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Can risk explain the profitability of technical trading in currency markets?*

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Abstract

Academic studies show that technical trading rules would have earned substantial excess returns over long periods in foreign exchange markets. However, the approach to risk adjustment has typically been rather cursory. We examine the ability of a wide range of models: CAPM, quadratic CAPM, downside risk CAPM, Carhart's 4-factor model, the C-CAPM, an extended C-CAPM with durable consumption, Lustig-Verdelhan (LV) carry-trade factor model, and models including macroeconomic factors, and foreign exchange volatility, skewness and liquidity, to explain these technical trading returns. No model plausibly accounts for much of the technical profitability. This failure implicitly supports non-risk based explanations such as adaptive markets.

JEL Codes: F31, G11, G12, G14

Keywords: Exchange rate; Technical analysis; Efficient markets hypothesis; Risk; Stochastic Discount Factor; Adaptive markets hypothesis.

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1. Introduction

It is a stylized fact that excess returns for currency-related trading strategies, such as technical trading rules (TTRs) and the carry trade, are weakly correlated with traditional risk factors, such as the CAPM's equity market factor. This is interpreted to imply that significantly positive excess returns constitute evidence of market inefficiency. But, as Fama (1970) has emphasized, any such test of market efficiency is inevitably a joint test of efficiency and of the particular asset pricing model chosen. An apparent inefficiency may simply result from having selected a misspecified risk model. This consideration has spurred the search for plausible risk factors to explain the observed anomalous returns.

The search for plausible risk factors has focused almost exclusively on explaining the excess returns to the carry trade, and several recent studies have proposed a variety of risk factors. These risk factors include consumption growth (Lustig and Verdelhan (2007)), a forward premium slope factor (Lustig, Roussanov, and Verdelhan (2011)), global exchange rate volatility (Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)), and foreign exchange skewness (Rafferty (2012)).

These currency risk factors succeed to varying degrees in explaining cross-sectional carry trade returns. Nevertheless, these factors would be more compelling if they also explained excess returns to other investment strategies (Burnside (2012)). Such explanatory ability would allay data-mining concerns and better establish the economic relevance of the newly proposed currency risk factors. On the other hand, the failure of risk factors to account for the profitability of technical returns would support other explanations, such as the adaptive markets hypothesis (Lo (2004), Neely, Weller and Ulrich (2009)) or limits to arbitrage (Shleifer and Vishny (1997)).

Technical analysis constitutes a long-standing puzzle in foreign exchange returns, one that has received less attention than the carry trade despite a well-documented history of success. A series of studies in the 1970s and 1980s demonstrated that technical analysis produced abnormal returns in foreign exchange markets (Dooley and Shafer (1976, 1984), Logue and Sweeney (1977), and Cornell and Dietrich (1978)). Although academics were initially very skeptical of these findings, the positive results of Sweeney (1986) and Levich and Thomas (1993) helped convince the profession of the existence of this puzzle. Allen and Taylor (1990) and Taylor and Allen (1992) confirmed this shift by surveying practitioners to establish that they commonly used technical analysis. Later research looked at the usefulness of technical patterns (Osler and Chang (1995)) and considered reasons for time variation in profitability (Neely, Weller, and Ulrich (2009)). Menkhoff and Taylor (2007) and Neely and Weller (2012) survey the literature. Recently, Hsu, Taylor, and Wang (2016) conclude that technical methods have significant economic and statistical predictive power for developed and emerging currencies. Park and Irwin's (2007) literature review concludes that technical analysis is particularly profitable in foreign exchange markets.

These studies and many more have established that technical analysis would have been profitable for long periods for a wide variety of currencies. In other words, the profitability of technical analysis in foreign exchange markets is an important financial market anomaly. Despite these findings, no study has definitively explained this profitability as the return to one or more risk factors. The risk adjustment procedures, however, have focused almost exclusively on applications of the CAPM. The risk factors that have recently explained carry-trade returns — and other anomalies — are natural candidates to explain the returns to technical analysis. A study of the extent to which such carry-trade factors also explain the returns to technical analysis will shed light on both the source of technical returns and the plausibility of the factors. If the carry trade factors explain the returns to technical analysis, then it is very likely that they are truly sources of undiversifiable risk. On the other hand, if the carry-trade factors fail to explain the technical returns, it suggests that the factors merit continued scrutiny and that the technical returns are likely to stem from non-risk causes, such as adaptive markets or limits to arbitrage.

