THE PROFITABILITY OF TECHNICAL TRADING RULES IN THE FOREIGN EXCHANGE MARKET: EVIDENCE FROM EIGHT CURRENCIES

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ABSTRACT

We examine the in- and out-of-sample behavior of two families of popular technical trading rules, filter and cross rules, for eight currencies using daily data with bid-ask spreads. In the early part of our sample, these rules make statistically significant profits, in-sample, as reported in the literature, and lower and sometimes significant profits out-of-sample. However, in the latter part of our sample, the in-sample profits fall in magnitude and significance, while the out-of-sample profits almost entirely disappear and are never significant. This decline in returns extends to uncovered interest rate parity.

Applicable JEL Categories: F30, F31, F36, G12, G15, M21.

I. INTRODUCTION

Technical trading rules are mechanical strategies that generate trade signals, based only on the history of the asset's price. A series of papers have examined the profitability of technical trading rules in the foreign exchange markets, to test aspects of market efficiency. Technical trading rules are designed to take advantage of time-dependencies in returns; if returns are strictly random, there will not be statistically significant profits. More generally, in an efficient market there should be no systematic profits after adjusting for risk-bearing and transactions costs.

The following conclusions represent fairly the findings in the literature:

1) Almost all the studies find statistically and economically significant technical trading profits.[1] This is true when the profits are computed in-sample, as in the earlier studies, and when they are computed out-of-sample.

2) A "filter" is the change required in the price for the trading strategy to trigger action. The general conclusion is that small filters produce higher returns than large filters. It is thought it is because small filter imply very frequent trading and unmeasured transactions costs are higher for small filters.

3) The profits generated by technical trading rules seem too large to represent likely return to risk-bearing. Furthermore, these profits cannot be justified as risk premia from simple CAPM or APT models with a constant price of risk.[2]

We re-examine the profitability of technical trading rules. We obtain daily data with bid-ask spreads for foreign exchange quotes as well as borrowing and lending Eurocurrency rates, all from a

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[1] There is a parallel "technical trading literature" for the stock market. In contrast to the foreign exchange markets literature, it seems to have come to the conclusion that apparently profitable technical rules exist for "small" filters, but that apparent excess profits would be swamped by the transactions costs incurred in following the strategies. See Fama and Blume (1966) and Allen and Karjalainen (1999) for further references.

London Eurobank. In contrast to the literature, these data make it possible to take into account explicitly at least the direct transactions costs of trading, rather than estimating or assuming them. Of course our data are also more recent than in the literature, since they extend from 1986 to the end of 2004.

Our results differ substantially from those in the literature:

1) Consistent with the literature, over our whole sample many technical rules make statistically significant profits, though their profits and statistical significance are somewhat lower than in the literature. Bid-ask spreads lower returns and significance but do not eliminate either.
2) We compare these profits to (i) a buy-and-hold or short-and-hold strategy (*UIRP*), and (ii) a *Hi-I* strategy that, for each currency, goes long when the currency's interest rate exceeds the US$ rate and short otherwise. We regard these strategies as useful benchmarks because they do not attempt to exploit time-dependencies in returns. We find that the trading strategy profits are never significantly higher at the 1% level than either *UIRP* or *Hi-I*, and rarely significantly higher at the 5% level; frequently they are lower. However the technical rules operate very differently than *Hi-I* and *UIRP*, and they generate their returns from time dependencies in returns and not from the well-documented failure of *UIRP*.
3) The profits of virtually *all* the technical trading strategies are considerably lower in the 2nd half of the sample, and that statistical significance is much scarcer.

[2] The time-invariant "betas" of currency returns (net of interest rate cost or not) have been shown to be very low for all risk factors that have been tested.

4) Most importantly, over the full sample, technical strategy profits are smaller and not statistically significant when the strategies are applied strictly out-of-sample.[3] Consistent with the rest of our findings, out-of-sample strategies generally make losses in the 2nd half of the sample.

We conclude that even if technical trading strategies made significant excess returns in the early part of the floating exchange rate period, the level and significance of these returns do not extend to the latter part, even in-sample. Furthermore, excess returns do not seem to be available out-of-sample reliably over the full sample period and particularly during the 2nd half of our sample.

II. LITERATURE REVIEW

Dooley and Shafer (1983) first document autocorrelation in daily foreign exchange rates and show that certain technical trading rules are profitable. Sweeney (1986) concludes that, "major exchange markets showed grave signs of inefficiency over the first 1,830 days of generalized managed float…" He examines the DM in detail and nine other currencies, from 1975 through 1980. Assuming normally distributed returns and constant risk premia he finds several cases of significant excess returns. He finds returns on the order of 4% - 5% per year, even after subtracting estimates of trading costs, which he puts at below 20 basis points. He also finds that most of these excess returns persist from one subperiod to the next.

Taylor and Allen (1992) present evidence that all surveyed foreign exchange traders rely at least to some extent on "chartist" information in making their trades; this lends credence to the claim that excess returns exist. Levich and Lee (1993) re-examine the profitability of technical rules using more

[3] This is a narrower version of the genetic programming search for the best strategy, reported in the literature. It is narrower because the range and nature of the strategies are defined and fixed over the whole experiment. The

recent data (1976-1990) and improved statistical methods, for five currencies. They enlarge the pool of trading strategies by including a set of "moving average" rules first introduced by Schulmeister (1988). To overcome the non-normality and heteroscedasticity of exchange rates, they use bootstrap methods to calculate p-values for the returns.[4] They find that "… mechanical trading rules have very often led to profits that are highly unusual…"; 15 of the 30 filter rules and 12 of 15 of the moving average rules they test are significant at the 1% level. They also report minor declines in the profitability of these rules in the last part of their sample but profits are still positive and significant.

More recently, Neely, Weller, and Dittmar (1997), analyze returns from technical rules for six currencies for the 1981-1995 period. They use a genetic programming approach to identify ex-post profitable technical rules as proposed by Allen and Karjalainen (1999) for the stock market. They apply these profitable strategies out-of-sample to assess their reliability, and find reasonably high (up to 6%) and reliable returns from technical strategies for all the currencies they examine.[5]

Though details differ, clearly there is general agreement in the literature that reliable excess returns are obtainable in the foreign exchange market.

III. THEORY AND METHODOLOGY

Market efficiency principles suggest that no replicable strategy that relies on publicly available information should make extraordinary profits reliably, adjusted for risk and the time value of money.

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advantage of this method is that the allowed strategies are simple and easily understood.

[4] They use *FX* Futures data, which obviates the need for interest rates but which creates the difficulty that contract maturity continuously changes in the sample.

[5] In a more recent paper, Neely and Weller (2003) use only one year of half-hourly trading data and search over a wide range of technical trading rules. They find reliable autocorrelations at these intraday frequencies but when they apply the most profitable of these rules out of sample, profits disappear, even when they assume small transactions

Thus, if we find that the j^{th} strategy happens to make "extraordinary profits" from t-n to t, (which in itself is not prohibited by market efficiency) this strategy should not continue to make profits in the periods following t. The fixed trading rules examined in the literature fulfill the requirement that they are replicable and that they rely on publicly available information at time t to implement time-t trading strategies.

III.a. The Measurement Of Returns

We follow the literature and measure trading strategy returns for zero-investment portfolios; such portfolios should make zero risk-adjusted returns. Our notional trader is either long in foreign currency and short in US$s, or short in foreign currency and long in US$s. A long position in foreign currency requires the trader to borrow in US$ at the lending rate and earn interest at the foreign currency deposit rate. A short position in foreign currency requires the trader borrow at the foreign currency lending rate and earn interest at the US$ deposit rate.

In the literature, daily portfolio returns are calculated, by "marking-to-market", which is equivalent to requiring the trader to close out his position daily. This procedure makes it possible to calculate average returns, variance, and measures of reliability. In the presence of bid-ask spreads this procedure must be modified.

If the trader is required to change her position at the end of the trading day, say to short the foreign currency, she must sell her foreign currency at the bid ($/foreign currency), though she had bought it at the ask price. Thus, on average she pays the bid-ask spread. However, when the position

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costs (1 bp for a one-way trade). Their one-year data length makes it difficult to compare with our results or with other results in the literature.

is closed out only for measurement purposes while the strategy's signal is "hold position", we must avoid penalizing the trader by the bid-ask spread. When the signal of the strategy is "hold", we use the ask price to evaluate the return of long positions and the bid to evaluate short positions, thus avoiding the bid-ask spread cost.

Let S_t^b, S_t^a be the foreign currency per US$ bid and ask prices (ask>bid), $i_d^{\$}, i_b^{\$}, i_d^{fc}, i_b^{fc}$, the deposit and borrowing rates for the US$ and the foreign currency, respectively, T the number of calendar days (T=1 except for weekends and holidays), and $c = 0$ a fixed cost paid at the time of a transaction in addition to the bid-ask spread.

There are four possible returns for each period, depending on the signal from the strategy evaluated: long-and-hold, short-and-hold, long-to-short, and short-to-long.[6] The instantaneous returns to an arbitrage portfolio are given below:

(1a) $$r_{long,hold,t} = \ln\left(\frac{S_t^a}{S_{t-1}^a}\right) + \left(i_{d,t-1}^{fc} - i_{b,t-1}^{\$}\right)\left(\frac{T}{360}\right),$$

(1b) $$r_{long-to-short,t} = \ln\left(\frac{S_t^b}{S_{t-1}^a}\right) + \left(i_{d,t-1}^{fc} - i_{b,t-1}^{\$}\right)\left(\frac{T}{360}\right) - c\,,$$

(1c) $$r_{short,hold,t} = -\ln\left(\frac{S_t^b}{S_{t-1}^b}\right) + \left(i_{d,t-1}^{\$} - i_{b,t-1}^{fc}\right)\left(\frac{T}{360}\right),$$

(1d) $$r_{short-to-long,t} = -\ln\left(\frac{S_t^a}{S_{t-1}^b}\right) + \left(i_{d,t-1}^{\$} - i_{b,t-1}^{fc}\right)\left(\frac{T}{360}\right) - c\,.$$

[6] The strategies generate the buy/sell/hold signals from the average of the bid and ask quotes of the exchange rates.

III.b. The Trading Strategies

We study two widely examined families of trading strategies and compare them to two far simpler ones. The *filter* rules work as follows. When the exchange rate starts rising, its value is the *local low*. When the exchange rate starts falling its value is the *local high*. A *f*% filter rule signals to go long when the currency rises *f*% above its most recent local low, and it signals to go short when the currency falls *f%* below it most recent local high. Otherwise hold the existing position.

We add a variation to the filter rules family, not previously used in the literature. Daily exchange rate data are often very volatile. This volatility can induce the filter rule to bounce from long to short too frequently when *f* is small. It is also possible that when *f* is large, the rule will not send a signal even though over the period the exchange rate may have gone up or down by more than *f*%. Our variation is to require the strategy to operate on a 5-day moving average of the exchange rate. We label this variation "MA5 filter".

The *cross* rules work as follows.[7] Each cross rule has two parameters, *m* and *n*. Construct a *near* moving average of the exchange rate of *m* days. Construct a *far* moving average of the exchange rate of *n* days, where $n > m$, so that each rule is defined by MA(m,n). When both the near and the far MA series are rising and the short MA series crosses the long one from below, go *long* in the currency; this is called the "golden cross". When both the near and far MA series are falling and the short series crosses the long one from above, go *short* in the currency; this is called the "death cross". Otherwise hold the existing position.

