

**DO TECHNICAL TRADING PROFITS REMAIN IN THE FOREIGN
EXCHANGE MARKET?
EVIDENCE FROM FOURTEEN CURRENCIES**

by

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ABSTRACT

We examine the in- and out-of-sample behavior of two popular trading systems, Alexander and Double MA filters, for fourteen developed-country currencies using daily data with bid-ask spreads. We find significant in-sample returns in the early periods. But out-of-sample returns are lower and only occasionally significant. We show that a currency risk factor proposed in the literature is systematically related to these returns. We find no support for the hypotheses that falling transactions costs are responsible for declining trading profits or for the Adaptive Market hypothesis. Importantly, we show that algorithms that simulate out-of-sample returns have serious instability difficulties.

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

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I. INTRODUCTION

Examining the profitability of technical trading systems has been the subject of much research, because it can reveal market inefficiencies and possible disequilibria in the FX market. These systems – sets of mechanical rules that generate buy, sell or hold signals based on historical data – are designed to take advantage of time-dependencies in price changes. Under the Efficient Markets Hypothesis (EMH), price changes should not be time-dependent; in particular, there should be no systematic profits, after adjusting for returns to risk-bearing and transactions costs. Under the Adaptive Market Hypothesis (AMH; see Lo 2004), price changes may be time-dependent, and the resulting profits are expected to dissipate only slowly.

The results in the literature to-date as to whether trading profits exist are inconclusive. The following four items summarize the findings in the literature on trading systems:

- 1) Almost all the studies find statistically and economically significant trading (system) profits when profits are computed in-sample, that is, when all the sample data are used to identify winning strategies.
- 2) Out-of-sample evidence is more mixed, particularly in the most recent papers we review below. Some studies find smaller, declining, and often insignificant out-of-sample returns from trading systems. “Out-of-sample” evaluations simulate trading using historical data but they use information available only at each decision date in the selection of strategies.
- 3) A “filter” is the minimum change required in the benchmark variable for the trading system to trigger action; the filter can be set to a variety of values. The general conclusion is that, ignoring transactions costs, small filters – triggered by small changes in the benchmark variable– produce higher returns than large filters. But because small filters imply very frequent trading, unaccounted-for transactions costs are high and trader profits are dissipated.

4) At least the in-sample profits documented for trading systems are often judged to be too large to represent likely returns to risk-bearing.²

The existence of trading system profits, if reliable, raises troubling questions about the efficiency of the FX markets. In this paper we investigate the main issue in FX market efficiency: do excess trading profits still exist?

We address this question by re-examining the profitability of two popular trading systems, a variant of the Alexander filter, and the Double Moving Average (Double MA) filter, from January 1986 to August 2009. We use daily data for 14 developed-country currencies, for which bid-ask spreads are available for both FX rates and Eurocurrency deposit and loan rates. The bid-ask spreads allow us to take into account explicitly the direct transactions costs of trading, rather than ignoring, estimating, or assuming them, as in the literature to-date.

We find that, consistent with the literature, these two trading systems often generate significant and positive returns (profits) when applied in-sample. When we take into account the bid-ask spreads, profits and their statistical significance is lower; however, with a few exceptions they retain significance at a lower confidence level. We confirm that in-sample trading profits are considerably lower in the second half of the sample; their statistical significance is much reduced or is nonexistent.

Also consistent with the literature, we find that trading system profits are economically smaller and generally statistically insignificant when the systems are simulated out-of-sample, and losses are much more frequent. We do find some evidence of significant out-of-sample excess returns in the beginning of our sample period (1989-91). However, the level and

² There are parallel “technical trading literatures” for the stock market and for commodity markets. In contrast to the FX markets literature, the general conclusion for the stock market is that apparently profitable trading systems exist for small filters, but that these excess profits would be swamped by the transactions costs incurred in following

significance of trading returns in the subsequent periods is very uncertain, and there are only a few instances in later subperiods where we find significant returns.

We use regression analysis to more formally test several hypotheses: (i) the risk premium hypothesis, which suggests that the exposure of the trading returns to market-wide risk factors is responsible for any measured profits, (ii) the hypothesis that lower transactions costs reduce profits by making it more attractive for less efficient traders to trade, and (iii) the AMH.

We find that the FX risk factor proposed by Lustig et al. (2008) is statistically significant for most currencies. In contrast, of the Fama-French risk factors only the market risk is occasionally significant, while the other two almost never are; this is true for both the in-sample and out-of-sample trading returns. Jensen's alphas are almost never statistically significant in the out-of-sample returns, consistent with Lustig et al. (2008) and contrary to Neely et al. (2009); they are frequently significant for the in-sample returns.

All the loadings on the FX and market factors are negative but small. This suggests that the speculative positions we examine provide a small level of hedging against FX and market risks.

Our results do not provide support for the hypothesis that lower transactions costs are responsible for declining trading returns. We also show that a time trend does not fit trading returns. Though lower second-period returns is consistent with the AMH, our inability to document a declining pattern in returns over time with this more specific test casts doubt on the hypothesis. However, since the AMH is not precisely articulated, this type of test cannot be said to reject it.

the system; see Allen and Karjalainen (1999) for further references. Also, significant profits are reported in commodity markets; see Lukac, Brorsen, and Irwin (1988).

A very important finding is that the out-of-sample returns are extremely sensitive to the parameters of the simulations that create them. We investigate the effect of two parameters of the trading algorithms: the starting date, and the training period of the algorithm. For example, when we start the Double MA algorithm for the Deutsche Mark (DM) on 5/13/86, the 23-year out-of-sample return is 1.3% and not statistically significant. But start the algorithm four months later, on 9/5/86, and the average return is 5.2% and statistically significant at the 5% level.

Our findings on out-of-sample returns and the very high sensitivity of the returns to the initial conditions of the algorithms, lead us to conclude that there are no reliable profits to be had with these two trading systems. Furthermore, our finding that simulation results are excessively dependent on initial conditions makes any past or future reports of out-of-sample success extremely suspect. It means that researchers or practitioners may examine the same data and trading systems and yet reach different conclusions about the profitability of a system because of small differences in the algorithm parameters.

The remainder of the paper is organized as follows. Section II provides a brief review of the relevant literature. Section III discusses the calculation of trading returns, the trading systems we study, and the procedures we use to evaluate the returns from both statistical and economic perspectives. Section IV describes the data sources and the statistical properties of the FX rates we use. Section V reports the in-sample and out-of-sample results, as well as tests of the risk exposure, the transactions costs, and the AMH explanations of trading returns. Importantly, it also describes a new source of instability related to the algorithms used to simulate out-of-sample returns. Section VI offers concluding remarks.

II. LITERATURE REVIEW

The early literature is mainly concerned with testing the existence of in-sample FX trading profits; the conclusion was that there were such profits. Dooley and Shafer (1983) were the first to document autocorrelation in daily FX rates and to show that certain technical trading systems are profitable. Sweeney (1986) examines the DM in detail, and supplements the analysis by examining nine other currencies, from 1975 through 1980. Assuming normally distributed returns and constant risk premia, he finds several cases of significant excess 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 excess returns tend to persist from one subperiod to the next. He concludes that, “major exchange markets showed grave signs of inefficiency over the first 1,830 days of generalized managed float....” (p. 178).

Taylor and Allen (1992) present evidence that all surveyed FX traders rely at least to some extent on “chartist” information to make their trades, lending credence to the claim that excess returns are available. Levich and Lee (1993) re-examine the profitability of trading systems using 1976-1990 data and improved statistical methods, for five currencies.³ They enlarge the pool of the trading systems by including a “moving average” system first introduced into this literature by Lukac et al. (1988), and Schulmeister (1988).⁴ To take into account the non-normality and heteroscedasticity of FX rates, Levich and Lee (1993) use bootstrap methods to calculate p-values for their returns.⁵ They find that “... mechanical trading rules have very often led to profits that are highly unusual...” (p. 451); 15 of the 30 simple filters and 12 of 15 of the moving average filters they test produce significant excess returns at the 1% level. They

³ 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.

⁴ See Patel (1980) for a thorough discussion of some 100 alternative technical trading systems.

report minor declines in the profitability of these filters in the last part of their sample but profits that are still positive and significant.

While in-sample trading profits were being documented, researchers refined the question by asking whether it was true that trading profits could be had “out-of-sample”, i.e., without use of *any* future information. After all, this is the critical question. The results of this inquiry are inconclusive.

Neely, Weller, and Dittmar (1997) analyze returns from trading systems for four currencies for the 1975-1995 period using a genetic programming approach to identify ex-post profitable trading rules as proposed by Allen and Karjalainen (1999) for the stock market. They apply these profitable rules out-of-sample to assess their reliability and find reasonably high (up to 6% per year) and reliable trading profits for all four currencies.⁶

One possible explanation for trading profits may be that the EMH is “too stringent” and it does not take adequately into account the realities of the marketplace. Lo (2004) proposes but does not quantify the Adaptive Markets hypothesis (AMH). In contrast to the EMH, the AMH suggests that one should not be surprised to find exploitable excess returns or even arbitrage opportunities. One should expect to find, however, that such profit opportunities erode over time, as more agents adapt their behavior to take advantage of them.

Olson (2004) studies a moving average crossover system for 18 currencies for the 1971-2000 period and finds significant profits for the early part of his sample, assuming normality of trading returns and ignoring interest differentials. He reports that profits decline throughout the

⁵ Brock, Lakonishok and LeBaron (1992) first study the benefits of bootstrapping methods to overcome inference biases that arise from departures from normality in the distribution of FX returns.

⁶ Neely and Weller (2003) use only one year of half-hourly trading data and search over a wide range of trading systems. They find reliable autocorrelations at these intraday frequencies but when they apply the most profitable of these systems out-of-sample, profits disappear, even when they assume small transactions costs (1 bp for a one-

sample; in a regression of 5-year average returns against time, the coefficient on time is negative and statistically significant. His findings support the AMH.

Pukthuanthong-Le and Thomas (2008) find that their “newly liquid” currencies produce higher trading profits than highly liquid currencies that have been trading for a long time; they also report declines in profits over time. This finding is also consistent with the AMH.

Neely, Weller and Ulrich (2009, henceforth NWU) reexamine the return performance of trading rules using data from 1973-2000 for 10 currencies. NWU test whether the trading systems discussed in five published studies continue to earn excess returns out-of-sample or whether these returns erode over time. They conclude that the returns documented in these studies were genuine and not due to data mining. They also show that these returns decline over time slowly rather than abruptly, which they interpret as evidence consistent with the AMH; they control for estimated transactions costs.

De Zwart et al. (2009) study mainly 21 developing country currencies over the 1997-2007 period. They show that combining trading system signals with economic fundamentals information (real interest rate differentials and GDP growth) produces better returns than the trading systems by themselves, and that these returns have high Sharpe ratios and are sometimes statistically significant.

Another possible explanation for trading profits is that they reflect risk-bearing. Lustig et al. (2008) propose a FX risk factor to explain “carry trade” profits. Carry trade profits rely on the empirical observation that an investor can earn positive returns by borrowing in low interest rate currencies and depositing in high interest rate currencies in the floating FX rate period.^{7,8}

way trade). Their one-year data length makes it difficult to compare with our results or with other results in the literature.

⁷ Carry trade profits are related to the empirical failure of UIRP. It is also 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

Using a sample of 37 currencies, Lustig et al. (2008) demonstrate the relevance of their single FX risk factor and show that, for portfolios of currencies, this factor “explains” the excess returns of the carry trade; they provide additional evidence that these returns are rewards for risk-taking. Also, their Jensen’s alphas are statistically insignificant.

An excellent review of the technical analysis literature is in Park and Irwin (2007).

III. THEORY AND METHODOLOGY

The trading systems we examine fulfill the requirements of being replicable and of relying on publicly available information at date t to signal trading action at date t . We discuss the measurement of trading returns, the trading systems to be studied, and how we evaluate trading returns.

III.a. The Measurement of Returns

We follow the recent literature and calculate trading returns for portfolios that should make zero risk-adjusted returns, i.e., zero-net-investment portfolios. Our notional trader is either long or short in a foreign currency. A long position in a foreign currency implies that the trader borrows in US\$ at the loan rate and earns interest at the foreign currency deposit rate, while a short position implies that the trader borrows at the foreign currency loan rate and earns interest at the US\$ deposit rate.

in FX rates. Later papers (Engel and Hamilton 1990, Evans and Lewis 1995) attempt to model FX 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 returns for 4 currencies during the 1980-1991 period.

⁸ The carry trade has been popular among traders. As early as the middle 1970s, the IMF used this principle and lent to client countries in the lowest interest rate currency, which at that time was frequently the Swiss Franc. Burnside et al. (2008) show that the carry trade is largely profitable for their 20 currencies (using monthly data), and they offer a peso problem explanation that relies on very large discount rates for “very bad” low-probability states of the world.

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 daily returns, variances, and measures of reliability. We modify this procedure so the bid-ask spreads are not charged each time we close out the position notionally in order to mark-to-market. For example, if the trader chooses 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 price, though she had bought it at the ask price. Thus, on average she pays the bid-ask spread. However, when the system’s signal is “hold position”, we use the ask price (not the bid price that would be used in an actual trade) to compute the daily return of long positions, and the bid price to compute the return of short positions.

Let S_t^b, S_t^a be the US\$ per foreign currency bid and ask prices (ask>bid), $i_{d,t}^{\$}, i_{\ell,t}^{\$}, i_{d,t}^{fc}, i_{\ell,t}^{fc}$, the annualized deposit and loan rates for the US\$ and the foreign currency (fc), respectively, τ the number of calendar days the position is held, and $c \geq 0$ a fixed cost paid at each transaction in addition to the bid-ask spread. There are four possible returns for each period: long-and-hold, short-and-hold, long-to-short, and short-to-long. The instantaneous one-business-day returns to a zero-net-investment portfolio starting at date = t and ending at date = $t + \tau$ are given below (except when weekends and holidays intervene $\tau = 1$):⁹

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

⁹ An underlying assumption common to all the studies is that both interest rates are known at the time of the trade. In order for this assumption to be tenable, we must assume that the trader enters into loan and deposit contracts with fixed interest rates whose maturity exceeds the time-interval that she is likely to hold the position; this last is inherently unknown. An additional assumption is that this trader can unwind the borrowing and lending she undertook without penalty before maturity. This also suggests that using forward prices instead of interest rates would exacerbate the difficulty of early unwinding, since forward contracts are not tradable and cannot be precisely offset by an opposite position; see also de Zwart et al. (2009).

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

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

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

III.b. Trading Systems We Evaluate

We study two widely examined trading systems, a variant of the “Alexander filter” and the Double MA filter. The “Alexander filter” work as follows. A new current *local low* is established each time the FX rate rises after it had been falling. A new current *local high* is established each time the FX rate falls after it had been rising. A $f\%$ filter signals to go long in the foreign currency when the currency rises $f\%$ above its current local low; it signals to go short in the foreign currency when the currency falls $f\%$ below its current local high. Otherwise, hold the existing position.

The variant of the Alexander filter we choose has not been used in the literature, but we find that it works better. The volatility typical of daily FX data can induce changes from long to short positions too frequently when f is small. It is also possible that when f is large, the filter will not send a signal even though over the period the FX rate may have gone up or down by more than $f\%$. Our variation is to require the filter to operate on a 5-day moving average of the FX rate, rather than the FX rate itself. We label this variation the “Alexander filter” since we report only its results.

The “Double Moving Average” filter (Double MA) works as follows.¹⁰ The filter is defined by two MA series of the FX rate, $MA(m,n; m < n)$; the m -day moving average is the “short MA”, and the n -day moving average is the “long MA”. When both the short and long MAs are rising and the short MA crosses the long from below, purchase the currency (go long). When both the short and long MAs are falling and the short MA crosses the long from above, borrow the currency (go short in the currency). Otherwise, hold the existing position. Each filter then is defined by its particular pair m, n .

III.c Statistical Evaluation of Returns

To evaluate the statistical significance of returns, we follow the recent literature and compute p-values using Monte Carlo simulations. It is inappropriate to rely on Normal distribution statistics, since the non-normality of daily FX returns is well-established (see section IV.b below). For each filter and each transaction cost, c , we create 10,000 simulations by randomly scrambling the data. In scrambling the data we keep together the growth rate of the FX rate at time t , the matching bid-ask spreads, and the time $t-1$ interest rates. Once a random iteration is created, we use the sequence of growth rates and the bid-ask spreads to create the FX “history” on which the filters operate. Thus, only the order of the returns is changed; this approach breaks any existing time series dependencies but retains the exact mean and variance of the distribution. We generate a distribution for each filter and compute the p-values from these distributions. All the p-values we report are obtained with this Monte Carlo method.

