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Do Momentum-Based Strategies Still Work in Foreign Currency Markets?

John Okunev and Derek White*

Abstract

This paper examines the performance of momentum trading strategies in foreign exchange markets. We find the well-documented profitability of momentum strategies during the 1970s and the 1980s has continued throughout the 1990s. Our approach and findings are insensitive to the specification of the trading rule and the base currency for analysis. Finally, we show that the performance is not due to a time-varying risk premium but rather depends on the underlying autocorrelation structure of the currency returns. In sum, the results lend further support to prior momentum studies on equities. The profitability to momentum-based strategies holds for currencies as well.

I. Introduction

For over three decades, investors in foreign exchange markets have disagreed with the academic belief that price behavior is entirely determined by market fundamentals. While most would concur that over the long run exchange rates should reflect fundamental value, many hold the view that short-term profitable opportunities exist due to market inefficiencies. In this paper, we examine the profitability of momentum trading strategies in foreign exchange markets.[1] We find the well-documented profitability of momentum strategies during the 1970s and the 1980s has continued throughout the 1990s. Furthermore, we find that this profitability is not due to compensation for bearing a time-varying risk premium.

A degree of market inefficiency must be present in foreign exchange markets for technical trading strategies to generate positive risk-adjusted returns. If foreign exchange markets are truly efficient, currencies must fluctuate randomly after controlling for interest rate differentials and the release of new information

*Okunev, okunev.john@principal.com, Principal Global Investors, Level 11, 888 7th Avenue, New York, NY 10019; White, derekw@unsw.edu.au, School of Banking and Finance, University of New South Wales, High Street Quad Building, Kensington, NSW 2052, Australia. The authors thank Stephen Brown (the editor), Martin Martens, Christopher Neely, Sheridan Titman (the referee), and Jian-Xin Wang for their helpful comments and suggestions. Any remaining errors are our own.

[1]We identify strong and weak momentum currencies through the use of moving average rules. This differs from the Jegadeesh and Titman (1993) approach of simply using prior n-month returns to identify strong and weak momentum financial assets. We do follow the Jegadeesh and Titman approach, however, in that our strategy only trades in the strongest and weakest momentum (as defined by the moving average rules) currencies.

(Fama (1965)). However, a substantial number of studies have cast doubt on the random walk hypothesis in foreign exchange markets. Taylor and Allen (1992) find statistically significant trends and a limited degree of serial correlation. A vast literature has arisen documenting successful technical trading strategies in foreign exchange (Sweeney (1986), Schulmeister (1988), Surajaras and Sweeney (1992), Levich and Thomas (1993), Taylor (1994), Kho (1996), Neely, Weller, and Dittmar (1997), LeBaron (1999), and Marsh (2000)). Taylor and Allen (1992) document that the London foreign exchange dealers prefer to use technical rather than fundamental analysis to determine their short-term, intra-day to one week, forecasting. They find, however, that fundamental analysis progressively attains greater prominence with an increase in the trading horizon.

Two commonly cited reasons for the presence of inefficiency in foreign exchange markets are noise trading and central bank intervention. One hypothesis is that noise traders, who make their trading decisions based upon prior directional movements in the currency, dominate the foreign exchange market. Shleifer and Summers (1990) argue that this type of trading behavior may push asset prices beyond their true value. Moreover, even if individual traders recognize mispricing in foreign exchange markets, they may be unable or unwilling to "trade against the market" due to their own loss limit restrictions. In fact, individual traders may find it in their best interest to stimulate serial correlation in currencies if they feel investor sentiment will remain stable in the short term. They can trade with the market over a relatively short time horizon and, as a result, act to drive currency values further from their fundamental value (Shleifer and Summers (1990)).

Another possible reason to doubt the efficiency in foreign exchange markets is that central banks lack the profit motive for trade. The primary objective for any central bank is not to earn trading profits, but instead to dampen foreign exchange volatility and to ensure that currencies reflect politically acceptable values. Concerted central bank intervention generates non-random exchange rate movements, and a large number of studies have examined whether profitable trading in currencies arises as a result (Sweeney (1997), Szakmary and Mathur (1997), Neely (1998), LeBaron (1999), and Frenkel and Stadtmann (2001)). Sweeney (1997) finds that central banks have made significant profits during interventions. Szakmary and Mathur (1997) and LeBaron (1999) find that moving average trading rules that trade against central bank intervention generate excess returns and suggest that central banks suffer losses. On the other hand, Neely (1998) finds that central bank intervention is more likely to be profitable in the long run. The finding that central bank intervention leads to technical trading profits is not universally held. Neely (2000) finds, using intra-day data, that technical trading rule profits occur prior to central bank intervention. That is, central bank intervention results from currency movements that have previously generated the technical trading rule profits.

Most of the studies cited above have examined the performance of trading rules using daily foreign exchange data (Sweeney (1986), Surajaras and Sweeney (1992), Levich and Thomas (1993), Taylor (1994), and Neely, Weller, and Dittmar (1997)). Kho (1996), on the other hand, uses weekly data. Recent studies have also examined the performance of technical trading rules using intra-day data (Raj (2000) and Neely and Weller (2001a)). With the notable exception of Kho (1996), the general conclusion is that technical trading rules are able to earn significant excess returns that cannot be easily explained by bearing additional risk when using daily or weekly data. Raj (2000) and Neely and Weller (2001a) have shown that technical trading rules do not produce significant profits using intra-day data.

One of the problems with prior research is that most studies have selected a small number of moving average strategies, basing their decisions on moving average combinations that are commonly employed by traders. Choosing a small number of moving average combinations may bias the results to those strategies that have performed well ex post. Neely, Weller, and Dittmar (1997), p. 406 point out: "these investigations have deliberately concentrated on the most common and widely used rules, but some doubt remains as to whether the reported excess returns could have been earned by a trader who had to make a choice about what rule or combination of rules to use at the beginning of the sample period."

To overcome this criticism, we evaluate 354 moving average rules for eight currencies from J 1980 to June 2000. The approach adopted is similar to that proposed by Jegadeesh and Titman (1993), (2000) where technical indicators are used to rank stocks from best to worst. Their strategy ranks stocks based upon the prior n-month return and then form decile portfolios. A long/short strategy is subsequently instigated, the long portfolio consisting of those stocks with the greatest previous n-month return (top decile) and the short portfolio including those stocks with the worst previous n-month return (low decile). They find significant excess returns both in sample and out of sample. We employ a similar ranking procedure for currencies, but instead of using the previous n-month return we use various combinations of moving averages. Our objective is to identify the most attractive and the least attractive currencies using the moving average rules. Once the strongest and weakest momentum currencies are identified, a long/short position is initiated by buying the strongest momentum currency and shorting the weakest momentum currency. For example, assume a manager in Switzerland, using the moving average strategy, identifies the Japanese yen to be the most unattractive currency and the Australian dollar to be the most attractive currency relative to the Swiss franc. The Swiss manager would sell futures contracts on the Japanese yen and then buy futures contracts on the Australian dollar.[2] This approach differs from most previous studies using technical indicators on foreign exchange markets.[3] In prior studies, long/short positions were set on each individual currency whereas we take positions in only the most attractive and the least attractive currencies.

We take the perspective of a long-term investor who has foreign currency exposure in Australia, Canada, France, Germany, Italy, Japan, the U.K., and the U.S. This could be a global equity manager who has purchased stocks in each of the above-mentioned countries. Alternatively, it could be a multinational com-

[2] At the same time a U.S. manager, using the same strategy, might also buy the Australian dollar but short the Swiss franc. The strategies identified in this paper all rely on moving averages relative to a *base currency of reference.*

[3] Surajaras and Sweeney (1992) did examine strategies that buy only the top rank currencies based upon "relative strength indices." They define a relative strength index as the ratio of the price of a currency relative to its historical average price. Many differences between their work and ours can be identified but perhaps the most important is that they find very weak results during the 1982–1986 period, whereas that is a period when we find profitability to be particularly strong.

pany that exports to those markets. Once a currency exposure is initiated it is held for one month, at which time the foreign exchange position is reevaluated. The strategy might require only three to four trades a year and would not be concerned with daily exchange rate volatility. Instead, the strategy focuses more on long-run exchange rate movements. While it is true that using daily data may identify changes in market sentiment more effectively, this might also induce a high frequency of noise trading that could prove to be costly in terms of transaction costs.

While the performance of individual technical trading rules may vary significantly from one subperiod to the next, our approach is not sensitive to any given moving average specification. By averaging across trading rules, our results are remarkably consistent across subperiods and base currencies of reference. In fact, the profits can be quite substantial, yielding total returns of over 6% per annum. This profitability can be explained neither by interest rate differentials across base currencies nor is it likely due to the forward premium anomaly. Furthermore, these profits most likely do not arise as compensation for bearing additional risk. The format of the paper is as follows. Section II describes the data and methodology, while Section III outlines the empirical results. Section IV concludes with a brief summary and discussion.

II. Data and Methodology

The data set consists of three-month government yields and spot exchange rates taken from the Global Financial Database.[4] We obtained end-of-month data for Australia, Canada, France, Germany, Japan, Switzerland, the U.K., and the U.S. from January 1975 through June 2000. In addition, we obtained MSCI capitalization weights for the same period from Morgan Stanley. We computed currency returns using each country as the domestic currency. That is, we computed all combinations of currency returns for the eight countries. We define this return series as base currency returns. The base currency returns from month $t-1$ to t are computed as

$$R_{B,t} = \frac{S_t}{S_{t-1}} - 1, \tag{1}$$

where the base currency return is $R_{B,t}$, the spot exchange rate at month t is S_t, and the spot exchange rate at month $t-1$ is S_{t-1}. All exchange rates are expressed as the ratio of units of domestic currency per unit of foreign currency.

