51.4%, and 52.1%, respectively. According to these results, the inclusion of the 0.5% threshold improves the number of correct signals generated by the RAYD model for the three time horizons. In addition, rather than using the same threshold for each horizon, other threshold systems are tested. One such system uses 0.5% for 1-day moves, 1.0% for 15-day moves, and 1.5% for 30 day moves. The rationale behind this scheme is to require larger changes in actual exchange rates for longer horizons, otherwise a lower threshold may capture too many noisy signals. Moreover, it seems reasonable to impose higher thresholds on 15-day and 30-day moves because these currencies will have had more time to adjust to exchange rate signals and to the stickiness of prices. In 2005, the optimal threshold level is 0.5% for 1-day, 1.0% for 15-day, and 1.5% for 30-day moves where the percent of total correct signals generated by the RAYD model is 64.3%, 57.4%, and 61.0%, respectively.

Returning back to discussion in the previous section, there are a couple of unknowns determining the successful prediction of short-run directional signals. The first unknown is the speed with which observed exchange rates adjust to signals generated by the RAYD model. Essentially, this unknown would measure how quickly arbitrage funds eliminate excess discernible yield differentials. In the framework of this paper, the strategy for handling this unknown variable is to determine the optimal time horizon for the given year. For the purpose of this investigation, the optimal time horizon is the one that generates the highest percentage of total correct signals for the whole year from the RAYD model. However, this paper also determines the optimal time horizon for the signals derived by outliers, by the total discrete threshold levels, and by outliers and the total discrete threshold levels together[8]. When considering the total signals for the whole year without respect to outliers or discrete threshold levels, the 1-day horizon generates the highest percentage of correct signals. The percentages of total correct signals are 54.5%, 50.3%, and 52.0% for 1-day, 15-day, and 30-day horizons, respectively. For the total signals with respect to the outliers, the 30-day horizon only performed

[8] The total signals for the four discrete threshold levels is calculated as the following: for each time horizon, the total number of correct signals generated from the different threshold levels is summed and is then divided by the total number of signals generated from the different threshold levels.

slightly better than both the 1-day horizon and the 15-day horizon. The percentages of correct signals are 50.4%, 50.0%, and 50.7% for the 1-day, 15-day, and 30-day horizon, respectively. When considering the total signals with respect to all four discrete threshold levels, the 1-day horizon generates the highest percentage of correct signals. The percentages of total correct signals are 62.9%, 54.2%, and 57.7% for 1-day, 15-day, and 30-day horizons, respectively. The percentages of total correct signals for each discrete threshold level are reported in the Appendix. For the total signals with respect to both outliers and the four discrete threshold levels, the 30-day time horizon generates the highest percentage of correct signals. The percentages of correct signals are 46.6%, 54.2%, and 57.7% for the 1-day, 15-day, and 30-day horizon, respectively. Given these results, it appears that when outliers are not considered, the 1-day horizon is optimal. However, if we are interested in focusing on currencies that produce sizable changes in actual exchange rates, then the 30-day horizon is optimal. Furthermore, these results indicate that when 30-day moves in exchange rates are sizable, or in other words, when the noise is filtered out, that the signals for outliers actually improve. These results may indicate that the speed with which observed exchange rates respond to the RAYD signals is slower for outlier currencies. This is not completely surprising since the outliers generated by the RAYD model tend to be currencies from developing countries; these currencies will generally have persisting yield-differentials due to limited access to arbitrage funds.

Reported Results for 2006:

The analysis of the reported results for 2006 follows in the same vein as the reported results for 2005, and therefore, will not require as much elaboration. Furthermore, all results are reported in the appendix. In 2006 the percentages of total signals that are correct (regardless of outliers) are 51.3% for 1-day, 53.0% for 15-day, and 51.3% for 30-day horizons. Furthermore, the percentage of total outlier signals that are correct follow: 55.3% for 1-day, 57.2% for 15-day, 52.4% for 30-day horizons. Using the 0.5% threshold, the actual currency moves over 1-day, 15-day, and 30-day horizons are found to have been consistent with the RAYD signals for all currencies, 53.1%, 57.1%, and 61.0%, respectively. According to these results, the inclusion of the outliers and of the 0.5% threshold improves the number of correct signals generated by the RAYD model for the three time horizons. For 2006 the optimal threshold level is 0.5% for every time horizon where the percentages of total correct signals generated by the RAYD model are 53.1%, 57.1%, and 61.0% for 1-day, 15-day, and 30-day moves, respectively.

Following the same strategy in 2005 for determining the optimal time horizon, the 15-day horizon generates the highest percentage of correct signals when considering the total signals without respect to outliers or discrete threshold levels. The percentages of total correct signals are 51.3%, 53.0%, and 51.3% for 1-day, 15-day, and 30-day horizons, respectively. For the total signals with respect to the outliers, the 15-day horizon generated the highest percentage of correct signals. Recall that the percentages of correct signals are 55.3%, 57.2%, and 52.4% for the 1-day, 15-day, and 30-day horizon, respectively. When considering the total signals with respect to all four discrete threshold levels, the 15-day horizon generates the highest percentage of correct signals. The percentages of total correct signals are 52.3%, 53.9%, and 48.4% for 1-day, 15-day, and 30-day horizons, respectively. The percentages of total correct signals for each discrete threshold level are reported in the Appendix. For the total signals with respect to both outliers and the four discrete threshold levels, the 30-day time horizon generates the highest percentage of correct signals. The percentages of correct signals are 52.9%, 57.3%, and 59.1% for the 1-day, 15-day, and 30-day horizon, respectively. As previously mentioned, these threshold values eliminate the noise caused by fluctuations in exchange rates by considering signals that are outliers and by ignoring currencies that do not experience a sizable change in the actual exchange rates. Evaluating the optimal time horizon with respect to both the outliers and the threshold level is probably the best indicator for the speed at which exchange rates adjust to signals generated by the RAYD model. Including these factors are important because they filter noise and focus on exchange rates that are expected to move. Because the results indicate similar conclusions for both years, the details will not again be elaborated on for 2006. However, an illustrative example will now be provided to demonstrate this process empirically.

In March 2006, the RAYD model forecasted that the Japanese Yen (JPY) would depreciate. Furthermore, the theoretical signal indicated that JPY is an outlier. The discrete threshold set for this time horizon is .5%. On the first business day of March, JPY was valued at 116.09 (Yen per Dollar), and at the end of the month (30 days later) JPY depreciated relative to USD at the value of 117.78 (Yen per Dollar). After comparing the exchange rate on the first and last business day of the month (30 days), the percent change is sizable at roughly 1.45%. Essentially, having a sizable change threshold for the exchange rate moves strengthens the argument that this theoretical signal is not validated due to chance alone. This issue will be further addressed later.

5.3 Directional Signals: Developing versus Developed

Although the previous section presented a useful approach for analyzing the signals generated by the RAYD model, it did not differentiate between developed and developing countries. Introducing this new factor offers a better understanding of how currency markets actually work.

