Forty Years, Thirty Currencies and 21,000 Trading Rules: A Large-scale, Data-snooping Robust Analysis of Technical Trading in the Foreign Exchange Market

Po-Hsuan Hsu

School of Economics and Finance at University of Hong Kong

Mark P. Taylor

Warwick Business School at University of Warwick

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Technical analysis (sometimes alternatively referred to as chartist analysis) is a set of techniques for deriving trading recommendations for financial assets by analyzing the time-series history of the particular asset price either graphically or mathematically. Although technical analysis is not rooted in underlying economic or financial theory – the 'fundamentals' – , the widespread use of technical analysis among financial practitioners in financial markets in general and in the foreign exchange market in particular is well documented (e.g., Frankel and Froot, 1990; Allen and Taylor, 1990; Taylor and Allen, 1992; Cheung and Chinn, 2001) and, following early work by Cornell and Dietrich (1978) and Sweeney (1986), the predictive ability and profitability of technical analysis in the foreign exchange market has been the subject of extensive analysis, most recently as a branch of behavioural finance and economics (e.g., Azzopardi, 2010).[1] Indeed, a recent literature survey on the topic (Menkhoff and Taylor, 2007) concludes that the 'obstinate passion' of foreign exchange professionals for technical analysis is an intrinsic part of the behaviour of practitioners in this market. Given this, and in the wake of the global financial crisis, an understanding of the drivers of financial markets, from the perspective of both economic fundamentals and behavioural considerations, is clearly of high interest.

Nevertheless, a comprehensive and up-to-date analysis of technical analysis in the foreign exchange market still seems to be lacking, since most previous studies of this issue tend to consider only a small number of currencies, short sample periods, limited sets of technical trading rules, simple performance metrics, and basic testing methods which may be subject to data-snooping bias.[2] As a result, the intriguing question of whether technical

[1] An incomplete list of studies in this area includes Allen and Taylor (1990), Taylor and Allen (1992), Levich and Thomas (1993), Kho (1996), Neely, Weller, and Dittmar (1997), LeBaron (1999), Gencay (1999), Chang and Osler (1999), Neely (2002), Okunev and White (2003), Qi and Wu (2006), Neely, Weller, and Ulrich (2009). See Menkhoff and Taylor (2007) for a literature survey. The academic literature on technical analysis in the equity market and financial markets in general is also very large; see, for example, Lo, Mamaysky and Wang (2000) and the references cited therein.

[2] Data-snooping bias arises whenever researchers continue searching for predictive models or rules but conduct only individual tests for each trial using the same data set. An early criticism of such an approach is given by Jensen and Benington's (1970) comment on Levy (1967): 'Likewise, given enough computer time, we are sure that we can find a mechanical trading rule which 'works' on a table of random numbers... (p.470).' Although there exist in the literature different labels for such bias, we use the name 'data snooping', following the usage of Lo and MacKinlay (1990), Sullivan, Timmermann, and White (1999), White (2000), and Schwert (2003).

analysis can beat the foreign exchange market calls for a large-scale investigation with an appropriate empirical design.

Moreover, even if the predictability and profitability of technical analysis exists with statistical significance for certain currencies at certain times, as some studies appear to show (Menkhoff and Taylor, 2007), a further question arises, namely *why* should technical analysis work in the foreign exchange market? Menkhoff and Taylor (2007) categorize the various explanations proposed in the literature into four positions: (i) technical analysis indicates not-fully-rational behavior or investor psychology and market sentiment (e.g. Frankel and Froot, 1990; Taylor and Allen, 1992; Oberlechner and Osler, 2012); (ii) technical analysis exploits or reinforces movements in the market caused by official intervention (e.g. Sweeney, 1986; LeBaron, 1999); (iii) technical analysis serves as a tool for processing information about fundamental influences on exchange rates (e.g. Treynor and Ferguson, 1985; Brown and Jennings, 1989; Blume, Easley, and O'Hara, 1994; Osler, 2003; Kavajecz and Odders-White, 2004; Zhu and Zhou, 2009); and, lastly, (iv) the profitability of technical analysis may be simply attributed to risk premia (e.g. Cornell and Dietrich, 1978; Kho, 1996). Previous empirical studies have not to date reached a conclusive verdict on these issues and a more complete examination is also, therefore, warranted from this perspective.

In this paper, we perform the most comprehensive study of technical trading rules in the foreign exchange market to date in order to assess the predictability of such rules and to provide further insights on what it is that may make them at times profitable. In addition, we also check a set of 'stylized facts' that may be gleaned from the literature on technical analysis in the foreign exchange market, such as that it may have diminished in profitability over time and that transaction costs do not necessarily eliminate its profitability.

Our study analyses daily data over a maximum of forty years (1971-2011) for thirty U.S. dollar exchange rates, covering both emerging and developed markets, which we use to examine the profitability of over 21,000 technical trading rules. In constructing our tests, we examine the investment performance of foreign currency traders and consider a range of performance metrics which summarize the overall performance of trading rules as well as splitting this into a dynamic, ‘market-timing’ component and a static, ‘tilt’ or ‘buy-and-hold’ component. In order to eliminate data-snooping bias from our analysis, we employ a stepwise test developed by a series of methodological studies including White (2000), Romano and Wolf (2005), Hansen (2005), and Hsu, Hsu, and Kuan (2010). This testing method is powerful in identifying predictive/profitable technical trading rules from the large rule set without data-snooping bias, and thus allows us to make appropriate statistical inferences.[3]

The rest of the paper is organized as follows. Section 1 introduces our data and technical trading rules, and Section 2 describes the various performance metrics we consider. Sections 3 and 4 report our testing strategy and empirical results, respectively, while Section 5 provides some concluding comments.

1. Data and Technical Trading Rules

1.1 Data

We consider daily data on foreign exchange rates between the U.S. dollar and thirty foreign currencies, including nine developed market currencies (Australian dollar, Canadian dollar, German mark/euro, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, Swiss franc, and U.K. pound) and twenty-one emerging market currencies (Argentine peso, Brazilian real, Chilean peso, Colombian peso, Czech koruna, Hungarian forint, Indian rupee,

[3] The reality check test proposed by White (2000) is the first formal testing method that corrects data-snooping bias for large-scale joint test problems. The stepwise test proposed by Hsu, Hsu, and Kuan (2010) combines the methods of Romano and Wolf (2005) and Hansen (2005) that improve the reality check test, and is able to identify predictive models in large-scale, multiple testing problems free of data-snooping bias. The reality check test has been used to examine the technical predictability and profitability in stock market indexes (Sullivan, Timmermann, and White, 1999; Hsu and Kuan, 2005), foreign exchange rates (Qi and Wu, 2006), and futures markets (Park and Irwin, 2010). The superior predictive ability test of Hansen (2005) has been used to investigate the technical predictability in stock market indexes (Hsu and Kuan, 2005) and futures markets (Park and Irwin, 2010). The stepwise reality check test of Romano and Wolf (2005) has been applied to examine the technical profitability in exchange traded funds (Hsu, Hsu, and Kuan, 2010). We recognize the existence of other testing methods in handling data-snooping bias, including the false discovery rate methodology (Barras, Scaillet, and Wermers, 2010) and the wild bootstrap reality check of Clark and McCracken (2012). The former is used by Bajgrowicz and Scaillet (2012) to test technical predictability in the Dow Jones Industrial Average index, while the latter is used by Neely, Rapach, Tu, and Zhou (2011) to examine whether technical indicators forecast equity risk premium.

Indonesian rupiah, Israeli shekel, Korean won, Mexican peso, Philippine peso, Polish zloty, Romanian new leu, Russian ruble, Singaporean dollar, Slovak koruna, South African rand, Taiwanese dollar, Thai baht, and Turkish lira). The sample periods for developed market currencies start from January 4, 1971 and end on July 29, 2011, while the sample periods for emerging market countries start from various dates due to data availability.[4] Israel has the earliest starting date (January 3, 1978) and is followed by South Africa (January 2, 1981), Singapore (January 4, 1982), and Taiwan (October 3, 1983); all emerging market data ends on July 29, 2011. Our data on exchange rates and short-term interest rates were kindly supplied by the London branch of the asset manager, BlackRock, and are based on midday quotations in the London market.

To measure the investment performance in currency trading, we calculate the daily gross return from buying one unit of a foreign currency and holding it for one day as $r_t = \ln(s_t / s_{t-1})$, where s_t denotes the spot foreign exchange rate (U.S. dollars per unit of a foreign currency) on day t. $s_t / s_{t-1} > 1$ indicates that the foreign currency appreciates against U.S. dollar.

Table 1 reports summary statistics of the daily returns on all foreign currencies and short-term interest rates (both in logarithm) ending on July 29, 2011. Among the nine developed currencies, the Swiss franc appreciates the most on average (1.6 basis points per day or 4.0% per year) and the U.K. pound depreciates the most (0.4 basis points per day or 0.9% per year). Among emerging market currencies, the Czech koruna appreciates the most (1.1 basis points per day or 2.7% per year), while the Turkish lira depreciates the most (11.7 basis points or 29.3% per year).

Interest rates are, of course, a major concern for technical currency traders since they affect the overall return from currency trading, even if technical analysts will typically only analyze exchange rate data in determining an exchange rate trading rule. Table I shows that

[4] Since we require both exchange rates and short-term interest rates to calculate currency investment returns, the sample periods for emerging currencies start from the date when both exchange rates and interest rates are available.

short-term interest rates available for daily trading in developed countries range from 0.9 basis points per day (or 2.3% per year) to 3.2 basis points (or 8.1% per year). It is also found that short-term interest rates vary greatly across emerging countries. The highest average short rate is as high as 14.9 basis points per day (or 37.1% per year) in Turkey since 1990, while the lowest average short rate is as low as 1.0 basis points per day (2.4% per year) in Singapore since 1982.

We also find that emerging currencies are in general more volatile than developed currencies. The most and least volatile currencies among developed countries are the Swiss franc (0.75%) and Canadian dollar (0.39%). Eight emerging currencies are associated with 1% or higher standard deviations. The most volatile currency is the Indonesian rupiah (1.50%), and the most stable currency is the Taiwanese dollar (0.30%). Such great variation in emerging countries' exchange rates suggests various risk degrees in trading different currencies, which require commensurate profits as risk compensation for currency traders.

Figure 1 serves as a basic check of the risk-return relation in the foreign exchange market by plotting each currency's mean excess return along the horizontal axis and the standard deviation along the vertical axis. Somewhat surprisingly, we do not observe a positive relation between mean excess return and risk as measured by the standard deviation of returns; in fact, the relationship appears to be random. This finding provides preliminary evidence against the argument that foreign exchange rates reflect risk compensation for volatility, at least from an unconditional perspective. It seems good news to long-term buy-and-hold investors because their bets on currency are not necessarily accompanied by greater uncertainty.[5]

Another important dimension of exchange rate fluctuations is the existence of trends that are reflected in persistent return series. In our sample, the first-order autocorrelation coefficients of the developed currency dollar exchange rates range from -0.028 to 0.066. The

[5] Volatility is only a very crude measure of risk, of course, since modern asset pricing specifies risks as arising from the covariances of returns with the sources of risks in the economy, and these risk factors are in turn the stochastic processes that drive the stochastic discount factor that prices all assets.

emerging market exchange rates present higher diversity in persistence: five emerging currencies carry first-order autocorrelation coefficients in excess of 0.1. The highest autocorrelation coefficient occurs in the Russian ruble (0.276) and the lowest autocorrelation coefficient occurs in the Mexican peso (-0.138). In Figure 2, we attempt to explore whether persistence correlates with currency investment returns by plotting each currency's mean excess return on the horizontal axis and first-order autocorrelation coefficients on the vertical axis. Our simple exploration does not support the existence of a systematic relationship between average returns and trends in currency trading as Figure 2 does not reveal any recognizable pattern. Thus, our basic analyses thus far indicate that the profits from simple currency trading, if any, cannot be simply attributed to volatility and persistence in foreign exchange rates.

1.2 Technical trading rules

Technical analysis can be performed in a qualitative form, relying mainly on the analysis of charts of past price behaviour and loose inductive reasoning that attempts to identify particular patterns in the data,[6] or it can be strictly quantitative, by constructing trading signals or forecasts through a quantitative analysis of time series data.[7] In this paper, we are concerned with analysing the profitability of quantitative technical trading rules as they are objective and readily computable.

The most widely used quantitative forms of technical analysis generally involve methods such as filter rules, moving average rules, support-resistance signals, channel breakouts and oscillator trading rules, in order to exploit trends and trend reversals in the foreign exchange market (Taylor and Allen, 1992; Menkhoff and Taylor, 2007). The filter

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[6] A few attempts have been made by researchers to identify technical patterns from market charts in a systematic manner (Levy, 1971; Chang and Osler, 1999; Lo, Mamaysky, and Wang, 2000). Nevertheless, technical charting remains a very subjective tool as the same figure may give two analysts entirely different inspirations.

[7] In many financial markets, technical analysts will supplement the price data with transactions volume data. This is generally not possible in the foreign exchange market, however, due to its decentralised nature. There is some anecdotal evidence, however, that some analysts may combine technical trading rules with proprietary data on foreign exchange order flow, although the evidence on the usefulness of the latter for foreign exchange prediction is mixed (Sager and Taylor, 2008).

rule is one of the simplest techniques of technical analysis (Alexander, 1961) and in the present context basically involves buying a currency against another currency whenever the exchange rate has risen by more than a given percentage above its most recent low and selling it when the rate drops by more than a given percentage below its most recent high. Moving average trading rules have been among the most widely used of technical trading rules in the foreign exchange market (Taylor and Allen, 1992), and attempt to ride trends and identify imminent breaks in trend or the emergence of new trends by the use of between one and three moving averages. In a simple moving average trading rule, for example, the local trend is approximated by a single moving average and a break in trend, which is a trading signal to initiate a new position or neutralise the current position, is indicated when the moving average is crossed by the spot rate. Traders often use a short-term moving average in place of the spot rate in rules of this kind, in which case an imminent upward break in trend might be signalled, for example, by a short moving average intersecting from below a longer moving average, and traders may also use a third moving average to confirm the signal. Support-resistance trading rules attempt to identify levels of the exchange rate above which the rate appears to have difficulty rising (a resistance level) and levels below which the rate appears to have difficulty penetrating (a support level); the premise is that a breach of a support or resistance level will trigger further rapid exchange rate movement in the same direction. In construction, support-resistance trading rules are similar to filter rules except that a trading signal is generated when the rate moves beyond a support or resistance level by a certain percentage, rather than beyond a recent high or a recent low. Under a channel breakout rule, a trading signal is generated when a trading channel—itself perceived as occurring when the highest level of the daily closing exchange rate over a previous given period is within a given range of the lowest level over the previous given period—occurs and the exchange rate penetrates beyond the upper or lower bound of the channel; the assumption is that once the channel is breached, there will be sustained movement of the exchange rate in the same direction. Oscillator, or 'overbought/oversold' indicators, are also widely used in the foreign exchange market (Taylor and Allen, 1992), although they have rarely been discussed in the academic literature; they are measures designed to indicate that price movements in a particular direction have recently been too rapid and that a correction in the opposite direction is imminent.

By considering a number of variants of each trading rule and a range of different plausible parameterizations of each, a very large number of possible trading rules is quickly arrived at. In the Appendix, we give precise details of each trading rule and of the various parameterizations considered. This leads us to consider a total of 21,195 distinct technical trading rules, including 2,835 filter rules, 12,870 moving average rules, 1,890 support-resistance signals, 3,000 channel breakout rules and 600 oscillator trading rules.