In addition, we computed a similar series of currency returns adjusted for interest rate differentials. An investor who uses futures to invest in currencies or borrows in one country to invest in another would actually experience these

[4]Because we employ one-month trading strategies, we should ideally use one-month yields in our dataset. However, we did not have access to this data for all the currencies for the time period of the analysis. We do not, however, believe that any resulting bias contributes to our findings. We discuss this issue in the bootstrapping analysis later in the paper.

returns.[5] The futures price at month $t-1$ is denoted as F_{t-1}. The interest-adjusted returns from month $t-1$ to t are computed as

$$(2) \qquad R_{I,t} = \frac{S_t}{F_{t-1}} - 1,$$

where $F_{t-1} = S_{t-1} \exp[(r - r_f) * (1/12)]$, $R_{I,t}$ is the interest-adjusted return, r is the domestic interest rate, and r_f is the foreign interest rate. Note that

$$(3) \qquad R_{I,t} \approx (r_f - r) * \left(\frac{1}{12}\right) + \frac{S_t}{S_{t-1}} - 1.$$

Note that we can subdivide the actual returns from investing in currency into two components: the return due to the interest differential between the non-domestic and domestic currency and the return due to pure currency appreciation. Direct examination of equation (3) reveals the return due to the interest differential to be

$$(4) \qquad (r_f - r) * \left(\frac{1}{12}\right),$$

and the return due to pure currency appreciation is

$$(5) \qquad \frac{S_t}{S_{t-1}} - 1.$$

We can see from equations and (5) that the return to investing in a relatively strong currency may be mitigated by the relative interest rate differential between the non-domestic and the domestic countries. In Section III, we will examine the component of trading rule returns due to the interest rate differential.

Table 1 lists summary statistics for the base currency returns of each country. Each base currency is listed in the far left column and the reference currencies in the subsequent columns. For example, using Australia as the domestic currency the average monthly appreciation of the Canadian dollar has been 0.192%. The MSCI column gives the return to a basket of currencies with the individual country allocation determined by its MSCI weight. The allocations are determined by excluding the MSCI weight of the domestic currency. That is, if we have three currencies, each with an MSCI weight of 33%, we would give each of the other two currencies a weight of 50% when we determine the MSCI-weighted return for each base currency. The Equal benchmark equally weights the other seven currencies for computing a return relative to a base currency.

We can easily observe from Table 1 that the Australian dollar has suffered the greatest depreciation during the previous 20 years. The Japanese yen has experienced the greatest appreciation. Because of the relatively large standard deviation in monthly foreign exchange returns, most of the base currency mean returns are insignificantly different from zero with the possible exception of the

[5]While the strategy we employ could, in theory, be considered zero-cost and the resulting returns infinite, we choose to frame the returns in terms of an unlevered position in currency futures where full margin is given for both long and short positions.

TABLE 1

Descriptive Statistics (Base Currency Returns)

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.	MSCI	Equal
Australia										
Mean Ret. (%)	NA	0.192	0.112	0.268	0.675*	0.336	0.165	0.292	0.392*	0.291
Median Ret. (%)	NA	−0.031	−0.230	0.107	0.005	−0.007	0.066	0.113	0.021	−0.088
Std. Dev. (%)	NA	2.790	4.044	4.229	4.344	4.428	3.824	2.913	3.086	3.290
t-Stat.	NA	1.081	0.434	0.993	2.436	1.192	0.679	1.570	1.991	1.390
Infor. Ratio	NA	0.069	0.028	0.063	0.155	0.076	0.043	0.100	0.127	0.088
Canada										
Mean Ret. (%)	−0.116	NA	−0.067	0.084	0.500*	0.155	−0.010	0.105	0.210	0.093
Median Ret. (%)	0.031	NA	−0.220	−0.189	−0.091	−0.163	−0.341	0.059	0.096	−0.149
Std Dev. (%)	2.731	NA	3.309	3.406	3.796	3.698	3.193	1.325	1.853	2.331
t-Stat.	−0.666	NA	−0.319	0.388	2.064	0.656	−0.048	1.239	1.778	0.625
Infor. Ratio	−0.042	NA	−0.020	0.025	0.132	0.042	−0.003	0.079	0.113	0.040
France										
Mean Ret. (%)	0.047	0.177	NA	0.152**	0.605**	0.222*	0.095	0.272	0.346*	0.224
Median Ret. (%)	0.230	0.220	NA	0.012	0.321	0.109	0.206	0.100	0.256	0.095
Std. Dev. (%)	3.952	3.321	NA	0.894	3.288	1.603	2.595	3.275	2.411	1.882
t-Stat.	0.188	0.837	NA	2.676	2.885	2.170	0.576	1.301	2.250	1.870
Infor. Ratio	0.012	0.053	NA	0.170	0.184	0.138	0.037	0.083	0.144	0.119
Germany										
Mean Ret. (%)	−0.094	0.032	−0.145**	NA	0.457*	0.069	−0.051	0.125	0.196	0.056
Median Ret. (%)	−0.107	0.190	−0.012	NA	−0.003	−0.033	0.097	0.114	0.143	0.097
Std. Dev. (%)	4.111	3.409	0.866	NA	3.326	1.328	2.667	3.349	2.500	1.979
t-Stat.	−0.359	0.146	−2.619	NA	2.154	0.818	−0.301	0.588	1.231	0.445
Infor. Ratio	−0.023	0.009	−0.167	NA	0.137	0.052	−0.019	0.037	0.078	0.028
Japan										
Mean Ret. (%)	−0.492	−0.358	−0.497*	−0.348	NA	−0.288	−0.425	−0.267	−0.286	−0.382*
Median Ret. (%)	−0.005	0.091	−0.320	0.003	NA	−0.111	0.040	0.066	0.101	−0.019
Std. Dev. (%)	4.136	3.682	3.185	3.224	NA	3.227	3.493	3.566	3.155	2.886
t-Stat.	−1.867	−1.526	−2.448	−1.694	NA	−1.401	−1.908	−1.174	−1.422	−2.077
Infor. Ratio	−0.119	−0.097	−0.156	−0.108	NA	−0.089	−0.121	−0.075	−0.091	−0.132
Swiss										
Mean Ret. (%)	−0.147	−0.019	−0.196	−0.052	0.396	NA	−0.106	0.074	0.138	−0.007
Median Ret. (%)	0.007	0.163	−0.109	0.033	0.111	NA	0.095	0.115	0.147	0.077
Std. Dev. (%)	4.279	3.674	1.576	1.326	3.297	NA	2.851	3.586	2.666	2.275
t-Stat.	−0.539	−0.081	−1.952	−0.611	1.882	NA	−0.584	0.322	0.811	−0.050
Infor. Ratio	−0.034	−0.005	−0.124	−0.039	0.120	NA	−0.037	0.021	0.052	−0.003
U.K.										
Mean Ret. (%)	−0.022	0.112	−0.028	0.123	0.555*	0.189	NA	0.209	0.304	0.163
Median Ret. (%)	−0.066	0.342	−0.206	−0.097	−0.040	−0.095	NA	0.152	0.180	0.100
Std. Dev. (%)	3.767	3.200	2.604	2.691	3.664	2.909	NA	3.233	2.643	2.354
t-Stat.	−0.090	0.547	−0.167	0.717	2.376	1.020	NA	1.012	1.805	1.083
Infor. Ratio	−0.006	0.035	−0.011	0.046	0.151	0.065	NA	0.065	0.115	0.069
U.S.										
Mean Ret. (%)	−0.209	−0.087	−0.165	−0.014	0.399	0.055	−0.105	NA	0.152	−0.018
Median Ret. (%)	−0.113	−0.059	−0.100	−0.114	−0.066	−0.115	−0.152	NA	0.001	−0.141
Std. Dev. (%)	2.826	1.317	3.241	3.334	3.675	3.607	3.218	NA	2.678	2.272
t-Stat.	−1.159	−1.038	−0.799	−0.066	1.702	0.241	−0.510	NA	0.888	−0.124
Infor. Ratio	−0.074	−0.066	−0.051	−0.004	0.109	0.015	−0.033	NA	0.057	−0.008

The dataset consists of monthly returns for individual currencies from January 1980 through June 2000. The period consists of 246 months. The base currency is denoted on the far left and the columns to the right give the return statistics of the seven other currencies with respect to the base currency. MSCI and Equal currency returns are calculated relative to the base currency. The MSCI column is calculated using the MSCI weights excluding the base currency. The Equal column calculates the currency return assuming an equal proportion allocated to the seven non-domestic currencies. ** and * indicate significance at the 1% and 5% levels, respectively.

Japanese yen relative to the Australian dollar, the Canadian dollar, the French franc, the German mark, and the British pound.[6]

[6]Throughout the paper, we assume currency returns are normally distributed when determining statistical significance. This assumption is incongruous with the fact that the reciprocals of normally distributed variables have Cauchy densities with infinite variance. For the strategies outlined later in this paper, the bootstrap simulations given in Table 8 may provide a more accurate measure of statistical significance.

Table 2 provides similar summary statistics for the interest-adjusted currency returns. These are the actual returns that an investor would face when trading in the currency markets. Of particular note, the interest-adjusted returns are much smaller in magnitude than the base currency returns. Any trading strategy relying on these returns would have a much higher hurdle to overcome to exceed a benchmark of simply holding the MSCI-weighted or Equal-weighted benchmark basket of currencies. Note that on an interest-adjusted basis the rankings of performance differ markedly from Table 1. The Swiss franc is now the worst performing currency, even though it was one of the strongest for base currency returns. (A high value for the MSCI-weighted and Equal-weighted benchmark with each base currency indicates positive returns to buying foreign currencies.) The Australian dollar's interest-adjusted performance is no longer quite so poor, and the Japanese yen has an interest-adjusted return very close to zero in magnitude.