Reported Results 2005:

As previously mentioned, this section is concerned with taking the earlier analysis of the theoretical signals generated by the RAYD model while introducing another important characteristic. For 2005, the percentages of total correct signals for developing currencies are 55%, 49.5%, and 51% for 1-day, 15-day, and 30-day horizons, respectively. The percentages of total correct signals for developed currencies are 54.2%, 52.2%, and 54.2% for 1-day, 15-day, and 30-day horizons, respectively. Furthermore, the percentages of total correct outlier signals are 52.0%, 48.0%, and 48.0% for developing currencies and are 48%, 54%, and 56% for developed countries, both for 1-day, 15-day, and 30-day horizons, respectively. The results for the percentage of correct outliers for developed currencies are surprising—one would expect that developed currencies would generate better signals with 1-day rather than with 30-day moves time horizons given the swiftness of arbitrage, the access to arbitrage funds, and the overall market liquidity. There are a few reasons to explain this surprising outcome. First, perhaps one day is far too long for these signals and instead, the adjustment occurs instantaneously. But this description does not explain why the 30-day horizon works better. Second, perhaps the relatively low yields have deterred investors from holding developed currencies, especially given the availability of high risk-high yield currencies and bonds. Finally, the explanation may be in the results obtained for the sizable thresholds. The strategy remains the same for determining the optimal time horizon, however the conclusions drawn from these results may help explain how adjustment times for exchange rates differ across countries in response to the signals generated by the RAYD model—this was the second unknown variable discussed in the previous section.

Recall that for developing currencies, 1-day is the optimal time horizon while for developed currencies both 1-day and 30-day horizons worked equally as well, so the results are ambiguous here. Also recall that for outliers, the 1-day horizon is optimal for developing currencies and the 30-day horizon is optimal for developed currencies. When considering the total signals with respect to all four discrete threshold levels, the 30-day horizon and the 1-day horizon are optimal for developing and developed currencies, respectively. For developing currencies, the percentage of total correct signals with respect to the discrete threshold level is 79.4% for the 30-day horizon. For developed currencies, this figure is 85.9% for the 1-day horizon. It should be noted here that the inclusion of the discrete threshold improved signals dramatically, perhaps by eliminating noise and focusing instead on sizeable exchange rate movements. For the total signals with respect to both outliers and the four discrete threshold levels, the 15-day horizon and 1-day horizon are optimal for developing and developed currencies, respectively. Including both the outliers and the discrete threshold level, the percentage of total correct signals is 53.8% and 65.8% for developing and developed currencies, respectively. These results agree with our *a priori* expectations that developing currencies will generate better signals with longer time horizons (which is mostly due to the persistence of yield-differentials) while developed currencies will generate better signals with shorter time horizons (which is mostly due to the risk-differential being immediately arbitraged away). It is interesting to note however, that the 30-day horizon is not the optimal time horizon for developing currencies and that the optimal horizon is instead the 15-day horizon. However, the percentages of correct signals generated from both horizons were relatively close in value, with 53.8% correct for the 15-day horizon and 52.7% correct for the 30-day horizon. In general, the number of correct signals generated by the RAYD model for both developing and developed currencies improved with a discrete threshold level of 1.0%, 1.5%, 2.5% for 1-day, 15-day, 30-day horizons, respectively. In other words, both developing and developed currencies have improved signals when the threshold level is progressively larger for each time horizon, highlighting the importance of filtering noise. The overall percentage of correct signals at the discrete threshold values is 66.9% and 58.6% for developing and developed currencies, respectively.[9]

Reported Results 2006:

Continuing the same analysis from 2005, the percentages of total correct signals for developing currencies are 55.8%, 54.4%, and 54.4% for 1-day, 15-day, and 30-day horizons, respectively. The percentages of total correct signals for developed currencies are 51.0%, 51.0%, and 44.8% for 1-day, 15-day, and 30-day horizons, respectively. Furthermore, the percentages of total correct outlier signals are 56.9%, 58.0%, and 54.9% for developing currencies and are 53.6%, 55.4%, and 46.4% for developed countries, both for 1-day, 15-day, and 30-day horizons, respectively. For both developing and developed currencies, when using the percentage of correct signals with respect to the outliers improved results for every horizon. Again, this strengthens the argument that the signals generated from the RAYD model are not validated due to chance alone. After examining the above data, for developing currencies, the 1-day horizon is optimal for the percentage of total correct signals while the 15-day horizon is optimal for the percentage of total correct outlier signals. For developed currencies, the 1-day and 15-day horizons are generating the same number of correct signals, so it is unclear at this point to determine the optimal horizon. For developed currencies, the 15-day horizon is optimal for the percentage of total correct outlier signals, which again will be investigated using the same approach as 2005.

Once again, the goal here is explore whether the adjustment speed for exchange rates, in response to the signals generated by the RAYD model, is the same across different currencies

[9] The overall percentage of correct signals for a given vector of discrete values is calculated by taking the sum of the number of correct signals generated in that threshold (for all horizons) divided by the sum of the number of total signals generated in that threshold (for all horizons). Essentially, this is the average number of correct signals for the given threshold over time.

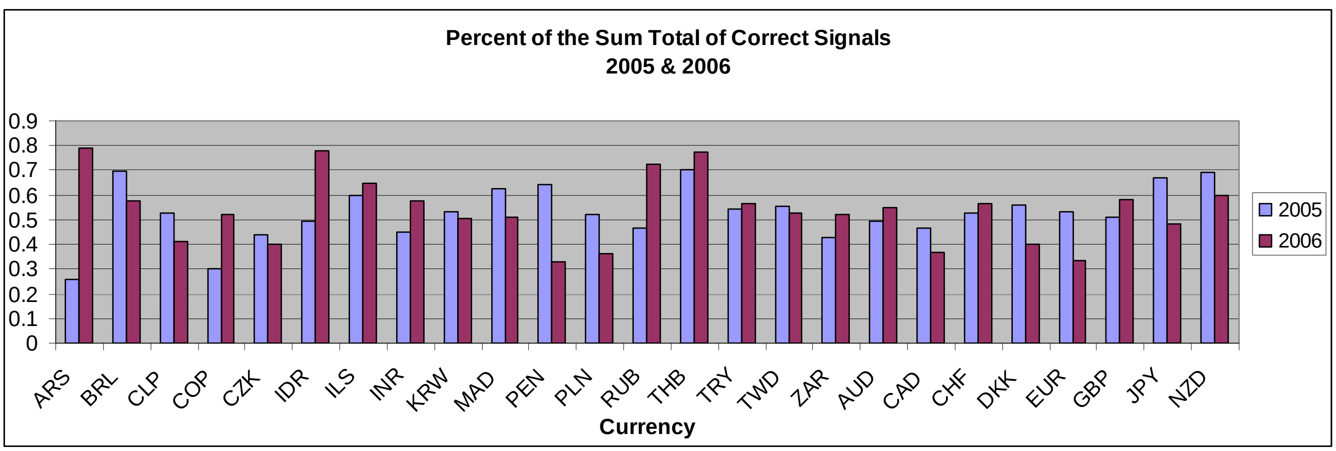
(recall that this is the second unknown variable). When considering the total signals with respect to all four discrete threshold levels, the 1-day horizon and the 15-day horizon is optimal for developing and developed currencies, respectively. For developing currencies, the percentage of total correct signals with respect to the discrete threshold level is 56.6% for the 1-day horizon. For developed currencies, this figure is 58.6% for the 15-day horizon. For the total signals with respect to both the outliers and the four discrete threshold levels, the 15-day horizon is optimal for both developing and developed currencies. Including both the outliers and the discrete threshold level, the percentage of total correct signals is 56.6% and 58.5% for developing and developed currencies, respectively. At first, it is somewhat surprising to find that the developed currencies had the same optimal time horizon as developing currencies. But recall that the USD was undergoing generalized appreciation during this time period, which has a tendency to mask appreciation signals in the RAYD model since it functions as the base currency. It then becomes less surprising that the adjustment time is longer for sizable moves in developed currencies.