2. Returns and Performance Metrics

2.1 Excess returns

The daily excess return from buying one unit of foreign currency (against U.S. dollars) and holding it for one day is defined as

$$r_t \equiv \ln(s_t / s_{t-1}) - \ln[(1+i_{t-1})/(1+i^*_{t-1})], \tag{1}$$

where i_{t-1} and i^*_{t-1} denote daily interest rates on U.S. dollar deposits and foreign currency deposits on day t – 1, respectively, and s_t and s_{t-1} denote the spot foreign exchange rate (U.S. dollars per unit of a foreign currency) on days t and t – 1.[8] The excess return is thus made up of the appreciation of the foreign currency relative to the domestic currency over the holding period, $\ln(s_t / s_{t-1})$, minus the interest carry associated with borrowing one unit of domestic currency and lending one unit of foreign currency overnight, $\ln[(1+i_{t-1})/(1+i^*_{t-1})]$. For an investor committing their own funds, $\ln(s_t / s_{t-1})$ represents the gross return and $\ln[(1+i_{t-1})/(1+i^*_{t-1})]$ represents the benchmark return, while for an investor who starts with

[8] The annualized short rate i_t^a is converted into daily rate i_t using the formula $i_t = \ln(1+i_t^a)/360$.

zero funds and borrows domestic currency in order to invest, the gross return is $\ln(s_t / s_{t-1}) - \ln[(1+i_{t-1})/(1+i^*_{t-1})]$ and the benchmark return is zero since there is zero commitment of funds (in which case the gross return and the excess return coincide).

In an informationally efficient market with risk neutrality (i.e. zero risk premium) and zero transaction costs, the expected period-*t* excess return based on information at time *t* – 1 is zero:

$$E(r_t / I_{t-1}) = E\left(\{\ln(s_t / s_{t-1}) - \ln[(1+i_{t-1})/(1+i^*_{t-1})]\} / I_{t-1}\right) = 0\,, \tag{2}$$

where $E(x_t / I_{t-1})$ denotes the expected value of a random variable x_t conditional on the information set at time *t* – 1, I_{t-1}. Equation (2) is the uncovered interest rate parity condition and there exists a voluminous empirical literature which tests for it as a means of testing foreign exchange market efficiency (Hodrick, 1987; Taylor, 1995; Sarno and Taylor, 2002). If I_{t-1} contains only information on the exchange rate in question dated *t* – 1 or earlier, then Equation (2) implies that the market is weak-form efficient in the classic definition of Fama (1970). Since technical trading rules are indeed based only on past exchange rates, testing for the profitability of technical trading rules is equivalent to testing for the weak-form efficiency of the foreign exchange market.

When r_t is negative, a positive return could have been made by shorting the foreign currency, i.e. selling one unit of foreign currency against domestic currency overnight. More generally, the daily excess return of the *j*-th technical trading rule is defined as

$$R_{j,t} \equiv S_{j,t-1} r_t\,, \tag{3}$$

for *j*=1,…, *J*, where $S_{j,t-1}$ denotes the daily position guided by *j*-th technical trading rule, which is determined by all historical prices tracking back from the closing spot rate of day *t* – 1. We shall mostly think of a position $S_{j,t-1}$ in a currency as taking a value of either +1 (long the foreign currency, short the U.S. dollar), –1 (short the foreign currency, long the U.S. dollar), or else 0 (neutral) based on information set at time *t* – 1.

In practice, traders may, of course, apply these rules with any size of position they wish (or are able to sustain in the market); this will just scale up returns from the trading rule but also increase the risk (as measured by the standard deviation of returns) by the same factor. Hence, increasing the size of a position indicated by a trading rule is equivalent to increasing the risk allocated to that trading rule. Thus, if a total of, say μ standard deviations is budgeted by a prudent trader to a particular trading rule, he or she will simply scale up a position of plus or minus one unit by the factor μ. Thus, a position of +1 can be thought of as long the whole risk budget in a particular currency and a position of –1 as going short the whole risk budget in a particular currency. It is also possible that a technical trading rule may generate buy or sell signals with different intensity, indicating that a long or short position should be initiated but at a level which is less than the total risk budget. Indeed, in one of the trading rules we examine—the triple moving average rule, which appears to be a popular strategy (Lequeux and Acar, 1998)—positions may also be generated of plus or minus one third of the risk budget (+1/3 or –1/3).

The discussion so far has assumed zero transaction costs; in practice these may be significant, especially when trading emerging market currencies (Burnside, Eichenbaum and Rebelo, 2007; Ramadorai, 2008). Indeed, a technical trading rule may predict exchange rate movements in sense of generating significantly positive excess returns but still not be profitable once the excess returns are adjusted for transaction costs (Timmerman and Granger, 2004). Daily excess returns can be adjusted for transaction costs as

$$R_{j,t} \equiv S_{j,t-1} r_t - c(S_{j,t-1}, S_{j,t-2}), \tag{4}$$

where $c(S_{j,t-1}, S_{j,t-2})$ denotes the transaction costs determined by the change in position holdings based on the j-th technical rule for the previous two days.

Based on the definitions of excess returns specified in Equations (1), (3) and (4), we then construct four performance metrics to be used in our empirical tests: the mean excess return, the Sharpe ratio, the relative mean excess return and the relative Sharpe ratio, all of which are defined below.

2.2 Performance metrics

Our first performance metric is the mean excess return of the j-th technical trading rule, which is defined simply as

$$\overline{R}_j \equiv 1/T\sum_{t=1}^{T} R_{j,t} \ , \tag{5}$$

and which is the simplest performance metric. Its major shortcoming is that it does not take into account the riskiness of the trading rule. Our second measure is the ex post Sharpe ratio (SR), which is a standard performance metric in the finance industry and measures units of average excess return per unit of risk with the latter measured as the standard deviation of excess returns (Sharpe, 1966). The Sharpe ratio of the j-th technical trading rule is defined as

$$SR_j \equiv \overline{R}_j / \sigma_j \ , \tag{6}$$

where σ_j is the standard deviation of excess returns generated by the j-th trading rule and is based on the heteroskedasticity and autocorrelation consistent (HAC) estimator of Politis and Romano (1994).

The Sharpe ratio is a more informative metric than the mean excess return as it adjusts mean excess returns by the associated volatility. Suppose, for example that we found that two trading rules *TR1* and *TR2* have the same mean return but the Sharpe ratio of *TR1* is twice that of *TR2*. By doubling the size of the positions taken by *TR1*, *TR1* could have earned twice the average return of *TR2* for the same level of risk as *TR2*, since doubling the positions taken will double both the mean return and the standard deviation of returns.[9]

Although the Sharpe ratio does adjust for standard deviation, it is possible that one currency provides consistently high returns with low volatility against the U.S. dollar due to country-specific risk premia. Profits from investing in foreign currencies, including interest differentials, may simply reflect risk compensation because these currencies are associated

[9] Scaling up the size of the positions taken is often referred to as scaling up the risk budget, since it scales up the standard deviation of excess returns and the volatility of standard deviations—i.e. risk—by the same factor.

with fundamental uncertainty such as unexpected government intervention or restricted repatriation of funds (e.g., Cornell and Dietrich, 1978; Hodrick and Srivastava, 1986; Froot and Thaler, 1990). Perhaps the simplest approach to measuring country-specific risk premia is through calculating the returns from a simple buy-and-hold position in the foreign currency (Sweeney, 1986), on the supposition that this must represent the compensation to a currency investor for holding risky foreign currency, which is one definition of a country risk premium to compensate various uncertainty including the Peso problem.[10]

Now, a standard method in the asset management industry for assessing the skill inherent in a strategy is to decompose a performance metric into a component due to 'tilting' (i.e. the component due to being on average long or short an asset, which could be replicated by a simple buy-and-hold strategy) and a component due to 'market timing' (i.e. the component due to timing trades to increase profits rather than just tilting). Thus, we can split daily excess returns into a tilt component (average foreign currency position over the whole sample period times foreign currency return for period *t*) and a market timing component (the remainder) as follows:

$$R_{j,t} \equiv R(Tilt)_{j,t} + R(Tim)_{j,t}\,, \tag{7}$$

where the tilt and timing components, $R(Tilt)_{j,t}$ and $R(Tim)_{j,t}$, respectively, are defined as:

$$R(Tilt)_{j,t} \equiv \left[\frac{1}{T}\sum_{t=1}^{T} S_{j,t-1}\right] r_t \tag{8}$$

and

$$R(Tim)_{j,t} \equiv R_{j,t} - \left[\frac{1}{T}\sum_{t=1}^{T} S_{j,t-1}\right] r_t\,. \tag{9}$$

According to the above argument, the tilt component of the excess return of a foreign exchange trading rule captures the country risk premium corresponding to the average position in the foreign currency and the timing component serves as an indicator of

[10] This assumes, of course, that risk premia remain constant over time.

performance adjusted for country risk premium.[11] Thus, in basing performance metrics on $R(Tim)_{j,t}$, the assumption is that a high market timing component of the excess return indicates that a trading rule provides returns in excess of risk premia associated country-specific risk factors including the Peso problem (measured with the tilt component). Further, one might argue that a profitable trading rule with a high timing component is in some sense more skillful than one with a high tilt component, since timing involves actively buying and selling the foreign currency while tilting is by definition more passive.

A simple performance metric based on the timing component of excess returns is simply the time-series mean of this component:

$$\overline{R}(Tim)_j \equiv \left[\overline{R}_j - \left[\frac{1}{T} \sum_{t=1}^{T} S_{j,t-1} \right] \frac{\sum_{t=1}^{T} r_t}{T} \right]. \tag{10}$$

The relative mean excess return, $\overline{R}(Tim)_j$, subtracts the average foreign currency position times the average foreign currency excess return from holding the foreign currency over the period, and is our third performance metric. In particular, it penalizes trading rules that have a high tilt component and which may simply collect risk premia by riding a trend appreciation or depreciation without timing well the trades into or out of the currency to exploit changes in direction.

Note that $\overline{R}(Tim)_j$ is very similar to the X-statistic introduced by Sweeney (1986) in his assessment of technical foreign exchange trading rules. In particular, Sweeney's X-statistic for a trading rule that allows long-short investing is defined as follows:

$$X_j = \overline{R}_j - \left[\frac{1}{T} \sum_{t=1}^{T} \iota(S_{j,t-1} > 0) - \frac{1}{T} \sum_{t=1}^{T} \iota(S_{j,t-1} < 0) \right] \frac{\sum_{t=1}^{T} r_t}{T}, \tag{11}$$

where, once more, $\iota(E)$ denotes the indicator function of the event E.[12] With foreign currency

[11] Note that we have omitted transaction costs in the above derivation for convenience.

[12] Sweeney (1986) originally conceived of the X-statistic as the mean return to a long-only strategy adjusted for risk aversion in the sense of 'foreign currency holding aversion': the greater the proportion of time a foreign currency position was held and the bigger that average position, the more X-statistic penalizes performance.

holdings normalized to zero or plus or minus one, $\overline{R}(Tim)_j$ and X_j are in fact equivalent. If, however, daily positions are allowed to take another value (as in our triple moving average rule, for example, where the daily position may also take a value of –1/3 or +1/3), the two will differ.[13] We therefore propose the mean excess return to market timing, $\overline{R}(Tim)_j$, as a generalization of the *X*-statistic and our third suggested performance metric.

Neither the *X*-statistic nor our $\overline{R}(Tim)_j$ statistic is adjusted for risk in the sense of the volatility of returns, however. Nevertheless, as with the mean excess return, we can easily adjust our measure of market timing performance by calculating the Sharpe ratio of the excess return relative to market timing:

$$SR(Tim)_j \equiv \overline{R}(Tim)_j / \sigma(Tim)_j \,, \tag{12}$$

where σ_j is the HAC estimator of the standard deviation of excess returns relative to market timing for the *j*-th trading rule.

Overall, therefore, we suggest four different performance criteria for the *j*-th trading rule: the mean excess return ($\overline{R}_j$), the Sharpe ratio (SR_j), the relative mean excess return ($\overline{R}(Tim)_j$), and the Sharpe ratio for market timing ($SR(Tim)_j$).

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[13] To see that $\overline{R}(Tim)_j$ is the more general performance measure of the two, note that $\overline{R}(Tim)_j$ has zero unconditional expectation when daily positions other than –1, 0 and +1 are allowed, while X_j does not. To see this, substitute the definition of the mean excess return, Equation (5), into the definition of $\overline{R}(Tim)_j$, Equation (10), and take expectations:

$$E\left[\overline{R}(Tim)_j\right] \equiv \frac{1}{T}\sum_{t=1}^{T} S_{j,t-1}E(r_t) - \left[\frac{1}{T}\sum_{t=1}^{T} S_{j,t-1}\right]\frac{\sum_{t=1}^{T} E(r_t)}{T} = 0 \,.$$

Doing the same with the definition of X_j, Equation (11), we have:

$$E(X_j) = \frac{1}{T}\sum_{t=1}^{T} S_{j,t-1}E(r_t) - \left[\frac{1}{T}\sum_{t=1}^{T}\iota(S_{j,t-1} > 0) - \frac{1}{T}\sum_{t=1}^{T}\iota(S_{j,t-1} < 0)\right]\frac{\sum_{t=1}^{T} E(r_t)}{T}$$

$$= \frac{1}{T}\sum_{t=1}^{T}[S_{j,t-1} - \iota(S_{j,t-1} > 0) + \iota(S_{j,t-1} < 0)]E(r_t)$$

Thus, $E(X_j) = 0$ if and only if $S_{j,t-1} = \iota(S_{j,t-1} > 0) - \iota(S_{j,t-1} < 0)$ for all *j*, which precludes non-integer positions.

3. Empirical Methods

To answer the intriguing question whether technical analysis carries predictive ability or profitability (i.e. can 'beat the market'), our empirical strategy is to test if there exist technical trading rules that generate significantly positive performance measures. In addition, we are also interested in understanding the characteristics of any outperforming rules. To achieve these goals, we construct a composite null hypothesis including a large number of individual null hypotheses:

$$H_0^{(j)} : \theta_j \leq 0, \tag{13}$$

where θ_j denotes the true performance metric of the j-th rule and j=1,…,J (J = 21,195). Each individual null hypothesis indicates 'the performance metric provided by the j-th technical rule is less than or equal to zero'.

To test empirically the above composite null hypothesis, we need a multiple testing method that is able to generate appropriate significance levels of the performance metrics of numerous technical trading rules. We thus adopt the stepwise test developed by a series of previous studies including White (2000), Romano and Wolf (2005), Hansen (2005), and Hsu, Hsu, and Kuan (2010). This method is designed for large-scale multiple testing problems with potential data-snooping bias and is a powerful method of identifying as many significant rules as possible given an exact significance or Type I error level.[14] In particular, this test allows us to jointly test each individual null hypothesis, $H_0^{(j)}$, such that the rejection of the j-th individual null hypothesis indicates that the j-th technical rule is of significantly predictive (or profitable) power free of data-snooping bias.

The implementation of the stepwise test with a pre-specified Type I error level α_0 for foreign exchange rate returns in a specific sample period is as follows:

[14] The error for which we control in such a multiple testing framework is the family-wise error, defined as the probability of rejecting at least one correct null hypothesis. That is, when we impose a 10% significance level in our testing, we expect a 10% chance of wrongly identifying any ineffective technical rules as predictive/profitable ones.

1. Compute the return matrix $\boldsymbol{R}$, in which each element R_{jt} denotes the excess return (with or without transaction costs) provided by each technical rule on each day (j=1,…,J, t=1,…,T).
2. Compute the performance metric for the j-th technical rule, d_j, based on $\boldsymbol{R}$.
3. Resample $\boldsymbol{R}$ using the stationary bootstrap method of Politis and Romano (1994), with pre-specified parameter set Q , for B times, and label each resample as $\boldsymbol{R}_b$, b = 1,…,B.
4. For each b, compute the performance metric (d_{jb}) for the j-th technical rule based on resample, $\boldsymbol{R}_b$ and let the loop indicator i = 1.

