The Returns to Following Currency Forecasts

By

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Abstract

This paper examines the profitability to following the recommendations of currency forecasters. Initially, we show in a Bayesian framework that the forecasts can be quite noisy and yet still allow the potential for profitable trading opportunities. Next, we analyze the recommendations of actual currency forecasts during the 1990 - 2003 period, ranking each currency by its expected appreciation to a base currency of reference. In general, we find limited evidence of positive but statistically insignificant returns by following the recommendations. Finally, when we combine the forecasted rankings with the rankings given by technical and interest rate signals, we find highly significant, positive returns.

The Returns to Following Currency Forecasts

I. Introduction

In spite of the tremendous volume of transactions that occur daily in the foreign exchange market, we know very little regarding the ability to profit from currency forecasts. In fact, while we know a great deal regarding both the performance and biases of equity analysts (Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Jegadeesh, Kim, Krische, and Lee (2003)), our knowledge of the value to following foreign exchange recommendations is sorely lacking. This is surprising given that the size of worldwide equity markets is dwarfed by foreign exchange.[1] This is also unfortunate given that active foreign exchange management must basically rely on one or more of three avenues to set and update currency positions: technical analysis, macroeconomic modeling, and/or subscribing to foreign exchange forecasts.

The profits to using technical analysis, while not universally accepted, have been well documented and analyzed in the academic literature (Sweeney (1986), Surajaras and Sweeney (1992), Levich and Thomas (1993), Taylor (1994), Kho (1996), Neely, Weller, and Dittmar (1997), Raj (2000), Neely and Weller (2001), Okunev and White (2003)). Unfortunately, the underlying source to technical trading profits is still not well understood.[2] Without any guidance as to what exactly drives the positive returns to technical analysis, we cannot know when they might end. It is quite understandable that some currency managers would feel some level of discomfort with the notion of exposing a large foreign exchange position to a trading platform lacking a solid theoretical or logical foundation. One could legitimately maintain that the presumption of care would necessarily be violated when large foreign exchange positions are predicated upon the madness of crowds.

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[1] According to www.forexstandard.com (dated December 13, 2003), "the foreign exchange market is the largest financial market in the world, with a volume of over $1.5 trillion daily; more than three times the aggregate amount of the US Equity and Treasury markets combined."

[2] Osler (2003) finds that one potential source to the positive returns from technical analysis arises from clustering in stop-loss and take-profit foreign exchange orders.

Without technical analysis, active foreign exchange management must either rely on macroeconomic modeling or subscribing to an external provider to supply currency forecasts. For those seeking guidance through sophisticated macroeconomic modeling, Meese and Rogoff (1983) long ago showed that a driftless random walk model performed much better than standard monetary or elaborate time series models. In fact, even though they used actual future values of macroeconomic factors in their prediction models (which would not have been available at the time), the driftless random walk model continued to dominate.[3] Even as this paper was still being absorbed, Meese and Rogoff (1988) followed with an analysis showing that little relation exists between real interest rates and real exchange rates. The Meese and Rogoff (1988) paper, which was later supported by Diebold and Nason (1990), also showed that little short-run predictability existed for exchange rate movements using macroeconomic factors.

The first real hope for formal macroeconomic modeling after the Meese and Rogoff bombshell was provided by Mark (1995) who showed that monetary fundamentals could generate better out-of-sample forecasts at long horizons. This result was also found by Chinn and Meese (1995). Unfortunately, Groen (1999) showed that these results may be sensitive to the sample period. Several later follow-up papers have also cast doubt on long-horizon predictability using macroeconomic factors (Berkowitz and Giorgianni (2001), Faust, Rogers, and Wright (2003)). More recent papers have attempted to resurrect the notion of long-horizon predictability through either Bayesian methods (Wright (2003)), or exploiting nonlinearities in the data (Kilian and Taylor (2003)).[4]

Given the probable futility and apparent complexity of directly employing macroeconomic factors to predict currency fluctuations, it is quite understandable that many foreign exchange managers might subscribe to an external provider of currency forecasts. At the very least, an external entity can provide a means to diffuse

[3] The types of macroeconomic factors often included in exchange rate determination models include: money supply measures, real income measures, short-term interest rate measures, expected inflation measures, and trading balance measures.

[4] Engel and West (2003) offer one potential explanation for the relatively weak relationship between changes in currency value and fundamentals. They show analytically that an asset price can exhibit near

responsibility. The third avenue available is to pay for the perception of expertise, to pay for the currency forecast.

One should acknowledge up-front that a currency forecast must come from somewhere; that is, it will not arise from cocktail conversations or the imagination of genius. It is now commonly understood that foreign exchange forecasters typically rely on technical indicators for short-term predictions and fundamentals for long-term expectations (Allen and Taylor (1989), Frankel and Froot (1990), and Cheung and Chinn (2000)). Unfortunately, the few studies that have analyzed the performance of these forecasts have found little relation between forecasted and realized returns.

One of the earliest studies to directly examine currency forecasts was by Frankel and Froot (1987). This paper analyzed forecasts from the American Express Banking Corporation poll (1976 to 1985), the Economist Financial Report (1981 to 1985), and Money Market Services, Inc. (1983 to 1985). After running numerous permutations of regressions of forecasted changes on actual changes and past changes in exchange rates, this paper concluded that significant bias existed in foreign exchange forecasts.[5] Frankel and Froot (1990) validated their earlier paper, finding that forecasters tend to extrapolate recent trends, while at long horizons they systematically forecast reversals. Drawing from an earlier version of the same forecasting dataset we use in our paper, Chinn and Frankel (2000) find some ability of forecasters to get the direction right for future changes, but that this result disappears once high inflation currencies are removed from the dataset. A more recent paper by Bofinger and Schmidt (2003) finds that the forecast quality of the Euro/U.S. dollar exchange rate has generally been quite poor.

A legitimate argument can be made that what matters most is whether currency forecasts function adequately as trade indicators. On this front, the evidence is slightly more promising, but still decidedly mixed. Marsh and Power (1996) examine the ability of 22

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random walk behavior if the fundamentals are integrated of order one and the factor for discounting them is near one.

currency forecasters to predict movements in three major exchange rates. With the exception of one forecaster, no position following the recommendations of the other 21 would have generated statistically significant profits. MacDonald and Marsh (1994) also provide limited, indirect evidence on the profitability to following currency forecasts with decidedly mixed results. Boothe and Glassman (1987) use a simple trading rule that initiates a long (short) position in a currency if the forecast rate is greater (less) than the forward rate. They find that some models show evidence of significant forecasting ability.

What is lacking in the literature is a thorough, comprehensive analysis of the returns that can be generated by following foreign exchange forecasts. We believe that any attempt to analyze or trade on all currencies at the same time is, at best, misguided. At any time, we are more certain of the movements of some currencies than we are of others. That is, we believe that any analysis of forecasting ability should focus not on individual currencies, but instead on individual ranks.

So how might we rank currencies using foreign exchange forecasts? Using the currency forecast data, each month we determine an expected return for each currency relative to a base currency of reference.[6] We then rank each of the currencies every month by this expected return and initiate our trades based upon this expected return. Our trading strategy is quite simple: buy the currency with the highest forecast return and short the currency with the lowest forecast return.[7]

We chose to confine our analysis to nine currencies, all expressed relative to the U.S. dollar. The currencies we examine include the Australian dollar, the British pound, the Canadian dollar, the Euro, the French franc, the German mark, the Japanese yen, the

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[5] According to Frankel and Froot (1987), "The simplest possible test of rational expectations is to see if expectations are unconditionally biased, if investors systematically overpredict or underpredict the future spot rate." (page 136)

[6] In all tables except one, the base currency of reference will be the U.S. dollar. In Table X we will examine the robustness of our result by using other currencies as the base currency of reference.

[7] In subsequent tests, we examined varying permutations of this strategy such as equally weighting a portfolio of the top 3 forecast ranks and shorting the bottom forecast rank. Using this alternative approach, we found stronger and more statistically significant results than that presented in this paper.

Swedish krona, and the Swiss franc. We have chosen to limit our analysis to these currencies because they comprise the largest and most liquid of the foreign exchange markets. That is, these are the foreign exchange markets in which a large international institution is most likely to conduct transactions. Because of this self-imposed restriction, one must be careful when attempting to generalize our findings to an institution trading across a wider array of currency markets.

Surprisingly, we have not been able to locate any paper that has examined profitability across ranks. Using a ranking methodology has a number of advantages over an examination at the individual currency level. First, the ranking methodology implicitly controls for any nonlinearities that may exist in the data. Rather than attempt to directly model the nonlinearity in a formal, econometric setting, it is perhaps more useful (and simple) to employ the nonparametric, model-free approach that ranking provides. Second, as we have already stated, at any given time we may be more confident of the forecast in some currencies than we are of others. A ranking measure will allow us to directly incorporate various levels of confidence into active currency positions. Finally, using a ranking methodology allows us to evaluate currency forecast performance in a manner that the literature has thus far overlooked.

One other unique aspect of this paper is the currency forecasting dataset that we use to conduct the analysis. Obtained from FX4casts.com, the exchange rate forecasts are compiled into a summary geometric mean on or about the fourth Thursday of each month from between 20 to 30 individual forecasters representing various organizations including investment and commercial banks, securities firms, and international financial institutions.[8] To preserve anonymity, the forecasts from individual providers are not reported by FX4casts.com.[9] In this study, we make use of one-month, three-month, six-month, and twelve-month forecast horizons – each reported on a monthly basis. We were

[8] FX4casts.com compiles forecasts of inflation, growth rates, current account balances, and unemployment rates in addition to foreign exchange. Not all contributing organizations make forecasts for all the measures and even those that contribute to foreign exchange forecasts may not cover all the exchange rates that FX4casts.com reports on. FX4casts.com was formerly known as *The Financial Times Currency Forecaster* and has been reporting on currency forecasts every month since 1984.

[9] A sample of the organizations contributing to FX4casts.com is given in Appendix A.

able to obtain this data for the period spanning December 1989 through the end of October 2003. To our knowledge, no study examining currency forecasts has had access to monthly currency forecasts besides the only other paper that has made use of an earlier version of this same dataset (Chinn and Frankel (2000)). Nor has any study of currency forecasts examined as long of a sample period as this one.

The findings of our paper are as follows. First, we show in a Bayesian framework that the noise in a currency forecast can be quite substantial and yet still allow for statistically significant, positive returns to either a long-short strategy or a strategy that buys all currencies with positive forecasted returns and shorts all currencies with negative forecasted returns. Next, we replicate the simplest of regressions relating forecast return to future actual return and show – consistent with the prior literature – that little to no relation exists between forecast return and actual future returns at the individual currency level. After accomplishing this, we examine the percentage of months that each of the currencies have had the highest or the lowest forecast return. In general, we find that the Australian dollar has most often been the currency with the greatest expected appreciation and the Japanese yen the currency with the largest forecast depreciation (all relative to the U.S. dollar). Next, we examine the performance to a simple strategy of buying the currency with the greatest expected appreciation and shorting the currency with the most extreme forecast depreciation. We do this test for all combinations of forecast period (one-month, three-month, six-month, and twelve-month) and holding period (one-month, three-month, six-month, and twelve-month).[10] We find that, while in most cases the returns are positive on average, they are rarely statistically significant.[11] In this analysis, we find that the one-month holding period usually dominates longer holding horizons and that the twelve-month forecasts are typically the most useful.[12]

[10] For multi-month holding periods, we rebalance 1/n of the currency portfolio each month where n is the length of the holding period.

[11] We should note that the strategies that we test in this paper are very basic with the most frequent trading at the one-month horizon. Certainly, dynamic strategies exist that will exceed the returns we document in this paper. Whether these dynamic strategies are identifiable on an ex-ante basis, though, must be left for future research.

[12] In fact, many of the results are significantly weakened by the poor performance of forecasts during the 1990 – 1994 subperiod. Since 1995, following the recommendations of many of the forecasts would have actually done fairly well.

In our analysis, we examine a naive strategy of providing one-third weight to a strategy following the forecast, one-third weight to a strategy following a simple technical trading rule (free from ex-post selection bias), and a one-third weight to a strategy of buying the highest yielding currency and shorting the currency offering the lowest interest rate. We compare the result with applying a 50-50 allocation to the simple technical and interest rate rule. In most, but not all, cases we find very little enhancement to using the currency forecasts.

To examine the generality of our findings, we convert all the forecasts into equivalents with respect to various base currencies and repeat the combined forecast horizon-holding period analysis. We find that the results using the U.S. dollar as the base currency of reference are fairly typical with that found from the perspective of other base currencies. We also further substantiate that the one-month holding period using the twelve-month forecast horizon appears to offer the most promise for positive returns.

To examine whether the greater performance of a few of the forecast horizon-holding period rules might be due to chance, we implement a bootstrap procedure to scramble the forecast ranks and then examine how often we would find levels of performance consistent with the strongest combinations. Our bootstrap approach employs two types of simulations. In the first – which we term the “no timing ability” approach – we scramble the rows of forecasts ranks but maintain the ordering within each row. Our second bootstrapping method – defined as the “no timing, no selection ability” approach – scrambles both the rows of ranks and the ordering of ranks within each row. In this analysis, we find only one or two instances where the best forecast horizon-holding period combinations achieves performance at a level unlikely to have been achieved by pure chance.

Finally, we examine whether the forecast ranks can be combined with the rankings of currencies given by the technical signal and/or the interest rate rule. In this analysis, we find that when we combine the forecast ranks with either the technical signal ranks or the interest rate rule ranks that we can achieve strongly positive, significant returns. In fact, we show that a fairly strong relation exists between the return on the long-short strategy using the forecast returns and the level of agreement with the technical and interest rate rules. In short, we show that it is may be possible to separate the months where the forecasts offer the greatest predictive ability from those months where they offer the least value-added.

In the next section we describe our data and the methodology. We will focus in particular on the Bayesian experiment to examine the noise level that must exist in forecasted returns to remove the profitability of the simple long-short approach to currency selection. In addition, we will outline the trading strategies analyzed in this paper. In Section III we will present the empirical results. Section IV concludes with a brief summary, discussion, and possible avenues for future research.

II. Data and Methodology

II.A. The Bayesian Experiment

We wish to begin with a simple question: If we receive unbiased currency forecasts every month where the forecasted return of the currency is equal to the actual return plus a noise element, how noisy would our forecast need to be before we would cease to earn significantly positive returns from a simple long-short strategy based on the extreme forecasts or a strategy of buying all the currencies with positive forecasted returns and shorting all the currencies with negative forecasted returns? That is, we will assume that the relation between the forecast return and the actual return over an *n*-month horizon *is* as follows:

$$r_{s,j,t}(n) = \left[\prod_{i=1}^{n}\left(1 + r_{j,t+i} + r_{\varepsilon,j,t+i}\right)\right] - 1 \qquad (1)$$

where $r_{s,j,t}(n)$ is the forecast currency return (the signal) for currency *j* at the end of month *t* for the return during the next *n* months, $r_{j,t+i}$ is the actual currency *j* return during the month $t + i$, and $r_{\varepsilon,j,t+i}$ is a random monthly noise element ~ N (0, $k\sigma_j^2$).[13] We will also assume that $r_j \sim N(\mu_j, \sigma_j^2)$. We wish to examine the profitability to our simple trading rules as we increase the value of *k*. That is, we wish to isolate the effect of increasing the noise in currency forecasts for varying lengths of forecast horizon.

We will assume that currency positions for an *n*-month forecast horizon are initiated through the use of forward contracts with *n* months to maturity. These forward contracts will be held for the duration of the forecast horizon. The actual monthly return for a given currency *j* during any given month *t* is expressed as follows:

$$r_{j,t} = \frac{F_{j,t}(n-t)}{F_{j,t-1}(n-(t-1))} - 1 \qquad (2)$$

where $F_{j,t}(n-t)$ is the forward price of currency *j* at the end of month *t* maturing in $n - t$ months. Note that the monthly returns for currency *j* will depend upon changes in the forward price until the end of the final month when the forward and spot prices will converge.

To increase the sample period for this analysis, we will use a different dataset for the actual currency values from that used for the rest of this paper. For this analysis, we will use currency spot values and short-term government interest rates obtained from the Global Financial Database for the Australian dollar, the British pound, the Canadian dollar, the Euro, the French franc, the German mark, the Japanese yen, the Swedish krona, and the Swiss franc all expressed relative to the U.S. dollar as the base currency.[14] The sample period for this analysis will span January 1980 through May 2003.

[13] We will assume (not entirely realistically) that the noise element is uncorrelated with the true return.
[14] With the introduction of the Euro at January 1999, we cease to use the French franc and the German mark.

Because we could not obtain market forward prices for all the currencies over the time period of this analysis, we compute the forward prices using theoretical values.[15] That is, we assume that:

$$F_{j,t}(n-t) \ = \ S_{j,t}\exp[(r - r_f) * (n-t)] \qquad (3)$$

where $S_{j,t}$ is the spot rate for currency j at time t expressed as the ratio of units of domestic currency per unit of foreign currency, r is the domestic interest rate, and r_f is the foreign interest rate.

Our Bayesian experiment proceeds as follows. First, for each month we add a random noise element to the true realized return of each currency.[16] Note that the true realized return of each currency is given by equation (2) and the random noise element will be determined by the length of the forecast horizon under question as well as the parameter *k*, which is a multiple of the underlying currency return variance. With greater values of *k*, we will receive more imprecise signals regarding the true, future return for each currency. With greater values of *k*, we will experience ever greater difficulty in separating out the currencies according to their true, future return.

Once we have added a random noise element to the true return of each currency each month, we treat this "noisy" return as the signal regarding the future return of each currency. This new, modified, dataset gives the return signals that the currency manager will face every month. In our analysis, we test two alternative strategies. The first strategy is to go long the currency with the highest expected return and short the currency with the lowest expected return. The second strategy is to equally weight a long position across all currencies with a positive expected return and equally weight a short position across all currencies with a negative expected return. Note that these portfolio positions will be held for the length of the forecast horizon. In our Bayesian analysis, we will test

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[15] Because these prices must hold under no arbitrage conditions, we do not expect that our results will be significantly affected by making this simplifying assumption.

[16] In order to handicap this experiment against our finding that the noise level can be quite large and still allow for significant returns, each month we truncate the greatest actual return to the level of the second-highest actual return as well as truncating the lowest actual return to the level of the second-lowest actual return. Note that these actual returns feed directly into the signal by equation (1).

the performance for the one-month, three-month, six-month, and twelve-month forecast horizon.

Unfortunately, we cannot directly use the signals as the expected return for each currency. The precision of these signals will depend upon the underlying variance in the noise. That is, with ever greater values of *k*, the precision of the signals will decline. With ever greater values of *k*, we will give less credence to the noisy signal that we receive and instead rely on our own unconditional expectation. This unconditional expectation may be as simple as the historical mean return of the currency. To control for the precision of the signal, we will need to find the Bayesian posterior expected return for each currency given its own noisy signal.