¹⁰ Levich and Lee (1993) label this system “moving average”, while Olson (2004) labels it “MA crossover”. We label it “Double MA,” following Sweeney (1986) and Surajaras and Sweeney (1992).

As does most of the literature, we report p-values that compare returns to zero, because regardless of how unlikely a particular return is, the relevant question for market efficiency and for practitioners is whether reliably positive returns can be obtained.^{11,12}

The additional trading cost of c bps is intended to proxy for proportional transactions costs other than the bid-ask spreads; $c > 0$ is observationally equivalent to a higher bid-ask spread for the FX rate, because it is incurred only when there is a trade. We wish only to quantify the effects of additional trading costs, since we have no data on them.¹³

III.d Economic Evaluation of Returns

We start by analyzing in-sample returns for the currencies for each half of the sample in order to assess whether returns decline through time, as would be consistent with the findings in the literature and with the AMH.

Next we simulate the performance of our trading systems “out-of-sample,” so that at every date the choice of the filter as well as its signal depends strictly on data that were available to traders at that date. We report four-year out-of-sample average returns for each currency and each trading system and examine their statistical significance and stability over time.

We then examine some proposed explanations for trading returns. We estimate the factor loadings of trading returns in a Fama-French 3-factor model that also includes the “currency risk

¹¹ We accomplish this by calculating t-statistics for the out-of-sample returns using the corresponding Monte-Carlo distributions. Even though daily *FX* returns are not Normal, the Monte-Carlo based distribution of each filter’s annual returns is indistinguishable from Normal, in accordance with the Central Limit theorem.

¹² Levich and 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. Comparing a return to the mean of its distribution reveals how unusual the return is compared to its Monte Carlo distribution. However, market efficiency is about whether reliable profits can be had and not about how improbable returns are judged by their distributions. Therefore, we report how likely it is that each return is reliably higher than zero, so we compute the p-values relative to zero. P-values relative to the means of the Monte-Carlo distribution are available from the authors on request.

¹³ The bid-ask spreads only affect the magnitude of the returns and have no effect on the trading signals. The filters generate the buy/sell signals from the average of the bid and ask quotes of the *FX* rates.

factor” proposed by Lustig et al. (2008), measures of transactions costs, and time. The four risk factors are intended to capture exposure to time-invariant systematic risk, the measures of transactions costs are intended to capture the effect of lower transactions costs on trading returns, while the time variable is intended to test the predictions of the AMH, namely, that excess profits ought to decline fairly smoothly over time.¹⁴

Finally, we examine the stability of the simulation algorithms’ results used to compute out-of-sample returns.

IV. DATA

In this section we describe the data and the statistical properties of the FX rates.

IV.a Data Sources and Construction

The FX and interest rate data are from DataStream (DS). We use only currencies for which bid-ask spreads are available for the FX rates and the relevant interest rates, in order to account for transactions costs. DS provides foreign currency per US\$ bid and ask prices (4:00 pm London) as well as daily Eurocurrency deposit and loan rates for several currencies and for the US\$. The 14 currencies we use are the Australian \$ (AU\$), Canadian \$ (C\$), Danish Kroner (DK), Euro (€), French Franc (FF), German Deutsche Mark (DM), Italian Lira (Lira), Japanese Yen (¥), Dutch Guilder (GLD), New Zealand \$ (NZ\$), Norwegian Kroner (NK), Singapore \$ (SP\$), the Swedish Krona (SK), Swiss Franc (SF), and the U.K. pound (£), from Barclays of

¹⁴ Sweeney (1986) and Surajaras and Sweeney (1992) assume that there is a constant risk premium associated with FX exposure. Both Sweeney (1986) and Levich and Lee (1993) use the average UIRP returns as a measure of the constant risk premium for a long position in the currency. If there is a constant risk premium, it must be earned when the investor is either long or short in the currency. Since our trading systems require both long and short positions over time, the return to risk (RP) earned would be $RP \cdot p - RP \cdot (1-p)$, where p is the proportion of time the trader holds a long (or short) position. Since for our filters it turns out p is $\cong 0.50$, 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

London from January 1986.¹⁵ We concatenate the € data to the DM, rather than have two fairly short-lived currencies, and we use German interest rates for the whole period. We exclude the Hong Kong \$ from the investigation because its currency board arrangement allows for only tiny fluctuations in the FX rate, while any interest differences from the U.S. rates primarily reflect the risk of failure of its currency board; uniquely, among the currencies we study, a long position in the Hong Kong \$ is a bet on the durability of its currency board.

The Fama-French factors are from Prof. Kenneth French's website.

After culling the data for obvious errors and inconsistencies, we have 5,952 observations.¹⁶

IV.b. Statistical Properties of the Exchange Rates

Figures 1.A-C show the time series of each currency, normalized to 1.0 on the first date of its availability; tables 1.A-B contain summary statistics. The figures and the tables show that all the currencies but the Lira appreciate against the US\$ over our sample period. For each currency, there are periods of large appreciations and depreciations as well as large one-day returns. The annualized daily standard deviations are very similar, except for the C\$ and the SP\$, which have almost half the standard deviation of the others. Skewness is close to zero for many of the currencies except for the AU\$, Lira, ¥, and SP\$. Kurtosis varies widely (2.0 - 17.0),

returns; Levich and Lee (1993) describe the identical situation. More recent studies do not address this issue directly.

¹⁵ Data for the C\$, DK, DM, ¥, SF, and the £ are available for the entire period. Even though spot rates are available for the entire period for this list of currencies, interest rate data start only in 1/4/1988 for the SP\$, and 4/1/1997 for the AU\$, NZ\$, NK, and SK. The FF, Lira, and GLD data end with their absorption into the Euro. DS has bid-ask data for additional currencies that joined the Euro but since these data are for very short periods we did not include them in our main sample. The full period consists of 6,153 observations, while the 1986-1998 period has 3,392.

¹⁶ We checked for outliers and deleted obviously erroneous data as well as data that violated basic arbitrage propositions, such as ask > bid. We deleted a total of 201 data points; many of the faulty observations were just before Easter and other holidays. For the regression results, we merge the Fama-French data, the spot and forward data, and our trading returns. Because U.K. and U.S. holidays overlap only partially, we lose an additional 108 observations.

with an average of 6.0. The Jarque-Bera statistics in table 1.A show that normality can be rejected uniformly for all the currencies at very high levels of significance. These data support the general consensus that FX rate distributions are not sufficiently Normal to warrant using Normal distribution statistics for inference; therefore, we use Monte Carlo simulations to compute p-values of returns.

The autocorrelations of the currencies' growth rates (not shown) are quite small; in absolute value, the largest is 0.07 (average is 0.02). However, the p-values of the Box-Pierce tests reported in table 1.A reject "no autocorrelation" at least at the 5% level for the AU\$, C\$, DM, Lira, NK, NZ\$, SP\$, SK, and £; they do not reject it for the DK, FF, ¥, GLD, and the SF. These results suggest that, if these autocorrelations are stable, exploitable patterns may exist.

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 DK have high contemporaneous correlations with each other. The £ has lower correlations with the other European currencies, while the non-European currencies have quite low correlations. The correlations between the ¥ and the other currencies are modest, while those of AU\$, C\$, and NZ\$ are rather low (except for the AU\$ - NZ\$ correlation).

Table 2 displays information on bid-ask spreads. The currency spreads are rather small, even for the less-traded currencies. The average bid-ask spread is 7.4 bps, and the highest is 17 bps (the NZ\$); the standard deviation of the averages is 3.8 bps. By comparison, the average interest rate bid-ask spread is 16 bps, with a standard deviation of 10 bps; the highest average is 42 bps for Italy.

We report the averages for the first and last quarters of the sample to see the extent of declines in transactions costs over time in our sample. For all the currencies, the last-quarter

spreads are lower. The differences seem small; the average decline is 32% but the average difference is only 3.4 bps. The interest rate bid-ask spread falls substantially by the last quarter of the sample for some currencies (e.g., from 67 to 12 for Italy); however, the average decline is only 8 bps (25%) and in three instances (SP\$, SF, £) the spread rises.

For both FX and interest rates, the maximum bid-ask spreads are quite high. However, almost all of the high values occur during the European ERM crisis (Nov 1992 - April 1993); the highest interest rate spreads are 1,521 bps for both the DK during the ERM crisis and the SP\$ during the Asian crisis.

V. RESULTS

First we present the in-sample and out-of-sample results of our trading systems. Next we assess the risk, transactions costs, and AMH explanations. We conclude by documenting serious instabilities in simulated out-of-sample returns.

V.a. In-Sample Results

For the Alexander filter we compute returns and p-values for filters from 0.5% to 5%, in 0.1% increments, and for additional trading costs $c = 0$ and 25 bps. For the Double MA filter we compute returns and p-values for short MAs 1–5 and long MAs 2–50, both in steps of one day. Again we compute these returns with $c = 0$ and 25 bps.

Figure 2.A shows the returns for the DM over the whole sample for a series of Alexander filters, with and without bid-ask spreads, and the effect of $c = 25$ bps.¹⁷ We show only the behavior of the DM to conserve space; though each currency differs in its details and in the level of returns, the DM illustrates key common features among the currencies.

¹⁷ The no bid-ask spread returns are computed from the average daily FX and interest rates.

The effect of bid-ask spreads on returns is a combination of the difference between deposit and loan rates incurred continuously and the FX bid-ask spread, which is 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 trades on 4.6% of the days, on average, and the bid-ask spreads lower average returns by 147 bps. But the 2% filter trades on only 1.4% of the days, and the bid-ask spreads lower average returns by 55 bps. As the filter size increases, trading returns start out low, peak, and then decline; the occurrences of the peaks are not the same for all filters and currencies but the general features are the same.

Panels A and B of figure 2.B show the returns for selected Double MA filters for the DM. Panel A shows the effect on returns of varying the short MA from one to four days. It shows that the length of the short filter's MA has a small and non-systematic effect on returns; this is true for all the currencies. Panel B 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 here also the return differences narrow as the long-MA becomes larger. However, there is no strong indication that returns decline as the long MA becomes larger.

In the full sample there are several statistically significant positive returns for both systems (not reported but available from the authors). Of the 14 currencies, the best Alexander filter shows statistically significant positive returns (at the 5% level, with bid-ask spreads) for the AU\$, DK, FF, DM, Lira, ¥, GLD, and NZ\$.¹⁸ The best Double MA filter produces very similar results: the same currencies plus the SF and £ have significant positive returns.¹⁹ These results are similar to those reported in the literature. In tables 3 and 4, we report the first and second

¹⁸ SP\$, C\$, NK, SK, SF, and £ returns are not statistically significant. The average return of the best Alexander filter over all the currencies is 4.67%.

¹⁹ SP\$, C\$, NK, and SK, returns are not statistically significant. The average return of the best Double MA filter over all the currencies is 5.72%.

half returns for our trading systems to help assess the extent to which returns may have declined over time.

In Table 3 in the column labeled “Filter,” we report results for f of 0.5%, 1.0%, and 2.0%, and the best-performing filters over a 0.5% - 5.0% range. In the column labeled “MA(m,n)” in table 4 we report returns for short MA = 1, and for long MAs of 5, 20, and 40, as well as for the best-performing m, n combination from the full range of short and long MAs. In all cases we choose the reported filters so as to balance parsimony with the need to represent the overall results fairly. The column labeled “Trans” shows the percent of days trades take place in each case. The columns that follow from left to right under “Returns” show returns excluding the bid-ask spreads, with the bid-ask spreads and $c = 0$ bps, and with bid-ask spreads and $c = 25$ bps. In the tables, the rows show the returns for the selected filters and the best-performing filter, with p-values relative to zero immediately below the returns in italics.²⁰

Table 3 shows the results for selected Alexander filters. It is clear that there are many more significant positive returns in the first half than in the second half of the sample.²¹

With bid-ask spreads and $c = 0$, several returns from the best filters are significant at the 1% level in the first period, but only one is significant in the second. The FF, Lira, ¥, GLD and the SP\$ have returns significant at the 1% level in the first half of their sample but of those only the Lira and the SP\$ have significant returns in the second half of their sample, and then only at the 5% level. In the first half of their sample, the AU\$, C\$, DK, and the £ have returns significant at the 5% level, but, of those, only the DK has significant returns in the second period. The NZ\$, NK, SK, and SF never have significant returns. The exception to this pattern

²⁰ We report p-values only for positive returns. The best-performing filter is selected from the calculations with the bid-ask spread and $c = 0$.

is the DM which has significant returns (at the 1% level) only in the second period. The average decline in returns for the best filters between the two periods is 281 bps; the average second period return is 3.76%

The bid-ask spreads significantly reduce returns in all cases. Compared to no bid-ask spreads, the average return for the best filters declines by 37 bps in the first half and by 56 bps in the second half of the samples.²² The bid-ask spreads cause the significance of the calculated returns to decline in many instances and to fall below conventional significance levels in isolated cases. Adding the 25 bp transactions cost further reduces and in some cases eliminates significance.

Table 4 shows returns from selected Double MA filters. The results are somewhat stronger than for the Alexander filters. Only the C\$, the NK, and the SK have no significant returns even for their best Double MA filters, with bid-ask spreads and $c = 0$.

The FF, Lira, ¥, GLD, SP\$, SF, and £ returns are significant at the 1% level for the first part of the sample, but of these only the SP\$ retains significant returns in the second half of the sample at the 5% level. Similarly, the AU\$, DK, DM, and NZ\$ have significant returns, but only the DK and the DM retain such returns in the second half of their sample. The average decline in returns for the best filters between the two periods is 342 bps; the average second period return is 4.80%, higher than for the Alexander filter.

Once again, transactions costs play an important but not critical role. Compared to no bid-ask spreads, the average return for the best filters declines by 134 bps in the first half and by

²¹ The middle of the sample is obviously not the same for each currency. For the C\$, DK, DM, ¥, SP\$, SF, and the £, the break is on 12/31/1996. For the Euro currencies, the FF, Lira, and the GLD, the break point is on 12/31/1992, and for the AU\$, NK, NZ, and SP\$, it is on 12/31/2003.

²² Since the bid-ask spreads fall over time, the higher transactions costs are likely due to more trading. Indeed, the best Alexander filter averages 1.8% in the first subperiod and 1.6% in the second, implying more trading in the second period.

138 bps in the second half of the samples; these are more than double the declines shown by the Alexander filter. In most instances the bid-ask spreads again reduce the significance of the calculated returns, but for the NK, SK (in the first half of their samples) and for the ¥ and Lira (in the second half of their samples), the inclusion of the bid-ask spreads drives the results to insignificance.²³

The differences between the returns and their significance across the two sample halves point to potential instability in the trading systems' returns. Another sign of instability is that the best filter in the first half of the sample is not the best filter in the second half of the sample; the exceptions are the Alexander filters for the ¥ and the GLD.

Table 5 documents this instability. The performance of the best filters is much poorer in the period in which they were *not* chosen as best. For example, for the Double MA filter, the average decline in returns of the best filters between the first and second periods is 3.4%; by comparison the average decline of first period's best filter returns in the second period is 9.4%, while the second period best filters' returns are 1.9% lower in the first period. This instability suggests that the dependence structures in the data change over time.

V.b. Out-Of-Sample Results

If time dependencies in the currencies are stable over time, we would expect the in-sample and out-of-sample performances of a trading system to be similar. If time dependencies are predictable but time-varying, then the out-of-sample performance should beat the in-sample one, because the selection algorithm would adapt to the predictably changing time patterns by switching to more profitable filters over time, compared to in-sample, where the filters remain

²³ It is noteworthy that roughly 80% to 95% of the bid-ask annual transactions costs come from the FX bid-ask spread, even though typically the FX bid-ask is less than half of the interest rate bid-ask spread. This is because the interest rate bid-ask spread is annualized, and the per day cost is small over the year. On the other hand, the smaller

fixed. However, if time dependencies are unpredictable, consistent with efficient markets, then the out-of-sample performance will be significantly worse than the in-sample one.

We test this hypothesis directly for both trading systems. At the end of every year, our notional investor selects the most profitable filter of each system, based on performance from year = $y-2$ to y . She then implements these filters to earn returns from year = y to $y+1$. The filters are updated annually. In this way, the filters are selected based only on past performance, and the simulated returns are strictly out-of-sample.²⁴

It is possible that trading portfolios of currencies would enhance returns while reducing variances; unfortunately, we must leave the exploration of that possibility to future research, as it would involve analysis of a very large set of potential portfolio trading schemes.²⁵ However, we do investigate the out-of-sample returns of an equally weighted portfolio. We create two portfolios, one for each trading system. Each consists of the equally weighted out-of-sample returns for each currency for that system.