5. Construct an empirical null distribution for the test statistics as follows:

   5.1. For each b, compute $s_{bi} = T^{1/2} \max_{j=1,\ldots,J} [d_{jb} - d_j + d_j\, \boldsymbol{\iota}(T^{1/2} d_j \leq -\sigma_j\, [2\log\log(T)]^{1/2})]$, where $\boldsymbol{\iota}(E)$ denotes the indicator function of the event E and σ_j denotes the standard deviation of the original return series of the j-th technical rule.

   5.2. Collect all $\{s_{bi}\}_{b=1,\ldots,B}$, rank them in descending order and then collect its (1–α_0)-th quantile as $q_i(\alpha_0)$.

6. Compare each technical rule's $T^{1/2}d_j$ to $q_i(\alpha_0)$, and treat the j-th null hypothesis as rejected at the i-th step if $T^{1/2}d_j > q_i(\alpha_0)$. Record all information of these rejected trading rules and label them as being rejected at the i-th step. Then, restart from Step 5, let $d_j = 0$ and $d_{jb} = 0$ for all rejected hypotheses j, and change the loop indicator from i to i + 1. However, if no technical rule is rejected given $q_i(\alpha_0)$, i.e. $T^{1/2}d_j \leq q_i(\alpha_0)$ for remaining j, then stop and go to Step 7.

7. Finally, restore the original d_j from $\boldsymbol{R}$ and estimate each technical rule's marginal p-value, p_j, as the percentile of $T^{1/2}d_j$ in the last $\{s_{bi}\}_{b=1,\ldots,B}$ as an empirical null distribution.

8. Compare each technical rule's p_j to α_0. If $p_j < \alpha_0$, we claim that technical rule j is of predictive ability or profitability for the foreign exchange rates in the sample period at a significance level of α_0. When there exists at least one predictive or profitable

technical rule for the foreign exchange rate in the sample period, we claim that the foreign currency is predictable or profitable at the significance level of α_0.

In our empirical tests, we set α_0 = 0.10, Q = 0.9, and B = 500 following the literature.[15] Moreover, we skip the observations of all currencies in the first year of their available sample periods in order to initialize some of the longer-term technical trading rules because they require up to 250 trading days to generate the first signals.

4. Empirical Results

4.1 The predictability of foreign exchange rates

We first examine the predictability of exchange rates based on technical analysis, i.e. whether technical trading rules can generate significantly positive excess returns without allowance for transaction costs. We focus on two indicators generated from the stepwise test: the first is the number of predictive rules that produce significantly positive performance metrics,[16] while the second is the p-value of the best rule that provides the highest performance metric among all rules. Table 2 reports the test results based on mean excess returns and Sharpe ratio and suggests that technical rules do indeed forecast foreign exchange rate movements in a general sense.

Based on performance in mean excess returns (Panel A), twenty out of thirty currencies are predictable at the 10% significance level, and seventeen currencies are predictable at the 5% significance level. Six out of nine developed currencies are found to be predictable: the German mark/euro, Japanese yen, New Zealand dollar, Swedish krona, Swiss franc, and U.K. pound. The German mark/euro appears to be the most predictable developed currency on this metric in that there exist 172 significantly predictive rules for this currency, with the most predictive one significant at the 1% level. The economic magnitude of the predictability is

[15] We have also performed a range of tests based on different parameter settings and have found similar results to those reported in the text.

[16] According to Timmermann and Granger (2004), the existence of a ‘thick’ set of outperforming models can be regarded as strong evidence for predictability.

also substantial: the annualized excess returns on the significant best performing rule in each developed currency range from 6.2% (Canadian dollar) to 14.8% (Japanese yen).

The evidence for technical predictability seems even stronger in emerging currencies as there are more predictive rules (in terms of mean excess returns) with low *p*-values. Fourteen emerging currencies are predictable at the 10% level, and nine are predictable at the 1% level. In fact, some emerging market currencies are predictable to a great extent, as there exist more than 100 significantly predictive trading rules in each of the following five currencies: the Colombian peso (272 significantly predictive rules), Philippine peso (149 significantly predictive rules), Taiwanese dollar (3,145 significantly predictive rules), Thai baht (221 significantly predictive rules) and Israeli shekel (757 significantly predictive rules). The economic magnitude of technical predictability also varies across emerging countries to a high degree. The annual returns generated by the best technical rule are as low as 4.2% (Singaporean dollar) and 5.9% (Taiwanese dollar) or as spectacularly high as 23.6% (Russian ruble) and 19.5% (Indonesian rupiah).

Table 2 also reports the test results based on the Sharpe ratio (Panel B),[17] and suggests that technical predictability in foreign exchange trading remains significant when adjustment is made for risk related to volatility. Five out of nine developed currencies remain significantly predictable, with the U.K. pound being the most predictable on this metric: there exist 36 outperforming technical rules for the U.K. pound, with the best rule providing a Sharpe ratio of 0.875 (*p*-value = 0.02). Our results for developed currencies are therefore largely consistent with the empirical findings of Qi and Wu (2006), whose study is based on a smaller set of technical trading rules and the one-step joint test of White (2000).[18]

Among our twenty-one emerging market exchange rates, fourteen are predictable at the 10% level and nine are predictable at the 5% level using the Sharpe ratio metric. While the

[17] The Sharpe ratio reported in Panel B has been annualized following LeBaron (2002). That is, we multiply the daily Sharpe ratio (i.e. the mean excess return divided by the standard deviation) by $\sqrt{250}$.

[18] Qi and Wu (2006) find empirical evidence for the predictability of six developed currencies (including the Canadian dollar, German mark, French franc, Italian lira, Japanese yen, Swiss franc, and U.K. pound) in the pre-euro period. In their study, Japanese yen provides the highest mean excess return (12.8%) and Sharpe ratio (1.24).

Taiwanese dollar is still strongly predictable on this metric, with find 1,763 significantly outperforming technical rules and a top Sharpe ratio of 1.295 (*p*-value = 0.00), the Colombian peso is overall most predictable after adjusting for volatility, with 385 outperforming rules and a top Sharpe ratio of 1.802.

We can also observe a geographic variation in the technical predictability of emerging currencies in that technical analysis performs well in the currencies of Asian and Latin American countries but not so strongly in those of developing European countries. We return to this intriguing phenomenon below.

Overall, we note that a majority of the thirty currencies are significantly predictable with technical trading rules using both mean excess returns and Sharpe ratio metrics. As a result, the prevailing technical predictability reported in Table 2 cannot be (fully) explained by risk related to volatility in foreign exchange rates. Nevertheless, we recognize that not all currencies are predictable in both metrics. On the one hand, the New Zealand dollar, Swedish krona, and South African rand are predictable according to the mean excess returns metric but not according to the Sharpe ratio metric, reflecting the importance of accounting for volatility in these currencies. On the other hand, the Australian dollar and Romanian new leu are predictable based on the Sharpe ratio metric but not based on the mean excess returns metric. This finding indicates the importance of considering multiple performance metrics to reach robust conclusions.

We next examine the technical predictability issue using a further two criteria, namely the relative mean excess return and the Sharpe ratio adjusted for tilt, which take the premia associated with country/currency-specific risk into consideration (or, alternatively viewed, measure trading performance stripped of the buy-and-hold element). As reported in Table 3, technical predictability remains strong based on these two criteria. When we compare Panel A of Table 3 to Panel A of Table II, we find that almost all predictable currencies (with the notable exception of the Brazilian real) retain their statistical significance after the adjustment for country/currency-specific risk premia by removing the tilt component. In addition, the number of predictive rules and the *p*-values of the best performing rules vary only by a small extent from Table 2 to Table 3, suggesting that our earlier findings of technical predictability cannot be simply attributed to risk premia or to largely buy-and-hold strategies. In addition, Panel B of Table 3 provides a strong pattern of technical predictability similar to the results reported in Panel B of Table 2, which further confirms our argument that country/currency-specific risk is not the main driving force for technical predictability.

Overall, our full-sample test results reported in Tables 2 and 3 may be summarized as follows. First, there is general evidence of the predictability of exchange rate movements using technical trading rules based on tests covering a large number of exchange rates, a large set of technical trading rules, multiple performance metrics, and data-snooping adjustment. Second, however, emerging market exchange rates, especially Asian and Latin American exchange rates, appear to be more predictable using technical analysis than developed country exchange rates, a finding that will be further examined below. Third, the predictability of exchange rates using technical trading rules cannot be fully explained by risk associated with exchange rate volatility and country-specific risk, or as tantamount to simple buy-and-hold strategies. Fourth, exchange rate volatility does explain a part of technical predictability, as we observe that evidence for technical predictability weakens when we move from using a simple mean excess return metric to using the Sharpe ratio. Last, country/currency-specific risk does not seem to help us understand more about technical predictability, as we observe almost no change when we remove the tilt component from the excess return.

4.2. Cross-sectional analysis

Motivated by the geographic variation in emerging currencies' technical predictability, we also perform a cross-sectional analysis, the results of which are reported in Table 4. For each currency, we compute the average number of outperforming rules across four performance metrics and the average *p*-value of the best rules in four performance metrics. These two statistics, reported in Panel A of Table 4, reflect the 'overall significance' of technical predictability in each currency. Among nine developed market currencies, the German mark/euro, Japanese yen, New Zealand dollar, Swiss franc, and U.K. pound appear to be significantly predictable, with 102.3, 104.0, 88.0, 5.3, and 25.5 average outperforming rules, respectively. In addition, the average *p*-values of the best rules for the German mark/euro, Swiss franc, and U.K. pound are below the 5% level, while the average *p*-values of the best rules for the Japanese yen and New Zealand dollar are below the 10% level. These findings further support the view that technical trading rules can significantly forecast developed currency movements.

For the twenty-one emerging currencies, we categorize them into three cultural/geographic groups: Latin America, Asia, and Europe. The Latin American group includes the Argentine peso, Brazilian real, Chilean peso, Colombian peso and Mexican peso. The Asian group includes the Indian rupee, Indonesian rupiah, Korean won, Philippine peso, Singaporean dollar, Taiwanese dollar and Thai baht. The European group includes the Czech koruna, Hungarian forint, Israeli shekel, Polish zloty, Romanian new leu, Russian ruble, Slovak koruna, South African rand and Turkish lira.

In the Latin American group, the Chilean peso and Colombian peso are significantly predictable on average, with 18.8, and 384.3 outperforming rules, respectively. It is noteworthy that all seven Asian countries are significantly predictable, the most predictable being the Taiwanese dollar, which is significantly predicted by a remarkable 2,481.0 technical rules on average. Equally surprisingly, we find that the grand average of the average numbers of outperforming rules in the Asia group is as high as 409.7 and the grand average of the average *p*-values in the group is as low as 3%, indicating that technical analysis beats Asian currency markets over long periods. In the European emerging market group, only the Israeli shekel, Russian ruble and Turkish lira appear to be significantly predictable by technical trading rules.

Panel A of Table 4 delivers a clear picture that the effectiveness of technical analysis varies not only by country but also by cultural/geographic grouping. Such a puzzling variation in technical predictability has not previously been reported in the literature and is certainly worth further investigation. Moreover, our empirical evidence thus far appears to militate against the serial correlation-based explanation for technical predictability proposed by, among others, Fama and Blume (1966) and Okunev and White (2003). However, among sixteen predictable currencies and according to the average *p*-values, six carry negative first-order autocorrelation coefficients (reported in Table I). As the most predictable currency, the Taiwanese dollar provides a first-order autocorrelation coefficient of -0.064. Among the three most negatively auto-correlated currencies, two are significantly predictable (Chilean peso and Taiwanese dollar). Moreover, technical analysis beats six out of ten negatively auto-correlated currencies. All these analyses strongly indicate that technical predictability cannot be attributed to serial correlation and trends, consistent with the early work of Cornell and Dietrich (1978).

Regarding the effect of volatility, we compare Table 4 to Figure 1 but do not observe a pattern between the volatility and predictability as the standard deviations of those predictable currencies are not particularly high in comparison with other currencies in the same group. Furthermore, we note that all Asian currencies are significantly predictable although, with the exception of the Indonesian rupiah, they do not exhibit particularly high volatility. Our results do not therefore support the hypothesis that technical trading rules are necessarily related to volatility.

4.3 Allowing for transaction costs

In this section, we investigate the importance of transaction costs for the profitability of technical trading rules. In particular, we consider two different approaches: first, we use fixed 0.025% one-way (or 0.05% round-trip) transaction costs (following, e.g., Neely, Weller, and Dittmar, 1997; Chang and Osler, 1999; Qi and Wu, 2006); and second, we compute the break-even costs which would be necessary for the predictive rules to maintain non-zero performance metrics (e.g., Bessembinder and Chan, 1995; Neely and Weller, 2003).

We first implement the stepwise test with 0.025% one-way transaction costs for each position change suggested by the individual trading rules.[19] Although transaction costs inevitably curtail profits, we still find strong evidence for technical profitability in many currencies, as shown in Tables 5 and 6. Nevertheless, the numbers of outperforming rules (and the *p*-values of the best rules) become lower (higher) than the corresponding numbers (*p*-values) in Tables 2 and 3. When we use the mean excess return as the performance metric, we find nineteen profitable currencies below the 10% significance level and sixteen below the 5% significance level (Panel A of Table 5). Interestingly, the predictability of the U.K. pound reported earlier does not imply profitability once transaction costs are imposed. When we use the Sharpe ratio as the performance metric, we find fifteen (nine) profitable currencies under the 10% (5%) significance level in Panel B of Table 5. Three predictable developed currencies (Australian dollar, Japanese yen, and U.K. pound) are now found to be unprofitable on this metric. This finding suggests that previous findings of predictability in developed currencies may not be robust to allowance for both volatility and transaction costs.

Interestingly, for six of the thirteen emerging market currencies that have a trading rule with a significant Sharpe ratio after allowing for transactions costs, the best-performing rule is the triple-moving average rule (denoted MA5—see Appendix) identified by Lequeux and Acar (1998) as a popular foreign exchange technical trading rule, while a further three currencies also favor a moving average rule, the Philippine peso favors a filter rule, Indian rupee an oscillator rule and Israeli shekel a support-resistance rule.

Test results based on the relative mean excess return, i.e. mean excess returns adjusting for country/currency-specific risk premia (or tilt component), are reported in Panel A of Table 6 and are very similar to the results reported in Panel A of Table 3: with the single exception of the U.K. pound, all currencies that were earlier found to be predictable are

[19] The 0.025% one-way transaction costs are used for each whole risk budget. For example, if a technical rule suggests +1 position today and 0 position yesterday, then we charge 0.025% from today's daily excess return of this technical rule. If that technical rule suggests –1 position today and +1 position yesterday, then we charge 0.05% from its daily excess return today.

found to be significantly profitable when allowance is made for transaction costs. Lastly, when we use the relative Sharpe ratio as the performance metric, we find nine (six) profitable currencies under the 10% (5%) significance level, as reported in Panel B of Table 6. Four previously predictable developed currencies (Australian dollar, Japanese yen, Swiss franc and U.K. pound) and four previously predictable emerging currencies (Chilean peso, Korean won, Russian ruble and Indonesian rupiah) are found to be unprofitable when transaction costs are imposed. These findings serve as important evidence that emerging currencies are more profitable than developed currencies in that, after allowance for transactions costs, we find almost no profitability in developed currencies but find several profitable emerging currencies with thick outperforming trading rule sets. Our empirical results indicate the existence of technical profitability in emerging currencies even after adjusting for volatility risk, country/currency-specific risk, and transaction costs.

Panel B of Table 4 presents the results of a cross-sectional comparison of foreign exchange profitability after allowance for transaction costs by averaging profitability indicators in four performance metrics (taken from Tables 5 and 6). We first observe that, among nine developed currencies, only the German mark/euro and Swiss franc appear to be lucrative based on average *p*-values. In comparison with Panel A, the Japanese yen, New Zealand dollar and U.K. pound are found to be predictable but not profitable for technical analysts employing quantitative rules. Our second observation is the significant profitability of technical rules for eleven emerging currencies (two from the Latin American group, all seven from the Asian group and two from the European group). Almost all predictable emerging currencies are also profitable after allowance for transaction costs, the exception being the Russian ruble. The cultural/geographic variation shown in predictability also carries over to profitability. Using grand averages across all currencies in each group, Asian currencies seem to be good targets for technical analysts, as there exist over 200 profitable rules in each Asian currency on average. Overall, Panel B strongly suggests that emerging currencies are more exploitable than developed currencies using technical trading rules, especially Asian emerging currencies.