As shown in Appendix B, the Bayesian multivariate model for the expected return at time *t* of *j* multiple assets given the receipt of *j* multiple correlated signals is as follows:

$$\mathbf{E_t}\,[\,\boldsymbol{r} \mid \boldsymbol{r_s} = \boldsymbol{r_s^*}\,] = \Sigma_{\boldsymbol{\varepsilon}}\left(\Sigma_{\boldsymbol{\varepsilon}} + \Sigma_{\boldsymbol{r}}\right)^{-1} \boldsymbol{\mu_r} + \Sigma_{\boldsymbol{r}}\left(\Sigma_{\boldsymbol{\varepsilon}} + \Sigma_{\boldsymbol{r}}\right)^{-1} \boldsymbol{r_s^*} \tag{4}$$

where the expectation is a vector of dimension (*j* x 1), $\boldsymbol{r_s^*}$ is the (*j* x 1) vector of signals received for each currency (given by equation (1)), $\Sigma_{\boldsymbol{\varepsilon}}$ is the (*j* x *j*) covariance matrix of the random noise elements, $\Sigma_{\boldsymbol{r}}$ is the (*j* x *j*) covariance matrix of the true, underlying currency returns, and $\boldsymbol{\mu_r}$ is the (*j* x 1) vector of unconditional expected returns for each currency.[17]

We can see from equation (4) that the Bayesian posterior expectation for any individual currency *j* in a multivariate setting can be quite complicated. The expected value for any individual currency will depend not only upon its own signal, but the signals that other correlated currencies also receive. Appendix B shows that the weight given to the unconditional expectations for any currency *j* is simply the sum of the values in the *j*th row of the matrix $\Sigma_{\boldsymbol{\varepsilon}}\left(\Sigma_{\boldsymbol{\varepsilon}} + \Sigma_{\boldsymbol{r}}\right)^{-1}$. Similarly, the weight given to all the signals for

[17] We used the trailing five-year average return for each currency as the unconditional expectation. We also tried using the trailing three-year average return with very little effect on our results.

currency j is the sum of the values in the jth row of the matrix $\Sigma_{\boldsymbol{r}}\left(\Sigma_{\varepsilon}+\Sigma_{\boldsymbol{r}}\right)^{-1}$. Fortunately, because of the way that we have modeled the noise in equation (1), we can employ a simplified approach to this analysis.

It is straightforward to show that as a special case if $\Sigma_{\varepsilon} = k\Sigma_{\boldsymbol{r}}$ then equation (4) reduces to:

$$\mathbf{E_t}\,[\,\boldsymbol{r}\mid \boldsymbol{r_s} = \boldsymbol{r_s^*}\,] = \frac{k}{1+k}\,\mu_{\boldsymbol{r}} + \frac{1}{1+k}\,\boldsymbol{r_s^*}\,. \tag{5}$$

We can easily see from equation (5) that when the covariance matrix of random noise elements is expressed as a multiple of the covariance matrix of the true, underlying currency returns, the expected return for each currency j is simply a linear combination of its own unconditional mean and its own signal. We can see that the greater the value of k, the less weight we will give to the signal and the greater the weight given to the unconditional mean. Extreme variance in the noise will cause us to have less confidence in the signal that we receive. Because of the way in which we have constructed each signal from equation (1), we can use equation (5) as the expectation for each currency's return at time t.[18] Equation (5) will be used to determine the expected return for each currency at the beginning of each forecast horizon.

The Bayesian experiment proceeds as follows. First, from our initial dataset of true currency returns we add a random noise element with variance set at various levels of k. Once we have added the noise element to the data, we will have a new dataset consisting of "signals" of future currency return. Recall that the greater the value of k, the greater the variance of the noise element and the less precise will be our signal. Once we have the signals, we will then use equation (5) to establish the expected return for each currency. We will then test the two strategies (long-short, and long all positive expected returns and short all negative expected returns). The currency positions will be held for the duration of the forecast horizon. We will repeat this process 1,000 times for each

[18] In fact, this is not strictly correct. We have not constructed the noise to have a multiple of the same covariance structure as the underlying returns for the off-diagonal elements. To test the robustness of our result, we also estimated the Bayesian model using equation (4) with no qualitative difference from the findings we report.

value of *k*. We will repeat the above steps for a one-month, three-month, six-month, and twelve-month forecast horizon.[19]

II.B. The Currency Forecasts

Once we have established the level of noise that must be present in currency forecasts before the returns of the simple long-short approach diminish to insignificance, we will wish to examine the performance of strategies that rely on actual currency forecasts. In order to accomplish this, we need to obtain actual currency forecasts over as long of a sample period as possible.

As stated in the introduction, our currency forecast data was obtained from FX4casts.com. These exchange rate forecasts are compiled into a summary geometric mean on or about the fourth Thursday of each month from between 20 to 30 individual forecasters representing various organizations including investment and commercial banks, securities firms, and various international financial institutions. FX4casts.com publishes the consensus forecasts for one-month, three-month, six-month, and twelve-month forecast horizons. The dataset spans the period December 1989 through the end of October 2003.[20] Even though FX4casts.com gives forecasts for over 25 currencies each month, we limit our analysis to what we believe are the most liquid foreign exchange markets. As with the Bayesian experiment, we will confine our analysis to the Australian dollar, the British pound, the Canadian dollar, the Euro, the French franc, the German mark, the Japanese yen, the Swedish krona, and the Swiss franc – all expressed relative to the value of the U.S. dollar.

In addition to the currency forecasts, we will need currency spot rates, and a means to construct forward rates. For the spot rates, we considered three alternative data sources:

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[19] Unlike with the analysis of actual currency forecasts, we do not rebalance (1/n) of the portfolio each month for multi-month forecast and holding periods. Instead it is assumed that a forward position is held for the duration of the forecast horizon.

[20] FX4casts.com stopped reporting the one-month forecast after September 2000. In addition, the following months were missing from the forecast dataset provided to us: February 1991, September 1991, November 1991, June 1992, December 1999, and June 2002.

Datastream, FX4casts.com, and Oanda. Oanda gives average spot rates during each trading day, whereas both Datastream and FX4casts.com provide point-in-time values.

While we were actually most comfortable with using the Oanda spot rates, we chose to use FX4casts.com for at least two reasons.[21] First, we wanted to choose spot rates that we expected to be in the closest alignment with the forecasts. Second, after finding largely insignificant results from the trading strategies using the forecasts, we wanted to shield ourselves from any criticism that we designed an experiment for the currency forecasts to fail. Finally, we, in fact, did test the robustness of our results by examining the performance using all three sources for spot rates. We found the same general pattern in the results no matter the source, but that using Oanda provided the best results for the currency forecasts, followed by FX4casts.com, then Datastream.[22]

The next data issue that we faced was whether to use actual forward currency prices or theoretical values as that constructed in the Bayesian experiment in Section II.A. We obtained forward currency prices for various maturities from Datastream for the various currencies in question. Ideally, we wished to find a forward price with a maturity equal to the horizons of the forecasts. If we were unable to obtain the desired maturity but another forward existed at that date for a different maturity, we converted that different forward into a forward price of the desired (but missing) maturity. If at a given date Datastream did not have any forward rates available for a given currency, we were forced to use theoretical forward prices.

We need the forward prices for two reasons. First, the actual returns realized from trading the currencies are identical to that given in equation (2). If we wish to trade currencies, then we must transact using forward prices. Second, when we produce forecasted returns for each of the currencies each month, that forecasted return will need to be relative to either the spot rate (forecast based on "base currency returns") or the

[21] We were most comfortable with Oanda because it is unlikely that a trading strategy will always use the end-of-day spot rates. Averaging the spot rate over an entire day would appear to control for the likelihood that most trades would occur sometime during the trading day rather than at the end.

forward rate (forecast based on "interest-adjusted currency returns"). That is, the forecasted return must be the forecasted spot rate divided by "something". That "something" could either be the current spot price or the current forward price.

We tested our results using both actual and theoretical forward prices.[23] In the end, we found that the choice did not qualitatively affect our results. Because we felt hidden problems might exist with mixing Datastream forward prices with FX4casts.com spot prices and since we did not have a complete dataset of actual forward prices to begin with, we decided to present our findings using the theoretical forward prices.[24]

While we will defer most of the discussion of the forecast data until we present the results, we now need to discuss the strategies that we examined using the actual currency forecasts. Our approach was actually very simple. Each month, we determined the forecast return for each currency relative to the U.S. dollar using the one-month, three-month, six-month, and twelve-month forecasts. This forecasted return was expressed relative to the current spot price and also to the current forward price. The forecast return at date *t* relative to the spot price is:

$$\text{Forecast Return (Base)}_{j,t} = \frac{\text{Forecast Spot Price}_{j,t}}{S_{j,t}} \qquad (6)$$

where, as before, all currencies are quoted as units of domestic currency per unit of foreign currency.

The forecast return at date *t* relative to the forward price is:

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[22] The difference in mean returns between the best and the worst returns using the differing spot rates was usually between five and ten basis points.

[23] Of course, if we use spot rates from FX4casts.com, we will need to convert the forward prices given by Datastream into a forward price based on the FX4casts.com spot rate. (We assumed that the forward price given by Datastream is a direct function of the spot rate given by Datastream, which we recognize may pose a problem.) To make the conversion, we simply divided the Datastream forward price by the Datastream spot price and then multiplied the result by the FX4casts.com spot price.

[24] As an example of one difficulty we experienced, when we divided the Datastream forward price by the Datastream spot price, we found interest rate differentials that did not align even closely with actual interest rate differentials. This either implies that interest-rate arbitrage does not hold very tightly with forward prices or that Datastream spot and forward rates do not correspond to exactly the same point in time. In any event, this issue is certainly outside the scope of our research.

$$\text{Forecast Return (Interest - Adjusted)}_{j,t} = \frac{\text{Forecast Spot Price}_{j,t}}{F_{j,t}} \qquad (7)$$

where the forward price has maturity equal to the holding period. Note that we may express equation (7) as:

$$\text{Forecast Return (Interest - Adjusted)}_{j,t} \approx \frac{\text{Forecast Spot Price}_{j,t}}{S_{j,t}} + (r_f - r) \qquad (8)$$

where the interest differential, $(r_f - r)$, corresponds to the maturity of the forward price.

We can see from equation (8) that if we rank currencies based upon interest-adjusted forecast return, that we directly incorporate the interest-rate spread into our decision process. That is, a ranking based upon equation (8) will have a bias to select high interest-rate currencies. On the other hand, ranking using forecasts of base currency returns will take no direct consideration of interest-rate differentials.[25]

Once we determine the forecast return, we will rank all currencies each month. Our simple strategy is to set a long position for the currency with the greatest forecast return and a short position for the currency with the lowest forecast return. We will do this using both forecasts of base currency returns and forecasts directly including interest differentials. We will examine all combinations of holding period (one-month, three-month, six-month, and twelve-month) and forecast horizon (one-month, three-month, six-month, and twelve-month). For multi-month holding periods, we will assume that only (1/*n*) of the currency portfolio is rebalanced each month where *n* corresponds to the length of the holding period.

III. Results

III.A. The Bayesian Experiment

The results of our Bayesian experiment are given in Table I. Recall that a noise level of

[25] Of course, the original forecast itself may have some relation to relative interest differentials across currencies. We will examine this issue in Section III.

one indicates that the error will have the same variance as the underlying currency return. A noise level of two will correspond to the error having twice the variance of the underlying currency. Table I clearly shows that for short forecasting horizons the noise element can be much more variable than that of the actual underlying currency return and yet still allow room for profitable trading strategies. For example, at the three-month forecast horizon, even if the noise element is five times more variable than the underlying currency return, we can still expect to earn about 53 basis points each month with the L1S1 (long top rank, short bottom rank) strategy. This is about the same magnitude as that claimed by most technical analysis papers for foreign currency markets.

For longer forecast and holding period horizons, the results are less striking but nevertheless encouraging for those who subscribe to or produce currency forecasts. Even with a twelve-month forecast horizon and holding period, the noise element can be twice as variable as the underlying currency return and still generate 42 basis points each month with the L1S1 strategy. One more important point comes out from the results of Table I. We can clearly see that performance improves with a shorter forecast horizon / holding period. This is due to the fact that with a short holding period, we have the chance to hit the best performing currencies more often. As a simple example, assume that we can select between two currencies. *Currency A* returns five percent in the first month and zero percent in the second month. *Currency B* returns zero percent in the first month and two percent in the second month. A one-month strategy would ideally pick *Currency A* in month one and *Currency B* in month two, yielding a total return of seven percent. The two-month strategy would ideally select *Currency A*, yielding a total return of five percent. Clearly, the one-month strategy allows the opportunity for greater returns. This effect explains the greater returns for shorter forecast horizons / holding periods in Table I.

We can determine from Table I and equation (5) the expected result from a regression of forecast return on the actual realized return. Assuming that currency forecasters provide some weight to their own private signal and to their unconditional expectation, we may use equation (5) to examine the relation between forecast and realized return: $Fcst_{j,t}(n)$

$$Fcst_{j,t}(n) \;=\; \alpha \; r_{s,\,j,t}(n) \;+ (1-\alpha\,)\,\mu_j \tag{9}$$

where $Fcst_{j,t}(n)$ is the forecasted return for currency *j* made at time *t* for an *n*-period horizon.

Using equation (1), we may rewrite equation (9) as:

$$Fcst_{j,t}(n) \;=\; \alpha \left\{ \left[\prod_{i=1}^{n} \left(1 + r_{j,t+i} + r_{\varepsilon,\,j,t+i}\right) \right] - 1 \right\} \;+\; (1-\alpha\,)\,\mu_j \tag{10}$$

Now assuming that the noise element is uncorrelated with the return, the expectation of equation (10) is:

$$\mathrm{E}\,[\,Fcst_{j,t}(n)\,] = \;\alpha \; r_j\,(n) \;+\; (1-\alpha\,)\,\mu_j \tag{11}$$

where

$$r_j\,(n) \;=\; \left[\prod_{i=1}^{n} \left(1 + r_{j,t+i}\right) \right] - 1 \;.$$

We can see from combining equation (11) with the Bayesian posterior expectation given by equation (5) what the expected slope coefficient will be for various levels of the noise parameter, *k*. For example, a slope coefficient of (1 / 3) would indicate that $k\; = 2$ and that the noise in the private signal received by forecasters is twice as variable as that of the underlying returns.

We will briefly examine the regression specified by equation (11) for both base and interest-adjusted returns in Table II and Table III. We should also point out that the regression equation specified by equation (11) has already been thoroughly examined by Chinn and Frankel (2000) for an earlier version of this dataset as well as by Frankel and Froot (1987). The general consensus is that the slope coefficient from the regression specified by equation (11) is at best terminally tiny, statistically insignificant, and possibly even of the wrong sign. In short, we have very little hope that we will find anything of significance from equation (11).

III.B. Descriptive statistics

Table II presents descriptive statistics for the base (spot and forecast) currency returns used in this study. The spot values used to determine these returns were obtained from FX4casts.com along with the monthly currency forecasts. In addition, Table II gives the mean forecasted return for various forecast horizons. Finally, Table II shows the slope coefficient from a simple regression of forecasted base return (dependent variable) on actual base return (independent variable).

First, we can observe that when returns are expressed relative to the spot rate, most currencies with the exception of the Japanese yen and the Swiss franc have stayed virtually flat with respect to the U.S. dollar. We can also see that the U.S. dollar appreciated relative to most currencies during the 1995-1998 period and has depreciated during 1999-2003.

Table II shows how wrong many of the forecasts have been during the past 13 years. While the Japanese yen was steadily appreciating, the consensus forecast held that it would decline. In fact, only for the Euro and the Swedish krona has the direction of the forecast even been the same as the ultimate return. Validating this result, the only slope coefficients from the regression of forecast return on actual return that are statistically significant have the wrong sign.[26]

Table III gives analogous measures to Table II, but this time examining interest-adjusted rather than base currency returns. That is, the returns (both forecast and actual) are

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[26] We use simple OLS t-statistics to determine significance. Because the regressions contain overlapping data, the residuals will be autocorrelated up to a lag equivalent to the number of months in the forecast horizon less one. While the coefficient estimates will remain unbiased through OLS estimation, the underlying covariance matrix for determining statistical significance will be biased. One of the most common remedies for nonspherical residuals is to resort to GMM. Given the very small values of the coefficients, that most are statistically insignificant, and that these regressions are not the focus of our paper, we report only OLS significance.

computed relative to a forward price rather than the current spot price. We can easily see from equation (8) that this forward price directly incorporates relative interest differentials into both forecast and actual return.

Consistent with the results of Table II, forecasted returns often bear little relation to the actual realized returns on the individual currencies. While the forecasts seem more on target for the Australian dollar, the Canadian dollar, and the Euro, they were also grossly incorrect for the British pound, the French franc, and the Japanese yen. Regressions of forecast return on actual return yielded very little of significance with the possible exception of the Japanese yen and perhaps the Canadian dollar.

In addition to the individual currency analysis, Table III presents results for two very simple trading strategies. The first strategy is to go long the currency with the highest interest rate and short the currency with the lowest interest rate each month. This strategy is termed the "interest rate rule".[27] The second strategy is purely technical, computing a short-run exponential moving average and a long-run moving average every month as follows:

$$SR_{j,t} = \frac{R_{B,t} + (j-1)SR_{j,t-1}}{j}, \tag{12}$$

$$LR_{k,t} = \frac{R_{B,t} + (k-1)LR_{k,t-1}}{k}, \tag{13}$$

where $R_{B,t}$ is the base currency return expressed as the ratio of spot rates. We will denote the technical rule as [*j* , *k*] where the parameter *j* is as given in equation (12) and the parameter *k* is as given in equation (13).

The technical rule will compute the difference $SR_{j,t} - LR_{k,t}$ for all currencies during each month. The currencies will then be ranked by this difference from first to last. After this, a long (short) position is taken in the currency with the greatest (least) moving

[27] The interest rate rule has been examined by Choie (1993) and by Okunev and White (2002).

average difference.

To overcome any criticisms of ex-post selection bias for the technical rule, we will compute the mean return across all combinations of rules using the moving average parameters ranging from [1 , 2] to [12 , 36] where the *k* must be greater than *j*. For example, using a short-run moving average of one month, we determine the currency positions using: $SR_{1,t} - LR_{2,t}$, $SR_{1,t} - LR_{3,t}$, . . . , $SR_{1,t} - LR_{36,t}$. Using a short-run moving average of two months, we determine the currency positions using: $SR_{2,t} - LR_{3,t}$, $SR_{2,t} - LR_{4,t}$, . . . , $SR_{2,t} - LR_{36,t}$. In total, we present the mean return to 354 moving average combinations as "the technical rule".[28]

We can see from the results presented in Table III that the interest rate rule has performed fairly well since 1995, but that the technical rule appears to have broken down since 1999. When we combine the rules with a naive 50-50 allocation, we can obtain a fairly significant improvement in performance and slight evidence of statistical significance.[29] Later in this paper, we will be particularly interested in the improvement that can be gained on this naive 50-50 allocation when we include trading rules based on the currency forecasts.

As we have stated in the introduction, we feel that if any value can be found through the use of currency forecasts, it will be at the extremes. That is, we wish to examine the performance of trading rules built upon buying the currencies with the strongest expected appreciation and shorting the currencies with the greatest forecast depreciation. The first

[28] This particular technical rule has been analyzed extensively in Okunev and White (2002) and Okunev and White (2003).

[29] All returns are presented without transactions costs. The foreign exchange literature commonly assumes that transactions costs will be somewhere between five and ten basis points; however, this probably overstates the expense to implementing these strategies. Unlike with trades in the underlying asset, trades in forwards or futures can be leveraged without cost to enhance returns. That is, even though the return for the 50-50 rule is only 34 basis points each month, we could double this return through leverage at an identical transactions cost. The most important measure of performance with currencies is *not* the reported return (as this can be scaled up and down at will) – rather it is the statistical significance of the return. In addition, unlike with trades in the underlying asset, shorting a forward or futures price does not pose a problem.

step in this process is to examine the percentage of months that each currency was ranked at one of the extremes.