III.c. Statistical Evaluation Of Returns

In order to evaluate the statistical significance of returns, we follow the literature and compute p-values by using Monte Carlo simulations. It is unwise to rely on normal distribution statistics, since the non-normality of daily exchange rate returns is well-established. For each trading rule and each transaction cost, *c*, we create 10,000 simulations by randomly scrambling the data.[8] This approach breaks any existing time series dependencies but retains the mean and variance of the distribution. In this way, we generate a distribution for each strategy, and the p-values of the empirical returns are computed from these distributions. All p-values we report are obtained with such Monte Carlo methods.

Most published studies assess the significance of returns by comparing them to zero, as in Sweeney (1986) and others.[9] We also report p-values that compare returns to zero, because regardless of how unlikely a particular return is, market participants need to know the reliability of positive returns.[10]

The additional trading cost *c*% is intended to proxy for proportional transactions cost other than the bid-ask spreads. This trading cost is observationally equivalent to a higher bid-ask spread for the

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[7] Levich and Lee (1993) label these rules "moving average". We borrow from the common designations of "golden cross" and "death cross" and label them "cross" rules instead, because we use the term MA in connection with our MA5 filter rules.

[8] The growth rate of the exchange rate at time *t*, its associated bid-ask spread, and the relevant time *t*-1 interest rates are kept together when we reshuffle the data. Once a random iteration is created, we use the sequence of growth rates and the bid-ask spreads to create an exchange rate "history" on which the trading rule operate. Thus, only the order (not the value) of the returns for each trading day is changed. We use MATLAB's random number generator.

[9] Levich & Lee (1993) report p-values that implicitly compare the empirical returns to the means of their simulated distributions rather than to zero. In our data, most of the Monte Carlo distribution means are negative. Sometimes this creates a substantial difference between the p-values relative to the means and the p-values relative to zero. P-values relative to the means of the Monte-Carlo distribution are available from the authors on request.

[10] We do this by calculating t-statistics for the empirical returns using the corresponding Monte-Carlo distributions, which are indistinguishable from Normal.

exchange rate, because it is incurred only when there is a trade. We only wish to quantify the effects of additional trading costs, since we have no data on them.[11]

III.d. Economic Evaluation Of Returns

The trading strategies we study are designed to exploit time dependencies in the data. So, comparing these strategies' returns to strategies that do not claim to exploit time dependencies can help clarify the origin of their returns and put them in perspective.

It is empirically well-documented that "uncovered" interest parity (*UIRP*) doesn't hold well; it is possible to make apparently significant profits by one of "buy-and-hold" or "short-and-hold" strategy, depending on the currency.[12] This empirical regularity suggests simple alternative strategies that do not rely on time dependencies in the data and can therefore serve as yardsticks. One such strategy is to go long in the currency when its interest rate exceeds that of the US$ and go short in the US$. And, if the foreign currency interest rate is below that of the US$, go short in the currency and long in the US$. We label this the *Hi-I* strategy.[13] The other strategies are even simpler: "always long" in the foreign currency and "always short" the foreign currency, or *UIRP* strategies.[14]

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[11] Note that *c* and the bid-ask spreads have no effect on the filter rule signals; they only affect the magnitude of the returns.

[12] This empirical finding is often referred to as the forward risk premium puzzle, and its economic origins are not resolved. Hansen and Hodrick (1980) establish the existence of risk premia in foreign exchange rates. Later papers (Engel and Hamilton 1990, Evans and Lewis 1995) attempt to model exchange rate behavior with time-varying processes that allow for time-varying risk premia. Kho (1996) shows evidence that time-varying risk premia and heteroscedasticity explain a large part of the observed technical trading rule returns for 4 currencies during the 1980-1991 period.

[13] We thank Prof. Andy Neumeyer for suggesting this *Hi-I* comparison to us. As early as the late 1970s, the IMF used this principle and lend to client countries in the lowest interest rate currency, which at that time was frequently the Swiss Franc.

[14] We have nothing to add to the debate on the economics of the failure of *UIRP* or its implications for market efficiency. We only note that the returns to the *Hi-I* and *UIRP* strategies are based on the failure of *UIRP* and are not related to any time dependencies in exchange rate returns, and that it is possible that a dynamic strategy may be simply taking advantage of the failure of *UIRP*.

We also address the issue of returns to risk-bearing.[15] We aggregate the returns to monthly frequency and compute their factor loadings against the 4-factor Fama and French asset pricing model, as well as additional macro factors.

Most importantly, we examine if such trading rules are successful out of sample. At the end of every year our notional investor selects the most profitable strategies, one each from each family of rules, based on performance from year = t-2 to t. She then implements these strategies to earn returns from year=t to t+1. The strategies are updated annually. In this way, the trading strategies are selected based only on past performance and the returns are strictly out-of-sample.

IV. DATA

The data are from DataStream. DS has daily foreign currency per US$ bid and ask prices (4 pm London) for the Canadian $ (C$), Danish Krona, French Franc (FF), German DM, Italian Lira, Japanese Yen (¥), Dutch Guilder (Guilder), and the U.K. pound (£) from Barclays of London from 1986.[16] DS also has daily Eurocurrency borrowing and lending rates for thes currencies and for the US$, for the same dates.[17] The foreign exchange data for the common currency countries (FF, DM, Lira, Guilder) of course end in 1998. Data for the remaining currencies are to the end of 2004. The period from 1986 to 2004 consists of 4482 business day observations, while the 1986-1998 period has

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[15] Both Sweeney (1986) and Levich & Lee (1993) use the average *UIRP* returns as a measure of the constant risk premium for a long position in the currency. But if there is a constant risk premium, then it must be earned either when the investor is long or short in the currency. Since the technical trading strategy require both long and short positions over time, the return to risk (*RP*) earned by a rule would have to be $RP \cdot p - RP \cdot (1\text{-}p)$, where p is the proportion of the time strategy required a long (or short) position. Since for most of these strategies p is close to 0.50, the net risk premium measured this way becomes vanishingly small, and it would require a very large *RP* to come close to explaining the observed returns. More recent studies do not address this issue directly.

[16] DS used to collected data from Midland and National Westminster banks as well. NatWest quotes were discontinued in January 1999, and Midland's were discontinued in December 1999.

3092 observations. Other macroeconomic data are also from DataStream. The Fama-French factors are from Prof. Kenneth French's website.

IV.a. Statistical Properties Of the Exchange Rates

Figures 1-A & B show the time series of each currency, normalized to 1.0 on the first date of the sample. Table 1-A and B contain summary statistics for all the currencies.

The figures and the tables show that all but the Lira appreciate on average against the US$ over our sample period but there are periods of large appreciations and depreciations for all the currencies. There are also remarkably large one-day returns for each currency. The annualized daily standard deviations are very similar, except for the Canadian $, which has roughly one half the standard deviation of the others. Skewness is close to zero for most of the currencies except the Lira and the ¥ but kurtosis varies widely (1.47 – 7.31).

The autocorrelations of the growth rates of the currencies (not shown) are quite small; in absolute value none is higher than 0.04. However, for each currency there is at least one autocorrelation that is statistically significant. The p-values of the Box-Pierce tests shown in the table reject "no autocorrelation" at the 5% level for the FF, Lira, Guilder, and the £; they do not reject for the C$, Krona, DM, and the ¥.[18] These results suggest that if these autocorrelations are stable there may exist exploitable patterns.

Table 1-B shows the contemporaneous correlations across currencies. It is not surprising that the EMU currencies that eventually joined the single-currency as well as the Krona, have high

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[17] We checked the data for outliers, and deleted data that violated basic arbitrage propositions, such as ask < bid. We deleted a total of 10 data points for the C$, 1 for the £, and 4 for the DM.

contemporaneous correlations. The £ has lower correlations with the other European currencies; the non-European currencies have quite low correlations. The correlations between the ¥ and the other currencies are modest, while C$'s are rather low.

Figure 2 compares empirical histograms of exchange rate growth rates to the Normal distribution for selected currencies. The growth rates are leptokurtic and most have significantly more mass at the extreme tails than the Normal.[19] The Jarque-Bera statistic in Table 1-A shows that normality can be rejected uniformly at very high levels of significance, for all the currencies; for this reason we use Monte Carlo simulations to compute p-values.

Information on bid-ask spreads is in Table 2. The currency bid-ask spreads are quite small, even for the less-traded currencies. The median bid-ask spread is 7.6 basis points, and the highest is 138 bps (for the Krona); the average standard deviation is 4.5 bps.[20] The median interest rate bid-ask spread is 17 bps, with a standard deviation of 31 bps.

We show the averages from the first quarter and last quarters of sample, to assess if there appear to be substantial efficiency changes in the markets over our sample. For all the currencies except the ¥ and the DM, the last quarter spreads are lower. However, the differences are small; the largest difference is 3.2 basis points. It doesn't seem that there have been major changes in efficiency over the sample period, at least by this measure.

For both exchange rates and interest rates the maximum values as well as the standard deviations are quite high. However, almost all of the high values occur during the European ERM crisis

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[18] It is interesting that the £ shows small but highly significant autocorrelations over a range of lags, even though it is a heavily traded currency, compared, say, to the Krona, which is not.

[19] This is a well-known property of daily exchange rates.

[20] These data show that Sweeney's (1986) estimate of 20 bps seriously overstates the *FX* bid-ask spread. Nonetheless, the overall transactions costs exceed 20 bps because of the interest rate bid-ask spread.

(Nov 1992 - April 1993); the highest interest rate spread in that period is 1,500 bps for the Krona. For currencies that are not heavily traded (C$, Krona, Lira), the bid-ask spread falls substantially (from 56.4 to 11 for Italy) in the last quarter of the sample but the declines are very small for the other currencies.

V. RESULTS

First we present the full sample results. Then we discuss accounting for risk, subsample stability, and out-of-sample behavior.

V.a. Full Sample Results

For filter rules we compute returns and p-values for filters from 0.5% to 5%, in 0.1% increments, and for the additional trading costs, *c*, from 0 to 100 bps in 25 bp increments. For the cross rules we compute returns and p-values for short MAs 1–4 and long MAs 2–50, both in steps of one day. We also compute these returns with *c* from 0 to 100 bps, in 25 bp increments.

The two panels of Figure 3-A show the returns for the DM over the whole sample, for a series of standard filter rules and our MA5 modification, with and without bid-ask spreads, and for $c = 25$ and 50 bps. We also show the returns to always-long and always short (*UIRP*). We show only the behavior of the DM to conserve space. Though each currency is different in the details and in the level of returns, Figure 3-A illustrates most of the features that are common across the currencies.

Returns are higher when bid-ask spreads are ignored. The effect of bid-ask spreads on returns is a combination of the difference between deposit and loan rates that is always incurred, and the exchange rate bid-ask spread, incurred only when a trade takes place. The difference in returns narrows as the filter size increases, because the number of trades falls. For example, the 0.5% filter strategy trades on 20% of the days, on average. As a result, the average reduction in returns due to the bid-ask spreads is 420 bps. But the 2% filter trades on only 2.5% of the days, and the average reduction in returns is only 70 bps.[21]

The trading returns are low for very small filters, peak and then decline. The peaks occur for different filters in different currencies; for the C$, the ¥, and the £, highest returns are for filters below 1%, while for the rest of the currencies highest returns occur for filters between 2.7% and 3.1%.[22]

Figure 3-B shows the returns for selected cross rules for the DM. The first panel shows the effect on returns of varying the short MA, from 1 to 4 days. It shows that the length of the short filter has a small and non-systematic effect on returns; this is true for all the currencies. The second panel shows the relation between returns and the long MA, when the short MA is one day (the current *FX* rate). Small long-MA values induce more trading, so that, similar to the filter rules, the return differences narrow as the long MA becomes larger. However, unlike the filter rules, there is no indication that returns decline as the long MA becomes larger.