In this spirit, the present paper investigates the ability of a wide variety of currency risk factors to explain excess returns for a group of ex ante technical portfolios developed in Neely and Weller (2013). By choosing rule-exchange rate combinations purely on the basis of ex ante information and forming them into portfolios, Neely and Weller (2013) minimized the danger of data mining and the size-distortions of multiple-test problems.[1] The present paper similarly constructs ex ante portfolios from a variety of popular technical indicators that the academic literature has studied. Such ex ante portfolios realistically portray trend-following returns.

We adjust returns for risk with the following models: CAPM, quadratic CAPM, downside risk CAPM, Carhart's 4-factor model, the C-CAPM, the C-CAPM with durable consumption and the market return, Lustig-Verdelhan (LV) carry-trade factor model, and models including factors such as global foreign exchange (FX) volatility and skewness, skewness in unemployment, and FX liquidity. No risk factors explain a substantial portion of the returns for this important class of currency portfolios. We highlight the dimensions along which the new risk factors fail to account for the behavior of technical portfolios. The inadequacies of extant currency risk factors underline the continuing challenges in explaining technical portfolio returns.

The rest of the paper is organized as follows. Section 2 describes the construction of trading rules, currency portfolios, and data, while Section 3 explains methods of risk adjustment. Section 4 reports the results from testing the many currency risk factors. Section 5 concludes.

[1] An alternative to ex ante rule selection would be to test many rule-exchange rate combinations on a given sample and correct for the multiple hypothesis testing problem, as Hsu, Taylor, and Wang (2016, 2019) did. Neely and Weller (2013) chose an ex ante, dynamic selection procedure to mimic the process that actual technical traders would have used. The difference between the two exercises is analogous to an out-of-sample forecasting exercise with ex ante selection of regressors (Neely and Weller (2013)) vs. a full sample econometric test with corrections for the multiple testing problem (Hsu, Taylor, and Wang (2016)). The present paper answers a different question: Does modern risk adjustment with new risk factors explain the out-of-sample returns to technical trading?

2. Methods of Portfolio Construction

2.1 *Trading Rules*

The goal of our paper is to examine whether recent advances in risk-adjustment can explain the seemingly very strong performance of traditional daily TTRs in foreign exchange markets. To do so, we must construct such returns in a manner consistent with the literature on their profitability. We dynamically choose daily trading rules from those studied in the academic literature, to exploit changing patterns in adaptive markets. In doing so, we follow Neely and Weller (2013) who construct portfolio strategies from a pool of frequently studied rules—7 filter rules, 3 moving average rules, 3 momentum rules, and 3 channel rules, and carry trade rules—on 21 dollar and 19 cross exchange rates.[2] All of these bilateral rules borrow in one currency and lend in the other to produce daily excess returns. These rule sets are among the most commonly studied in the academic literature. Although there are many possible variations on rule selection procedures, experimentation leads us to believe that reasonable perturbations of methods are unlikely to substantially change inference about profitability or risk adjustment. The rules in the present paper differ in one notable respect from those in Neely and Weller (2013): to isolate the determinants of TTRs, the present paper does not use carry trade rules.

We will first describe the trading rules before detailing the dynamic rebalancing procedure for trading strategies. We distinguish between trading "rules" and trading "strategies." A technical trading rule is a particular rule applied to a specific exchange rate. A technical trading strategy switches between individual rule-currency pairs with a selection criterion.

A filter rule buys (sells) a foreign currency when the exchange rate S_t (the domestic price of

[2] Dooley and Shafer (1984) and Sweeney (1986) look at filter rules; Levich and Thomas (1993) look at filter and moving average rules; Jegadeesh and Titman (1993) consider momentum rules in equities, citing Bernard (1984) on the topic; and Taylor (1994) tests channel rules, for example.

foreign currency) rises (declines) by more than y percent above (below) its most recent low (high).

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

where z_t takes the value +1 for a long position in foreign currency and –1 for a short position. n_t is the most recent local minimum of S_t and x_t the most recent local maximum. There are seven filter sizes (y): 0.005, 0.01, 0.02, 0.03, 0.04, 0.05, and 0.1.

A moving average rule generates a buy (sell) signal when a short-horizon (S) moving average of past exchange rates crosses a long-horizon moving average (L) from below (above). We denote these rules by MA(S, L), where S and L are the respective number of days in the short and long moving averages, respectively. We use MA(1, 5), MA(5, 20), and MA(1, 200) rules.

Momentum rules take a long (short) position when the cumulative exchange rate return over an n-day window is positive (negative). We consider 5, 20 and 60 day windows.[3]

A channel rule takes a long (short) position if the exchange rate exceeds (is less than) the maximum (minimum) over the previous n days plus (minus) the band of inaction (x).

