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ABSTRACT
The adaptive markets hypothesis posits that trading strategies evolve as traders adapt their behavior to changing circumstances. This paper studies the evolution of trading strategies for a hypothetical trader who chooses portfolios from foreign exchange (forex) technical rules in major and emerging markets, the carry trade, and U.S. equities. A backtesting procedure chooses optimal portfolios that outperform nonadaptive rules. We also find that forex trading alone dramatically outperforms the S&P 500, with at least twice the Sharpe ratio over the whole sample, but there is little gain to coordinating forex and equity strategies, which explains why practitioners consider these tools separately. Forex trading returns dip significantly in the 1990s but recover and outperform an equity position since 1998. Overall, trading rule returns still exist in forex markets—with substantial stability in the types of rules—though they have migrated to emerging markets to a considerable degree.

Keywords: exchange rate, technical analysis, technical trading, efficient markets hypothesis, adaptive markets hypothesis

JEL Codes: F31, G14, G11, G15

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1. Introduction

The literature on technical analysis has established that simple technical trading rules on dollar exchange rates provided 15 years of positive, risk-adjusted returns during the 1970s and 1980s before those returns were extinguished (Levich and Thomas, 1993; LeBaron, 2002; Olson 2004).[1] More recently, more complex and less studied rules have produced more modest returns for a similar length of time (Neely et al., 2009). Researchers have extensively investigated explanations that rely on risk adjustment and/or central bank intervention but found that these do not plausibly justify the observed excess returns produced by simple technical trading rules, nor can data mining explain the apparent profitability of technical analysis (Neely et al., 2009).

Andrew Lo's (2004) adaptive markets hypothesis (AMH) offers a plausible explanation for this technical trading puzzle, however. The AMH posits that profit opportunities will generally exist in financial markets but that learning and competition will gradually erode these opportunities as they become known. A core principle of the AMH is that traders learn over time, adapting their behavior to changing circumstances. This suggests that one should expect to see an evolution of strategies and desired investment currencies. In the context of technical trading in the foreign exchange market, a number of studies have confirmed the prediction that profits associated with particular rules will gradually decline as more traders learn about them.

But another important prediction of the AMH, that adaptive trading strategies will show superior performance to simple fixed rules, has been largely ignored. The present paper focuses on examining this prediction. Ideally, one might like to examine the evolution of technical trading strategies by directly looking at the trading records of technicians. As these data are not available, an alternative approach is to consider how a hypothetical trader would have adapted to

[1] Menkhoff and Taylor (2007) and Neely and Weller (2012) review the literature on technical analysis in the foreign exchange market from different perspectives.

changing market conditions using simple rules of thumb. Traders face a number of practical problems as they choose strategies to maximize their welfare. How to choose rules, individually or as part of a portfolio? How to combine technical rules in foreign exchange (forex) with carry trade or equity strategies? In practice, traders must make these choices by backtesting rules on existing data. In this paper we model adaptive behavior in terms of a simple backtesting procedure applied to a group of commonly used technical and carry-trade rules in tradable currencies.[2]

Specifically, we investigate whether a hypothetical trader could use past performance of trading rule-currency pairs—i.e., combinations of a specific trading rule applied to a particular exchange rate—to predict future performance and construct a dynamic trading strategy superior to individual trading rules. To mimic the decision process of a forex trader, we construct a dynamic strategy as follows: We start with a pool of rule-currency pairs (including carry trades) and rank them at month *t* according to the Sharpe ratio over some past time window.[3] We then form portfolios of the highest-ranked *N* rules and measure the return to the portfolio over month *t* + 1. Each month individual rule-currency pairs are re-ranked and the results of the ex ante ranking are allowed to determine the composition of the portfolio for the next month.

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[2] This paper considers the lessons learned by a hypothetical trader who chooses trading strategies and portfolios by backtesting from a group of commonly used technical and carry-trade rules in tradable currencies. Researchers have independently examined both technical trading rules and the carry trade (Brunnermeier et al., 2009; Jordà and Taylor, 2009; Farhi et al., 2009; Burnside et al., 2011a, 2011b; Menkhoff et al., 2012a,b) and practitioners widely use both sorts of trading strategies, but researchers have done little comparison between them (Menkhoff et al., 2012b).

[3] Given that none of the returns appear to have systematic risk, the Sharpe ratios allow one to easily compare performance from strategies with differing volatility. Ingersoll, Spiegel, Goetzmann, and Welch (2007) demonstrate how a clever fund manager can dynamically manipulate his portfolio to maximize his Sharpe ratio. The manager essentially reduces (increases) the size of his investments after a successful (unsuccessful) investment run to increase the relative weight of more positive outcomes. The dynamic strategies studied in this paper do not change leverage over time and so the Sharpe ratios calculated here are not subject to this problem. Therefore, we focus on Sharpe ratios as our metric for rule/strategy performance.

In addition, we investigate whether such a trader would benefit from an adaptive approach to diversification. Given the well-documented fact that currency trading rule returns typically display very low correlation with stock market returns, one would expect that combining equity with a dynamic currency trading strategy would substantially improve over the latter.

What does our trader learn? Backtesting works well. Past performance clearly *does* predict the future: Rule-currency pairs that are more highly ranked in backtesting have higher ex post Sharpe ratios. Indeed, the Sharpe ratio of the dynamic trading strategy is much superior to that of the S&P 500. The success of backtesting supports the prediction that an adaptive trading strategy fares better than using fixed rules. It also suggests that the positive results in the literature are not due to data mining. The backtesting methodology is fairly robust to the selection window. Both ex ante optimal and 1/*N* portfolios produce very good Sharpe ratios in every subsample, clearly exceeding those of their constituent rules. The ex ante optimal forex combinations are somewhat more profitable than 1/*N* portfolios over the entire sample.

The research does, however, confirm a dip in the profitability of major investment currencies in the 1990s and a switch to emerging market currencies in the 1990s. In contrast, the types of rules chosen are fairly stable over time, with the exception of the increased importance of the carry trade from the mid-1990s.

There is no payoff to diversifying across equities and currencies. We show that this finding is consistent with the observed levels of excess return and volatility in currency and equity markets. Given the substantially higher Sharpe ratio of the dynamic currency strategy, the equity allocation in the optimally diversified portfolio is rather small and so equity’s impact on performance is also very small, even ignoring parameter uncertainty and sampling error. This lack of benefit to active diversification is consistent with the prevalence of the previously puzzling “compartmentalization” of forex and equity trading activities by practitioners.

We also find that the selection strategies do not select the bilateral carry trades in the top-ranked rules until the mid-1990s. The fact that carry trade strategies did not measure up well to the best-ranked technical rules might in part explain the almost complete lack of academic interest in the carry trade before 2006. For example, Google Scholar reports only 5 articles with the phrase “carry trade” in the title from 1990 through 2005 but 98 since 2005.

In studying how a trader would have learned about the properties of adaptive rules, our paper differs from the vast majority of research on technical trading. Early papers considered the profitability of simple nonadaptive (static) technical rules (e.g., Sweeney (1986)), or the statistical significance of this profitability (e.g., Levich and Thomas (1993)). Later papers evaluated more complex nonadaptive rules (Osler (2003, 2005)) or considered explanations for the profitability of nonadaptive rules, such as central bank intervention (LeBaron (1999) and Neely (2002)) or data mining (Neely et al (2009)). Neely et al (2009), for example, ruled out data mining as an explanation for technical rule success by examining the true, ex post out-of-sample profitability of several sets of fixed, nonadaptive rules from previous papers. Several papers have looked at time variation in the profitability of nonadaptive rules (Levich and Thomas (1993) and Neely et al (2009)).

We wish to emphasize, however, that this paper does not test the AMH. We believe that existing evidence suggests that the AMH is the most plausible explanation for the changing patterns of profitability in forex markets but we recognize that this remains a hypothesis. Rather, we examine the actions of a hypothetical trader to discover what such a trader would have learned and how those lessons reflect on other observed patterns in the forex market.

Two studies examine trading strategies with adaptive features, although they differ from our approach in important respects. Olson (2004) dynamically selects the best moving average rule for each of 18 developed market currencies in successive 5-year periods from 1971–2000 and then tests these in successive 5-year out-of-sample periods. He finds that returns declined from the 1970s to about zero in the 1990s. Okunev and White (2003) construct momentum strategies by using moving averages to identify the strongest and weakest momentum currencies. The strategies thus switch between different currencies over time. The authors find that the returns generated by these momentum strategies appear to have been more persistent, at least until the end of their sample in 2000.

2. Methodology

We examine the performance of portfolios of technical trading rules that are rebalanced monthly by applying a performance criterion. We use a standard pool of rules that we consider representative of those that the academic literature has investigated: 7 filter rules, 3 moving average rules, 3 channel rules, and 1 carry trade rule.[4]

A filter rule generates a buy signal for a foreign currency when the exchange rate (dollar price of foreign currency) has risen by more than y percent above its most recent low. It generates a sell signal when the exchange rate has fallen by more than the same percentage from its most recent high. Thus,

$$z_t = \begin{array}{lll} 1 & \text{if} & S_t \geq n_t(1+y) \\ -1 & \text{if} & S_t \leq x_t(1-y), \\ z_{t-1} & & \text{otherwise,} \end{array}$$

where z_t is an indicator variable that takes the value +1 for a long position and –1 for a short position. We denote the exchange rate at date t (\$ per unit of foreign currency) by S_t; n_t is the

[4] Dooley and Shafer (1984) and Sweeney (1986) look at filter rules; Levich and Thomas (1993) look at both filter and moving average rules; and Taylor (1994) looks at channel rules, for example.

most recent local minimum and x_t the most recent local maximum. The seven filter rules have filter sizes (y) of 0.005, 0.01, 0.02, 0.03, 0.04, 0.05, and 0.1.