Our allowance for transaction costs has so far been limited to the imposition of 0.025% one-way transaction costs. Another way of approaching this is to work out the break-even transaction costs—i.e. the level of one-way transaction costs that would reduce profitability to exactly zero, following Bessembinder and Chan (1995) and Neely and Weller (2003).[20] Table 7 reports the break-even costs and the number of trades of the significantly predictive technical rules from Tables 2 and 3, strongly supporting the potential profitability from technical predictability. Some predictive rules are long-term strategies with only a few trades, and their break-even costs are well above 1% per one-way trip.

We first focus on the results based on the mean excess return for the analyses. The outperforming rules for the New Zealand dollar and Swedish krona result in 213 and 123 trades and bear one-way transaction costs as high as 97.6 and 313.7 basis points, respectively; in addition, the outperforming rules for the Brazilian real, South African rand, and Turkish lira lead to 49, 213, and 91 trades and afford 336.0, 114.8, and 228.7 basis points costs, respectively.

It is also worth mentioning that technical trading rule profitability is not restricted to long-term technical rules. For example, even for the outperforming rules in the German mark/euro and U.K. pound that generate 643 and 3,767 trades, they can afford 28.5 and 5.5 basis points of break-even costs, while for the Swedish krona the break-even transaction costs are as high as 313.7 basis points.

When we consider the results based on the Sharpe ratio metric, we find that some significantly predictive rules in emerging currencies provide break-even costs in excess of 1,000 basis points for three countries, namely Brazilian, Romania and Turkey; the lowest break-even transaction cost is for the Korean won, at 6.5 basis points. Similar patterns are observed in the results based on the other two performance metrics.

[20] The level of the break-even transaction costs can be interpreted as the economic magnitude of the profitability of predictive technical rules. When a technical rule can afford higher break-even costs there is greater leeway for technical analysts to convert its predictive power to real wealth.

As a result, Table 7 delivers the following two implications. First, technical predictability can be converted to profitability given a reasonable level of transaction costs in both developed and emerging currencies. Second, the observation that the best predictive rules include all long, medium, and short-term technical rules confirms the robustness of technical profitability because transaction costs would not be a major concern for long and medium-term technical rules. Even individual technical analysts who only trade in developed currencies may focus on less frequent trading rules and still collect good payoffs. Our results therefore strongly support the argument of Menkhoff and Taylor (2007) that transaction costs do not necessarily eliminate the possibility of making significant profits using technical rules.

4.4 Sub-period analysis

In a discussion of the empirical literature on technical analysis in foreign exchange markets, Menkhoff and Taylor (2007) suggest that technical trading rules may have become less profitable over time, reflecting an increase in informational efficiency. Our long sample of data series allows us to investigate the issue of the time-varying predictability and profitability of technical trading rules in the foreign exchange market. We split the whole sample period into eight subsamples, 1972-1976, 1977-1981, 1982-1986, 1987-1991, 1992-1996, 1997-2001, 2002-2007, and 2008-2011.[21] Given that the first year of data (1971) is required to initialise some of the trading rules, our eight subsamples largely divide the full sample into five-year periods, with the exception of the last two. However, they coincide with some natural break points related to important events in the foreign exchange market, including the Maastricht Treaty in 1992, the East Asian currency crisis in 1997, the appearance of physical Euro in 2002 and the global financial crisis since 2008.

For each currency in every subsample period, we conduct the stepwise test based on the mean excess return criterion, and report the numbers of significantly predictive and profitable

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[21] The last sample period ends on July 29, 2011. For emerging market currencies, we only conduct tests for available subsamples. Our sample splitting follows Levich and Thomas (1993), which splits the entire sample period into three five-year subsample periods for time-series analysis.

rules (with allowance for 0.025% one-way transaction costs) in Panels A and B of Table 8, respectively.[22]

In the upper part of the table, we observe that developed currencies are predictable and even exploitable for technical analysts in earlier subsample periods. In fact, most predictive rules occur in the first sample period (1972-1976). Then, there are only a few predictive and profitable rules found in the 1980s, and none since the 1992-1996 period. The disappearance of the predictability of developed currencies using technical trading rules since the early 1990s, noted by Menkhoff and Taylor (2007), is consistent the findings of LeBaron (2002), Olson (2004), and Neely, Weller, and Ulrich (2009), among others. The downward trend in the performance of technical rules also supports the unavoidable ‘self-destruction’ process of Timmermann and Granger (2004) and Timmermann (2008): specific technical rules generate profits from uncovering and exploiting important information or market sentiment and such profitability will sooner or later be identified and arbitraged away by technical analysts.

However, we cannot rule out the possibility of underestimated technical predictability due to test power: there may exist predictive rules that are not detected by the stepwise test due to the relatively short subsample periods. As a result, although our earlier findings based on the whole sample indicate the existence of technical profitability, we could not claim that there is still a viable profit margin for technical analysts in today’s developed currencies. Perhaps a safe statement is that technical predictability and profitability *used to* exist in developed foreign exchange rates but can no longer be established.

There is an interesting question regarding the disappearance of developed currencies’ predictability and profitability: Are they wiped out suddenly or do they diminish gradually over time? We attempt to answer the above question by visualizing the time-varying predictability and profitability in Panels A and B of Figure 3, in which we report the average *p*-values of the best rules (based on the mean excess return) across all nine developed currencies in each subsample period. We observe a clear upward-sloping trend in both Panels

[22] Tables based on other performance metrics present similar patterns and, thus, are unreported.

A and B in Figure 3. Although the upper part of Table 8 indicates the disappearance of technical predictability and profitability since the 1992-1996 period, we do not observe a regime switch since 1992 in Figure 3. Our empirical evidence thus supports that technical predictability and profitability have diminished gradually in developed currencies.

The lower part of Table 8 shows the time-series variation of the technical predictability and profitability for emerging market currencies. Emerging market currencies seem to be more predictable and profitable in their inception years, such as the Israeli shekel in the 1982-1986 period, the Taiwanese dollar in the 1987-1991 period and the Argentine peso and Chilean peso in the 1997-2001 period. In the bottom row of the table, we calculate the average number of predictive/profitable rules across all available emerging currencies as the first aggregate indicator of the technical predictability/profitability of emerging currencies in each subsample period. The average number of predictable rules decreases almost monotonically from 576.3 (1982-1986) to 5.3 (2008-2011), and the average number of profitable rules decline from 444.7 (1982-1986) to 3.2 (2008-2011).

Panels C and D of Figure 3 plot the average *p*-values of the best rules (based on the mean excess return) across all twenty-one emerging currencies in each subsample period. We observe upward-sloping average *p*-values, yet not as significant and monotonic as those in developed currencies. Collectively, Table 8 and Figure 3 not only present gradually weakening technical predictability and profitability of the foreign exchange market, but also highlight market maturity as a determinant of the performance of technical trading rules.

An important implication of the evidence we present in this section is that technical predictability/profitability does not coincide with the structural changes of the foreign exchange market, such as the Maastricht Treaty in 1992, or market turmoil such as the Asian currency crisis in 1997, Mexican peso crisis in 1994 or Russian ruble crisis in 1998. Thus, our time-series analysis also does not support the proposition that technical analysis performs better in volatile periods and the time-variant risk premia argument. Moreover, since investors tend to be less rational and market sentiment is usually higher during financial crises, foreign currency traders' not-fully-rational behavior and market sentiment may not be the main driving force for technical predictability and profitability.

Also, our time-series analysis does not support the proposition that central bank intervention leads to technical predictability,[23] since we do not observe particularly strong predictability in currencies during periods with intensive central bank intervention such as during the recent global financial crisis (Melvin and Taylor, 2009).

4.5 Portfolio analysis

The discussion so far suggests that technical analysis has been profitable in the past for both developed and emerging market currencies, while the profitability of technical trading rules may have diminished over time. It may still be profitable in a number of emerging foreign currency markets. Our analysis to this point has been conducted entirely in terms of single-currencies, albeit with comparisons made between currencies. In this section, we provide a glimpse of the kind of investment performance that could have been obtained over the entire sample period, by using the best-performing trading rules for each of the thirteen emerging market currencies that recorded a significant Sharpe ratio in Panel B of Table 5, in a simple portfolio made up of those thirteen emerging market currencies, namely the Brazilian real, Chilean peso, Colombian peso, Indian rupee, Indonesian rupiah, Israeli shekel, Korean won, Philippine peso, Romanian new leu, Singaporean dollar, Taiwanese dollar, Thai baht and Turkish lira.

No attempt at portfolio optimization is made: we simply allocate one dollar of risk evenly across all currencies such that the total gross position always adds up to one dollar overall and is evenly distributed across currencies. Because we do not have data on all of these currencies from the beginning of the data period, we start the portfolio analysis in January 1978 and add in currencies as data on them become available, reducing the risk

[23] This implication is in accordance with the findings of other authors that technical trading profits cannot be attributed purely to central bank intervention (e.g., Cornell and Dietrich, 1978; Neely and Weller, 2001; Neely, 2002).

budget on other currencies in the portfolio whenever a new country enters in order to maintain the equal weighting. We allow for one-way transaction costs of 2.5 basis points.

The cumulative performance of the resulting portfolio, as shown in Figure 4, is little short of spectacular: it reveals a strong cumulative return of 746% over the full 23.58 year sample period, or an average annual compound return of 9%. Further, there appear no significant drawdowns for the portfolio over the period, and the whole-period Sharpe ratio is an enormous 7.76 (while the annualised Sharpe ratio is 1.31). Given that each of the trading rules is selected with a safeguard against data-snooping bias, this provides extremely strong evidence for the profitability of technical trading rules in emerging markets.

5. Conclusion

Researchers have reported the widespread use and significant profitability of technical analysis in the foreign exchange market since the 1970s. However, most previous evidence is based on small sets of technical trading rules applied to a handful of currencies, with simple performance metrics and testing methods that have often been subject to data-snooping bias. As a result, the long-debated issue of whether and why technical analysis beats the foreign exchange market has not been satisfactorily answered and several intriguing issues call for further exploration.

The present study takes the challenge and carries out a large-scale investigation of the effectiveness of technical trading rules in forecasting foreign exchange rates across thirty currencies in long sample periods in an analysis of over 21,000 technical trading rules. With the aid of a recently developed testing method, we are able to make formal statistical inferences for several important research questions while safeguarding against data-snooping bias. We conclude that technical analysis indeed has predictive power for both developed and emerging currencies during certain periods, emerging currencies are in general more predictable than developed currencies, and most Asian currencies appear to be highly predictable. Among developed currencies, however, strong technical predictability exists in the 1970s and 1980s but then gradually disappears since the early 1990s. On the other hand, we find strong evidence for technical predictability in emerging currencies even in the 2000s.

This finding of predictability using technical analysis may be also converted to profitability, as we find statistical significance in a number of technical trading rules remains even after adjustment for appropriate transaction costs, especially in emerging markets. Moreover, an equally weighted portfolio of technical trading rules applied to emerging currencies yields an average compound return of 9% per annum over the last thirty years or so and an annual Sharpe ratio of 1.31.

Our empirical investigation also indicates that technical predictability and profitability in the foreign exchange market cannot be simply attributed to the autocorrelation, risk premia, volatility, market crises or central bank intervention. Instead, our analysis favors the explanation of temporary not-fully-rational behavior as the basis for technical predictability and profitability: this is consistent with our finding that the profitability of technical analysis has diminished over time in developed currencies but remains in certain emerging currencies.

We conclude, therefore, that market maturity, and the associated degree of informational efficiency, is an important determinant of technical predictability and profitability in the foreign exchange market.

Appendix: Details of Technical Trading Rules

A.1 *Oscillator trading rules*

One technical device that is widely used in the foreign exchange market (Taylor and Allen, 1992) is the 'overbought/oversold' indicator, or oscillator, although it has rarely been discussed in the academic literature. Oscillators are measures designed to indicate that price movements in a particular direction have recently been too rapid and that a correction in the opposite direction is imminent; they may take a number of precise forms. One popular form is the relative strength indicator (RSI) (Levy, 1967; Wilder, 1978), which is defined as:

$$RSI_t(h) = 100\left[\frac{U_t(h)}{U_t(h) + D_t(h)}\right], \tag{A1}$$

where $U_t(h)$ denotes the cumulated 'up movement' (i.e. the close-to-close increase on a day when the exchange rate has closed higher than the previous day's closing rate) over the previous h days, and $D_t(h)$ denotes the cumulated absolute 'down movement' (the absolute close-to-close decrease on a day when the exchange rate has closed lower than the previous day's closing rate) over the same period:[24]

$$U_t(h) = \sum\nolimits_{j=1}^{h} \iota(s_{t-j} - s_{t-1-j} > 0)(s_{t-j} - s_{t-1-j}) \tag{A2}$$

$$D_t(h) = \sum\nolimits_{j=1}^{h} \iota(s_{t-j} - s_{t-1-j} < 0)\,|\, s_{t-j} - s_{t-1-j}\,|, \tag{A3}$$

where $\iota(.)$ is an indicator variable that takes the value one when the statement in parentheses is true and zero otherwise. The RSI thus attempts to measure the strength of 'up movements' relative to the strength of 'down movements' and is normalised to lie between 0 and 100. Common values at which a particular currency is deemed to have been overbought (signalling an imminent downward correction) or oversold (signalling an imminent upward correction) are 70 and 30, respectively (see, e.g., Henderson, 2002). Note that the RSI is a kind of 'reversal' indicator, since it is designed to anticipate a reversal in trend.

A standard oscillator trading rule based on the RSI may be expressed as follows:

[24] Some expositions of the RSI define U_t and D_t in terms of average rather than cumulated up and down movements. This is equivalent to our definition, however, since it just involves dividing by the total number of days and this factor cancels out when the RSI is calculated.

O1: If $RSI_t(h)$ moves above 50+v for at least d days and then subsequently moves below 50+v, go short the currency. If $RSI_t(h)$ moves below 50-v for at least d days and then subsequently moves above 50-v, go long the currency.

A variation on the standard RSI trading rule imposes a pre-specified holding period for a position:

O2: If $RSI_t(h)$ moves above 50+v for at least d days and then subsequently moves below 50+v, go short the currency for k days and then neutralize the position. If $RSI_t(h)$ moves below 50-v for at least d days and then subsequently moves above 50-v, go long the currency for k days and then neutralize the position.

Note that a trading signal is *not* generated when the RSI *enters* the overbought or oversold region (i.e. goes above 50+v or below 50-v) but as it *exits* the region (i.e. crosses 50+v from above or crosses 50-v from below). This is because the currency can remain overbought or oversold for long periods and may become even more overbought or oversold for a while. The oscillator trading rule is designed to allow the spot rate to continue moving in the desired direction until a trend change becomes evident.

We consider a total of 600 oscillator trading rules. The specifications of oscillator trading rules we consider are described as below:

$h \in \{5, 10, 15, 20, 25, 50, 100, 150, 200, 250\}$, $\#h = 10$.

$v \in \{10, 15, 20, 25\}$, $\#v = 4$.

$d \in \{1, 2, 5\}$, $\#d = 3$.

$k \in \{1, 5, 10, 25\}$, $\#k = 4$.

O1: This trading rule has three parameters, *h, v* and *d*. The number of versions of *O1* considered is therefore $\#O1=\#h \times \#v \times \#d = 10 \times 4 \times 3 = 120$.