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

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

We apply these 16 bilateral rules —7 filter rules, 3 moving average rules, 3 momentum rules, and 3 channel rules— to daily data on 21 dollar and 19 cross exchange rates.

[3] Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) argue that moving average rules, which they consider to be benchmark technical rules, behave quite differently from cross-sectional, momentum rules. We obtained the monthly returns constructed by Menkhoff et al. (2012b) from the *Journal of Financial Economics* website and similarly investigated the relation between those rules and the monthly returns to our portfolios. We found fairly low correlations, as low as zero, with a median value of 0.13, and therefore we concur with Menkhoff et al.'s (2012b) conclusion that monthly cross-sectional rules are only quite weakly related to traditional technical rules.

2.2 *Construction of trading rule returns*

The rules/strategies we consider may switch between long and short positions in the domestic and foreign currencies at a business day frequency. If a trading rule signals a long position in the foreign currency at date *t*, the trader borrows the domestic currency at the domestic interest rate, converts it to foreign currency at the exchange rate for date *t* and earns the foreign overnight rate. We denote the overnight domestic (foreign) overnight interest rate by i_t (i_t^*). Then the one-business day (d_t calendar days) gross excess return, R_{t+1}^e, to a long position in foreign currency is

$$R_{t+1}^e = \frac{S_{t+1}(1+i_t^*)^{d_t/365}}{S_t(1+i_t)^{d_t/365}}. \tag{3}$$

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

$$r_{t+1}^e = \ln(S_{t+1}) - \ln(S_t) + \left(\frac{d_t}{365}\right) * [\ln(1+i_t^*) - \ln(1+i_t)] \tag{4}$$

The cumulative excess return from a single round-trip trade (go long at date t, go short at date t+k), with one-way proportional transaction cost, c_t, is calculated as follows: [4]

$$r_{t,t+k}^e = \sum_{i=1}^{k} r_{t+i}^e + \ln(1-c_{t+k}) - \ln(1+c_t). \tag{5}$$

2.3 *Data and sample inclusion*

Table 1 details the exchange rates and the dates on which we permit trading for each. The sample starts in April 1973, shortly after the breakdown of the Bretton-Woods System, and goes through the original Neely and Weller (2013) sample in 2012. Exchange rates enter the sample as they become tradeable and are removed if they cease to be tradable.[5]

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[4] Trading strategies may incur transaction costs even when individual trading rules do not, and conversely. If a strategy switches between two rules holding different positions but the rules themselves signal no change of position, then the strategy incurs a transaction cost but the individual rules do not. On the other hand, if a strategy switches from a rule requiring—e.g., a long position at time t to a different rule requiring a long position in the same currency at time t+1—then it incurs no cost, even though the individual rules may have changed position.

[5] The DEM series was spliced with EUR series after January 1, 1999. We denote the spliced series as the EUR.

The data are identical to those in Neely and Weller (2013). Haver provides the daily exchange rates. The Board of Governors H.10 statistical release is the original source for most rates, which are quoted at noon U.S. ET, but the Wall Street Journal provides some emerging market rates from the New York close. The Bank for International Settlements (BIS) provided most of the daily overnight interest rate data. Central banks provided overnight interbank or money market interest rates for Australia, Euro-area, Russia, the United States, and the United Kingdom. Japan's interest rate was constructed by splicing three series: one from the Bank of Japan and two from the BIS.

We restrict simulated trading for many currencies on account of capital controls or market disruption: the South African rand (April 1, 1995), Brazilian real (May 1, 1999), Mexican peso (January 1, 1996), New Zealand dollar (August 1, 1987), Turkish lira (January 1, 2002), Peruvian nuevo sol (April 1, 1996), Israeli shekel (January 1, 1995) and Taiwanese dollar (January 1, 1998).[6]

2.4 *Transaction costs*

Any study of trading performance, especially for exotic currencies, requires close attention to transaction costs. Spreads in emerging markets are typically much larger than those in developed countries and so are more important for emerging market currencies (Burnside et al. (2007)).