A moving average rule generates a buy signal when a short-horizon moving average of past exchange rates crosses a long-horizon moving average from below. It generates a sell signal when the short moving average crosses the long moving average from above. We denote these rules by vma(S, L), where S and L are the number of days in the short and long moving averages, respectively. The moving average rules are vma(1, 5), vma(5, 20), and vma(1, 200). Thus, vma(1, 5) compares the current exchange rate with its 5-day moving average and records a buy (sell) signal if the exchange rate is currently above (below) its 5-day moving average.

A channel rule counsels to buy (sell) if the price exceeds (is less than) the maximum (minimum) over the previous n days plus (minus) the band of inaction (x).[5] Thus,

$$z_t = \begin{cases} 1 & \text{if} \quad S_t \geq \max\left(S_{t-1}, S_{t-2}, \ldots S_{t-n}\right)(1+x) \\ -1 & \text{if} \quad S_t \leq \min\left(S_{t-1}, S_{t-2}, \ldots S_{t-n}\right)(1-x), \\ z_{t-1} & \text{otherwise.} \end{cases}$$

We set n to be 5, 10, and 20, and x to be 0.001 for all rules.

We consider an individual currency carry trade in which the rule takes a long position if the overnight interest rate for the foreign currency is greater than the dollar rate and a short position otherwise. This is the form of bilateral carry trade examined by Burnside et al. (2011a).

We thus generate a pool of 14 rules applied to 14 dollar exchange rates: British pound (GBP), Swiss franc (CHF), Australian dollar (AUD), Canadian dollar (CAD), Swedish krona (SEK), Hong Kong dollar (HKD), Singapore dollar (SGD), Korean won (KRW), Japanese yen

[5] We define the channel rule following Taylor (1994). Sullivan et al. (1999) instead call this rule a “support-and-resistance” rule. Sullivan et al.’s (1999) definition of the channel rule is similar to Taylor’s (1994), but the rule is conditioned on a formed channel—that is, the minimum and maximum over the last n days must be within a certain distance of each other.

(JPY), South African rand (ZAR), Thai baht (THB), Czech koruna (CZK), Russian ruble (RUB), and Deutschmark/euro (DEM/EUR). The series for the DEM was spliced with that for the EUR after January 1, 1999.

We sort all rules with at least 500 days of data (since the beginning of the respective samples) by Sharpe ratio. There is a maximum of (14*14=) 196 rules on any given day, but missing data for some exchange rates often leave fewer than half that number of rules. The ranking and rebalancing procedures are performed every 20 business days. Thus, the top-ranked portfolio's returns will be generated by a given trading rule applied to a particular currency for a minimum of 20 days, at which point it may (or may not) be replaced by another rule applied to the same or a different currency.

In any study of trading performance—especially when using exotic currencies—it is important to pay close attention to transaction costs. Rules and strategies that may appear to be profitable when such costs are ignored turn out not to be attractive once the appropriate adjustments have been made. The impact of transaction costs depends both on their magnitude and on the frequency with which positions are changed. For example, in research on intraday technical trading strategies Neely and Weller (2003) found that realistic transaction costs eliminated very high gross excess returns in the case of four highly liquid currencies, the German mark, the Japanese yen, the British pound and the Swiss franc. This result was driven by the high trading frequencies for the rules considered. In the case of emerging market currencies the size of the spread plays an important role. Burnside, Eichenbaum and Rebelo (2007) found that bid-ask spreads for emerging market currencies over the period 1997 to 2006 were between two and four times as large as those for developed market currencies. Thus using the same transaction cost for all currencies will exaggerate the relative profitability of trading in emerging market currencies.

In order to account for variation in transaction costs both over currencies and over time we used Bloomberg data on one-month forward bid-ask spreads when available as the basis for estimating transaction costs. We discovered, however, that the quoted spreads appear to substantially overestimate the spreads actually available to traders.[6] After comparing spreads from Bloomberg with those on actual trader's screens and then discussing the size of spreads with traders, we concluded that actual spreads were roughly one third of the quoted spreads. Therefore, we calculated transaction costs as follows. Before the spread data from Bloomberg were available (December 1995) the cost of a one-way trade for advanced countries (UK, Germany, Switzerland, Australia, Canada, Sweden, Japan) was set at 5 basis points in the 1970s, 4 basis points in the 1980s and 3 basis points in the 1990s. For all other countries it was set at one third of the average of the first 500 bid-ask observations.[7] Once Bloomberg data become available, we use the figure of one third of the quoted one-month forward spread, except in the case of Hong Kong and Singapore. For those two countries we have only spot spreads. After the same correction (multiplication by one third) we increase the spread by ten percent since that is roughly the amount by which forward spreads exceed spot spreads in our data. We use a minimum of one basis point transaction cost for all currencies. Figure 1 shows the estimated transaction costs for each currency over time. The greater magnitude and volatility of these costs for emerging market currencies is readily apparent.

3. Data

Table 1 shows the 14 countries whose exchange rates—noon Eastern Standard Time buying rates—versus the U.S. dollar (USD) were used. All exchange rates are from the Haver daily

[6] This emerged from correspondence with several foreign exchange traders and with the head of the foreign exchange department of a commercial bank.
[7] The costs during the 1970s and 1980s are consistent with triangular arbitrage estimates originally done by Frenkel and Levich (1975, 1977) and McCormick (1979), and used by Sweeney (1986) and Levich and Thomas (1993).

database. The original source is the Board of Governors of the Federal Reserve System statistical release H.10 (Foreign Exchange Rates). The DEM/USD return series was spliced with the EUR/USD return series at the date of the introduction of the euro, January 1, 1999. We take a conservative view of the periods in which emerging markets currencies can be traded. To avoid periods in which capital controls or market disruption would have prevented actual trading, we restricted simulated trading in the Thai baht and South African rand to start on July 2, 1997, and April 3, 1995, respectively.[8] Our rules stopped simulated trading in the baht after 2006.

The Bank for International Settlements (BIS) provided most of the interest rate data, which were mostly overnight money market rates. For several countries, overnight interbank or money market interest rate series were obtained from their central banks: Australia, Europe, South Korea, Russia, the United States, and the United Kingdom. Interest rate data for Thailand were constructed by splicing a series from the BIS with a series from the Bank of Thailand. Japan's interest rate was constructed by splicing three series: one from the Bank of Japan and two from the BIS. Switzerland, Singapore, and Japanese interest rate data exhibited a few negative values, typically early in the data. We set these interest rate observations to zero for return calculations.

4. The performance criterion

We now turn to the measure of excess return, which is the performance criterion we use in conjunction with the Sharpe ratio for both technical trading rules and the carry trade. We first distinguish between technical trading "rules" and technical trading "strategies." Examples of a technical trading *rule* are a 1% filter applied to the Japanese yen or a moving average rule vma(5, 20) applied to the Hong Kong dollar. A technical trading *strategy* uses some selection criterion to switch between individual rule-currency pairs.

[8] De Zwart et al. (2009) report that the Thai baht was freely traded using deliverable forward contracts from July 1997. A dual exchange rate system was in operation for the rand until March 1995 (Farrell and Todani, 2004).

The rules and therefore also the strategies we consider switch between long and short positions in the foreign currency. We assume that a margin is held in U.S. dollars against borrowing and is reinvested daily at the domestic overnight interest rate. If a trading rule signals a long position in the foreign currency at date *t*, the borrowed dollars are converted to foreign currency at the closing rate for date *t* and earn the foreign overnight rate. We denote the domestic (foreign) overnight interest rate by i_t (i_t^*). Then the excess return, R_{t+1}, to a long position in foreign currency is given by

$$R_{t+1} = \frac{S_{t+1}}{S_t}\frac{(1+i_t^*)}{(1+i_t)}. \tag{1}$$

We denote the continuously compounded (log) excess return by $z_t r_{t+1}$, where z_t is an indicator variable taking the value +1 for a long position and –1 for a short position, and r_{t+1} is defined as

$$r_{t+1} = \ln S_{t+1} - \ln S_t + \ln(1+i_t^*) - \ln(1+i_t). \tag{2}$$

The cumulative excess return from a single round-trip trade (go long at date t, go short at date t + k), with one-way proportional transaction cost c_t, is

$$r_{t,t+k} = \sum_{i=1}^{k} r_{t+i} + \ln(1-c_{t+k}) - \ln(1+c_t) \tag{3}$$

Note that a trading strategy may incur transaction costs even when individual trading rules do not, and conversely. This will happen if a strategy requires a switch between two rules holding different positions but the rules themselves signal no change of position. In this case, the strategy incurs a transaction cost but the individual rules do not. If, on the other hand, a strategy dictates a switch from a rule requiring—let us say, a long position at time *t* to a different rule requiring a long position in the same currency at time $t+1$—then no transaction cost is incurred, even though one or both individual rules may have signaled a change of position from time *t* to $t+1$.