O2: This trading rule has four parameters, *h, v, d* and *k*. The number of versions of *O2* considered is therefore $\#O2=\#h \times \#v \times \#d \times \#k = 10 \times 4 \times 3 \times 4 = 480$.

A.2 *Filter rules*

The filter rule is one of the simplest techniques of technical analysis (Alexander, 1961) and in the present context basically involves buying a currency against another currency whenever the exchange rate has risen by more than a given percentage above its most recent low and selling it when the rate drops by more than a given percentage below its most recent high. A simple filter rule for trading a currency may be stated as follows:

F1: If the daily closing spot exchange rate of the currency moves up at least x percent above its most recent low and remains so for d days, go long the currency. If the daily closing spot rate moves down below its most recent high at least x percent and remains so for d days, go short the currency.

In this context, we define the most recent high (low) as the most recent closing price that is greater (less) than the *j* previous daily closing prices, for a given value of *j*.

A variation on this basic filter rule allows for neutral positions rather than requiring that positions always be either long or short after the first position is initiated:

F2: If the daily closing spot exchange rate of the currency moves up at least x percent above its most recent low and remains so for d(x) days, go long the currency until its daily closing spot rate moves down at least y percent below the subsequent high and remains so for d(y) days, at which time sell the currency and neutralize the long position. If the daily closing spot exchange rate of the currency moves down at least x percent below its most recent high and remains so for d(x) days, go short the currency until its daily closing spot rate moves up at least y percent above the subsequent low and remains so for d(y) days, at which time buy the currency and neutralize the short position. y is less than x. d(y) is less than or equal d(x).

Subsequent lows and highs in this context are again defined with respect to the previous *j* days.

A third, more naïve variation on the filter rule imposes a pre-specified holding period that is adhered to ignoring all other signals:

F3: If the daily closing spot exchange rate of the currency moves up at least x percent above its most recent low and remains so for d days, go long the currency for k days and then neutralize the position. If the daily closing spot exchange rate of the currency moves down at least x percent below its most recent high and remains so for d days, go short the currency for k days and then neutralize the position.

In our empirical work, we examine a total of 2,835 filter rules, the parameterization of which is described as below:

$x \in$ {0.05, 0.1, 0.5, 1.0, 5.0, 10.0, 20.0} in %, # x = 7.

$y \in$ {0.05, 0.1, 0.5, 1.0, 5.0, 10.0, 20.0} in %. Given $y<x$, the number of x-y combinations: $\#(x\text{-}y)=\sum_{j=1}^{6} j = 21$.

$d \in$ {0, 1, 2, 3, 4, 5}, #d = 6.

$d(x) \in$ {0, 1, 2, 3, 4, 5}, $d(y) \in$ {0, 1, 2, 3, 4}. Given d($y) \leq d(x)$, the number of $d(x)$-$d(y)$ combinations: $\#[d(x)\text{-}d(y)]=\sum_{j=1}^{5} j = 15$.

$j \in$ {1, 2, 5, 10, 20}, #j = 5.

$k \in$ {5, 10, 15, 20, 25}, #k = 5.

FR1: This trading rule has three parameters, x, d and j. The number of versions of *FR1* considered is therefore $\#FR1=\#x \times \#d \times \#j = 7 \times 6 \times 5 = 210$.

FR2: This trading rule has five parameters, x, y, $d(x)$, $d(y)$ and j. The number of versions of *FR2* considered is therefore $\#FR2=\#(x\text{-}y) \times \#[d(x)\text{-}d(y)] \times \#j = 21 \times 15 \times 5 = 1{,}575$.

FR3: This trading rule has four parameters, x, d, j and k. The number of versions of *FR3* considered is therefore $\#FR3=\#x \times \#d \times \#k \times \#j = 7 \times 6 \times 5 \times 5 = 1{,}050$.

A.3 *Moving average trading rules*

Moving average trading rules can range in construction from very simple to complex, and have been among the most widely used of technical trading rules in the foreign exchange market (Taylor and Allen, 1992). This family of rules attempts to ride trends and identify imminent breaks in trend or the emergence of new trends. In a simple (single) moving average trading rule, for example, the local trend is approximated by the moving average and a break in trend, which is a trading signal to initiate a new position or neutralise the current position, is indicated when the moving average is crossed by the spot rate. Traders often use a short-term moving average in place of the spot rate in rules of this kind, in which case an imminent upward break in trend might be signalled by a short moving average intersecting from below a longer moving average. Conversely, a downward break in trend would be signalled by the short moving average crossing the long moving average from above.

If we define the simple moving average of the exchange rate over *j* days as

$$MA_t(j) = \frac{1}{j}\sum_{i=0}^{j-1} s_{t-i} \ , \qquad \text{(A4)}$$

then a single moving average trading rule may be expressed as follows:

MA1: If the daily closing spot exchange rate of the currency moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the currency until its daily closing spot rate moves down at least x percent below $MA_t(q)$ and remains so for d days, at which time go short the currency. If the daily closing spot exchange rate of the currency moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the currency until the daily closing spot rate moves up at least x percent above $MA_t(q)$ and remains so for d days, at which time go long the currency.

As before, a simple variation that pre-specifies the holding period, ignoring all other signals during the holding period, would be as follows:

MA2: If the daily closing spot exchange rate of the currency moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the currency for k days and then neutralize the position. If the daily closing spot exchange rate of the currency moves down at least x *percent below $MA_t(q)$ and remains so for d days, go short the currency for k days and then neutralize the position.*

A double moving average trading rule may be formulated in the following fashion:

MA3: If $MA_t(p)$ moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the currency until $MA_t(p)$ moves down at least x percent below $MA_t(q)$ and remains so for d days, at which time go short the currency. If $MA_t(p)$ moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the currency until $MA_t(p)$ moves up at least x percent above $MA_t(q)$ and remains so for d days, at which time go long the currency. p is less than q.

And the pre-specified holding period version is of the form:

MA4: If $MA_t(p)$ moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the currency for k days and then neutralize the position. If $MA_t(p)$ moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the currency for k days and then neutralize the position. p is less than q.

Finally, consider a triple moving average rule (Lequeux and Acar, 1998):[25]

MA5: If the daily closing spot exchange rate of the currency moves up at least x percent above any two of MA_t (n), MA_t (p) and MA_t (q) and remains so for d days, go long the currency with one third of the risk budget (currency position=+1/3). If the daily closing spot rate of the currency moves up at least x percent above all three of MA_t (n), MA_t (p) and MA_t (q) and remains so for d days, go long the currency with the whole of the risk budget (currency position=+1). If the daily closing spot exchange rate of the currency moves down up at least x percent below any two of MA_t (n), MA_t (p) and MA_t (q) and remains so for d

[25] Lequeux and Acar (1998) report that the correlation of excess returns generated by a particular parameterization of this strategy with those of the median Commodity Trading Advisor (CTA) was approximately 0.85 over their simulation period. This trading rule therefore appears to replicate well a key constituent of the investment strategy of an informed and active group trading in the foreign exchange market that is known predominantly to use technical trading rules (Sager and Taylor, 2006).

days, go short currency with one third of the risk budget (currency position=-1/3). If the daily closing spot rate moves down at least x percent below all three of MA_t (n), MA_t (p) and MA_t (q) and remains so for d days, go short the currency with the whole of the risk budget (currency position=-1). n is less than p, which is less than q.

Clearly, the trading rule never indicates a neutral position—for example if the spot rate is above only one moving average, it must be below two of them and a one third short position is indicated.

We consider a total of 12,870 moving average trading rules, the details of the specifications are described as below:

$q \in \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250\}$, $\#q = 11$.

$p \in \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200\}$. Given $p<q$, the number of p-q combinations: $\#(p\text{-}q)= \sum_{j=1}^{10} j = 55$.

$n \in \{2, 5, 10, 15, 20, 25, 50, 100, 150\}$. Given $n<p<q$, the number of n-p-q combinations: $\#(n\text{-}p\text{-}q)= \sum_{J=1}^{9}\sum_{j=1}^{J} j = 165$.

$x \in \{0, 0.05, 0.1, 0.5, 1.0, 5.0\}$ in %, $\#x = 6$.

$d \in \{0, 2, 3, 4, 5\}$, $\#d = 5$.

$k \in \{5, 10, 25\}$, $\#k = 3$.

MA1: This trading rule has three parameters, *q*, *x* and *d*. The number of versions of *MA1* considered is therefore $\#MA1=\#q \times \#x \times \#d = 11 \times 6 \times 5 = 330$.

MA2: This trading rule has four parameters, *q*, *x*, *d* and *k*. The number of versions of *MA2* considered is therefore $\#MA2=\#q \times \#x \times \#d \times \#k = 11 \times 6 \times 5 \times 3 = 990$.

MA3: This trading rule has four parameters, *p*, *q*, *x* and *d*. The number of versions of *MA3* considered is therefore $\#MA3=\#(p\text{-}q) \times \#x \times \#d = 55 \times 6 \times 5 = 1{,}650$.

MA4: This trading rule has five parameters, *p, q, x, d* and *k*. The number of versions of *MA4* considered is therefore $\#MA4=\#(p\text{-}q) \times \#x \times \#d \times \#k = 55 \times 6 \times 5 \times 3 = 4{,}950$.

MA5: This trading rule has five parameters, *n, p, q, x* and *d*. The number of versions of *MA5* considered is therefore $\#MA5=\#(n\text{-}p\text{-}q) \times \#x \times \#d = 165 \times 6 \times 5 = 4{,}950$.

A.4 *Support-resistance trading rules*

Support-resistance trading rules attempt to identify levels of the exchange rate above which the rate appears to have difficulty rising (a resistance level) and levels below which the rate appears to have difficulty penetrating (a support level). These trading rules are based on the premise that a breach of a support or resistance level will trigger further rapid exchange rate movement in the same direction. In construction, support-resistance trading rules are similar to filter rules except that a trading signal is generated when the rate moves beyond a support or resistance level by a certain percentage, rather than beyond a recent high or a recent low.

The support and resistance levels have to be pre-specified. We define a resistance level as the highest closing rate of the j previous closing rates and we define a support level as the lowest closing rate of j previous closing rates:

SR1: If the daily closing spot exchange rate of the currency moves up at least x percent above the highest closing of the j previous closing rates and remains so for d days, go long the currency. If the daily closing spot rate moves down at least x percent below the lowest closing of the j previous closing rates and remains so for d days, go short the currency.

The pre-specified holding period version of the support-resistance rule is also analogous to the corresponding filter rule:

SR2: If the daily closing spot exchange rate of the currency moves up at least x percent above the highest closing of the j previous closing rates and remains so for d days, go long the currency for k days and then neutralize the position. If the daily closing spot rate moves down at least x percent below the lowest closing of the j previous closing rates and remains so for d days, go short the currency for k days and then neutralize the position.

The details of our parameterization of a total of 1,890 support-resistance trading rules are provided as below:

$x \in \{0.05, 0.1, 0.5, 1.0, 2.5, 5.0, 10.0\}$ in %, $\#x = 7$.

$d \in \{0, 1, 2, 3, 4, 5\}$, $\#d = 6$.

$j \in \{2, 5, 10, 15, 20, 25, 50, 100, 250\}$, $\#j = 9$.

$k \in \{1, 5, 10, 25\}$, $\#k = 4$.

SR1: This trading rule has three parameters, *x*, *d* and *j*. The number of versions of *SR1* considered is therefore $\#SR1 = \#x \times \#d \times \#j = 7 \times 6 \times 9 = 378$.

SR2: This trading rule has four parameters, *x*, *d*, *j* and *k*. The number of versions of *SR2* considered is therefore $\#SR2 = \#x \times \#d \times \#j \times \#k = 7 \times 6 \times 9 \times 4 = 1{,}512$.

A.5 *Channel breakout trading rules*

A trading channel for an exchange rate is perceived as occurring when the highest level of the daily closing exchange rate over a previous given period is within a given range of the lowest level over the previous given period so that, in a sense, there are time-varying support and resistance levels that appear to be drifting together within a certain range. These time-varying support and resistance levels are the lower and upper bounds of the trading channel. Under a channel breakout rule, a trading signal is generated when a trading channel occurs and the exchange rate penetrates beyond the upper or lower bound of the channel. The assumption is that once the channel is breached, there will be sustained movement of the exchange rate in the same direction.

A *c%* trading channel for an exchange rate may be defined as occurring when the high level of the daily closing exchange rate over the previous *j* days is within *c*% of the low over the previous *j* days so that, in a sense, there are time-varying support and resistance levels that appear to be drifting together with about *c*% or less separation. These time-varying support and resistance levels are the lower and upper bounds of the trading channel. The upper bound of the trading channel on a particular day will be *c%* above the low of the previous *j* days and the lower bound will be *c%* below the high of the previous *j* days.

CB1: If a c% trading channel exists and if the daily closing spot exchange rate of the currency moves up at least x percent above the upper bound of the channel and remains so for d days, go long the currency. If a c% trading channel exists and if the daily closing spot exchange rate of the currency moves down at least x percent below the lower bound of the channel and remains so for d days, go short the currency.

And the pre-specified holding period version is:

CB2: If a c% trading channel exists and if the daily closing spot exchange rate of the currency moves up at least x percent above the upper bound of the channel and remains so for d days, go long the currency for k days and then neutralize the position. If a c% trading channel exists and if the daily closing spot exchange rate of the currency moves down at least x percent below the lower bound of the channel and remains so for d days, go short the currency for k days and then neutralize the position..

We analyse a total of 3,000 channel breakout rules, the parameterization of which is described as below:

$x \in \{0.05, 0.1, 0.5, 1.0, 5.0\}$ in %, $\#x = 5$.

$d \in \{0, 1, 2\}$, $\#d = 3$.

$j \in \{5, 10, 15, 20, 25, 50, 100, 200\}$, $\#j = 8$.

$c \in \{0.1, 0.5, 1.0, 5.0, 10.0\}$ in %, $\#c = 5$.

$k \in \{1, 5, 10, 25\}$, $\#k = 4$.

CB1: This trading rule has four parameters, x, d, j and c. The number of versions of *CB1* considered is therefore $\#CB1 = \#x \times \#d \times \#j \times \#c = 5 \times 3 \times 8 \times 5 = 600$.

CB2: This trading rule has five parameters, x, d, j, c and k. The number of versions of *CB2* considered is therefore $\#CB2 = \#x \times \#d \times \#j \times \#c \times \#k = 5 \times 3 \times 8 \times 5 \times 4 = 2{,}400$.

A.6 *Total technical trading rules*

The total number of different calibrations of trading rules considered is therefore:

(*#O1+#O2*) + (*#FR1+ #FR2+ #FR3*) + (*#MA1+ #MA2+ #MA3+ #MA4+ #MA5*) + (*#SR1+ #SR2*) + (*#CB1+ #CB2*) = 600 + 2,835 + 12,870 + 1,890 + 3,000 = 21,195.