We follow Neely and Weller (2013) in calculating transaction costs. After consulting with foreign exchange traders of a commercial bank, these authors concluded that quoted Bloomberg forward spreads substantially overstated spreads available to traders. Therefore, Neely and Weller calculated transaction costs as follows: a one-way trade for advanced countries (UK, Germany, Switzerland, Australia, Canada, Sweden, Norway, New Zealand and Japan) cost 5 basis points in the 1970s, 4 basis points in the 1980s and 3 basis points in the 1990s. The authors set the cost at one third of the average of the first 500 spreads for all other countries. Once Bloomberg data

[6] A dual exchange rate system was in operation for the rand until March 1995. De Zwart et al. (2009) provide information on the tradability of these currencies.

become available in 1995, the authors estimated the spread as one third of the quoted one-month forward spread. Deliverable forwards are available for all countries but Russia, Brazil, Peru, Chile and Taiwan, for which only non-deliverable forward data are available. For cross-rate transaction costs, Neely and Weller (2013) use the maximum of the two transaction costs against the dollar. All currencies have a minimum of one basis point transaction cost at all times. Appendix A of the present paper further details these calculations.[7]

2.5 *Dynamic Trading Strategies*

We would like to construct dynamic strategies to mimic the actions of foreign exchange traders who backtest potential rules on historical data to determine trading strategies. Accurately modeling potential trading returns provides the most realistic environment for assessing whether risk adjustment explains such returns. We therefore employ the previously described trading rules to construct dynamic trading strategies. Each trading strategy uses rules and exchange rate combinations that vary over time.

We construct dynamic trading strategies (which are distinct from rules) as follows:

1. We apply the 16 bilateral rules to all tradable exchange rates at each point in the sample, calculating the historical return statistics for each exchange rate-rule pair at each point. There is a maximum of (16*40=) 640 exchange rate-rules, but missing data for some exchange rates often leave fewer than half that number of currency-rule pairs.

2. Starting 1020 days into the sample, we evaluate the Sharpe ratios of all exchange rate-rule

[7] To study the sensitivity of our results to transactions costs, we have also calculated most results from this paper with 25% and 50% greater costs. Results were similar; no important inference was changed. Della Corte, Sarno and Tsiakas (2009) take another perspective on transaction costs, calculating how high costs would have to be to set trading rule profits to zero. All appendices (i.e., A, B, C and D) are available online at https://s3.amazonaws.com/real.stlouisfed.org/itemattachments/17158/Online-Appendices-WP2014033-20191029.pdf

pairs with at least 250 days of data.[8] We then sort the rate-rule pairs by their ex post Sharpe ratios over the entire previous sample, ranking the rate-rule pairs by Sharpe ratio from 1 to 640.[9] We then measure the performance of the strategies over the next 20 days.[10]

3. Every 20 business days, we evaluate, sort and rank all available rate-rule pairs using the complete sample of data available to that point. For a given 20-day period, the returns on the top-ranked strategy pair will be generated by a given rule applied to a particular exchange rate for those 20 days, at which point the rule-rate combination may (or may not) be replaced as the top strategy by another rule applied to the same or a different currency.

We emphasize that our strategies do not use 20-day holding periods for positions. The holding periods for the trading rules are always 1-day. Each strategy, however, can switch rule/exchange rate combinations every 20-days. Within each 20-day period, the rule can instruct the strategy to switch back and forth between long and short positions in the particular exchange rate.

Although we select the rate-rule pairs for the dynamic strategies based upon historical performance, as described above, we evaluate the strategies' performances after they are selected. That is, all return performance and risk-adjustment statistics in this paper are for strategies that were chosen ex ante and are thus implementable in real time.

2.6 *Currency portfolios*

As is customary in the related asset-pricing literature, we examine the risk-adjustment of TTRs

[8] We chose an initial window of 1020 days to provide a universe of at least 300 rule-rate combinations. This causes the first eligible date in the trading series to be 4/7/1976.
[9] We do not sort on Sharpe ratios because we consider univariate volatility to be the primary measure of risk. Rather, sorting on Sharpe ratios corrects for a potential problem stemming from the relation of volatility and leverage in constructing trading rules. If two exchange rates, X and Y, have identical directional movements but Y has twice the volatility, then Y will produce twice X's return to a given trading rule. But Y's risk-return ratio could be easily replicated in X by doubling the leverage of the investment in X. In contrast to the return measure, the Sharpe ratios for X and Y would be identical because returns and standard deviation scale identically with leverage. Therefore, sorting by Sharpe ratios avoids the illusion that a high volatility exchange rate is more attractive for trading rules.
[10] Inference is very similar with shorter performance windows, the Sortino ratio or net returns instead of the Sharpe ratio as a performance metric, or a 250-day rebalancing interval or when one restricts the exchange rate set to USD rates or even G10 rates. The online appendices C and D detail these alternative results.

in the following way: Using strategies 1 to 300 as test assets, we form 12 equally weighted portfolios of 25 strategies each.[11] Thus portfolio p1 at time t consists of the 25 currency-rule pairs with Sharpe ratios ranked 1 to 25. Portfolio p2 consists of the 25 currency-rule pairs with Sharpe ratios ranked 26 to 50, and so on. These portfolios' makeup may change from period to period.