5. Results

5.1 Average rule performance

As a benchmark for comparison, Table 2 presents the average performance of all rules by individual currency. That is, for each exchange rate, we construct an equally weighted portfolio consisting of the 14 rules over the available data. For most currencies the net annual returns are modest—in the range of 0 to 5%—but the Sharpe ratios are respectable, averaging 0.35. About half the exchange rates produce statistically significant net returns. Average trading frequency is modest, ranging from about 9 to 19 trades per year.

5.2 Ex ante strategy performance

Of course, choosing an almost-random group of trading rules and currencies would not be a sensible trading strategy. Some rules may consistently outperform others or the level of performance may vary, with certain rules doing well for a while and then declining. In practice, traders seek to exploit such patterns by choosing rules that "backtest" well. In other words, traders choose rules on the basis of past performance. To emulate this behavior, we construct ex ante portfolios with the simple procedure described in Section 1. After an initial period of 500 business days, we commence the following selection procedure each month (20-day period): We rank all rules according to Sharpe ratio over a selection window at the current date; We then measure the performance of *N* ranked strategies over the next month in an out-of-sample test. To investigate the impact of time variation on rule profitability, we investigated three lengths of selection windows: the full available sample and the 1000- and 500-observation periods prior to the portfolio construction date. We emphasize that all portfolios are constructed with only ex ante information, thus ensuring that traders could have implemented the strategies. Having measured and ranked the N rules by their past performance each month, we then label portfolio strategies according to the rank, *n*, of the rule. Thus the strategy corresponding to $n = 1$ selects the top-ranked rule every 20 days. The strategy corresponding to $n = 2$ selects the second-ranked rule every 20 days, and so on. Thus, strategies with small values of *n* will switch between rules that have had relatively high Sharpe ratios over previous data. The composition of these ex ante strategies will vary with the profitability of rule-exchange rate pairs over time, as markets gradually adapt and agents arbitrage away previously profitable trading opportunities.

Table 3 details the performance of the top 10 ex ante strategies. Thus, portfolio 1 describes the performance of the strategy for which trades are determined each period by the signals of the top-ranked rule. Portfolio 2 describes the performance of the strategy using the signals of the second-ranked rule, and so on. Over the full sample period (April 1975–March 2010), the best ex ante strategy earns a gross annual excess return of 6.53%. Since the strategy trades 13.75 times a year, transaction costs lower the gross return to a net return of 5.95%. The associated Sharpe ratio is a healthy 0.59. Figure 2, which plots the Sharpe ratios for the top 100 ranked strategies, reveals that higher-ranked strategies tend to have better net excess returns and Sharpe ratios.[9] As rank declines, return also declines and becomes more volatile across ranks; this supports the hypothesis that the ranking and selection procedures do indeed improve performance.

Figure 3 illustrates a striking pattern of trade frequency across rank. The top-ranked strategies have the lowest trade frequency, with portfolio 1 trading only 13.75 times a year. Trade frequency rises to reach a maximum of 35.4 trades for strategy 42 and then declines. Note that the trading strategies almost always trade more than individual rules (see Table 2) because of changes made at rebalancing periods when the strategy often switches rules/positions. The pattern is likely to have been influenced by the use of filter rules. Neely et al. (2009) find that filter rules of intermediate size generate the highest excess returns. These rules trade less

[9] A graph of net excess returns by portfolio rank is almost identical, except for scale.

frequently than small filters and more frequently than large ones. In addition small filter rules do better than large ones. These facts would tend to produce the pattern in Figure 3.

We next consider the performance of the strategies over time. Figure 4 shows the net annual excess return over time for the top 5 strategies and for their average. The consistent profitability until the early 1990s emerges clearly, as does the overall decline in performance in 1990 and subsequently. The first conclusion we can draw from this finding is that although a strategy of switching between rules and currencies may mitigate the 1990s' decline in profitability of individual rules, it does not eliminate it. The second conclusion is that profitability returns in the late 1990s. The portfolio of the top 5 ranked strategies has positive Sharpe ratios in 11 of the 14 years from 1997 through 2010 and its average during that period is a very respectable 0.52. Third, the portfolio provides clear diversification benefits. The average annual standard deviations of the individual strategies ranged from 9.1% to 9.6% but the average annual standard deviation of the portfolio was only 6.22%.

5.3 Currency portfolios and diversification

A stylized fact in the literature on technical trading in currency markets is that returns to individual rules and portfolios of rules are uncorrelated with stock returns (e.g., Neely, Weller and Dittmar (1997), Neely and Weller (1999)). Therefore, one would expect significant diversification benefits from combining the returns from a technical trading strategy and a stock market index. One possible approach is to consider the performance of an ex ante optimally weighted portfolio for a mean-variance investor. However, DeMiguel et al. (2009) argue that the naïve 1/*N* allocation rule is more robust and outperforms the optimally weighted portfolio in the context of stock portfolios because means and covariances of returns are imprecisely estimated. This issue has not been investigated in the context of forex rates, however. It is therefore of interest to be able to compare the performance of naïve and optimal portfolios of rules.

We form ex ante optimal portfolios as follows. At each date t, we choose the ex ante best N (N = 10 and N = 50) individual rules according to their Sharpe ratios. We calculate the mean annual excess return and the covariance matrix of the returns to these rules over the previous 500 observations. (Note that this is not the same as the covariance matrix of the trading strategy returns because the identities of the rules making up the strategy change over time.) So, for example, if N = 2 and the best 2 rules according to the selection criterion at time t are “GBP filter 0.005” and “CHF vma(1,5),” then we calculate the mean and covariance matrix for those 2 rules over the previous 500 observations. Denoting the covariance matrix by V_t and the mean return by μ_t, we obtain portfolio weights

$$w_t = V_t^{-1}\mu_t. \tag{4}$$

We set negative weights to zero and scale the weight vector to sum to 1. If the non-negativity constraint is not binding, then these weights maximize the Sharpe ratio of a portfolio consisting of the N rules. Next we compute the return to a portfolio consisting of the N forex rules with optimal weights over period t + 1. We also construct a naïve portfolio consisting of equal weights attached to each of the N rules. Using these sequences of past returns (from currency portfolios with either naïve or optimal weights) and returns on the S&P500 equity index, we use the same procedure to arrive at ex ante optimal weights for the two-asset portfolio consisting of equity and the dynamically rebalanced portfolio of trading rule returns.

We construct 12 different portfolios that vary according to (1) whether they use the top 10 or 50 trading strategies; (2) how the forex trading strategies are constructed (optimal or naïve weights); and (3) whether they use an optimal combination with equity, a naïve (50-50) combination with equity, or no equity in the final portfolio. Table 4 displays the results for these

12 portfolios. For ease of reference, we label the various portfolios as follows:

Optimal currency–optimal equity	OO
Optimal currency–naïve equity	ON
Optimal currency–no equity	OX
Naïve currency–optimal equity	NO
Naïve currency–naïve equity	NN
Naïve currency–no equity	NX

If we also wish to distinguish between 10-rule and 50-rule currency portfolios, we write, for example, OO-10 or ON-50.

Both the portfolios with N = 10 and N = 50 perform very well in almost all subsamples. Table 4 shows that the portfolios NO and OO have Sharpe ratios ranging from 0.82 to 0.92 over the whole sample period (1975–2010). The OO-10 and OO-50 portfolios have similar performances for both the full sample and for all three subsamples. Over the full sample, OO-10 has a Sharpe ratio of 0.82 compared with a value of 0.92 for OO-50. However, there is no evidence of significant diversification benefit from combining the currency portfolio strategies with equity. The overall performance of OX and NX portfolios is not detectably different from that of the OO and NO portfolios. In other words, the high Sharpe ratios are attributable entirely to the currency portfolio strategies. The only subsample for which there is some evidence to the contrary is 1987–98, when the OO-10 portfolio, with a Sharpe ratio of 0.59, outperformed the OX-10 portfolio, which had a Sharpe ratio of 0.43. Naïve combinations of currency and equity tend to perform noticeably worse than the currency portfolios on their own; the only exception again occurs during the long bull market that largely coincided with the 1987–98 subsample.

The absence of any detectable diversification benefit from combining the currency portfolios with equity might appear surprising in light of the fact that they show slightly negative correlations. (The top 10 forex strategies have daily correlations between –0.03 and –0.07 with the S&P 500 total return series over the full sample.) Nonetheless the lack of diversification benefit is perfectly consistent with the measured levels of return and volatility. Over the full sample, the net returns to equity and the dynamic trading strategy OX-10 are 5.67% and 4.70%, respectively, but the Sharpe ratios are 0.35 and 0.78 because the forex returns are much less volatile.[10] To illustrate how such numbers translate into portfolio weights, consider an example in which equity and the dynamic strategy earn the same annual return of 5%, the annual standard deviations of the equity portfolio and dynamic strategy are 15% and 5%, respectively. If the two return series are uncorrelated, then the optimal equity portfolio weight is 0.1. However, the Sharpe ratio of the optimally diversified portfolio is only 5.4% higher than that of the low-volatility dynamic strategy return. If we were to adopt a Bayesian perspective to account for parameter uncertainty, the improvement from diversification would be even smaller. The intuition for the very marginal benefit from diversification is as follows: Excess returns for the two investment strategies are fairly similar, whereas Sharpe ratios are dramatically different because equity returns are much more volatile than currency returns. This means that there are only very modest benefits to diversification even when the two return series are uncorrelated.