The strategy for the paper is to simulate the performance of moving average rules, using the base currency returns to determine the currency allocations and the interest-adjusted currency returns to compute the actual realized returns. Thus, this strategy would mimic the returns an investor would earn through the use of futures contracts or borrowing in one currency to invest in another. The strategy is very simple: use the base currency returns to compute a short-run and a long-run moving average applying prior monthly returns for each currency relative to the domestic base, rank the seven non-domestic currencies by the short-run moving average less the long-run moving average difference, then initiate a long position in the currency with the highest rank and short the currency with the lowest rank. To test the generality of our results, the strategy will be repeated using all eight currencies as the base currency of reference.[7]

We now need to define the moving average rules. At time t the short-run moving average and the long-run moving averages are computed as

$$\text{SR}_{j,t} = \frac{R_{B,t} + (j-1)\text{SR}_{j,t-1}}{j}, \tag{6}$$

$$\text{LR}_{k,t} = \frac{R_{B,t} + (k-1)\text{LR}_{k,t-1}}{k}, \tag{7}$$

where $\text{SR}_{j,t}$ is the short-run moving average at month t using the prior j months of returns and $\text{LR}_{k,t}$ is the long-run moving average at month t using the prior k months of returns.[8]

In the presentation of the results, we will not focus on any one moving average rule. Instead, the strategy will determine the currency allocations using many short-run/long-run moving average combinations at each month t. The moving average specifications will then be equally weighted to determine a weighted allocation for each currency. For example, if we use three different moving average rules and two of the three give a buy signal to the U.S. dollar and one gives a buy

[7]Since it is highly unlikely that a random variable and its reciprocal are identically distributed, the analysis and resulting inference should be substantiated across multiple base currencies. An examination using only one base currency simply cannot provide a sufficient statistical basis to extrapolate the results.

[8]Return-based momentum strategies are more appropriate as the price momentum strategy would tend to favor currencies with greater price adjustments such as the yen. The largest change in price may not reflect the largest change in percentage terms.

TABLE 2

Descriptive Statistics (Interest-Adjusted Currency Returns)

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.	MSCI	Equal
Australia										
Mean Ret. (%)	NA	0.076	−0.007	−0.104	0.145	−0.145	0.105	0.021	0.084	0.013
Median Ret. (%)	NA	−0.162	−0.290	−0.363	−0.618	−0.671	−0.081	−0.183	−0.242	−0.366
Std. Dev. (%)	NA	2.800	4.017	4.193	4.334	4.414	3.837	2.931	3.085	3.274
t-Stat.	NA	0.426	−0.029	−0.388	0.525	−0.517	0.430	0.111	0.426	0.062
Infor. Ratio	NA	0.027	−0.002	−0.025	0.033	−0.033	0.027	0.007	0.027	0.004
Canada										
Mean Ret. (%)	0.001	NA	−0.069	−0.169	0.088	−0.209	0.048	−0.050	0.018	−0.051
Median Ret. (%)	0.162	NA	−0.225	−0.362	−0.415	−0.482	−0.290	−0.095	−0.057	−0.295
Std. Dev. (%)	2.756	NA	3.325	3.419	3.814	3.724	3.244	1.359	1.876	2.357
t-Stat.	0.006	NA	−0.325	−0.775	0.361	−0.880	0.231	−0.572	0.148	−0.342
Infor. Ratio	0.000	NA	−0.020	−0.049	0.023	−0.056	0.015	−0.037	0.010	−0.022
France										
Mean Ret. (%)	0.165	0.180	NA	−0.100	0.193	−0.141	0.154	0.119	0.157	0.082
Median Ret. (%)	0.291	0.225	NA	−0.135	−0.114	−0.207	0.219	−0.132	−0.005	−0.023
Std. Dev. (%)	3.940	3.336	NA	0.876	3.272	1.588	2.624	3.287	2.410	1.867
t-Stat.	0.659	0.845	NA	−1.784	0.927	−1.397	0.921	0.569	1.019	0.685
Infor. Ratio	0.042	0.054	NA	−0.114	0.059	−0.089	0.059	0.036	0.065	0.044
Germany										
Mean Ret. (%)	0.276	0.287	0.107*	NA	0.299	−0.042	0.260	0.226	0.268	0.202
Median Ret. (%)	0.364	0.363	0.135	NA	−0.152	−0.134	0.391	0.116	0.259	0.239
Std. Dev. (%)	4.114	3.439	0.856	NA	3.329	1.338	2.704	3.376	2.515	1.981
t-Stat.	1.053	1.308	1.965	NA	1.407	−0.489	1.507	1.049	1.669	1.598
Infor. Ratio	0.067	0.083	0.125	NA	0.090	−0.031	0.096	0.067	0.107	0.102
Japan										
Mean Ret. (%)	0.035	0.054	−0.089	−0.190	NA	−0.241	0.043	−0.009	0.012	−0.057
Median Ret. (%)	0.621	0.416	0.114	0.152	NA	−0.143	0.492	0.271	0.388	0.284
Std. Dev. (%)	4.176	3.733	3.195	3.239	NA	3.260	3.535	3.612	3.191	2.914
t-Stat.	0.133	0.228	−0.436	−0.922	NA	−1.158	0.190	−0.039	0.061	−0.305
Infor. Ratio	0.008	0.014	−0.028	−0.059	NA	−0.074	0.012	−0.002	0.004	−0.020
Swiss										
Mean Ret. (%)	0.336	0.348	0.167	0.060	0.350	NA	0.316	0.286	0.323	0.266
Median Ret. (%)	0.676	0.484	0.208	0.134	0.143	NA	0.517	0.348	0.329	0.302
Std. Dev. (%)	4.310	3.726	1.578	1.340	3.324	NA	2.901	3.639	2.709	2.306
t-Stat.	1.221	1.465	1.657	0.698	1.650	NA	1.711	1.233	1.869	1.810
Infor. Ratio	0.078	0.093	0.106	0.045	0.105	NA	0.109	0.079	0.119	0.115
U.K.										
Mean Ret. (%)	0.040	0.057	−0.085	−0.186	0.087	−0.231	NA	−0.001	0.035	−0.046
Median Ret. (%)	0.081	0.291	−0.218	−0.390	−0.490	−0.514	NA	−0.024	−0.116	−0.105
Std. Dev. (%)	3.785	3.245	2.632	2.708	3.671	2.932	NA	3.268	2.674	2.382
t-Stat.	0.164	0.277	−0.506	−1.078	0.370	−1.234	NA	−0.003	0.208	−0.300
Infor. Ratio	0.011	0.018	−0.032	−0.069	0.024	−0.079	NA	−0.000	0.013	−0.019
U.S.										
Mean Ret. (%)	0.063	0.068	−0.012	−0.112	0.142	−0.153	0.107	NA	0.079	0.015
Median Ret. (%)	0.183	0.095	0.132	−0.115	−0.270	−0.347	0.024	NA	−0.124	−0.030
Std. Dev. (%)	2.869	1.356	3.266	3.354	3.698	3.643	3.274	NA	2.706	2.307
t-Stat.	0.346	0.787	−0.057	−0.526	0.604	−0.660	0.515	NA	0.461	0.101
Infor. Ratio	0.022	0.050	−0.004	−0.033	0.038	−0.042	0.033	NA	0.029	0.007

The dataset consists of interest-adjusted monthly returns for individual currencies from January 1980 through June 2000. The period consists of 246 months. The base currency is denoted on the far left and the columns to the right give the return statistics of the seven other currencies with respect to the base currency. MSCI and Equal currency returns are calculated relative to the base currency. The MSCI column is calculated using the MSCI weights excluding the base currency. The Equal column calculates the currency return assuming an equal proportion allocated to the seven non-domestic currencies
** and * indicate significance at the 1% and 5% levels, respectively.

signal to the German mark, then two-thirds of our long portfolio will be allocated to dollars and one-third to marks.

In this analysis, the short-run moving average values range from one to 12 months, while the long-run moving average values range from two to 36 months. For all combinations of short-run/long-run moving average rules, the number of months used to compute the short-run moving average must be less than the number of months used to compute the long-run moving average. For example, using a short-run moving average of one month, we determine the currency positions using: $(\mathrm{SR}_{1,t} - \mathrm{LR}_{2,t}, \mathrm{SR}_{1,t} - \mathrm{LR}_{3,t}, \ldots, \mathrm{SR}_{1,t} - \mathrm{LR}_{36,t}$. Using a short-run moving average of two months, we determine the currency positions using: $\mathrm{SR}_{2,t} - \mathrm{LR}_{3,t}, \mathrm{SR}_{2,t} - \mathrm{LR}_{4,t}, \ldots, \mathrm{SR}_{2,t} - \mathrm{LR}_{36,t}$. In total, we evaluate 354 moving average combinations.[9]

At the end of each month for each individual moving average combination, the seven non-domestic currencies are ranked from best to worst by using the return-based momentum indicator, which is equal to the short-run moving average less the long-run moving average. The currency that has the largest positive deviation is the most attractive and is defined as Rank 1, the currency that is second most attractive is Rank 2, and so on for other rankings. The currency determined to be the most unattractive is Rank 7. These rankings are determined using each of the 354 moving average rules. Each short-run/long-run moving average rule will determine a Rank 1 and a Rank 7 currency. Our approach is to give equal weight to each of the short-run/long-run moving average combinations, and therefore to determine a weighted allocation for each of the non-domestic currencies. Positions are then taken through futures and held for a month. On a monthly basis, the rankings are reevaluated and new positions are taken if warranted.