Although the purpose of this paper is to evaluate the risk-adjusted returns to ex ante technical portfolios, as constructed and described in Neely and Weller (2013), we would also like to briefly inform readers about the performance and makeup of the best rules.

Figure 1 shows the excess annual return, standard deviation, Sharpe ratio, skewness and kurtosis for each of the 12 portfolios. The top-left panel shows that all 12 portfolios have positive excess returns, generally declining as one goes from p1 (4.41% per annum) to p12 (0.69% per annum), and highly ranked portfolio returns (p1 to p4) also tend to be somewhat more volatile. The upper-right panel shows that ex post Sharpe ratios tend to be higher for the more highly ranked portfolios, ranging from 0.81 for p1 to 0.17 for p12.[12] The bottom left panel shows that daily portfolio returns have little skewness but skewness tends to increase in monthly and quarterly portfolio returns. Finally, the bottom-right panel of Figure 1 shows little excess kurtosis in monthly and quarterly returns but (unsurprisingly) a lot of excess kurtosis in daily returns. More highly ranked portfolios (p1 to p3) tend to have much lower kurtosis at the daily frequency.

To examine the prevalence of types of rules and groups of exchange rates in the top-ranked portfolios, we divide the rules into 5 types and the exchange rates into 5 groups. The five groups of rules are moving average, momentum, channel, small filter and large filter. Small filters are those less than or equal to 0.02; large filters are those greater than 0.02. There are 3 rules in each

[11] At any given time, t, we only use the top 300 strategies, i.e., we do not use strategies 301 to 640.
[12] If one breaks the portfolio returns down into their exchange rate and interest differential components, one finds that the exchange rate component is responsible for almost all of the expected return.

of the five rule groups, except for large filters, which have 4 rules. The five groups of exchange rates are Advanced, Developing Europe, Latin American, Other, and Advanced Cross-rates. Table 1 details the membership for each group.[13]

The top panels of Figure 2 show the raw proportions of how often a member of a given group of rules or exchange rates appears in the top 25 ex ante trading strategies while the bottom panels adjust those proportions by the number of rules or exchange rates in each group. That is, the lower panels of Figure 2 downweight (upweight) the proportions of rules in large (small) groups to show an average frequency for each group.

The left-hand panels of Figure 2 show temporal stability in rule selection for the top-ranked ex ante portfolio. Channel rules dominate over the whole sample while momentum and moving average rules are the next most commonly used rules. Since 1985 channel rules have lost ground to the momentum and moving average rules. Because the groups of rules are similarly sized, adjusting for group size makes almost no difference.

The right-hand panels of Figure 2 show that all trading in the top-ranked portfolio was in the currencies of relatively advanced economies until the mid 1990s. Among those rates, USD rates were relatively more important than cross rates. Legal restrictions and capital controls limited trading in emerging market currencies before the early 1990s. By the late 1990s, Latin American exchange rates became very prevalent in the top portfolio and they retain that status. The most recent trend is toward use of developing-European exchange rates in the top portfolio.

To supplement the analysis of these broad rule and exchange rate categories, the top panel of Table 2 presents the frequency with which individual strategies appeared in four of the top-ranked portfolios over the whole sample, while the middle panel of Table 2 shows the variation in most-

[13] Exchange rates are against the USD unless otherwise specified as cross rates.

used strategies in the top portfolio across four subsamples. Finally, the third panel of Table 2 shows the rule-rate combinations with the highest Sharpe ratios over their respective samples. The most frequently used strategy for portfolio 1 over the whole sample was the Chilean peso/U.S. dollar (CLP/USD) CH(20), which appeared 14.7% of the time (top panel). The third and fourth middle subpanels of Table 2 show that this peso/dollar CH(20) strategy appeared 16.0 and 38.8% of the time in the top-ranked portfolio in the 1993-2002 and 2003-2012 subsamples, respectively. As might be expected from Figure 2, both developed and emerging market currencies are represented in the top-ranked portfolio and they are used in conjunction with all types of rules but particularly channel rules. The middle-right panel shows that emerging market currencies dominate the top portfolio during 2003 – 2012.