Whether or not one finds benefits to diversification depends on the choice of baseline portfolio. Levich and Pojarliev (2011) report that investors with a global equity exposure gain significant diversification by adding returns generated by currency managers. This is certainly what we find for a baseline S&P 500 portfolio. Our result is stronger in that it says that there is no detectable advantage to adding equity exposure to a baseline currency portfolio generated by

[10] Serban (2010) notes the superiority of Sharpe ratios from a forex strategy that combines momentum and mean-reversion elements to an equity position.

our adaptive trading strategy.

Another result of interest is that the OX portfolios substantially outperform equity alone. The last panel of Table 4 shows that the Sharpe ratio of the S&P 500 over the full sample is 0.35, whereas OX-10 (50) has a Sharpe ratio of 0.78 (0.88). Only over the strong (mostly) bull market of 1987–98 does equity outperform the OX portfolios. The most dramatic divergence of performance occurs over the last decade (1999–2010) where for OX-10 (50) the Sharpe ratio is 0.69 (0.51), but for the S&P 500 is only 0.04. In contrast to results in equity markets, there is little evidence to suggest that naïve (1/*N*) portfolios of forex trading strategies outperform optimal portfolios in terms of Sharpe ratios. That is, the average Sharpe ratio produced by the NO, NN, and NX portfolios is almost the same as the average Sharpe ratio produced by the OO, ON, and OX portfolios. In contrast, optimal combinations of the forex strategies with equity (OO and NO) do seem to produce higher Sharpe ratios than the 1/*N* portfolios (ON and NN).

Figure 5 shows the time series of rolling Sharpe ratios for several of the top 10 strategy portfolios, both with and without equity, as well as the rolling Sharpe ratio to a buy-and-hold position in the S&P 500. The top (center) panel displays 1-year rolling Sharpe ratios from the OO-10 and OX-10 (NO-10 and NX-10) strategy portfolios from 1990 to 2010. We choose to start the graphs in 1990 because previous research (e.g., Neely et al., 2009) has dated the decline of traditional currency trading rules to approximately this year. Contrary to the general perception in the literature, forex technical trading rules tend to perform much better over the 2001–10 period than over the 1991–2000 period. This is due to the greater inclusion of emerging market currencies in the latter sample. When only non-emerging currencies are used, the portfolios generally earn negative excess returns in the past decade, consistent with the literature and the results of Pukthuanthong-Le et al. (2007), and Pukthuanthong-Le and Thomas (2008), who find that emerging market currencies appear to provide profit opportunities to technical rules.[11] The bottom panel of Figure 5 displays the 1-year rolling Sharpe ratios to the S&P 500. The ratios are quite variable and show no obvious trend.

5.4 Currency portfolio composition

Our findings support the view that traders could have improved on the performance of individual trading rules by implementing a simple backtest procedure to switch between different rules at different times. In other words, rules can be reliably ranked according to expected future performance, and these rankings change over time (see Figure 2). How does the composition of the portfolio strategy vary over time? Table 5 presents the frequency with which different rules appeared in the top 5 ranked portfolios. The ch(10,.001,1) rule applied to DEM/EUR was the overall "winner" in that it was used 20.3% of the time in the top-ranked portfolio. The ch(10,.001,1) rule for the British pound was the next most frequently used rule in the top portfolio, with a frequency of 14.7%. The KRW carry-trade rule was used 9.4% of the time.

Moving average, filter, channel rules, and the carry trade all appear among the most-used rules in the top portfolio, and both developed and emerging market currencies are represented. However, the analysis for the full sample masks substantial variation across subsamples. Some of this variation is driven mechanically by the fact that data for some emerging markets are either not available or cannot be used for certain (earlier) periods because of the presence of capital controls or other restrictions on market activity. Table 6 reproduces the information for the top-ranked portfolio divided into four distinct subperiods. The GBP ch(10,.001,1) rule during the first subperiod (1973-81) was very dominant; it was used 76.5% of the time. The next most frequently used rule was the DEM/EUR vma(5,20), which was used 12.9% of the time. This rule

[11] Hsu and Taylor (2012) use stepwise tests against data snooping in exploring the profitability of a vast number of technical rules, finding continued profitability in emerging markets.

continued to be popular in the second subperiod (1982-90), where it was used 12.4% of the time. But again, one rule in the second subperiod appeared in the top-ranked strategy far more frequently than any other: the DEM/EUR ch(10,.001,1) rule, which the top-ranked strategy used 77.9% of the time. It is not until the third subperiod (1991–99) that emerging market currencies acquire a significant role. Although the JPY vma(5, 20) rule was used often, 4 of the top 5 rules were from emerging markets, including the SGD 0.005 filter and THB ch(20,.001,1) rule which were used 41.0% and 10.3% of the time, respectively. In the most recent subperiod (2000-10), all 5 most frequently used rules involve the KRW, RUB, or THB. In addition, the bilateral carry trade for the KRW, used 31.6% of the time, becomes dominant in the last subperiod.

Figure 6 shows the frequency with which various rule classes appeared in the top-ranked portfolios. The top panel depicts the prevalence of types of trading rules in the best 10 ex ante trading rule strategies. The bottom panel shows the difference between each raw frequency and the percentage of the total rules that the group represents. That is, the bottom panel adjusts for the fact that some rule groups contain more rules and therefore would have a better chance of being represented in the top 10 trading strategies. So positive (negative) numbers in the lower panel indicate that a rule group is overrepresented (underrepresented) in the top 10 ex ante trading strategies. Over the whole sample, channel rules dominate, followed by the moving average rule, small filter rules (up to 0.02), large filter rules (greater than 0.02), and the carry trade rule. Perhaps the most striking feature is that significant appearance of the bilateral carry trades occurs only from the mid-1990s on.[12] The top 10 portfolio strategies use bilateral carry trades only 2.6% of the time over the whole sample (Figure 6). But the KRW carry trade

[12] The comparison of the carry-trade frequency with that of the other rules is not entirely "fair" in the sense that the bilateral carry trade is only one rule, whereas there are three channel rules, for example. In addition, reducing the performance evaluation window from the whole sample to 500 business days increases the representation of the carry trade in the first 10 strategies to 14.7% over the whole sample in this comparison. It also increases the representation of the filter rule at the expense of the channel and moving average rules.

becomes dominant in the last subsample, appearing as the top-ranked rule 31.6% of the time.[13] (The rule is usually long in the KRW.) The carry trade is used by the other top 10 strategies fairly frequently in the last subsample as well (see Figure 6).

The rule group prevalence seems to be reasonably stable over time with a few caveats. First, the channel rules tend to decline in importance toward the end of the 1990s, recovering only recently. Second, as remarked above, the carry trade is unimportant until the mid-1990s.

Figure 7 shows the prevalence of exchange rates in the top 10 trading strategies. To more easily summarize the prevalence of rules over time, we divide the 15 currencies into 4 currency groups. The advanced market exchange rates consist of the GBP, CHF, AUD, CAD, SEK, JPY, and DEM/EUR; the CZK and RUB are the developing European exchange rates; the HKD, SGD, KRW, and THB are the developing Asian currencies; and the ZAR is the African group. As the composition of the exchange rate groups varies during the sample, we again normalize the frequency of each group's representation by subtracting each group's contribution to the total number of exchange rates. These statistics are in the lower panel of the figure.

Exchange rates from advanced economies dominate the top 10 ex ante trading strategies in the early part of the sample because there were few or no developing currencies in our data sample before the early to mid-1990s. In the late 1990s, currencies from developing Asian economies began to dominate the top 10 ex ante strategies and they did so until the 2007–09 financial crisis, when the advanced market and emerging European groups rose in importance.[14] Shortening the selection period window from the whole sample to 1000 or 500 observations produces a similar pattern but emerging Asian markets become important 2 or 3 years sooner. In

[13] Here the bilateral carry trade is defined as a single currency strategy against a reference currency, in this case the U.S. dollar. For each foreign currency the rule takes a long position if the foreign interest rate is higher than the reference currency interest rate and vice versa.

[14] The Russian ruble accounted for almost all of the increase in emerging European currencies.

addition, the shorter selection windows produce greater weights on the South African rand.

6. Discussion and conclusion

The "efficient markets hypothesis" holds that no trading strategy should be able to generate unusual profits based on publicly available information—such as past prices—except by bearing unusual risk. Previous research has established that the standard approach to risk adjustment using the CAPM cannot explain the observed positive excess returns to technical trading in currency markets. This is a consequence of the very low and sometimes negative correlation between returns to technical trading rules and stock market returns. The long-term profitability of technical strategies in the forex market suggests that the adaptive markets hypothesis would better describe market functioning. Adaptive behavior allows for the possibility that profit opportunities persist for considerable periods of time. Eventually, however, traders learn about these opportunities and compete them away. A number of studies of the forex market have confirmed this prediction. However there has been little attention paid to the distinct question of whether an adaptive trading strategy can outperform a nonadaptive strategy. Previous research has very largely focused on nonadaptive strategies, namely fixed trading rules or fixed portfolios of these rules. The contribution of this paper is to examine the performance of explicitly adaptive trading strategies and to compare them to nonadaptive strategies.