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Table 1
Summary statistics of daily returns on foreign currencies and daily short rates

Countries	**Gross returns on foreign currencies**					**Short-term interest rates**					**Sample period**
	Mean (%)	Max	Min	Std. dev.	1st auto.	Mean (%)	Max (%)	Min (%)	Std. dev. (%)	1st auto.	
Developed											
Australia	-0.0001	0.1073	-0.1925	0.0069	0.003	0.0320	0.2441	0.0025	0.0155	0.962	1/4/1971 – 7/29/2011
Canada	0.0005	0.0505	-0.0434	0.0039	0.019	0.0292	0.0852	0.0008	0.0167	1.000	1/4/1971 – 7/29/2011
Germany/E.U.	-0.0006	0.0462	-0.0421	0.0059	0.031	0.0165	0.0491	0.0011	0.0097	1.000	1/4/1971 – 7/29/2011
Japan	0.0145	0.0950	-0.0626	0.0064	0.013	0.0191	0.0580	0.0000	0.0179	1.000	1/4/1971 – 7/29/2011
New Zealand	-0.0022	0.0995	-0.2050	0.0074	0.005	0.0322	0.1837	0.0079	0.0142	0.995	1/4/1971 – 7/29/2011
Norway	0.0026	0.0646	-0.0682	0.0065	-0.009	0.0272	0.1960	0.0063	0.0143	0.978	1/4/1971 – 7/29/2011
Sweden	-0.0019	0.0555	-0.1507	0.0066	0.001	0.0300	0.2986	0.0000	0.0179	0.992	1/4/1971 – 7/29/2011
Switzerland	0.0161	0.0643	-0.0678	0.0075	-0.028	0.0091	0.3251	-0.0060	0.0141	0.347	1/4/1971 – 7/29/2011
U.K.	-0.0037	0.0467	-0.0392	0.0059	0.066	0.0275	0.0657	0.0020	0.0142	0.972	1/4/1971 – 7/29/2011
U.S.	-	-	-	-	-	0.0222	0.0665	0.0000	0.0125	0.999	1/4/1971 – 7/29/2011
Emerging											
Argentina	-0.0279	0.4925	-0.3418	0.0095	0.025	0.0409	0.5920	0.0051	0.0591	0.979	4/1/1991 – 7/29/2011
Brazil	-0.0099	0.1178	-0.1080	0.0098	0.061	0.0771	3.5618	0.0275	0.0511	0.857	7/4/1994 – 7/29/2011
Chile	-0.0011	0.1114	-0.1160	0.0066	-0.081	0.0025	0.0305	0.0000	0.0028	0.558	1/3/1994 – 7/29/2011
Colombia	-0.0202	0.0562	-0.0508	0.0058	0.108	0.0577	0.1297	0.0132	0.0353	1.000	1/3/1992 – 7/29/2011
Mexico	-0.0400	0.2231	-0.2231	0.0124	-0.138	0.0726	0.4839	0.0146	0.0636	0.995	1/1/1987 – 7/29/2011
India	-0.0166	0.0552	-0.1281	0.0045	-0.048	0.0307	0.2778	0.0002	0.0227	0.847	1/1/1991 – 7/29/2011
Indonesia	-0.0303	0.2361	-0.3576	0.0150	0.035	0.0504	0.2934	0.0000	0.0373	0.983	1/2/1986 – 7/29/2011
Korea	-0.0063	0.2012	-0.1809	0.0089	0.236	0.0290	0.0966	0.0086	0.0203	0.997	1/3/1992 – 7/29/2011
Philippines	-0.0112	0.1015	-0.0860	0.0049	0.121	0.0369	0.2802	0.0021	0.0223	0.885	1/2/1987 – 7/29/2011
Singapore	0.0069	0.0414	-0.0276	0.0033	-0.054	0.0097	0.0259	0.0005	0.0069	0.989	1/4/1982 – 7/29/2011
Taiwan	0.0043	0.0430	-0.0420	0.0030	-0.064	0.0150	0.0690	0.0012	0.0089	0.992	10/3/1983 – 7/29/2011
Thailand	-0.0031	0.0741	-0.2077	0.0064	-0.032	0.0182	0.0948	0.0005	0.0173	0.992	1/2/1991 – 7/29/2011
Czech	0.0108	0.0681	-0.0707	0.0077	-0.043	0.0218	0.3755	0.0029	0.0198	0.949	4/22/1992 – 7/29/2011
Hungary	-0.0172	0.0520	-0.0842	0.0082	-0.011	0.0578	0.1191	0.0194	0.0278	1.000	6/3/1991 – 7/29/2011
Israel	-0.0883	0.0645	-0.1725	0.0063	0.085	0.1010	0.9012	0.0022	0.1483	0.999	1/3/1978 – 7/29/2011
Poland	-0.0115	0.1259	-0.0715	0.0082	0.002	0.0423	0.1132	0.0049	0.0280	0.952	6/4/1993 – 7/29/2011
Romania	-0.0527	0.0953	-0.3887	0.0108	0.016	0.0897	0.5238	0.0047	0.0804	0.990	1/1/1997 – 7/29/2011
Russia	-0.0578	0.2779	-0.3863	0.0144	0.276	0.0506	0.4583	0.0031	0.0677	0.972	9/1/1994 – 7/29/2011
Slovak	0.0066	0.0462	-0.1097	0.0068	0.010	0.0277	0.2954	0.0010	0.0243	0.963	4/27/1993 – 7/29/2011
South Africa	-0.0276	0.1440	-0.1030	0.0097	0.000	0.0466	0.0840	0.0000	0.0150	0.985	1/2/1981 – 7/29/2011
Turkey	-0.1171	0.2231	-0.3348	0.0119	0.139	0.1485	1.4754	0.0249	0.0951	0.958	1/2/1990 – 7/29/2011

We report descriptive statistics of daily log returns on holding foreign currencies for U.S. investors and daily log short-term interest rates in all countries. Developed countries are listed in alphabetical order, and emerging countries are in alphabetical order within three cultural/geographic groups (Latin America, Asia and Europe).

Table 2
The predictive performance of technical trading rules in foreign exchange rates: Common criteria

Countries	A. Mean excess return # predictive rules	Highest return (*p*-values)	Best rule	B. Sharpe ratio # predictive rules	Highest ratio (*p*-values)	Best rule
Developed						
Australia	0	0.079 (0.19)	MA5	1	0.739 (0.05)*	CB1
Canada	0	0.062 (0.35)	FR3	0	0.622 (0.17)	CB2
Germany/E.U.	172	0.093 (0.00)**	MA1	11	0.773 (0.01)**	FR3
Japan	105	0.148 (0.07)*	MA4	12	0.802 (0.07)*	FR2
New Zealand	169	0.100 (0.04)**	FR3	0	0.608 (0.23)	MA4
Norway	0	0.097 (0.22)	SR2	0	0.628 (0.19)	MA5
Sweden	62	0.130 (0.08)*	MA4	0	0.637 (0.18)	SR2
Switzerland	5	0.089 (0.02)**	MA2	2	0.703 (0.05)**	MA2
U.K.	12	0.106 (0.03)**	MA1	36	0.875 (0.02)**	SR2
%Sig. dvlpd	67%			56%		
Emerging						
Argentina	0	0.069 (0.83)	O1	0	0.624 (0.58)	MA5
Brazil	37	0.183 (0.01)**	FR1	2	1.368 (0.03)**	MA5
Chile	21	0.133 (0.00)**	FR1	20	1.327 (0.05)**	CB2
Colombia	272	0.156 (0.00)**	MA1	385	1.802 (0.00)**	CB2
Mexico	0	0.064 (0.99)	O1	0	0.733 (0.12)	O2
India	58	0.062 (0.02)**	SR1	1	0.931 (0.08)*	O2
Indonesia	10	0.195 (0.03)**	FR1	27	0.945 (0.04)**	CB2
Korea	24	0.168 (0.01)**	MA1	91	1.605 (0.01)**	CB2
Philippines	149	0.106 (0.00)**	FR1	83	1.263 (0.00)**	FR1
Singapore	70	0.042 (0.00)**	MA4	9	0.799 (0.03)**	MA4
Taiwan	3145	0.059 (0.00)**	MA3	1763	1.295 (0.00)**	MA4
Thailand	221	0.092 (0.01)**	MA3	1	0.933 (0.09)*	MA4
Czech	0	0.083 (0.42)	FR3	0	0.681 (0.73)	FR3
Hungary	0	0.080 (0.62)	FR3	0	0.669 (0.63)	MA5
Israel	757	0.082 (0.00)**	MA4	170	0.920 (0.02)**	SR2
Poland	0	0.108 (0.12)	FR3	0	0.835 (0.24)	FR3
Romania	0	0.104 (0.68)	O1	1	1.018 (0.08)*	MA5
Russia	19	0.236 (0.02)**	FR1	3	1.045 (0.09)*	FR1
Slovak	0	0.088 (0.15)	SR2	0	0.843 (0.29)	SR2
South Africa	1	0.152 (0.10)*	FR3	0	0.686 (0.15)	SR2
Turkey	6	0.148 (0.04)**	FR3	7	0.928 (0.07)*	MA5
%Sig emrging	67%			67%		

We examine the predictive performance of total 21,195 technical rules over available sample periods. We implement the stepwise test to inspect if there exist technical rules that are able to provide significantly positive performance, i.e. having predictive power for foreign currencies. We consider mean excess return and Sharpe ratio as two performance metrics. "# predictive rules" denotes the number of technical rules that provide significantly positive mean excess returns and Sharpe ratios at the 10% level. "Highest return/ratio" denotes the best rules' positive mean excess returns and Sharpe ratios with *p*-values in parentheses. The best rules are defined as technical rules providing the highest performance metric among all trading rules in the sample period. All mean excess returns and Sharpe ratios have been annualized. ** and * denote statistical significance at the 5% and 10% levels, respectively. The sample periods are reported in Table I.

Table 3
The predictive performance of technical trading rules in foreign exchange rates: Timing criteria

Countries	A. Mean excess return (Tim)			B. Sharpe ratio (Tim)		
	# predictive rules	Highest return (*p*-values)	Best rule	# predictive rules	Highest ratio (*p*-values)	Best rule
Developed						
Australia	0	0.081 (0.15)	MA5	1	0.732 (0.05)*	CB2
Canada	0	0.058 (0.47)	FR3	0	0.621 (0.17)	CB2
Germany/E.U.	217	0.093 (0.01)**	MA1	9	0.790 (0.01)**	FR3
Japan	292	0.148 (0.07)*	MA4	7	0.793 (0.09)*	MA2
New Zealand	182	0.100 (0.03)**	MA4	1	0.656 (0.10)*	MA5
Norway	0	0.096 (0.20)	SR2	0	0.650 (0.11)	MA5
Sweden	169	0.129 (0.08)*	MA4	0	0.639 (0.18)	MA5
Switzerland	13	0.089 (0.02)**	MA2	1	0.705 (0.07)*	MA2
U.K.	22	0.109 (0.02)**	MA1	32	0.872 (0.02)**	SR2
%Sig. dvlpd	67%			67%		
Emerging						
Argentina	0	0.069 (0.83)	O1	0	0.562 (0.70)	MA5
Brazil	0	0.135 (0.11)	MA4	0	0.898 (0.42)	MA4
Chile	21	0.133 (0.00)**	FR1	13	1.326 (0.05)**	CB2
Colombia	481	0.158 (0.00)**	MA1	399	1.861 (0.00)**	CB2
Mexico	0	0.059 (0.99)	FR3	0	0.401 (0.88)	MA5
India	68	0.062 (0.01)**	SR1	1	0.940 (0.09)*	O2
Indonesia	7	0.197 (0.04)**	FR1	32	0.950 (0.04)**	CB2
Korea	18	0.167 (0.01)**	MA1	28	1.605 (0.01)**	CB2
Philippines	246	0.106 (0.00)**	FR1	112	1.261 (0.00)**	FR1
Singapore	179	0.042 (0.00)**	MA4	7	0.838 (0.01)**	MA5
Taiwan	3178	0.058 (0.00)**	MA3	1838	1.293 (0.00)**	MA4
Thailand	106	0.092 (0.02)**	MA3	0	0.920 (0.16)	MA4
Czech	0	0.074 (0.63)	MA2	0	0.626 (0.91)	MA2
Hungary	0	0.072 (0.76)	MA3	0	0.628 (0.80)	MA5
Israel	816	0.085 (0.00)**	FR3	325	0.950 (0.00)**	SR2
Poland	0	0.101 (0.15)	MA2	0	0.812 (0.28)	MA2
Romania	0	0.100 (0.71)	MA4	0	0.780 (0.47)	MA4
Russia	10	0.229 (0.03)**	FR1	3	1.084 (0.09)*	FR1
Slovak	0	0.079 (0.30)	SR2	0	0.746 (0.56)	SR2
South Africa	1	0.153 (0.09)*	FR3	0	0.693 (0.14)	SR2
Turkey	100	0.157 (0.02)**	FR3	66	1.026 (0.03)**	MA3
%Sig. emrgng	62%			52%		

We examine the predictive performance of total 21,195 technical rules over available sample periods. We implement the stepwise test to inspect if there exist technical rules that are able to provide significantly positive performance, i.e. having predictive power for foreign currencies. We consider mean excess return (Tim) and Sharpe ratio (Tim) as two performance metrics. "# predictive rules" denote the number of technical rules that provide significantly positive mean excess returns (Tim) and Sharpe ratios (Tim) at the 10% significance level. "Highest return/ratio" denotes the best rules' mean excess returns (Tim) and Sharpe ratios (Tim) with *p*-values in parentheses. The best rules are defined as technical rules providing the highest performance metric among all trading rules in the sample period. All mean excess returns (Tim) and Sharpe ratios (Tim) have been annualized. ** and * denote statistical significance at 5% and 10%, respectively. The sample periods are reported in Table 1.

Table 4
The overall predictability and profitability of foreign exchange rates

	A: Predictability		B: Profitability	
	Average # of outperforming rules	Ave. *p*-values of best rules	Average # of outperforming rules	Ave. *p*-values of best rules
Developed				
Australia (AUS)	0.5	(0.11)	0.0	(0.22)
Canada (CA)	0.0	(0.29)	0.0	(0.35)
Germany/E.U. (EU)	102.3	(0.01) **	43.8	(0.04) *
Japan (JP)	104.0	(0.07) *	30.0	(0.10)
New Zealand (NZ)	88.0	(0.10) *	52.3	(0.10)
Norway (NOR)	0.0	(0.18)	0.0	(0.24)
Sweden (SWE)	57.8	(0.13)	39.0	(0.17)
Switzerland (SWI)	5.3	(0.04) **	1.5	(0.08) *
U.K. (UK)	25.5	(0.02) **	0.0	(0.20)
Average (developed)	**42.6**	**(0.11)**	**18.5**	**(0.17)**
%Sig. (developed)		**56%**		**22%**
Emerging				
Argentina (ARG)	0.0	(0.74)	0.0	(0.71)
Brazil (BRA)	9.8	(0.14)	9.5	(0.15)
Chile (CHI)	18.8	(0.02) **	3.5	(0.09) *
Colombia (COL)	384.3	(0.00) **	202.3	(0.00) **
Mexico (MEX)	0.0	(0.75)	0.0	(0.74)
Average (Lat. Amr.)	**82.6**	**(0.33)**	**43.1**	**(0.34)**
%Sig. Lat. Amer.		**40%**		**40%**
India (IND)	32.0	(0.06) *	10.5	(0.06) *
Indonesia (IDO)	19.0	(0.04) **	0.8	(0.09) *
Korea (KOR)	40.3	(0.01) **	10.0	(0.06) *
Philippines (PHI)	147.5	(0.00) **	50.8	(0.03) **
Singapore (SNG)	66.3	(0.01) **	6.5	(0.04) **
Taiwan (TAI)	2481.0	(0.00) **	1495.3	(0.01) **
Thailand (THA)	82.0	(0.07) *	35.8	(0.10) *
Average (Asia)	**409.7**	**(0.03) ****	**229.9**	**(0.05) ***
%Sig. Asia		**100%**		**100%**
Czech (CZE)	0.0	(0.67)	0.0	(0.73)
Hungary (HUN)	0.0	(0.70)	0.0	(0.68)
Israel (ISR)	517.0	(0.01) **	263.5	(0.01) **
Poland (POL)	0.0	(0.20)	0.0	(0.23)
Romania (ROM)	0.3	(0.49)	0.3	(0.52)
Russia (RUS)	8.8	(0.06) *	5.0	(0.11)
Slovak (SLO)	0.0	(0.33)	0.0	(0.39)
South Africa (SFA)	0.5	(0.12)	0.3	(0.13)
Turkey (TUR)	44.8	(0.04) **	29.0	(0.04) **
Average (Europe)	**63.5**	**(0.29)**	**33.1**	**(0.32)**
%Sig. Europe		**33%**		**22%**

In this table, we report the average number of outperforming rules across four performance metrics for each currency and the average of the best rules' *p*-values across four performance metrics: mean excess return, Sharpe ratio, mean excess return (Tim) and Sharpe ratio (Tim). These two averages serve as measures of overall significance of the predictive ability (Panel A) and profitability (Panel B) of technical rules in thirty countries. In Panel B, we impose one-way transaction costs of 0.025% (2.5 basis points) in returns. The averages reported in Panel A are based on data from Tables 2 and 3, while the averages reported in Panel B are based on data from Tables 5 and 6. Developed currencies are listed in alphabetical order, and emerging market currencies are in alphabetical order within three cultural/geographic groups (Latin America, Asia, and Europe). The sample periods are reported in Table 1.