Finally, Figure 3 illustrates cumulative returns to the 12 portfolios. The most conspicuous feature is the well-known dropoff in most portfolio returns after the early 1990s. Only the top-ranked portfolio remains profitable after 1993 or so. Since at least Levich and Thomas (1993), researchers have known that TTR profitability in major foreign exchange rates started to decline in the late 1980s or early 1990s. Neely, Weller and Ulrich (2009) argue that the adaptive markets hypothesis is the most convincing explanation for this. These authors emphasize that returns to less studied or more complex rules, such as channel rules, ARIMA, genetic programming, and Markov models, probably still exist. Pukthuanthong-Le, Levich and Thomas (2007), Pukthuanthong-Le and Thomas (2008) and de Zwart et al. (2009) argue that emerging market currencies continue to provide technical profit opportunities. Consistent with this interpretation, portfolio 1 remained profitable through the end of the sample in December 2012.

An adaptive markets hypothesis (AMH) explanation for the declining pattern of profitability to many common TTRs does not rule out an important role for risk in generating technical trading profits. The decline in performance for many portfolios is a distinct issue from whether any risk factor explains the exchange rate TTR excess returns that existed both before and after 1993. Therefore, it is important to investigate whether known risk factors explain those excess returns. A failure to find a risk-based explanation lends further credence to an AMH explanation.

Despite the post-1993 decline in the returns to the lower ranked portfolios, technical analysis would still be useful to our hypothetical trader after 1993. Optimization shows that a trader would only use a small number (N* = 18 or 19) of the top-ranked strategies to maximize the historical Sharpe ratio of an equally weighted portfolio. Thus, reduced profitability for lower ranked strategies would be irrelevant as the trader would never use them.

Figure 3 also fails to depict any obvious declines in technical excess returns during currency/financial crises, such as the peso crisis of 1994-1995, the Asian crisis of 1997-1998 or the financial crisis of 2007-2008. If anything, Figure 3 appears to show a temporary upward spike in technical returns during 2008-2009. The next section outlines the formal framework for assessing risk-adjustment of returns.

3. Methods of Risk Adjustment

3.1 *Theoretical framework*

To provide a general framework within which to measure risk exposure we need to characterize equilibrium in the foreign exchange market. We assume the existence of a representative, US-based investor and introduce a stochastic discount factor (SDF), M_{t+1}, that prices payoffs in dollars.[14] It represents a marginal rate of substitution between present and future consumption in different states of the world. The first order conditions for utility maximization subject to an

[14] Although we motivate the SDF framework with a representative investor, much weaker assumptions are sufficient. In particular, absence of arbitrage implies the existence of a SDF framework, as in equation (3).

intertemporal budget constraint imply that any asset return R_{t+1} must satisfy

$$E(M_{t+1}R_{t+1}|I_t) = 1 \tag{6}$$

where I_t denotes the information available to the investor at time *t*. Equation (6) implies that the risk-free asset return R_t^f is given by

$$R_t^f = \frac{1}{E(M_{t+1}|I_t)} \quad . \tag{7}$$

Using (6), (7) and the definition of covariance, it follows that

$$E(R_{t+1}^e|I_t) = E(R_{t+1}|I_t) - R_t^f = -\frac{\mathrm{cov}(M_{t+1}, R_{t+1}|I_t)}{E(M_{t+1}|I_t)} \tag{8}$$

An expected excess return must have the opposite sign of the risky return's covariance with M. So if an excess return pays off in a bad (low consumption) state it acts as a consumption hedge and has a relatively low return. This then raises the questions of how to model the SDF and how to test whether some variant of equation (8) explains excess returns.

One could test the extent to which the SDF framework explains excess returns to the trading rules in several ways. The most direct would be to model the SDF, M_{t+1}, in (6) with a specific utility function and calibrated parameters and test whether the errors from (6) are mean zero. Alternatively, one could estimate the parameters of M_{t+1} with the generalized method of moments (GMM) and test the overidentifying restrictions. Finally, one could linearize the SDF, M_{t+1}, with a Taylor series expansion, estimate a linear time series or a return-beta model and evaluate whether the risk factors explain the expected returns. The next subsections detail those procedures.