We draw several conclusions from our analysis. First, a portfolio trading strategy that switches between different rule-currency pairs according to past Sharpe ratios improves substantially on the average performance of the rule-currency pairs (Figure 2). That is, backtesting is an effective adaptive strategy because rule-currency performance is persistent. Second, there are benefits to diversifying among forex trading strategies: The optimal currency portfolio strategies (OX-10 and OX-50) outperform strategies based on using a single currency rule at a time. They also turn out to be very significantly superior to a pure equity portfolio (S&P 500) in terms of Sharpe ratios (Table 4). But the portfolio strategy optimally combined with equity generally produces no detectable improvement in performance compared with the portfolio strategy on its own. The naïve strategies that combine portfolios split evenly between equity and a currency strategy (ON and NN) are generally inferior to the currency portfolio strategies on their own (OX and NX). The lack of a diversification benefit may help to explain why firms typically treat their forex and equity positions separately. There is little or no advantage to be gained from coordinating them.

Although the performance of the currency portfolio strategies has fluctuated, with a noticeable dip in the 1990s, Sharpe ratios have rebounded over the most recent decade (Figure 5). This observation sharply contrasts with the evidence from other studies that the profitability of individual technical trading rules had disappeared by the early 1990s. It lends support to the prediction of the Adaptive Markets Hypothesis that adaptive strategies will outperform nonadaptive strategies. The rebound in optimal rule profitability since 1998 coincides with a strong shift in the optimal strategies away from major currencies to emerging markets, first in Asia in the late 1990s and then to Russia starting in 2004 (Figure 7).

The types of rules used by the optimal rule portfolios are fairly stable over time (Figure 6). Channel rules decline in importance after the mid-1980s and small filter rules become more important. The most interesting change, however, is that the single currency carry trade becomes prominent only during the past decade (1999–2010). This shortly predates a surge in academic and practitioner interest in carry-trade rules. The relatively poor performance of the carry trade compared with the best technical strategies prior to 1999 might explain the dearth of interest in the carry trade until recently.

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Table 1

Data description.

Country	Currency abbreviation versus the USD	# of trading obs	Trading start date	Trading end date
UK	GBP	8664	1/2/1975	3/31/2010
Switzerland	CHF	9011	4/3/1973	3/31/2010
Australia	AUD	8337	4/7/1976	3/31/2010
Canada	CAD	8668	1/2/1975	3/31/2010
Sweden	SEK	6609	1/3/1983	3/31/2010
Hong Kong	HKD	6782	1/4/1982	3/31/2010
Singapore	SGD	4935	1/2/1990	3/31/2010
Korea	KRW	2740	5/6/1999	3/31/2010
Japan	JPY	8943	4/3/1973	3/31/2010
South Africa	ZAR	3634	4/3/1995	3/31/2010
Thailand	THB	2237	7/2/1997	12/29/2006
Czech Republic	CZK	4355	1/5/1993	3/31/2010
Russia	RUB	2373	8/1/2000	3/31/2010
Euro Area	DEM/EUR	8984	4/3/1973	3/31/2010

Notes: The table depicts the 14 exchange rates (versus the USD) used in our sample along with the starting and ending dates of the samples.

Table 2

Average trading rule statistics by foreign exchange rate

Currency	Gross AR	Net AR	Net AR t-statistic	Sharpe	Sharpe (s.e.)	Trades per year per rule	Observations
GBP	2.37	1.94	2.18	0.35	0.16	15.24	8663
CHF	2.67	2.13	2.04	0.35	0.17	17.17	9010
AUD	1.84	1.37	1.29	0.24	0.17	14.90	8336
CAD	0.82	0.46	0.86	0.15	0.17	12.39	8667
SEK	1.98	1.45	1.27	0.25	0.19	16.22	6608
HKD	0.14	0.04	0.11	0.02	0.19	9.51	6781
SGD	0.90	0.63	1.05	0.25	0.23	11.27	4934
KRW	3.31	2.66	1.52	0.41	0.27	13.88	2739
JPY	3.16	2.72	3.10	0.49	0.16	14.75	8942
ZAR	3.98	2.18	0.86	0.24	0.26	18.80	3633
THB	6.11	4.65	2.19	0.68	0.28	12.80	2236
CZK	2.31	1.50	1.00	0.25	0.24	16.78	4354
RUB	3.44	2.92	2.82	0.66	0.22	10.21	2372
DEM/EUR	3.84	3.37	3.71	0.60	0.16	15.25	8983
Mean	2.63	2.00	1.71	0.35	0.20	14.23	6161

Notes: The table presents the annual gross and net (of transaction costs) excess return and Sharpe ratio averaged across all 14 trading rules for each currency over the full data sample. Sample periods differ by currency.

Table 3

Top 10 ex ante portfolio results

Portfolio #	Gross AR	Net AR	Net AR t-statistic	Sharpe	Sharpe (s.e.)	Trades per year
1	6.53	5.95	3.46	0.59	0.17	13.75
2	5.21	4.42	2.64	0.45	0.17	16.72
3	7.59	6.60	3.74	0.63	0.17	20.79
4	5.58	4.69	2.66	0.44	0.17	20.04
5	5.34	4.47	2.61	0.43	0.17	19.86
6	7.05	6.10	3.60	0.60	0.17	21.72
7	4.65	3.84	2.22	0.37	0.17	20.68
8	7.06	6.30	3.34	0.59	0.18	19.74
9	2.76	1.95	1.11	0.18	0.17	21.41
10	5.93	5.11	3.17	0.54	0.17	19.72
Mean	5.77	4.94	2.86	0.48	0.17	19.44

Notes: The table presents for the top 10 ranked ex ante portfolio rules gross annual excess return (Gross AR) and annual excess return net of transaction costs (Net AR). The sample for the ex ante portfolios is April 1975 to March 2010.

Table 4

Portfolios of technical trading rules and equity: Sharpe ratios

			Top 10 ex ante rules				Top 50 ex ante rules			
Construction of FX Portfolio	Combination with Equity		1975-2010	1975-1986	1987-1998	1999-2010	1975-2010	1975-1986	1987-1998	1999-2010
Naive	Optimal	NO	0.88	1.32	0.73	0.59	0.85	1.56	0.80	0.35
			(0.17)	(0.29)	(0.29)	(0.29)	(0.17)	(0.29)	(0.31)	(0.30)
	50-50 equity	NN	0.61	0.82	0.90	0.19	0.55	0.74	0.90	0.08
			(0.18)	(0.29)	(0.34)	(0.31)	(0.18)	(0.29)	(0.36)	(0.31)
	No equity	NX	0.84	1.41	0.53	0.54	0.80	1.64	0.54	0.22
			(0.16)	(0.29)	(0.28)	(0.28)	(0.16)	(0.28)	(0.27)	(0.30)
Optimal	Optimal	OO	0.82	1.18	0.59	0.72	0.92	1.65	0.67	0.50
			(0.16)	(0.28)	(0.28)	(0.27)	(0.17)	(0.28)	(0.29)	(0.29)
	50-50 equity	ON	0.59	0.75	0.86	0.23	0.57	0.76	0.88	0.15
			(0.18)	(0.29)	(0.34)	(0.30)	(0.18)	(0.29)	(0.36)	(0.31)
	No equity	OX	0.78	1.25	0.43	0.69	0.88	1.70	0.47	0.51
			(0.16)	(0.28)	(0.29)	(0.27)	(0.16)	(0.28)	(0.28)	(0.28)
	S&P 500		0.35	0.30	0.79	0.04				
			(0.18)	(0.29)	(0.36)	(0.31)				

Notes: The table reports Sharpe ratios with standard errors in parentheses. The trading rule portfolios consist of the top 10 and top 50 ranked rules, respectively, in the left-hand and right-hand panels. The columns labeled “Optimal equity” and “50-50 equity” show the results for 2-asset portfolios consisting of the technical trading strategies in the forex market with an S&P 500 position. The “optimal equity portfolio” uses ex ante optimal mean-variance weights; the “50-50 equity” assigns equal weights to the technical trading portfolios and the S&P 500. The “no equity” portfolio denotes the portfolios consisting of just the top N technical trading strategies. Rows labeled “naïve” weight each technical trading strategy equally; rows labeled “Optimal” use optimal ex ante weighting on the technical strategies. The bottom panel displays the Sharpe ratio to a buy-and-hold position in the S&P 500 over various samples.