. In general, the number of correct signals generated by the RAYD model for developed currencies improved with a discrete threshold level of 1.0%, 1.5%, 2.5% for 1-day, 15-day, and 30-day horizons, respectively. The percentage of correct signals for this discrete threshold vector is 51.6% for developing currencies. Developing countries however, improved their number of correct signals by maintaining a constant discrete threshold of 0.5% across all three horizons. The percentage of correct signals for this discrete threshold is 53.9% for developing currencies. These results may indicate that sizable exchange rate moves for developed currencies had more noise on average, which is not surprising given the economic climate in 2006.

5.4 Directional Signals: Individual Currencies

By using the same analysis presented in the previous sections but aggregating data by currency, this paper will now focus on the signals generated for individual currencies and then attempt to determine how quickly adjustments take place over time for individual currencies. Illustrative examples will be provided in this section rather than reporting results for every currency—all signals and other relevant data are reported in the Appendix.

In general, the RAYD model performs slightly better in 2005 than it does in 2006—the percentage of the sum total of correct signals generated for each currency in 2005 exceeded the same figure for 2006.[10] It is important to note however, that this result is marginal—13 of the 25 individual currencies performed better in 2005 compared to 12 in 2006. Furthermore, given the sum total of signals for each currency, 16 of 25 currencies have at least 51.3% of their signals validating actual exchange rate moves. Figure 5.4.1 plots the information presented above, where the vertical axis measures the percentage of the sum total of correct signals for both 2005 and 2006 for currency:



[10] The sum total number of correct signals includes the following: total number of correct signals, total number of correct outliers, total number of correct signals given a sizable change in the exchange rate, and the total number of correct signals given if a currency is both an outlier and experiences a sizable change in the exchange rate.

After determining the percentage of the sum total of correct signals over both years, the Thai Baht (THB), Israeli Shekel (ILS), Indonesian Rupiah (IDR), Brazilian Real (BRL), and New Zealand Dollar (NZD) are found to generate many more correct signals than compared to other currencies. For instance, 73.8% of the signals generated for THB are correct, 64.6% for ILS are correct, 63.7% for IDR are correct, 63.6% for BRL are correct, and 62.4% for NZD are correct. One explanation for these currencies' impressive performance may relate to their status as outliers. More often than not, all five currencies tend to be outliers. When these currencies are outliers, they are often extreme values. The resulting large gap between the extreme outliers and the standard error band may indicate a "stronger" signal relative to currencies falling closer to the standard error band. For example, the fitted value for BRL in April (2005) is 7.9 with a 90% confidence interval of [5.097, 10.695] for the standard error band. The actual yield for BRL is 20.1, which is 12.2 units above the fitted value. Furthermore, the actual yield for BRL is 9.4 units above the upper-bound of the standard error band. Given that the residual standard error for this regression is 5.31, BRL is definitely a significant outlier. But does the exchange rate agree with the outcome this analysis? It does, in fact, agree because the signal generated for BRL in April (2005) is correct for 1-day, 15-day, and 30-day horizons. The signal for BRL is also correct for each time horizon given a sizable change in the observed exchange rate (thresholds ranging from 0.5% to 2.5%). While this illustrative example does not theoretically establish the link between excess (or deficient) yields and the short-run exchange rate moves, it does provide empirical support of this claim. In fact, there are other examples produced by the RAYD model that also provide empirical support for this claim.[11]

[11] In order to determine the relationship between excess yields and short-run exchange rate movements, a Pearson's Product-Moment Correlation test is employed. The ratio between the initial exchange rate, e_t and the realized future exchange rate, e_{t+1} is calculated for each currency as e_t / e_{t+1}. The ratio is calculated in this manner in order to express appreciation as an increase in this ratio. Then, this ratio is compared to the residuals for each currency by

For now, this paper will turn to the questions posed earlier about the exchange rate adjustment process, specifically, whether adjustments occur at different times based on the individual currency. While this appears to be true in some cases, it is not necessarily true in all instances—for the 25 currencies examined between 2005 and 2006, 18 (72%) currencies have at least a generalized time horizon. Furthermore, 5 of these 18 currencies are found to adjust within the same time horizon in both 2005 and 2006. For the purposes of this paper, the generalized time horizons will not be further examined because of the many unknowns involved. As indicated, however, at least 20% of the currencies have the same time horizon for adjustment, which will now be further discussed.

The individual currencies are considered to have the same time horizon for adjustment if the optimal time horizon in 2005 is also the optimal time horizon in 2006. The "optimal" level is where total number of correct signals is maximized. The five currencies that meet these requirements are the Chilean Peso (CLP), Czech Koruna (CZK), Indonesian Rupiah (IDR), Russian Ruble (RUB), and the New Taiwan Dollar (TWD). The time horizons for adjustment are 1-day for CLP and IDR, 15-day for CZK, and 30-day for RUB and TWD. The remaining question is whether there is a common underlying difference between the currencies in each separate time horizon. After further evaluation of the data, a potential explanation arises from the relationship between the standard error band and the fitted implied yield values. One should expect that the currencies with higher standard error terms relative to their fitted implied yield values are also going to have higher variance, which may indicate higher levels of composite

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using Pearson's Correlation test. The relationship between the residuals and theoretical signals is as follows: a positive residual value indicates an appreciation signal, and vice versa. The results for 2005 indicate that the correlation between the residuals and exchange rate ratio is >0 with a 95% confidence interval of [.00569, 1.00000], where t =1.7471 and p = .04084—therefore, there is a positive correlation between the residuals and the exchange rate ratio. In other words, a higher residual corresponds to an appreciation in the exchange rate. The same result is found for 2006 with a 95% confidence interval of [.01313, 1.00000], where t = 1.8737, and where p-value = .03099.

risk. If this is indeed the case, then the access to arbitrage funds will be limited for currencies with relatively high standard error because the potential risk is greater due to the larger variance (more volatile signals). As a result, the adjustment time is expected to be greater for currencies with higher standard error relative to their fitted implied yield values. This is, indeed, confirmed by data. The standard error to fitted value ratio is higher for currencies with a 30-day time horizon in both 2005 and 2006. Furthermore, it is also true that currencies with a 15-day time horizon have higher ratios compared to currencies with a 1-day time horizon. For example, in February (2005), the standard error to implied yield ratios are as follows: 0.766 for CLP, 0.821 for IDR, 1.595 for CZK, 1.876 for TWD, and -7.127 for RUB. Recall that the optimal time horizons for CLP, IDR, CZK, TWD, and RUB are 1-day, 1-day, 15-day, 30-day, and 30-day, respectively. It is important to note that these results did agree with the expectation that higher ratios between standard errors to implied yields tend to have longer time horizons due to their risky nature. These results indicate that the ratio between standard error and implied yields might help explain why certain currencies perform better at different time horizons. Another explanation for why certain currencies perform better at different time horizons is simply that a currency's status as an outlier one year need not imply that it is an outlier the following year. In other words, there is no reason to expect yield differentials to persist in the long-run, as they will most likely be arbitraged away. However, there are currencies that are outliers more frequently than others—these tend to be the riskier currencies. One last alternative explanation for why certain currencies perform better at different time horizons is that exchange rates are affected by changes in global risk appetite. If global risk appetite is high, then investors are more willing to hold riskier currencies; if global risk appetite is low, then investors are generally less willing to hold riskier currencies. Global risk appetite is an exogenous variable that can impact exchange rate trends for individual currencies.