Table 5

The potential profitability of technical trading rules in foreign exchange rates: Common criteria

Countries	A. Mean excess return # predictive rules	Highest return (*p*-values)	Best rule	B. Sharpe ratio # predictive rules	Highest ratio (*p*-values)	Best rule
Developed						
Australia	0	0.079 (0.19)	MA5	0	0.588 (0.26)	MA5
Canada	0	0.060 (0.40)	FR3	0	0.557 (0.26)	MA5
Germany/E.U.	93	0.085 (0.02)**	MA1	1	0.705 (0.06)*	FR3
Japan	23	0.143 (0.08)*	MA4	0	0.727 (0.13)	MA4
New Zealand	103	0.098 (0.05)**	FR3	0	0.598 (0.22)	MA4
Norway	0	0.088 (0.34)	SR2	0	0.627 (0.18)	MA5
Sweden	38	0.129 (0.08)*	MA4	0	0.594 (0.35)	SR2
Switzerland	2	0.082 (0.04)**	MA2	1	0.648 (0.10)*	MA2
U.K.	0	0.081 (0.14)	FR3	0	0.616 (0.27)	FR3
%Sig. dvlpd	56%			22%		
Emerging						
Argentina	0	0.068 (0.83)	O1	0	0.623 (0.51)	MA5
Brazil	36	0.182 (0.01)**	FR1	2	1.367 (0.03)**	MA5
Chile	6	0.096 (0.03)**	SR1	1	1.010 (0.10)*	MA5
Colombia	148	0.110 (0.00)**	MA1	165	1.212 (0.00)**	MA1
Mexico	0	0.064 (0.99)	O1	0	0.709 (0.11)	O2
India	20	0.059 (0.05)**	SR1	1	0.923 (0.08)*	O2
Indonesia	1	0.183 (0.04)**	FR1	1	0.921 (0.07)*	MA5
Korea	8	0.142 (0.02)**	FR1	29	1.161 (0.02)**	CB2
Philippines	55	0.071 (0.01)**	FR3	1	0.933 (0.04)**	FR3
Singapore	7	0.038 (0.04)**	MA4	1	0.724 (0.08)*	MA4
Taiwan	2189	0.053 (0.00)**	MA4	801	1.175 (0.01)**	MA4
Thailand	113	0.088 (0.02)**	MA2	1	0.919 (0.10)*	MA5
Czech	0	0.080 (0.49)	FR3	0	0.657 (0.77)	FR3
Hungary	0	0.078 (0.65)	FR3	0	0.668 (0.58)	MA5
Israel	484	0.078 (0.00)**	FR3	51	0.842 (0.02)**	SR2
Poland	0	0.105 (0.14)	FR3	0	0.811 (0.26)	FR3
Romania	0	0.104 (0.67)	O1	1	1.018 (0.08)*	MA5
Russia	12	0.214 (0.03)**	MA1	0	0.947 (0.20)	MA1
Slovak	0	0.085 (0.20)	SR2	0	0.811 (0.34)	SR2
South Africa	0	0.148 (0.10)*	FR3	0	0.667 (0.17)	SR2
Turkey	5	0.147 (0.04)**	FR3	7	0.927 (0.06)*	MA5
%Sig. dvlpd	62%			62%		

We impose one-way transaction costs of 0.025% (2.5 basis points) in returns and then re-examine the performance of total 21,195 technical rules over available sample periods. We implement the stepwise test to inspect if there exist technical rules that are able to provide significantly positive performance, i.e. having profitable ability for foreign currencies. We consider mean excess return and Sharpe ratio as two performance metrics. "# profitable rules" denote the number of technical rules that provide significantly positive mean excess returns and Sharpe ratios at the 10% significance level. "Highest return/ratio" denotes the best rules' mean excess returns and Sharpe ratios with *p*-values in parentheses. The best rules are defined as technical rules providing the highest performance metric among all trading rules in the sample period; see the Appendix for details of the various trading rules. All mean excess returns and Sharpe ratios have been annualized. ** and * denote statistical significance at the 5% and 10% levels, respectively. The sample periods are reported in Table 1.

Table 6
The potential profitability of technical trading rules in foreign exchange rates: Timing criteria

Countries	A. Mean excess return (Tim) # predictive rules	Highest return (*p*-values)	Best rule	B. Sharpe ratio (Tim) # predictive rules	Highest ratio (*p*-values)	Best rule
Developed						
Australia	0	0.081 (0.14)	MA5	0	0.572 (0.30)	MA5
Canada	0	0.056 (0.52)	FR3	0	0.581 (0.22)	MA5
Germany/E.U.	80	0.085 (0.02)**	MA1	1	0.721 (0.05)*	FR3
Japan	97	0.143 (0.07)*	MA4	0	0.728 (0.13)	MA4
New Zealand	105	0.099 (0.04)**	MA4	1	0.655 (0.10)*	MA5
Norway	0	0.087 (0.33)	SR2	0	0.650 (0.11)	MA5
Sweden	118	0.128 (0.08)*	MA4	0	0.638 (0.18)	MA5
Switzerland	3	0.082 (0.02)**	MA2	0	0.650 (0.14)	MA2
U.K.	0	0.080 (0.12)	FR3	0	0.611 (0.26)	FR3
%Sig. dvlpd.	56%			22%		
Emerging						
Argentina	0	0.069 (0.83)	O1	0	0.560 (0.65)	MA5
Brazil	0	0.133 (0.12)	MA4	0	0.886 (0.44)	MA4
Chile	7	0.092 (0.03)**	SR1	0	0.919 (0.21)	SR1
Colombia	298	0.113 (0.00)**	SR1	198	1.260 (0.00)**	SR1
Mexico	0	0.056 (0.99)	FR3	0	0.397 (0.87)	MA5
India	20	0.059 (0.02)**	SR1	1	0.932 (0.09)*	O2
Indonesia	1	0.185 (0.06)*	FR1	0	0.818 (0.17)	FR2
Korea	3	0.140 (0.03)**	FR1	0	1.158 (0.16)	CB2
Philippines	137	0.074 (0.01)**	MA3	10	0.937 (0.04)**	MA3
Singapore	16	0.038 (0.02)**	MA4	2	0.837 (0.01)**	MA5
Taiwan	2200	0.053 (0.00)**	MA4	791	1.173 (0.01)**	MA4
Thailand	29	0.088 (0.04)**	MA2	0	0.867 (0.23)	MA2
Czech	0	0.071 (0.73)	MA2	0	0.602 (0.92)	MA2
Hungary	0	0.072 (0.76)	MA3	0	0.626 (0.74)	MA5
Israel	404	0.082 (0.00)**	FR3	115	0.865 (0.01)**	SR2
Poland	0	0.097 (0.19)	MA2	0	0.784 (0.33)	MA2
Romania	0	0.096 (0.77)	MA4	0	0.750 (0.55)	MA4
Russia	8	0.204 (0.04)**	MA1	0	0.987 (0.17)	MA1
Slovak	0	0.076 (0.41)	SR2	0	0.714 (0.62)	SR2
South Africa	1	0.150 (0.09)*	FR3	0	0.689 (0.14)	MA5
Turkey	61	0.155 (0.03)**	FR3	43	1.015 (0.03)**	MA3
%Sig. emrgng.	62%			33%		

We impose one-way transaction costs of 0.025% (2.5 basis points) in rule returns and reexamine the performance of total 21,195 technical rules over available sample periods. We implement the stepwise test to inspect if there exist technical rules that are able to provide significantly positive performance, i.e. having profitable ability for foreign currencies. We consider mean excess return (Tim) and Sharpe ratio (Tim) as two performance metrics. "# profitable rules" denote the number of technical rules that provide significantly positive mean excess returns (Tim) and Sharpe ratios (Tim) at the 10% significance level. "Highest return/ratio" denotes the best rules' mean excess returns (Tim) and Sharpe ratios (Tim) with *p*-values in parentheses. The best rules are defined as technical rules providing the highest performance metric among all trading rules in the sample period; see the Appendix for details of the various trading rules. All mean excess returns (Tim) and Sharpe ratios (Tim) have been annualized. ** and * denote statistical significance at the 5% and 10% levels, respectively. The sample periods are reported in Table 1.

Table 7
The break-even transaction costs for predictive technical rules

Criteria	Mean ex. ret.		Sharpe ratio		Mean ex. ret. (Tim)		Sharpe ratio (Tim)	
	Cost	Trade	Cost	Trade	Cost	Trade	Cost	Trade
Developed								
Australia	-	-	3.6	(3008)	-	-	3.6	(3008)
Canada	-	-	-	-	-	-	-	-
Germany/E.U.	28.5	(643)	28.5	(659)	28.5	(643)	29.1	(659)
Japan	72.5	(466)	4.5	(5899)	72.5	(466)	27.2	(947)
New Zealand	97.6	(213)	-	-	232.8	(95)	3386.8	(8)
Norway	-	-	-	-	-	-	-	-
Sweden	313.7	(123)	-	-	312.2	(123)	-	-
Switzerland	31.8	(836)	31.8	(836)	31.6	(836)	31.7	(836)
U.K.	5.5	(3767)	7.8	(2024)	4.6	(4651)	7.8	(2024)
Emerging								
Argentina	-	-	-	-	-	-	-	-
Brazil	336.0	(49)	2173.4	(10)	-	-	-	-
Chile	7.0	(1738)	7.9	(2133)	7.9	(2129)	7.5	(2133)
Colombia	8.5	(1893)	7.4	(1714)	8.4	(1894)	7.4	(1714)
Mexico	-	-	-	-	-	-	-	-
India	53.9	(123)	107.8	(20)	26.9	(320)	116.4	(20)
Indonesia	38.4	(680)	14.7	(1272)	37.6	(681)	14.6	(1272)
Korea	7.9	(2174)	6.5	(2626)	6.0	(3364)	6.4	(2626)
Philippines	5.6	(2419)	7.9	(2657)	7.7	(2657)	7.7	(2657)
Singapore	26.5	(299)	26.0	(308)	27.4	(308)	1975.4	(7)
Taiwan	19.4	(441)	27.0	(541)	19.1	(441)	26.8	(541)
Thailand	35.8	(277)	29.2	(503)	29.5	(371)	-	-
Czech	-	-	-	-	-	-	-	-
Hungary	-	-	-	-	-	-	-	-
Israel	46.2	(400)	29.2	(856)	51.4	(277)	29.2	(856)
Poland	-	-	-	-	-	-	-	-
Romania	-	-	4143.7	(4)	-	-	-	-
Russia	19.4	(1078)	30.2	(1123)	28.2	(1123)	33.6	(931)
Slovak	-	-	-	-	-	-	-	-
South Africa	114.8	(213)	-	-	41.5	(273)	-	-
Turkey	228.7	(91)	3647.0	(4)	250.9	(99)	111.5	(92)

We report the highest one-way break-even transaction costs (in basis points) that will reduce the performance metrics of the most predictive rules (from Tables 2 and 3) to zero. Four performance metrics are considered in this table: Mean excess return, Sharpe ratio, mean excess return (Tim), and Sharpe ratio (Tim). Numbers of trades are reported in the parentheses. “-” denotes that, given the foreign exchange rate and performance metric, there does not exist any significantly profitable technical rule. The sample periods are reported in Table 1.

Table 8
The number of technical rules with significantly positive mean excess returns in eight subsample periods

	A. No transaction costs								B. With one-way transaction costs of 0.025%							
Subsample	1972 -1976	1977 -1981	1982 -1986	1987 -1991	1992 -1996	1997 -2001	2002 -2007	2008 -2011	1972 -1976	1977 -1981	1982 -1986	1987 -1991	1992 -1996	1997 -2001	2002 -2007	2008 -2011
Developed																
Australia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Canada	31	0	14	14	0	0	0	0	3	0	0	0	0	0	0	0
Germany/E.U.	2	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Japan	11	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
New Zealand	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Norway	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Sweden	60	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0
Switzerland	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U.K.	658	2	0	0	0	0	0	0	593	2	0	0	0	0	0	0
Avg.(developed)	84.9	0.8	1.8	1.6	0	0	0	0	66.8	0.3	0.1	0	0	0	0	0
%Sig. dvlpd.	89%	44%	33%	11%	0%	0%	0%	0%	44%	22%	11%	0%	0%	0%	0%	0%
Emerging																
Argentina						698	0	0						676	0	0
Brazil						0	24	2						0	19	2
Chile						717	0	1						689	0	0
Colombia						8	100	4						0	36	0
Mexico					0	1	0	0					0	1	0	0
India					0	0	169	0					0	0	87	0
Indonesia				0	226	6	2	95				0	225	6	0	65
Korea						1	5	0						0	0	0
Philippines				74	1	2	705	0				65	0	0	704	0
Singapore			0	0	0	0	0	0			0	0	0	0	0	0
Taiwan				895	399	1	6	5				581	155	0	0	0
Thailand					0	0	5	0					0	0	2	0
Czech						0	0	0						0	0	0
Hungary						0	0	0						0	0	0
Israel			1729	0	0	0	2	1			1334	0	0	0	0	0
Poland						0	0	0						0	0	0
Romania							2	0							2	0
Russia						0	1	3						0	1	1
Slovak						0	0	0						0	0	0
South Africa			0	0	0	0	0	0			0	0	0	0	0	0
Turkey					0	1	253	0					0	0	251	0
Ave. (emerging)			576.3	161.5	62.6	71.8	60.7	5.3			444.7	107.7	38.0	68.6	52.5	3.2
%Sig.(emerging)			33%	33%	33%	45%	57%	33%			33%	33%	20%	25%	38%	14%

This table reports the numbers of technical rules (out of a total of 21,195) that provide significantly positive mean excess returns (based on the stepwise test) over eight subsample periods: 1972-1976, 1977-1981, 1982-1986, 1987-1991, 1992-1996, 1997-2001, 2002-2007, and 2008-2011. We design the subsample periods based on historical events, including the Maastricht Treaty in 1992, Asia currency crisis in 1997, the appearance of physical Euro in 2002, and the global banking crisis since 2008. One-way transaction costs of 0.025% are imposed in returns reported in Panel B for the test of profitability.