Table 5

Rule prevalence over the full sample

1			2			3			4			5		
FX rate	**rule**	**% used**	**FX rate**	**rule**	**% used**	**FX rate**	**rule**	**% used**	**FX rate**	**rule**	**% used**	**FX rate**	**rule**	**% used**
DEM/EUR	Ch(10,.001,1)	20.3	DEM/EUR	vma(5,20)	13.8	DEM/EUR	vma(5,20)	15.2	DEM/EUR	vma(5,20)	14.7	DEM/EUR	vma(5,20)	14.1
GBP	Ch(10,.001,1)	14.7	DEM/EUR	Ch(10,.001,1)	10.7	DEM/EUR	Ch(10,.001,1)	7.4	JPY	vma(5,20)	13.2	DEM/EUR	Ch(10,.001,1)	13.8
SGD	filter .005	10.7	JPY	vma(5,20)	10.3	JPY	vma(5,20)	6.7	JPY	Ch(5,.001,1)	8.5	JPY	Ch(5,.001,1)	8.5
KRW	Carry Trade	9.4	GBP	vma(5,20)	7.1	THB	vma(5,20)	6.5	DEM/EUR	Ch(10,.001,1)	7.4	JPY	vma(5,20)	7.6
DEM/EUR	vma(5,20)	6.5	THB	Ch(20,.001,1)	6.0	DEM/EUR	Ch(5,.001,1)	5.8	THB	vma(5,20)	7.1	DEM/EUR	Ch(20,.001,1)	4.7
THB	Ch(20,.001,1)	5.1	SGD	Ch(10,.001,1)	4.5	RUB	vma(5,20)	4.5	GBP	Ch(5,.001,1)	5.8	GBP	Ch(5,.001,1)	4.2
RUB	vma(1,200)	5.1	RUB	vma(1,200)	4.2	KRW	filter .03	4.2	THB	filter .01	3.8	JPY	filter .01	4.0
JPY	vma(5,20)	4.0	RUB	vma(5,20)	4.0	JPY	Ch(10,.001,1)	4.2	KRW	vma(5,20)	2.7	THB	Ch(20,.001,1)	3.8
RUB	filter .005	2.9	KRW	Carry Trade	4.0	JPY	Ch(5,.001,1)	3.6	KRW	Carry Trade	2.5	KRW	vma(5,20)	3.8
THB	vma(5,20)	2.7	THB	vma(5,20)	4.0	RUB	Ch(10,.001,1)	3.3	THB	Ch(20,.001,1)	2.2	KRW	filter .03	2.9

Notes: The table reports the largest 10 trading rule frequencies for the top 5 ranked ex ante portfolios over the full sample, 1973-2010. Thus the left-most columns indicate that for the strategy using the top ranked rule, Ch(10,.001,1) applied to DEM/EUR appeared 20.3 percent of the time, the Ch(10,.001,1) applied to the GBP appeared 14.7 percent of the time, and so on.

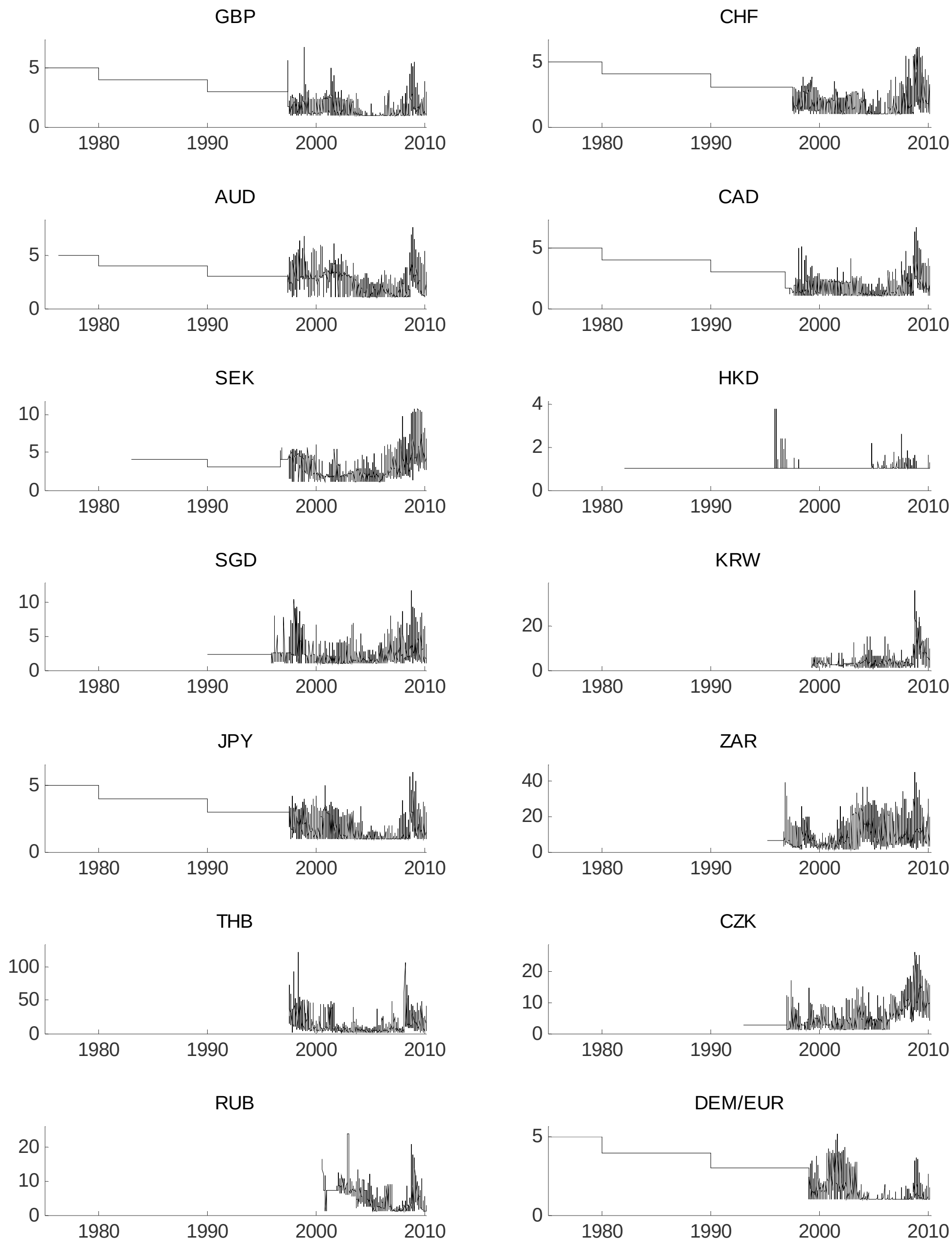
Table 6

Rule prevalence over subsamples

1973-1981			1982-1990			1991-1999			2000-2010		
FX rate	**rule**	**% used**	**FX rate**	**rule**	**% used**	**FX rate**	**rule**	**% used**	**FX rate**	**rule**	**% used**
GBP	Ch(10,.001,1)	76.5	DEM/EUR	Ch(10,.001,1)	77.9	SGD	filter .005	41.0	KRW	Carry Trade	31.6
DEM/EUR	vma(5,20)	12.9	DEM/EUR	vma(5,20)	12.4	JPY	vma(5,20)	14.5	RUB	vma(1,200)	17.3
GBP	vma(5,20)	7.1	HKD	vma(5,20)	3.5	THB	Ch(20,.001,1)	10.3	RUB	filter .005	9.8
DEM/EUR	Ch(10,.001,1)	2.4	SEK	filter .05	1.8	SGD	Ch(10,.001,1)	7.7	THB	Ch(20,.001,1)	8.3
GBP	vma(1,5)	1.2	JPY	vma(5,20)	0.9	ZAR	vma(1,200)	6.0	KRW	filter .03	8.3

Notes: The table reports the largest 5 trading rule frequencies for the top ranked portfolio over different sample subperiods. Thus the top row entries indicate that for the strategy using the top ranked ex ante rule in the 1973-1981 subsample, the channel rule applied to the GBP with a 10 day window and a .001 band appeared 76.5 percent of the time in the top rule and so on.

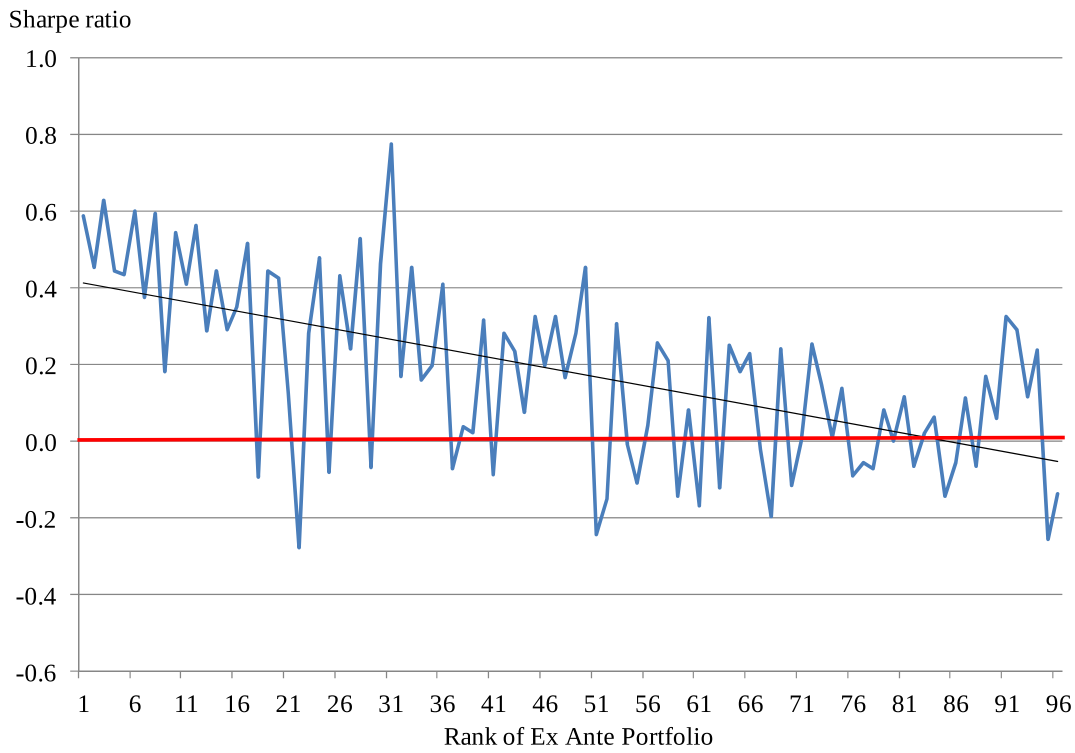
Figure 1
Transaction costs



Notes: The figure displays the time series of transaction costs used for each exchange rate in basis points.