Panels A and B of table 6 report full-sample and roughly 4-year averages of out-of-sample returns for the two systems. Over the whole period, no return is statistically significant at the 1% level, and there are only 4 statistically significant returns in 30 entries, all at the 5% level.²⁶ The portfolio returns are quite low (1.9% for the Alexander filter and 1.1% for the Double MA) and 12 of the 30 are negative; the Double MA filter does somewhat better than the

FX bid-ask spread is paid in full each time there is a transaction. Using sample averages and 7% of the days trading, the FX bid-ask is responsible for 91% of the total costs.

²⁴ This is a narrower version of the genetic programming search for the best strategy in the sense that the range and nature of the strategies are defined and fixed over the whole experiment. The advantage of this method is that the allowed strategies are straightforward.

²⁵ Surajaras and Sweeney (1992) examine several portfolio schemes but they do not find significantly better results; the subsequent literature does not examine portfolio results.

²⁶ 14 currencies + the equally weighted portfolio, two filters each. At the 5% level one would expect one significant observation, but, since the standard deviation is approximately 2.4, having four significant observations is within reasonable bounds of randomness. Of course, this rough indication doesn't take into account the correlations across currencies.

Alexander filter. All the returns are substantially lower than the corresponding returns obtained by the in-sample best-performing filters, except for the SK for the Alexander and DK for the Double MA filters. The average decline of the out-of-sample returns compared to the best in-sample ones is 520 bps for the Alexander and 604 bps for the Double MA filters. The 4-year returns are positive just 56% of the time for Double MA and 53% of the time for the Alexander filter.

Table 6 also shows how the out-of-sample success of the trading systems varies greatly over the 4-year subperiods.²⁷ This division is of course arbitrary, and we use it only to illustrate the nature of trading returns; yet, in the fast-moving world of finance, it seems to be a time frame more than adequate for market participants to establish views about currencies and take action.

For both trading systems there are several significant positive returns for the 1988-91 and the 1996-98 periods. For the rest of the subperiods, there are no significant returns, except for the DK in 2005-09. The subperiod returns are characterized not only by numerous negative returns but also by some fairly high, though not statistically significant, positive returns. Another way to see the scope of the variation is to note that while for 1989-91 the returns were positive for 9 of the 10 currencies (90%) for both filters, for 1999-01 returns were positive for only 3 of 11 currencies (27%) for the Double MA and 4 of 11 currencies (36%) for the Alexander filters.

The data in table 6 suggest a decline in the out-of-sample returns, as reported in the literature (see Olson 2004, NWU 2009, and others). However, excluding the 1988-91 period, such a decline is not obvious. Figure 3 illustrates both the large variation in trading returns and

²⁷ The “4-year” subperiods are not exactly of the same length. The precise dates are: 1/1/88–12/31/91 with 1,092 days, 1/1/92–12/31/95 with 1,455 days, 1/1/96–12/31/98 with 1,192 days, 1/1/99–12/31/01 with 1,092 days, 1/1/02–6/30/05 with 1,094 days, and 7/1/05–7/31/00 with 907 days. We made the subperiods somewhat unequal in

their uncertain decline by plotting the average return (across currencies) by year. The figure shows that, other than the first two or three years of the sample, when average returns seem quite high, there is no obvious pattern of rising or declining returns. These results do not support the claim in the existing literature that trading returns decline reliably over time.²⁸

Table 7 shows the Sharpe ratios for the in-sample and out-of-sample returns for the two systems. The Sharpe ratios are less than impressive for any of the returns, including the in-sample ones (see also NWU 2009).²⁹ It is clear that the Sharpe ratios shrink considerably for the out-of-sample strategies; the average Sharpe ratio goes from 0.30 to 0.10 for the Alexander filter and from 0.42 to 0.22 for the Double MA filter.

Finally, we saw in table 1.B that some currency growth rates are highly correlated, particularly among the currencies that eventually entered the Euro; the DK, DM, FF, and the GLD exhibit cross-correlations of 90% or higher with each other. This raises the possibility that our “effective” sample is smaller than the 14 currencies we have. We investigate this issue by computing cross-correlations for the trading returns for these currencies. Our findings are reassuring: the cross-correlations of the trading returns are considerably lower than those of the currencies’ growth rates. For example, the five highest growth rate correlations are DK-DM (0.95), DM-GLD (0.95), DK-GLD (0.94), DM-FF (0.92), and DK-FF (0.91); the corresponding trading return correlations for the double-MA filter are 0.62, 0.78, 0.68, 0.61, and 0.64, and almost all the corresponding cross-correlations for the Alexander filter returns are even smaller.

order to accommodate in a reasonable way the partial year data for 2009, and the entry and departure of several currencies during the sample. We did not experiment with alternative break points.

²⁸ Our data start later than Olson’s (1971-2000) and NWU’s (1973-2000) because the available bid-ask data start in 1986; of course our data end later. Thus, potentially we miss any large declines in returns that may have happened before our sample starts. However, Sweeney (1986) reports no declines in returns, and Levich and Lee (1993), whose data overlap ours, find only hints of a decline in returns through time. So it appears that declines in returns happened mostly within our sample period.

This implies that the trading returns depend to a substantial degree on the idiosyncratic components of each currency's movements, even as the currencies comove.

We proceed to investigate the potential economic determinants and assess the implications.

V.c. Economic Evaluation and Possible Explanations

One explanation for trading returns proposed by Lustig et al. (2008) suggests that the observed carry trade returns are risk-related. They propose and test a FX risk factor they label HML_{FX} ; it is constructed much like the HML Fama-French factor. They find strong empirical support for it.

We follow Lustig et al. (2008) and construct an analogue to their currency risk factor; we label it $UIRPF$. As in their study, we collect spot and forward data (without bid-ask spreads) for 21 additional currencies, yielding a total of 35 currencies.³⁰ For each of these currencies, we compute daily forward premia and *uncovered* returns whenever data are available. Then we sort the currencies into five portfolios from high to low forward premia (a high premium means a high foreign interest rate); the portfolios are updated quarterly. Thus this quarter's first portfolio ($UIRP1$) contains the average uncovered returns for the currencies with the largest forward premia at the end of the previous quarter, while $UIRP5$ contains the average uncovered returns for the currencies with the smallest forward premium at the end of the previous quarter. The currency risk factor, then, is $UIRPF = UIRP1 - UIRP5$.³¹

²⁹ Over the same period the Sharpe ratio for excess market return is 0.41; of course the risks are dissimilar, so an attractive strategy need not have a Sharpe ratio in excess of the market's.

³⁰ The additional currencies are for Austria, Belgium, Czech Republic, Finland, Greece, Hungary, India, Indonesia, Ireland, Kuwait, Malaysia, Mexico, Philippines, Poland, Portugal, Saudi Arabia, South Africa, South Korea, Spain, Taiwan, and Thailand.

³¹ We create 5 rather than 6 factors (as in Lustig et al.) in order to guarantee that almost all the portfolios contain at least 2 currencies; the only portfolios that contain only 1 currency are the middle portfolios until 1988:02. The

An alternative explanation is that lower transactions costs make it more attractive for less efficient traders to trade, which depresses returns. Finally, the AMH only requires that profits dissipate over time. We saw that Olson (2004), NWU (2009), and others before them report evidence of systematic decline of returns over time, and that NWU (2009) interpret their findings as supportive of the AMH.

We perform a simultaneous test of these alternative hypotheses by estimating the following regressions for each currency i , using daily data:

(2)

$$SPR_{i,t} = \beta_{i,0} + \beta_{i,uirpf} UIRPF_t + \beta_{i,mkt} RMKT_t + \beta_{i,hml} HML_t + \beta_{i,smb} SMB_t + \beta_{i,fpem} ABSFPR_{i,t} + \beta_{i,fxba} FXBA_{i,t} + \beta_{i,inba} INBA_{i,t} + \beta_{US,iba} USINBA_{i,t} + \beta_{i,time} TIME_t + \beta_W WEEKDAYS_t + \varepsilon_t'$$

where,

<i>SPR</i>	Trading returns for each currency, in-sample and out-of-sample,
<i>UIRPF</i>	The currency risk factor described in the data section, (Lustig et al.'s <i>HLM_{FX}</i>),
<i>RMKT</i>	U.S. market excess returns (Fama-French 3-factor model),
<i>HML</i>	High - Low book-to-market returns (Fama-French 3-factor model),
<i>SBM</i>	Small - Large firm returns (Fama-French 3-factor model),
<i>ABSFPR</i>	The absolute value of the forward premium for each currency,
<i>FXBA</i>	The currency bid-ask spread for each currency, as a % of the currency's value,
<i>INBA</i>	The interest rate bid-ask spread for each currency,
<i>USINBA</i>	The interest rate bid-ask spread for the U.S.,
<i>TIME</i>	Linear or log-linear time trend,
<i>WEEKDAY</i>	Dummies for Monday, Tuesday, Thursday and Friday.
<i>S</i>	

A significant currency risk factor (*UIRPF*) supports the proposition that trading profits are at least in part related to this foreign currency risk. Similarly, significant Fama-French

sample averages are very similar to those reported by Lustig et.al.; the average return is 4.55% for the high-interest-rate portfolio and that 0.02% for the low-interest-rate portfolio.

factors (*RMKT*, *HML*, *SBM*) indicate that the trading strategy returns are exposed to related economy-wide risks.³²

ABSFRP is the absolute value of the currency's forward premium. Small interest rate differentials generally mean very similar inflation rates and monetary policies; we hypothesize that such economic circumstances may adversely affect trading returns.

The bid-ask spread variables, (*FXBA*, *INBA*, and *USINBA*) are intended to capture the possible relation between excess returns and transactions costs; we would expect to find positive and significant coefficients for these variables if transactions costs play an important role in trading returns. These are directly measurable costs but, to the extent that they are correlated with other costs and market restrictions, they may also proxy for broader costs.

Finally *TIME* or *LOGTIME* is intended to capture any secular decline (or increase) in trading returns, consistent with the AMH described above; negative significant coefficients would provide support for the AMH. Days-of-the-week are included to control weekly seasonality often present in daily returns.

Table 8 displays the t-statistics of coefficient estimates from the regression model for each currency. Panel A shows results for the best in-sample and out-of-sample returns for the Alexander filter, and Panel B shows the analogous returns for the Double MA filter.

The results for both systems are similar, except that the Double MA results seems slightly stronger, judged by the slightly larger number of significant coefficients. *UIRPF* seems to be the only variable that has systematically significant explanatory power in these regressions.

It does better for the Double MA than the Alexander filter, and it does a little better for the in-

³² Neither the Fama-French nor the *UIRPF* factors address the possibility of time-varying risk. Assessing the possible existence of time-varying risk is well beyond the scope of this paper. However, Okunev and White (2001) find no GARCH effects in their currencies that could account for a time-varying risk premium. On the other hand, Lustig et al. (2008) supply evidence of time-varying risk premia in the FX market.

sample than the out-of-sample returns. In contrast, the three Fama-French factors are only occasionally significant: Out of 60 instances, *RMKT* is significant in seven, *SMB* in four and *HML* in two.

All the coefficients (not reported) for *UIRPF* and *RMKT* are negative.³³ This suggests that these speculative positions provide some hedging against FX and market risks. However, this effect is small because of the very small coefficients. The average coefficient for *UIRPF* for the out-of-sample returns is -0.083 (max is -0.274), and for *RMKT* it is -0.016 (max is -0.051). The contribution to expected return is minimal; based on the average returns of these factors it would be roughly -38 bps from *UIRPF* and -10 bps from *RMKT*.³⁴ This means that traders ought to be willing to accept slightly negative returns because of the hedging properties of these portfolios. This, of course, goes the wrong way in explaining possible excess profits.

A significant and positive Jensen's alpha is evidence of excess returns unaccounted for by the risk model. NWU (2009) find occasionally significant Jensen's alphas in their sample, while Lustig et al. (2008) do not. Table 8 also shows estimates of alphas; these estimates are obtained from a regression that includes *only* the risk factors (i.e., it is *not* the constant of the reported regression). For our sample, Jensen's alphas are generally significant for the in-sample returns, more strongly so for the Double MA filter. However, for the out-of-sample returns Jensen's alphas are significant only for the DK and SP\$ for the Double MA filter, and then only at the 5% level; they are never significant for the Alexander filter. These results suggest that there are no excess returns to be explained in the out-of-sample returns of these trading systems.

³³ The same regressions estimated for carry trade returns all have positive coefficients, consistent with Lustig et al. (2008); the average coefficient there is 0.31.

³⁴ It is hard to predict ex-ante the sign of the factor loadings for *UIRPF*, on trading returns, because the trading systems short currency as often as they go long in it.

Table 9 displays the t-statistics of the remaining coefficient estimates from the model shown in equation (1). Again, panel A shows results for the best in-sample and out-of-sample returns for the Alexander filter, while panel B shows the analogous results for the Double MA filter.³⁵

The hypothesis that declining transactions costs explain the decline in returns is not systematically supported by the data; there are three instances of a significant coefficient for *FXBA*, none for *INBA*, and three for *USINBA* (of which one has the wrong, i.e., negative sign). Most significant coefficients are for the in-sample results.

We also do not find support for the AMH in our results. To the extent that it can be proxied by *LOGTIME* there is no evidence of a systematic significant decline in returns over time. There are just three instances of a significant coefficient at 5% significance, one of which has the wrong (positive) sign; for the most part the coefficients are negative.³⁶ In a broader context, there is no evidence to suggest that trading profits have dissipated slowly over time, even for the well-known systems we study. Of course, since the AMH is not sufficiently well-articulated to generate precise empirical predictions, testing it cannot be conclusive.

It is possible that the transactions costs variables as well as *LOGTIME* would not do well in high-frequency regressions because they are necessarily slow-moving variables. We reestimate the same regressions with the data averaged over quarters, and find insignificant differences in the results, except for higher R^2 s (not reported but available from the authors); neither the transactions costs nor the AMH hypotheses receive any support.

³⁵ There is no evidence of systematic day-of-the-week seasonality; the associated dummies are rarely significant (results are available from the authors).

³⁶ We report the *LOGTIME* results because that variable fares a little better in the regressions compared to *TIME*. A priori one would surmise that *LOGTIME* would be a better fit than *TIME*, to the extent that the incentives to search out and take advantage of profit opportunities decline with a decline in those opportunities. However, this choice has no effect on any of our conclusions.

V.d. An Additional Source of Instability

The “instability” of the returns we and many others document is not confined to large variations in trading returns over time. Another type of instability arises in the simulated out-of-sample returns that is not reported in the literature, to our knowledge. Its existence further suggests that chasing foreign currency trading profits may be, as a recent *Economist* article suggests, “...like picking up nickels in front of steamrollers....”³⁷ The type of instability we document below raises serious doubts about whether meaningful inferences can be drawn from *any* out-of-sample procedure, using current methods.

Recall that our out-of-sample results are obtained by choosing the best performing filter of each trading system over the past two years and applying it to the following year’s data; the filter is updated every year. That means that there are two parameters in these simulations, the “starting date” and the “training window”. In the results we have reported, the starting date is the first day for which we have data for the currency, and the training window is 24 months.

We perform two experiments to gauge the stability of the out-of-sample returns by varying both the “starting date” and the “training window.” First we vary the starting date by two weeks at a time for the first year of the currency’s entrance into our sample and recompute the average 23-year out-of-sample returns.³⁸ If the process is stable, such a small change in the starting date ought to have a negligible effect on the average return over the following 23 years. But it turns out that the differences in returns are substantial; the standard deviation of returns thus obtained, averaged across all currencies is 1.5%, very large for such a small change.³⁹ For the DK, DM, Lira, NK, and SP\$ there is at least one return that is positive and significant at the

³⁷ “Carry on Speculating,” *The Economist*, 2/22/2007. The article discusses carry trade profits.

³⁸ In other words the largest difference in the number of observations used in the means is around 255 days.

5% level. An example will make this variation concrete: In the Double MA system for the DK, if we start the training period on 1/2/86, the average annual return over the next 23 years is 5.2% and significant at the 5% level. But if we start the process just four months later, on 3/27/86, the average annual return is 0.4% and statistically insignificant! This is not an isolated case. Figure 4 Panels A and B illustrate this point; they show the out-of-sample average returns for the whole period for the C\$, DK, DM, ¥, and the £. These results are for currencies with data for the full sample but they are representative of the other currencies.