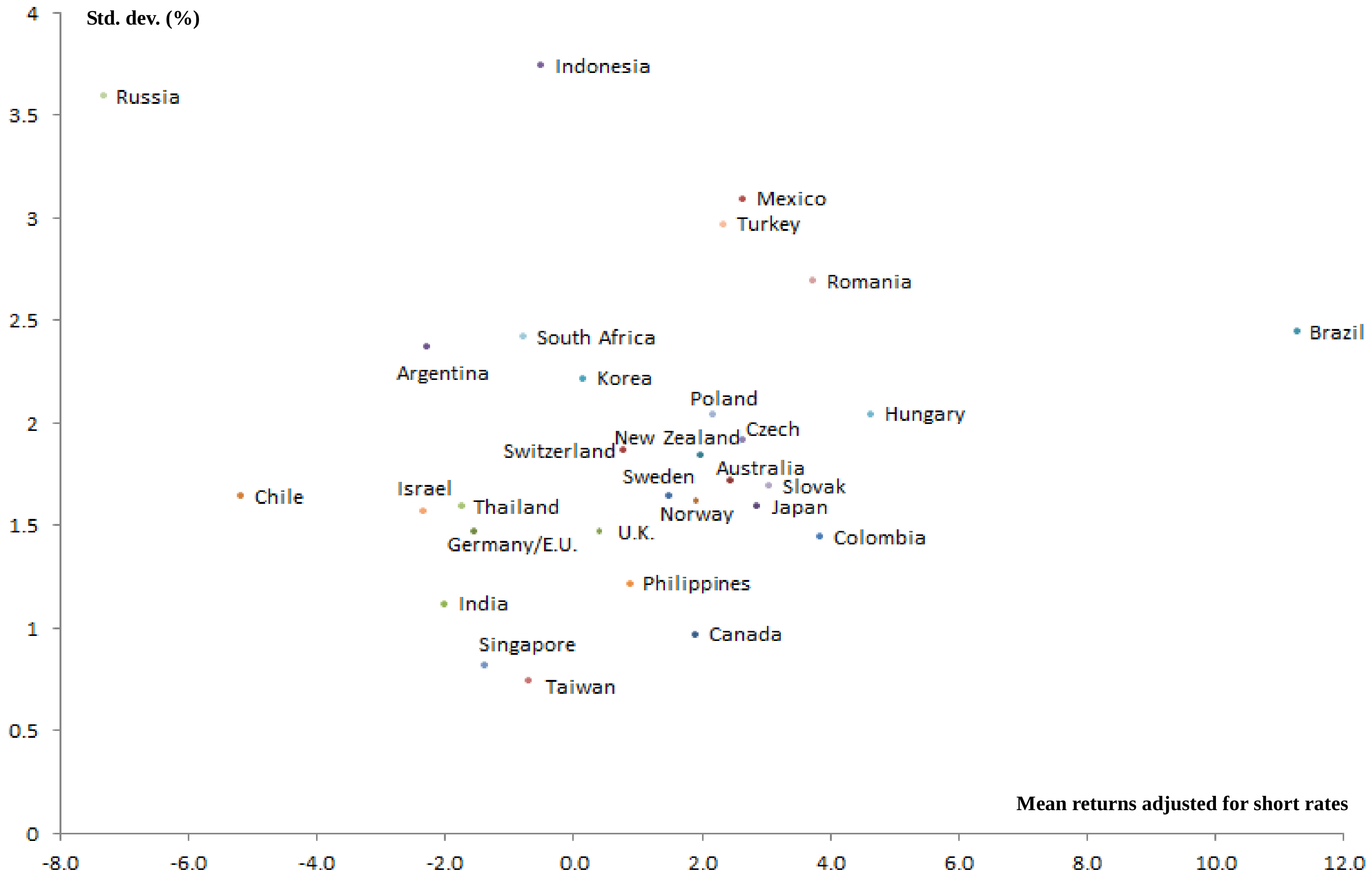

Figure 1

The mean excess returns and standard deviations of all thirty exchange rates

This figure plots the mean excess returns (gross returns in excess of short rate differentials) on the horizontal axis and standard deviations of daily returns on the vertical axis of all thirty exchange rates considered in our empirical study. Both mean excess returns and standard deviations are annualized in percentage. The sample periods have been reported in Table I.

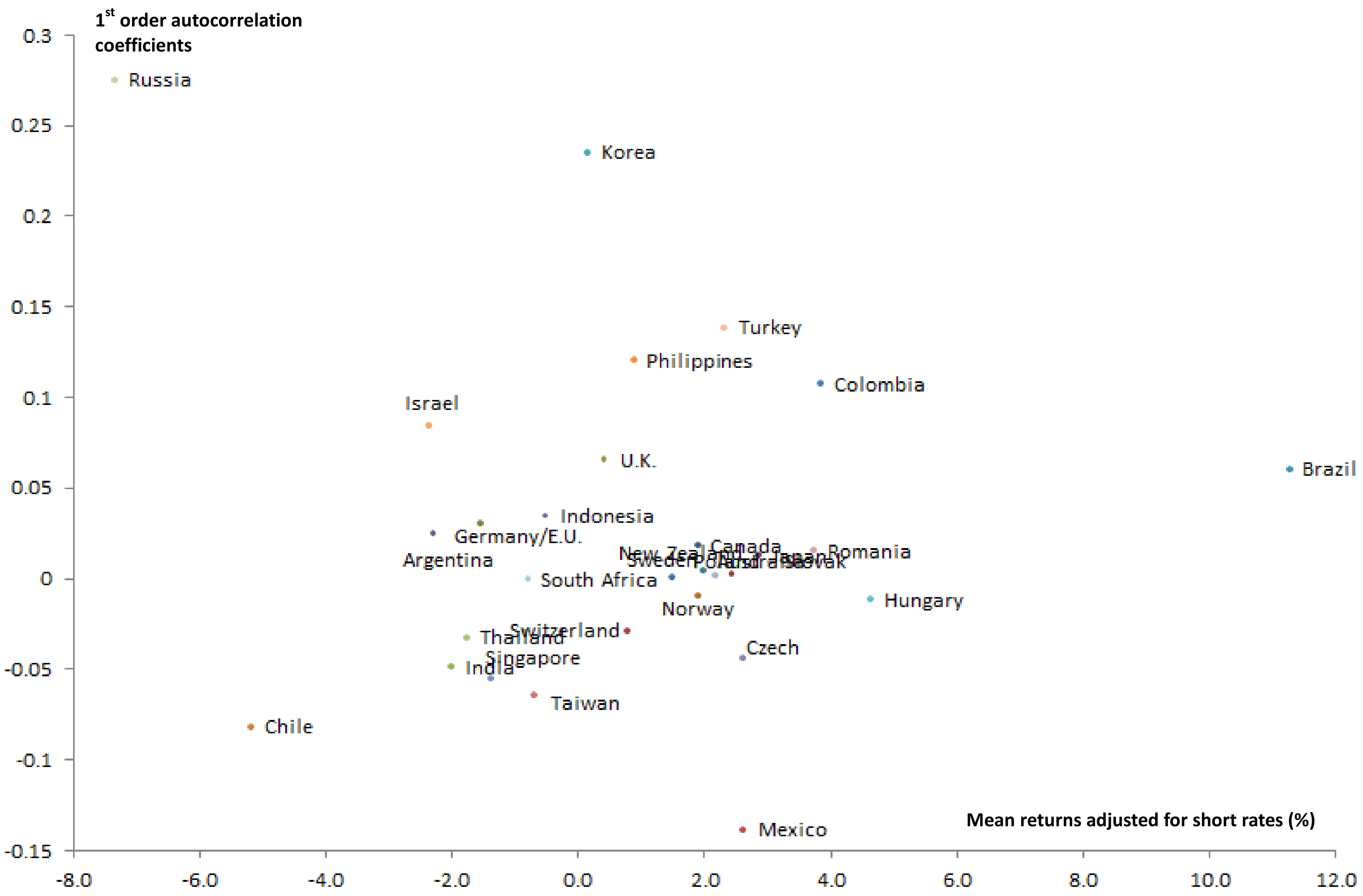

Figure 2

The mean excess returns and first-order autocorrelation coefficients of all thirty exchange rates

This figure plots the mean excess returns (returns in excess of short rate differentials) on the horizontal axis and first-order autocorrelation coefficients of daily returns on the vertical axis for all thirty exchange rates considered in our empirical study. Mean excess returns are annualized in percentage. The sample periods have been reported in Table I.

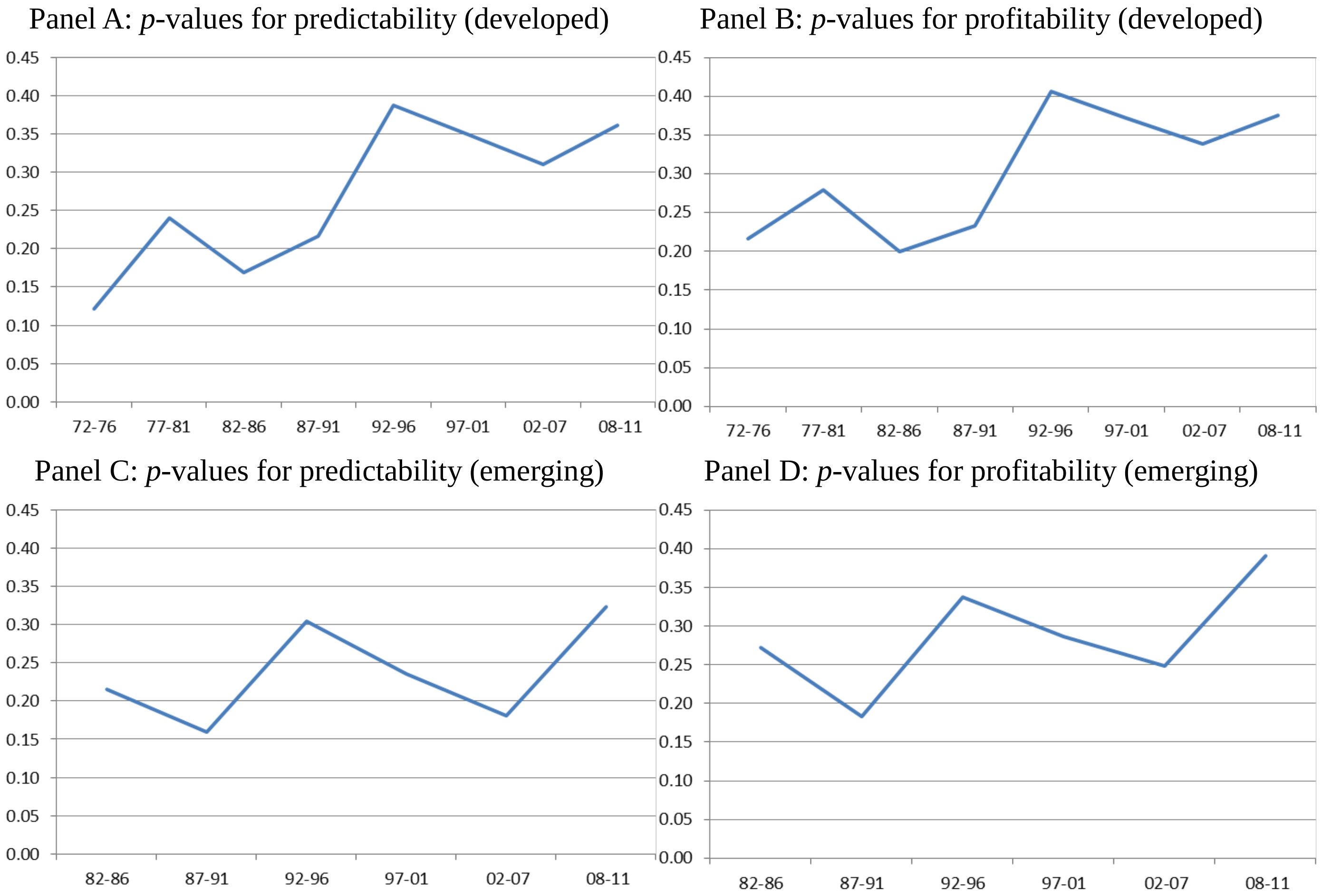

Figure 3
The average *p*-values of the best rules in subsample periods

We report the averages of the *p*-values of the best rules (in mean excess returns) across all developed currencies (Panels A and B) or all emerging currencies (Panels C and D) in subsample periods. The best rules are defined as technical rules providing the highest mean excess returns among all trading rules in the subsample period. Panel A is based on developed currencies without transaction costs; Panel B is based on all developed currencies with one-way transaction costs of 0.025%; Panel C is based on emerging currencies without transaction costs; and Panel D is based on emerging currencies with one-way transaction costs of 0.025%. Subsample periods are 1972-1976, 1977-1981, 1982-1986, 1987-1991, 1992-1996, 1997-2001, 2002-2007, and 2008-2011.

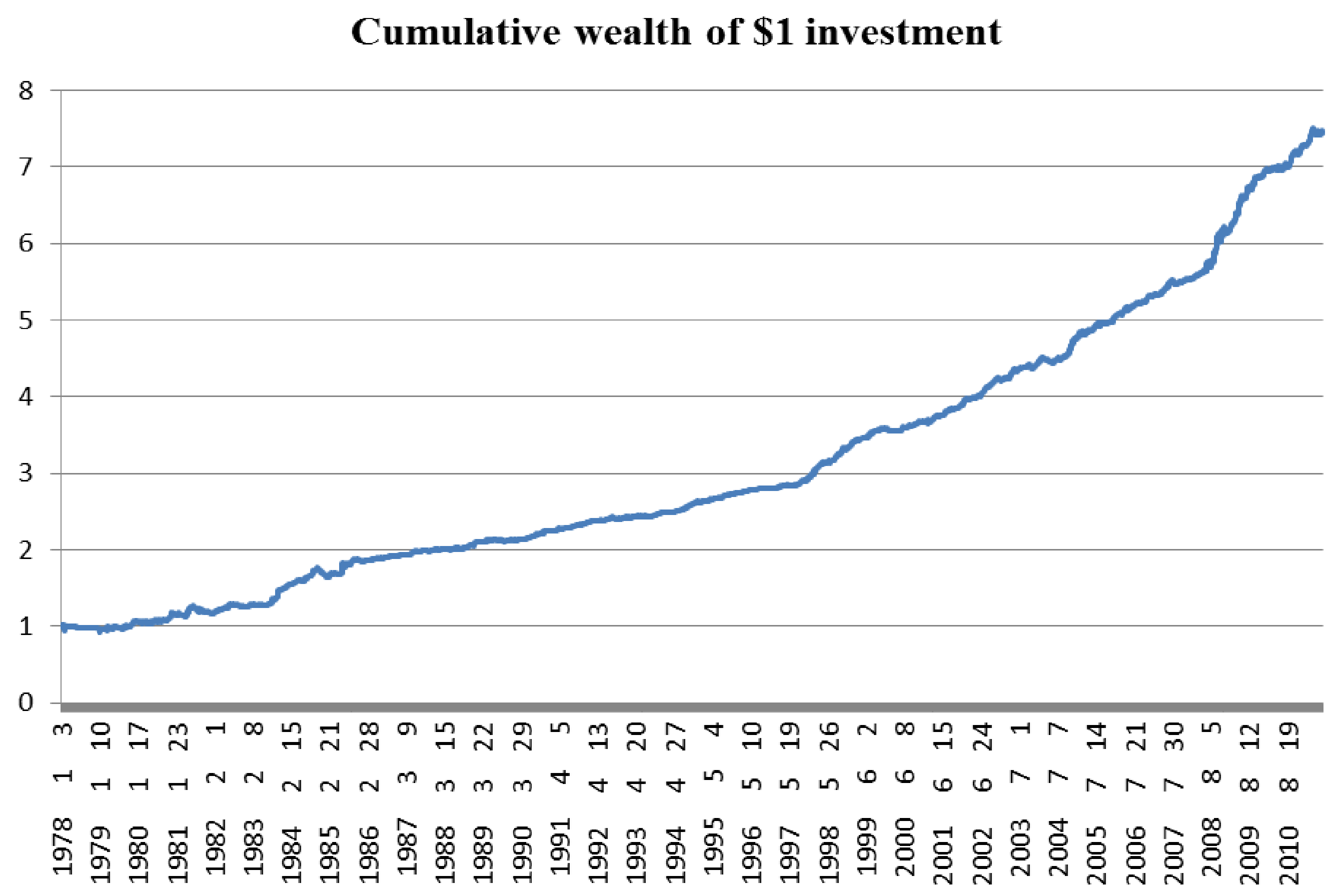

Figure 4

The cumulative return on an equally-weighted portfolio using the best rules

We illustrate the time series of the wealth from investing $1 in an equally-weighted portfolio of thirteen predictable emerging market currencies using the best trading rule listed in Panel B of Table 5. The best rules are defined as technical rules providing the highest Sharpe ratios among all trading rules in the whole sample period. One-way transaction costs of 0.025% are applied.