Tables 3 and 4 show detailed results for selected filter and cross rules. We report returns without and with bid-ask spreads, and for $c = 0$ and 25 bps.[23] We choose the strategies to report so as to balance parsimony with the need to represent the overall results fairly.

For the filter rules we report results for filters of 0.5%, 1.0%, and 2.0%, and the best-performing rule over the 0.5% - 5.0% range. We report detailed results only for MA5 rules in Table 3,

[21] The filter rules that use the MA5 specification trade less than the standard filter rules; for the 0.5% filter trading occurs in only 6.5% of all trading days, and the bid-ask spread lowers returns by 140 bps. For the 2% filter trading takes place in 1.7% of the days and returns are lower by 50 bps.

[22] Unlike the other six currencies, the returns for the C$ and the FF are quite similar across a wide range of filter values.

because there many more significant returns for the MA5 than for the standard filter rules.[24] For the cross rules we report returns for short MA = 1, and for long MAs of 5, 20, and 40. We also report the best-performing cross rule over the full range of short and long MAs.

For each currency, the first row shows the long *UIRP* return and the return of the *Hi-I* strategy.[25] The subsequent rows show the returns for the selected filters and the best-performing filter, with p-values relative to zero returns; the filters are listed in the column labeled "Filter".[26] The column labeled "Transactions" shows the percent of days each strategy trades. The columns that follow from left to right under "Total Returns" show returns excluding bid-ask spreads, with bid-ask spreads, and with bid-ask spreads plus c = 25 bps.

For the case with bid-ask spreads and c=0, no return is significantly greater than zero at the 1% level. The 2%- and the best-performing filters generate positive returns significant at the 5% level for the Krona, the FF, and the Guilder but only the best-performing filter generates significant returns for the Lira and the ¥. The C$, the DM, and the £, show no significant returns at the 5% level. Across currencies, the best-performing rule returns average 4.72%, ranging from 0.99% to 6.85%.

The bid-ask spreads naturally reduce the returns for all the rules relative to their no bid-ask values. The average return reduction for the 0.5% filter is 143 bps (228 - 88), but only 61bps for the best-performing filter (111 - 18). This is because the best-performing filters are larger than 0.5% and thus require fewer transactions. The addition of a 25 bp transactions cost further reduces the returns for the small filters and in some cases reduces significance levels.

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[23] The no bid-ask spread returns are computed on the average daily *FX* and interest rates.

[24] None of the returns for the standard filter rules are statistically significant at the 1% level, and very few are significant at the 5% level.

[25] Interestingly, the *Hi-I* strategy has considerably higher returns than *UIRP*, except for the Lira.

The two rightmost columns labeled "Ret - *Hi-I*" and "Ret - *UIRP*" report the vest-performing strategy's returns net of the *Hi-I* returns, and net of the positive *UIRP* returns. There is no instance where a filter rule does significantly better than either of these strategies. For the C$ and the £, just going long in the currency beats all the filter strategies. For the C$, Krona, and the £, the *Hi-I* strategy beats all the filter rules.

Table 4 shows returns to selected cross strategies. The table is constructed the same way as Table 3, except that the column labeled MA(m,n) shows the cross rules; the *UIRP* and *Hi-I* returns are repeated for convenience. The results are stronger than for the filter rules. For the case with bid-ask spreads and c=0, the best-performing rules generate positive returns significant at the 1% level for the Krona, Lira, ¥, and the Guilder, and significant returns at the 5% level for the FF, DM, and the £; only the C$ shows no significant returns. In addition, the Krona, FF, DM, and the Lira, show significant returns for MA(1,20), and the Krona and ¥ for the MA(1,40) rules. Across currencies, the best-performing rule returns average 6.45%, with a range of 1.72% to 9.37%, all higher than the filter rules. There are many more cases of significant returns (5% level) when the bid-ask spreads are ignored.[27] When 25 bp transactions costs are included, all 11 statistically significant returns remain positive but only 2 remain statistically significant.[28]

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[26] We report p-values only for positive returns. The best-performing filter is selected from the calculations that include the bid-ask spread but with c = 0.

[27] The average reduction in returns induced by the bid-ask spread is 328 bps for the MA(1,5) rule (513 - 247) but only 98 bps (164 - 49) for the best-performing rule.

[28] Many of the returns we show are in the 5% and even in the 1% tail of their respective Monte-Carlo distributions, with and without transactions costs. But since bid-ask spreads and c>0 reduce substantially the distribution's mean, the p-values relative to zero returns that we report in the tables are considerably lower.

The best-performing cross rule return for the Lira is significantly higher than either *Hi-I* or *UIRP*, and for the ¥ it is only higher than the *UIRP*. *Hi-I* beats all cross rules for the C$ and the Krona; in all cases at least the best-performing rule does better (but not significantly) than *UIRP*.[29]

Our main reason for comparing the trading rules to *UIRP* and *Hi-I* is to investigate the extent to which the filter and cross rules take advantage of the failure of the *UIRP* rather than time dependencies in the data. Table 5 shows an analysis of how the cross rules operate, compared to *Hi-I* and *UIRP*; the results for the filter rules are very similar. The two left columns show the percent of days each strategy is long in the foreign currency. The cross rule strategies are very similar across the currencies; they are long in the foreign currency slightly more than 50% of the days, regardless of the overall patterns of each currency over the period. By contrast, the *Hi-I* strategies differ greatly across currencies and from the cross rules in this regard. For example, since the Lira interest rates were almost always higher than the US$, its *Hi-I* strategy is almost always long in Lira. The two right-hand columns show that the correlations of daily returns between cross rules and *Hi-I* and *UIRP* are very small.

We conclude that the cross rules do not seem to derive their returns from the failure of *UIRP*, even though they generate comparable returns. It follows that the rule profits must be related to time dependencies in the data.

These results are qualitatively similar to those in the literature. We find several statistically significant profits from trading rules across all currencies, and the cross rules do better that the filter rules.[30] However, we find somewhat lower returns and substantially lower significance levels than those

[29] It is notable that there doesn't seem to be any particular relation between the degree of autocorrelation in the currencies, reported in Table 1-A, and the level or frequency of significant returns to trading strategies.

[30] No comparisons are made with *UIRP* or the *Hi-I* strategies in the literature.

reported in the literature. The bid-ask spreads modestly decrease returns and their statistical significance.

V.b. Is It Risk?

The returns we document can be judged as high if the strategies do not involve significant systematic risk, which leads us to examine its possible presence. We integrate each of the returns to a monthly level, and regress them on the Fama and French factors, as well as other variables that have been shown to be related to systematic risk in the literature, jointly and separately.[31]

We find absolutely no statistical evidence of a relation between any of these returns and any of the above potential risk factors. The factor loadings are quite small and p-values are uniformly very large. We conclude that systematic risk is a highly implausible explanation of these returns.

Table 6 reports Sharpe ratios for the best-performing strategies for filter and cross rules. The table shows that the Sharpe ratios are uniformly very low. Even though we cannot document that these returns accrue to systematic risk, it is clear that there is very large volatility associated with them.

V.c. Stability of the Results

It is not extraordinary to find ex-post profitable trading rules in returns generated by efficient markets. But in efficient markets the ex-post profitable strategies should not continue to deliver excess profits in the future. As a first step in investigating the stability of returns to these trading rules, we

[31] We also use the growth rate of *Industrial Production*, the *CPI* inflation rate, the growth rate in *Employment*, and the ratio of the *Trade Deficit* to *Industrial Production*. Detailed results are available from the authors on request.

compare their profitability in the 1st and 2nd halves of the sample. This partitioning of the data is of course arbitrary but it is unbiased and it provides valuable insights.

Tables 7 and 8 show comparisons of the returns for the 1st and 2nd halves of the sample for the filter and cross rules, respectively.[32] The construction of these tables is analogous to Tables 3 and 4. An examination of the two tables reveals three important regularities:

1) In the 1st period, going long in all the currencies except the ¥ produces positive returns. By contrast, going long in the foreign currency in the 2nd period results in negative returns for all currencies except the £; the returns to going long decline for all the currencies, by an average of 744 bps. Similarly, the average return for the *Hi-I* strategy declines somewhat (on average by 198 bps), though by contrast, its returns increase in the 2nd period for 4 of the 8 currencies.

2) Similarly, the returns for both the filter and cross rules are uniformly and markedly lower in the 2nd period. The 2nd period returns are lower in 29 of the 32 cases we report for the filter and in 30 of 32 cases for the cross rules. The average decline for the filter rules is 550 bps (1st period average is 5.4%) and for the cross rules it is 500 bps (1st period average is 6.3%).[33]

3) The number of statistically significant returns is much lower in the 2nd period for both filter and cross rules. For the filter rules, there are no returns significant at the 1% level; with bid-ask spreads, only the Krona and the Lira have statistically significant returns at the 5% level. For the cross rules only the Krona and the Lira have significant returns at the 1% level, and the ¥ and Guilder at the 5%

[32] Since data for the common currency countries end in 1998, the breakpoint for those currencies is earlier than for the rest. For the C$, Danish Krona, the ¥, and the £, the 1st half is 10/86 to 08/95 with 2,240 observations, and the 2nd half is 09/95 to 07/04, also with 2,240 observations. For French Franc, the DM, the Lira, and the Guilder, the 1st half is 10/86 to 08/92 (just before the ERM crisis) with 1,500 observations, and the 2nd half is 09/92 to 12/98 (the adoption of the common currency) with 1,600 observations

level, all for the best-performing rules. In Table 9 we summarize the performance of the best-performing strategies, along with the corresponding *UIRP* and *Hi-I*, to make comparisons easy.

Levich and Lee (1993) discuss briefly a minor decline of returns in the last part of their sample, but evidence for this in our sample is much stronger; of course our 2nd period is outside the range of their sample.

V.d. Out-Of-Sample Behavior

This apparent instability in rule returns implies that it may not be possible to obtain significant and reliable excess returns out-of-sample. We test this hypothesis directly for our filter and cross rules by applying the out-of-sample procedure discussed in section III.d.

If time dependencies in the currencies are stable over time, we would expect the in- and out-of-sample performances of the rules to be the same, within sampling error. If time dependencies are predictable but vary slowly over time, then the out-of-sample performance should beat the in-sample one, because the rules would adapt to the predictably changing time patterns. However, if time dependencies are unstable and unpredictable (consistent with efficient markets), then the out-of-sample performance will be significantly worse than the in-sample one.

Table 10 reports the results of our out-of-sample procedure for the two families of rules. Of the returns over the full sample, none is statistically significant at the 1% level, and there are only 4 statistically significant returns in 24 entries.[34] Returns are quite low and 8 of the 24 are negative. All the

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[33] For the best-performing rules the declines are: 587 bps (1st period average is 9.15%) for the filter rules, and 582 bps (1st period average is 10.83%) for the cross rules. Note that the best-performing rules for the two periods are computed only with the corresponding data and therefore they are frequently not the same.

[34] 8 countries, 3 rules each. At the 5% level one would expect 1 significant observation but since the standard deviation is approximately 2.4, 4 significant observations are within reasonable bounds of randomness.

returns are substantially lower than the corresponding returns reaped by the in-sample best-performing rules; the average decline in returns is 340, 510, and 410 bps, for the standard filter, the MA5 filter, and the cross rules, respectively. The year-by-year returns are positive slightly more than ½ the time (56%). Even for the Lira cross rules, the returns are positive just 70% of the time. Still, cross rules do better than filter rules, on average.

Table 10 also shows the corresponding returns for 1st and 2nd periods. For all the countries and trading rules 2nd period returns are almost always lower than in the 1st period (exceptions are the C$, Krona and Lira for the simple filter, Krona and Lira for the cross rules). This is consistent with our findings for the in-sample performance of the rules.