We also experiment by varying the “training period” from 400 days (a little less than two years) to 1,000 days (close to four years) in 200 day increments. The best filter is still applied to the following year and a new best filter is chosen each year. The instability in out-of-sample returns is very large in this case as well. In this experiment, the average standard deviation of mean returns across all currencies is 1.6%. For the DK, FF, Lira, and SP\$, there is again at least one out-of-sample average return that is positive and statistically significant at the 5% level or better. Again, we illustrate with a concrete example: In the Double MA system for the FF, if we use a 400-day training period, the average return over the subsequent 23 years is 6.3% and significant at 5%. But if we use an 800-day training period, the average return is 0.7% and not significant; in both examples, trading in the currencies starts on 12/14/89.

We document a great deal of instability in simulated out-of-sample returns. This raises serious doubts about the reliability of any out-of-sample procedure and warrants considerable caution about any conclusions that may be drawn from such exercises.⁴⁰

³⁹ As a benchmark, we computed the average UIRP returns in the same manner; the standard deviation of the mean returns averaged across currencies is only 0.3%.

⁴⁰ This process is “chaotic,” in the sense that small changes in initial conditions produce possibly large changes in outcomes. Investigating these out-of-sample processes along these lines is beyond the scope of this paper.

VI. CONCLUSION

We examine the profitability of “Alexander” and “Double MA” technical trading systems for 14 developed-country currencies, from 1986 to 2009, to assess whether technical trading still makes excess returns in the FX markets. A positive return to a zero-net-investment portfolio governed by such a trading system is either a return to risk-bearing or an “excess” return or profit, once transactions costs have been taken into account. Our bid-ask spread data for FX and interest rates allow us to take into account explicitly an important component of transactions costs, which previously were only estimated or imputed.

Our main result is that we find no reliable out-of-sample trading profits. We also show that results from the standard methodology used to simulate out-of-sample trading are very sensitive to the algorithms’ starting conditions. Thus, researchers or practitioners may examine the same data and the same trading systems and still reach different conclusions about the profitability of a system because of small differences in the parameters of their simulations.

Consistent with the literature, we find substantial and statistically significant in-sample returns over the whole sample, mainly in the first subperiod, for both trading systems. Significant positive returns are much harder to come by in the second subperiod, which is also consistent with the literature. The bid-ask spreads reduce both the magnitude and statistical significance of profits but eliminate neither, except in isolated instances.

When we simulate our trading systems out-of-sample we find that overall trading returns are low, rarely significant at the 5% level, and never at the 1% level. We show that there appear to be substantial and significant out-of-sample returns for the 1988-91 period but only isolated significant returns thereafter; many of the returns are negative.

Using daily returns, we report tests of various explanations for trading returns: payment for risk, falling transactions costs, and the AMH. We find that the FX risk factor, introduced by Lustig et al. (2008), is highly significant but negative for most of the in- and out-of-sample trading returns. The Fama-French risk factors are generally insignificant, with except for the market factor in some instances; its coefficients are negative as well. The Jensen's alphas are generally highly significant for the in-sample returns but almost uniformly insignificant for the out-of-sample returns. Expected returns for these hedging portfolios would be slightly negative, and they provide a small degree of hedging against FX and market risks.

Our measures of transactions costs and a time variable are also not significant. Thus, neither the proposition that declining transactions costs result in lower trading profits nor the AMH finds support in our results, in contrast to Neely et al. (2009).

We show that small variations in the parameters of the out-of-sample simulations produce substantial differences in the returns obtained and in the inferences of significance. This has not been reported in the literature. It implies that traders operating the same trading system but with slightly different "training parameters" for their algorithms are likely to realize very different speculative returns.

This finding casts further doubt on the existence of reliable profit opportunities from trading systems or any single simulated out-of-sample documentation of such profits. We must leave to future research how to incorporate this additional source of instability in drawing proper inferences.

REFERENCES

- Allen, Franklin, and Risto Karjalainen (1999) "Using Genetic Algorithms to Find Technical Trading Rules," *Journal of Financial Economics*, Vol. 51, pp: 245-271.
- Bradley Efron, and Robert Tibshirani (1986) "Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy," *Statistical Science*, vol. 1, no. 1, pp. 54-77.
- Brock, William, Josef Lakonishok, and Blake LeBaron (1992) "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance*, Vol. 47, No. 5, pp: 1731-1764.
- Burnside, Craig, Martin Eichenbaum, Isaac Kleshchelski, and Sergio Rebelo (2008) "Do Peso Problems Explain the Returns to the Carry Trade?" NBER Working Paper #14054.
- De Zwart, Gerben, Thijs Markwart, Laurence Swinkels and Dick van Dijk (2009) "The Economic Value of Fundamentals and Technical Information in Emerging Currency Markets," *Journal of International Money and Finance*, in press.
- DiCiccio, Thomas, and Robert Tibshirani (1987) "Bootstrap Confidence Intervals and Bootstrap Approximations", *Journal of the American Statistical Association*, Vol. 82, No. 397. (Mar.), pp. 163-170.
- Dooley, Michael, and Jeffrey Shafer (1983) "Analysis of Short-Run Exchange Rates Behavior: March 1973-November 1981," in D. Bigman and T. Taya, eds. *Exchange Rate and Trade Instability*, Cambridge Massachusetts: Ballinger Publishing. Based on their International Finance Discussion, Federal Reserve Board paper #76, released in 1976.
- Engel, Charles, and James Hamilton (1990) "Long Swings in the Dollar: Are They in the Data and Do the Markets Know It?" *American Economic Review*, vol. 80, no. 4, pp. 689-713.
- Evans, Martin, and Karen Kewis (1995) "Do Long-Term Swings in the Dollar Affect Estimates of the Risk Premia," *The Review of Financial Studies*, Vol. 8, No. 3, pp. 709-742.
- Hansen, Lars, and Robert Hodrick (1980) "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis," *The Journal of Political Economy*, Vol. 88, No. 5, pp. 829-853.

- Kho, Bong-Chan (1996) "Time-Varying Risk Premia, Volatility, and Technical Trading Rules Profits: Evidence from Foreign Currency Futures Markets," *Journal of Financial Economics*, Vol. 41, No. 2, pp. 249-190.
- LeBaron, Blake (1999) "Technical Trading Rule Profitability and Foreign Exchange Rate Intervention," *Journal of International Economics*, Vol. 49, Vol. 1, pp. 125-143.
- Levich, Richard, and Thomas Lee (1993) "The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: a Bootstrap Approach," *Journal of International Money and Finance*, Vol. 12, pp. 451-474.
- Lo, Andrew "The Adaptive Market Hypothesis: Market Efficiency from an Evolutionary Perspective," *Journal of Portfolio Management*, 30th Anniversary Issue (2004), pp. 15-29.
- Lukac, Louis P., B. Wade Brorsen, and Scott H. Irwin (1988) "A Test of Futures Market Disequilibrium Using Twelve Different Trading Systems," *Applied Economics*, Vol. 20, pp: 623-639.
- _____ (2001) *International Financial Markets; Prices and Policies* second edition, McGraw-Hill, Irwin, N.Y.
- Lustig, Hanno, Nick Roussanov, and Adrien Verdelhan (2008) "Common Risk Factors in Currency Markets" UCLA Working Paper.
- Neely, Christopher (2002) "The Temporal Pattern of Trading Rule Returns and Exchange Rate Intervention: Intervention Does Not Generate Technical Trading Rule Profits," *Journal of International Economics*, Vol. 58, No. 2, pp. 211-232.
- Neely, Christopher, and Paul Weller (2001) "Technical Analysis and Central Bank Intervention," *Journal of International Money and Finance*, vol. 20, No. 4, pp. 949-970.
- Neely, Christopher, and Paul Weller (2003) "Intra Day Technical Trading in the Foreign Exchange Market," *Journal of International Money and Finance*, vol. 22, No. 2, pp. 223-237.
- Neely, Christopher, Paul Weller, and Robert Dittmar (1997) "Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach," *Journal of Financial and Quantitative Analysis*, vol. 32, No. 2, pp. 405-426.

- Neely, Christopher, Paul Weller and Joshua M. Ulrich (2009) "The Adaptive Markets Hypothesis: Evidence From the Foreign Exchange Market," *Journal of Financial and Quantitative Analysis*, in press.
- Okunev, John, and Derek White (2001) "Do Momentum-Based Strategies Still Work in Foreign Currency Markets?" Working Paper University of New South Wales.
- Olson, Dennis (2004) "Have Trading Rule Profits in the Currency Markets Declined Over Time?" *Journal of Banking and Finance*, Vol. 28, pp: 85-105.
- Park, Cheol-Ho, and Scott H. Irwin (2007) "What Do We Know about the Profitability of Technical Analysis?" *Journal of Economic Surveys*, Vol. 21, Issue 4, pp: 786-826.
- Patel, Charles (1980) Technical Trading Systems for Commodities and Stocks, Trading Systems Research.
- Pukthuanthong-Le, Kuntara, and Lee R. Thomas III (2008) "Weak-Form Efficiency in Currency Markets," *Financial Analysts Journal* 64, 3, pp. 31- 52.
- Schulmeister, Stephan (1988) "Currency Speculation and Dollar Fluctuations," *Quarterly Review Banca Nazionale de Lavoro*, vol. 176, pp. 343-365.
- Surajaras, Patchara, and Richard Sweeney (1992) Profit-Making Speculation in Foreign Exchange Markets, Westview Press, Boulder.
- Sweeney, Richard J. (1986) "Beating the Foreign Exchange Market," *The Journal of Finance*, vol. 41, No. 1 (March), pp. 163-182.
- Taylor, Mark, and Helen Allen (1992) "The Use of Technical Analysis in the Foreign Exchange Market," *Journal of International Money and Finance*, Vol. 11, pp. 304-314.