Table IV and Table V present the percentage of months that each of the currencies was ranked first, second, last, or next to last by the currency forecast. Table IV presents the results with forecasts based on spot rates and Table V presents the results based on interest-adjusted returns (forward rates).

We first should note that the currency rankings are remarkably consistent between Table IV and Table V. In all three time periods, the Australian dollar appears to have had the highest forecast return most often and the Japanese yen appears to have the lowest forecast return through much of the fourteen-year sample period. We can also obtain some idea of the value to the forecasts from an examination of these tables and the returns given in Table III.

Even though Table III shows that investing in the Australian dollar would have lost 32 basis points each month on average during the 1995 – 1998 period, it was ranked first far more often by the foreign exchange forecasts than any other currency. However, we should also look at the recommendation on the short side. From Table IV and Table V, we can see that the Japanese yen was most often ranked last, and Table III reveals that shorting the yen would have returned 59 basis points each month. As such, trades that simultaneously bought the Australian dollar and shorted the Japanese yen would have been profitable during this time period. For the 1999 – 2003 period, the picture is even more clear. During this time, the Japanese yen was almost always ranked last and the Australian dollar was ranked first the most. A trading strategy that bought the Australian dollar and shorted the Japanese yen over this entire period would have returned 50 basis points a month. Finally, we should note that the greatest inconsistency in ranks occurred during the 1990 – 1994 period.

III.C. The Returns to Following Currency Forecasts

In Table VI we present the returns to the long-short strategy with all combinations of forecast horizon (one-month, three-month, six-month, and twelve-month) and holding period (one-month, three-month, six-month, and twelve-month). The first four columns examine the performance when ranking is with respect to the spot rate and the final four columns examine returns when the forecast is with respect to the forward price.

With very few exceptions, we find that the returns generated – while positive – are usually statistically insignificant. Casual inspection appears to show that the forecasts performed particularly poorly during 1990 – 1994, and that this is probably hurting the mean return to the forecasting strategies. Consistent with our finding in the Bayesian experiment, short holding periods appear to outperform longer horizons. In particular, it appears that a one-month holding period is optimal and that the twelve-month forecast has proved to be the most useful.[30]

It is of interest to examine the return due to the interest differential for the various forecast rule trading strategies. For the forecasts relative to the forward rate, we find that the return due to the interest differential explains a substantial proportion of the total return even with the best rules. For example, the twelve-month forecast, one-month holding period rule (interest adjusted) has returned on average 39 basis points a month over the entire sample period. However, this does not necessarily indicate that the currencies with the greatest pure appreciation were recommended. Looking further down in Table VI, we see that 28 of the 39 monthly basis point performance was due purely to the guaranteed interest differential.

For the forecasts relative to the spot rate, we find that the return due to the interest differential is nearly non-existent. That is, it does appear that these forecasts are fundamentally different in some manner from the interest-adjusted forecasts. We do find,

[30] The astute reader may notice that the best performing rule uses a three-month forecast horizon and a three-month holding period. We will examine this rule (and the other most significant rules from Table VI) in the bootstrap analysis summarized in Table XI.

however, that the interest differentials on this side of Table VI are typically positive, but with very marginal magnitudes.

As a first pass to determine whether any value can be gained from including the forecast rule with the interest rate rule and the technical rule, Table VI presents the returns to a naive strategy of applying an equal (1/3) allocation across the three strategies. These results should be compared to the 50-50 naive strategy presented in Table III. In general, while we do find that diversifying across strategies improves performance relative to the forecasting rule, the interest rate rule, or the technical rule in isolation, the incremental benefit to adding the forecasting rule to the 50-50 naive interest rate/ technical rule is relatively insignificant. In short, while the returns to following the forecast rules have a positive mean, they are statistically insignificant and of very little to no incremental benefit when used in concert with other foreign exchange trading strategies.[31]

Table VII presents the returns to a strategy of initiating an equally-weighted long (short) position across all currencies with positive (negative) forecasted returns. It is immediately apparent from an analysis of this table that virtually no benefit is obtained through following this approach. The immediate conclusion that we can reach after even a cursory examination of this table is that if any benefit is to be found with following foreign exchange forecasts, it will be at the extremes – certainly not across all currencies.

Table VIII (forecasts using spot rates) and Table IX (forecasts using interest-adjusted returns) present the returns for the individual forecasted ranks. In these two tables, "R1" is the highest ranked currency and "R(L)" is the lowest ranked currency. Each of the tables are divided into three sections: the total return to each rank, the return due to the interest differential with each rank, and the residual return for each rank. The residual return is defined as the difference between the total return and the return due to the interest differential.

[31] It is certainly possible, however, that this conclusion is reached due to the poor performance of the forecasting rules during 1990 – 1994.

Direct inspection of the total returns in Table VIII and Table IX reveals that while the mean return to the highest rank is generally greater than the mean return to the lowest rank, that this difference is not necessarily stable over the three-subperiods nor is the relationship between return and rank monotonic. In particular, the R3 return and the R(L-1) return both appear to be greater than the return to R1 in many cases. While the fact that the R1 return is greater than the return to R(L) is an interesting result, we cannot say that the returns even closely align along forecast rank.[32]

While the total returns do not align well based on rank, it is particularly interesting to examine the interest differential returns across rank in Table IX. In this table, we find a nearly monotonic relation between currency rank and the level of the interest differential. In fact, we find that the alignment is strongest when the forecasting rules appear to have achieved their greatest returns – during the 1995 – 2003 period. This result may partially explain the results we will later find in Table XIII, Table XIV, Table XV, and Table XVI. That is, screening the forecasts based upon their alignment with the interest differential may enhance performance. Finally, direct examination of the residual return in Table VIII and Table IX shows about the same relation as with actual returns. Especially for currency forecasts based on forward prices, the return alignment by rank appears to be primarily due to the underlying interest differential between the non-U.S. and U.S. currency.

To examine the robustness of our results, we replicated Table VI across various base currencies besides the U.S. dollar. That is, we first converted all forecasts, spot rates, and forward prices to another reference currency and then examined the profitability to all 32 forecast trading rules in Table VI.[33] Consistent with our earlier findings, very rarely are any of the forecasting rules statistically significant. Table VI does appear to validate,

[32] After preparing Table VIII and Table IX, we tested a strategy of applying equal weight to the top three ranks and shorting the bottom rank. In many cases, we were able to generate about the same mean return with a decline in standard deviation of between 15 and 20 percent.

[33] We did not include the Euro, the French franc, and the German mark as these currencies did not have continuous returns series over the entire sample period.

however, the potential promise of the one-month holding period combined with a twelve-month forecast horizon.[34]

We have found in Table VI that while every forecast trading rule with one notable exception has generated positive but statistically insignificant returns, a few do stand out as viable possibilities upon which to build a trading platform. Table XI analyzes whether this performance may have been due to chance. In particular, Table XI conducts bootstrap tests of the top five performing currency forecast rules based on spot rates and based on forward prices.

In Table XI, we conduct four types of bootstrapping tests. First, we examine the probability that the return performance for the best rules could have been generated by scrambling the rows of rank data but maintaining the ordering in each row. We call this bootstrap procedure the "no timing ability" test.[35] Next, we find the chance that the return performance for the best rules could have been earned by scrambling not only the rows of rank data, but also the ranks within each row. We call this bootstrap procedure the "no timing ability, no selection ability" test. Third, we examine the maximum performance across all rules for the "no timing ability" test and present the number of times that these random returns fell short of the actual performance to each of the top five rules. Finally, we examine the maximum performance across all rules for the "no timing ability, no selection ability" test and total the number of times that this randomly generated rule fell short of the actual returns to each of the top five rules.

Table XI basically validates the significance levels reported in Table VI. When the bootstrap procedures are implemented for each rule in isolation, several appear to be highly significant. However, when we recognize that one of 32 forecast trading rules could have easily generated those returns by chance, then we need to exercise more

[34] Once again, we intentionally ignore the three-month holding period, three-month forecast rule based on spot currency returns. We will analyze this particular rule in Table XI.
[35] Recall from Table V that during the 1999 – 2003 period the twelve-month interest-adjusted forecast shorted the Japanese yen in over 98 percent of the months. Of course, scrambling only the forecast rows will not affect performance in this case (at least on the short side), but a legitimate argument could be made that a decision to continuously short the yen implies no timing ability in the first place.

caution. Even after the bootstrap tests, the three-month holding period, three-month forecast horizon rule with forecast relative to the spot rate appears to be significant, but given that this same rule was not significant for any other base currency in Table X, we have to view this result with a healthy measure of skepticism. Finally, it is interesting to note that the interest differential performance is unusually (and significantly) low for the forecasts based on spot rates and unusually (and significantly) high for forecasts based on forward prices.

III.D. Timing in the Application of the Forecast Trading Rules

So far we have found limited evidence that some positive returns can be earned using foreign currency forecasts. But these returns appear to be statistically insignificant. We should point out, however, that we are aware of no paper that has found as great of a use for currency forecasts as we have thus far. Still, it is somewhat unsatisfactory that the returns generated by following the currency forecasts may be entirely due to chance.

In this section, we wish to analyze whether the forecast rankings might be combined with the rankings given by technical and/or interest rate signals. That is, we will first provide a score to each month based upon the level of agreement between the forecast and the technical and/or interest rate signal. We will then analyze the returns during the following month based upon this score.

The complete description for our method to determine agreement between forecast rank and the technical and/or interest rate signal rank is given in Table XII. Basically, our process was to first identify the top and bottom ranked currency by using the currency forecast each month. We then compared the top-ranked (bottom-ranked) currency using the forecast with either the top (bottom) two (strict matching criteria) or the top (bottom) four (less strict matching criteria) currencies by using the technical and/or interest rate rule.[36]

[36] Since the technical rule is based upon the average of 354 different parameterizations, when we ranked currencies by the technical rule we first identified the average rank across the parameterizations for each currency each month.

If we found agreement for both the long and short position forecast position then we classified the month as "1". If we found agreement with only the long (short) side, then we classified the month as "2" ("3"). If we found no agreement on the ranks, then we classified the month as "4". We performed this classification for the forecast rule with the technical rule, then again using the forecast rule with the interest rate rule.

We also wished to identify the agreement of the forecast with both the technical and the interest rate rule together. The algorithm that we used to do this is also given in Table XII, but basically if the forecast agreed (disagreed) with both the technical and the interest rate rule, then the month was coded as "1" ("6"). Classifications between "1" and "6" corresponded to less than perfect agreement with lower numbers corresponding to greater agreement.

Table XIII (forecasts relative to spot rates) and Table XIV (forecasts relative to forward prices) present the results when we applied the strict criteria for determining agreement between the forecast and the technical/interest rate signal. In nearly every case, we see that the returns to the forecast are greater when a given month is classified as "1", "2", or "3", than when it is classified as "4". The results are even more striking when we examine the combined classifications.

These results should be compared directly with the returns for the rules based on currency forecasts in isolation given in Table VI. For example, using forecasts on spot rates, the return to a forecast strategy based on the six-month forecast and one-month holding period (H1F6) is 10 basis points a month – hardly significant. Yet, when we examine Table XIII (agreement with the technical signal), we can identify 23 months when this same strategy returned on average 84 basis points and 63 more months with an average return of 93 basis points each month. The reason that this particular forecast rule performed so poorly was the 74 months when it lost on average 83 basis points a month.

We should point out that all these results would have been easily predicted in advance by examining agreement with the technical signal. We have also presented the returns during three subperiods in our sample. In general, we find that our result is stable across subperiods.

In Table XIII and Table XIV, we have also presented the returns to a strategy that only uses the forecasts when a month is not classified as "4" (Rule-ex 4) and also for the combined signal case when a month is classified as "1", "2", or "3" (Rule-ex 4,5,6). In many cases, the returns to following the forecasts (subject to agreement with the other signals) now become statistically significant. For example, once again looking at Table XIII, we see that when we condition our trading strategy upon agreement with the technical signal, we can realize 49 basis points a month for the H1F6 strategy.

In addition to using only the currency forecasts, we employ a strategy that equally weights the forecast rule, the technical rule, and the interest rate rule only when the month is not classified as "4" (compare with technical or interest rate rule in isolation) or classified as "1", "2", or "3" (compare with both the technical and interest rate rule). This rule is denoted as "Rule & Nv" in the tables. In many cases, we find that this combined approach is also statistically significant.

Table XV (forecasts relative to spot rates) and Table XVI (forecasts relative to forward prices) present the results when we applied the less strict criteria for determining agreement between the forecast and the technical/interest rate signal. The results here are even more striking. When we use agreement with the interest rate rule or the combined signal, we find positive returns, many of which are significant at the one percent level. For example, once again sticking with the H1F6 trading strategy (with forecast relative to spot rates), Table XV shows that the "Rule and Nv" approach earns 35 basis points a month (using only the interest rate rule) and 34 basis points a month (using the combined classification). This may not sound impressive by itself, but each of these returns is significant at the one percent level and can be levered without cost to generate very respectable returns with acceptable risk. We should also point out that some of the other rules do even better than the one we have chosen as an example.

In short, we are able to determine on an ex-ante basis the months where the currency forecasts appear to work and the months where they should not be used. Our approach has been very simple, and we believe that even more effective screens are likely present to cull the currency forecast months. At a minimum, we feel confident in stating that – at least from 1990 to 2003 – the level of agreement between the forecast and technical / interest rate signals has been a reliable predictor for the future return that can be earned by following the foreign exchange forecast.[37]

IV. Conclusion

We have shown through the Bayesian analysis that currency forecasts can be quite noisy and yet still allow for the possibility of significant trading profits. Unfortunately, when we examine the relation between actual and forecast returns through a simple OLS regression framework, we find little statistical evidence that the forecasts are even remotely related to the true, future returns. However, we believe that this type of analysis is, at best, misguided.

We choose, instead, to rank the currencies by their forecast appreciation to a base currency of reference and then to initiate long-short trades in the extreme currencies. We find that, although the mean returns are positive in many cases they remain statistically insignificant. We also find that this result is robust to the base currency of reference. Finally, we examine through various bootstrap procedures the likelihood that the returns that we witness might be due to chance. The bootstrap analysis does not eliminate the

[37] In addition, we tested whether we could identify better performing months by using the technical rule or the interest rate rule in an analogous fashion as we did for the currency forecast rule. That is, we performed several tests where we used the technical or the interest rate rule as the base case and then compared the other (including currency forecasts) rankings. As with the currency forecasts, we found similar improvement for determining which months to use either the technical or the interest rate rules. Finally, we also found significant diversification benefits by combining all methods into one master foreign exchange portfolio.

possibility that the positive mean returns of even the best of the currency forecast trading rules might have been due to chance.

Finally, we examine whether the currency forecast ranks might be combined with the technical signal and interest rate rule ranks to predict the months when the currency forecasts might achieve better performance. On this front, our results are much more promising. We find strong evidence that the currency forecasts are highly useful when used in concert with other trading signals.[38]

We should point out that the screening criteria that we use in this paper are very basic and that substantial improvements can likely be made by using better technical indicators and perhaps by incorporating other signals such as those based upon the macroeconomic factors commonly used in currency forecasting models. One would be ill-advised to ever employ the technical trading signal that we use in this paper. The only purpose for using this technical signal is to minimize ex-post selection critiques. We know for a fact that better screening signals exist than what we have reported in this study.

Both the providers and end-users of currency forecasts should find direct application from this study. For the end-user, any tool to know when to give greater reliance to currency forecasts should prove to have immense value. This would be true not only for active traders, but also to large international institutions with significant foreign exchange exposure. For the provider, any tool that gives a confidence measure to foreign exchange recommendations would certainly merit examination.

The avenues of future research based upon this study are manifold. First, the generality of these results should be tested against the currency forecasts of other providers. We need to establish that the strong results of this paper are not due to some unknown

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[38] The reader may wonder whether the trading strategy identified in this paper was determined after trying many alternatives that did not work. In fact, we planned two tests based on agreement across signals before beginning this study. In the first test, we attempted to implement a trading method based upon the Bayesian experiment used earlier in this paper. This did not work. Our second test was exactly as given in Table XIII and Table XIV. After viewing the results from Table XIII and Table XIV, we slightly modified our method to produce Table XV and Table XVI.

peculiarity with our particular currency forecast provider. Second, the screening tools that we have used in this paper are extremely basic and, one could argue, ad-hoc. Better screens must exist to cull the better performing forecasting months from the months that would act as a drag on realized returns. Third, the literature on currency forecasts using macroeconomic factors should be revisited with a focus on currency ranks rather than individual currencies.[39] Perhaps the poor results initially found in Meese and Rogoff (1983) are due to contamination by the "middle currencies". If we first have some mechanism to screen (and rank) the currencies, we may find more promising results. Future research will have to determine the most appropriate screening methods. Finally, the literature on technical trading rules should be updated to incorporate agreement with other foreign exchange trading signals.

Given the size and importance of the foreign exchange market, we know much less than we should regarding the quality of currency forecasts. This is perhaps not surprising given that many forecast providers are reluctant to open their individual forecasts to rigorous inspection. As a first pass, the providers of currency forecasts should go back and reproduce this work using their own predictions. Perhaps, if they also find promising results, then our work will be further substantiated. Of course, we will never hear from a forecast provider where our method does not work.[40] But perhaps someone will one day trace down an alternative forecasting dataset to demonstrate a negative result. In that case, a "no" result would prove to be a very interesting finding.

[39] We should note, however, that the findings of Engel and West (2003) may once again pose some difficulty for determining the relation between macroeconomic factors and rank currency returns.

[40] We should point out that FX4casts.com made no condition on what we could report from this study before providing the forecast data.

Appendix A

The list of providers to FX4casts.com as at December 2003:

ABN AMRO
Allied Irish Bank
ANZ Bank
Banca Intesa
Bank Julius Baer
Bank of America
Bank of New York
Bank One
Barclays Capital
BBVA
Citigroup
Commerzbank
Credit Suisse – First Boston
Daiwa Securities
Deutsche Bank
Dresdner Kleinwort Wasserstein
Goldman Sachs
HSBC
Hypo Vereinsbank
Industrial Bank of Japan
ING Barings Capital Management
JP Morgan Chase
Mellon
Merrill Lynch
Morgan Stanley
National Australia Bank
Nomura Research Institute
Nordea
Rabobank
Royal Bank of Canada
Scotia Bank
Societe Generale
Suntrust
UBS Warburg
Wachovia
Westdeutsche Landesbank
Wespac

Appendix B

We wish to establish the Bayesian posterior expectation for multiple assets receiving multiple, correlated signals. We will begin with the univariate case and then proceed to the multivariate setting. We should point out that nothing in this appendix is original, and, in fact, any rigorous Bayesian statistics textbook should provide a similar proof. We are presenting this appendix merely as a reference for those who wish to apply Bayesian analysis to finance applications.

B.1. The Univariate Case

The problem we consider is the case where the forecaster receives a noisy signal regarding the true, future return of an asset. In this setting we will assume $r \sim N(\mu_r, \sigma_r^2)$ where r is the true return of the asset. The forecaster's signal can then be written as: $f = r + \varepsilon$ where ε represents the forecast error. We will assume that ε is uncorrelated with r and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. It immediately follows that $f \sim N(\mu_r, \sigma_r^2 + \sigma_\varepsilon^2)$.