5.5 Potential Problems

As previously discussed, there are some potential issues that pose a problem to the RAYD model. The first problem arises with the measurement error found in the LR variable, which is due to the reporting of the bid-ask spread. The bid-ask spread is reported for the last transaction of each day, rather than as an average for all transactions of the day. This erodes the link between liquidity risk and the bid-ask spread because the latter is skewed by the size of the last transaction of the day and does not adequately reflect the average bid-ask spread. But little can be done for a measurement error because data on averages of the bid-ask differential is proprietary and not in the public domain. Although this can possibly skew the data, it does so by underestimating the effects of LR and weakening the variation explained by the three independent risk variables. Given that the adjusted R^2 values in some cases are near 80%, this underestimation of the impact of LR on IY is not of grave concern.

6. Model Comparison: Random Walk

As it has been discussed in this paper, the random walk model has been challenged for its failure to account for parameter instability. In other words, it did not consider the unstable relationship between exchange rates and country fundamentals over time. Furthermore, the random walk model was tested against economic models that may have had stochastic movements in the true underlying variables. Examples of this problem include abrupt changes in trade patterns or changes in policy regimes. Also, there are concerns that these economic models had issues with misspecification—some do not account for UIP while others do not measure inflation expectations well. Unlike the random walk model, the RAYD model does not need to adjust for parameter instability over time due to its use of daily market variables (with the exception of SR). Furthermore, there is no simultaneity involved with the RAYD model because the independent variables expressed on the RHS are already known. However, the focus of this paper is to address whether the RAYD model outperforms the random walk model for obtaining directional signals on exchange rates in the short-run, which is discussed in the forthcoming section.

6.1 Directional Signals: Random Walk or RAYD model?

Although the pioneering work of Meese & Rogoff (1983) used the forecasted error term to compare the performance of the random walk model against the structural economic models, the goal of this paper is to obtain directional signals rather than to forecast future exchange rate levels. As such, the method for testing the RAYD model against the random walk model is to compare the signals generated from each model. Accordingly, the random walk model is expected to generate correct signals for 50% of the total signals for each year. Therefore, if the RAYD model generates correct signals for more than 50% of the total signals, then it is considered an improvement over the random walk model. The cumulative probability is then calculated for the total number of correct signals in order to determine whether the random walk model correctly predicts as many signals as the RAYD model[12]. The NORMDIST function returns the cumulative probability that the observed "X" (the number of correct signals divided by the number of total signals) takes on values less than or equal to the specified mean (0.5 in

[12] The cumulative probability is calculated using Excel's "NORMDIST" function. This test is appropriate since the error terms are normally distributed. Furthermore, the Shapiro-Wilk test for multivariate normality does not reject the null hypothesis that the data is normally distributed for both 2005 and 2006 data. Using the "mshapiro.test" function in R-Project, for 2005, the test statistic is W = 0.9704 and the p-value = 0.05707. For 2006, the test statistic W = 0.8493 and the p-value = 0.1211.

In addition to the above explanation, using Excel's "NORMDIST" function is appropriate because it's assumed that the random walk model's results follow a binomial distribution with p = 50.00%, and the sample size is large enough that the binomial distribution can be very closely approximated by the normal distribution.

this case). In other words, this function returns the probability that the observed "X" would be observed if the random walk model were correct. Essentially, it finds the probability that “X” is above 0.50. The normal cumulative probability is found with 0.50 as the specified mean since the goal is to test the RAYD model against the random walk model.[13] Furthermore, if the cumulative probability is above 0.5, then the RAYD model is generating correct signals more often than incorrect signals.[14]

The following table summarizes the results of the directional signals obtained from the RAYD model in 2005:

[13] The specified mean for the random walk model is 0.50 because it is a simple Gaussian (binomial) distribution.
[14] This result is not surprising given that the percentage of total correct signals over total signals is often above 50.00%.

Total for Year 2005			
	1 Day	**15 Day**	**30 Day**
Total Signals Correct	157	151	156
Total Signals	288	300	300
Percent Correct	**0.55**	**0.50**	**0.52**
Norm Dist	**0.94**	**0.55**	**0.76**
Total Outliers Correct	71	74	75
Total Outliers	141	148	148
Percent Correct	0.50	0.50	0.51
Norm Dist	**0.53**	**0.50**	**0.57**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**0.50%**	**0.50%**
Total Signals & Sig Change Correct	54	107	124
Total Sig Change	**84**	**208**	**238**
Percent Correct	0.64	0.51	0.52
Norm Dist	**0.99**	**0.66**	**0.74**
Number of Signal Correct (Outlier and has a Significant Change)	23	53	60
Total outlier & Sig Change	40	104	115
Percent Correct	0.58	0.51	0.52
Norm Dist	**0.83**	**0.58**	**0.68**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**1.00%**	**1.50%**
Total Signals & Sig Change Correct	54	74	81
Total Sig Change	84	129	133
Percent Correct	**0.64**	**0.57**	**0.61**
Norm Dist	**0.99**	**0.95**	**0.99**
Number of Signal Correct (Outlier and has a Significant Change)	23	36	35
Total outlier & Sig Change	54	64	58
Percent Correct	**0.43**	**0.56**	**0.60**
Norm Dist	**0.14**	**0.84**	**0.94**
Significant Change (Between E(t) and E(t+1)):	**1%**	**1.50%**	**2.50%**
Signals & Sig Change Correct	23	54	42
Total Sig Change	40	92	62
Percent Correct	**0.58**	**0.59**	**0.68**
Norm Dist	**0.83**	**0.95**	**0.99**
Number of Signal Correct (Outlier and has a Significant Change)	23	27	21
Total outlier & Sig Change	54	46	28
Percent Correct	**0.43**	**0.59**	**0.75**
Norm Dist	**0.14**	**0.88**	**0.99**

The above table provides compelling evidence against the null hypothesis, which states that exchange rates follow a random walk pattern. With 95% confidence, the null hypothesis is rejected seven times out of the twenty-four NORMDIST tests. In fact, there are five instances where the NORMDIST result is above 0.99, which implies that the random walk model can only generate the same number of correct signals as the RAYD model <1% of the time. For a 90% confidence level, the null hypothesis is rejected in nine instances in the NORMDIST results. According to the table, the RAYD model generates correct signals more often than incorrect signals—in fact, out of the twenty-four NORMDIST tests, there are twenty-one instances where the test results exceed 50%. In other words, 87.5% of the NORMDIST tests indicate that more than 50% of total directional signals were correctly generated by the RAYD model. Interestingly, although not surprising, the RAYD model performed best when discrete thresholds were introduced. The inclusion of discrete thresholds allows the RAYD model to target signals that are synchronized with sizable movements in exchange rates rather than including the noise produced by relatively small exchange rate adjustments. Furthermore, the NORMDIST results indicate that the RAYD model performed best when imposing a discrete threshold of 0.5% (1-day), 1.0% (15-days), and 1.5% (30-days). Overall, the RAYD model generated a higher number of correct signals compared to the random walk model—as mentioned earlier, the RAYD model frequently had more than 50% of its total signals generating correct forecasts. Furthermore, the null hypothesis is rejected with a 95% confidence level in seven NORMDIST results. For a 90% confidence level, the null hypothesis is rejected in nine instances for the NORMDIST results. The following table summarizes the results of the directional signals obtained from the RAYD model in 2006:

Total for Year 2006			
	1 Day	**15 Day**	**30 Day**
Total Signals Correct	154	165	154
Total Signals	300	300	300
Percent Correct	**0.51**	**0.53**	**0.51**
Norm Dist	**0.68**	**0.96**	**0.68**
Total Outliers Correct	99	107	98
Total Outliers	179	187	187
Percent Correct	0.55	0.57	0.52
Norm Dist	**0.92**	**0.98**	**0.74**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**0.50%**	**0.50%**
Total Signals & Sig Change Correct	119	113	118
Total Sig Change	**229**	**216**	**234**
Percent Correct	0.52	0.52	0.50
Norm Dist	**0.72**	**0.75**	**0.55**
Number of Signal Correct (Outlier and has a Significant Change)	77	76	72
Total outlier & Sig Change	145	133	118
Percent Correct	0.53	0.57	0.61
Norm Dist	**0.77**	**0.95**	**0.99**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**1.00%**	**1.50%**
Total Signals & Sig Change Correct	119	88	60
Total Sig Change	229	159	128
Percent Correct	**0.52**	**0.55**	**0.47**
Norm Dist	**0.72**	**0.91**	**0.24**
Number of Signal Correct (Outlier and has a Significant Change)	77	55	34
Total outlier & Sig Change	145	93	60
Percent Correct	**0.53**	**0.59**	**0.57**
Norm Dist	**0.77**	**0.96**	**0.85**
Significant Change (Between E(t) and E(t+1)):	**1%**	**1.50%**	**2.50%**
Signals & Sig Change Correct	93	56	35
Total Sig Change	175	101	78
Percent Correct	**0.53**	**0.55**	**0.45**
Norm Dist	**0.80**	**0.86**	**0.18**
Number of Signal Correct (Outlier and has a Significant Change)	59	33	20
Total outlier & Sig Change	112	60	35
Percent Correct	**0.53**	**0.55**	**0.57**
Norm Dist	**0.71**	**0.78**	**0.80**

Similar to the results produced in 2005, the table above also provides compelling evidence against the null hypothesis that exchange rates are random walks. With 95% confidence, the null hypothesis is rejected five times out of the twenty-four NORMDIST tests. Furthermore, for a 90% confidence level, the null hypothesis is rejected seven times out of the twenty-four NORMDIST tests. According to the table, the RAYD model generates correct signals more often than incorrect signals—in fact, out of the twenty-four NORMDIST tests, there are twenty-two instances where the test results exceed 50%. Specifically, 91.6% of the NORMDIST tests indicate that more than 50% of total directional signals were correctly generated by the RAYD model. While this particular figure was slightly better than the same result from 2005, the null hypothesis is rejected more often for 2005. Introducing outliers to the analysis of signals definitely improved the RAYD model's performance in 2006 as well. For example, the NORMDIST test for the one-day horizon is 0.6779 for the total correct signals and is to .9222 for outliers. Unlike the results from 2005, the RAYD model performed best when discrete thresholds were kept constant at 0.5% for each time horizon. Overall, 91.6% of the NORMDIST tests indicate that the RAYD model forecasted more than 50% of its currency moves correctly—which strengthens the evidence against the null hypothesis that exchange rates are random walks. Thus, the RAYD model outperformed the random walk model in terms of obtaining correct directional signals on currencies. Furthermore, the removal of noise from small fluctuations in the short-run exchange rates improves the performance of the RAYD model. This further strengthens the conclusion that the RAYD model is superior to random walk in generating directional signals for currency movements in the short-run.

7. Concluding Remarks

Throughout this paper, the RAYD model has demonstrated its capacity to obtain directional signals on short-run exchange rate movements. Furthermore, the RAYD model outperformed the random walk model, especially when examining the NORMDIST values. In addition to testing the total number of correct signals generated by RAYD model against those generated by the random walk model, this paper looked at both the outliers and the different threshold levels for movements in actual exchange rates. Including one or both of these factors yielded a higher percentage of correct signals for the RAYD model in most cases, which indicates the importance of focusing upon sizable changes as well as filtering noise. Despite the problems facing the RAYD model, these issues are far less severe than those found in the random walk model for exchange rates. Specifically, the random walk model ignores parameter instability, and as a result, falsely rejects the claim that the fundamentals of a country are unrelated to its exchange rate. As Rossi pointed out, this is not the case. In fact, the fundamentals of a country may indeed influence its exchange rate but this relationship is not stable over time. The RAYD model found a significant relationship between sovereign default risk and implied yields, which is insightful given the positive correlation between changes in IY and movements in exchange rates. In summation, the null hypothesis that exchange rates are random walks is rejected in this paper given the promising results of the RAYD model. Future research should perhaps look into comparing the performance of the RAYD model against other economic models to further determine the best method for obtaining directional signals on exchange rate movements.

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Appendix

A. RAYD Model Currencies

		Numerical Assignment		
Currency Code	Country	Month 1	Month 2	Month 3
ARS	Argentinean Peso	1	28	55
BRL	Brazilian Real	2	29	56
CLP	Chilean Peso	3	30	57
COP	Colombian Peso	4	31	58
CZK	Czech Koruna	5	32	59
INR	Indian Rupee	6	33	60
IDR	Indonesian Rupiah	7	34	61
ILS	Israeli Shekel	8	35	62
MAD	Moroccan Dirham	10	37	64
PEN	Peruvian Sol	11	38	65
PLN	Polish Zloty	12	39	66
RUB	Russian Ruble	13	40	67
ZAR	South African Rand	14	41	68
KRW	South Korean Won	15	42	69
THB	Thai Baht	17	44	71
TRY	Turkish Lira	18	45	72
AUD	Australian Dollar	19	46	73
CAD	Canadian Dollar	20	47	74
DKK	Danish Krone	21	48	75
EUR	Euro	22	49	76
JPY	Japanese Yen	24	51	78
NZD	New Zealand Dollar	25	52	79
CHF	Swiss Franc	26	53	80
GBP	British Pound	27	54	81

B. Regressions

Jan 2005 – Mar 2005

Estimating the Determinants of Implied Yields

Jan 2005 – Mar 2005

Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	3.157 (3.614)
β_2	1.184 (3.594)
β_3	1.688 (3.447)
Liquidity Risk	3547.023 *** (821.649)
Low Risk	2.165 (2.492)
Medium Risk	-2.334 (2.691)
Volatility Risk	-0.022 (0.291)
Observations R-squared Adjusted R-Squared	81 0.4619 0.411