We focus on four possible strategies using the short-run/long-run moving average combinations. First, as described above, we consider a strategy that provides equal weight to all momentum strategies where the short-run moving average rules range from one to 12 months and the long-run moving average rules range from two to 36 months. In all cases, the number of months used to compute the short-run moving average must be less than the number of months used to compute the long-run moving average. *Strategy one* will consist of 354 equally weighted moving average combinations. This strategy will invest in the currency with the highest rank determined by the difference between the short-run and long-run moving average and will short the currency with the lowest rank. *Strategy two* will use the same moving average rules as *strategy one*, but instead of investing in only the Rank 1 currency will give a one-third weight to each of the top three ranks and continue to short the lowest rank. *Strategy three* is identical to *strategy one* except that it will only consider moving average combinations with the short-run moving average months ranging from four to six, and the long-run moving average months ranging from five to 36. In total, *strategy three* will consist of 93 equally weighted moving average combinations. *Strategy four* is identical to *strategy two* with the exception that it also will only consider moving average combinations with short-run months ranging from four to six and long-run months ranging from five to 36. With all the strategies, many of the individual moving average rules will rank the currencies in exactly the same order. Table 3 gives a summary of these strategies.

As specified in equations (4) and (5), the moving average rules will use *base currency returns* when determining the short-run/long-run moving average

[9]In additional tests, we do analyze the profitability to each of the 354 strategies in isolation, however, this ex post analysis is not the focus of the paper. We can state that nearly all of the 354 strategies generate mean returns greater than zero, the MSCI benchmark, and the Equal benchmark. This will be discussed below with Table 4. By averaging across moving average specifications, we adopt a more conservative approach as some moving average rules will prove to be much more profitable (ex post) than others.

TABLE 3
Definition of Strategies

Strategy	Moving Average Rule Range	Long/Short
One	[1, 2]–[12, 36] (354 equally weighted MA combinations)	Long Rank 1 Short Rank 7 (for each MA combination)
Two	[1, 2]–[12, 36] (354 equally weighted MA combinations)	Long Rank 1 Long Rank 2 Long Rank 3 (equal weight to top 3 ranks) Short Rank 7 (for each MA combination)
Three	[4, 5]–[6, 36] (93 equally weighted MA combinations)	Long Rank 1 Short Rank 7 (for each MA combination)
Four	[4, 5]–[6, 36] (93 equally weighted MA combinations)	Long Rank 1 Long Rank 2 Long Rank 3 (equal weight to top 3 ranks) Short Rank 7 (for each MA combination)

Each month from January 1980 through June 2000 each currency is ranked from 1 to 7 based upon the difference between the short-run moving average and long-run moving average of prior returns using either 354 (*strategy one* and *strategy two*) or 93 (*strategy three* and *strategy four*) different combinations. Each of the returns to the moving average combinations are given equal weight each month, generating monthly returns for strategies 1 to 4. In the above table, the notation [1, 2] corresponds to a ranking of individual currencies using the difference between a short-run moving average with parameter 1 and a long-run moving average using the parameter 2. The notation [1, 2]–[12, 36] would imply considering all short-run/long-run moving average combinations where the short-run moving average parameter ranges from 1 to 12 and the long-run moving average parameter ranges from 1 + the short-run moving average parameter to 36.

ranks.[10] The actual realized returns, however, will depend upon the *interest-adjusted returns.* As Table 2 shows, the interest-adjusted returns are generally markedly smaller in magnitude than the base currency returns. The tests are repeated using each currency as the base currency.

III. Results

Table 4 presents summary measures regarding the performance of the strategies considered in this paper from January 1980 through June 2000. We will initially confine our analysis to an examination of the performance of *strategy one* and *strategy two.* We can easily observe that these two strategies perform quite well over the entire sample period for all base currencies of reference. Across the base currencies, the mean monthly return to the moving average strategies ranges from 45 to 60 basis points each month. In all cases, these mean monthly returns are significantly different from zero.[11] The mean return for *strategy one,* [Rank 1–Rank 7], is slightly greater than that for *strategy two,* [Rank(1, 2, 3)–Rank 7]. However, *strategy one* in all cases has a higher level of risk than does *strategy two.* If we evaluate the strategies using the information ratio (mean return divided by standard deviation), we see that for all currencies *strategy two* outperforms

[10]The tests were repeated using *interest-adjusted returns* to determine the currency ranks. The results were nearly exactly identical to those presented here.

[11]We did not include a transactions cost in the analysis. Most studies use a 10 basis point round-trip transactions cost for trading in currency futures markets.

strategy one.[12] As a basis for comparison, the information ratios of *strategy one* and *strategy two* for each base currency are slightly greater than the Sharpe ratios of their respective equity markets.[13]

No consensus exists regarding the appropriate benchmark for risk adjusting the strategies. If currency returns are unpredictable, one might argue the appropriate benchmark is a zero expected return. On the other hand, an appropriate benchmark might be to maintain a currency exposure with the same composition as a broad international index such as the MSCI. However, using the MSCI-weighted currency index may likewise be an inappropriate benchmark to use to evaluate currency performance. The MSCI has, at times, given excessive weight to one individual currency—most recently, the U.S. dollar. As a basis of comparison, a benchmark that equally weights currency exposure should also be relevant. These

TABLE 4

Performance of Long/Short Strategies (January 1980–June 2000)

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.
Strategy One								
Mean Ret. (%)	0.601**	0.532*	0.545**	0.549**	0.466*	0.456*	0.480*	0.505*
Median Ret. (%)	0.806	0.512	0.619	0.574	0.563	0.587	0.600	0.525
Std. Dev. (%)	2.934	3.252	3.238	3.224	3.207	3.180	3.387	3.294
Infor. Ratio	0.205	0.164	0.168	0.170	0.145	0.143	0.142	0.153
Interest Diff. (%)	0.106	0.096	0.101	0.101	0.093	0.084	0.085	0.111
Prob > 0 (%)	63.415	60.163	60.163	61.382	57.724	58.130	60.569	59.350
Prob > MSCI (%)	56.504	59.756	54.065	56.098	52.846	53.252	56.504	55.691
paired *t*-test	0.783	1.302	0.808	1.386	2.701**	1.215	0.636	1.251
Wilcoxon test	2.014*	3.156**	0.936	1.500	−0.589	0.432	1.999*	1.097
Prob > Equal (%)	55.285	58.130	56.504	58.130	58.943	56.911	57.317	59.350
paired *t*-test	1.098	1.637	1.389	2.073*	3.117**	1.864	1.177	1.970*
Wilcoxon test	0.962	2.043*	1.584	1.698	2.181*	1.602	1.807	2.589**
Proportion > 0 (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Proportion > MSCI (%)	92.655	100.000	94.068	100.000	100.000	98.305	91.808	100.000
Proportion > Equal (%)	98.023	100.000	99.718	100.000	100.000	100.000	99.153	100.000
Strategy Two								
Mean Ret. (%)	0.597**	0.511**	0.537**	0.552**	0.520**	0.461**	0.505**	0.468*
Median Ret. (%)	0.857	0.526	0.740	0.615	0.594	0.641	0.745	0.625
Std. Dev. (%)	2.634	2.785	2.831	2.789	2.820	2.730	2.985	2.887
Infor. Ratio	0.227	0.183	0.190	0.198	0.184	0.169	0.169	0.162
Interest Diff. (%)	0.107	0.075	0.091	0.097	0.061	0.080	0.076	0.083
Prob > 0 (%)	64.634	61.789	62.195	63.415	63.008	60.569	64.634	61.382
Prob > MSCI (%)	56.098	58.537	53.659	53.252	54.472	53.659	58.130	54.878
paired *t*-test	0.803	1.385	0.843	1.532	3.016**	1.330	0.786	1.244
Wilcoxon test	1.749	2.506*	0.860	−0.196	0.081	0.651	2.835**	0.712
Prob > Equal (%)	56.504	59.350	58.943	62.602	57.317	56.911	59.350	61.382
paired *t*-test	1.134	1.750	1.485	2.299*	3.470**	2.038*	1.377	2.046*
Wilcoxon test	1.496	2.520*	2.688**	3.607**	0.980	1.330	2.712**	3.584**
Proportion > 0 (%)	100.000	100.000	100.000	100.000	99.718	100.000	100.000	100.000
Proportion > MSCI (%)	91.808	99.153	96.045	99.435	100.000	98.870	96.610	99.153
Proportion > Equal (%)	97.740	100.000	99.435	99.718	100.000	100.000	99.435	100.000

(continued on next page)

[12]We chose to use the information ratio instead of the Sharpe ratio as no consensus exists regarding the appropriate risk-free rate for a zero-cost, zero expected return strategy in international currency markets.

[13]If we use the average three-month yield as the proxy for the risk-free rate to each base currency, the monthly Sharpe ratios for the respective equity markets are as follows: Australia 0.089; Canada 0.098; France 0.175; Germany 0.154; Japan 0.085; Swiss 0.168; U.K. 0.145; and U.S. 0.177.