3.2 *Testing a Calibrated SDF*

We will initially follow Lustig and Verdelhan (2007) in using a version of the C-CAPM that employs Yogo's (2006) representative agent framework with Epstein-Zin preferences over durable consumption, D_t, and nondurable consumption, C_t. The one-period utility function is given by

$$u(C,D) = \left\{(1-\alpha)C^{1-(1/\rho)} + \alpha D^{1-(1/\rho)}\right\}^{1/(1-(1/\rho))} \tag{9}$$

where α is the weight on durables and ρ is the elasticity of substitution between durable and nondurable consumption. Yogo shows that intertemporal utility is given by a recursive function

$$U_t = \left\{(1-\delta)u(C_t, D_t)^{(1-1/\sigma)} + \delta E_t\left[U_{t+1}^{1-\gamma}\right]^{1/\kappa}\right\}^{1/(1-1/\sigma)}$$

and that the SDF takes the form

$$M_{t+1} = \left[\delta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\sigma}\left(\frac{v(D_{t+1}/C_{t+1})}{v(D_t/C_t)}\right)^{1/\rho-1/\sigma} R_{W,t+1}^{1-1/\kappa}\right]^{\kappa}, \tag{10}$$

where $v\left(\frac{D}{C}\right) = \left[1-\alpha+\alpha\left(\frac{D}{C}\right)^{1-1/\rho}\right]^{1/(1-1/\rho)}$, $R_{W,t}$ is the market portfolio return, and $\kappa = (1-\gamma)/(1-1/\sigma)$. See equation (6) in Yogo (2006).

This Epstein-Zin durable consumption CAPM (EZ-DCAPM) nests two other models of interest: the durable consumption CAPM (DCAPM) and the CCAPM. The DCAPM holds under the restriction $\gamma = 1/\sigma$. The CCAPM holds if, in addition, one imposes $\rho = \sigma$. To initially assess the performance of these models, we follow Lustig and Verdelhan's (2007) calibration exercise and choose Yogo's (2006) parameter values: $\sigma = 0.023, \alpha = 0.802, \rho = 0.700$. Then we use durable and non-durable consumption data and the market return to generate pricing errors, $E(M_{t+1}R_{t+1}^{ei}|I_t)$, where R_{t+1}^{ei} is the excess return to portfolio pi, and $\text{i} = 1, \ldots, 12$.[15] The coefficient of relative risk aversion, γ, is chosen to minimize the sum of squared pricing errors in the EZ-DCAPM. Appendix B details the construction of all the variables in this paper.

Table 3 presents the results for the C-CAPM, D-CAPM, EZ-CCAPM and EZ-DCAPM. All

[15] Recall that portfolios p1 to p12 each consist of 25 currency-rule pairs, ranked every 20 days by ex ante Sharpe ratio. p1 contains strategies 1 to 25; p2 contains strategies 26 to 50 and so on.

models clearly perform very poorly; the R^2 is negative in every case.[16] The portfolios with the highest returns have negative betas; p1 has a beta of -1.97 (betas not shown in the tables). This implies that the top technical portfolio return covaries positively with M_{t+1}, contrary to theory.

3.3 *Linear Factor Models*

We consider linear SDFs of the form

$$M_t = a + b' f_t \tag{11}$$

where a is a scalar, b is a $k \times 1$ parameter vector and f_t is a $k \times 1$ vector of demeaned risk factors.

The model's return-beta representation implies that an asset's expected return is proportional to its covariance with the risk factors. The betas of the N test assets are defined as

$$r_{i,t}^e = a_i + \beta_i' \tilde{f}_t + \varepsilon_{i,t}, \qquad t = 1, \dots, T, \quad i = 1, \dots, N, \tag{12}$$

where $r_{i,t}^e$ is the log excess return to asset i at time t, $\tilde{f}_t$ is the non-demeaned factor at time *t*. In the special case that the factors, $\tilde{f}_t$, are excess returns, then the intercepts (a_i) in the time series representation (12) are zero.

For tests of more general sets of factors, Fama and MacBeth (1973) suggest a two-stage procedure that first estimates the βs for each test asset with the time series regression (12).[17] The second stage then estimates the factor prices, λ, from a cross-sectional regression of average excess test-assets returns on the betas.

$$E(r_i^e) = \beta_i' \lambda + \alpha_i, \tag{13}$$

where λ is the price-of-risk coefficient to be estimated and the α_is are the pricing errors. The model implies no constant in (13) but one is often included to pick up estimation error in the riskless rate.

[16] The R^2 can be negative because we are assessing the predictive value of a calibrated, ex ante model, not the predictive value of a model estimated to maximize the R^2.
[17] Fama and MacBeth (1973) originally used rolling regressions to estimate the βs and cross-sectional regressions at each point in time to estimate λ and α_i for each time period, then used averages of those estimates to get overall estimates. The time series of λ and α_i estimates could then be used to estimate standard errors for the overall estimates that correct for cross-sectional correlation.

A large α_i or a significant change in the model fit with a constant indicates a poor fit (Burnside (2011)).