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Apr 2005 – Jun 2005

Estimating the Determinants of Implied Yields April 2005 – June 2005	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	4.253 * (1.9277)
β_2	4.148 * (1.896)
β_3	4.517 * (1.8468)
Liquidity Risk	1703.013 ** (528.376)
Low Risk	-2.016 (1.466)
Medium Risk	-4.112* (1.603)
Volatility Risk	0.182 (0.159)
Observations R-squared	81 0.613 0.577

Adjusted R-Squared	

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Jul 2005 – Sep 2005

Estimating the Determinants of Implied Yields June 2005 – Sep 2005	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.0086 *** (1.116)
β_2	4.6181 *** (1.119)
β_3	3.9299 ** (1.181)
Liquidity Risk	-49.9215 (178.333)
Low Risk	-5.6698 *** (0.916)
Medium Risk	-5.5953 *** (1.038)
Volatility Risk	0.5902 *** (0.111)
Observations R-squared	81 .789 0.769

Adjusted R-Squared	

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Oct 2005 – Dec 2005

Estimating the Determinants of Implied Yields Oct 2005 – Nov 2005	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	4.128 ** (1.440)
β_2	4.366 ** (1.443)
β_3	5.356 *** (1.486)
Liquidity Risk	-36.293 (433.417)
Low Risk	-5.601 *** (1.062)
Medium Risk	-4.929 *** (1.140)
Volatility Risk	0.547 *** (0.125)
Observations	81 0.754

R-squared Adjusted R-Squared	0.731

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Jan 2006 – Mar 2006

Estimating the Determinants of Implied Yields Jan 2006 – Mar 2006	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.524 *** (1.253)
β_2	4.919 *** (1.285)
β_3	5.269 *** (1.249)
Liquidity Risk	658.055 * (273.220)
Low Risk	-4.070 *** (0.904)
Medium Risk	-4.545 *** (1.006)
Volatility Risk	0.338 ** (0.123)
Observations	81 0.803

R-squared Adjusted R-Squared	0.784

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Apr 2006 – Jun 2006

Estimating the Determinants of Implied Yields **April 2005 – June 2005**	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.843 *** (1.093)
β_2	5.813 *** (1.130)
β_3	4.907 *** (1.243)
Liquidity Risk	276.362 (287.561)
Low Risk	-3.820 ***

	(0.849)
Medium Risk	-4.181 *** (0.941)
Volatility Risk	0.294 *** (0.075)
Observations R-squared Adjusted R-Squared	81 0.828 0.810

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Jul 2006 – Sep 2006

Estimating the Determinants of Implied Yields Jul 2005 – Sep 2005	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.161 *** (1.310)
β_2	5.625 *** (1.243)
β_3	5.902 *** (1.177)

Liquidity Risk	-109.298 (196.002)
Low Risk	-4.573 *** (0.886)
Medium Risk	-5.287 *** (1.014)
Volatility Risk	0.450 *** (0.093)
Observations R-squared Adjusted R-Squared	81 0.819 0.801

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Oct 2006 – Dec 2006

Estimating the Determinants of Implied Yields **Oct 2006 – Dec 2006**	
Dependent Variable: Implied Yields	
Independent Variables	**(1)**
β_1	5.787 *** (1.311)
β_2	5.674 *** (1.287)
β_3	5.259 *** (1.358)

Liquidity Risk	364.508 (547.557)
Low Risk	-4.550 *** (0.944)
Medium Risk	-4.536 *** (1.060)
Volatility Risk	0.437 *** (0.120)
Observations	81
R-squared	0.791
Adjusted R-Squared	0.771

Estimated coefficients are interpreted as percentages.
Standard errors are reported in parentheses.
Signif. codes: 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

C. 2005 Analysis

Total for Year 2005			
	1 Day	**15 Day**	**30 Day**
Total Signals Correct	157	151	156
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Total outlier & Sig Change	54	46	28
Percent Correct	**0.43**	**0.59**	**0.75**
Norm Dist	**0.14**	**0.88**	**0.99**

2005 Analysis – Developing v. Developed

2005 Developing v. Developed						
	Developing			**Developed**		
	1 Day	**15 Day**	**30 Day**	**1 Day**	**15 Day**	**30 Day**
Total Signals Correct	105	101	104	52	50	52
Total Signals	192	204	204	96	96	96
Percent Correct	0.55	0.50	0.51	0.54	0.52	0.54
Norm Dist	**0.90**	**0.44**	**0.61**	**0.79**	**0.66**	**0.79**
Total Outliers Correct	47	47	47	24	27	28
Total Outliers	91	98	98	50	50	50
Percent Correct	0.52	0.48	0.48	0.48	0.54	0.56
Norm Dist	**0.62**	**0.34**	**0.34**	**0.39**	**0.71**	**0.80**
Significant Change Level (Between E(t) and E(t+1)):	0.50%	0.50%	0.50%	0.50%	0.50%	0.50%
Total Signals & Sig Change Correct	33	68	79	21	39	45

Total Sig Change	53	132	153	31	76	85
Percent Correct	0.62	0.52	0.52	0.68	0.51	0.53
Norm Dist	**0.96**	**0.64**	**0.66**	**0.98**	**0.59**	**0.71**
Number of Signal Correct (Outlier and has a Significant Change)	12	31	34	11	22	26
Total outlier & Sig Change	23	62	68	17	42	47
Percent Correct	0.52	0.50	0.50	0.65	0.52	0.55
Norm Dist	**0.58**	**0.50**	**0.50**	**0.89**	**0.62**	**0.77**
Significant Change Level (Between E(t) and E(t+1)):	0.50 %	1.00%	1.50%	0.50 %	1.00%	1.50%
Total Signals & Sig Change Correct	33	44	48	21	30	33
Total Sig Change	53	79	82	31	50	51
Percent Correct	0.62	0.56	0.59	0.68	0.60	0.65
Norm Dist	**0.96**	**0.84**	**0.94**	**0.98**	**0.92**	**0.98**
Number of Signal Correct (Outlier and has a Significant Change)	12	19	16	11	17	19
Total outlier & Sig Change	23	35	30	17	29	28
Percent Correct	0.52	0.54	0.53	0.65	0.59	0.68
Norm Dist	**0.58**	**0.69**	**0.64**	**0.89**	**0.82**	**0.97**
Significant Change (Between E(t) and E(t+1)):	1.00 %	1.50%	2.50%	1.00 %	1.50%	2.50%
Signals & Sig Change Correct	13	31	23	7	23	19
Total Sig Change	24	51	39	9	41	23
Percent Correct	0.54	0.61	0.59	0.78	0.56	0.83
Norm Dist	**0.66**	**0.94**	**0.87**	**0.95**	**0.78**	**0.99**
Number of Signal Correct (Outlier and has a Significant Change)	5	14	9	3	13	12
Total outlier & Sig Change	12	22	14	4	24	14
Percent Correct	0.42	0.64	0.64	0.75	0.54	0.86
Norm Dist	**0.28**	**0.90**	**0.86**	**0.84**	**0.66**	**0.99**

D. 2006 Analysis

Total for Year 2006			
	1 Day	**15 Day**	**30 Day**
Total Signals Correct	154	165	154
Total Signals	300	300	300
Percent Correct	**0.51**	**0.53**	**0.51**
Norm Dist	**0.68**	**0.96**	**0.68**