TABLE 4 (continued)

Performance of Long/Short Strategies (January 1980–June 2000)

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.
Strategy Three								
Mean Ret. (%)	0.685**	0.597**	0.631**	0.601**	0.505*	0.527*	0.536*	0.593*
Median Ret. (%)	0.907	0.532	0.679	0.623	0.581	0.388	0.645	0.498
Std. Dev. (%)	3.303	3.606	3.603	3.593	3.534	3.554	3.774	3.628
Infor. Ratio	0.207	0.166	0.175	0.167	0.143	0.148	0.142	0.163
Interest Diff. (%)	0.097	0.094	0.089	0.096	0.085	0.081	0.086	0.105
Prob > 0 (%)	61.789	60.976	60.976	60.569	58.943	59.350	59.350	59.756
Prob > MSCI (%)	57.317	55.691	55.285	54.878	54.065	56.504	56.098	56.911
paired *t*-test	1.026	1.456	1.070	1.486	2.684**	1.395	0.789	1.492
Wilcoxon test	2.282*	0.939	1.594	0.932	−0.075	2.003*	1.680	1.451
Prob > Equal (%)	55.285	59.756	56.098	57.724	56.098	58.130	58.130	58.130
paired *t*-test	1.312	1.760	1.613	2.114*	3.066**	2.002*	1.295	2.173*
Wilcoxon test	0.833	2.771**	1.365	1.626	0.624	2.133*	2.144*	1.659
Proportion > 0 (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Proportion > MSCI (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Proportion > Equal (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Strategy Four								
Mean Ret. (%)	0.693**	0.589**	0.608**	0.601**	0.602**	0.516**	0.536*	0.557**
Median Ret. (%)	0.858	0.590	0.750	0.653	0.640	0.547	0.700	0.606
Std. Dev. (%)	2.952	3.103	3.136	3.076	3.096	3.054	3.326	3.155
Infor. Ratio	0.235	0.190	0.194	0.195	0.194	0.169	0.161	0.176
Interest Diff. (%)	0.109	0.078	0.089	0.101	0.058	0.086	0.079	0.086
Prob > 0 (%)	65.041	61.382	60.976	62.195	63.415	60.569	60.569	61.382
Prob > MSCI (%)	57.317	58.943	52.439	53.659	54.878	51.626	56.098	56.911
paired *t*-test	1.101	1.612	1.095	1.659	3.178**	1.489	0.863	1.520
Wilcoxon test	2.144*	2.563*	0.149	0.068	0.004	−0.650	1.737	1.473
Prob > Equal (%)	57.317	61.382	58.537	60.976	59.350	54.878	59.350	60.163
paired *t*-test	1.397	1.933	1.703	2.377*	3.599**	2.160*	1.419	2.289*
Wilcoxon test	1.705	3.344**	2.575*	2.884**	1.887	0.179	2.750**	2.619**
Proportion > 0 (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Proportion > MSCI (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Proportion > Equal (%)	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000

The base currency is denoted at the top of each column. The mean monthly return is denoted with an asterisk if it is significantly different from zero. The information ratio is the ratio of mean return to standard deviation. The interest differential details the return due to the interest differential between the non-domestic and domestic currency. The [Prob >] rows give the percentage of the total months that the given strategy exceeded zero, the MSCI benchmark, and the Equal benchmark. The paired *t*-test is used to test the significance of the excess returns of the strategies relative to the MSCI and the Equal benchmark. The Wilcoxon is a nonparametric test of the excess returns. The [Proportion >] rows give the percentage of the individual MA rules for each strategy that exceeds zero, the MSCI benchmark, and the Equal benchmark average return. ** and * indicate significance at the 1% and 5% levels, respectively.

benchmarks are computed using the base currency returns presented in Table 1.[14]

The paired *t*-tests presented in Table 4 measure the statistical significance of excess returns for the short-run/long-run moving average strategies against the MSCI-weighted and Equal-weighted benchmarks.[15] The Wilcoxon test is a nonparametric test of the statistical significance of the excess returns. Related to an examination of excess returns, Table 4 also provides the percentage of months the strategies had a positive return, a return greater than the MSCI-weighted benchmark, and a return greater than the Equal-weighted benchmark.

[14]An additional benchmark not tested might be a policy of completely hedging currency exposure through the use of futures contracts. In this case, the benchmark expected return would be the interest rate differentials. The average interest rate differential may be calculated by subtracting the mean return to the MSCI-weighted and Equal-weighted currency benchmarks of Table 1 from Table 2. Because these differences are typically lower in magnitude than the base currency returns identified in Table 1, any test that shows significance relative to the base currency returns would likely have even greater significance using interest rate differentials.

[15]This test is identical to the standard *t*-test for statistical significance on excess returns.

For all base currencies, the short-run/long-run moving average strategies had a positive return in about 60% of the months. The probabilities that the returns were greater than the MSCI-weighted and Equal-weighted benchmarks were also greater than 50% for all base currencies, and for most currencies were above 55%. For most base currencies, either the paired *t*-test or the Wilcoxon test also showed the strategies to yield statistically significant excess returns. However, the statistical significance of the short-run/long-run moving average returns was, in general, not as great with the MSCI-weighted and Equal-weighted benchmarks as it was with the zero benchmark.

In addition to considering the returns to the strategies, we examine the proportion of the 354 individual moving average strategies that have average returns greater than the three individual benchmarks. We see that for all base currencies nearly all, if not all, of the strategies outperform all of the benchmarks. We may therefore state that over the duration of the sample period the exact parameterization of the moving average rule matters little.[16] The results we present are robust to the technical trading rule employed.[17]

The *forward premium anomaly* is well known in currency markets. In simple terms, the fact that currencies with high relative interest rates tend to appreciate with respect to low interest rate currencies gives rise to the forward premium anomaly.[18] We can indirectly test whether our results are simply another manifestation of this empirical regularity by examining the return due to the interest differentials for each of the strategies. Recall from equation (4) that the interest differential gives the portion of return due to the spread in relative interest rates between two currencies. A positive interest differential indicates that the strategy tends to invest in higher relative interest rate currencies or short lower interest rate currencies.

Consistent with the forward premium anomaly, every strategy in every base currency has a positive interest differential. However, the magnitude of the interest differential is very small—typically less than 10 basis points each month. In additional tests, we examined a simple approach of buying the currency with the highest interest rate and shorting the currency with the lowest interest rate. In general, we found that the risk/return profile and the specific currency composition differed substantially from the strategies documented in this paper. Because the interest differentials are so small in magnitude, the returns to our strategies are primarily due to changes in currency value. As a result of the relatively tiny magnitude of the interest differential, we do not expect that the profitability of the strategies is entirely (or even substantially) due to the forward premium anomaly.

In sum, the short-run/long-run moving average strategies clearly outperform a benchmark of zero over the entire sample period. Relative to the MSCI-weighted and Equal-weighted benchmarks, the results are less conclusive but continue to

[16] We show in Table 6, however, that for significantly long subperiods certain specifications of moving average rules will strongly outperform alternative parameterizations.

[17] In additional tests, we replicated the analysis using momentum as defined by Jegadeesh and Titman (1993) (prior one-, three-, six-, nine-, and 12-month currency returns) instead of moving average rules to determine the long and short currency positions. In general, we found the moving average rules to work much better than Jegadeesh and Titman momentum in currency markets. The table documenting this analysis can be provided upon request.

[18] See Froot and Thaler (1990) for an excellent discussion of the forward premium anomaly.

provide evidence of outperformance. Clearly, if it is believed that expected interest-adjusted currency returns are zero, the moving average strategies should provide an excess return of about 5%–6% per year.[19]

While the overall results are insensitive to the exact specification of the moving average strategy, direct examination of the average performance with the parameterizations does reveal some to be more reasonable than others. Table 5 presents summary measures for *strategy one* and *strategy two*. Examination of the individual results revealed these strategies generally outperform alternative parameterizations.[20] In all cases, limiting the moving average rules to a tighter range increases the performance of the strategies by five to 10 basis points per month on average. That is, by tightening the specification, the additional return gained would likely cover the total transactions cost to the moving average strategies.

Direct examination of the individual rank returns reveals a general downtrend in average performance as we move from Rank 1 to Rank 7 currencies. It is interesting to note, though, that in all cases outside the U.S. the Rank 2 currency actually outperforms Rank 1. This, in part, was the motivation behind the tests for *strategy two* and *strategy four*. We should also note that for many currencies the return to the long/short strategy may rely primarily on either the long or the short position. For example, from Table 1 we clearly see that both the Japanese yen and the Swiss franc have been the strongest performing currencies during the previous 20 years. However, while the Japanese yen has experienced the bulk of its returns from the short side, the Swiss franc has generated all of its returns through buying foreign currencies. This result can easily be explained by examining Table 2. Currencies with relatively low interest-adjusted returns have generated most of their returns through buying higher yielding currencies while currencies with relatively high interest-adjusted returns have experienced the greatest returns on the short side. While the Japanese yen has historically offered very low yields, its appreciation has been substantial enough to offset the interest yields to investing in foreign currencies. The Swiss franc, while also offering relatively low yields, did not appreciate sufficiently to offset the rewards to investing in higher yielding currencies.

One final point can be made concerning Table 5. For all base currencies, we find a downtrend in the interest differential as we move from the Rank 1 to the Rank 7 currency. We see that the difference is typically very small—on the order of 10 basis points, but once again we find very limited evidence that the currencies with the greatest appreciation tended to offer the relatively greater yields.

Table 6 provides subperiod analysis for *strategy one* (given in the row with the short-run moving average range from 1 to 12), *strategy three* (given in the row with the short-run moving average range from 4 to 6), the MSCI-weighted currency benchmark, the Equal-weighted currency benchmark, as well as long-short

[19]The tests were repeated with the Japanese yen excluded from the analysis. The mean returns to the strategies were only marginally and never significantly lower. The overall results were not materially affected.

[20]We should note that the specifications for *strategy three* and *strategy four* were determined after direct examination of the results and may not be optimal for future periods. We will examine this issue more closely when we present the results in Table 6.