Now, the forecaster wishes to determine how much confidence to give to the private signal f. The greater the variance of ε, the less confidence that the forecaster will have in the private signal. Ultimately, the forecaster is interested in finding the expected value of the actual return, r, given a certain forecast, f. Using Bayes rule, the probability density function for $[\, r \mid f\,]$ can be written as:

$$\mathrm{pdf}_{r|f}(r \mid f) \;=\; \frac{\mathrm{pdf}_{f|r}(f \mid r) * \mathrm{pdf}_r(r)}{\mathrm{pdf}_f(f)} \tag{B1}$$

where

$$\mathrm{pdf}_r(r) \;=\; \frac{1}{\sqrt{2\pi}\sigma_r}\mathrm{Exp}\left[\frac{-1}{2\sigma_r^2}(r-\mu_r)^2\right], \tag{B2}$$

$$\text{pdf}_f(f) \;=\; \frac{1}{\sqrt{2\pi(\sigma_r^2+\sigma_\varepsilon^2)}}\text{Exp}\left[\frac{-1}{2(\sigma_r^2+\sigma_\varepsilon^2)}(f-\mu_r)^2\right], \tag{B3}$$

$$\text{pdf}_{f|r}(f\,|\,r) \;=\; \text{pdf}_\varepsilon(f-r) \;=\; \frac{1}{\sqrt{2\pi}\sigma_\varepsilon}\text{Exp}\left[\frac{-1}{2\sigma_\varepsilon^2}(f-r)^2\right]. \tag{B4}$$

We will define the ratio of the variance of the random error to the underlying variance as k:

$$k \;=\; \frac{\sigma_\varepsilon^2}{\sigma_r^2}. \tag{B5}$$

Now, we can rewrite equation (B1) using equations (B2) – (B5).

$$\text{pdf}_{r|f}(r\,|\,f) \;=\; \frac{1}{\sqrt{2\pi\frac{k}{1+k}\sigma_r^2}}\text{Exp}\left[\frac{-1}{2\sigma_r^2}\left(\frac{(f-r)^2}{k}+(r-\mu_r)^2-\frac{(f-\mu_r)^2}{1+k}\right)\right]. \tag{B6}$$

Using basic algebra, equation (B6) can be rewritten as:

$$\text{pdf}_{r|f}(r\,|\,f) \;=\; \frac{1}{\sqrt{2\pi\frac{k}{1+k}\sigma_r^2}}\text{Exp}\left[\frac{-1}{2\frac{k}{1+k}\sigma_r^2}\left(r-\frac{k\mu_r+f}{1+k}\right)^2\right]. \tag{B7}$$

We can see immediately that equation (B7) is the pdf of a normal distribution. It immediately follows that:

$$[\,r\,|\,f\,] \;\sim\; \text{N}\left(\frac{k\mu_r+f}{1+k},\frac{k}{1+k}\sigma_r^2\right). \tag{B8}$$

Replacing k with its definition in equation (B5) gives:

$$[\,r\,|\,f\,] \sim \text{N}\left(\frac{\sigma_\varepsilon^2\mu_r+\sigma_r^2 f}{\sigma_r^2+\sigma_\varepsilon^2},\frac{\sigma_r^2\sigma_\varepsilon^2}{\sigma_r^2+\sigma_\varepsilon^2}\right). \tag{B9}$$

Using equation (B8) we can see that the weight that the forecaster will give to the unconditional mean is:

$$w(\mu_r) \;=\; \frac{k}{1+k}, \tag{B10}$$

and the weight given to the signal is:

$$w(f) = \frac{1}{1+k}. \tag{B11}$$

Obviously, $w(\mu_r) + w(f) = 1$.

Direct inspection of equation (B5) with equations (B10) and (B11) reveals that as the noise level in the forecast increases, the forecaster will give less weight to the signal and greater weight to the unconditional mean. We are now ready to progress to the multivariate setting.

B.2. The Multivariate Case

Let n denote the number of assets that we wish to forecast. We will define an (n x 1) vector of returns, $\boldsymbol{r} \in \Re^n$. We will assume that $\boldsymbol{r} \sim \mathbf{N}(\boldsymbol{\mu_r}, \boldsymbol{\Sigma_r})$, where $\boldsymbol{\mu_r} \in \Re^n$ and $\boldsymbol{\Sigma_r} \in \Re^{nxn}$. The ($n$ x 1) vector of forecasts will be denoted as $\boldsymbol{f} \in \Re^n$ with $\boldsymbol{f} = \boldsymbol{r} + \boldsymbol{\varepsilon}$. We will assume that $\boldsymbol{\varepsilon} \sim \mathbf{N}(\mathbf{0}, \boldsymbol{\Sigma_\varepsilon})$ and is uncorrelated with $\boldsymbol{r}$.

As an analogue to Bayes rule we will use multivariate inverse regression (Morrison 1990)) to find the expected value of $\boldsymbol{r}$ given a certain forecast $\boldsymbol{f}$. We will define:

$$\boldsymbol{S} = \begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{\varepsilon} \end{bmatrix}_{\boldsymbol{2n} \times \mathbf{1}}, \tag{B12}$$

with covariance matrix:

$$\boldsymbol{\Sigma_S} = \begin{bmatrix} \boldsymbol{\Sigma_r} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma_\varepsilon} \end{bmatrix}_{\boldsymbol{2n} \times \boldsymbol{2n}}. \tag{B13}$$

We can transform $\boldsymbol{S}$ such that:

$$\boldsymbol{S'} = \begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{f} \end{bmatrix} = \begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{r} + \boldsymbol{\varepsilon} \end{bmatrix}. \tag{B14}$$

It follows that $\boldsymbol{S'} = \boldsymbol{A}\,\boldsymbol{S}$ with $\boldsymbol{A} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{I} & \mathbf{I} \end{bmatrix}_{\boldsymbol{2n} \times \boldsymbol{2n}}$. (B15)

The covariance matrix of $\boldsymbol{S}$ now transforms to:

$$\Sigma_{\boldsymbol{S'}} = \boldsymbol{A}\ \Sigma_{\boldsymbol{S}}\ \boldsymbol{A'} = \begin{bmatrix} \Sigma_{\boldsymbol{r}} & \Sigma_{\boldsymbol{r}} \\ \Sigma_{\boldsymbol{r}} & \Sigma_{\boldsymbol{r}} + \Sigma_{\varepsilon} \end{bmatrix}_{\boldsymbol{2n} \times \boldsymbol{2n}} . \tag{B16}$$

These transformations can be found in Morrison (1990). Now, using inverse regression we find:

$$\begin{aligned} \mathrm{E}[\,\boldsymbol{r} \,|\, \boldsymbol{f} = \boldsymbol{f}^*\,] &= \boldsymbol{\mu_r} + \Sigma_{\boldsymbol{r}} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}} (\,\boldsymbol{f}^* - \boldsymbol{\mu_r}\,) \\ &= \left(\left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)\Sigma_{\boldsymbol{r}}^{-1} - \mathbf{I}\right)\Sigma_{\boldsymbol{r}} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}} \boldsymbol{\mu_r} - \Sigma_{\boldsymbol{r}} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}} \boldsymbol{f}^* \\ &= \Sigma_{\varepsilon} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}} \boldsymbol{\mu_r} + \Sigma_{\boldsymbol{r}} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}} \boldsymbol{f}^* . \end{aligned} \tag{B17}$$

Note the similarity between equation (B17) and the expected value in equation (B9). The Bayesian posterior expectation in a multivariate setting is of the same form as in the univariate case.

We can see that if $\Sigma_{\varepsilon} = k\ \Sigma_{\boldsymbol{r}}$ then equation (B17) reduces to:

$$\mathrm{E}[\,\boldsymbol{r} \,|\, \boldsymbol{f} = \boldsymbol{f}^*\,] = \frac{\boldsymbol{k}}{\boldsymbol{1}+\boldsymbol{k}} \boldsymbol{\mu_r} + \frac{\boldsymbol{1}}{\boldsymbol{1}+\boldsymbol{k}} \boldsymbol{f}^* . \tag{B18}$$

Now that we have defined the conditional expectation in the multivariate setting, we now wish to define the total weight given to the forecast and the unconditional mean. Due to the matrix structure we are initially confronted with $2n^2$ weights. The expected value for currency i is not only a linear combination of f_i and $\mu_{r,i}$ but also all other $f_{j \neq i}$ and $\mu_{r,\,j \neq i}$. Using equation (B17), we can see that the total weight given to $\boldsymbol{\mu_r}$ is $\Sigma_{\varepsilon} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}}$ and the total weight given to $\boldsymbol{f}^*$ is $\Sigma_{\boldsymbol{r}} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}}$. Obviously, the sum of these weights is $\boldsymbol{1}_{\boldsymbol{n} \times \boldsymbol{1}}$.

Note that the *i*th row of $\Sigma_{\varepsilon} \left(\Sigma_{\varepsilon} + \Sigma_{\boldsymbol{r}}\right)^{-\boldsymbol{1}}$ gives the sum of the unconditional expected return weights allocated to currency i and that the ith row of $\Sigma_{\boldsymbol{r}}\left(\Sigma_{\boldsymbol{\varepsilon}}+\Sigma_{\boldsymbol{r}}\right)^{-\mathbf{1}}$ gives the sum of the forecast weights allocated to currency i.

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Table I
A Simulation of the Bayesian Updating Approach for Currency Selection

For each month from January 1980 through September 2003 a noisy signal is received regarding the future return (with respect to the U.S. dollar) of the Australian dollar, the British pound, the Canadian dollar, the Euro (1999 – 2003), the French franc (1980 - 1998), the German mark (1980 - 1998), the Japanese yen, the Swedish krona, and the Swiss franc. The signal that is received is:

$$r_s = r_x + r_\varepsilon$$

where r_s is the signal received, r_x is the true future return, and r_ε is a random noise element ~ N(0, k * σ_x^2). Note that k is the noise level and is expressed as a multiple of the trailing five year currency variance. The max and min extreme signals are truncated to the next largest or smallest values. From these signals a Bayesian forecast of the future return to each currency is generated for the appropriate holding period. From this expectation either one long and one short currency is selected (L1, S1) or long (short) positions are initiated in all currencies with positive (negative signals) (L(+), (S(–)). The positions are then held until the end of the holding period and subsequently reconstituted. The results presented are the mean values from 1,000 simulations on monthly returns. The "Mean Only" rows use only the trailing five year average return as the expected future return for each currency. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		L1, S1 Holding Period				L(+), S(–) Holding Period			
Noise Level		1 Month	3 Months	6 Months	12 Months	1 Month	3 Months	6 Months	12 Months
0.00	Mean	5.27***	3.30***	2.53***	1.69***	3.11***	2.07***	1.58***	1.12***
	Std Dev	2.89	3.02	3.30	3.24	1.64	2.21	2.17	2.14
	t-stat	(30.52)	(18.27)	(12.86)	(8.73)	(31.86)	(15.70)	(12.21)	(8.74)
	Prob > 0	100.00	91.49	79.79	70.21	100.00	85.46	79.08	71.63
1.00	Mean	2.20***	1.40***	1.06***	0.71***	1.60***	1.08***	0.82***	0.60***
	Std Dev	3.22	3.25	3.28	3.26	2.12	2.08	2.09	2.04
	t-stat	(11.47)	(7.24)	(5.44)	(3.66)	(12.66)	(8.70)	(6.57)	(4.93)
	Prob > 0	77.57	68.42	64.54	61.02	78.55	70.70	66.03	62.63
2.00	Mean	1.63***	0.99***	0.70***	0.42**	1.15***	0.75***	0.55***	0.37***
	Std Dev	3.27	3.26	3.30	3.29	2.06	2.01	2.02	2.04
	t-stat	(8.37)	(5.07)	(3.55)	(2.16)	(9.35)	(6.27)	(4.53)	(3.06)
	Prob > 0	70.61	63.28	59.99	57.32	71.43	64.96	61.17	58.07
3.00	Mean	1.34***	0.76***	0.50**	0.29	0.93***	0.59***	0.42***	0.25**
	Std Dev	3.29	3.29	3.30	3.33	2.00	1.98	2.01	2.08
	t-stat	(6.85)	(3.88)	(2.51)	(1.45)	(7.79)	(4.99)	(3.49)	(2.00)
	Prob > 0	66.89	60.39	57.47	55.37	67.76	61.97	58.78	55.60
4.00	Mean	1.16***	0.63***	0.39**	0.17	0.79***	0.49***	0.34***	0.17
	Std Dev	3.30	3.31	3.32	3.35	1.96	1.98	2.03	2.11
	t-stat	(5.89)	(3.20)	(1.98)	(0.85)	(6.73)	(4.11)	(2.80)	(1.32)
	Prob > 0	64.70	58.71	56.08	53.75	65.29	60.21	57.10	54.09
5.00	Mean	1.01***	0.53***	0.29	0.10	0.69***	0.43***	0.29**	0.12
	Std Dev	3.30	3.32	3.34	3.38	1.94	1.98	2.05	2.14
	t-stat	(5.13)	(2.67)	(1.46)	(0.49)	(6.00)	(3.61)	(2.37)	(0.91)
	Prob > 0	62.96	57.67	54.75	52.69	63.56	58.86	56.17	53.19
6.00	Mean	0.94***	0.45**	0.25	0.06	0.63***	0.37***	0.24**	0.07
	Std Dev	3.31	3.33	3.35	3.40	1.93	2.00	2.07	2.16
	t-stat	(4.74)	(2.26)	(1.26)	(0.30)	(5.46)	(3.14)	(1.98)	(0.56)
	Prob > 0	61.85	56.59	54.31	52.23	62.38	57.95	55.22	52.45
7.00	Mean	0.84***	0.40**	0.18	0.02	0.57***	0.33***	0.21*	0.04
	Std Dev	3.32	3.34	3.37	3.39	1.92	2.01	2.09	2.19
	t-stat	(4.25)	(2.00)	(0.89)	(0.11)	(5.01)	(2.77)	(1.66)	(0.28)
	Prob > 0	60.81	55.84	53.37	51.71	61.26	57.03	54.56	51.72
8.00	Mean	0.78***	0.34*	0.15	-0.03	0.52***	0.31**	0.17	0.02
	Std Dev	3.31	3.34	3.39	3.41	1.92	2.02	2.11	2.19
	t-stat	(3.95)	(1.72)	(0.75)	(-0.13)	(4.57)	(2.56)	(1.38)	(0.13)
	Prob > 0	60.11	55.25	53.03	51.04	60.31	56.76	54.00	51.43
9.00	Mean	0.73***	0.30	0.10	-0.06	0.50***	0.28**	0.15	0.00
	Std Dev	3.31	3.35	3.38	3.43	1.92	2.04	2.12	2.20
	t-stat	(3.67)	(1.52)	(0.51)	(-0.28)	(4.34)	(2.31)	(1.17)	(-0.03)
	Prob > 0	59.49	54.83	52.43	50.55	59.88	56.22	53.58	51.01
Mean Only	Mean	-0.49**	-0.56**	-0.58**	-0.62***	-0.18	-0.21	-0.32**	-0.32**
	Std Dev	3.60	3.67	3.82	3.71	2.34	2.37	2.45	2.27
	t-stat	(-2.26)	(-2.52)	(-2.50)	(-2.75)	(-1.26)	(-1.47)	(-2.17)	(-2.33)
	Prob > 0	45.04	46.10	43.62	41.49	50.71	48.94	46.45	44.68

Table II
Descriptive Statistics (Base Currency Returns)

The dataset is based on actual and forecasted base monthly returns for individual currencies spanning the period January 1990 through November 2003. The returns for the French franc and the German mark cover the period prior to the introduction of the Euro. All currency returns are with respect to the U.S. dollar. The one month forecasts span the period December 1989 through September 2000. The other forecasts span the entire period of December 1989 through October 2003. The Equal column gives equal weight to all individual currencies. The rows labeled "Beta" give the OLS slope coefficient of the regression of forecasted return (dependent) on actual return (independent). OLS t-stats are used to determine significance. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Australia	Canada	Euro	France	Germany	Japan	Sweden	Switzerland	United Kingdom	Equal
Base	1 Mo Ret	-0.03	-0.06	0.08	0.07	0.06	0.22	-0.07	0.15	0.07	0.05
	Std Dev	2.64	1.53	3.38	2.85	2.98	3.25	3.25	3.35	2.83	2.06
	t-stat	(-0.16)	(-0.52)	(0.17)	(0.27)	(0.21)	(0.88)	(-0.29)	(0.58)	(0.32)	(0.34)
	Prob > 0	50.00	46.99	43.86	51.38	48.62	49.40	47.59	49.40	54.82	48.19
	Ret (90-94)	0.00	-0.29	n.a.	0.18	0.20	0.64	-0.24	0.32	0.02	0.10
	Ret (95-98)	-0.42	-0.21	n.a.	-0.01	-0.07	-0.23	-0.09	0.05	0.18	-0.10
	Ret (99-03)	0.25	0.29	0.08	n.a.	n.a.	0.16	0.12	0.06	0.04	0.13
	3 Month Ret	-0.10	-0.17	0.25	0.23	0.19	0.83	-0.20	0.52	0.23	0.17
	6 Month Ret	-0.18	-0.32	0.56	0.52	0.42	2.33	-0.37	1.32	0.51	0.38
	12 Month Ret	-0.33	-0.54	1.45	1.32	1.02	10.12	-0.60	4.39	1.29	0.90
	1 Month Forecast Ret	0.04	0.04	0.25	-0.17	-0.15	-0.23	-0.27	-0.22	-0.25	n.a.
	3 Month Forecast Ret	0.63	0.30	0.72	-0.85	-0.76	-1.46	-0.75	-0.76	-1.09	n.a.
	6 Month Forecast Ret	1.95	0.83	3.42	-1.66	-1.49	-3.49	-1.52	-1.38	-2.31	n.a.
	12 Month Forecast Ret	3.61	1.24	7.66	-1.60	-1.29	-4.27	-1.46	-1.11	-2.74	n.a.
	Beta (1 month)	0.00	0.00	-0.02	0.00	-0.01	0.01	-0.01	-0.02	-0.01	n.a.
	Beta (3 month)	-0.06**	0.00	-0.08	0.00	-0.01	0.01	-0.04	-0.02	-0.04	n.a.
	Beta (6 month)	-0.03	-0.02	-0.15**	-0.04	-0.03	0.07	-0.03	-0.04	-0.07	n.a.
	Beta (12 month)	0.00	0.02	-0.09	-0.09**	-0.08	-0.01	-0.03	0.00	-0.01	n.a.