The 2nd period returns across currencies are negative in 26 of 32 instances. The cross rules results illustrate starkly the differences between the two subperiods. All but the C$ have positive and significant returns in the 1st period. No currency shows significantly positive returns in the 2nd period, and all but the Krona and Lira have negative returns.

This poor out-of-sample performance coupled with the decline of the in- and out-of-sample returns in the 2nd period is strong evidence that excess returns to the mechanical trading rules we examine here are low, elusive, highly uncertain, and therefore economically unimportant.

VI. CONCLUSION

We examine the profitability of "filter" and "cross" families of trading rules for eight currencies, from 1986 to 1998 for the four single-currency countries and to 2004 for the other four, by calculating returns to zero-net-investment portfolios. Any positive returns to such portfolios are either returns to risk-bearing or "excess" returns. We take into account explicitly an important component of transactions costs, previously only estimated or imputed, because our data include bid-ask spreads for both the exchange rates and the interest rates.

Consistent with the literature, we find substantial and statistically significant returns overall, and particularly in the 1st part of the sample, for both families of rules.

However, these returns have very low Sharpe ratios, they are rarely significantly higher than the "*UIRP*" or "*Hi-I*" strategy returns at the 5% level and never at the 1% level. The bid-ask costs reduce both the magnitude and statistical significance of profits but eliminate neither. We also show, that generally-accepted risk factor models do not explain these returns.

The new and different results concern the 2nd part of our sample and the out-of-sample performance of these strategies. We show that for every currency there are major declines in the returns of all the strategies in the 2nd half of the sample, including for *UIRP* and to a lesser extend for *Hi-I*; this decline extends to the statistical significance of the returns.

Most importantly, we test the out-of-sample performance of a notional investor who selects the best-performing strategies based on the previous two years performances, and uses them to earn returns in the following year. We find that excess returns are low and never significant at the 1% level. Second period performance is much worse for these out-of-sample returns as well; most returns are negative.

We conclude that there may have been statistically significant "excess return" opportunities in the earlier part of our sample, as documented in the literature. However, we present strong evidence that profit opportunities are scarce and elusive in the 2nd half of our sample. Most important, there is very little evidence that excess returns are available to out-of-sample application of filter or cross rules, particularly during the 2nd half of our sample.

One interpretation of our findings is that they illustrate strict market efficiency, that an in-sample winning strategy is not likely to be a winner when applied out-of-sample. A somewhat different interpretation is that they illustrate practical market efficiency: if a winning strategy is uncovered it will be exploited, and therefore it will disappear. This second interpretation is supported by our finding that *all* "excess" returns decline in the 2nd period of the sample.

We must keep in mind that macroeconomic and political conditions were very different in the 2nd half of our sample. European economies converged to the common currency criteria, which required closer monetary policy coordination among the participants and declining and converging interest rates and inflation. Their capital markets became much more open, and this was true of other countries in our sample as well. Finally, several researchers have documented a recent and worldwide decline in the measured volatility of many macroeconomic variables.

It is possible that these changing market conditions enabled market participants to take advantage of relatively small but known excess return opportunities in the foreign exchange markets that were previously unexploitable for institutional reasons.

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Figure 1-A
History of the Exchange Rates
Non-EMU Currencies: 1986 - 2003

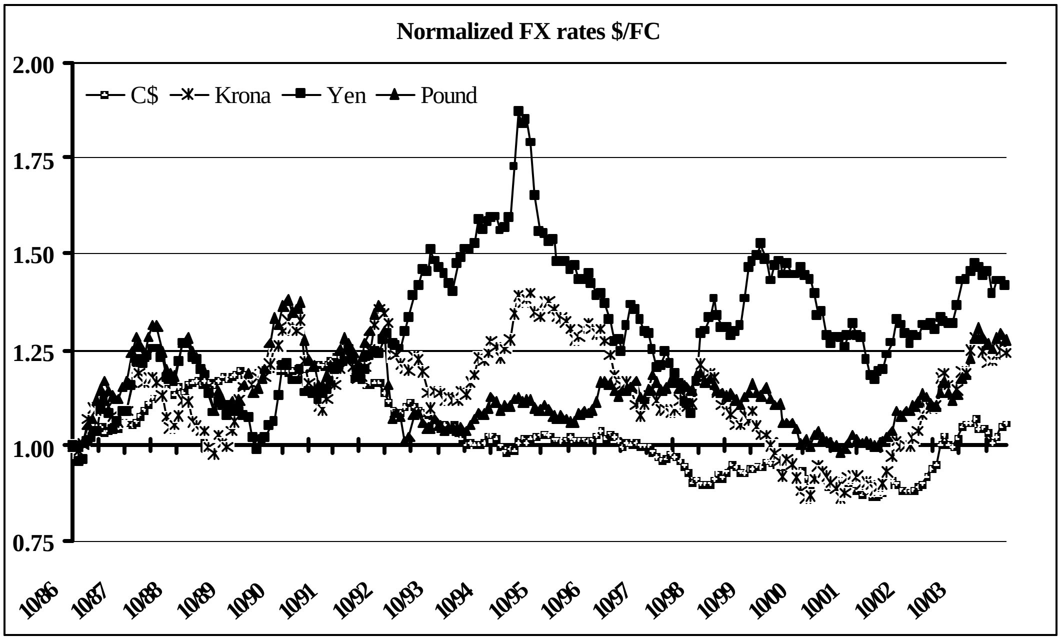


Figure 1-B
History of the Exchange Rates
EMU Currencies: 1986 - 1998

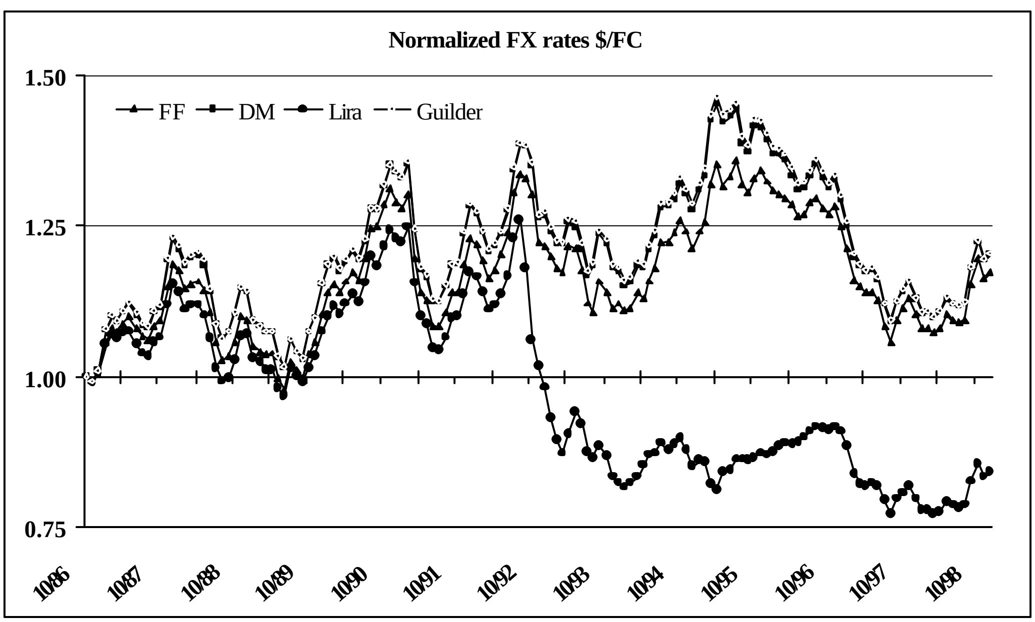


Figure 2
Comparisons of Empirical Histograms to the Normal Distribution

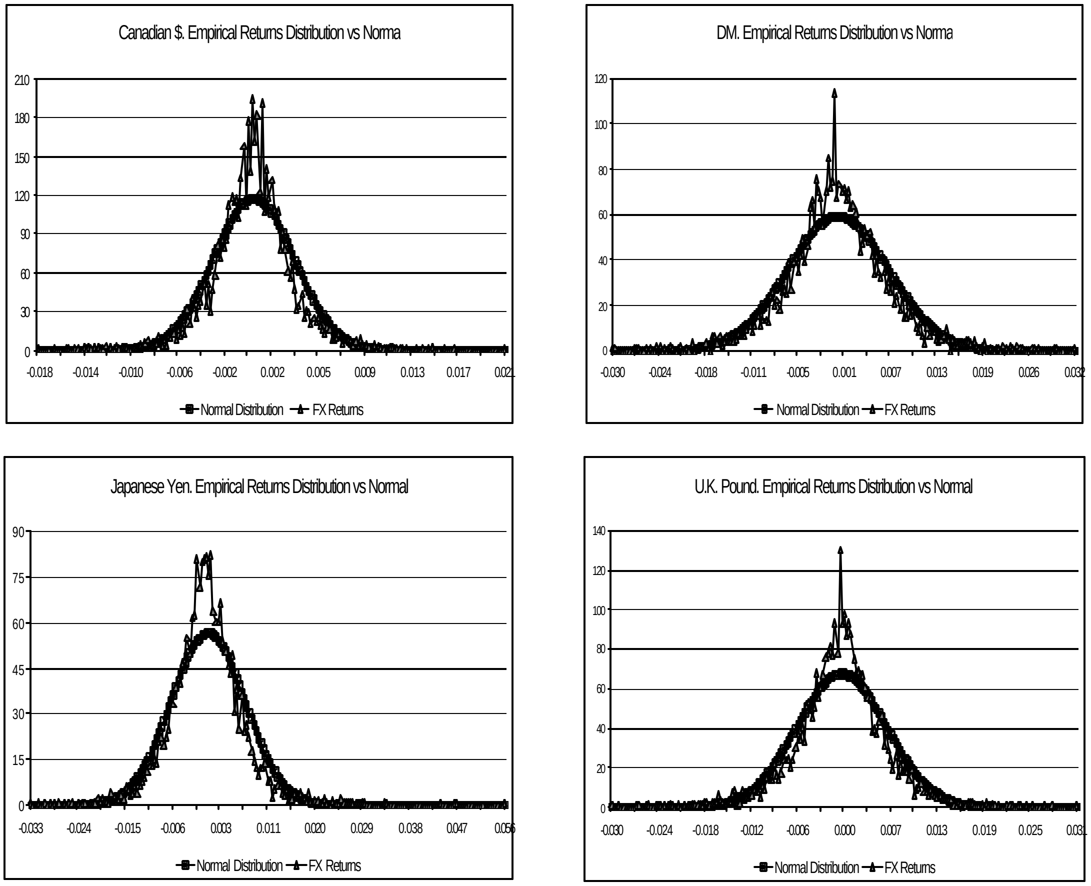
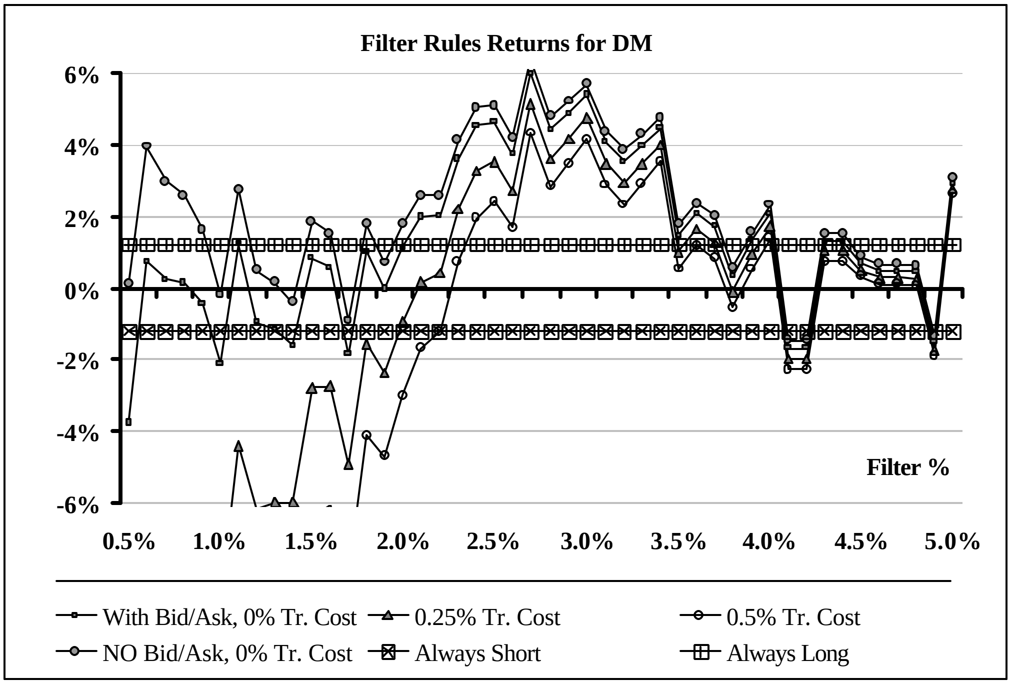