TABLE 5

Individual Rank Analysis for *Strategies One* and *Two* (January 1980–June 2000)

	Rank						
	1	2	3	4	5	6	7
Australia							
Mean Ret. (%)	0.254	0.262	0.234	0.029	−0.120	−0.222	−0.347
Median Ret. (%)	0.021	−0.126	−0.214	−0.301	−0.478	−0.427	−0.724
Std. Dev. (%)	3.593	3.426	3.456	3.643	3.683	3.522	3.673
Infor. Ratio	0.071	0.077	0.068	0.008	−0.032	−0.063	−0.095
Interest Diff. (%)	−0.243	−0.222	−0.261	−0.269	−0.289	−0.314	−0.349
Canada							
Mean Ret. (%)	0.185	0.204	0.102	−0.088	−0.117	−0.301	−0.347
Median Ret. (%)	0.095	0.082	−0.185	−0.259	−0.404	−0.563	−0.412
Std. Dev. (%)	2.769	2.556	2.581	2.887	2.908	2.820	3.039
Infor. Ratio	0.067	0.080	0.040	−0.030	−0.040	−0.107	−0.114
Interest Diff. (%)	−0.097	−0.112	−0.144	−0.140	−0.153	−0.176	−0.193
France							
Mean Ret. (%)	0.315	0.384**	0.218	0.156	−0.050	−0.222	−0.231
Median Ret. (%)	0.091	0.266	0.204	0.017	−0.036	−0.290	−0.147
Std. Dev. (%)	2.785	2.341	2.407	2.402	2.140	2.150	2.647
Infor. Ratio	0.113	0.164	0.091	0.065	−0.023	−0.103	−0.087
Interest Diff. (%)	−0.096	−0.113	−0.110	−0.133	−0.153	−0.196	−0.197
Germany							
Mean Ret. (%)	0.417*	0.474**	0.370*	0.245	0.131	−0.092	−0.132
Median Ret. (%)	0.435	0.420	0.300	0.292	0.138	−0.023	−0.057
Std. Dev. (%)	2.818	2.371	2.432	2.506	2.263	2.258	2.764
Infor. Ratio	0.148	0.200	0.152	0.098	0.058	−0.041	−0.048
Interest Diff. (%)	0.182	0.172	0.179	0.153	0.141	0.109	0.081
Japan							
Mean Ret. (%)	0.125	0.301	0.109	−0.014	−0.220	−0.356	−0.342
Median Ret. (%)	0.615	0.555	0.380	0.275	−0.026	0.134	−0.008
Std. Dev. (%)	3.509	3.131	3.014	3.180	3.188	3.420	3.444
Infor. Ratio	0.035	0.096	0.036	−0.004	−0.069	−0.104	−0.099
Interest Diff. (%)	0.386	0.348	0.327	0.342	0.310	0.273	0.292
Swiss							
Mean Ret. (%)	0.474*	0.504**	0.460**	0.261	0.177	−0.032	0.018
Median Ret. (%)	0.506	0.476	0.469	0.414	0.339	0.050	0.092
Std. Dev. (%)	3.084	2.583	2.705	2.698	2.528	2.567	3.088
Infor. Ratio	0.154	0.195	0.170	0.097	0.070	−0.012	0.006
Interest Diff. (%)	0.300	0.292	0.296	0.268	0.275	0.258	0.216
U.K.							
Mean Ret. (%)	0.175	0.207	0.219	0.014	−0.246	−0.383*	−0.305
Median Ret. (%)	−0.053	0.079	0.031	−0.204	−0.246	−0.378	−0.330
Std. Dev. (%)	2.977	2.799	2.570	2.829	2.785	2.679	3.193
Infor. Ratio	0.059	0.074	0.085	0.005	−0.089	−0.143	−0.095
Interest Diff. (%)	−0.169	−0.171	−0.192	−0.224	−0.213	−0.238	−0.254
U.S.							
Mean Ret. (%)	0.255	0.203	0.198	−0.016	−0.095	−0.192	−0.250
Median Ret. (%)	0.335	0.057	0.133	−0.165	−0.142	−0.224	−0.333
Std. Dev. (%)	2.720	2.548	2.594	2.900	2.909	2.731	2.990
Infor. Ratio	0.094	0.080	0.077	−0.006	−0.032	−0.070	−0.084
Interest Diff. (%)	0.091	0.073	0.028	0.020	0.018	0.011	−0.019

Each month each currency is ranked from 1 to 7 based upon the difference between the short-run and long-run moving average of prior returns using 354 different short-run/long-run moving average combinations ranging from [1, 2] to [12, 36]. Each of the moving average combinations are given equal weight each month, generating monthly returns for ranks 1 to 7. The base currency is denoted on the far left. The mean monthly return to each rank is denoted with an asterisk if it is significantly different from zero. The information ratio is the ratio of the mean return to the standard deviation. The interest differential details the return due to the interest differential between the non-domestic and domestic currency. ** and * indicate significance at the 1% and 5% levels, respectively.

strategies that use alternative short-run moving average ranges. For example, the short-run moving average range row given as (1–3) uses exactly the same approach as *strategy three* except that instead of confining the short-run moving average range between 4 and 6, it uses the range of 1 to 3. The analysis is divided into five-year intervals across all base currencies.

TABLE 6

Subperiod and Sensitivity Analysis (Mean Return of Rank 1–Rank 7)

Short-Run MA Range	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.
1980–1984								
(1–12)	0.587	0.507	0.695	0.576	0.821*	0.370	0.402	0.526
(1–3)	0.561	0.533	0.775*	0.549	0.875**	0.320	0.422	0.595
(4–6)	0.699	0.624	0.759	0.656	0.828*	0.423	0.420	0.672
(7–9)	0.528	0.380	0.582	0.482	0.726*	0.292	0.352	0.370
(10–12)	0.549	0.471	0.632	0.617	0.844*	0.458	0.408	0.426
MSCI	0.313	0.023	1.337**	0.885*	−0.099	0.680	1.017**	−0.441
Equal	−0.142	−0.460	0.980**	0.457	−0.590	0.244	0.563	−0.687*
1985–1989								
(1–12)	0.941*	0.843	0.786	0.856	0.726	0.760	0.989	0.697
(1–3)	0.352	0.274	0.170	0.245	0.264	0.002	0.336	0.202
(4–6)	1.017*	0.830	0.800	0.847	0.673	0.777	0.993	0.713
(7–9)	1.265**	1.266*	1.194*	1.273*	1.045	1.231*	1.461*	1.065
(10–12)	1.286**	1.157	1.149*	1.232*	1.065	1.241*	1.341*	0.939
MSCI	0.605	0.241	−0.414	−0.609	−0.648	−0.417	−0.097	0.863*
Equal	0.838	0.443	−0.302	−0.505	−0.371	−0.308	0.062	0.698
1990–1994								
(1–12)	0.446	0.266	0.246	0.299	−0.040	0.294	0.162	0.328
(1–3)	0.815*	0.677	0.694	0.753	0.562	0.627	0.541	0.608
(4–6)	0.564	0.455	0.423	0.413	0.105	0.454	0.282	0.491
(7–9)	0.239	0.036	0.008	0.081	−0.395	0.135	0.010	0.140
(10–12)	0.032	−0.269	−0.317	−0.214	−0.643	−0.179	−0.332	−0.045
MSCI	0.295	0.576*	0.124	0.107	−0.542	−0.018	0.350	0.379
Equal	0.211	0.522	0.000	−0.017	−0.538	−0.157	0.214	0.151
1995–2000								
(1–12)	0.447	0.513	0.463	0.472	0.368	0.406	0.378	0.470
(1–3)	0.341	0.547	0.498	0.525	0.422	0.368	0.420	0.467
(4–6)	0.482	0.490	0.549	0.499	0.423	0.460	0.457	0.504
(7–9)	0.490	0.532	0.501	0.541	0.363	0.495	0.388	0.514
(10–12)	0.498	0.474	0.268	0.287	0.231	0.291	0.211	0.383
MSCI	0.358	0.019	0.337	0.383	0.106	0.291	−0.020	−0.163
Equal	0.261	−0.113	0.220	0.269	−0.062	0.174	−0.157	−0.214
1980–2000								
(1–12)	0.601**	0.532*	0.545**	0.549**	0.466*	0.456*	0.480*	0.505*
(1–3)	0.513**	0.509*	0.533*	0.518*	0.528*	0.330	0.429	0.468*
(4–6)	0.685**	0.597**	0.631**	0.601**	0.505*	0.527*	0.536*	0.593*
(7–9)	0.627**	0.553*	0.570*	0.593**	0.433	0.537*	0.549*	0.522*
(10–12)	0.589**	0.459	0.429	0.476*	0.371	0.449	0.402	0.425
MSCI	0.392*	0.210	0.346*	0.196	−0.286	0.138	0.304	0.152
Equal	0.291	0.093	0.224	0.056	−0.382*	−0.007	0.163	−0.018

Table 6 gives the mean monthly returns (in percent) to a strategy that initiates a long position in the Rank 1 currency and shorts the Rank 7 currency where a currency's rank is determined by its short-run/long-run moving average difference. The short-run moving averages used for a given test are specified in column 2 and the associated long-run rules range from 1 + the short-run moving average parameter value to 36. For example, if the short-run moving average range is (1–3) then all short-run/long-run moving average strategies from [1, 2] to [3, 36] are evaluated and the resulting performance is averaged. The MSCI and Equal rows give the MSCI-weighted and Equal-weighted currency returns during the appropriate time period for each base currency. The mean monthly returns are denoted with an asterisk if they are significantly different from zero. ** and * indicate significance at the 1% and 5% levels, respectively.