Total Outliers Correct	99	107	98
Total Outliers	179	187	187
Percent Correct	0.55	0.57	0.52
Norm Dist	**0.92**	**0.98**	**0.74**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**0.50%**	**0.50%**
Total Signals & Sig Change Correct	119	113	118
Total Sig Change	**229**	**216**	**234**
Percent Correct	0.52	0.52	0.50
Norm Dist	**0.72**	**0.75**	**0.55**
Number of Signal Correct (Outlier and has a Significant Change)	77	76	72
Total outlier & Sig Change	145	133	118
Percent Correct	0.53	0.57	0.61
Norm Dist	**0.77**	**0.95**	**0.99**
Significant Change Level (Between E(t) and E(t+1)):	**0.50%**	**1.00%**	**1.50%**
Total Signals & Sig Change Correct	119	88	60
Total Sig Change	229	159	128
Percent Correct	**0.52**	**0.55**	**0.47**
Norm Dist	**0.72**	**0.91**	**0.24**
Number of Signal Correct (Outlier and has a Significant Change)	77	55	34
Total outlier & Sig Change	145	93	60
Percent Correct	**0.53**	**0.59**	**0.57**
Norm Dist	**0.77**	**0.96**	**0.85**
Significant Change (Between E(t) and E(t+1)):	**1%**	**1.50%**	**2.50%**
Signals & Sig Change Correct	93	56	35
Total Sig Change	175	101	78
Percent Correct	**0.53**	**0.55**	**0.45**
Norm Dist	**0.80**	**0.86**	**0.18**
Number of Signal Correct (Outlier and has a Significant Change)	59	33	20
Total outlier & Sig Change	112	60	35
Percent Correct	**0.53**	**0.55**	**0.57**
Norm Dist	**0.71**	**0.78**	**0.80**

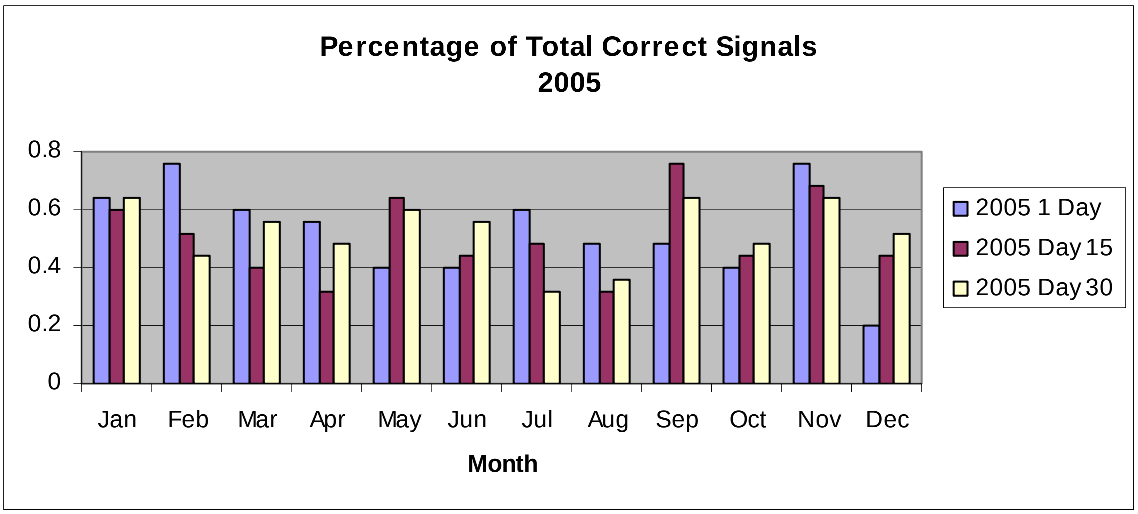
2006 Analysis – Developing v. Developed

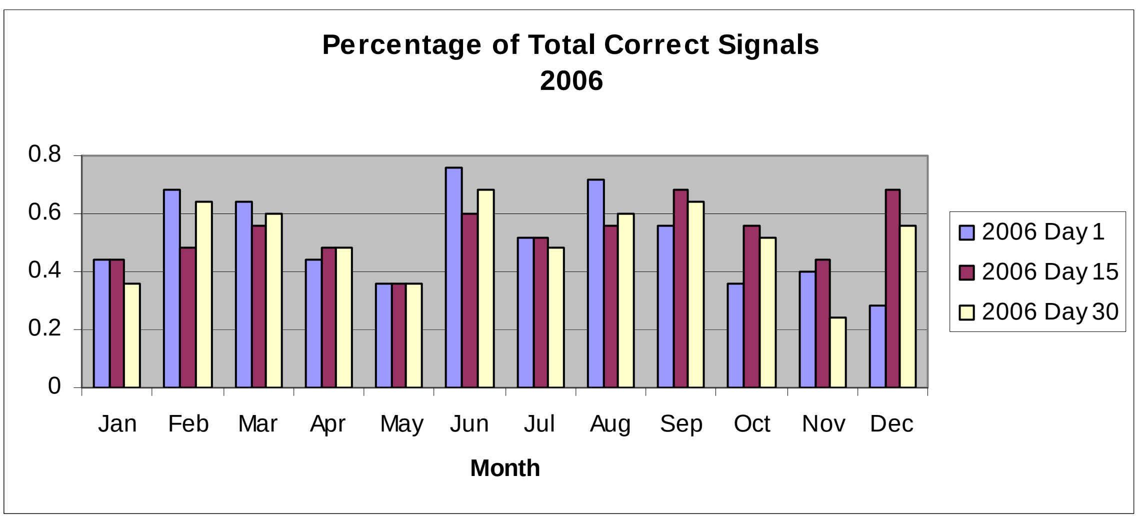
2006 Developing v. Developed						
	Developing			**Developed**		
	1 Day	**15 Day**	**30 Day**	**1 Day**	**15 Day**	**30 Day**