Table III
Descriptive Statistics (Interest-Adjusted Currency Returns)

The dataset is based on actual and forecasted base monthly returns for individual currencies spanning the period January 1990 through November 2003. The returns for the French franc and the German mark cover the period prior to the introduction of the Euro. All currency returns are with respect to the U.S. dollar. The one month forecasts span the period December 1989 through September 2000. The other forecasts span the entire period of December 1989 through October 2003. The Equal column gives equal weight to all individual currencies. The Interest Rate Rule initiates a long position in the highest interest rate currency each month and shorts the lowest interest rate currency. The technical rule is constructed as follows. Each month from January 1990 through October 2003 each currency is ranked from best to worst based upon the difference between the short-run moving average and long-run moving average of prior returns using 354 different combinations ranging from [1 , 2] to [12 , 36]. The technical rule will give equal weight to all combinations where the short-run moving average parameter ranges from 1 to 12 and the long-run moving average parameter ranges from 1 + the short-run moving average parameter to 36. The interest differential gives the return due to the interest differential between the non-U.S. and U.S. currencies. The rows labeled "Beta" give the OLS slope coefficient of the regression of forecasted return (dependent) on actual return (independent). OLS t-stats are used to determine significance. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Australia	Canada	Euro	France	Germany	Japan	Sweden	Switzerland	United Kingdom	Equal	Interest Rate Rule	Technical Rule	50/50 Int Rate/ Technical
Interest-Adjusted	1 Mo Ret	0.15	0.04	0.08	0.25	0.12	0.02	0.11	0.09	0.27	0.12	0.25	0.44*	0.34*
	Std Dev	2.67	1.55	3.43	2.88	2.99	3.28	3.28	3.37	2.84	2.09	3.79	2.94	2.37
	t-stat	(0.74)	(0.32)	(0.18)	(0.89)	(0.43)	(0.08)	(0.43)	(0.35)	(1.24)	(0.77)	(0.86)	(1.92)	(1.85)
	Interest Differential	0.19	0.10	0.00	0.17	0.06	-0.20	0.18	-0.06	0.20	0.07	0.50	0.02	0.26
	Prob > 0	54.82	51.81	45.61	52.29	50.46	46.99	48.80	50.60	56.02	49.40	54.82	58.43	54.82
	Ret (90-94)	0.31	-0.03	n.a.	0.54	0.41	0.64	0.20	0.50	0.39	0.37	-0.52	0.77	0.14
	Ret (95-98)	-0.32	-0.23	n.a.	-0.07	-0.18	-0.59	-0.02	-0.20	0.29	-0.17	0.96	0.78	0.90
	Ret (99-03)	0.38	0.33	0.08	n.a.	n.a.	-0.12	0.13	-0.09	0.14	0.11	0.43	-0.44	0.08
	3 Month Ret	0.54	0.12	0.26	0.93	0.41	0.06	0.37	0.30	1.07	0.42	n.a.	n.a.	n.a.
	6 Month Ret	1.36	0.25	0.58	2.73	1.00	0.12	0.87	0.70	3.27	1.03	n.a.	n.a.	n.a.
	12 Month Ret	4.59	0.57	1.51	12.94	3.00	0.26	2.49	1.88	17.25	3.10	n.a.	n.a.	n.a.
	1 Month Forecast Ret	0.21	0.14	0.02	-0.06	-0.12	-0.43	-0.08	-0.28	-0.05	n.a.	n.a.	n.a.	n.a.
	3 Month Forecast Ret	1.16	0.58	0.24	-0.59	-0.71	-2.05	-0.24	-0.96	-0.53	n.a.	n.a.	n.a.	n.a.
	6 Month Forecast Ret	2.99	1.38	1.08	-1.15	-1.39	-4.66	-0.54	-1.77	-1.20	n.a.	n.a.	n.a.	n.a.
	12 Month Forecast Ret	5.64	2.31	2.16	-0.56	-1.11	-6.63	0.45	-1.94	-0.58	n.a.	n.a.	n.a.	n.a.
	Beta (1 month)	0.00	0.02	-0.02	0.01	0.00	0.02	0.00	-0.01	0.00	n.a.	n.a.	n.a.	n.a.
	Beta (3 month)	-0.04	0.04**	-0.03	0.00	0.00	0.05*	-0.04	-0.01	-0.03	n.a.	n.a.	n.a.	n.a.
	Beta (6 month)	-0.01	0.01	-0.04	-0.02	-0.01	0.13***	-0.04	-0.02	-0.07	n.a.	n.a.	n.a.	n.a.
	Beta (12 month)	0.01	0.07***	0.01	-0.02	-0.01	0.11***	-0.05	0.04	-0.07	n.a.	n.a.	n.a.	n.a.

Table IV
Forecasted Currency Ranks (Base Currency Returns)

Using forecasts of future currency values, a forecasted return is generated relative to the current spot rate (with respect to the U.S. dollar). Each currency is then ranked by this forecasted return each month. The table below gives the proportion of months each currency was ranked first (R1), second (R2), next to last (R(L-1)), or last (R(L)) for each forecast horizon. The one month forecasts span the period December 1989 – September 2000. The three, six, and twelve month forecasts cover December 1989 – October 2003.

Period	Horizon	Rank	Australia	Canada	Euro	France	Germany	Japan	Sweden	Switzerland	United Kingdom
1990 - 1994	One Month Fcst	R1	26.67	15.00	n.a.	6.67	3.33	23.33	13.33	10.00	1.67
		R2	18.33	30.00	n.a.	6.67	15.00	11.67	8.33	8.33	1.67
		R(L-1)	5.00	20.00	n.a.	10.00	15.00	8.33	16.67	10.00	15.00
		R(L)	31.67	5.00	n.a.	6.67	8.33	6.67	15.00	11.67	15.00
	Three Month Fcst	R1	33.33	31.67	n.a.	0.00	5.00	21.67	1.67	5.00	1.67
		R2	18.33	36.67	n.a.	8.33	10.00	21.67	3.33	1.67	0.00
		R(L-1)	8.33	16.67	n.a.	20.00	15.00	3.33	16.67	15.00	5.00
		R(L)	20.00	1.67	n.a.	13.33	5.00	3.33	25.00	5.00	26.67
	Six Month Fcst	R1	46.67	35.00	n.a.	0.00	1.67	11.67	1.67	3.33	0.00
		R2	25.00	50.00	n.a.	1.67	13.33	6.67	1.67	1.67	0.00
		R(L-1)	6.67	10.00	n.a.	11.67	18.33	8.33	23.33	11.67	10.00
		R(L)	15.00	1.67	n.a.	11.67	1.67	8.33	26.67	5.00	30.00
	Twelve Month Fcst	R1	43.33	36.67	n.a.	0.00	3.33	16.67	0.00	0.00	0.00
		R2	28.33	50.00	n.a.	1.67	13.33	1.67	0.00	5.00	0.00
		R(L-1)	1.67	3.33	n.a.	13.33	10.00	5.00	33.33	11.67	21.67
		R(L)	10.00	0.00	n.a.	10.00	1.67	8.33	31.67	8.33	30.00
1995 - 1998	One Month Fcst	R1	45.83	27.08	n.a.	2.08	4.17	2.08	2.08	10.42	6.25
		R2	18.75	29.17	n.a.	6.25	4.17	12.50	10.42	10.42	8.33
		R(L-1)	4.17	4.17	n.a.	10.42	12.50	20.83	8.33	22.92	16.67
		R(L)	12.50	0.00	n.a.	14.58	10.42	16.67	12.50	22.92	10.42
	Three Month Fcst	R1	58.33	27.08	n.a.	2.08	4.17	0.00	4.17	4.17	0.00
		R2	27.08	52.08	n.a.	8.33	8.33	0.00	4.17	0.00	0.00
		R(L-1)	6.25	2.08	n.a.	16.67	12.50	12.50	12.50	20.83	16.67
		R(L)	2.08	0.00	n.a.	4.17	0.00	31.25	14.58	31.25	16.67
	Six Month Fcst	R1	70.83	18.75	n.a.	2.08	2.08	2.08	4.17	0.00	0.00
		R2	16.67	58.33	n.a.	6.25	8.33	4.17	0.00	6.25	0.00
		R(L-1)	4.17	4.17	n.a.	12.50	10.42	16.67	14.58	20.83	16.67
		R(L)	0.00	0.00	n.a.	4.17	2.08	25.00	10.42	29.17	29.17
	Twelve Month Fcst	R1	79.17	14.58	n.a.	2.08	2.08	2.08	0.00	0.00	0.00
		R2	16.67	62.50	n.a.	6.25	2.08	10.42	2.08	0.00	0.00
		R(L-1)	0.00	4.17	n.a.	12.50	8.33	18.75	18.75	20.83	16.67
		R(L)	0.00	0.00	n.a.	4.17	2.08	16.67	8.33	35.42	33.33
1999 - 2003	One Month Fcst	R1	42.86	14.29	14.29	n.a.	n.a.	0.00	0.00	23.81	4.76
		R2	23.81	14.29	19.05	n.a.	n.a.	4.76	4.76	28.57	4.76
		R(L-1)	9.52	19.05	9.52	n.a.	n.a.	28.57	14.29	14.29	4.76
		R(L)	4.76	0.00	4.76	n.a.	n.a.	52.38	4.76	14.29	19.05
	Three Month Fcst	R1	43.10	5.17	5.17	n.a.	n.a.	0.00	13.79	27.59	5.17
		R2	27.59	22.41	20.69	n.a.	n.a.	0.00	8.62	17.24	3.45
		R(L-1)	3.45	41.38	5.17	n.a.	n.a.	3.45	15.52	13.79	17.24
		R(L)	1.72	1.72	5.17	n.a.	n.a.	79.31	5.17	3.45	3.45
	Six Month Fcst	R1	51.72	1.72	8.62	n.a.	n.a.	0.00	13.79	22.41	1.72
		R2	8.62	10.34	29.31	n.a.	n.a.	1.72	24.14	20.69	5.17
		R(L-1)	0.00	55.17	3.45	n.a.	n.a.	3.45	5.17	1.72	31.03
		R(L)	0.00	1.72	1.72	n.a.	n.a.	93.10	1.72	1.72	0.00
	Twelve Month Fcst	R1	55.17	0.00	3.45	n.a.	n.a.	0.00	24.14	17.24	0.00
		R2	6.90	3.45	20.69	n.a.	n.a.	0.00	18.97	46.55	3.45
		R(L-1)	0.00	65.52	1.72	n.a.	n.a.	1.72	1.72	1.72	27.59
		R(L)	0.00	3.45	0.00	n.a.	n.a.	94.83	0.00	0.00	1.72

Table V
Forecasted Currency Ranks (Interest-Adjusted Currency Returns)

Using forecasts of future currency values, a forecasted return is generated relative to the current forward rate (with respect to the U.S. dollar). Each currency is then ranked by this forecasted return each month. The table below gives the proportion of months each currency was ranked first (R1), second (R2), next to last (R(L-1)), or last (R(L)) for each forecast horizon. The one month forecasts span the period December 1989 – September 2000. The three, six, and twelve month forecasts cover December 1989 – October 2003.

			Australia	Canada	Euro	France	Germany	Japan	Sweden	Switzerland	United Kingdom
1990 - 1994	One Month Fcst	R1	31.67	10.00	n.a.	8.33	1.67	18.33	18.33	8.33	3.33
		R2	18.33	31.67	n.a.	13.33	6.67	6.67	8.33	3.33	11.67
		R(L-1)	8.33	20.00	n.a.	6.67	20.00	15.00	5.00	18.33	6.67
		R(L)	26.67	6.67	n.a.	3.33	5.00	21.67	6.67	16.67	13.33
	Three Month Fcst	R1	38.33	30.00	n.a.	8.33	0.00	5.00	8.33	3.33	6.67
		R2	25.00	35.00	n.a.	8.33	5.00	10.00	6.67	0.00	10.00
		R(L-1)	8.33	8.33	n.a.	5.00	23.33	11.67	6.67	18.33	18.33
		R(L)	18.33	3.33	n.a.	5.00	8.33	20.00	10.00	16.67	18.33
	Six Month Fcst	R1	51.67	36.67	n.a.	0.00	0.00	1.67	6.67	0.00	3.33
		R2	30.00	51.67	n.a.	1.67	1.67	3.33	1.67	1.67	8.33
		R(L-1)	0.00	11.67	n.a.	10.00	26.67	5.00	6.67	33.33	6.67
		R(L)	8.33	0.00	n.a.	3.33	6.67	33.33	3.33	23.33	21.67
	Twelve Month Fcst	R1	60.00	35.00	n.a.	0.00	0.00	0.00	1.67	0.00	3.33
		R2	28.33	56.67	n.a.	0.00	0.00	1.67	6.67	0.00	6.67
		R(L-1)	1.67	0.00	n.a.	0.00	41.67	16.67	5.00	26.67	8.33
		R(L)	1.67	1.67	n.a.	1.67	6.67	40.00	1.67	33.33	13.33
1995 - 1998	One Month Fcst	R1	58.33	16.67	n.a.	0.00	0.00	2.08	4.17	6.25	12.50
		R2	14.58	39.58	n.a.	8.33	2.08	2.08	18.75	6.25	8.33
		R(L-1)	6.25	4.17	n.a.	12.50	22.92	16.67	6.25	25.00	6.25
		R(L)	8.33	0.00	n.a.	10.42	4.17	39.58	4.17	31.25	2.08
	Three Month Fcst	R1	70.83	16.67	n.a.	2.08	4.17	0.00	6.25	0.00	0.00
		R2	14.58	60.42	n.a.	10.42	4.17	0.00	4.17	4.17	2.08
		R(L-1)	10.42	0.00	n.a.	12.50	16.67	16.67	8.33	20.83	14.58
		R(L)	0.00	2.08	n.a.	2.08	2.08	50.00	2.08	41.67	0.00
	Six Month Fcst	R1	83.33	8.33	n.a.	2.08	2.08	0.00	4.17	0.00	0.00
		R2	8.33	70.83	n.a.	10.42	4.17	0.00	6.25	0.00	0.00
		R(L-1)	6.25	2.08	n.a.	8.33	14.58	14.58	10.42	29.17	14.58
		R(L)	0.00	0.00	n.a.	4.17	0.00	45.83	0.00	43.75	6.25
	Twelve Month Fcst	R1	85.42	10.42	n.a.	0.00	4.17	0.00	0.00	0.00	0.00
		R2	10.42	75.00	n.a.	6.25	0.00	0.00	6.25	0.00	2.08
		R(L-1)	0.00	0.00	n.a.	6.25	10.42	20.83	10.42	41.67	10.42
		R(L)	0.00	0.00	n.a.	4.17	0.00	43.75	0.00	43.75	8.33
1999 - 2003	One Month Fcst	R1	57.14	14.29	4.76	n.a.	n.a.	0.00	0.00	14.29	9.52
		R2	14.29	23.81	33.33	n.a.	n.a.	0.00	0.00	4.76	23.81
		R(L-1)	9.52	14.29	14.29	n.a.	n.a.	19.05	9.52	14.29	19.05
		R(L)	4.76	0.00	4.76	n.a.	n.a.	71.43	4.76	14.29	0.00
	Three Month Fcst	R1	63.79	3.45	8.62	n.a.	n.a.	0.00	8.62	10.34	5.17
		R2	13.79	18.97	13.79	n.a.	n.a.	0.00	15.52	15.52	22.41
		R(L-1)	0.00	43.10	3.45	n.a.	n.a.	10.34	5.17	29.31	8.62
		R(L)	0.00	0.00	1.72	n.a.	n.a.	87.93	1.72	8.62	0.00
	Six Month Fcst	R1	63.79	3.45	10.34	n.a.	n.a.	0.00	8.62	10.34	3.45
		R2	15.52	10.34	25.86	n.a.	n.a.	0.00	25.86	10.34	12.07
		R(L-1)	1.72	55.17	3.45	n.a.	n.a.	3.45	3.45	13.79	18.97
		R(L)	0.00	0.00	1.72	n.a.	n.a.	94.83	0.00	3.45	0.00
	Twelve Month Fcst	R1	63.79	0.00	6.90	n.a.	n.a.	0.00	18.97	8.62	1.72
		R2	12.07	3.45	32.76	n.a.	n.a.	0.00	41.38	5.17	5.17
		R(L-1)	0.00	63.79	1.72	n.a.	n.a.	1.72	0.00	22.41	10.34
		R(L)	0.00	0.00	0.00	n.a.	n.a.	98.28	0.00	1.72	0.00

Table VI
The Returns to Following Currency Forecasts (R1 – R(last))

This table presents summary statistics of monthly returns for all combinations involving one, three, six, and twelve month forecasts and one, three, six, and twelve month holding periods. The strategy analyzed is to go long the currency with the greatest forecasted return (relative to the spot or forward rate) and short the currency with the least forecasted return. The returns span the period January 1990 – October 2000 for the one-month forecasts and January 1990 – November 2003 for all other forecasts. The interest differential gives the mean return each month due to the interest rate differential between the non-U.S. and U.S. currencies. The naive analysis considers a strategy that gives equal weight to the forecast strategy, the interest rate rule, and the technical rule. For multi-month holding periods, 1/n of the currency portfolio is rebalanced each month where n corresponds to the holding period. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Ranking Relative to Spot (Base) Holding Period				Ranking Relative to Forward (Int Adj) Holding Period			
		1 Month	3 Months	6 Months	12 Months	1 Month	3 Months	6 Months	12 Months
One Month Forecast	Mean	0.05	0.34	0.07	-0.04	0.33	-0.08	-0.12	-0.10
	Std Dev	3.44	3.45	2.78	2.21	3.49	3.60	2.86	2.53
	t-stat	(0.16)	(1.09)	(0.28)	(-0.19)	(1.05)	(-0.24)	(-0.48)	(-0.44)
	Int Diff	0.02	0.00	0.02	0.02	0.17	0.15	0.16	0.18
	Prob > 0	46.15	53.85	46.15	45.38	51.54	51.54	45.38	49.23
	Ret (90-94)	-0.24	0.55	0.45	0.02	0.09	0.07	0.21	0.02
	Ret (95-98)	0.68	0.46	0.02	0.14	1.08	0.15	-0.06	0.05
	Ret (99-03)	-0.64	-0.52	-0.54	-0.12	-0.74	-0.97	-0.82	-0.36
	Naïve Ret	0.21	0.32*	0.28	0.22	0.30	0.18	0.21	0.20
	Naïve Std Dev	2.17	2.18	1.98	1.96	2.23	2.34	2.09	2.12
	Naïve t-stat	(1.08)	(1.67)	(1.60)	(1.34)	(1.51)	(0.89)	(1.17)	(1.09)
Three Month Forecast	Mean	0.25	0.51*	0.22	0.13	0.31	0.37	0.15	0.07
	Std Dev	4.04	3.74	3.21	3.02	3.69	3.70	3.33	3.18
	t-stat	(0.79)	(1.73)	(0.88)	(0.53)	(1.08)	(1.25)	(0.58)	(0.28)
	Int Diff	0.06	0.04	0.04	0.07	0.23	0.21	0.21	0.23
	Prob > 0	51.20	57.23	56.02	51.81	53.01	55.42	53.61	51.81
	Ret (90-94)	0.59	0.52	0.23	0.09	0.23	0.11	0.04	-0.19
	Ret (95-98)	0.24	0.73	0.12	-0.11	0.39	0.68	0.15	-0.04
	Ret (99-03)	-0.07	0.31	0.30	0.36	0.33	0.37	0.28	0.43
	Naïve Ret	0.30*	0.40**	0.30*	0.27*	0.32*	0.35*	0.28	0.25
	Naïve Std Dev	2.20	2.08	2.03	2.01	2.39	2.34	2.24	2.23
	Naïve t-stat	(1.74)	(2.46)	(1.92)	(1.73)	(1.72)	(1.92)	(1.60)	(1.45)
Six Month Forecast	Mean	0.10	0.04	0.08	0.05	0.23	0.20	0.12	0.14
	Std Dev	3.90	3.69	3.32	3.11	3.84	3.66	3.37	3.25
	t-stat	(0.34)	(0.14)	(0.32)	(0.18)	(0.75)	(0.69)	(0.46)	(0.56)
	Int Diff	0.10	0.09	0.09	0.11	0.27	0.25	0.25	0.27
	Prob > 0	48.19	51.20	53.01	55.42	51.20	53.01	53.01	55.42
	Ret (90-94)	-0.08	-0.56	-0.32	-0.36	-0.12	-0.63	-0.48	-0.16
	Ret (95-98)	-0.04	0.32	0.28	0.08	0.26	0.97	0.64	0.21
	Ret (99-03)	0.41	0.43	0.33	0.44	0.55	0.42	0.32	0.41
	Naïve Ret	0.25	0.24	0.26	0.24	0.30	0.29*	0.27	0.28
	Naïve Std Dev	2.25	2.07	2.06	2.03	2.41	2.19	2.24	2.22
	Naïve t-stat	(1.43)	(1.50)	(1.60)	(1.54)	(1.55)	(1.73)	(1.54)	(1.60)
Twelve Month Forecast	Mean	0.41	0.02	0.07	0.02	0.39	0.25	0.22	0.17
	Std Dev	3.86	3.78	3.54	3.30	3.73	3.83	3.64	3.52
	t-stat	(1.35)	(0.08)	(0.26)	(0.08)	(1.33)	(0.83)	(0.77)	(0.60)
	Int Diff	0.09	0.08	0.08	0.10	0.28	0.28	0.28	0.28
	Prob > 0	53.61	50.60	50.00	53.61	53.01	53.01	53.61	57.23
	Ret (90-94)	0.14	-0.31	-0.34	-0.39	0.07	-0.01	-0.10	-0.15
	Ret (95-98)	0.78	0.25	0.27	0.07	0.48	0.32	0.25	0.20
	Ret (99-03)	0.37	0.18	0.33	0.41	0.64	0.46	0.53	0.47
	Naïve Ret	0.36**	0.24	0.25	0.23	0.35*	0.31*	0.30*	0.28
	Naïve Std Dev	2.11	2.04	2.03	2.01	2.35	2.21	2.25	2.25
	Naïve t-stat	(2.14)	(1.49)	(1.60)	(1.50)	(1.89)	(1.82)	(1.73)	(1.62)