Because of the relatively high standard deviation of the strategies and the limited number of months in each subperiod, the results are, in general, not statistically significant. With the exception of Japan from 1990–1994, *strategy one* and *strategy three* have positive mean returns in all subperiods for all base currencies. The results appear to be the strongest during the 1980s for most of the base currencies. The outcomes during 1990–1994 appear to have been the weakest.

We can use Table 6 to evaluate the stability for specific ranges of moving average rules. For example, using a short-run moving average range of 7 to 9 or 10 to 12 would have performed extremely well from 1985–1989. However, these same rules were the worst performing from 1990–1994. It is interesting to note that the optimal strategies (ex post) are highly correlated across the base currencies no matter whether the base currency is strongly appreciating or rapidly depreciating.[21] We easily see from Table 6 the dangers to selecting a single, optimal technical trading specification ex post. This was the primary motivation behind the approach we take in this paper. While we make no claim to be able to predict the optimal moving average specification, it does appear, however, that the performance with following a short-run moving average strategy above 7 is much more volatile than with the lower ranges. Finally, the results are not sensitive to the moving average rules employed. In general, the returns for *strategy one* and *strategy three* exceeded the returns of the three benchmarks in all subperiods.[22]

We have found that a very simple moving average strategy can generate positive excess returns across multiple time periods and also multiple countries. Papers such as Kho (1996) suggest that the performance of such strategies in currency markets could be due to a time-varying risk premium. Kho's paper, in particular, tests a moving average strategy using weekly currency data.

While a time-varying risk premium could, in fact, explain the performance of technical trading strategies with intra-day, daily, or weekly data, many reasons exist to doubt the validity of that explanation for the results in this study. First, most of the studies test for the existence of time-varying risk premia through the use of univariate or multivariate GARCH models. It is well known that monthly return data, in general, does not possess GARCH characteristics. Second, Kho in particular shows his result to be due to a time-varying covariance with the broad world market index. Most long/short strategies have a near zero covariance with the market.[23] Finally, as we will show, no evidence exists that large returns in magnitude are correlated with future large returns in magnitude for the short-run/long-run moving average strategies.

Table 7 presents the autocorrelations of the monthly and squared monthly returns to the long/short strategies. We do find evidence of weak negative autocorrelation in the returns to the strategies—particularly at the fourth lag, however, tests of the joint significance of the first 10 autocorrelations typically fail at the 5% significance level. In all cases for the squared monthly returns, the autocorrelations are close to zero and statistically insignificant. Large magnitude returns are not followed by large magnitude returns for the strategies identified in this paper. In additional tests, we used a GARCH model to test for the existence of time-varying volatility. As expected, we found the relation between current volatility and prior volatility to be statistically insignificant for the strategies identified in this paper. We can state with a strong degree of confidence that the results of this paper cannot be explained by a time-varying risk premium.

Since we are fairly confident that time-varying risk cannot explain the results, we now wish to further narrow the possible explanations. Since the strategies

[21]In separate tests, we did find the correlations to the strategies to be quite high across base currencies—typically above 0.9.

[22]The most notable exceptions are France, Germany, Switzerland, and the U.K. relative to the MSCI benchmark from 1980–1984.

[23]In additional tests, we found the correlation between the strategies identified in this paper and the local equity market, the MSCI-weighted equity index, the Equal-weighted currency index, and the MSCI-weighted currency index to be very close to zero.

TABLE 7

Autocorrelation and GARCH Analysis *(Strategy One)*

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.
Autocorrelations Returns								
1	−0.138*	−0.092	−0.125	−0.124	−0.059	−0.107	−0.099	−0.079
2	0.014	−0.015	−0.008	−0.013	−0.005	−0.021	−0.032	−0.009
3	−0.036	−0.007	−0.018	−0.010	0.007	−0.014	−0.041	−0.024
4	−0.135*	−0.088	−0.138*	−0.140*	−0.164*	−0.135*	−0.153*	−0.155*
5	0.099	0.104	0.103	0.100	0.104	0.071	0.116	0.104
6	−0.105	−0.028	−0.011	−0.011	0.009	0.034	−0.035	−0.003
7	0.108	−0.001	−0.018	−0.014	−0.051	−0.017	−0.031	−0.022
8	−0.071	0.085	0.077	0.079	0.125	0.077	0.048	0.072
9	−0.069	−0.116	−0.117	−0.119	−0.079	−0.128	−0.082	−0.107
10	0.019	−0.023	−0.008	−0.014	−0.003	−0.039	0.006	0.005
LBP(10)	19.738*	12.039	15.963	16.116	16.071	14.799	14.690	14.335
p-value	(0.968)	(0.718)	(0.899)	(0.904)	(0.902)	(0.860)	(0.856)	(0.842)
Autocorrelations Squared Returns								
1	0.034	0.017	0.036	0.040	0.034	0.057	0.005	0.015
2	−0.009	0.007	0.006	−0.002	0.060	−0.020	0.044	−0.013
3	−0.069	−0.043	−0.058	−0.048	−0.002	−0.043	−0.038	−0.025
4	0.075	−0.033	0.027	0.021	0.023	0.033	0.033	0.029
5	−0.022	−0.039	−0.048	−0.053	−0.035	−0.047	−0.027	−0.048
6	−0.014	−0.042	−0.041	−0.040	0.011	−0.049	−0.054	−0.026
7	0.008	0.053	0.057	0.054	0.079	0.082	0.031	0.042
8	0.098	0.054	0.040	0.058	0.073	0.061	0.025	0.056
9	−0.057	0.046	0.053	0.055	0.061	0.038	0.051	0.022
10	−0.052	−0.066	−0.081	−0.076	−0.066	−0.070	−0.035	−0.064
LBP(10)	6.864	4.560	5.813	5.833	6.441	6.866	3.313	3.536
p-value	(0.262)	(0.081)	(0.169)	(0.171)	(0.223)	(0.262)	(0.027)	0.034
GARCH								
c	0.003	0.006	0.008	0.009	0.017	0.017	0.018	0.013
γ	0.098	0.009	−0.069	−0.123	−0.348	−0.374	−0.375	−0.216
ω	0.000*	0.001	0.001	0.001	0.001*	0.001	0.001	0.001
α_1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
α_2	0.025	0.012	0.019	0.014	0.022	0.019	0.019	0.018
β	0.157	0.045	0.051	0.101	0.000	0.000	0.166	0.017

Table 7 presents the autocorrelations to returns and squared returns for *strategy one*. The base currency is denoted at the top of each column. The Ljung and Box *Q*-statistic is denoted as LBP(10) and tests whether the 10 autocorrelations are jointly significant. The *p*-value for the *Q*-statistic is given below the LBP(10) row. The GARCH model estimated is as

$$\tilde{r}_t = c + \gamma\sigma_{t-1} + \tilde{\varepsilon}_t$$

where

$$\begin{aligned} \tilde{\varepsilon}_t &= \tilde{z}_t\sigma_t \\ \tilde{z}_t &= N[0,1] \\ \sigma_t^2 &= \omega + \alpha_1\varepsilon_{t-2}^2 + \alpha_2 I(\varepsilon_{t-1}) + \beta\sigma_{t-1}^2 \\ I(\varepsilon_{t-1}) &= \varepsilon_{t-1} \quad \text{if} \quad \varepsilon_{t-1} > 0 \\ &= 0 \quad \text{if} \quad \varepsilon_{t-1} \leq 0. \end{aligned}$$

Standard errors for the GARCH parameter estimates are computed using Quasi Maximum Likelihood. ** and * indicate significance at the 1% and 5% levels, respectively.

use multiple currencies, it is possible that the performance is due to the cross-correlations among the currencies. In addition, the differential mean return of the currencies might explain the significant moving average results. Some currencies have tended to fall in relative value over the testing period while others have generally appreciated. It is possible that the strategies defined are simply taking advantage of this general trend. Another theory, somewhat supported by the evidence in Table 7, is that the returns to the strategies might be due to a complicated function of the autocorrelation process underlying the interest-adjusted return series. Finally, the performance of the moving average strategy might be explained by the most basic reason of all: higher overall risk.

A bootstrap methodology was employed to determine if the correlations across currency returns or the differential mean return could explain the performance of the moving average strategy with each of the base currencies. The bootstrap method randomly selected with replacement a row of base currency returns and the associated interest-adjusted returns from the 246 rows of data available. In this way, a new data set was generated possessing all the original characteristics of the original data with the exception of the original autocorrelation structure. From this new data set, the results to the short-run/long-run moving average returns were generated in exactly the same fashion as in Table 4. One completion of this cycle constituted one simulation. This process was repeated 1,000 times for each base currency.

Table 8 presents summary results for *strategy one.* Similar results were found with the other three strategies. For various measures of performance, Table 8 gives the mean from the simulation and the count of the number of simulations that were less than the actual value from Table 4. For example, 1,000 out of 1,000 simulations for the moving average strategy had a mean return less than the actual mean return of 0.601% in Australia. For Canada, 999 of the 1,000 simulations had a mean return to the moving average strategy less than the actual mean return of 0.532%. Table 8 clearly shows that the results depend upon the autocorrelation structure in the original interest-adjusted returns data. In addition, it is interesting to note that the interest differential in the bootstrap tests is much smaller in magnitude than that revealed in the actual results. The correlation structure and the mean for the interest-adjusted currency returns do not explain the statistical significance of the moving average returns.[24]

Table 8 allows us to determine the extent to which risk contributes to the performance of *strategy one.* First, note that for all base currencies the bootstrap standard deviations of *strategy one* are slightly but not significantly lower than the actual standard deviations given in Table 4. The risk of *strategy one* remains but performance deteriorates markedly when the underlying autocorrelation process is scrambled. Second, in the bootstrap simulations pseudo MSCI-weighted and pseudo Equal-weighted currency indices were generated and then evaluated relative to the simulated returns to *strategy one.* In nearly every case, the bootstrap performance of *strategy one* relative to the pseudo MSCI-weighted and pseudo Equal-weighted currency benchmarks was significantly less than the actual performance documented in Table 4. We feel confident in stating that the strategies documented in this paper have positive risk-adjusted returns.[25]

The bootstrap tests also allow an indirect examination as to whether using an incorrect proxy for the short-term interest rate can explain our results. The bootstrapped data will possess the same potential bias as the original data caused by using the three-month interest rate instead of the one-month interest rate to determine the arbitrage-free futures prices. Because the strategies identified in the paper do not work with the bootstrapped data, we can state that any bias that

[24]In additional work, we examined the autocorrelations for the interest-adjusted currency returns reported in Table 2. Nearly all of the autocorrelations were statistically insignificant and no clear patterns emerged in the autocorrelation structure.