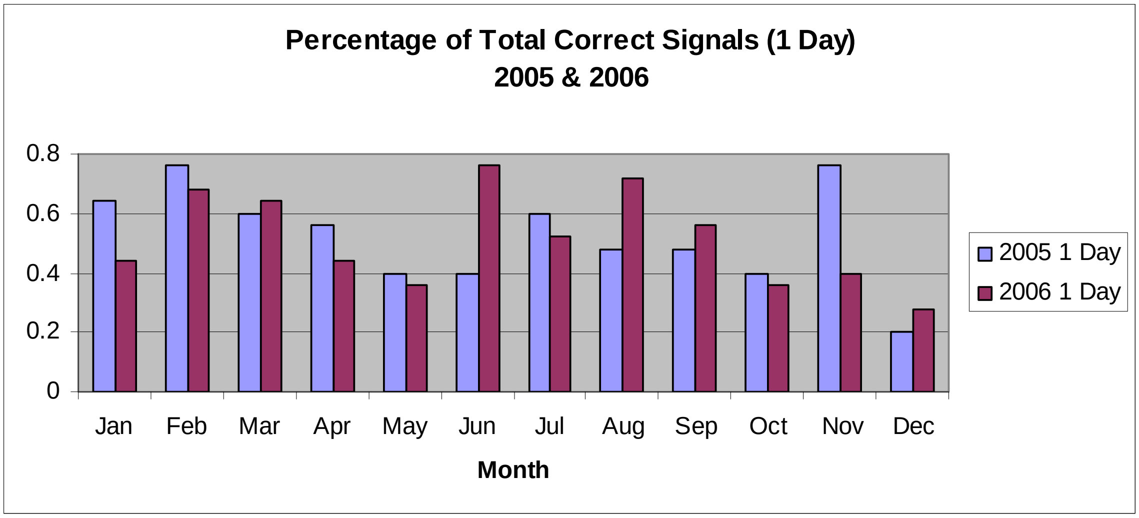
Total Signals Correct	107	111	111	49	49	43
Total Signals	192	204	204	96	96	96
Percent Correct	0.56	0.54	0.54	0.51	0.51	0.45
Norm Dist	**0.94**	**0.90**	**0.90**	**0.58**	**0.58**	**0.15**
Total Outliers Correct	70	76	72	30	31	26
Total Outliers	123	131	131	56	56	56
Percent Correct	0.57	0.58	0.55	0.54	0.55	0.46
Norm Dist	**0.94**	**0.97**	**0.87**	**0.70**	**0.79**	**0.30**
Significant Change Level (Between E(t) and E(t+1)):	0.50%	0.50%	0.50%	0.50%	0.50%	0.50%
Total Signals & Sig Change Correct	83	68	84	37	46	34
Total Sig Change	152	135	155	76	81	79
Percent Correct	0.55	0.50	0.54	0.49	0.57	0.43
Norm Dist	**0.87**	**0.53**	**0.85**	**0.41**	**0.89**	**0.11**
Number of Signal Correct (Outlier and has a Significant Change)	56	48	56	21	28	21
Total outlier & Sig Change	102	86	102	42	47	47
Percent Correct	0.55	0.56	0.55	0.50	0.60	0.45
Norm Dist	**0.84**	**0.86**	**0.84**	**0.50**	**0.91**	**0.23**
Significant Change Level (Between E(t) and E(t+1)):	0.50%	1.00%	1.50%	0.50%	1.00%	1.50%
Total Signals & Sig Change Correct	83	50	40	37	39	20
Total Sig Change	152	94	79	76	65	49
Percent Correct	0.55	0.53	0.51	0.49	0.60	0.41
Norm Dist	**0.87**	**0.73**	**0.54**	**0.41**	**0.95**	**0.10**
Number of Signal Correct (Outlier and has a Significant Change)	56	33	24	21	22	13
Total outlier & Sig Change	102	56	48	42	37	32
Percent Correct	0.55	0.59	0.50	0.50	0.59	0.41
Norm Dist	**0.84**	**0.91**	**0.50**	**0.50**	**0.88**	**0.14**
Significant Change (Between E(t) and E(t+1)):	1.00%	1.50%	2.50%	1.00%	1.50%	2.50%
Signals & Sig Change Correct	61	30	24	32	27	11
Total Sig Change	112	58	51	63	43	27
Percent Correct	0.54	0.52	0.47	0.51	0.63	0.41
Norm Dist	**0.83**	**0.60**	**0.34**	**0.55**	**0.95**	**0.17**
Number of Signal Correct (Outlier and has a Significant Change)	40	18	14	19	15	8
Total outlier & Sig Change	74	33	33	38	27	19
Percent Correct	0.54	0.55	0.42	0.50	0.56	0.42
Norm Dist	**0.76**	**0.70**	**0.19**	**0.50**	**0.72**	**0.25**

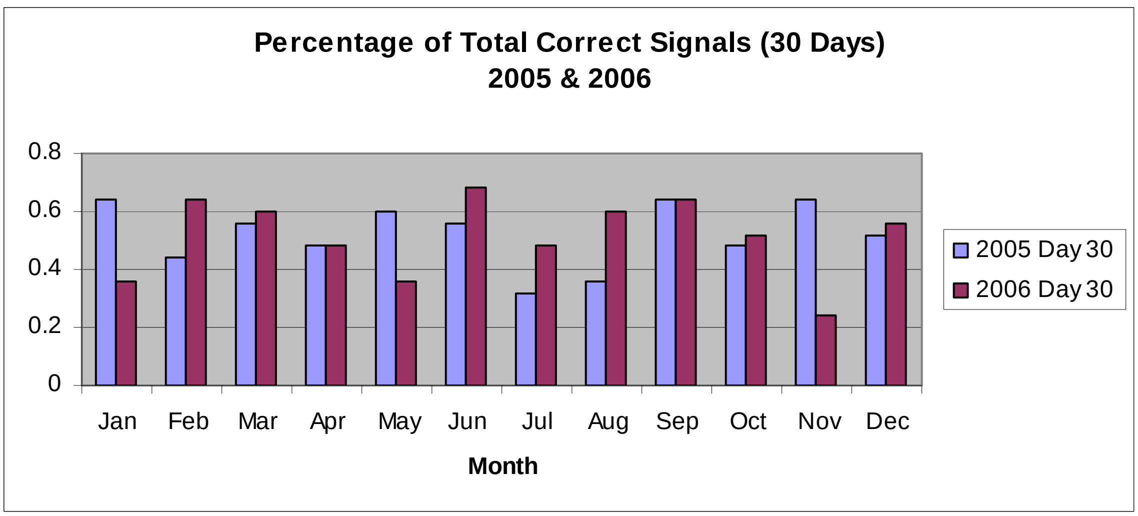
*2005 & 2006 Data Analysis by Currency can be provided upon request.

G. Relevant Graphs



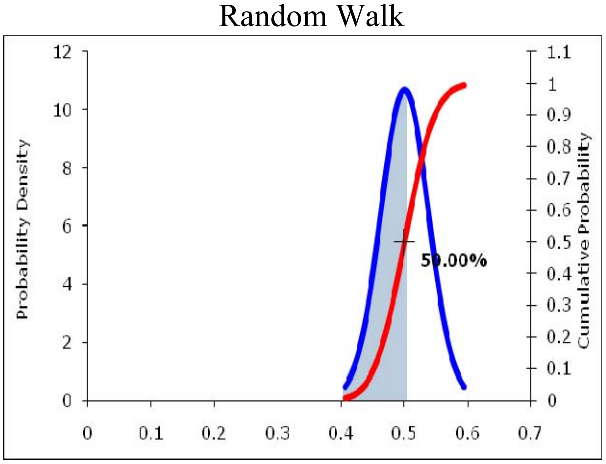




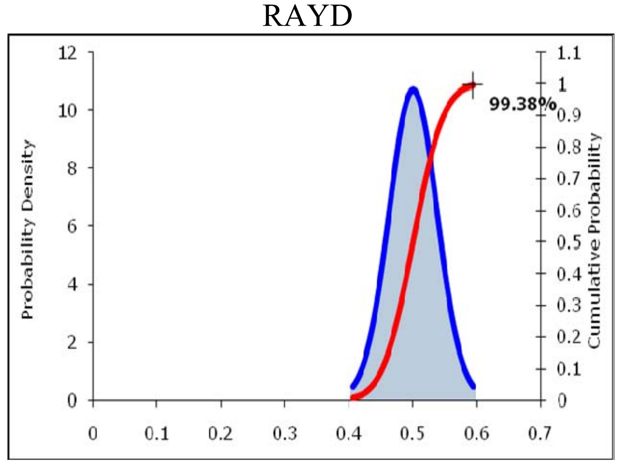


Normal PDF & CDF

Random Walk



RAYD



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