Table VII

The Returns to Following Currency Forecasts (Long(+) , Short(–))

This table presents summary statistics of monthly returns for all combinations involving one, three, six, and twelve month forecasts and one, three, six, and twelve month holding periods. The strategy analyzed is to go long all currencies with a positive forecasted return (relative to the spot or forward rate) and short all currencies with a negative forecasted return. The long and short sides are each equally weighted across currencies. The returns span the period January 1990 – October 2000 for the one-month forecasts and January 1990 – November 2003 for all other forecasts. The interest differential gives the mean return each month due to the interest rate differential between the non-U.S. and U.S. currencies. The naive analysis considers a strategy that gives equal weight to the forecast strategy, the interest rate rule, and the technical rule. For multi-month holding periods, 1/n of the currency portfolio is rebalanced each month where n corresponds to the holding period. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Ranking Relative to Spot (Base) Holding Period				Ranking Relative to Forward (Int Adj) Holding Period			
		1 Month	3 Months	6 Months	12 Months	1 Month	3 Months	6 Months	12 Months
One Month Forecast	Mean	-0.10	-0.11	-0.09	-0.09	-0.05	0.12	0.01	-0.06
	Std Dev	2.36	2.43	2.11	1.72	2.38	2.37	2.03	1.62
	t-stat	(-0.48)	(-0.52)	(-0.46)	(-0.61)	(-0.21)	(0.56)	(0.07)	(-0.40)
	Int Diff	0.01	-0.04	-0.03	0.01	0.08	0.06	0.07	0.08
	Prob > 0	46.15	49.23	44.62	48.46	48.46	54.62	53.08	48.46
	Ret (90-94)	-0.25	-0.17	0.06	-0.02	-0.26	0.22	0.18	-0.03
	Ret (95-98)	0.34	0.20	-0.04	-0.01	0.40	0.30	0.05	0.07
	Ret (99-03)	-0.72	-0.63	-0.28	-0.24	-0.50	-0.56	-0.22	-0.20
Three Month Forecast	Mean	0.06	0.02	-0.02	-0.01	0.01	0.02	0.01	0.00
	Std Dev	2.59	2.60	2.51	2.32	2.58	2.59	2.42	2.17
	t-stat	(0.29)	(0.09)	(-0.08)	(-0.04)	(0.03)	(0.12)	(0.04)	(0.00)
	Int Diff	0.03	0.03	0.03	0.03	0.09	0.08	0.08	0.09
	Prob > 0	53.61	51.81	51.20	47.59	53.61	53.01	52.41	50.00
	Ret (90-94)	0.16	-0.19	-0.26	-0.21	0.07	-0.14	-0.17	-0.18
	Ret (95-98)	-0.01	0.06	0.01	-0.12	-0.04	0.01	-0.02	-0.11
	Ret (99-03)	0.02	0.20	0.21	0.29	-0.02	0.21	0.21	0.28
Six Month Forecast	Mean	0.00	-0.10	-0.13	-0.07	0.14	-0.04	-0.05	-0.02
	Std Dev	2.61	2.68	2.47	2.34	2.71	2.81	2.55	2.37
	t-stat	(-0.01)	(-0.46)	(-0.67)	(-0.40)	(0.67)	(-0.17)	(-0.26)	(-0.11)
	Int Diff	0.05	0.04	0.04	0.05	0.11	0.12	0.12	0.12
	Prob > 0	51.81	49.40	48.80	46.99	55.42	54.22	53.01	51.20
	Ret (90-94)	-0.31	-0.53	-0.57	-0.38	-0.11	-0.48	-0.45	-0.30
	Ret (95-98)	0.10	0.10	0.02	-0.11	0.13	0.03	-0.09	-0.14
	Ret (99-03)	0.22	0.19	0.20	0.28	0.41	0.37	0.39	0.37
Twelve Month Forecast	Mean	0.05	0.01	0.00	-0.04	0.05	0.06	0.01	0.00
	Std Dev	2.67	2.74	2.54	2.48	2.65	2.72	2.51	2.47
	t-stat	(0.22)	(0.04)	(-0.02)	(-0.20)	(0.23)	(0.29)	(0.04)	(-0.01)
	Int Diff	0.04	0.03	0.03	0.03	0.15	0.14	0.13	0.14
	Prob > 0	53.61	53.61	53.61	51.20	57.23	56.02	53.01	52.41
	Ret (90-94)	-0.22	-0.28	-0.35	-0.35	-0.23	-0.43	-0.36	-0.28
	Ret (95-98)	-0.02	-0.09	0.00	-0.08	0.06	0.24	0.02	-0.12
	Ret (99-03)	0.37	0.39	0.35	0.32	0.32	0.42	0.38	0.38

Table VIII
The Returns to Following Currency Forecasts by Rank (Forecasts of Base Currency Returns)

Using forecasts of future currency values, a forecasted return is generated relative to the current spot rate (with respect to the U.S. dollar). Each currency is then ranked by this forecasted return each month. The realized monthly return, return due to interest differential, and the residual return (actual return less return due to interest differential) are given below for each rank. Note that the dataset contains eight non-U.S. currencies before the Euro and seven after the Euro's introduction. Because of this, some overlap will exist between R4 and R(-3). The returns span the period January 1990 – October 2000 for the one-month forecasts and January 1990 – November 2003 for all other forecasts.

		Actual Return				Return Due to Interest Differential				Residual Return			
		One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast	One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast	One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast
1990 - 2003	R1	0.04	0.18	0.09	0.18	0.09	0.08	0.11	0.11	-0.05	0.10	-0.02	0.07
	R2	-0.26	0.02	0.30	0.04	0.05	0.06	0.05	0.04	-0.31	-0.04	0.25	0.00
	R3	0.22	0.25	0.09	0.23	0.05	0.00	-0.01	-0.01	0.17	0.25	0.10	0.24
	R4	-0.06	0.18	0.06	0.34	0.07	0.09	0.09	0.08	-0.13	0.09	-0.02	0.26
	R(L-3)	-0.06	0.16	0.19	0.23	0.10	0.07	0.09	0.07	-0.16	0.09	0.11	0.16
	R(L-2)	0.02	0.11	0.20	0.10	0.08	0.10	0.09	0.11	-0.05	0.01	0.11	-0.01
	R(L-1)	-0.03	0.34	0.14	0.25	0.06	0.11	0.11	0.11	-0.09	0.23	0.02	0.14
	R(L)	-0.01	-0.07	-0.01	-0.23	0.07	0.02	0.01	0.02	-0.07	-0.09	-0.02	-0.25
1990 - 1994	R1	0.47	0.58	0.22	0.25	0.21	0.17	0.20	0.20	0.26	0.41	0.02	0.05
	R2	0.19	0.29	0.55	0.17	0.20	0.16	0.20	0.21	-0.01	0.13	0.36	-0.04
	R3	0.40	0.84	0.55	0.80	0.22	0.16	0.11	0.12	0.18	0.69	0.44	0.68
	R4	0.72	0.35	0.36	0.71	0.25	0.26	0.29	0.25	0.48	0.10	0.07	0.45
	R(L-3)	0.14	0.26	0.68	0.49	0.31	0.27	0.28	0.26	-0.17	-0.01	0.39	0.24
	R(L-2)	0.19	0.41	0.45	0.51	0.26	0.33	0.30	0.31	-0.07	0.08	0.15	0.20
	R(L-1)	0.50	0.60	0.21	0.27	0.32	0.35	0.34	0.35	0.18	0.25	-0.14	-0.09
	R(L)	0.71	-0.01	0.30	0.12	0.34	0.42	0.39	0.41	0.37	-0.43	-0.09	-0.29
1995 - 1998	R1	0.10	-0.07	-0.10	0.00	0.03	0.05	0.07	0.08	0.07	-0.13	-0.17	-0.08
	R2	-0.17	0.00	0.08	-0.12	-0.06	-0.01	-0.04	-0.05	-0.10	0.01	0.12	-0.07
	R3	0.42	-0.32	-0.16	-0.39	-0.08	-0.16	-0.15	-0.16	0.50	-0.16	0.00	-0.23
	R4	-0.74	-0.14	-0.26	0.04	-0.06	-0.02	-0.06	-0.06	-0.67	-0.12	-0.20	0.10
	R(L-3)	-0.05	-0.23	-0.15	-0.05	-0.06	-0.11	-0.06	-0.10	0.02	-0.12	-0.09	0.04
	R(L-2)	0.06	-0.21	-0.36	-0.34	-0.06	-0.07	-0.09	-0.06	0.12	-0.14	-0.27	-0.28
	R(L-1)	-0.38	-0.05	-0.32	0.32	-0.12	-0.07	-0.09	-0.11	-0.26	0.02	-0.24	0.42
	R(L)	-0.58	-0.31	-0.06	-0.78	-0.12	-0.15	-0.11	-0.08	-0.47	-0.16	0.05	-0.70
1999 - 2003	R1	-1.24	0.00	0.12	0.26	-0.09	0.03	0.04	0.04	-1.14	-0.02	0.08	0.23
	R2	-1.68	-0.24	0.24	0.04	-0.10	0.01	-0.01	-0.05	-1.58	-0.25	0.25	0.08
	R3	-0.71	0.15	-0.16	0.21	-0.09	-0.01	0.01	0.00	-0.61	0.16	-0.16	0.20
	R4	-0.58	0.29	0.05	0.22	-0.09	0.02	0.02	0.02	-0.49	0.27	0.03	0.20
	R(L-3)	-0.62	0.39	0.00	0.21	-0.11	0.02	0.02	0.02	-0.51	0.37	-0.02	0.20
	R(L-2)	-0.51	0.09	0.43	0.06	-0.11	0.02	0.02	0.06	-0.40	0.07	0.40	0.00
	R(L-1)	-0.62	0.43	0.46	0.17	-0.21	0.02	0.05	0.05	-0.41	0.41	0.41	0.12
	R(L)	-0.60	0.08	-0.29	-0.11	-0.25	-0.23	-0.28	-0.28	-0.35	0.31	-0.01	0.16

Table IX
The Returns to Following Currency Forecasts by Rank (Forecasts of Interest-Adjusted Currency Returns)

Using forecasts of future currency values, a forecasted return is generated relative to the current forward rate (with respect to the U.S. dollar). Each currency is then ranked by this forecasted return each month. The realized monthly return, return due to interest differential, and the residual return (actual return less return due to interest differential) are given below for each rank. Note that the dataset contains eight non-U.S. currencies before the Euro and seven after the Euro's introduction. Because of this, some overlap will exist between R4 and R(-3). The returns span the period January 1990 – October 2000 for the one-month forecasts and January 1990 – November 2003 for all other forecasts.

		Actual Return				Return Due to Interest Differential				Residual Return			
		One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast	One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast	One Month Forecast	Three Month Forecast	Six Month Forecast	Twelve Month Forecast
1990 - 2003	R1	0.04	0.22	0.12	0.25	0.14	0.14	0.15	0.15	-0.10	0.07	-0.02	0.10
	R2	-0.16	0.00	0.11	0.19	0.12	0.09	0.10	0.11	-0.28	-0.09	0.01	0.09
	R3	0.07	0.13	0.30	0.24	0.10	0.09	0.08	0.14	-0.04	0.04	0.22	0.10
	R4	-0.02	0.46	0.10	0.23	0.10	0.10	0.11	0.13	-0.12	0.36	-0.02	0.10
	R(L-3)	0.25	0.38	0.20	0.15	0.08	0.09	0.07	0.08	0.17	0.29	0.13	0.07
	R(L-2)	-0.04	-0.03	0.12	0.30	0.04	0.05	0.06	0.05	-0.08	-0.08	0.05	0.25
	R(L-1)	0.09	0.29	0.14	-0.15	0.02	0.06	0.06	0.01	0.07	0.23	0.08	-0.16
	R(L)	-0.29	-0.10	-0.10	-0.14	-0.03	-0.08	-0.12	-0.13	-0.26	-0.01	0.01	-0.01
1990 - 1994	R1	0.32	0.53	0.24	0.30	0.26	0.26	0.27	0.28	0.06	0.27	-0.03	0.02
	R2	0.19	0.31	0.20	0.32	0.28	0.26	0.26	0.29	-0.09	0.05	-0.07	0.03
	R3	0.53	0.27	0.66	0.45	0.31	0.23	0.24	0.38	0.22	0.03	0.42	0.07
	R4	0.35	0.43	0.49	0.57	0.27	0.29	0.35	0.37	0.08	0.14	0.14	0.20
	R(L-3)	0.62	0.64	0.75	0.69	0.26	0.27	0.27	0.26	0.36	0.37	0.47	0.43
	R(L-2)	0.60	0.51	0.44	0.84	0.23	0.22	0.28	0.22	0.36	0.29	0.16	0.62
	R(L-1)	0.48	0.34	0.19	-0.08	0.23	0.30	0.26	0.18	0.25	0.04	-0.08	-0.27
	R(L)	0.23	0.30	0.36	0.23	0.27	0.28	0.18	0.13	-0.03	0.02	0.18	0.10
1995 - 1998	R1	0.27	-0.14	-0.17	-0.13	0.07	0.08	0.09	0.09	0.21	-0.22	-0.26	-0.22
	R2	-0.07	0.06	-0.13	-0.07	0.01	-0.04	-0.03	-0.02	-0.08	0.09	-0.10	-0.05
	R3	-0.04	-0.05	0.06	0.17	-0.03	0.01	-0.01	0.02	0.00	-0.05	0.07	0.15
	R4	-0.34	0.11	0.07	0.11	-0.02	-0.06	-0.01	-0.01	-0.32	0.17	0.08	0.12
	R(L-3)	0.13	-0.44	0.05	-0.23	-0.06	-0.05	-0.06	-0.05	0.19	-0.39	0.11	-0.18
	R(L-2)	-0.24	-0.54	-0.35	0.00	-0.11	-0.08	-0.12	-0.12	-0.13	-0.46	-0.23	0.11
	R(L-1)	-0.24	0.20	-0.45	-0.57	-0.15	-0.11	-0.13	-0.19	-0.09	0.31	-0.32	-0.38
	R(L)	-0.80	-0.53	-0.42	-0.61	-0.23	-0.29	-0.27	-0.26	-0.57	-0.24	-0.15	-0.35
1999 - 2003	R1	-1.27	0.21	0.26	0.53	-0.03	0.08	0.08	0.07	-1.25	0.13	0.18	0.46
	R2	-1.31	-0.35	0.23	0.29	-0.05	0.02	0.04	0.03	-1.25	-0.37	0.19	0.26
	R3	-0.92	0.15	0.14	0.10	-0.14	0.02	0.01	0.02	-0.79	0.13	0.14	0.08
	R4	-0.27	0.78	-0.27	0.00	-0.09	0.03	-0.01	0.01	-0.18	0.74	-0.26	-0.02
	R(L-3)	-0.45	0.82	-0.22	-0.06	-0.10	0.03	-0.01	0.00	-0.35	0.79	-0.20	-0.06
	R(L-2)	-1.28	-0.12	0.20	0.02	-0.13	0.01	0.01	0.03	-1.15	-0.13	0.19	0.00
	R(L-1)	-0.21	0.31	0.59	0.13	-0.15	-0.03	0.01	0.00	-0.06	0.34	0.57	0.14
	R(L)	-0.53	-0.13	-0.30	-0.11	-0.36	-0.27	-0.28	-0.29	-0.17	0.15	-0.01	0.18

Table X
The Returns to Following Currency Forecasts From the Perspective of Various Base Currencies (R1 – R(last))

The strategy of initiating a long position in the highest ranked currency by forecasted return and shorting the currency with the least forecasted return is replicated from the perspective of Australia, Canada, Japan, Sweden, Switzerland, and the United Kingdom. The monthly returns with the U.S. dollar as the base currency are presented for comparison. The notation H1F1 corresponds to a one-month holding period based on the one-month forecasted return. The other strategies are defined analogously. The returns span the period January 1990 – October 2000 for the one-month forecasts and January 1990 – November 2003 for all other forecasts. For multi-month holding periods, 1/n of the currency portfolio is rebalanced each month where n corresponds to the holding period. (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Australia	Canada	Japan	Sweden	Switzerland	United Kingdom	United States
Forecasts of Base Currency Returns	H1F1	-0.20	0.03	-0.05	0.08	0.10	-0.16	0.05
	H1F3	0.10	0.22	0.08	0.27	0.10	0.19	0.25
	H1F6	0.09	0.08	-0.03	0.21	0.07	0.25	0.10
	H1F12	0.23	0.42	0.17	0.37	0.19	0.43	0.41
	H3F1	0.00	0.11	0.15	-0.07	0.01	0.08	0.34
	H3F3	0.24	0.46	0.10	0.31	0.37	0.41	0.51*
	H3F6	0.07	0.00	-0.20	-0.12	0.04	0.18	0.04
	H3F12	0.06	0.00	-0.08	-0.10	0.01	0.27	0.02
	H6F1	-0.17	-0.03	0.13	-0.02	-0.07	-0.11	0.07
	H6F3	0.05	0.21	0.04	0.13	0.16	0.15	0.22
	H6F6	-0.06	0.01	-0.11	-0.09	0.04	0.09	0.08
	H6F12	0.01	0.09	-0.06	0.00	0.08	0.30	0.07
	H12F1	-0.13	-0.07	-0.06	-0.03	-0.10	-0.07	-0.04
	H12F3	0.05	0.15	-0.02	0.14	0.09	0.09	0.13
	H12F6	-0.03	0.06	-0.09	0.04	0.04	0.08	0.05
	H12F12	-0.08	0.04	-0.10	0.05	0.04	0.10	0.02
Forecasts of Interest-Adjusted Currency Returns	H1F1	0.25	0.34	0.20	0.29	0.11	0.11	0.33
	H1F3	0.26	0.27	0.18	0.35	0.13	0.18	0.31
	H1F6	0.19	0.30	0.19	0.25	0.22	0.22	0.23
	H1F12	0.31	0.48*	0.40	0.42	0.52*	0.37	0.39
	H3F1	0.11	0.08	0.21	-0.03	-0.17	0.15	-0.08
	H3F3	0.21	0.26	0.17	0.26	0.38	0.30	0.37
	H3F6	0.35	0.34	-0.19	0.17	0.16	0.09	0.20
	H3F12	0.27	0.31	0.10	0.34	0.46	0.32	0.25
	H6F1	-0.03	-0.02	0.17	-0.02	-0.17	-0.05	-0.12
	H6F3	0.07	0.14	0.15	0.22	0.20	0.13	0.15
	H6F6	0.06	0.19	-0.12	0.17	0.12	0.11	0.12
	H6F12	0.17	0.29	0.10	0.29	0.36	0.27	0.22
	H12F1	-0.02	-0.05	0.06	-0.03	-0.10	-0.15	-0.10
	H12F3	0.05	0.13	0.06	0.13	0.12	0.08	0.07
	H12F6	0.09	0.20	0.06	0.17	0.17	0.15	0.14
	H12F12	0.11	0.22	0.12	0.22	0.22	0.19	0.17

Table XI
Bootstrap Tests of the Best Performing Forecasting Rules (R1 – R(last))

The top five forecasting strategies using both forecasts of base currency returns and forecasts of interest-adjusted currency returns are analyzed to determine the likelihood that the realized performance is due to chance. For the columns labeled "No Timing" the months (rows) of forecasts are scrambled without replacement, but the forecast structure ranking the currencies in each row is maintained. In fact, for the "No Timing" case the forecasts falling within the 1990-1994 period are kept in this time period (but scrambled). Similarly, the forecasts in 1995-1998 remain in 1995-1998, and the forecasts in 1999-2003 remain in 1999-2003. For the columns labeled "No Timing, No Selection" the forecasted ranks are scrambled entirely each month. The "Simulated This Rule" columns analyze the performance of the specific rule, whereas the "Simulated Max All Rules" looks at the performance of the best performing rule during each simulation. The bootstrap tests are repeated 100,000 times and the "<" columns give the number of times that the bootstrap value is less than the actual value. The "value" columns give the mean bootstrap value over the 100,000 iterations.