[25]In the bootstrap tests, we also examined higher moments of the distribution, but did not find any evidence that skewness or kurtosis could explain our results.

TABLE 8

Bootstrap Simulations *(Strategy One)*

	Australia	Canada	France	Germany	Japan	Swiss	U.K.	U.S.
Mean Ret.								
Sim. Mean (%)	−0.003	−0.003	−0.004	−0.003	0.006	−0.008	−0.011	−0.002
Sim. Count <	1000	999	999	999	988	992	993	998
Median Ret.								
Sim. Mean (%)	0.010	0.006	0.007	0.007	0.009	0.002	0.002	0.013
Sim. Count <	1000	995	999	999	997	999	999	997
Std. Dev.								
Sim. Mean (%)	2.802	3.020	3.005	2.988	2.914	2.845	3.075	3.027
Sim. Count <	777	859	866	872	939	946	938	885
Infor. Ratio								
Sim. Mean (%)	−0.001	−0.001	−0.001	−0.001	0.002	−0.003	−0.004	−0.001
Sim. Count <	998	995	995	998	985	983	986	991
Interest Diff.								
Sim. Mean (%)	0.018	0.018	0.016	0.016	0.012	0.013	0.018	0.020
Sim. Count <	996	988	993	998	999	978	976	999
Prob > 0 (%)								
Sim. Mean (%)	50.188	50.083	50.094	50.160	50.126	50.035	50.036	50.138
Sim. Count <	1000	99	999	1000	986	992	1000	999
Prob > MSCI (%)								
Sim. Mean (%)	49.282	49.607	47.292	48.671	49.299	48.508	48.983	50.436
Sim. Count <	983	998	985	990	850	918	994	932
Prob > Equal (%)								
Sim. Mean (%)	50.104	50.830	48.174	50.280	50.315	50.748	50.010	51.229
Sim. Count <	937	988	992	992	995	968	986	992
Proportion > 0 (%)								
Sim. Mean (%)	49.023	49.246	49.010	49.005	50.603	47.739	47.916	48.808
Sim. Count <	954	951	952	952	944	951	949	953
Proportion > MSCI (%)								
Sim. Mean (%)	9.091	21.032	9.611	22.863	83.519	30.558	13.670	30.305
Sim. Count <	984	990	988	984	510	942	971	961
Proportion > Equal (%)								
Sim. Mean (%)	16.143	37.276	18.369	40.689	91.272	50.328	26.857	52.632
Sim. Count <	967	957	993	947	379	900	962	889

For each base currency, each simulation builds a dataset consisting of 246 months by randomly selecting interest-adjusted monthly returns with replacement for the other seven currencies. In the simulated dataset for each base currency, each currency is ranked from 1 to 7 based upon the difference between the short-run and long-run moving average of prior returns using 354 different short-run/long-run moving average (MA) combinations ranging from [1–2] to [12–36]. Each of the MA combinations are given equal weight each month, generating a simulated series of monthly returns to the individual rankings. The simulations are repeated 1,000 times for each base currency. The (Sim. Mean) gives the average of the simulated values for the relevant statistic and the (Sim. Count <) gives the count of the number of simulations that are less than the actual value of the statistic from the original data. Each base currency is listed at the top of each of the columns.

does exist from using an incorrect proxy for the short-term interest rate does not contribute to our findings.

In addition to the autocorrelation structure, another possible reason these strategies have continued to persist during the previous two decades is that they are not risk free. Figure 1 presents rolling 12-month returns and excess returns for *strategy one* with respect to the MSCI-weighted currency benchmark using the U.S. dollar as the base currency.[26] Figure 1 reveals that strictly following the strategy identified in this paper would lead to significant time periods when performance could be negative or seriously underperform the MSCI-weighted currency benchmark. Comparison of Table 1 with Table 4 reveals that, with the notable exception of Australia and possibly Japan, the moving average strategies have higher standard deviations than the MSCI-weighted and the Equal-weighted currency benchmarks. However, we should emphasize that the tests in Table 4 and

[26]The results were very similar for all strategies across all base currencies.

Table 8 showed excess returns to be, on average, significantly positive. Moreover, the standard deviation of the strategies is typically less than the standard deviation for individual currencies. The strategies may have higher risk, but this alone does not explain the higher returns to the moving average strategies.

FIGURE 1

Rolling 12-Month *Strategy One* Returns (U.S.)

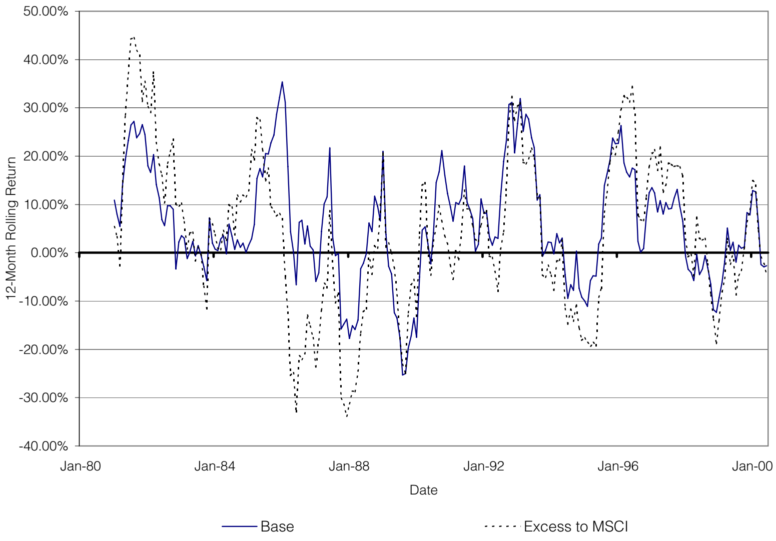

Figure 1 displays the rolling 12-month base and excess returns for *strategy one* using the U.S. dollar as the base currency. The rolling 12-month excess returns are relative to the U.S. MSCI-weighted currency index.

At this stage, we have eliminated the differential mean returns across currencies, the correlation structure across currencies, and, most likely, time-varying risk premia as possible explanations for the performance of the short-run/long-run moving average strategies. We have also determined that the autocorrelation structure in the original data is a necessary precondition to the findings of the paper. Perhaps most importantly and most basically, the strategies may also have higher returns because they have higher risk. Greater risk, however, is not a sufficient condition to our findings.

IV. Conclusion

Our results indicate that the potential exists for investors to generate excess returns in foreign exchange markets by adopting a momentum strategy using the moving average rules identified in this paper. It is not at all apparent that foreign exchange markets operate in an efficient manner and that returns are determined entirely by fundamental information. In fact, very simple technical rules can generate quite significant returns beyond those that can be explained by transactions costs or risk.

The strategies identified are robust to the time period of analysis, the base currency of reference, and the benchmark of comparison. The long/short returns do not possess any of the risk characteristics we would expect of an asset impacted by time-varying risk premia. We have determined the results are not driven by the long-term drift of the currencies, the cross-correlation structure across the currencies, or by the differential risk levels of the currencies. While risk may explain a portion of the long/short returns, it is not sufficient to generate the levels of returns witnessed in this paper. We do know that the autocorrelation structure in the underlying currency return data is necessary to the success of the long/short strategy and we also find very limited evidence that the results may be minimally affected by the forward currency premium anomaly.

Unlike many prior studies of technical trading rules in foreign exchange markets, the strategies we have identified do not require frequent trading. We have simply applied the Jegadeesh and Titman technique to a small sample of eight assets—the eight currencies. These strategies would be most appropriate for an international fund manager who wishes to generate additional returns for the base portfolio. In addition, a manager in a large multi-national might also wish to make use of the techniques identified to more effectively allocate foreign exchange exposures.

Beyond refuting the hypothesis of a time-varying risk premium and determining that the performance is due to the original structure in the data, we have made no attempt to explain the strong results in this paper. Our results are largely consistent with those in Sweeney (1986), Schulmeister (1988), Surajaras and Sweeney (1992), Levich and Thomas (1993), Taylor (1994), Kho (1996), Neely, Weller, and Dittmar (1997), and LeBaron (1999). We have documented that the type of momentum strategy used in Jegadeesh and Titman (1993), (2000) in equity markets is effective in foreign exchange markets as well. While central bank intervention might explain a portion of the results for foreign exchange, the fact that this strategy is profitable in equities as well forces us to examine additional explanations. Future papers might wish to examine the economic or behavioral rationale to the underlying structure of the foreign exchange data. Perhaps the returns to the long/short strategy are due to the economic cycle. Perhaps they are due to underreaction or overreaction to the release of news. Perhaps trend chasing and noise traders determine the short-term direction of the foreign exchange market. What we do know is that a very simple momentum strategy has been profitable for the previous 20 years.

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