Figure 1.A
History of the Exchange Rates
 Non-EMU Currencies: 1986 - 2009

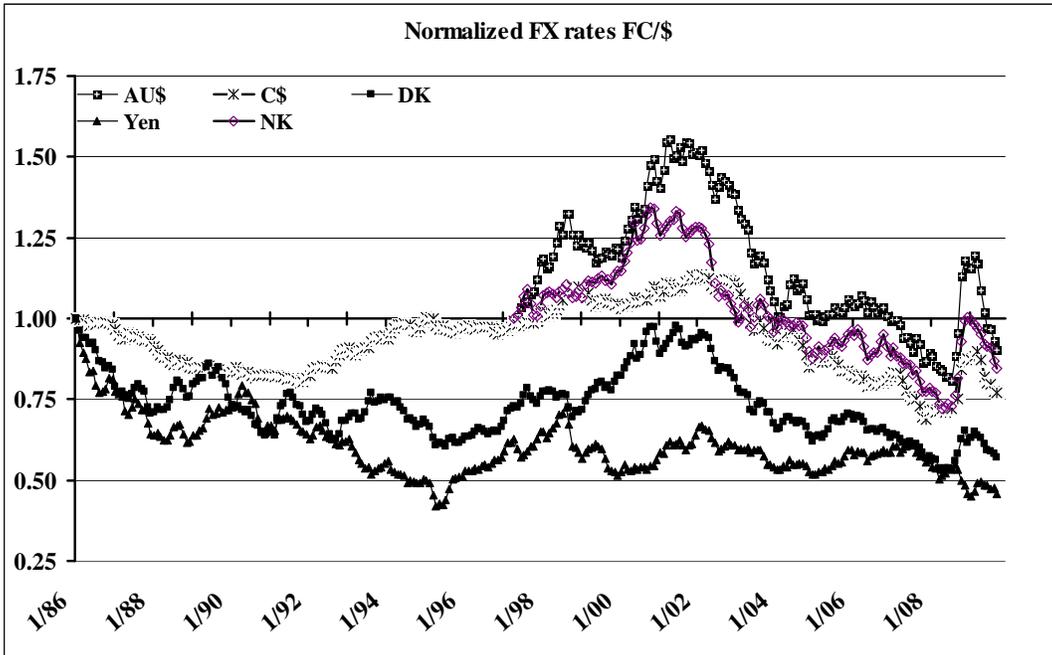


Figure 1.B
History of the Exchange Rates
 Non-EMU Currencies: 1986 - 2009

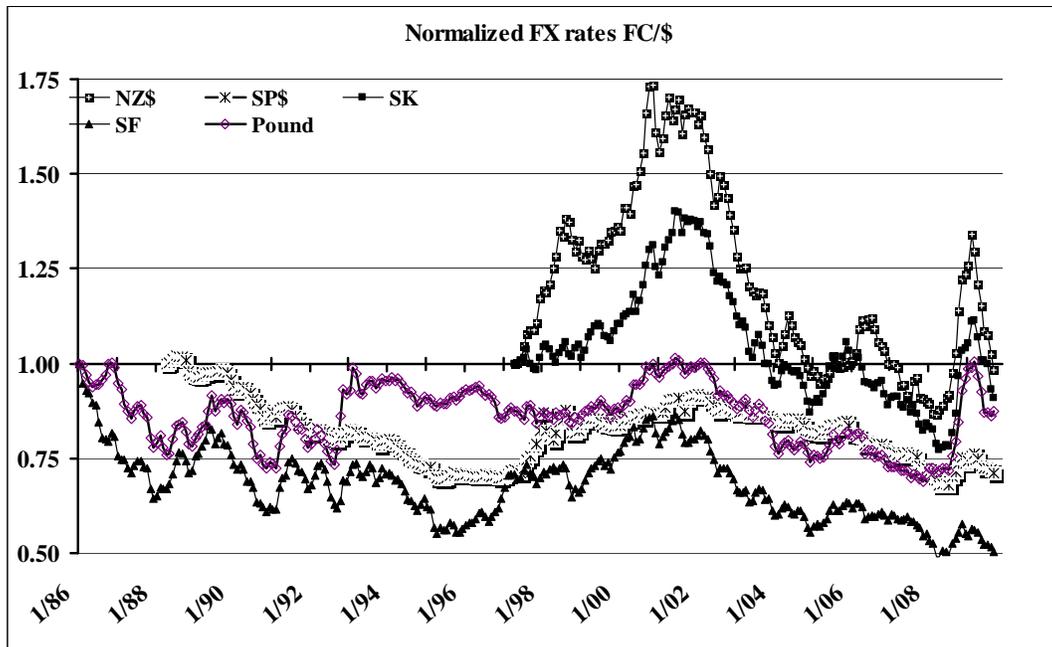


Figure 1.C

History of the Exchange Rates
EMU Currencies: 1986 - 2009

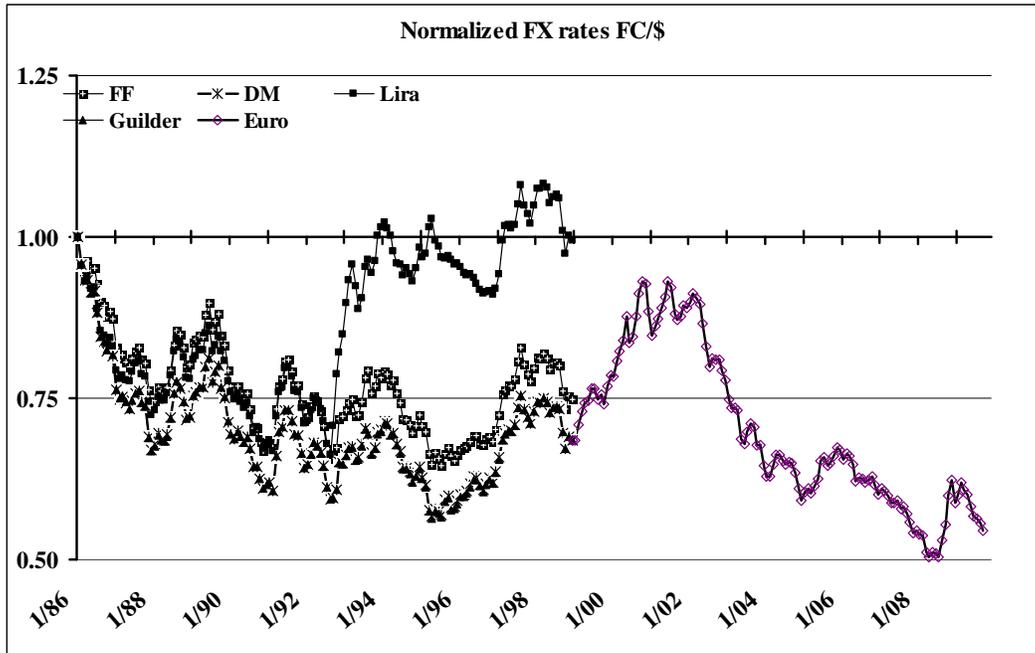


Figure 2.A

**Typical Behavior of $f\%$ Modified Alexander Filters.
The German DM: 1986 – 2009**

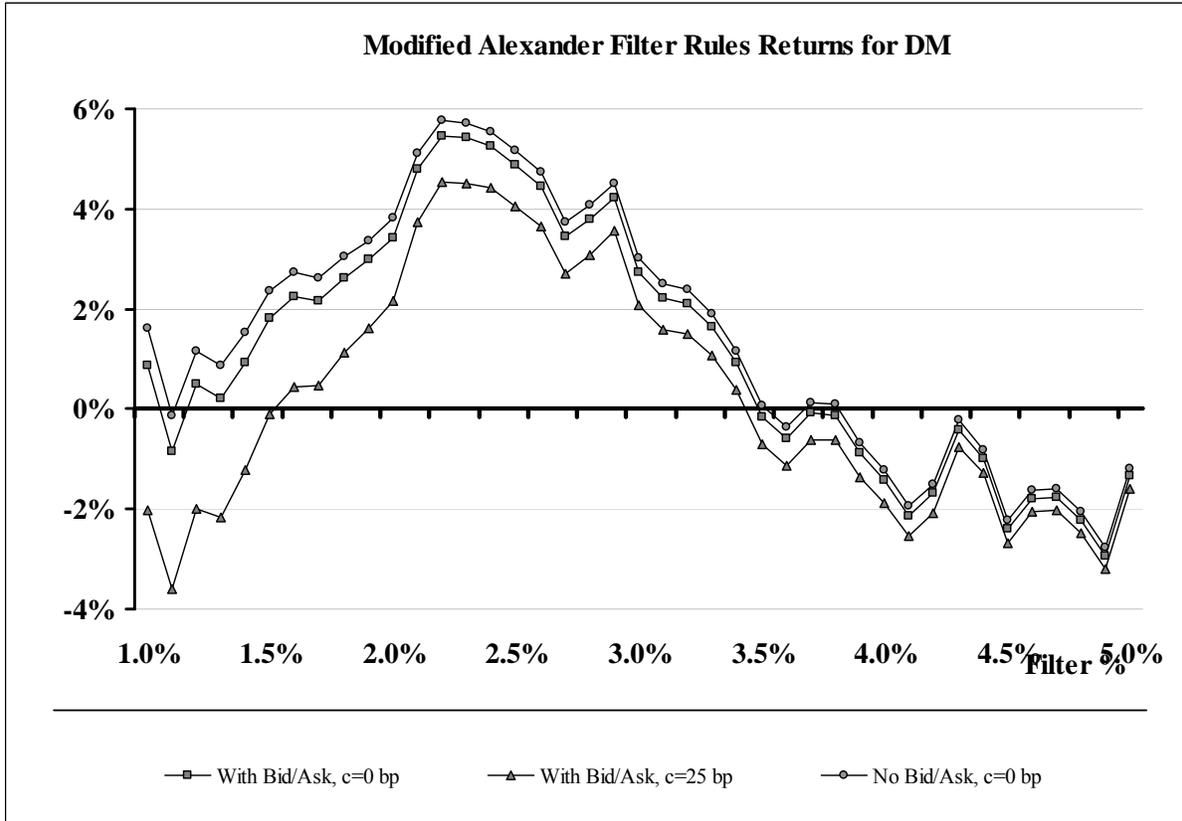
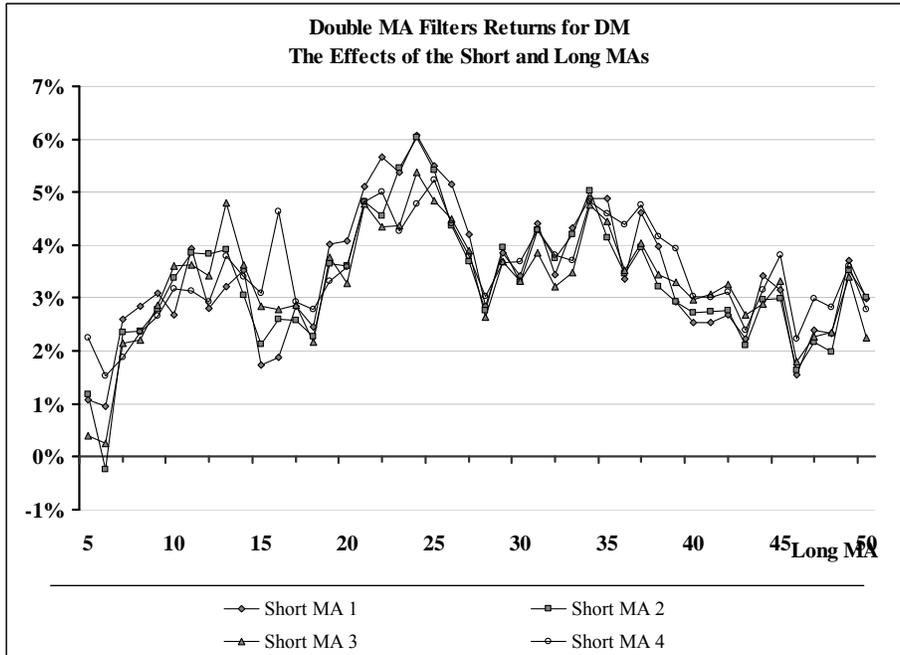


Figure 2.B

**Double MA Returns
The German DM: 1986 – 2009**

Panel A



Panel B

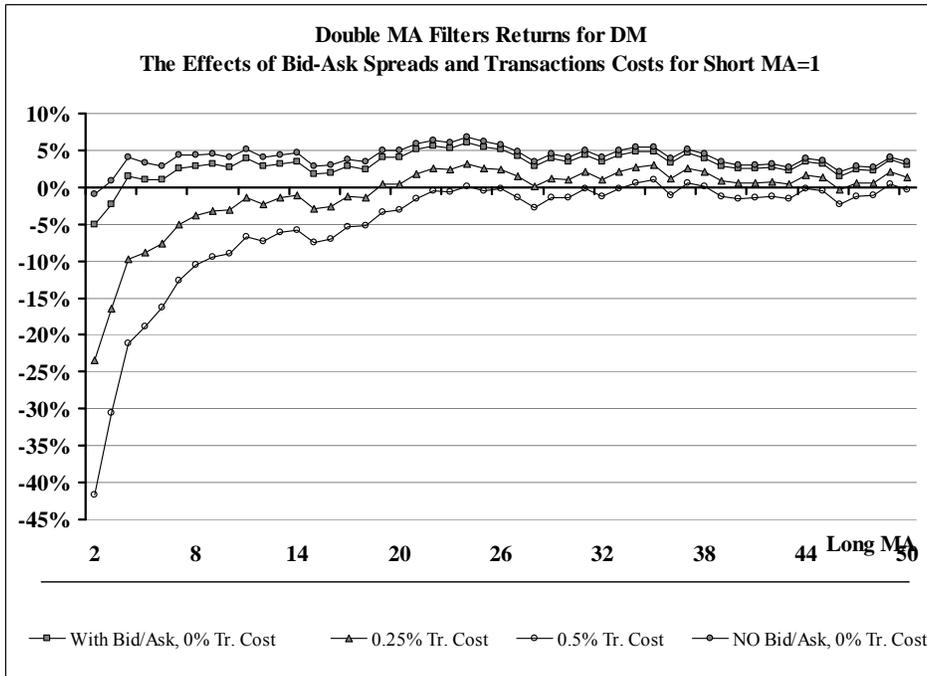


Figure 3
Time Trends of Out-of-Sample Returns;
Annual Averages Across Currencies
1988 – 2009

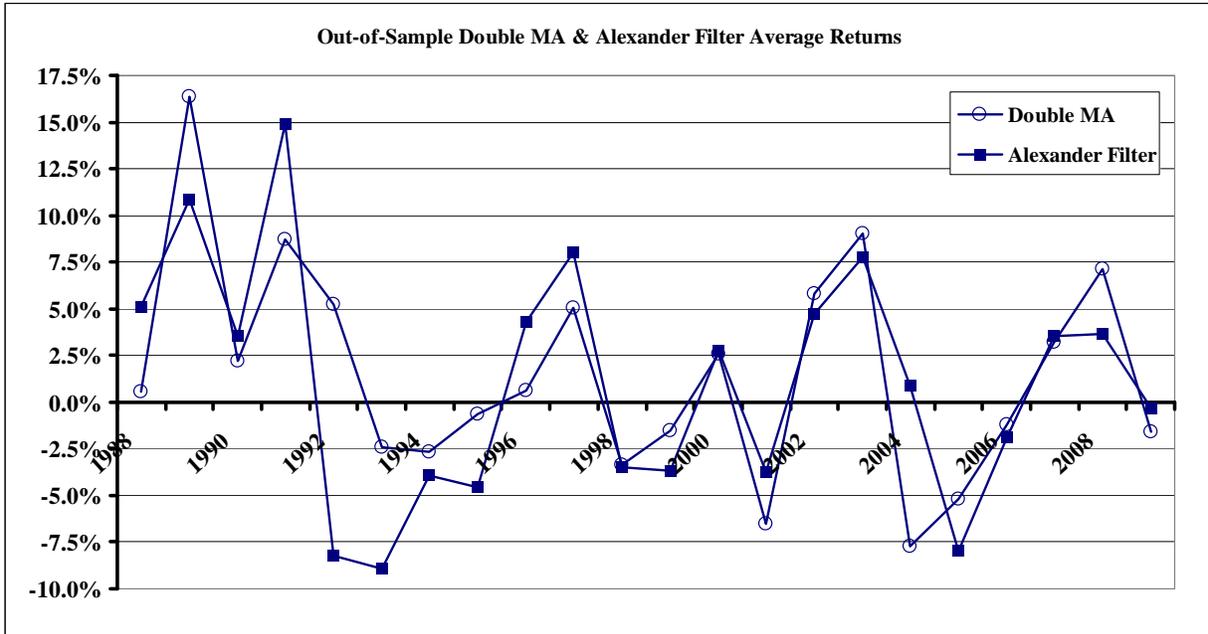
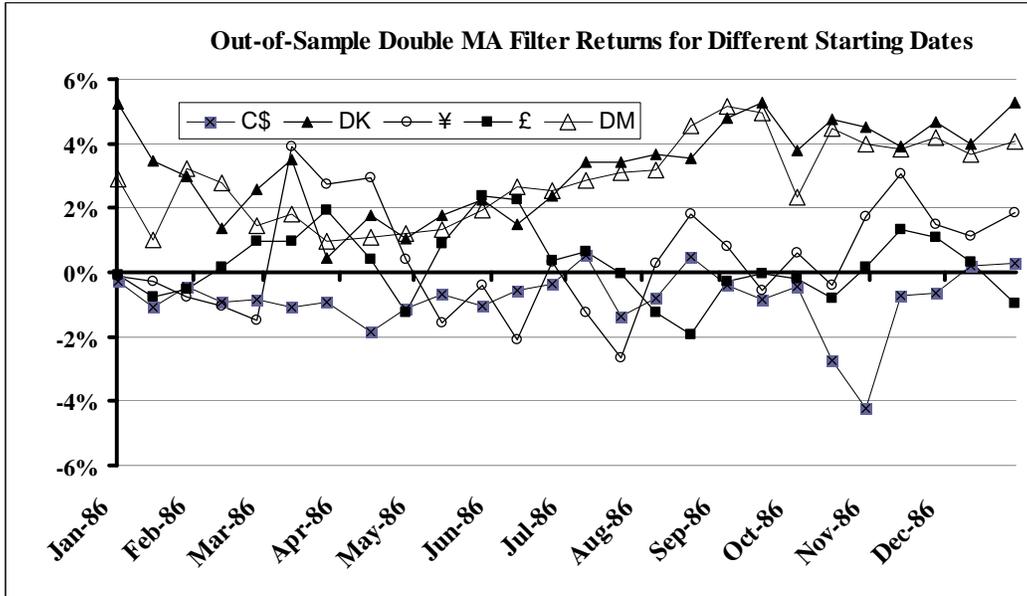


Figure 4
Out-of-Sample Average Returns As Starting Date Changes
 January 1986 – December 1986

Panel A
Double MA Filter



Panel B
Alexander Filter

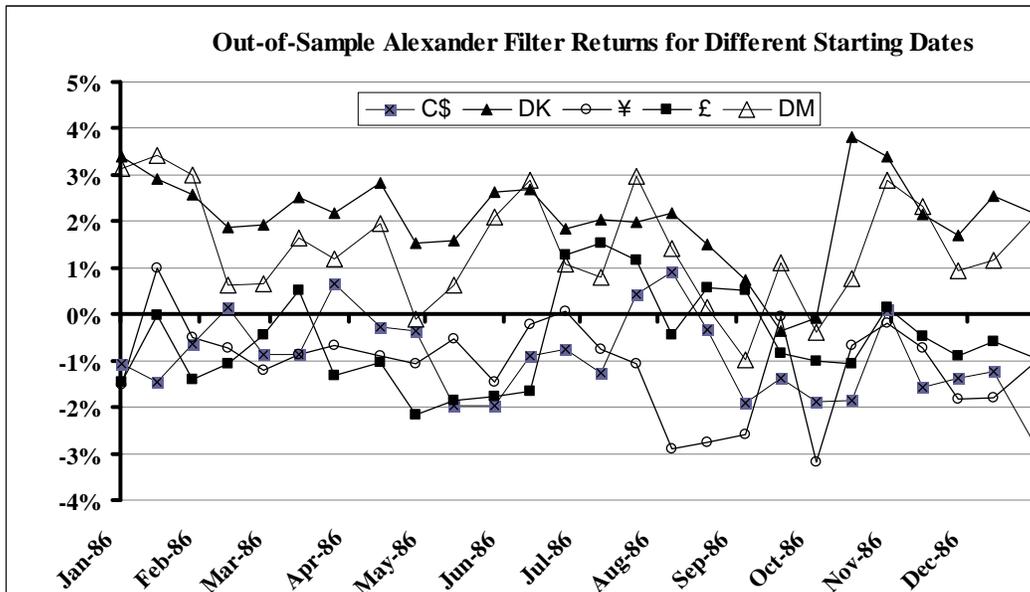


TABLE 1.A
Summary Statistical Properties

	AU\$	C\$	DK	FF	DM	Lira	¥	GLD	NK	NZ\$	SP\$	SK	SF	£
Summary Statistics:														
Return (annualized)	-1.25%	-1.64%	-3.33%	-3.24%	-3.60%	-0.01%	-4.65%	-4.25%	-1.30%	-1.72%	-2.40%	-0.03%	-4.09%	-0.89%
Stdev (Annualized)	267%	163%	242%	245%	246%	244%	259%	248%	258%	279%	121%	256%	269%	227%
Max % Change/Day	8.36%	3.23%	2.98%	3.69%	3.04%	6.57%	3.39%	3.09%	6.90%	5.89%	2.70%	6.01%	3.41%	4.80%
Min % Change/Day	-6.23%	-5.72%	-4.24%	-4.05%	-4.24%	-3.09%	-5.49%	-3.10%	-6.54%	-6.33%	-4.06%	-6.17%	-5.29%	-4.85%
Skewness	0.81	-0.37	-0.07	-0.03	-0.08	0.68	-0.48	0.02	0.18	0.50	-0.83	0.02	-0.20	0.22
Kurtosis	11.50	10.69	1.99	2.63	1.97	6.71	4.05	1.95	6.70	6.79	16.97	5.67	2.21	3.73
NOBS	5843	5843	5843	3233	5843	3233	5843	3233	5843	5843	5843	5843	5843	5843
Jarque-Berra Normality Test:														
JB (Critical Value 9.21)	32,764	27,915	964.8	926.3	953.3	6,292	4,210	511.6	10,932	11,459	70,677	7,803	1,224	3,425
Box-Pierce P-Values:														
First 5	0.006 [‡]	0.367	0.166	0.450	0.035	0.008 [‡]	0.453	0.150	0.002 [‡]	0.046 [*]	0.002 [‡]	0.498	0.498	0.002 [‡]
First 10	0.024 [*]	0.190	0.538	0.707	0.081	0.017 [*]	0.109	0.184	0.003 [‡]	0.020 [*]	0.000 [‡]	0.129	0.686	0.015 [*]
First 25	0.048 [*]	0.000 [‡]	0.087	0.791	0.035 [*]	0.011 [*]	0.082	0.104	0.001 [‡]	0.002 [‡]	0.000 [‡]	0.003 [‡]	0.583	0.000 [‡]