Figure 3-A

Typical Behavior of *f*% Filter Rules.
The German DM: 1986 - 1998



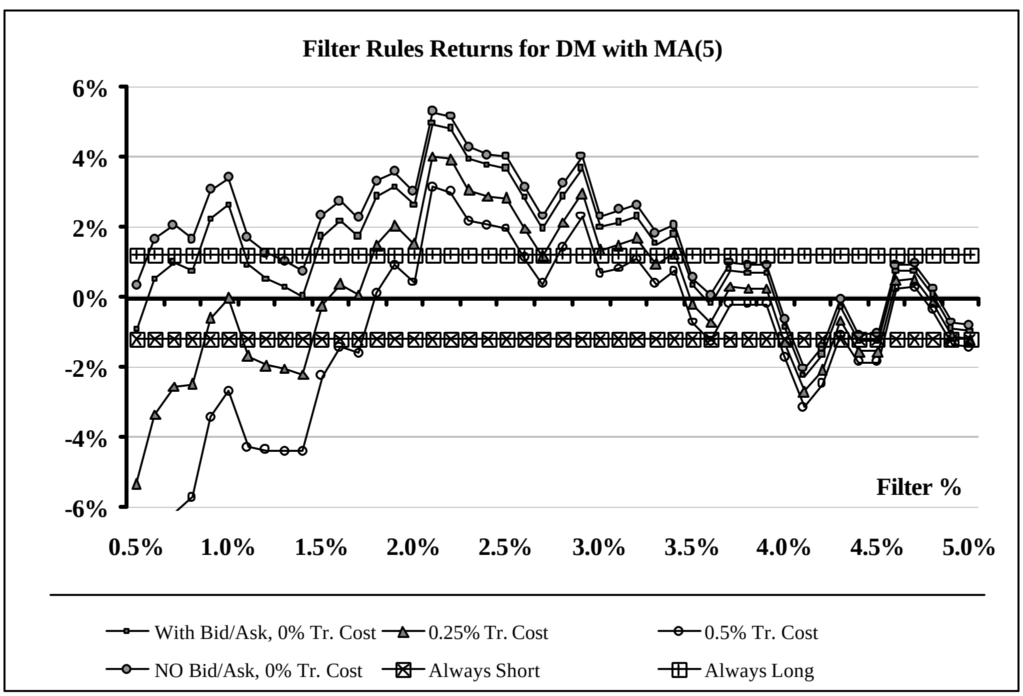
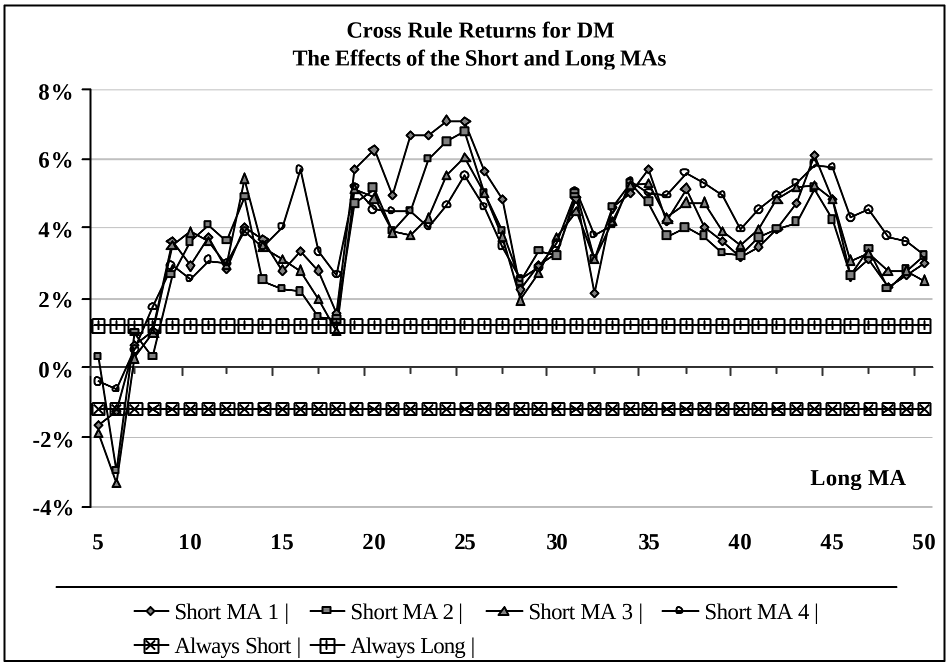


Figure 3-B

Typical Behavior of Cross Rules.
The German DM: 1986 - 1998



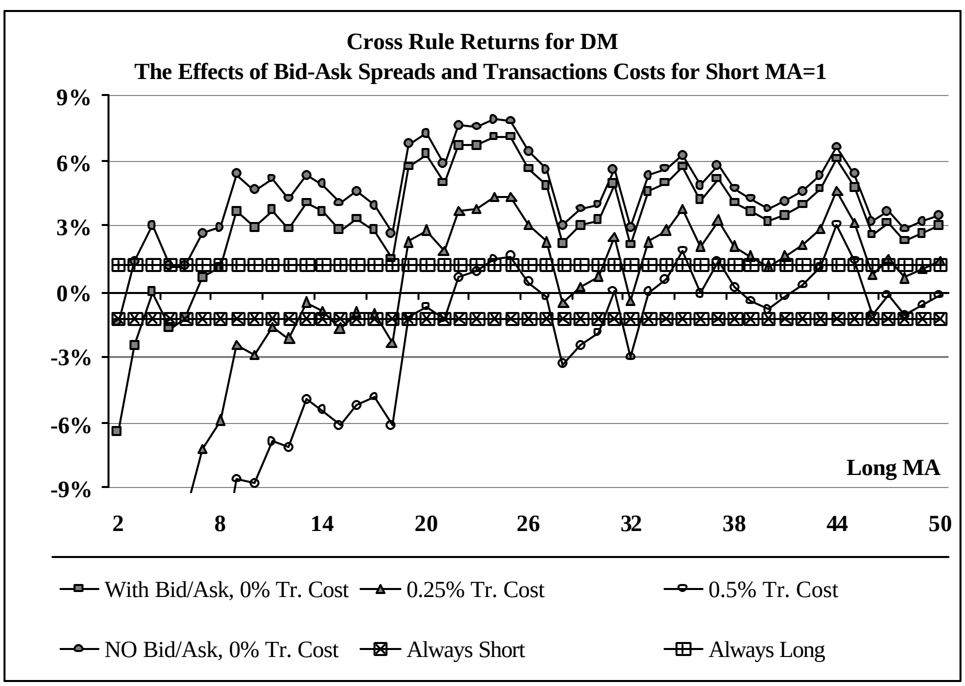


TABLE 1-A
Summary Statistical Properties

	Canada	Denmark	France	Germany	Italy	Japan	Netherlands	UK
<u>Summary Statistics</u>								
Return (annualized)	0.25%	1.23%	1.26%	1.45%	-1.44%	1.96%	1.47%	1.40%
Stdev (Annualized)	122.0%	234.3%	236.2%	241.5%	235.3%	253.0%	239.0%	211.9%
Max/Min % Change/Day	2.10 / -1.80	2.98 / -2.98	4.05 / -3.69	3.14 / -3.04	3.09 / -6.57	5.49 / -3.39	3.10 / -3.09	3.06 / -3.08
Skewness	-0.08	-0.03	0.02	0.02	-0.76	0.45	-0.03	-0.20
Kurtosis	2.82	1.47	2.78	1.84	7.31	4.13	1.91	2.29
NOBS	4471	4481	3091	3088	3088	4471	3088	4471
<u>Jarque-Bera Normality Test</u>								
JB	1,479	399	1,000	432	6,051	3,661	458	977
Critical Value	9.21	9.21	9.21	9.21	9.21	9.21	9.21	9.21
<u>Box-Pierce P-Values</u>								
1^{st} 5	0.705	0.210	0.036^{*}	0.096	0.096	0.198	0.032^{*}	$0.000^{\dagger}$
1^{st} 10	0.607	0.320	0.031^{*}	0.054	0.033^{*}	0.022^{*}	0.015^{*}	$0.000^{\dagger}$
1^{st} 25	0.740	0.325	$0.007^{\dagger}$	0.165	0.012^{*}	0.087	0.031^{*}	$0.008^{\dagger}$

TABLE 1-B
Contemporaneous Cross-Correlations

	Canada	Denmark	France	Germany	Italy	Japan	Netherlands	UK
Canada	**1**	0.14	0.01	0.01	0.06	0.06	0.02	0.12
Denmark		**1**	0.82	0.83	0.71	0.47	0.84	0.68
France			**1**	0.93	0.82	0.47	0.93	0.65
Germany				**1**	0.80	0.50	0.96	0.68
Italy					**1**	0.40	0.81	0.62
Japan						**1**	0.50	0.39
Netherlands							**1**	0.66
UK								**1**

TABLE 2
Bid-Ask Spreads in Basis Points

		Currency	Interest Rates
Canada	**Average/Maximum**	6.5/82	17.3/112
	First ¼ of sample	7.9	24.2
	Last ¼ of Sample	5.0	11.8
Denmark	**Average**	8.3/138	32.9/1,500
	First ¼ of sample	8.0	27.8
	Last ¼ of Sample	4.8	14.0
France	**Average**	9.6/99	15.3/300
	First ¼ of sample	9.0	14.5
	Last ¼ of Sample	9.0	13.3
Germany	**Average**	6.4/69	12.8/75
	First ¼ of sample	5.7	12.8
	Last ¼ of Sample	6.1	13.5
Italy	**Average**	11.5/81	38.0/400
	First ¼ of sample	11.9	56.4
	Last ¼ of Sample	9.1	11.0
Japan	**Average**	7.7/35	9.4/69
	First ¼ of sample	7.5	11.4
	Last ¼ of Sample	6.2	8.4
Netherlands	**Average**	6.4/63	12.0/50
	First ¼ of sample	6.0	12.8
	Last ¼ of Sample	5.4	10.2
U.K.	**Average**	5.9/64	10.3/112
	First ¼ of sample	6.2	10.3
	Last ¼ of Sample	4.7	10.8
U.S.	**Average**	n.a.	11.6/69
	First ¼ of sample	n.a.	12.6
	Last ¼ of Sample	n.a.	9.4