				Simulated This Rule No Timing Ability		Simulated This Rule No Timing, No Selection Ability		Simulated Max All Rules No Timing Ability		Simulated Max All Rules No Timing No Selection Ability	
			Actual	Value	<	Value	<	Value	<	Value	<
Forecasts of Base Currency Returns	H3F3	Mean	0.51*	0.06	97,769	0.00	98,314	0.32	89,882	0.21	92,962
		Std Dev	3.74	3.56	82,896	2.97	99,988	3.81	28,999	3.13	99,837
		Int Diff	0.04	0.10	474	0.00	91,660	0.14	0	0.02	81,588
		Prob > 0	57.23	51.69	94,780	49.97	96,035	55.98	73,194	53.91	82,658
	H1F12	Mean	0.41	0.02	98,105	0.00	95,460	0.32	76,415	0.21	85,628
		Std Dev	3.86	3.63	91,265	3.02	99,998	3.81	65,579	3.13	99,982
		Int Diff	0.09	0.13	0	0.00	100,000	0.14	0	0.02	98,874
		Prob > 0	53.61	49.14	94,157	48.18	91,165	55.98	6,248	53.91	45,478
	H3F1	Mean	0.34	-0.06	91,964	0.00	88,793	0.32	58,913	0.21	76,253
		Std Dev	3.45	3.40	60,686	2.93	98,310	3.81	141	3.13	94,767
		Int Diff	0.00	0.05	7,651	0.00	52,180	0.14	0	0.02	26,654
		Prob > 0	53.85	49.14	85,146	49.97	77,757	55.98	11,391	53.91	48,259
	H1F3	Mean	0.25	0.07	78,937	0.00	85,063	0.32	34,633	0.21	63,056
		Std Dev	4.04	3.59	99,073	3.02	100,000	3.81	95,238	3.13	99,999
		Int Diff	0.06	0.10	7	0.00	99,955	0.14	0	0.02	94,665
		Prob > 0	51.20	50.24	58,301	48.18	76,199	55.98	70	53.91	20,562
	H6F3	Mean	0.22	0.13	73,314	0.00	91,197	0.32	26,156	0.21	57,691
		Std Dev	3.21	2.93	94,376	2.09	100,000	3.81	0	3.13	66,497
		Int Diff	0.04	0.10	482	0.00	90,190	0.14	0	0.02	79,206
		Prob > 0	56.02	52.59	86,148	49.98	92,517	55.98	47,216	53.91	70,740
Forecasts of Interest-Adjusted Currency Returns	H1F12	Mean	0.39	0.02	98,318	0.00	94,567	0.34	68,506	0.21	83,338
		Std Dev	3.73	3.77	42,100	3.01	99,984	3.95	3,704	3.13	99,840
		Int Diff	0.28	0.28	56,820	0.00	100,000	0.29	38,376	0.02	100,000
		Prob > 0	53.01	50.71	79,784	48.21	88,280	57.02	315	53.94	37,081
	H3F3	Mean	0.37	0.12	89,185	0.00	93,735	0.34	61,917	0.21	80,228
		Std Dev	3.70	3.69	51,019	2.97	99,976	3.95	1,771	3.13	99,742
		Int Diff	0.21	0.24	6,057	0.00	100,000	0.29	0	0.02	100,000
		Prob > 0	55.42	53.52	70,183	49.99	90,262	57.02	16,424	53.94	67,924
	H1F1	Mean	0.33	-0.04	89,830	0.00	88,163	0.34	51,281	0.21	75,165
		Std Dev	3.49	3.66	19,470	3.01	97,901	3.95	3	3.13	96,349
		Int Diff	0.17	0.17	42,486	0.00	100,000	0.29	0	0.02	99,999
		Prob > 0	51.54	48.63	74,253	48.10	76,135	57.02	11	53.94	22,974
	H1F3	Mean	0.31	0.12	81,767	0.00	90,063	0.34	47,413	0.21	73,307
		Std Dev	3.69	3.73	41,981	3.01	99,955	3.95	1,493	3.13	99,701
		Int Diff	0.23	0.24	5,082	0.00	100,000	0.29	0	0.02	100,000
		Prob > 0	53.01	51.72	63,154	48.21	88,280	57.02	315	53.94	37,081
	H3F12	Mean	0.25	0.02	92,084	0.00	85,241	0.34	27,315	0.21	62,357
		Std Dev	3.83	3.78	63,676	2.97	99,998	3.95	17,424	3.13	99,973
		Int Diff	0.28	0.28	49,776	0.00	100,000	0.29	8,962	0.02	100,000
		Prob > 0	53.01	52.93	46,711	49.99	75,311	57.02	315	53.94	37,081

Table XII
The Description for Table XIII, XIV, XV, and XVI

Each month from December 1989 through September 2000 (one month forecast) or December 1989 through October 2003 (all other forecasts), the high and low rank currency by forecasted returns is determined. This forecasted rank is then compared with the average rank for each currency using the technical rule or the rank for each currency using the interest rate rule. Using the algorithm given below, each month is then classified according to the strength of agreement between the two signals. The analysis given in Table XIII, Table XIV, Table XV, and Table XVI examines the monthly return performance of following the currency forecasts (long Rank 1 and short Rank Last) according to the classification of the forecast month.

The Algorithm to Determine Agreement Between the Forecast Signal and the Technical Signal or Interest Rate Signal

Strict Matching Criteria			Less Strict Matching Criteria		
Forecast Rank	Technical or Interest Rate Rank	Classification	Forecast Rank	Technical or Interest Rate Rank	Classification
1	1 or 2	1	1	Pre Euro: 1,2,3, or 4 Post Euro: 1,2, or 3	1
L	L or L-1		L	Pre Euro: L, L-1, L-2, or L-3 Post Euro: L, L-1, or L-2	
1	1 or 2	2	1	Pre Euro: 1,2,3,or 4 Post Euro: 1,2, or 3	2
L	Not (L or L-1)		L	Pre Euro: Not (L, L-1, L-2, or L-3) Post Euro: Not (L, L-1, or L-2)	
1	Not (1 or 2)	3	1	Pre Euro: Not (1,2,3, or 4) Post Euro: Not (1,2, or 3)	3
L	L or L-1		L	Pre Euro: L, L-1, L-2, or L-3 Post Euro: L, L-1, or L-2	
1	Not (1 or 2)	4	1	Pre Euro: Not (1,2,3, or 4) Post Euro: Not (1,2, or 3)	4
L	Not (L or L-1)		L	Pre Euro: Not (L, L-1, L-2, or L-3) Post Euro: Not (L, L-1, or L-2)	

The Algorithm to Determine Agreement Between the Forecast Signal and the Combined Technical and Interest Rate Signal

Technical Rule Classification	Interest Rate Rule Classification	Combined Classification
1	1	1
2	1	2
1	2	2
3	1	2
1	3	2
2	2	3
2	3	3
3	2	3
3	3	3
1	4	4
4	1	4
2	4	5
3	4	5
4	2	5
4	3	5
4	4	6

The Description of Trading Rules

Table	Rule	Strategy
XIII, XIV	Rule(ex4)	When a month is classified as 1,2, or 3 set long-short position, otherwise do not trade
XIII, XIV	Rule(ex4,5,6)	When a month is classified as 1,2, or 3 by the Combined Signal set long-short position, otherwise do not trade
XV, XVI	Rule(1)	When a month is classified as 1 set long-short position, otherwise do not trade
XIII, XIV, XV, XVI	Rule & Nv	This rule always is placed directly to the right of one of the three above listed rules. When one of the above rules (immediately to the left of this) gives a trade signal then this rule gives equal weight to the currency forecast strategy, the technical strategy, and the interest rate strategy in the appropriate month. If a trade signal is not given, then no trade takes place for the relevant month.

Table XIII
Combined Signal Analysis, Strict Criteria to Match (Forecasts of Base Currency Returns)

A complete description of this table is given in Table XII. . (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Compare to Technical Rule Ranks					Compare to Interest Rate Rule Ranks					Compare to Both Technical Rule and Interest Rate Rule Ranks							
		1	2&3	4	Rule (ex4)	Rule & Nv	1	2&3	4	Rule (ex4)	Rule & Nv	1	2	3	4	5	6	Rule (ex4,5,6)	Rule & Nv
H1F1	Months	11	50	64	125	125	20	43	62	125	125	3	7	17	18	52	28	125	125
	Ret	1.62	-0.07	-0.13	0.12	0.12	0.29	0.61	-0.42	0.26	0.23	1.97	0.60	1.34**	0.42	-0.52	-0.26	0.26*	0.21*
	Std Dev	3.90	3.12	3.65	2.33	1.71	3.33	2.99	3.82	2.22	1.64	2.13	4.08	2.73	3.70	2.91	4.35	1.53	1.21
	t-stat	(1.38)	(-0.15)	(-0.29)	(0.56)	(0.79)	(0.39)	(1.34)	(-0.86)	(1.29)	(1.59)	(1.61)	(0.39)	(2.03)	(0.48)	(-1.29)	(-0.32)	(1.93)	(1.90)
90-94	Months	7	25	24	56	56	3	10	43	56	56	1	2	4	6	25	18	56	56
	Ret	1.50	-0.29	-0.69	0.06	-0.10	1.36	0.78	-0.58	0.21	0.04	0.37	1.86	1.38	1.69	-0.57	-1.05	0.17	0.01
95-98	Months	4	17	27	48	48	9	26	13	48	48	2	2	12	7	17	8	48	48
	Ret	1.83	0.70	0.50	0.40	0.52	0.68	0.83	0.38	0.58	0.73	2.78	0.25	1.45	0.26	-0.10	1.14	0.49	0.55
99-03	Months	0	8	13	21	21	8	7	6	21	21	0	3	1	5	10	2	21	21
	Ret	n.a.	-1.01	-0.41	-0.38	-0.20	-0.55	-0.48	-0.93	-0.37	-0.38	n.a.	-0.01	-0.10	-0.88	-1.12	1.16	-0.01	-0.05
H1F3	Months	21	72	67	160	160	38	63	59	160	160	6	22	24	25	65	18	160	160
	Ret	0.38	0.52	-0.07	0.28	0.21	0.40	-0.25	0.69	0.00	0.26	0.96	1.21*	-0.43	-0.59	0.25	0.95	0.14	0.18
	Std Dev	2.96	3.83	4.65	2.80	1.79	3.79	3.94	4.43	3.09	2.01	2.56	2.97	4.14	4.06	3.91	5.73	2.07	1.64
	t-stat	(0.58)	(1.15)	(-0.13)	(1.28)	(1.48)	(0.66)	(-0.50)	(1.19)	(0.00)	(1.64)	(0.92)	(1.90)	(-0.51)	(-0.73)	(0.51)	(0.70)	(0.84)	(1.40)
90-94	Months	9	32	15	56	56	0	6	50	56	56	0	1	3	8	31	13	56	56
	Ret	-0.10	1.02	0.09	0.57	0.16	n.a.	1.10	0.53	0.12	0.04	n.a.	-1.98	2.49	0.14	0.84	0.03	0.10	0.03
95-98	Months	8	16	24	48	48	19	21	8	48	48	4	10	6	9	15	4	48	48
	Ret	0.30	1.02	-0.31	0.39	0.55	0.64	-0.23	0.50	0.15	0.76	0.46	2.26	-0.50	-1.31	-0.33	1.67	0.45	0.60
99-03	Months	4	24	28	56	56	19	36	1	56	56	2	11	15	8	19	1	56	56
	Ret	1.61	-0.48	0.03	-0.09	-0.03	0.17	-0.48	10.03	-0.25	0.05	1.96	0.53	-0.99	-0.51	-0.26	10.03	-0.09	-0.03
H1F6	Months	23	63	74	160	160	46	55	59	160	160	10	28	17	21	56	28	160	160
	Ret	0.84	0.93*	-0.83*	0.49**	0.28**	0.91*	-0.45	-0.01	0.11	0.19	1.63**	0.66	1.23	0.49	-0.47	-0.81	0.35**	0.26**
	Std Dev	2.66	3.82	4.22	2.64	1.77	3.19	4.22	4.18	3.05	2.02	2.34	3.58	3.37	2.63	4.52	4.35	2.02	1.59
	t-stat	(1.52)	(1.92)	(-1.68)	(2.33)	(2.02)	(1.93)	(-0.79)	(-0.02)	(0.44)	(1.16)	(2.20)	(0.97)	(1.50)	(0.85)	(-0.78)	(-0.99)	(2.18)	(2.08)
90-94	Months	10	23	23	56	56	1	5	50	56	56	1	2	2	7	22	22	56	56
	Ret	0.20	0.78	-1.07	0.36	-0.05	3.15	-0.82	-0.07	-0.02	-0.03	3.15	-1.63	-0.64	0.30	0.90	-1.14	-0.02	-0.05
95-98	Months	6	13	29	48	48	19	20	9	48	48	5	7	4	8	18	6	48	48
	Ret	1.40	1.51	-1.03	0.58	0.61	1.10	-1.28	0.33	-0.10	0.41	0.62	3.57	-0.21	-0.24	-1.63	0.37	0.57	0.55
99-03	Months	7	27	22	56	56	26	30	0	56	56	4	19	11	6	16	0	56	56
	Ret	1.29	0.77	-0.31	0.53	0.33	0.68	0.17	n.a.	0.41	0.21	2.50	-0.17	2.09	1.68	-1.05	n.a.	0.53	0.33
H1F12	Months	14	64	82	160	160	47	57	56	160	160	8	26	18	19	59	30	160	160
	Ret	1.57**	0.87*	-0.14	0.49**	0.27**	1.15**	-0.19	0.41	0.27	0.33**	1.60*	1.22*	0.24	0.98	0.08	-0.20	0.31**	0.25**
	Std Dev	2.46	3.87	4.09	2.61	1.73	3.37	3.66	4.48	2.91	1.82	2.35	3.54	3.33	3.27	4.14	4.60	1.96	1.55
	t-stat	(2.38)	(1.80)	(-0.32)	(2.36)	(1.96)	(2.34)	(-0.39)	(0.68)	(1.17)	(2.28)	(1.92)	(1.76)	(0.30)	(1.30)	(0.15)	(-0.24)	(1.97)	(2.04)
90-94	Months	4	25	27	56	56	1	6	49	56	56	0	1	3	4	24	24	56	56
	Ret	0.00	1.06	-0.70	0.47	0.04	2.44	-1.44	0.28	-0.11	-0.02	n.a.	2.44	-2.41	0.00	1.24	-0.73	-0.09	-0.01
95-98	Months	5	11	32	48	48	18	25	5	48	48	3	8	5	9	18	5	48	48
	Ret	2.41	1.53	0.27	0.60	0.59	1.45	0.24	1.10	0.67	0.94	0.98	3.82	-0.92	0.19	0.08	1.10	0.60	0.59
99-03	Months	5	28	23	56	56	28	26	2	56	56	5	17	10	6	17	1	56	56
	Ret	1.97	0.45	-0.07	0.40	0.22	0.91	-0.31	1.81	0.31	0.16	1.97	-0.07	1.61	2.81	-1.56	5.90	0.44	0.22

Table XIV
Combined Signal Analysis, Strict Criteria to Match (Forecasts of Interest-Adjusted Currency Returns)