TABLE 1.B
Contemporaneous Cross-Correlations

	AU\$	C\$	DK	FF	DM	Lira	¥	GLD	NK	NZ\$	SP\$	SK	SF	£
AU\$	1													
C\$	0.46	1												
DK	0.33	0.27	1											
FF	0.09	0.03	0.91	1										
DM	0.32	0.25	0.95	0.92	1									
Lira	0.10	0.08	0.81	0.83	0.81	1								
¥	0.08	0.01	0.44	0.56	0.45	0.49	1							
GLD	0.10	0.03	0.94	0.93	0.96	0.82	0.58	1						
NK	0.37	0.32	0.83	0.82	0.82	0.73	0.35	0.84	1					
NZ\$	0.70	0.39	0.34	0.15	0.33	0.14	0.12	0.16	0.38	1				
SP\$	0.35	0.23	0.42	0.36	0.42	0.32	0.41	0.37	0.40	0.36	1			
SK	0.38	0.34	0.81	0.76	0.78	0.73	0.32	0.76	0.80	0.37	0.39	1		
SF	0.24	0.19	0.88	0.87	0.91	0.75	0.51	0.91	0.74	0.27	0.37	0.71	1	
£	0.34	0.28	0.68	0.69	0.70	0.65	0.32	0.70	0.64	0.35	0.34	0.61	0.64	1

TABLE 2
Bid-Ask Spreads in Basis Points

		Currency		Interest Rates	
		Average	Maximum	Average	Maximum
AU\$	Full Sample	10.85	134.10	17.13	177.43
	First ¼ of sample	12.00		20.92	
	Last ¼ of Sample	6.49		18.03	
C\$	Full Sample	6.24	82.00	16.80	88.72
	First ¼ of sample	7.33		24.28	
	Last ¼ of Sample	5.16		12.63	
DK	Full Sample	7.66	137.98	30.34	1520.8
	First ¼ of sample	8.09		29.44	
	Last ¼ of Sample	5.27		16.63	
FF	Full Sample	9.65	98.72	15.96	304.17
	First ¼ of sample	9.57		16.91	
	Last ¼ of Sample	9.11		13.95	
DM	Full Sample	5.46	68.73	10.46	75.00
	First ¼ of sample	5.89		12.77	
	Last ¼ of Sample	3.06		6.71	
Lira	Full Sample	11.65	80.65	42.00	405.55
	First ¼ of sample	13.23		67.11	
	Last ¼ of Sample	9.09		11.62	
¥	Full Sample	7.17	35.13	9.56	107.73
	First ¼ of sample	7.39		10.90	
	Last ¼ of Sample	5.48		9.56	
GLD	Full Sample	6.42	63.09	12.29	76.04
	First ¼ of sample	6.40		13.25	
	Last ¼ of Sample	5.45		10.22	
NK	Full Sample	7.11	82.17	25.69	106.46
	First ¼ of sample	8.61		31.95	
	Last ¼ of Sample	4.83		18.06	
NZ\$	Full Sample	16.97	178.63	19.77	177.43
	First ¼ of sample	24.93		27.18	
	Last ¼ of Sample	8.93		21.13	
SP\$	Full Sample	8.79	68.73	29.06	1520.8
	First ¼ of sample	6.51		18.37	
	Last ¼ of Sample	6.40		20.13	
SK	Full Sample	10.30	90.50	13.17	60.83
	First ¼ of sample	8.94		13.92	
	Last ¼ of Sample	8.35		10.45	
SF	Full Sample	6.59	138.89	12.88	102.40
	First ¼ of sample	7.63		13.19	
	Last ¼ of Sample	5.00		13.39	
£	Full Sample	5.26	68.73	11.08	114.06
	First ¼ of sample	6.38		10.53	
	Last ¼ of Sample	2.79		12.73	
\$	Full Sample	n.a.	n.a.	11.13	101.39
	First ¼ of sample	n.a.		12.79	
	Last ¼ of Sample	n.a.		8.72	

TABLE 3
Annualized Returns in % For Selected Alexander Filters
First and Second Halves of the Sample

	First Half of Sample Returns					Second Half of Sample Returns				
	Filter %	Trans	No B/A	c=0 bps	c=25 bps	Filter %	Trans	No B/A	c=0 bps	c=25 bps
AU\$	0.50	5.06	3.90 17.62	1.35 37.73	-3.21 n.a.	0.50	5.38	0.33 48.03	-1.04 n.a.	-5.88 n.a.
	1.00	3.03	7.42 3.84*	5.79 8.82	3.06 24.77	1.00	4.00	-1.82 n.a.	-2.86 n.a.	-6.46 n.a.
	2.00	1.42	6.38 6.63	5.53 9.97	4.25 17.02	2.00	1.85	5.89 18.67	5.34 21.14	3.67 29.61
	Best	1.50	2.00	9.51 1.22*	8.42 2.47*	6.63 6.96	2.10	1.85	6.12 17.64	5.57 20.54
C\$	0.50	2.68	-0.41 n.a.	-1.27 n.a.	-3.69 n.a.	0.50	4.25	-0.59 n.a.	-1.53 n.a.	-5.36 n.a.
	1.00	1.18	-2.32 n.a.	-2.78 n.a.	-3.84 n.a.	1.00	2.73	0.06 48.97	-0.57 n.a.	-3.03 n.a.
	2.00	0.25	-0.52 n.a.	-0.76 n.a.	-0.98 n.a.	2.00	0.85	2.13 18.89	1.86 22.22	1.10 33.22
	Best	2.70	0.08	3.24 2.12*	3.06 3.02*	2.98 3.25*	2.10	0.75	3.48 7.66	3.23 9.11
DK	0.50	4.62	3.08 16.78	1.14 36.45	-3.02 n.a.	0.50	4.89	0.15 47.95	-0.98 n.a.	-5.37 n.a.
	1.00	3.12	3.44 14.20	2.02 26.98	-0.79 n.a.	1.00	3.32	0.73 39.84	-0.06 n.a.	-3.05 n.a.
	2.00	1.30	5.84 3.50	5.05 6.19	3.88 12.71	2.00	1.44	4.49 5.57	4.09 7.50	2.79 17.17
	Best	1.70	1.65	6.28 2.37*	5.35 5.06*	3.86 12.53	2.40	0.83	6.70 0.85*	6.41 1.13*
FF	0.50	4.92	3.24 22.51	1.43 37.32	-2.99 n.a.	0.50	4.41	-1.68 n.a.	-3.29 n.a.	-7.26 n.a.
	1.00	3.56	2.57 27.50	1.27 38.67	-1.94 n.a.	1.00	2.57	4.56 11.19	3.55 17.69	1.24 38.01
	2.00	1.27	11.01* 0.53*	10.44 0.85*	9.30 2.00*	2.00	1.06	4.31 12.44	3.81 15.71	2.86 23.34
	Best	1.60	1.58	11.10 0.49*	10.42 0.87*	9.00 2.39*	0.90	2.67	5.06 8.82	4.03 14.39
DM	0.50	4.77	2.57 21.57	1.30 34.85	-3.00 n.a.	0.50	4.97	0.11 48.49	-0.81 n.a.	-5.29 n.a.
	1.00	3.11	2.74 20.36	1.90 28.58	-0.89 n.a.	1.00	3.32	0.41 44.28	-0.25 n.a.	-3.24 n.a.
	2.00	1.40	3.00 18.09	2.53 22.33	1.27 35.65	2.00	1.44	4.24 6.69	3.92 8.38	2.62 18.67
	Best	2.10	1.15	4.90 6.66	4.53 8.39	3.49 15.35	2.30	0.92	7.25 0.53*	7.00 0.65*
Lira	0.50	4.76	21.57 2.74*	1.12 39.97	-3.16 n.a.	0.50	4.59	-2.71 n.a.	-4.90 n.a.	-9.03 n.a.
	1.00	3.48	20.36 3.00*	1.96 32.83	-1.17 n.a.	1.00	2.11	7.49 2.01*	6.46 4.26*	4.56 12.51
	2.00	1.19	18.09 4.90*	11.55 0.49*	10.48 1.17*	2.00	1.06	-0.32 n.a.	-1.08 n.a.	-2.03 n.a.
	Best	2.10	1.03	12.97 0.14*	12.19 0.28*	11.26 0.69*	1.20	1.71	7.73 1.76*	6.87 3.36*
¥	0.50	4.71	3.46 13.66	2.02 26.76	-2.22 n.a.	0.50	5.22	-1.05 n.a.	-2.38 n.a.	-7.08 n.a.
	1.00	2.51	6.73 1.62*	5.89 3.36*	3.64 14.14	1.00	3.08	0.33 46.01	-0.50 n.a.	-3.27 n.a.
	2.00	1.55	3.17 15.70	2.61 20.72	1.21 35.75	2.00	1.79	-3.02 n.a.	-3.53 n.a.	-5.15 n.a.
	Best	1.20	2.10	8.82 0.27*	8.08 0.55*	6.18 3.40*	1.20	2.78	1.64 30.45	0.89 39.55

GLD	0.50	4.68	4.16 16.77	2.98 24.98	-1.23 n.a.	0.50	5.07	-4.65 n.a.	-5.78 n.a.	-10.34 n.a.
	1.00	3.56	2.46 28.36	1.40 37.47	-1.81 n.a.	1.00	2.58	2.64 24.92	2.01 30.55	-0.31 n.a.
	2.00	1.34	9.88 1.01*	9.40 1.44*	8.19 3.29*	2.00	0.88	2.99 22.07	2.71 24.51	1.92 31.87
	Best	2.10	1.19	12.17 0.23*	11.73 0.33*	10.66 0.87*	2.10	0.88	3.03 21.91	2.74 24.11
NZ\$	0.50	4.47	8.90 2.37*	6.02 9.66	2.00 34.12	0.50	5.47	1.11 43.33	-0.78 n.a.	-5.70 n.a.
	1.00	2.97	7.17 5.37	5.16 12.90	2.49 30.13	1.00	4.59	-1.47 n.a.	-3.06 n.a.	-7.19 n.a.
	2.00	1.78	1.12 40.13	-0.11 n.a.	-1.71 n.a.	2.00	2.68	-4.25 n.a.	-5.24 n.a.	-7.64 n.a.
	Best	0.70	3.79	9.75 1.53*	7.26 5.77	3.85 21.53	3.60	0.95	5.89 19.09	5.45 21.20
NK	0.50	4.76	4.69 11.28	3.57 18.13	-0.71 n.a.	0.50	5.93	-9.82 n.a.	-11.02 n.a.	-16.36 n.a.
	1.00	2.89	3.57 18.11	2.84 23.65	0.24 47.73	1.00	4.16	-6.59 n.a.	-7.46 n.a.	-11.21 n.a.
	2.00	1.71	2.28 28.02	1.77 32.71	0.23 47.79	2.00	2.39	-7.11 n.a.	-7.66 n.a.	-9.82 n.a.
	Best	0.70	3.62	5.29 9.06	4.40 12.96	1.14 39.41	3.90	0.94	0.40 47.25	0.10 49.30
SP\$	0.50	1.44	2.95 0.53*	2.34 2.56*	1.04 22.08	0.50	2.64	2.09 12.18	0.68 35.76	-1.70 n.a.
	1.00	0.64	2.77 0.62*	2.44 1.58*	1.86 6.49	1.00	1.46	2.49 8.01	1.48 20.86	0.16 46.66
	2.00	0.10	0.92 23.13	0.70 29.01	0.61 32.01	2.00	0.41	3.96 1.39*	3.44 2.94*	3.08 5.12
	Best	0.80	0.74	3.63 0.06*	3.23 0.29*	2.57 2.16*	1.50	0.73	4.77 0.35*	4.15 1.08*
SK	0.50	4.72	4.10 15.09	2.29 28.65	-1.96 n.a.	0.50	5.14	3.14 29.50	1.54 39.77	-3.09 n.a.
	1.00	3.45	-1.11 n.a.	-2.45 n.a.	-5.55 n.a.	1.00	3.76	2.43 33.77	1.23 41.76	-2.16 n.a.
	2.00	1.64	-0.83 n.a.	-1.50 n.a.	-2.98 n.a.	2.00	2.18	-2.83 n.a.	-3.55 n.a.	-5.51 n.a.
	Best	0.50	4.72	4.10 14.95	2.29 28.35	-1.96 n.a.	0.50	5.14	3.14 29.75	1.54 39.70
SF	0.50	5.07	1.76 31.32	0.21 47.74	-4.35 n.a.	0.50	5.21	-1.05 n.a.	-2.16 n.a.	-6.85 n.a.
	1.00	3.31	4.58 10.20	3.46 17.34	0.48 45.02	1.00	3.23	0.71 40.83	-0.02 n.a.	-2.92 n.a.
	2.00	1.86	1.04 38.65	0.39 45.69	-1.28 n.a.	2.00	1.53	2.85 17.46	2.46 21.18	1.08 36.71
	Best	3.00	1.00	5.52 6.03	5.09 7.91	4.19 12.74	1.60	2.10	3.37 13.36	2.87 17.55
£	0.50	4.65	4.24 8.91	3.07 16.90	-1.18 n.a.	0.50	4.54	0.68 39.80	-0.12 n.a.	-4.27 n.a.
	1.00	2.80	4.22 8.67	3.47 13.48	0.91 39.13	1.00	2.80	0.33 45.02	-0.20 n.a.	-2.75 n.a.
	2.00	1.38	3.33 14.38	2.88 18.10	1.62 30.99	2.00	1.31	-1.74 n.a.	-2.04 n.a.	-3.24 n.a.
	Best	3.30	0.60	6.17 2.68*	5.91 3.31*	5.36 5.12	3.90	0.31	1.98 22.41	1.83 24.29

TABLE 4
Annualized Returns in % For Selected Double MA Filters
First and Second Halves of the Sample

	First Half of Sample Returns					Second Half of Sample Returns				
	MA (<i>m,n</i>)	Trans	No B/A	<i>c</i> = 0 bps	<i>c</i> = 25 bps	MA (<i>m,n</i>)	Trans	No B/A	<i>c</i> = 0 bps	<i>c</i> = 25 bps
AU\$	(1,5)	10.71	2.10	-3.08	-12.71	(1,5)	10.69	0.12	-2.48	-12.10
	(1,20)	3.41	31.04	<i>n.a.</i>	<i>n.a.</i>	(1,20)	3.59	49.26	<i>n.a.</i>	<i>n.a.</i>
			5.18	3.46	0.39			4.65	3.70	0.47
	(1,40)	2.24	11.31	21.68	46.71	(1,40)	2.53	24.28	29.17	47.37
Best	(3,18)	2.87	2.09	0.89	-1.13	(1,35)	2.37	3.71	3.00	0.72
			31.18	41.96	<i>n.a.</i>			29.27	33.12	45.98
C\$	(1,5)	10.73	1.28	-1.55	-11.21	(1,5)	11.10	0.17	-2.18	-12.17
	(1,20)	3.34	16.65	<i>n.a.</i>	<i>n.a.</i>	(1,20)	4.10	47.14	<i>n.a.</i>	<i>n.a.</i>
			1.88	0.81	-2.19			1.11	0.20	-3.49
	(1,40)	2.70	7.68	28.10	<i>n.a.</i>	(1,40)	2.74	32.32	46.77	<i>n.a.</i>
Best	(3,19)	2.93	<i>n.a.</i>	<i>n.a.</i>	<i>n.a.</i>	(1,4)	12.27	36.74	47.54	<i>n.a.</i>
			2.97	2.02	-0.62			2.78	0.16	-10.89
DK	(1,5)	11.08	5.14	0.95	-9.02	(1,5)	10.90	3.12	0.81	-9.01
	(1,20)	3.31	5.17	38.85	<i>n.a.</i>	(1,20)	4.03	13.23	38.89	<i>n.a.</i>
			7.98	6.46	3.48			3.49	2.59	-1.04
	(1,40)	2.32	0.55 [‡]	2.40 [*]	16.21	(1,40)	2.38	10.71	18.25	<i>n.a.</i>
Best	(2,15)	3.63	3.96	2.80	0.71	(5,25)	2.33	2.65	2.05	-0.10
			10.62	19.69	42.01			17.41	23.76	<i>n.a.</i>
FF	(1,5)	10.73	5.53	1.68	-7.98	(1,5)	11.29	-2.83	-6.90	-17.07
	(1,20)	3.40	10.16	35.61	<i>n.a.</i>	(1,20)	3.43	<i>n.a.</i>	<i>n.a.</i>	<i>n.a.</i>
			10.04	8.77	5.71			4.61	3.24	0.15
	(1,40)	2.40	0.97 [‡]	2.44 [*]	11.65	(1,40)	2.21	10.96	20.31	48.61
Best	(4,14)	3.12	2.54	1.47	-0.69	(1,19)	3.34	2.33	1.45	-0.53
			27.88	37.12	<i>n.a.</i>			26.77	35.46	<i>n.a.</i>
DM	(1,5)	11.49	3.12	0.31	-10.03	(1,5)	10.77	3.57	1.74	-7.96
	(1,20)	3.96	16.93	46.33	<i>n.a.</i>	(1,20)	4.03	10.47	27.40	<i>n.a.</i>
			6.66	5.65	2.09			3.30	2.58	-1.04
	(1,40)	2.17	2.05 [*]	4.55 [*]	28.18	(1,40)	2.38	12.19	18.39	<i>n.a.</i>
Best	(1,24)	3.16	2.56	1.95	0.00	(5,25)	2.33	2.86	2.40	0.25
			21.89	28.19	<i>n.a.</i>			15.80	20.32	46.75
Lira	(1,5)	10.50	6.55	1.73	-7.72	(1,5)	12.48	-4.50	-10.25	-21.49
	(1,20)	3.01	6.26	35.14	<i>n.a.</i>	(1,20)	4.08	<i>n.a.</i>	<i>n.a.</i>	<i>n.a.</i>
			12.53	11.02	8.31			3.33	1.47	-2.21
	(1,40)	2.24	0.19 [‡]	0.76	4.39 [*]	(1,40)	2.58	18.45	35.37	<i>n.a.</i>
Best	(1,11)	4.92	5.89	4.65	2.63	(2,21)	2.97	1.73	0.62	-1.70
			8.70	15.17	29.24			32.28	43.72	<i>n.a.</i>
¥	(1,5)	10.20	7.43	4.33	-4.86	(1,5)	11.06	1.18	-1.47	-11.42
	(1,20)	4.01	0.91 [‡]	9.51	<i>n.a.</i>	(1,20)	4.16	35.74	<i>n.a.</i>	<i>n.a.</i>
			8.52	7.20	3.59			0.42	-0.66	-4.40
	(1,40)	2.02	0.33 [‡]	1.33 [*]	15.31	(1,40)	2.34	44.93	<i>n.a.</i>	<i>n.a.</i>
Best	(5,42)	1.01	10.49	9.80	7.99	(4,44)	1.54	2.26	1.63	-0.47
			0.04 [‡]	0.12 [‡]	1.07 [*]			24.31	30.96	<i>n.a.</i>
Best	(5,42)	1.01	12.82	12.42	11.51	(4,44)	1.54	5.49 [*]	5.05	3.66
			0.00 [‡]	0.00 [‡]	0.03			4.69 [*]	6.33	14.55