TABLE 3
Returns For Selected Filter Rules
Full Sample (MA-5)

				Total Return			
Canada		**UIRP long**	= 1.09%	**Hi-I**	= 3.76%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	4.6%	-1.17%	-2.05%	-4.95%		
			n.a	*n.a*	*n.a*		
	1.00%	2.4%	-1.99%	-2.49%	-4.00%		
			n.a	*n.a*	*n.a*		
	2.00%	0.6%	-0.97%	-1.21%	-1.59%		
			n.a	*n.a*	*n.a*		
Best	2.80%	0.2%	1.17%	0.99%	0.84%	-2.76%	-0.09%
			17.89%	*21.79%*	*25.90%*	*n.a*	*n.a*
Denmark		**UIRP long**	= 2.50%	**Hi-I**	= 7.10%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	6.9%	0.96%	-0.67%	-4.98%		
			34.71%	*n.a.*	*n.a.*		
	1.00%	4.6%	2.32%	1.16%	-1.72%		
			17.00%	*31.96%*	*n.a.*		
	2.00%	1.9%	6.11% †	5.49% *	4.32% *		
			0.62%	*1.31%*	*4.57%*		
Best	2.00%	1.9%	6.11% †	5.49% *	4.32% *	-1.61%	3.00%
			0.64%	*1.36%*	*4.68%*	*n.a*	*19.26%*
France		**UIRP long**	= 2.42%	**Hi-I**	= 5.52%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	6.6%	0.88%	-0.81%	-4.91%		
			38.28%	*n.a.*	*n.a.*		
	1.00%	4.4%	3.40%	2.26%	-0.47%		
			12.48%	*22.74%*	*n.a.*		
	2.00%	1.6%	7.37% †	6.85% *	5.83% *		
			0.63%	*1.14%*	*3.05%*		
Best	2.00%	1.6%	7.37% †	6.85% *	5.83% *	1.33%	4.43%
			0.63%	*1.13%*	*3.03%*	*62.92%*	*14.44%*
Germany		**UIRP long**	= 1.08%	**Hi-I**	= 2.19%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	7.0%	0.33%	-0.95%	-5.33%		
			45.71%	*n.a.*	*n.a.*		
	1.00%	4.2%	3.41%	2.61%	-0.04%		
			12.68%	*19.48%*	*n.a.*		
	2.00%	1.7%	3.02%	2.62%	1.53%		
			15.92%	*19.53%*	*31.45%*		
Best	2.10%	1.4%	5.28% *	4.93%	4.04%	2.75%	3.86%
			4.00%	*5.27%*	*9.99%*	*27.44%*	*18.11%*

TABLE 3 (continued)

			Total Return				
Italy		**UIRP long**	= 2.37%	**Hi-I**	= 1.48%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	6.6%	0.48%	-1.80%	-5.95%		
			43.56%	*n.a.*	*n.a.*		
	1.00%	4.0%	5.76%*	4.39%	1.90%		
			2.43%	*7.20%*	*27.38%*		
	2.00%	1.5%	5.46%*	4.71%	3.78%		
			3.28%	*5.93%*	*11.30%*		
Best	1.20%	3.2%	6.21%*	5.10%*	3.11%	3.62%	2.73%
			1.70%	*4.48%*	*16.10%*	*21.34%*	*25.17%*
Japan		**UIRP long**	= -0.91%	**Hi-I**	= 4.27%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	7.2%	1.83%	0.35%	-4.14%		
			23.81%	*44.65%*	*n.a.*		
	1.00%	4.1%	2.65%	1.75%	-0.81%		
			15.35%	*25.36%*	*n.a.*		
	2.00%	2.5%	-0.67%	-1.26%	-2.85%		
			n.a.	*n.a.*	*n.a.*		
Best	1.20%	3.5%	5.61%*	4.82%*	2.62%	0.55%	4.12%
			1.56%	*3.45%*	*17.26%*	*44.30%*	*12.96%*
Netherlands		**UIRP long**	= 1.21%	**Hi-I**	= 1.37%	**Ret – Hi-I**	**Ret – UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	6.9%	-0.13%	-1.27%	-5.58%		
			n.a.	*n.a.*	*n.a.*		
	1.00%	4.4%	2.85%	2.03%	-0.70%		
			16.98%	*25.15%*	*n.a.*		
	2.00%	1.6%	5.39%*	5.01%*	4.03%		
			3.52%	*4.84%*	*9.84%*		
Best	2.10%	1.4%	6.77%*	6.40%*	5.51%*	5.04%	5.19%
			1.18%	*1.71%*	*3.90%*	*12.86%*	*11.04%*
U.K.		**UIRP long**	= 3.67%	**Hi-I**	= 4.17%	**Ret - Hi-I**	**Ret - UIRP**
	Filter	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	0.50%	6.4%	3.33%	2.29%	-1.68%		
			6.57%	*15.40%*	*n.a.*		
	1.00%	3.8%	2.15%	1.49%	-0.91%		
			16.39%	*25.22%*	*n.a.*		
	2.00%	1.8%	1.45%	1.07%	-0.04%		
			25.72%	*31.63%*	*n.a.*		
Best	0.60%	5.6%	4.10%*	3.16%	-0.36%	-1.01%	-0.51%
			2.90%	*7.53%*	*n.a.*	*n.a*	*n.a*

TABLE 4
Returns For Selected Cross Rules
Full Sample

			Total Return				
Canada		**UIRP long**	= 1.09%	**Hi-I**	= 3.76%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	15.6%	0.28%	-2.40%	-12.11%		
			41.30%	*n.a.*	*n.a.*		
	(1,20)	4.9%	2.13%*	1.16%	-1.90%		
			4.67%	*19.05%*	*n.a.*		
	(1,40)	3.7%	0.19%	-0.58%	-2.89%		
			43.92%	*n.a.*	*n.a.*		
Best	(1,15)	6.2%	2.91%*	1.72%	-2.15%	-2.03%	0.64%
			1.10%	*9.70%*	*n.a.*	*n.a*	*36.32%*
Denmark		**UIRP long**	= 2.50%	**Hi-I**	= 7.10%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	15.7%	4.53%*	1.10%	-8.67%		
			3.13%	*33.36%*	*n.a.*		
	(1,20)	5.3%	6.01%†	4.72%*	1.43%		
			0.69%	*3.09%*	*30.19%*		
	(1,40)	3.3%	5.14%*	4.23%*	2.17%		
			1.79%	*4.63%*	*21.16%*		
Best	(2,24)	4.1%	7.68%†	6.63%†	4.06%	-0.47%	4.13%
			0.08%	*0.39%*	*6.44%*	*n.a*	*11.68%*
France		**UIRP long**	= 2.42%	**Hi-I**	= 5.52%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	15.8%	1.01%	-2.94%	-12.84%		
			36.55%	*n.a.*	*n.a.*		
	(1,20)	5.0%	7.26%†	5.91%*	2.79%		
			0.73%	*2.79%*	*20.25%*		
	(1,40)	3.3%	3.37%	2.40%	0.32%		
			12.67%	*21.54%*	*46.11%*		
Best	(2,13)	6.2%	8.12%†	6.48%*	2.62%	0.96%	4.06%
			0.29%	*1.67%*	*21.24%*	*58.89%*	*17.79%*
Germany		**UIRP long**	= 1.08%	**Hi-I**	= 2.19%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	16.8%	1.13%	-1.67%	-12.13%		
			35.35%	*n.a.*	*n.a.*		
	(1,20)	5.6%	7.25%†	6.27%*	2.78%		
			0.82%	*2.15%*	*20.38%*		
	(1,40)	3.2%	3.78%	3.17%	1.17%		
			10.64%	*15.34%*	*36.29%*		
Best	(1,24)	4.5%	7.91%†	7.09%*	4.29%	4.91%	6.02%
			0.51%	*1.23%*	*10.41%*	*13.60%*	*8.64%*

TABLE 4 (continued)

			Total Return				
Italy		**UIRP long**	= 2.37%	**Hi-I**	= 1.48%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	16.5%	0.27%	-4.86%	-15.16%		
			46.39%	*n.a.*	*n.a.*		
	(1,20)	5.0%	9.27%†	7.64%†	4.52%		
			0.08%	*0.67%*	*8.85%*		
	(1,40)	3.3%	5.66%*	4.54%	2.46%		
			2.74%	*6.99%*	*22.83%*		
Best	(2,21)	3.9%	10.64%†	9.37%†	6.94%*	7.90%*	7.01%*
			0.02%	*0.12%*	*1.79%*	*3.82%*	*4.88%*
Japan		**UIRP long**	= -0.91%	**Hi-I**	= 4.27%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	15.1%	5.89%*	2.87%	-6.55%		
			1.23%	*14.86%*	*n.a.*		
	(1,20)	5.9%	4.60%*	3.32%	-0.36%		
			3.70%	*10.47%*	*n.a.*		
	(1,40)	3.0%	7.14%†	6.48%†	4.63%		
			0.33%	*0.81%*	*5.41%*		
Best	(1,43)	2.6%	8.37%†	7.77%†	6.15%*	3.51%	7.08%*
			0.07%	*0.18%*	*1.57%*	*17.84%*	*2.28%*
Netherlands		**UIRP long**	= 1.21%	**Hi-I**	= 1.37%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	16.2%	0.94%	-1.83%	-11.93%		
			37.51%	*n.a.*	*n.a.*		
	(1,20)	5.6%	5.96%*	4.92%	1.39%		
			2.30%	*5.46%*	*33.82%*		
	(1,40)	3.0%	4.78%	4.16%	2.24%		
			5.51%	*8.73%*	*24.84%*		
Best	(2,23)	4.1%	8.60%†	7.85%†	5.29%	6.48%	6.64%
			0.20%	*0.50%*	*5.26%*	*6.35%*	*6.40%*
U.K.		**UIRP long**	= 3.67%	**Hi-I**	= 4.17%	**Ret - Hi-I**	**Ret - UIRP**
	MA(*m*,*n*)	**Transactions**	**No Bid/Ask**	**0 bps**	**25 bps**		
	(1,5)	16.2%	1.97%	-0.50%	-10.61%		
			18.74%	*n.a.*	*n.a.*		
	(1,20)	5.6%	3.96%*	3.02%	-0.47%		
			3.55%	*8.92%*	*n.a.*		
	(1,40)	3.5%	3.12%	2.50%	0.27%		
			7.87%	*13.40%*	*45.65%*		
Best	(4,38)	2.5%	5.18%†	4.69%*	3.11%	0.52%	1.01%
			0.87%	*1.68%*	*9.26%*	*43.41%*	*37.09%*

TABLE 5
Features Of the Golden Cross, Hi-I, and UIRP Rules

	Cross Rules % of Time Long	Hi-I Strategy % of Time Long	Correlation Cross Rule with Hi-I	Correlation Cross Rule with UIRP
Canada	53.1%	70.7%	0.07	-0.02
Denmark	50.0%	62.6%	0.16	-0.01
France	50.8%	62.0%	0.06	0.01
Germany	51.2%	34.4%	-0.06	0.03
Italy	51.8%	93.7%	-0.06	-0.03
Japan	50.4%	15.9%	-0.01	0.09
Netherlands	51.2%	35.9%	-0.02	0.04
U.K.	54.0%	91.7%	0.02	-0.02

TABLE 6
Sharpe Ratios For The Best-Performing Rules
Full Sample

	Filter MA 5	Cross Rules
Canada	0.009	0.016
Denmark	0.023	0.027
France	0.029	0.031
Germany	0.020	0.034
Italy	0.018	0.044
Japan	0.018	0.030
Netherlands	0.027	0.040
U.K.	0.015	0.012