A complete description of this table is given in Table XII. . (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Compare to Technical Rule Ranks					Compare to Interest Rate Rule Ranks					Compare to Both Technical Rule and Interest Rate Rule Ranks							
		1	2&3	4	Rule (ex4)	Rule & Nv	1	2&3	4	Rule (ex4)	Rule & Nv	1	2	3	4	5	6	Rule (ex4,5,6)	Rule & Nv
H1F1	Months	13	46	66	125	125	45	37	43	125	125	7	17	15	27	36	23	125	125
	Ret	1.10	0.92**	-0.24	0.45**	0.24	0.64	0.34	-0.01	0.33	0.33**	2.04**	1.18	0.91	-0.21	0.21	-0.39	0.38**	0.29**
	Std Dev	2.86	3.10	3.87	2.15	1.76	3.66	3.11	3.76	2.79	1.78	2.18	3.55	2.85	3.76	3.04	4.37	1.83	1.38
	t-stat	(1.39)	(2.01)	(-0.50)	(2.35)	(1.54)	(1.17)	(0.67)	(-0.02)	(1.33)	(2.10)	(2.49)	(1.37)	(1.24)	(-0.29)	(0.41)	(-0.43)	(2.35)	(2.38)
90-94	Months	5	25	26	56	56	6	15	35	56	56	2	2	8	5	22	17	56	56
	Ret	0.71	0.48	-0.41	0.28	-0.04	2.24	-0.37	-0.08	0.14	0.08	2.27	1.86	0.07	0.83	0.07	-0.57	0.16	0.02
95-98	Months	8	17	23	48	48	25	17	6	48	48	5	11	7	12	9	4	48	48
	Ret	1.35	1.56	0.63	0.78	0.67	0.89	1.27	1.31	0.91	0.97	1.95	1.14	1.88	0.07	1.03	1.53	0.74	0.74
99-03	Months	0	4	17	21	21	14	5	2	21	21	0	4	0	10	5	2	21	21
	Ret	n.a.	0.94	-1.14	0.18	0.01	-0.49	-0.66	-2.74	-0.48	-0.44	n.a.	0.94	n.a.	-1.06	-0.66	-2.74	0.18	0.01
H1F3	Months	27	70	63	160	160	72	51	37	160	160	14	38	17	33	49	9	160	160
	Ret	0.27	0.77*	-0.18	0.38*	0.24	0.60	0.01	0.18	0.27	0.33*	1.22*	0.90*	-0.38	-0.54	0.68	-1.12	0.28	0.19
	Std Dev	3.21	3.56	4.11	2.72	2.04	3.63	4.10	3.46	3.37	2.23	2.35	3.23	4.35	4.34	3.75	2.83	2.29	1.90
	t-stat	(0.44)	(1.81)	(-0.34)	(1.78)	(1.47)	(1.40)	(0.02)	(0.31)	(1.03)	(1.85)	(1.94)	(1.71)	(-0.36)	(-0.71)	(1.27)	(-1.19)	(1.55)	(1.28)
90-94	Months	10	30	16	56	56	4	15	37	56	56	2	5	5	5	30	9	56	56
	Ret	-0.16	0.74	-0.49	0.37	0.02	3.82	-0.60	0.18	0.11	0.12	3.31	1.20	-1.71	-1.11	0.81	-1.12	0.07	-0.11
95-98	Months	11	15	22	48	48	32	16	0	48	48	8	13	5	14	8	0	48	48
	Ret	0.62	1.43	-0.43	0.59	0.62	0.31	0.55	n.a.	0.39	0.73	0.59	2.01	-0.50	-1.34	1.16	n.a.	0.59	0.62
99-03	Months	6	25	25	56	56	36	20	0	56	56	4	20	7	14	11	0	56	56
	Ret	0.35	0.41	0.25	0.22	0.13	0.50	0.04	n.a.	0.33	0.18	1.43	0.10	0.67	0.47	-0.03	n.a.	0.22	0.13
H1F6	Months	26	71	63	160	160	71	61	28	160	160	13	42	23	29	44	9	160	160
	Ret	0.58	0.90**	-0.68	0.49**	0.38**	0.57	0.00	-0.16	0.25	0.30*	1.03	0.90**	0.70	-0.31	-0.13	-1.81	0.42**	0.37**
	Std Dev	2.44	3.82	4.32	2.76	1.95	3.68	4.18	3.83	3.57	2.31	2.58	3.25	4.32	4.01	4.27	3.98	2.49	1.86
	t-stat	(-1.20)	(1.98)	(-1.25)	(2.26)	(2.47)	(1.31)	(0.01)	(-0.22)	(0.90)	(1.66)	(1.43)	(1.79)	(0.77)	(-0.41)	(-0.20)	(-1.37)	(2.13)	(2.53)
90-94	Months	10	31	15	56	56	4	24	28	56	56	1	8	13	4	21	9	56	56
	Ret	-0.06	0.21	-0.84	0.10	0.03	2.05	-0.44	-0.16	-0.04	0.02	4.16	-0.29	-0.61	0.39	0.66	-1.81	-0.11	0.01
95-98	Months	9	14	25	48	48	33	15	0	48	48	7	14	2	14	11	0	48	48
	Ret	0.44	3.15	-1.43	1.00	0.91	0.32	0.11	n.a.	0.26	0.69	-0.18	2.97	3.90	-1.75	-1.04	n.a.	1.00	0.91
99-03	Months	7	26	23	56	56	34	22	0	56	56	5	20	8	11	12	0	56	56
	Ret	1.67	0.51	0.25	0.45	0.27	0.64	0.42	n.a.	0.55	0.25	2.09	-0.07	2.02	1.27	-0.68	n.a.	0.45	0.27
H1F12	Months	21	75	64	160	160	73	64	23	160	160	13	43	29	25	38	12	160	160
	Ret	0.75	0.67	-0.05	0.41**	0.32**	0.69	0.26	-0.17	0.42	0.36**	1.74***	0.39	0.61	0.15	0.38	-1.05	0.36*	0.31**
	Std Dev	2.36	3.62	4.32	2.65	1.90	3.62	3.65	4.61	3.37	2.27	2.24	3.21	3.78	4.30	3.87	5.08	2.45	1.84
	t-stat	(1.45)	(1.60)	(-0.09)	(1.97)	(2.12)	(1.62)	(0.56)	(-0.17)	(1.56)	(1.99)	(2.81)	(0.80)	(0.87)	(0.18)	(0.61)	(-0.72)	(1.84)	(2.15)
90-94	Months	9	30	17	56	56	7	27	22	56	56	1	11	16	3	14	11	56	56
	Ret	-0.31	0.60	-0.66	0.27	0.15	0.96	-0.03	-0.09	0.11	0.08	4.16	-0.45	0.46	0.21	0.55	-0.97	0.12	0.13
95-98	Months	7	16	25	48	48	34	13	1	48	48	7	13	3	14	10	1	48	48
	Ret	1.23	1.22	-0.20	0.59	0.66	0.76	-0.06	-1.89	0.52	0.76	1.23	1.85	-1.52	-0.49	0.38	-1.89	0.59	0.66
99-03	Months	5	29	22	56	56	32	24	0	56	56	5	19	10	8	14	0	56	56
	Ret	1.97	0.43	0.60	0.40	0.19	0.55	0.75	n.a.	0.64	0.28	1.97	-0.12	1.49	1.26	0.22	n.a.	0.40	0.19

Table XV
Combined Signal Analysis, Less Strict Criteria to Match (Forecasts of Base Currency Returns)

A complete description of this table is given in Table XII. . (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Compare to Technical Rule Ranks					Compare to Interest Rate Rule Ranks					Compare to Both Technical Rule and Interest Rate Rule Ranks							
		1	2&3	4	Rule (1)	Rule & Nv	1	2&3	4	Rule (1)	Rule & Nv	1	2	3	4	5	6	Rule (1)	Rule & Nv
H1F1	Months	50	44	31	125	125	42	46	37	125	125	17	32	14	26	30	6	125	125
	Ret	0.36	-0.25	-0.03	0.14	0.18	0.51	-0.23	-0.13	0.17	0.19	1.12	0.53	0.61	-0.59	-1.85***	5.45***	0.15	0.23**
	Std Dev	3.49	2.87	4.24	2.21	1.81	3.62	3.04	3.85	2.11	1.43	3.53	3.44	1.70	3.47	2.64	3.13	1.36	1.18
	t-stat	(0.73)	(-0.58)	(-0.04)	(0.73)	(1.10)	(0.91)	(-0.51)	(-0.20)	(0.91)	(1.52)	(1.31)	(0.87)	(1.35)	(-0.87)	(-3.84)	(4.27)	(1.25)	(2.22)
90-94	Months	26	20	10	56	56	11	19	26	56	56	5	13	5	14	16	3	56	56
	Ret	0.04	-0.56	-0.29	0.02	-0.01	0.74	-0.75	-0.28	0.15	0.05	-0.42	1.05	-0.04	-0.03	-2.42	4.83	-0.04	0.01
95-98	Months	21	16	11	48	48	22	19	7	48	48	11	14	7	7	7	2	48	48
	Ret	0.94	0.29	0.76	0.41	0.50	0.76	0.43	1.12	0.35	0.52	1.66	0.32	1.32	-0.66	-1.45	7.75	0.38	0.58
99-03	Months	3	8	10	21	21	9	8	4	21	21	1	5	2	5	7	1	21	21
	Ret	-0.83	-0.57	-0.62	-0.12	-0.06	-0.39	-0.55	-1.36	-0.17	-0.14	2.85	-0.27	-0.24	-2.08	-0.96	2.70	0.14	0.04
H1F3	Months	50	71	39	160	160	53	61	46	160	160	19	32	31	33	38	7	160	160
	Ret	0.90	-0.46	0.73	0.28	0.21*	0.92*	-0.74	0.79	0.31*	0.31***	2.30***	-0.44	-1.21**	0.62	0.29	2.39	0.27**	0.26***
	Std Dev	4.11	3.85	4.35	2.34	1.39	3.78	3.66	4.73	2.22	1.46	3.40	3.63	3.40	4.29	4.24	5.56	1.39	1.12
	t-stat	(1.54)	(-1.01)	(1.04)	(1.52)	(1.93)	(1.78)	(-1.58)	(1.14)	(1.74)	(2.65)	(2.95)	(-0.68)	(-1.98)	(0.83)	(0.42)	(1.14)	(2.49)	(2.88)
90-94	Months	25	23	8	0	56	4	14	38	56	56	2	6	6	19	19	4	56	56
	Ret	0.63	0.98	-0.65	n.a.	0.06	2.05	0.16	0.60	0.15	0.06	2.08	1.54	0.64	0.34	0.41	0.41	0.07	0.03
95-98	Months	16	21	11	48	48	28	13	7	48	48	13	8	11	10	4	2	48	48
	Ret	1.60	-1.60	1.76	0.53	0.59	1.30	-2.22	0.54	0.76	0.87	2.37	-1.80	-2.10	1.47	-0.43	2.52	0.64	0.66
99-03	Months	9	27	20	56	56	21	34	1	56	56	4	18	14	4	15	1	56	56
	Ret	0.39	-0.81	0.71	0.06	0.05	0.20	-0.54	10.03	0.08	0.06	2.17	-0.49	-1.29	-0.17	0.32	10.03	0.15	0.13
H1F6	Months	49	71	40	160	160	63	56	41	160	160	25	36	28	26	35	10	160	160
	Ret	0.92*	0.23	-1.11*	0.28*	0.27**	0.88**	-0.96*	0.36	0.35*	0.35***	2.35***	-0.21	-0.89	-0.37	0.57	-1.99*	0.37***	0.34***
	Std Dev	3.63	4.20	3.66	2.05	1.44	3.57	3.68	4.57	2.28	1.70	2.69	3.69	3.92	3.93	4.34	3.82	1.37	1.16
	t-stat	(1.77)	(0.45)	(-1.92)	(1.73)	(2.37)	(1.96)	(-1.95)	(0.51)	(1.92)	(2.58)	(4.37)	(-0.35)	(-1.20)	(-0.48)	(0.77)	(-1.65)	(3.41)	(3.75)
90-94	Months	22	24	10	56	56	6	13	37	56	56	4	5	7	15	18	7	56	56
	Ret	0.08	0.88	-2.74	0.03	-0.05	1.52	-2.05	0.35	0.16	0.14	2.13	-0.57	-2.53	-0.22	1.82	-3.13	0.15	0.10
95-98	Months	15	19	14	48	48	27	17	4	48	48	12	11	10	7	5	3	48	48
	Ret	1.16	-0.64	-0.51	0.36	0.55	0.97	-1.75	0.44	0.54	0.63	2.54	-0.64	-1.79	-1.47	0.17	0.68	0.63	0.68
99-03	Months	12	28	16	56	56	30	26	0	56	56	9	20	11	4	12	0	56	56
	Ret	2.14	0.25	-0.61	0.46	0.35	0.67	0.10	n.a.	0.36	0.31	2.21	0.11	0.96	0.97	-1.14	n.a.	0.35	0.29
H1F12	Months	45	64	51	160	160	58	64	38	160	160	25	24	31	29	42	9	160	160
	Ret	0.83*	0.41	0.05	0.23*	0.20**	1.33***	-0.56	0.66	0.48***	0.37***	1.74***	0.00	-0.49	0.95	0.49	-1.15	0.27**	0.26***
	Std Dev	3.22	4.41	3.82	1.75	1.29	3.51	3.54	4.71	2.21	1.53	3.14	3.33	4.03	3.60	4.32	4.61	1.39	1.17
	t-stat	(1.73)	(0.74)	(0.09)	(1.69)	(1.96)	(2.88)	(-1.27)	(0.86)	(2.76)	(3.05)	(2.77)	(-0.01)	(-0.68)	(1.41)	(0.74)	(-0.75)	(2.47)	(2.77)
90-94	Months	20	22	14	56	56	3	17	36	56	56	1	3	9	18	18	7	56	56
	Ret	-0.39	1.56	-1.35	-0.14	-0.18	-0.59	-0.45	0.47	-0.03	0.03	-3.97	0.70	-0.77	-0.21	2.14	-2.62	-0.07	-0.02
95-98	Months	14	16	18	48	48	26	21	1	48	48	14	6	10	6	11	1	48	48
	Ret	2.30	-0.68	0.89	0.67	0.71	2.16	-0.99	2.12	1.17	1.01	2.30	0.72	-1.51	3.26	-0.51	2.12	0.67	0.71
99-03	Months	11	26	19	56	56	29	26	1	56	56	10	15	12	5	13	1	56	56
	Ret	1.18	0.10	0.28	0.23	0.14	0.78	-0.29	5.90	0.40	0.15	1.52	-0.43	0.58	2.32	-0.93	5.90	0.27	0.14

Table XVI
Combined Signal Analysis, Less Strict Criteria to Match (Forecasts of Interest-Adjusted Currency Returns)

A complete description of this table is given in Table XII. . (One, two, and three asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.)

		Compare to Technical Rule Ranks					Compare to Interest Rate Rule Ranks					Compare to Both Technical Rule and Interest Rate Rule Ranks							
		1	2&3	4	Rule (1)	Rule & Nv	1	2&3	4	Rule (1)	Rule & Nv	1	2	3	4	5	6	Rule (1)	Rule & Nv
H1F1	Months	45	49	31	125	125	71	32	22	125	125	26	37	14	27	16	5	125	125
	Ret	0.90**	0.00	0.01	0.32*	0.20	0.47	0.09	0.20	0.27	0.37**	1.33**	-0.05	1.35**	0.26	-2.04***	3.01	0.28**	0.30***
	Std Dev	3.01	3.47	4.24	1.86	1.71	3.68	2.75	4.12	2.78	1.72	3.21	3.49	2.16	3.56	2.88	5.45	1.56	1.31
	t-stat	(2.01)	(0.00)	(0.01)	(1.95)	(1.29)	(1.08)	(0.19)	(0.22)	(1.08)	(2.39)	(2.11)	(-0.09)	(2.33)	(0.39)	(-2.83)	(1.24)	(1.98)	(2.57)
90-94	Months	20	27	9	56	56	20	18	18	56	56	6	18	8	10	11	3	56	56
	Ret	0.43	0.00	-0.43	0.15	-0.08	0.42	-0.26	0.06	0.15	0.17	1.21	0.12	1.28	0.04	-2.48	4.02	0.13	0.07
95-98	Months	24	13	11	48	48	35	10	3	48	48	19	11	5	10	2	1	48	48
	Ret	1.21	0.14	1.89	0.61	0.59	0.85	1.36	2.78	0.62	0.83	1.28	-0.24	1.79	1.28	0.06	8.12	0.51	0.68
99-03	Months	1	9	11	21	21	16	4	1	21	21	1	8	1	7	3	1	21	21
	Ret	2.85	-0.20	-1.52	0.14	0.04	-0.29	-1.47	-5.12	-0.22	-0.15	2.85	-0.18	-0.37	-0.86	-1.83	-5.12	0.14	0.04
H1F3	Months	62	69	29	160	160	92	49	19	160	160	39	50	24	26	20	1	160	160
	Ret	0.56	0.17	0.13	0.22	0.20	0.82**	-0.36	-0.38	0.47**	0.47***	1.45***	-0.36	0.54	0.60	-0.69	-2.59	0.35**	0.31***
	Std Dev	3.78	3.67	3.89	2.37	1.64	3.60	4.01	3.45	2.76	1.83	3.28	3.63	4.29	4.31	2.77	0.00	1.74	1.37
	t-stat	(1.17)	(0.38)	(0.18)	(1.17)	(1.57)	(2.18)	(-0.63)	(-0.48)	(2.15)	(3.28)	(2.75)	(-0.71)	(0.62)	(0.71)	(-1.12)	n.a.	(2.57)	(2.90)
90-94	Months	28	24	4	56	56	14	23	19	56	56	9	16	9	8	13	1	56	56
	Ret	-0.03	0.91	-2.02	-0.02	-0.11	1.24	0.12	-0.38	0.31	0.09	0.86	0.31	1.43	-0.50	-0.47	-2.59	0.14	0.02
95-98	Months	22	17	9	48	48	41	7	0	48	48	20	14	5	9	0	0	48	48
	Ret	1.31	-1.11	0.97	0.60	0.70	0.95	-2.89	n.a.	0.81	1.18	1.90	-1.20	-2.23	0.97	n.a.	n.a.	0.79	0.84
99-03	Months	12	28	16	56	56	37	19	0	56	56	10	20	10	9	7	0	56	56
	Ret	0.59	0.31	0.19	0.13	0.09	0.51	-0.01	n.a.	0.34	0.25	1.07	-0.32	1.13	1.21	-1.12	n.a.	0.19	0.15
H1F6	Months	56	68	36	160	160	99	46	15	160	160	40	47	23	28	21	1	160	160
	Ret	0.74	0.25	-0.61	0.26	0.29**	0.46	-0.27	0.20	0.29	0.46***	1.22**	-0.27	0.78	0.07	-0.87	-1.46	0.31**	0.34***
	Std Dev	3.50	4.05	4.11	2.10	1.48	4.02	3.77	3.50	3.17	2.04	3.54	3.77	4.22	4.40	3.41	0.00	1.85	1.36
	t-stat	(1.58)	(0.51)	(-0.90)	(1.56)	(2.46)	(1.14)	(-0.48)	(0.22)	(1.14)	(2.84)	(2.19)	(-0.50)	(0.88)	(0.09)	(-1.17)	n.a.	(2.09)	(3.17)
90-94	Months	21	28	7	56	56	18	23	15	56	56	7	17	11	8	12	1	56	56
	Ret	-0.39	0.57	-2.10	-0.15	-0.07	0.01	-0.43	0.20	0.00	0.25	0.02	-0.26	0.70	-0.49	-0.41	-1.46	0.00	0.06
95-98	Months	22	13	13	48	48	43	5	0	48	48	22	10	3	11	2	0	48	48
	Ret	1.46	-1.34	-0.19	0.67	0.78	0.48	-1.69	n.a.	0.43	0.84	1.46	-0.96	-2.61	-0.17	-0.31	n.a.	0.67	0.78
99-03	Months	13	27	16	56	56	38	18	0	56	56	11	20	9	9	7	0	56	56
	Ret	1.35	0.68	-0.31	0.31	0.22	0.65	0.34	n.a.	0.44	0.35	1.52	0.06	2.00	0.87	-1.82	n.a.	0.30	0.24
H1F12	Months	50	72	38	160	160	101	52	7	160	160	39	47	29	26	19	0	160	160
	Ret	0.69	0.10	0.54	0.22	0.22**	0.63	0.07	-0.67	0.40	0.40**	1.19**	-0.18	0.30	0.53	0.11	n.a.	0.29**	0.26***
	Std Dev	3.42	3.77	4.28	1.94	1.37	3.95	3.50	3.40	3.15	2.00	3.30	3.77	3.68	4.75	3.22	n.a.	1.71	1.30
	t-stat	(1.43)	(0.23)	(0.78)	(1.41)	(2.06)	(1.61)	(0.15)	(-0.52)	(1.60)	(2.51)	(2.26)	(-0.32)	(0.44)	(0.57)	(0.15)	n.a.	(2.16)	(2.57)
90-94	Months	19	30	7	56	56	25	24	7	56	56	8	21	13	7	7	0	56	56
	Ret	-0.61	0.78	-1.12	-0.21	-0.10	0.31	0.05	-0.67	0.14	0.26	0.04	0.37	0.65	-1.77	-0.02	n.a.	0.01	0.02
95-98	Months	19	14	15	48	48	41	7	0	48	48	19	10	4	12	3	0	48	48
	Ret	1.69	-1.06	0.39	0.67	0.72	0.84	-1.60	n.a.	0.71	0.89	1.69	-0.62	-2.16	0.69	-0.84	n.a.	0.67	0.72
99-03	Months	12	28	16	56	56	35	21	0	56	56	12	16	12	7	9	0	56	56
	Ret	1.18	-0.04	1.41	0.25	0.12	0.62	0.66	n.a.	0.39	0.11	1.18	-0.63	0.74	2.54	0.54	n.a.	0.25	0.12