GLD	(1,5)	10.26	7.48 4.19*	4.71 14.68	-4.52 n.a.	(1,5)	12.12	-5.15 n.a.	-7.87 n.a.	-18.77 n.a.
	(1,20)	3.40	8.01 3.19*	6.98 5.80	3.92 20.58	(1,20)	4.36	4.25 13.68	3.26 20.59	-0.66 n.a.
	(1,40)	2.08	4.73 13.48	4.06 17.78	2.18 32.08	(1,40)	2.21	2.92 22.93	2.37 27.81	0.38 46.51
	Best	(2,13)	3.51	13.20 0.12*	12.11 0.28*	8.96 2.96*	(4,41)	1.36	5.86 6.70	5.48 8.19
NZ\$	(1,5)	11.72	-0.99 n.a.	-8.24 n.a.	-18.79 n.a.	(1,5)	11.28	2.41 35.86	-1.30 n.a.	-11.46 n.a.
	(1,20)	3.70	4.33 16.69	1.90 34.13	-1.43 n.a.	(1,20)	4.04	0.34 48.00	-1.04 n.a.	-4.68 n.a.
	(1,40)	2.58	6.02 9.12	4.44 17.09	2.12 33.52	(1,40)	2.68	6.95 15.06	5.99 19.04	3.58 30.85
	Best	(5,18)	2.91	9.53 1.76*	7.64 4.80*	5.01 15.15	(1,4)	12.21	9.63 7.57	5.64 20.88
NK	(1,5)	10.98	2.86 23.14	0.54 44.57	-9.35 n.a.	(1,5)	11.70	0.82 44.40	-1.35 n.a.	-11.89 n.a.
	(1,20)	4.19	0.68 43.04	-0.33 n.a.	-4.10 n.a.	(1,20)	4.98	-3.37 n.a.	-4.37 n.a.	-8.84 n.a.
	(1,40)	2.33	4.81 11.26	4.17 15.03	2.08 31.67	(1,40)	3.63	-5.38 n.a.	-6.14 n.a.	-9.42 n.a.
	Best	(1,10)	6.32	7.36 2.93*	5.95 6.65	0.25 47.66	(1,3)	15.06	7.22 10.92	4.44 22.56
SP\$	(1,5)	11.24	0.36 38.03	-2.63 n.a.	-12.75 n.a.	(1,5)	11.16	0.95 29.56	-3.55 n.a.	-13.60 n.a.
	(1,20)	3.84	3.03 0.43*	1.87 6.58	-1.59 n.a.	(1,20)	3.72	3.15 3.98*	1.63 19.89	-1.72 n.a.
	(1,40)	1.83	3.96 0.02*	3.32 0.25*	1.67 12.17	(1,40)	1.98	1.70 16.91	0.80 33.62	-0.99 n.a.
	Best	(1,36)	1.70	4.60 0.00*	4.01 0.04*	2.48 4.27*	(2,32)	2.11	5.02 0.26*	4.07 1.58*
SK	(1,5)	11.07	1.07 39.22	-2.99 n.a.	-12.95 n.a.	(1,5)	10.49	-0.49 n.a.	-3.75 n.a.	-13.19 n.a.
	(1,20)	3.78	2.88 22.99	1.48 35.66	-1.92 n.a.	(1,20)	3.48	6.14 14.81	5.00 20.21	1.87 38.47
	(1,40)	2.16	2.86 23.64	2.00 31.24	0.05 49.51	(1,40)	2.93	-3.40 n.a.	-4.40 n.a.	-7.03 n.a.
	Best	(1,9)	6.77	7.75 2.52*	5.20 10.13	-0.90 n.a.	(5,6)	7.94	9.31 5.26	6.82 12.51
SF	(1,5)	11.35	2.28 26.55	-1.17 n.a.	-11.38 n.a.	(1,5)	11.10	-1.58 n.a.	-3.81 n.a.	-13.80 n.a.
	(1,20)	4.11	5.38 6.71	3.98 14.09	0.28 47.18	(1,20)	4.56	0.92 38.15	-0.04 n.a.	-4.14 n.a.
	(1,40)	1.92	8.38 1.09*	7.58 2.14*	5.86 7.11	(1,40)	2.47	-0.76 n.a.	-1.34 n.a.	-3.56 n.a.
	Best	(1,35)	2.02	11.26 0.10*	10.49 0.25*	8.67 1.48*	(5,37)	1.72	2.98 16.48	2.55 20.59
£	(1,5)	11.30	2.67 20.02	-0.05 n.a.	-10.36 n.a.	(1,5)	11.01	1.56 27.50	-0.22 n.a.	-10.27 n.a.
	(1,20)	4.01	5.98 2.92*	4.93 6.35	1.27 35.82	(1,20)	4.42	0.78 38.30	0.01 49.89	-4.03 n.a.
	(1,40)	2.35	5.81 3.10*	5.15 5.22	3.01 18.91	(1,40)	2.56	0.65 40.23	0.15 47.70	-2.18 n.a.
	Best	(1,11)	5.80	9.36 0.13*	7.86 0.76*	2.57 23.01	(3,9)	5.94	3.52 8.87	2.50 17.23

TABLE 5
The Instability of the “Best” In-Sample Filters

Currency	Double MA			Alexander Filter		
	AU\$	First Half Return	Second Half Return	AU\$	First Half Return	Second Half Return
First Half Best Filter	MA(3,18)	8.43%	5.31%	1.50%	8.42%	1.19%
		2.59%*	22.00%		2.47%*	
Second Half Best Filter	MA(1,35)	-0.27%	8.52%	2.10%	6.91%	5.57%
		52.42%	10.63%		5.45%	
C\$						
First Half Best Filter	MA(3,19)	2.02%	-3.26%	2.70%	3.06%	-1.56%
		7.10%	90.62%		3.02%*	
Second Half Best Filter	MA(1,4)	-1.28%	0.16%	2.10%	-0.54%	3.23%
		81.52%	47.43%		64.54%	
DK						
First Half Best Filter	MA(2,15)	7.59%	1.62%	1.70%	5.35%	3.27%
		1.21%*	28.65%		5.06%	
Second Half Best Filter	MA(5,25)	3.44%	5.83%	2.40%	2.04%	6.41%
		14.67%	1.99%*		26.42%	1.13%*
FF						
First Half Best Filter	MA(4,14)	11.07%	-0.38%	1.60%	10.42%	0.14%
		0.56% [†]	53.99%		0.87% [†]	
Second Half Best Filter	MA(1,19)	8.03%	4.82%	0.90%	3.45%	4.03%
		3.53%*	10.58%		21.74%	
DM						
First Half Best Filter	MA(1,24)	7.35%	4.52%	2.10%	4.53%	4.74%
		1.44%*	5.77%		8.39%	4.88%*
Second Half Best Filter	MA(5,25)	5.58%	5.75%	2.30%	3.20%	7.00%
		4.56%*	2.40%*		16.57%	0.65%
Lira						
First Half Best Filter	MA(1,11)	12.92%	-1.11%	2.10%	12.19%	-2.03%
		0.22% [†]	61.19%		0.28% [†]	
Second Half Best Filter	MA(2,21)	12.39%	5.54%	1.20%	4.54%	6.87%
		0.28% [†]	7.52%		15.03%	3.36%*
¥						
First Half Best Filter	MA(5,42)	12.42%	2.06%	1.20%	8.08%	0.89%
		0.00% [†]	26.82%		0.55% [†]	
Second Half Best Filter	MA(4,44)	9.41%	5.05%	1.20%	8.08%	0.89%
		0.14% [†]	6.33%		0.55% [†]	

TABLE 5 Continued
The Instability of the “Best” In-Sample Filters

		Double MA		Alexander Filter		
		GLD		GLD		
First Half Best Filter	MA(2,13)	12.11%	-0.58%	2.10%	11.73%	2.74%
		0.28% [†]	55.78%		0.33% [†]	24.11%
Second Half Best Filter	MA(4,41)	4.30%	5.48%	2.10%	11.73%	2.74%
		16.09%	8.19%		0.33% [†]	24.11%
		NZ\$		NZ\$		
First Half Best Filter	MA(5,18)	7.64%	-9.34%	0.70%	7.26%	-5.41%
		4.80% [*]	91.81%		5.77%	78.92%
Second Half Best Filter	MA(1,4)	-8.07%	5.64%	3.60%	2.76%	5.45%
		95.68%	20.88%		27.21%	21.20%
		NK		NK		
First Half Best Filter	MA(1,10)	5.95%	-11.05%	0.70%	4.40%	3.12%
		6.65%	96.93%		12.96%	28.96%
Second Half Best Filter	MA(1,3)	-2.75%	4.44%	3.90%	-4.17%	0.10%
		75.80%	22.56%		85.55%	49.30%
		SP\$		SP\$		
First Half Best Filter	MA(1,36)	4.01%	2.05%	0.80%	3.23%	0.63%
		0.04% [†]	13.87%		0.29% [†]	36.59%
Second Half Best Filter	MA(2,3)	3.47%	4.07%	1.50%	1.63%	4.15%
		0.15% [†]	1.58% [*]		7.42%	1.08% [*]
		SK		SK		
First Half Best Filter	MA(1,9)	5.20%	-4.50%	0.50%	2.29%	1.54%
		10.13%	77.63%		28.35%	39.70%
Second Half Best Filter	MA(5,6)	-5.35%	6.82%	0.50%	2.29%	1.54%
		90.94%	12.51%		28.35%	39.70%
		SF		SF		
First Half Best Filter	MA(1,35)	10.49%	0.58%	3.00%	5.09%	-1.62%
		0.25% [†]	42.47%		7.91%	70.12%
Second Half Best Filter	MA(5,37)	8.11%	2.55%	1.60%	2.83%	2.87%
		1.36% [*]	20.59%		22.30%	17.55%
		£		£		
First Half Best Filter	MA(1,11)	7.86%	-2.28%	3.30%	5.91%	0.18%
		0.76% [†]	80.37%		3.31% [*]	47.22%
Second Half Best Filter	MA(3,9)	3.07%	2.50%	3.90%	1.37%	1.83%
		17.13%	17.23%		33.39%	24.29%

TABLE 6
Out-Of-Sample Performance of Trading Systems
(Filter revised annually; 2-year rolling window)

PANEL A
Alexander Filters

	All	88-91	92-95	96-98	99-01	02-05	05-09
AU\$	4.25% <i>0.15</i>	--	--	--	-0.28% <i>n.a.</i>	10.01% <i>0.13</i>	0.38% <i>0.95</i>
C\$	-1.06% <i>n.a.</i>	6.49% <i>0.05</i>	-0.32% <i>n.a.</i>	-4.34% <i>n.a.</i>	-5.53% <i>n.a.</i>	1.54% <i>0.67</i>	0.67% <i>0.84</i>
DK	3.40% <i>0.07</i>	21.71% <i>0.00[‡]</i>	-13.44% <i>n.a.</i>	5.25% <i>0.35</i>	3.70% <i>0.51</i>	3.44% <i>0.51</i>	-0.55% <i>n.a.</i>
FF	0.98% <i>0.38</i>	11.51% <i>0.02[*]</i>	-11.46% <i>n.a.</i>	9.11% <i>0.10</i>	--	--	--
DM	3.15% <i>0.08</i>	19.10% <i>0.00[‡]</i>	-17.83% <i>n.a.</i>	17.53% <i>0.00[‡]</i>	5.28% <i>0.36</i>	3.67% <i>0.49</i>	-0.53% <i>n.a.</i>
Lira	3.82% <i>0.12</i>	14.58% <i>0.00[‡]</i>	-2.40% <i>n.a.</i>	2.58% <i>0.64</i>	--	--	--
¥	-1.51% <i>n.a.</i>	3.67% <i>0.49</i>	3.48% <i>0.51</i>	-3.04% <i>n.a.</i>	-8.79% <i>n.a.</i>	-6.84% <i>n.a.</i>	-3.92% <i>n.a.</i>
GLD	4.23% <i>0.09</i>	16.67% <i>0.00[‡]</i>	-9.84% <i>n.a.</i>	16.34% <i>0.00[‡]</i>	--	--	--
NK	-0.56% <i>n.a.</i>	--	--	--	-10.63% <i>n.a.</i>	3.97% <i>0.50</i>	-3.60% <i>n.a.</i>
NZ\$	-2.86% <i>n.a.</i>	--	--	--	5.03% <i>0.51</i>	6.61% <i>0.33</i>	-6.64% <i>n.a.</i>
SP\$	-0.45% <i>n.a.</i>	-0.26% <i>n.a.</i>	1.71% <i>0.50</i>	-2.71% <i>n.a.</i>	-0.05% <i>n.a.</i>	-4.51% <i>n.a.</i>	-0.51% <i>n.a.</i>
SK	3.46% <i>0.18</i>	--	--	--	-0.92% <i>n.a.</i>	7.27% <i>0.21</i>	-3.74% <i>n.a.</i>
SF	3.33% <i>0.09</i>	15.69% <i>0.00[‡]</i>	-6.05% <i>n.a.</i>	13.90% <i>0.03[*]</i>	1.64% <i>0.79</i>	3.69% <i>0.53</i>	-1.56% <i>n.a.</i>
£	-1.47% <i>n.a.</i>	1.23% <i>0.80</i>	-8.41% <i>n.a.</i>	-10.12% <i>n.a.</i>	-5.25% <i>n.a.</i>	7.15% <i>0.16</i>	-0.40% <i>n.a.</i>
EQ Portfolio	1.86% <i>0.01[*]</i>	0.12% <i>0.97</i>	-0.06% <i>n.a.</i>	0.04% <i>0.99</i>	-0.02% <i>n.a.</i>	0.03% <i>0.99</i>	-0.02% <i>n.a.</i>