TABLE 7
Returns For Selected MA 5 Filter Rules
1st and 2nd Subperiods

		1st Half Return		2nd Half Return	
Canada		**UIRP long/Hi-I**	*2.21%/3.10%*	**UIRP long/Hi-I**	*-0.18%/4.28%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	0.84%	-0.01%	-3.05%	-3.96%
		25.41%	*n.a.*	*n.a.*	*n.a.*
	1.00%	-1.12%	-1.56%	-2.77%	-3.34%
		n.a.	*n.a.*	*n.a.*	*n.a.*
	2.00%	-1.43%	-1.68%	-0.72%	-0.95%
		n.a.	*n.a.*	*n.a.*	*n.a.*
Best	1st 2.1%	3.97%†	3.78%†	1.52%	1.33%
	2nd 1.2%	*0.10%*	*0.17%*	*12.07%*	*15.35%*
Denmark		**UIRP long/Hi-I**	*6.26%/5.42%*	**UIRP long/Hi-I**	*-1.25%/8.80%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	4.73%*	2.79%	-2.71%	-4.02%
		2.64%	*13.30%*	*n.a.*	*n.a.*
	1.00%	3.56%	2.08%	1.03%	0.18%
		7.15%	*n.a.*	*33.53%*	*47.08%*
	2.00%	6.52%†	5.68%*	6.09%†	5.69%*
		0.38%	*1.08%*	*0.63%*	*1.07%*
Best	1st 1.2%	7.52%†	6.58%†	6.09%†	5.69%*
	2nd 4.4%	*0.09%*	*0.37%*	*0.61%*	*1.04%*
France		**UIRP long/Hi-I**	*7.0%/10.28%*	**UIRP long/Hi-I**	*-2.03%/0.91%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	4.34%	2.68%	-1.99%	-3.68%
		6.98%	*18.83%*	*n.a.*	*n.a.*
	1.00%	4.20%	2.98%	3.39%	2.32%
		7.74%	*16.18%*	*12.57%*	*22.11%*
	2.00%	12.72%†	12.22%†	3.13%	2.59%
		0.00%	*0.00%*	*14.46%*	*19.43%*
Best	1st 2.1%	12.72%†	12.22%†	4.79%	3.71%
	2nd 2.1%	*0.00%*	*0.00%*	*5.36%*	*11.16%*
Germany		**UIRP long/Hi-I**	*5.34%/2.44%*	**UIRP long/Hi-I**	*-3.12%/1.73%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	5.42%*	4.13%	-4.07%	-5.32%
		3.78%	*9.22%*	*n.a.*	*n.a.*
	1.00%	6.90%*	6.02%*	0.90%	0.18%
		1.05%	*2.36%*	*38.13%*	*47.68%*
	2.00%	9.01%†	8.62%†	-1.76%	-2.15%
		0.14%	*0.24%*	*n.a.*	*n.a.*
Best	1st 3.3%	11.61%†	11.27%†	2.88%	2.69%
	2nd 4.7%	*0.01%*	*0.01%*	*16.64%*	*18.37%*

TABLE 7 (continued)

		1st Half Return		2nd Half Return	
Italy		**UIRP long/Hi-I**	*8.32%/8.32%*	**UIRP long/Hi-I**	*-3.37%/-5.09%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	3.64%	1.44%	-2.16%	-4.51%
		10.84%	*31.84%*	*n.a.*	*n.a.*
	1.00%	5.78%*	4.14%	7.08%†	5.97%*
		2.38%	*8.40%*	*0.77%*	*2.33%*
	2.00%	10.33%†	9.63%†	2.28%	1.51%
		0.02%	*0.07%*	*22.06%*	*30.84%*
Best	1st 2.1%	10.92%†	10.24%†	7.74%†	6.82%*
	2nd 1.2%	*0.01%*	*0.03%*	*0.44%*	*1.23%*
Japan		**UIRP long/Hi-I**	*4.10%/2.85%*	**UIRP long/Hi-I**	*-5.78%/5.57%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	3.05%	1.60%	0.15%	-1.36%
		11.72%	*27.08%*	*n.a.*	*n.a.*
	1.00%	6.88%†	6.03%*	-2.13%	-3.08%
		0.40%	*1.12%*	*n.a.*	*n.a.*
	2.00%	3.85%	3.31%	-6.37%	-7.00%
		7.27%	*10.82%*	*n.a.*	*n.a.*
Best	1st 1.2%	9.83%†	9.11%†	1.39%	1.17%
	2nd 4.4%	*0.01%*	*0.03%*	*29.67%*	*32.69%*
Netherlands		**UIRP long/Hi-I**	*5.86%/0.60%*	**UIRP long/Hi-I**	*-3.30%/1.89%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	4.84%	3.76%	-3.96%	-5.14%
		5.14%	*10.75%*	*n.a.*	*n.a.*
	1.00%	4.91%*	4.02%	1.75%	1.00%
		4.99%	*9.22%*	*27.88%*	*37.04%*
	2.00%	9.48%†	9.10%†	2.37%	1.98%
		0.07%	*0.13%*	*21.38%*	*25.59%*
Best	1st 2.1%	12.25%†	11.92%†	2.46%	2.07%
	2nd 2.1%	*0.00%*	*0.00%*	*20.31%*	*24.42%*
U.K.		**UIRP long/Hi-I**	*4.38%/4.65%*	**UIRP long/Hi-I**	*2.97%/3.70%*
	Filter	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	0.50%	5.86%†	4.72%*	0.93%	-0.01%
		0.40%	*1.78%*	*33.73%*	*n.a.*
	1.00%	4.32%*	3.57%	0.25%	-0.32%
		2.47%	*5.46%*	*45.42%*	*n.a.*
	2.00%	6.17%†	5.73%†	-2.88%	-3.19%
		0.27%	*0.53%*	*n.a.*	*n.a.*
Best	1st 3.3%	8.35%†	8.10%†	2.91%	2.79%
	2nd 4.7%	*0.01%*	*0.01%*	*10.23%*	*11.28%*

TABLE 8
Returns For Selected Cross Rules
1st and 2nd Subperiods

		1st Half Return		2nd Half Return	
Canada		**UIRP long/Hi-I**	*2.21%/3.10%*	**UIRP long/Hi-I**	*-0.18%/4.28%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	0.80%	-2.09%	-0.37%	-2.83%
		26.17%	*n.a.*	*n.a.*	*n.a.*
	(1,20)	3.59%†	2.57%*	0.94%	0.03%
		0.23%	*2.62%*	*22.98%*	*49.20%*
	(1,40)	0.25%	-0.54%	0.54%	-0.20%
		42.04%	*n.a.*	*33.40%*	*n.a.*
Best	1st (2,19)	4.00%†	3.02%*	2.62%*	1.54%
	2nd (1,15)	*0.07%*	*1.01%*	*1.95%*	*12.30%*
Denmark		**UIRP long/Hi-I**	*6.26%/5.42%*	**UIRP long/Hi-I**	*-1.25%/8.80%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	5.75%†	1.70%	3.35%	0.53%
		0.92%	*25.44%*	*8.47%*	*41.79%*
	(1,20)	8.53%†	7.03%†	3.49%	2.40%
		0.02%	*0.27%*	*7.64%*	*17.14%*
	(1,40)	5.79%†	4.62%*	5.02%*	4.38%*
		0.89%	*3.31%*	*2.02%*	*4.09%*
Best	1st (4,19)	10.16%†	8.90%†	7.82%†	7.29%†
	2nd (2,35)	*0.00%*	*0.02%*	*0.06%*	*0.17%*
France		**UIRP long/Hi-I**	*7.00%/10.28%*	**UIRP long/Hi-I**	*-2.03%/0.91%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	2.92%	-0.86%	-0.75%	-4.86%
		16.02%	*n.a.*	*n.a.*	*n.a.*
	(1,20)	12.57%†	11.32%†	3.30%	1.86%
		0.00%	*0.01%*	*13.35%*	*27.33%*
	(1,40)	6.13%*	5.13%*	2.04%	1.15%
		1.89%	*4.62%*	*24.47%*	*35.34%*
Best	1st (4,20)	13.47%†	12.55%†	5.84%*	4.67%
	2nd (1,25)	*0.00%*	*0.00%*	*2.43%*	*6.42%*
Germany		**UIRP long/Hi-I**	*5.34%/2.44%*	**UIRP long/Hi-I**	*-3.12%/1.73%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	3.75%	1.14%	-1.08%	-4.05%
		10.58%	*35.66%*	*n.a.*	*n.a.*
	(1,20)	13.04%†	12.21%†	2.88%	1.76%
		0.00%	*0.00%*	*16.98%*	*28.51%*
	(1,40)	6.53%*	5.95%*	2.54%	1.93%
		1.57%	*2.76%*	*20.10%*	*26.68%*
Best	1st (3,19)	14.02%†	13.35%†	5.04%*	4.48%
	2nd (1,37)	*0.00%*	*0.00%*	*4.74%*	*7.34%*

TABLE 8 (continued)

		1st Half Return		2nd Half Return	
Italy		**UIRP long/Hi-I**	*8.32%/8.32%*	**UIRP long/Hi-I**	*-3.37%/-5.09%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	3.12%	-1.55%	-2.08%	-7.62%
		14.38%	*n.a.*	*n.a.*	*n.a.*
	(1,20)	13.26%†	11.78%†	6.72%*	4.95%*
		0.00%	*0.01%*	*1.11%*	*5.47%*
	(1,40)	7.50%†	6.31%*	3.86%	2.82%
		0.55%	*2.01%*	*9.52%*	*17.98%*
Best	1st (4,19)	15.42%†	14.21%†	9.02%†	7.75%†
	2nd (2,21)	*0.00%*	*0.00%*	*0.12%*	*0.62%*
Japan		**UIRP long/Hi-I**	*4.10%/2.85%*	**UIRP long/Hi-I**	*-5.78%/5.57%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	6.86%†	3.84%	4.48%*	1.46%
		0.44%	*8.14%*	*4.35%*	*29.80%*
	(1,20)	7.08%†	5.72%*	1.19%	-0.01%
		0.30%	*1.53%*	*32.20%*	*n.a.*
	(1,40)	9.82%†	9.17%†	3.60%	2.92%
		0.01%	*0.03%*	*8.60%*	*13.98%*
Best	1st (1,43)	10.85%†	10.29%†	6.51%†	6.03%*
	2nd (3,44)	*0.00%*	*0.01%*	*0.64%*	*1.18%*
Netherlands		**UIRP long/Hi-I**	*5.86%/0.60%*	**UIRP long/Hi-I**	*-3.30%/1.89%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	5.57%*	2.92%	-3.09%	-5.97%
		3.01%	*17.20%*	*n.a.*	*n.a.*
	(1,20)	12.68%†	11.86%†	1.64%	0.43%
		0.00%	*0.01%*	*29.16%*	*44.45%*
	(1,40)	8.08%†	7.49%†	3.24%	2.68%
		0.35%	*0.73%*	*13.97%*	*19.07%*
Best	1st (2,21)	15.32%†	14.64%†	6.06%*	5.27%*
	2nd (1,25)	*0.00%*	*0.00%*	*2.14%*	*4.29%*
U.K.		**UIRP long/Hi-I**	*4.38%/4.65%*	**UIRP long/Hi-I**	*2.97%/3.70%*
	MA(*m*,*n*)	**No Bid/Ask**	**0 bps**	**No Bid/Ask**	**0 bps**
	(1,5)	1.53%	-1.17%	2.42%	0.17%
		24.53%	*n.a.*	*13.78%*	*47.08%*
	(1,20)	6.89%†	5.90%†	1.17%	0.28%
		0.08%	*0.43%*	*29.71%*	*45.09%*
	(1,40)	6.56%†	5.91%†	0.18%	-0.42%
		0.15%	*0.44%*	*46.78%*	*n.a.*
Best	1st (4,24)	10.35%†	9.65%†	3.67%*	3.05%
	2nd (2,27)	*0.00%*	*0.00%*	*4.80%*	*8.74%*