Figure 2

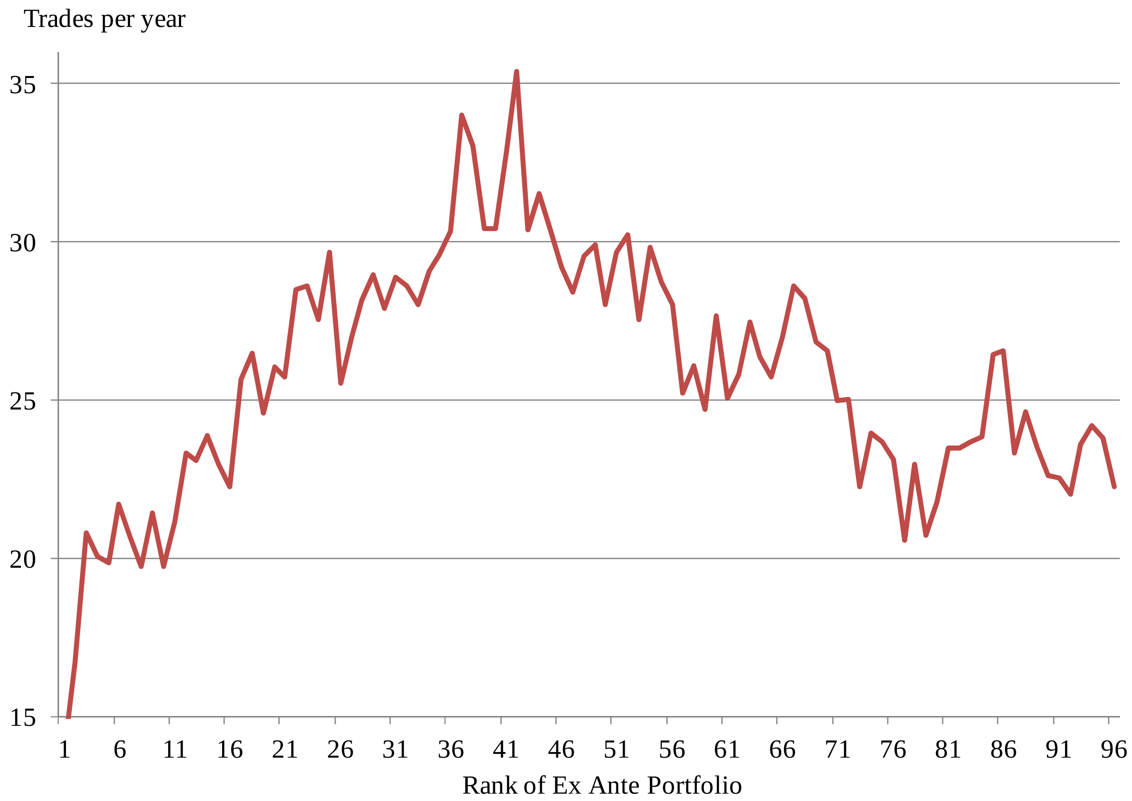
Sharpe ratios from the top 100 strategies



Notes: The figure displays the Sharpe ratios for the top 100 ex ante portfolio rules along with a trendline.

Figure 3

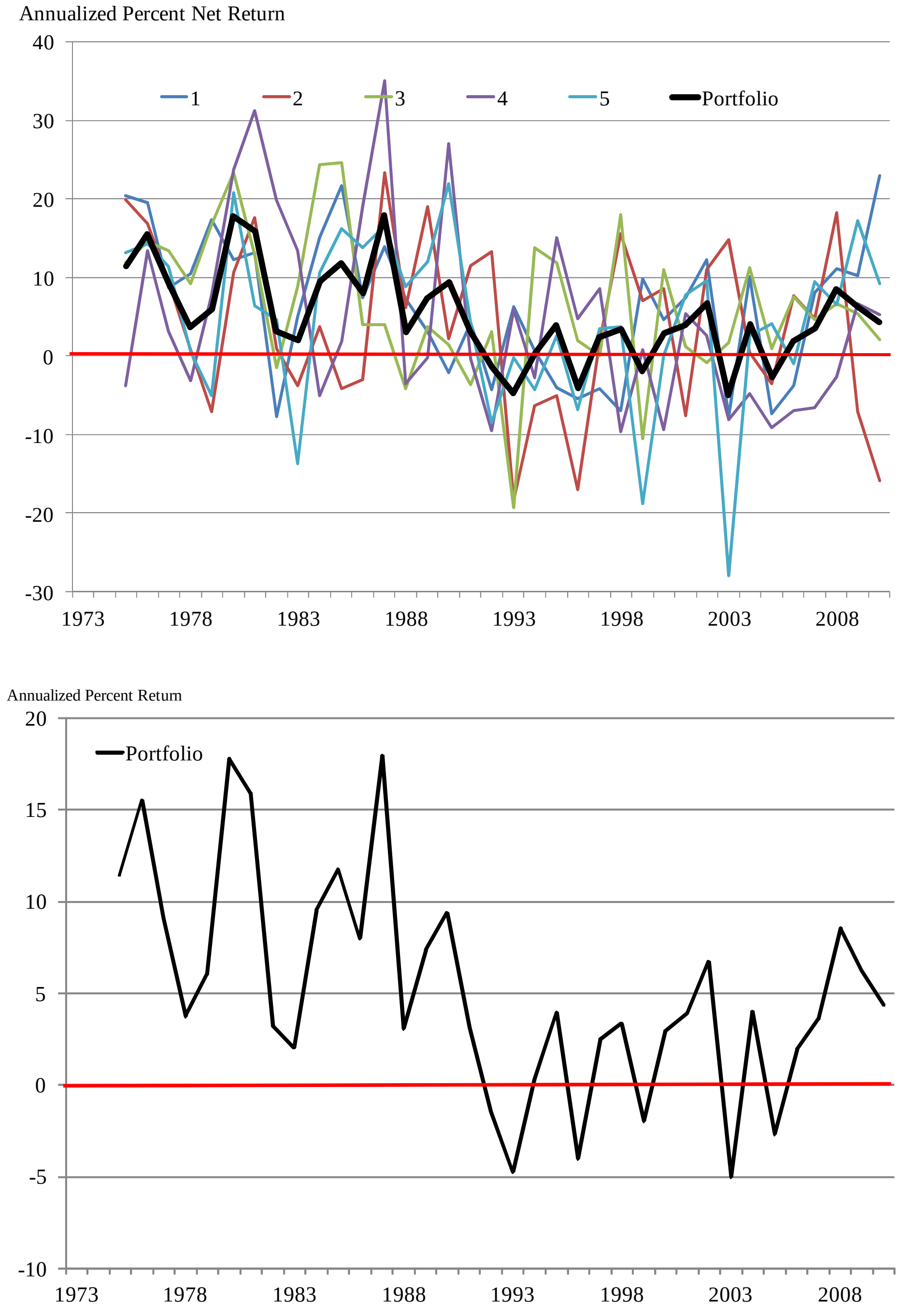
Trades per year



Notes: The panel displays the average number of annual trades for the top 100 ex ante portfolio rules.

Figure 4

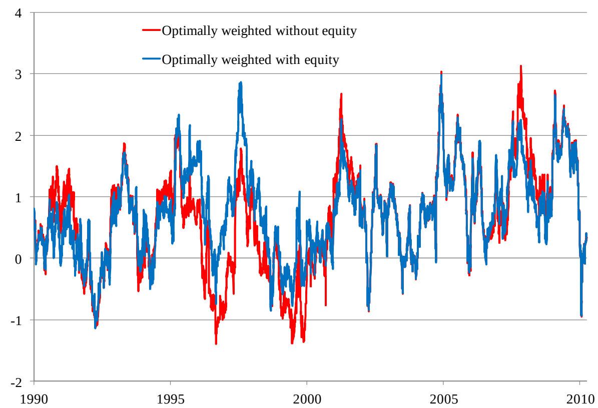
Net returns for the top 5 ranked strategies

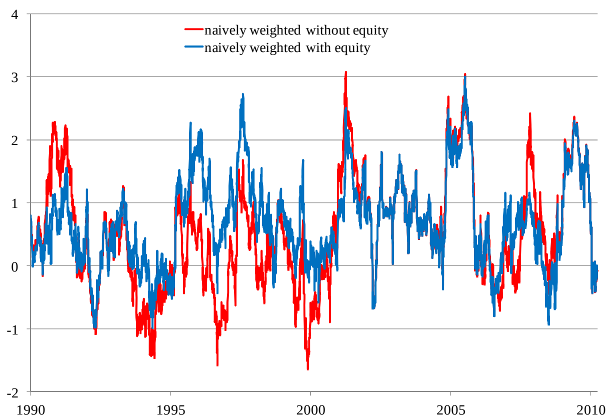


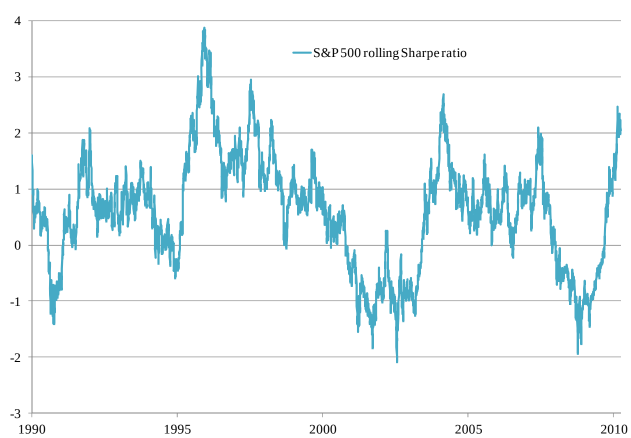
Notes: The top panel displays the net annual returns for the top 5 ex ante portfolio rules, along with the average net annual return. The bottom panel displays the average net annual return from the top 5 rules for clarity.