PANEL B
Double Moving Average

	All	88-91	92-95	96-98	99-01	02-05	05-09
AU\$	-1.92% <i>n.a.</i>	--	--	--	-6.50% <i>n.a.</i>	6.32% <i>0.33</i>	-8.50% <i>n.a.</i>
C\$	-0.27% <i>n.a.</i>	3.13% <i>0.34</i>	-1.14% <i>n.a.</i>	-8.28% <i>n.a.</i>	-0.47% <i>n.a.</i>	3.62% <i>0.30</i>	-1.50% <i>n.a.</i>
DK	5.22% <i>0.01*</i>	15.91% <i>0.00[‡]</i>	1.62% <i>0.74</i>	4.87% <i>0.39</i>	1.89% <i>0.74</i>	5.28% <i>0.31</i>	12.26% <i>0.01*</i>
FF	3.41% <i>0.16</i>	10.66% <i>0.03</i>	-2.40% <i>n.a.</i>	5.90% <i>0.29</i>	--	--	--
DM	2.90% <i>0.10</i>	8.23% <i>0.10</i>	-0.94% <i>n.a.</i>	-0.65% <i>n.a.</i>	2.52% <i>0.66</i>	5.88% <i>0.27</i>	6.24% <i>0.20</i>
Lira	6.23% <i>0.04*</i>	16.54% <i>0.00[‡]</i>	5.85% <i>0.21</i>	-3.36% <i>n.a.</i>	--	--	--
¥	-0.12% <i>n.a.</i>	2.57% <i>0.63</i>	-1.26% <i>n.a.</i>	0.85% <i>0.89</i>	-1.69% <i>n.a.</i>	-5.30% <i>n.a.</i>	3.68% <i>0.48</i>
GLD	4.08% <i>0.11</i>	15.72% <i>0.00[‡]</i>	-2.71% <i>n.a.</i>	2.67% <i>0.64</i>	--	--	--
NK	3.38% <i>0.22</i>	--	--	--	-5.02% <i>n.a.</i>	-2.51% <i>n.a.</i>	3.62% <i>0.50</i>
NZ\$	-1.18% <i>n.a.</i>	--	--	--	-4.06% <i>n.a.</i>	7.82% <i>0.25</i>	9.37% <i>0.13</i>
SP\$	2.77% <i>0.03*</i>	16.94% <i>0.00[‡]</i>	1.71% <i>0.50</i>	10.88% <i>0.00[‡]</i>	1.53% <i>0.61</i>	0.73% <i>0.79</i>	1.03% <i>0.68</i>
SK	0.28% <i>0.47</i>	--	--	--	-1.40% <i>n.a.</i>	0.64% <i>0.91</i>	1.97% <i>0.72</i>
SF	-0.79% <i>n.a.</i>	-0.92% <i>n.a.</i>	-0.03% <i>n.a.</i>	9.24% <i>0.15</i>	-0.90% <i>n.a.</i>	-5.08% <i>n.a.</i>	-7.24% <i>n.a.</i>
£	-0.06% <i>n.a.</i>	10.01% <i>0.03*</i>	-1.77% <i>n.a.</i>	-10.26% <i>n.a.</i>	-5.51% <i>n.a.</i>	-0.63% <i>n.a.</i>	4.49% <i>n.a.</i>
EQ Portfolio	1.06% <i>0.10</i>	9.29% <i>0.00[‡]</i>	-0.11% <i>n.a.</i>	1.19% <i>0.70</i>	-1.11% <i>n.a.</i>	1.05% <i>0.72</i>	-1.11% <i>n.a.</i>

TABLE 7
Sharpe Ratios For The Best-Performing Filters in and Out-of-Sample
Full Sample

	Double MA Best In-Sample	Double MA Best Out-of- Sample	Alexander Best in-Sample	Alexander Best Out-of-Sample
AU\$	0.45	0.26	0.42	0.26
C\$	-0.06	-0.03	0.11	-0.12
DK	0.46	0.42	0.40	0.28
FF	0.54	0.27	0.57	0.08
DM	0.48	0.23	0.43	0.25
Lira	0.74	0.45	0.49	0.31
¥	0.56	-0.01	0.30	-0.11
GLD	0.57	0.59	0.32	0.33
NK	0.16	-0.08	-0.01	-0.19
NZ\$	0.41	0.20	0.40	-0.03
SP\$	0.60	0.42	0.51	-0.07
SK	0.30	0.02	0.13	0.23
SF	0.46	0.25	-0.05	0.24
£	0.27	-0.01	0.19	-0.13
EQ Portfolio	n.a.	0.28	n.a.	0.18

TABLE 8
T-Statistics of Risk Factor Regression Coefficients
Daily Data

Panel A: Alexander Filters

	Best In-Sample					Out-of-Sample				
	Alpha ¹	UIRPF	RMKT	SMB	HML	Alpha ¹	UIRPF	RMKT	SMB	HML
AU\$	1.94	-2.09*	-1.01	1.14	0.65	1.03	-0.93	-0.96	0.72	0.40
C\$	0.71	-2.63*	0.52	-0.54	1.60	-0.39	-0.90	-1.43	-0.25	-0.99
DK	2.47*	-3.58 [‡]	-0.50	0.81	-0.03	1.71	-2.00*	-0.42	0.48	0.80
FF	2.48*	-3.12 [‡]	-1.05	-0.51	-0.20	0.19	0.29	-1.45	-2.44*	-0.22
DM	2.62 [‡]	-4.78 [‡]	-0.29	1.09	0.48	1.46	-3.21 [‡]	-0.17	0.16	0.73
Lira	1.93	-1.60	-0.74	-0.47	-0.08	0.94	-4.71 [‡]	2.52*	-0.06	1.90
¥	2.12*	-2.81 [‡]	-1.69	2.32*	-0.36	-0.44	-1.27	-1.38	0.20	0.46
GLD	2.52*	-4.01 [‡]	-0.45	-0.47	-0.13	1.12	-0.47	0.00	-1.78*	0.19
NK	0.20	-1.30	-1.51	0.27	0.12	-0.63	-1.12	-1.11	0.75	-0.87
NZ\$	1.73	-0.51	0.17	1.05	1.06	0.10	-3.60 [‡]	-2.80 [‡]	0.88	0.11
SP\$	2.83 [‡]	-1.70	-2.05*	-0.02	0.11	-0.27	-1.47	-2.32*	1.42	-1.37
SK	0.63	-1.65	-0.50	0.83	0.88	1.13	-3.28 [‡]	-1.13	1.40	0.87
SF	1.45	-1.49	-1.27	0.32	1.00	1.27	-1.98	-1.37	-0.30	1.34
£	1.02	-1.61	-0.28	0.94	1.34	-0.84	-1.31	-0.32	0.63	2.85 [‡]

Panel B Double MA Filters

	Best In-Sample					Out-of-Sample				
	Alpha ¹	UIRPF	RMKT	SMB	HML	Alpha ¹	UIRPF	RMKT	SMB	HML
AU\$	2.21*	-2.63 [‡]	-1.54	0.33	0.39	-0.30	-3.15 [‡]	-0.85	1.24	0.11
C\$	-0.17	-2.79 [‡]	-1.06	-0.45	0.05	0.17	-2.76 [‡]	-1.61	-1.00	-0.43
DK	2.74 [‡]	-2.65 [‡]	-1.89	1.22	0.33	2.32*	-2.20*	-1.91	0.03	0.32
FF	2.50	-2.59 [‡]	-1.49	0.39	-0.11	1.07	-1.15	-0.76	-1.23	0.11
DM	2.90 [‡]	-2.75 [‡]	-1.84	0.94	0.08	1.33	-2.80 [‡]	-1.73	-0.50	0.84
Lira	3.10 [‡]	-1.16	-1.21	-1.21	0.13	1.94	-0.67	-1.45	-1.98*	-0.29
¥	3.59 [‡]	-4.30 [‡]	-4.47 [‡]	-0.54	-0.75	0.23	-2.31*	-2.69 [‡]	-0.23	-0.95
GLD	2.53*	-1.32	-1.90	-0.80	-1.05	1.30	-1.13	-0.76	-1.41	-0.15
NK	0.80	-2.37*	-1.21	0.70	-0.43	-0.15	-2.23	-0.03	0.15	0.75
NZ\$	1.99*	-3.00 [‡]	-1.53	1.43	0.04	1.04	-2.64 [‡]	-0.30	0.73	0.64
SP\$	3.60 [‡]	-3.10 [‡]	-2.50*	0.04	0.24	2.40*	-3.24 [‡]	-1.61	0.61	0.27
SK	1.37	-1.83	-1.53	0.29	-0.09	0.36	-3.30 [‡]	-1.42	0.61	0.23
SF	2.63 [‡]	-1.76*	-0.56	-0.22	1.41	-0.31	-2.46*	-1.14	-0.75	0.80
£	1.41	-3.14 [‡]	-0.26	0.95	1.14	-0.08	-1.69	-0.57	1.23	2.90 [‡]

¹ The alphas shown here are the constants of a regression that includes *only* the risk factors shown in the table. They are *not* the regression constants of the full model.

TABLE 9
T-Statistics of Transactions Costs and Time Coefficients
Daily Data

Panel A: Alexander Filters

	Best In-Sample						Out-of-Sample					
	ABSFPR	FXBA	INBA	US INBA	LTIME	RSQ	ABSFPR	FXBA	INBA	US INBA	LTIME	RSQ
AU\$	0.88	0.47	-0.89	-0.41	0.18	0.017	1.60	1.34	-0.90	-0.46	1.16	0.010
C\$	-1.02	0.04	-0.92	-0.16	-0.38	0.008	0.27	-0.03	-1.19	-0.20	-1.65	0.006
DK	-0.45	0.12	-0.34	-1.67	-1.34	0.008	-1.61	-0.14	0.39	-1.57	-1.52	0.005
FF	0.36	0.23	-1.62	-1.07	-1.08	0.013	-0.93	-0.64	-0.89	0.85	-0.71	0.009
DM	-0.57	1.83	1.23	-2.14*	-0.73	0.012	-3.02 [‡]	1.54	1.28	-1.94	-1.02	0.009
Lira	-0.26	1.50	0.23	-0.72	-0.08	0.007	-1.91	0.54	1.93	1.04	1.34	0.052
¥	-0.76	0.71	0.57	-0.91	-2.00*	0.011	-0.26	0.38	0.22	-0.79	-1.17	0.004
GLD	-0.16	1.45	-1.06	-0.47	-1.23	0.020	-0.89	0.76	-0.29	1.45	-1.02	0.007
NK	0.58	-0.04	-1.24	-0.40	-0.83	0.007	1.88	0.91	-1.41	0.16	-0.17	0.008
NZ\$	0.04	-0.09	-0.16	-0.89	-0.11	0.003	-1.24	-1.34	0.11	0.05	-1.63	0.037
SP\$	-1.57	1.06	-1.12	1.04	1.16	0.007	-0.19	-1.10	-1.08	1.03	-0.35	0.012
SK	-0.46	0.25	-0.39	0.15	0.66	0.005	-0.29	1.04	0.46	0.47	0.81	0.019
SF	0.93	2.00*	1.57	-1.65	-0.69	0.005	-0.15	0.97	1.10	-1.66	-1.34	0.006
£	1.70	1.88	-0.58	0.12	0.91	0.005	2.03*	0.70	-0.38	0.10	1.68	0.007

Panel B: Double MA Filters

	Best In-Sample						Out-of-Sample					
	ABSFPR	FXBA	INBA	US INBA	LTIME	RSQ	ABSFPR	FXBA	INBA	US INBA	LTIME	RSQ
AU\$	1.14	2.70 [‡]	-0.83	0.55	2.28*	0.024	0.76	0.52	-0.34	-0.43	0.13	0.034
C\$	-0.86	-0.11	0.86	2.94 [‡]	1.41	0.015	0.86	1.42	-0.09	-0.11	0.42	0.010
DK	-1.03	0.63	0.11	0.07	-0.04	0.006	-1.04	0.04	0.36	0.22	-0.44	0.005
FF	0.37	0.01	-1.01	-0.79	-1.04	0.011	-1.04	0.12	-1.57	-1.47	-0.98	0.007
DM	0.06	2.45*	1.05	-0.17	0.49	0.007	-0.72	1.62	0.60	0.06	0.19	0.007
Lira	0.66	1.11	0.27	-1.14	0.28	0.008	0.30	0.41	0.34	-0.47	-0.11	0.009
¥	-0.59	1.36	1.28	-1.34	-1.13	0.020	-0.38	0.02	0.37	-1.70	-0.88	0.009
GLD	0.41	1.01	-1.15	-0.42	-0.89	0.006	-0.49	0.86	-0.23	-0.03	-1.94	0.006
NK	0.39	-0.57	-0.59	1.31	-0.12	0.013	-0.24	-0.07	-1.26	0.43	-0.39	0.013
NZ\$	0.37	0.81	0.46	0.45	0.94	0.019	1.03	0.86	0.99	0.07	0.42	0.018
SP\$	-0.86	1.00	-1.54	0.33	0.14	0.014	-1.17	0.82	-1.36	-0.92	-1.17	0.013
SK	0.99	0.69	1.55	-0.50	1.39	0.009	-0.15	1.01	-0.52	0.02	0.03	0.017
SF	0.14	0.60	0.80	-0.07	-0.38	0.003	1.26	0.80	0.89	-0.30	-0.23	0.006
£	2.25*	1.34	-0.36	0.80	1.19	0.008	1.30	-0.36	0.50	2.62 [‡]	0.31	0.010

NOTES FOR THE TABLES

Notes For Table 1:

Table 1.A reports relevant statistical properties for the 14 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.

Notes For Table 2:

The table shows the average and maximum bid/ask spreads for the FX rate and for 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.

Notes For Tables 3 and 4:

Table 3 shows returns for the modified Alexander filter in for the first and second halves of the sample. We show details for the filters 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 double MA filters for the first and second halves of the sample. 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 filter in the interval *short* = 1, 5, and *long* = 2, 50, both in increments of 1 day.

For each half of the sample, the columns from left to right show the size of the filter (labeled “filter”), the % of days in which there is a transaction (labeled “Trans”), the returns to each filter excluding the bids-ask spreads (labeled “no B/A”), and the returns to each filter including the bid/ask spreads (labeled 0 bps), and also including an additional 25bps per transaction (labeled “25 bps”).

There are 2 rows for each filter. The first row shows the return while the second 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%.

Notes For Table 5:

Table 5 shows the return and p-values for filters that were “best” in the first and second periods. For each currency, the first two rows show the first period’s best filter and its performance both periods, first for the double MA and then for the Alexander filter. The 3rd and 4th rows show the second period’s best filter and its performance in both periods, again first for the double MA and then for the Alexander filters.

In each case, the first row is the return in annualized % and the second row is its p-value in italics. Note that the performance of the first period’s best filter in the first period and the second period’s best filter in the second period are also shown in tables 3 and 4.

We designate p-values of 1% or less with “*”, and p-values between 1% and 5 % with “.”.

Notes For Table 6:

The table shows the simulated out-of-sample returns for the full period as well as for 6 subperiods, each roughly 4 years long. We report returns for our modified Alexander filter (Panel A), and for the double MA filter (panel B). Data from years $t-2$ to t are used to identify the best in-sample filter. Then the filter 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-values for the full period are calculated by Monte-Carlo simulations with 10,000 replications. To compute the p-values for the subperiods we use the standard deviations for the full period and adjust it by the corresponding number of observations.

Notes For Table 7:

The table shows Sharpe ratios for the best-performing filter for in-sample and out-of-sample returns, for the full sample. The Sharpe ratio is calculated as the ratio of the average daily return divided by the daily standard deviation, and it is annualized.

Notes For Table 8:

The 2 panels of table 8 show the results of regressions on in-sample and out-of-sample trading returns for our two systems for each currency, using daily data. We report only the t-statistics and their level of significance. From left to right: Jensen’s alpha, the currency risk factor *UIRPF* from Lustig et al. (2008), and the 3 Fama-French risk factors, *RMKT*, *SMB*, *HML*.

The regression from which the results are taken includes the above variables, the variables shown on table 9, and weekday dummies for Monday, Tuesday, Thursday, and Friday; Wednesday is omitted because of the constant. Leaving out the variables shown in table 9 does not materially change the results. However, the Jensen’s alpha we report is from regressions without the additional variables shown in table 9, and it *is not* the regression constant.

We designate p-values of 1% or less with “*”, and p-values between 1% and 5 % with “.”.

Notes For Table 9:

The 2 panels of table 9 display results for the additional variables we include in the regressions shown in table 8. From left to right: the absolute value of the forward premium of the respective currency, *ABFRP*, measures of bid-ask spreads – the FX and interest rate bid-ask spreads of the respective currency, *FXBA* and *INBA*, the U.S. interest rate bid-ask spread, *USINBA*, the log of “time” (1-5844), *LTIME*, and the R^2 of each regression. We report only the t-statistics and their level of significance.

We designate p-values of 1% or less with “*”, and p-values between 1% and 5 % with “.”.