TABLE 9
Summary of Returns For UIRP, Hi-I and the Best-Performing Cross and Filter Rules
Overall, 1st, and 2nd Subperiods

	Long UIRP Ret	High Interest Rate Strategy	Filter Rules Best	Cross Rules Best
Canada	1.09%	3.76%	0.99%	1.72%†
1st Half	2.21%	3.10%	3.78%†	3.02%†
2nd Half	-0.18%	4.28%	1.33%	1.54%
Denmark	2.50%	7.10%	5.49%*	6.63%†
1st Half	6.26%	5.42%	6.58%†	8.90%†
2nd Half	-1.25%	8.80%	5.69%*	7.29%†
France	2.42%	5.52%	6.85%*	6.48%†
1st Half	7.00%	10.28%	12.22%†	12.55%†
2nd Half	-2.03%	0.91%	3.71%	4.67%
Germany	1.08%	2.19%	4.93%	7.09%*
1st Half	5.34%	2.44%	11.27%†	13.35%†
2nd Half	-3.12%	1.73%	2.69%	4.48%
Italy	2.37%	1.48%	5.10%*	9.37%†
1st Half	8.32%	8.32%	10.24%†	14.21%†
2nd Half	-3.37%	-5.09%	6.82%*	7.75%†
Japan	-0.70%	4.27%	4.82%*	7.77%†
1st Half	4.10%	2.85%	9.11%†	10.29%†
2nd Half	-5.78%	5.57%	1.17%	6.03%*
Netherlands	1.21%	1.37%	6.40%*	7.85%†
1st Half	5.86%	0.60%	11.92%†	14.64%†
2nd Half	-3.30%	1.89%	2.07%	5.27%*
U.K.	3.67%	4.17%	3.16%	4.69%*
1st Half	4.38%	4.65%	8.10%†	9.65%†
2nd Half	2.97%	3.70%	2.79%	3.05%
AVERAGES				
Full Sample	**1.91%**	**3.73%**	**4.72%**	**6.45%**
1st Half	**5.43%**	**4.71%**	**9.15%**	**10.83%**
2nd Half	**-2.01%**	**2.72%**	**3.28%**	**5.01%**

TABLE 10
Out-Of-Sample Performance Of the Trading Rules
(Filter revised annually; 2-year rolling window)

	Simple Filter			MA(5) Filter			Cross		
	All	**1st Half**	**2nd Half**	**All**	**1st Half**	**2nd Half**	**All**	**1st Half**	**2nd Half**
Canada	0.72%	0.33%	0.95%	-0.88%	1.99%	-3.14%	-2.80%	-2.44%	-3.09%
	28.87%	*39.88%*	*23.04%*	*n.a.*	*5.93%*	*n.a.*	*n.a.*	*n.a.*	*n.a.*
Denmark	4.30%[*]	1.68%	6.44%[†]	-1.55%	3.64%	-5.68%	4.78%[*]	6.16%[†]	3.70%
	3.98%	*24.68%*	*0.44%*	*n.a.*	*7.16%*	*n.a.*	*2.77%*	*0.68%*	*6.88%*
France	-1.18%	4.11%	-4.45%	0.52%	3.73%	-1.46%	2.09%	10.12%[†]	-2.85%
	n.a.	*8.57%*	*n.a.*	*43.17%*	*10.70%*	*n.a.*	*24.62%*	*0.05%*	*n.a.*
Germany	5.08%[*]	7.00%[*]	3.90%	0.37%	2.67%	-1.04%	2.53%	9.94%[†]	-2.04%
	4.56%	*1.00%*	*9.75%*	*45.14%*	*19.04%*	*n.a.*	*21.16%*	*0.08%*	*n.a.*
Italy	0.53%	-0.63%	1.25%	1.87%	10.06%	-3.17%	6.06%[*]	11.09%[†]	2.97%
	42.95%	*n.a.*	*33.85%*	*26.65%*	*0.04%*	*n.a.*	*2.50%*	*0.02%*	*16.86%*
Japan	-4.81%	3.02%	-10.93%	-2.90%	0.58%	-5.69%	2.44%	6.23%[†]	-0.59%
	n.a.	*13.80%*	*n.a.*	*n.a.*	*41.38%*	*n.a.*	*18.07%*	*0.99%*	*n.a.*
Netherlands	-2.36%	-1.73%	-2.75%	-0.56%	2.60%	-2.51%	2.37%	13.24%[†]	-4.33%
	n.a.	*n.a.*	*n.a.*	*n.a.*	*19.49%*	*n.a.*	*21.87%*	*0.00%*	*n.a.*
U.K.	0.60%	2.40%	-0.82%	0.18%	0.46%	-0.05%	1.32%	5.98%[†]	-2.32%
	39.60%	*14.39%*	*n.a.*	*46.76%*	*41.70%*	*n.a.*	*27.42%*	*0.34%*	*n.a.*
Average	**0.36%**	**2.02%**	**-0.80%**	**-0.37%**	**3.22%**	**-2.84%**	**2.35%**	**7.54%**	**-1.07%**

NOTES FOR THE TABLES

<u>Notes For Table 1:</u>
Table 1-A reports relevant statistical properties for the 8 currencies in the study. The average returns and standard deviation are daily annualized %. The maximum and minimum one-day returns are not annualized. We also report skewness, kurtosis and the number of observations (NOBS) for each currency.

We report the value of the Jarque-Bera normality test along with its critical value. We also report the Box-Pierce p-values for the first 5, 10, and 25 autocorrelations. The symbol "†"denotes p-values of 1% or less, and "*" denotes p-values between 5% and 1%.

Table 1-B reports contemporaneous daily cross-correlations for the currencies. We do not report statistical significance.

<u>Notes For Table 2:</u>
The table shows the average and maximum bid/ask spreads for the *FX* rate and the interest rates for each currency over the whole sample. In order to determine if there are substantial changes in the bid/ask spreads over the sample, we also report the average values for the first and last quarter of the sample.

<u>Notes For Tables 3 and 4:</u>
Table 3 shows returns and other relevant properties of selected filter rules. We show details for rules that use a 5-day moving average of the *FX* rate (MA5), and filter = 0.5%, 1%, and 2%, as well as the best-performing rule in the filter interval of 0.5% to 5% in increments of 0.1%.

Table 4 shows returns and other relevant properties of selected cross rules. We show details for MA(*short*, *long*) where *short* = 1 day (the *FX* rate itself) and long = 5, 20, and 40 days, as well as the best performing rule in the interval *short* = 1, 4, and *long* = 2, 50, both in increments of 1 day.

The first row for each country shows the always-long return, labeled *UIRP long*, and the return to being long in the high interest rate currency compared to the US$ and short in the other, in a pairwise comparison, (labeled *Hi-I*).

The columns from left to right show the size of the rule (labeled "filter" or "MA(*m,n*)"), the proportion of the days the rule trades (labeled "transactions"), the returns to each filter excluding the bids-ask spreads (labeled "no bid/ask"), the returns to each filter including the bid/ask spreads (labeled "0 bps"), and the returns to each filter with *c* = 25 bps in addition to the bid/ask spreads (labeled "25 bps").

There are 2 rows for each rule. The 1st row shows the return while the 2nd row shows its p-value. The p-values are the probability that the return is greater than zero, and they are calculated from Monte-Carlo simulations with 10,000 replications, to avoid making distributional assumptions about the returns. We report p-values only for rules that have positive returns. The symbol “†“denotes p-values of 1% or less, and “*” denotes p-values between 5% and 1%.

There are two additional columns: “Ret – Hi-I” shows the difference between the filter and the Hi-I return, and “Ret – UIRP” shows the difference between the filter and positive UIRP return. We show these calculations only for the best-performing filter to reduce number congestion in the table.

<u>Notes For Table 5:</u>
The four columns of the table from left to right show the % of time the cross rule is long in the foreign currency (cross rules % of time long), the % of time the *Hi-I* strategy is long in the foreign currency (“Hi-I Strategy % Of Time Long”), the daily contemporaneous correlation of the cross rule and *Hi-I* returns (“Correlation of Cross Rule with Hi-I”), and the daily contemporaneous correlation of the cross rule and *UIRP* returns (“Correlation of Cross Rule with UIRP”). The analogous results for the filter rules are very similar; we do not report them to conserve space.

<u>Notes For Table 6:</u>
The table shows Sharpe ratios for the best-performing rule over the full sample. The Sharpe ratio is calculated as the ratio of the average daily return divided by the daily standard deviation.

<u>Notes For Tables 7 and 8:</u>
Table 7 shows returns for the filter rules in Table 3 for the 1st and 2nd halves of the sample, while Table 8 shows returns for the cross rules in Table 4 for the 1st and 2nd halves of the sample.

For each country, the first row shows the always-long return labeled *UIRP* long, and the return to being long in the high interest rate currency compared to the US$ (labeled *Hi-I*), respectively. The two returns are separated by a “/” for each subsample. The values are shown for both halves of the sample.

The columns from left to right show the size of the filter (labeled “filter”), the returns to each filter excluding the bids-ask spreads (labeled “no bid/ask”), and the returns to each filter including the bid/ask spreads (labeled 0 bps). We do not report returns with additional transactions costs to conserve space.

There are 2 rows for each filter. The 1st row shows the return while the 2nd row shows its p-value. The p-values are the probability that the return is greater than zero, and they are calculated from Monte-Carlo simulations with 10,000 replications, to avoid making distributional assumptions about the returns. We report p-value only for rules that have positive returns. The symbol “†“denotes p-values of 1% or less, and “*” denotes p-values between 5% and 1%.

The rows labeled “best” show the return of the best-performing filter or cross rule over the two halves of the sample, using the same search ranges discussed in Tables 3 and 4. The “1^{st}” and “2^{nd}” designation refers to the best-performing strategy for the 1^{st} and 2^{nd} subsamples respectively.

Notes For Table 9:

The table shows a summary of the overall returns and the 1^{st} and 2^{nd} subperiod returns from left to right: Always being long (“Long UIRP Ret”), the *Hi-I* strategy, the best-performing filter rule in each subperiod, and the best-performing cross rule in each subperiod. We do not report p-values but we do designate p-values of 1% or less with “✝”, and p-values between 1% and 5 % with “*”. The p-values are based on Monte-Carlo simulations, as elsewhere in the paper.

Notes For Table 10:

The table shows returns for ex-ante filter and cross rules for the full period as well as the two subperiods. We report returns for the standard filter rule discussed in the literature, for our MA5 modification of it, and for cross rules. Data from years t-2 to t are used to identify the best in-sample rule. Then the rule is applied to the following year. The procedure is repeated for the whole sample. The symbol “✝“denotes p-values of 1% or less, and “*” denotes p-values between 5% and 1%.

The p-value calculations are based on the standard deviation of the best-performing filter. Monte-Carlo simulations for 10,000 replications for the ex-ante filters are extremely time-consuming (well over a week for each case). We performed some exploratory Monte-Carlo simulations to test our assumption that the best-performing rule standard errors were applicable. We found that the “correct” standard errors were slightly higher than the best-performing filter ones; this means we slightly overstate the significance of the returns in the table.