Figure 5

1-year Rolling Sharpe ratios from 1990 for the top 10 strategies and the S&P 500



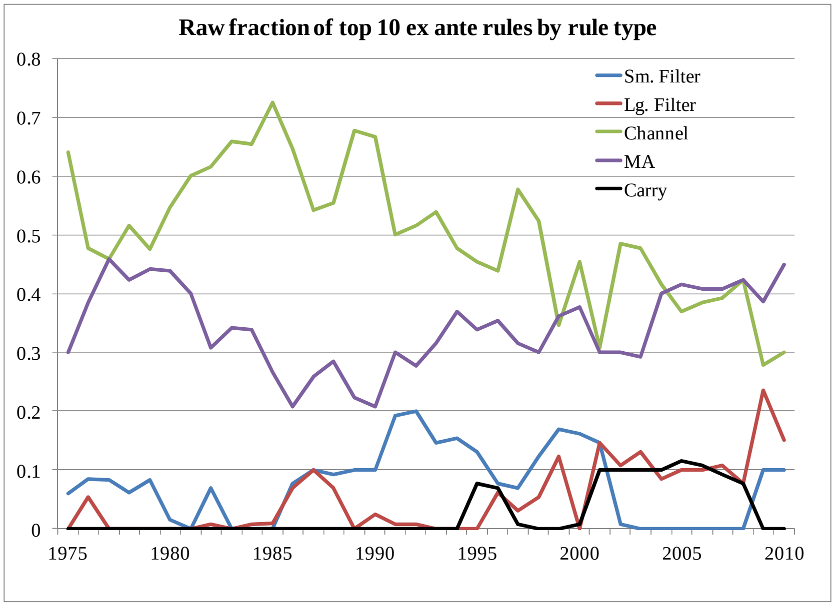


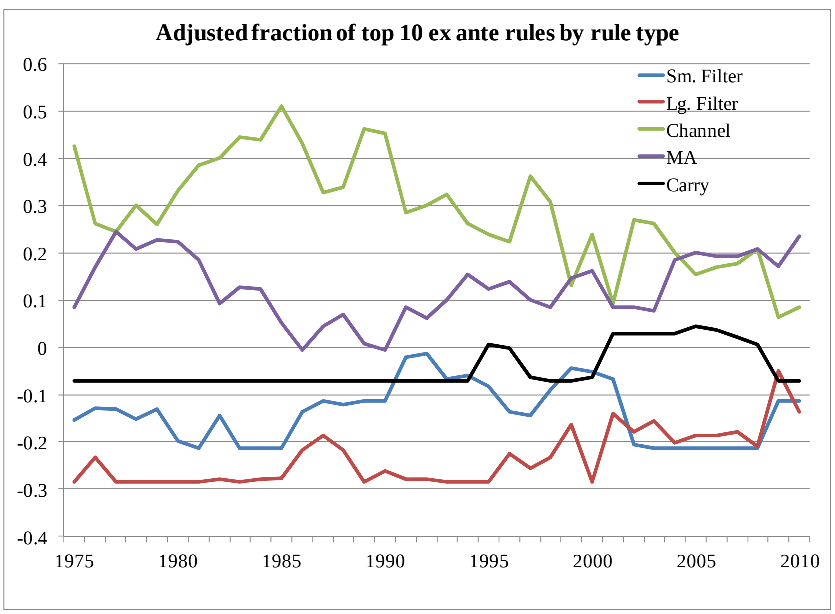


Notes: The top (center) panel displays 1-year rolling Sharpe ratios from the optimally (naively) combined technical trading rule 10 strategy portfolios with and without optimal combination with equity, from 1990 to 2010. The bottom panel displays the 1-year rolling Sharpe ratios to the S&P 500.

Figure 6

Trading rule prevalence over time

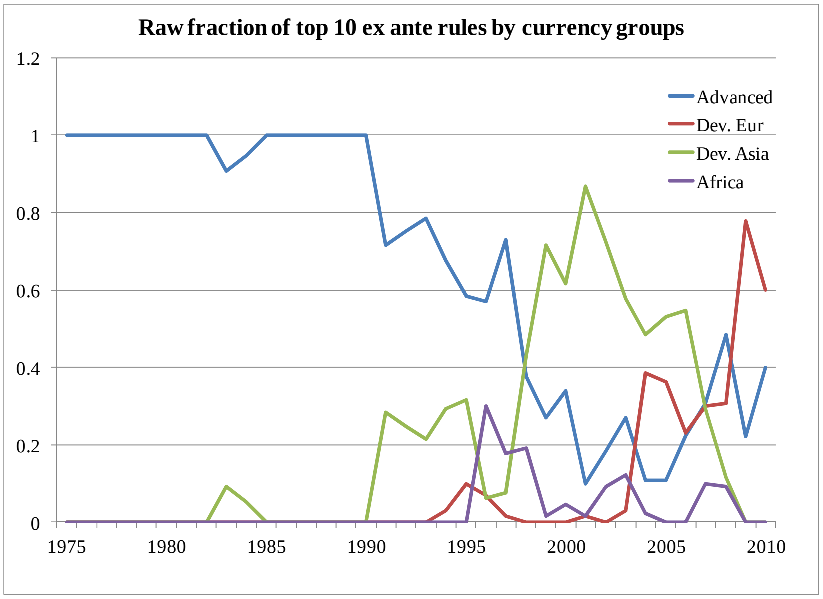


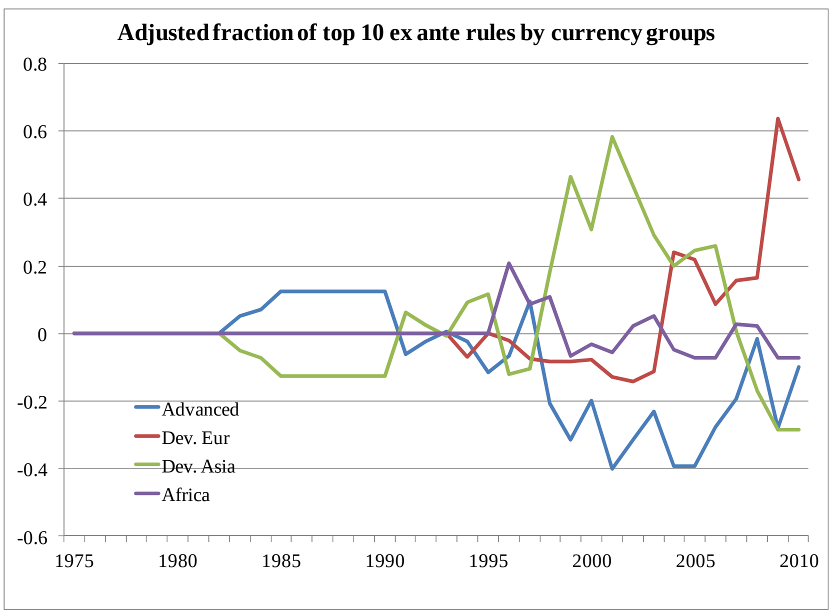


Notes: The panels denote the prevalence of types of trading rules in the best 10 ex ante trading rule strategies. The panel on the top denotes the raw frequency of the rule groups, whereas those on the bottom subtract from each raw frequency the percentage of the total rules that the group represents. Small filters are those less than or equal to 0.02; large filters are those greater than 0.02. MA, Moving average.

Figure 7

Exchange rate prevalence over time in the top 10 trading strategies





Notes: The panels denote the prevalence of currency groups in the best 10 ex ante trading rule strategies. The top panel illustrates the raw prevalence of each group, whereas those on the bottom subtract from each raw frequency the percentage of the total rules that the group represents (i.e., the bottom panel adjusts for the numbers of currencies in the group). The advanced market exchange rates consist of the GBP, CHF, AUD, CAD, SEK, JPY and DEM/EUR; the CZK and RUB are the developing European exchange rates; the HKD, SGD, KRW, and THB are the developing Asian currencies, and the ZAR is the African group.