One can simultaneously estimate (12) and (13) with GMM, obtaining the same point estimates as the 2-stage procedure and properly accounting for cross-sectional correlation, heteroskedasticity and the uncertainty about $\hat{\beta}_i'$ in the covariance matrix of the parameters (see Cochrane (2005 chapter 10)). The moment restrictions for the simultaneous estimation are

$$\begin{gathered} E\left(r_{i,t}^e - a_i - \beta_i \tilde{f}_t\right) = 0 \\ E\left(\left(r_{i,t}^e - a_i - \beta_i \tilde{f}_t\right)\tilde{f}_t\right) = 0 \\ E(r_i^e - \beta_i \lambda) = 0 \end{gathered} \quad . \tag{14}$$

4. Results

Figure 1 showed that the ex post Sharpe ratios of the technical strategies varied with their ex ante ranks. That is, past returns tend to predict future returns. This section tests whether any risk factor explains the cross-section of expected returns to portfolios p1-p12.

4.1 *CAPM models applied to the returns of portfolios p1 through p12*

We first look at whether any of four variants of the CAPM model, the basic CAPM, the quadratic CAPM, the downside risk CAPM (DR-CAPM) and the Carhart 4-factor model, can explain the excess returns to the 12 portfolios.

The basic CAPM regression equation for portfolio "i" is as follows:

$$r_{i,t}^e = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}\,, \qquad i = 1, \ldots, N, \tag{15}$$

where $r_{i,t}^e$ is the excess return to the dynamic portfolio strategy and R_m is the market excess return. Because the factor is an excess return, the intercept α, must not be significantly positive if the model is to fully explain the return. The quadratic CAPM adds the squared market return factor $R_{m,t}^2$ to the CAPM equation.

$$r_{i,t}^e = \alpha_i + \beta_{i,Rm} R_{m,t} + \beta_{i,R_m^2} R_{m,t}^2 + \varepsilon_{i,t}, \qquad i = 1, \ldots, N \tag{16}$$

Lettau, Maggiori and Weber (2014) have successfully explained returns to the carry trade with the

DR-CAPM of Ang, Chen and Xing (2006). This DR-CAPM allows the price of risk and the beta of currency portfolios to depend nonlinearly on the market return.

$$E\left[r_{i,t}^{e}\right] = \beta_i\lambda + (\beta_i^{-} - \beta_i)\lambda^{-}, \qquad i = 1, \dots, N \tag{17}$$

where $\beta_i = \frac{cov(R_i,R_m)}{var(R_m)}$ and $\beta_i^{-} = \frac{cov(R_i,R_m|R_m<\delta)}{var(R_m|R_m<\delta)}$ are the unconditional and conditional market betas, where the latter is specified for an exogenous threshold δ. The prices of unconditional and downside risk are λ and λ^{-}, respectively. We follow Lettau, Maggiori and Weber (2014) in setting λ equal to the average excess market return and defining δ as the average excess market return less one standard deviation. Finally, we examine Carhart's (1997) 4-factor extension of the Fama and French (1993) 3-factor model, where the risk factors are the excess return on the U.S. stock market (R_m), the size factor (R_{SMB}), the value factor (R_{HML}) and the momentum factor (R_{UMD}).[18]

$$r_{i,t}^{e} = \alpha_i + \beta_{i,m}R_{m,t} + \beta_{i,SMB}R_{SMB,t} + \beta_{i,HML}R_{HML,t} + \beta_{i,UMD}R_{UMD,t} + \varepsilon_{i,t} \tag{18}$$

Panel A of Table 4 shows the results for the first stage of the Fama-MacBeth asset pricing tests. The CAPM and Carhart variants have similar problems. Contrary to theory, the beta coefficients tend to be statistically significantly negative and the alpha coefficients (the constants) tend to actually be larger than the mean excess returns in the last column of Panel A. This indicates that the risk factors increase risk-adjusted profitability, deepening the technical trading puzzle. In addition, one cannot reject the nulls of equal beta coefficients in the CAPM model or any of the four Carhart beta vectors (bottom of Panel A). Thus, one cannot identify these prices of risk. Perhaps because of this lack of identification, the monthly Carhart factor means are 0.58% (R_m), 0.24% (R_{SMB}), 0.29% (R_{HML}) and 0.68% (R_{UMD}), which are not close to prices of risk in panel B

[18] Fama and French (1993) showed that 3-factors, market return, firm size and book-to-market ratios, very effectively explained the returns of certain test assets. The 4 factors used in equation (18) are excess returns to zero-investment portfolios that are simultaneously long/short in stocks that are in the highest/lowest quantiles of the sorted distributions. For example, the small-minus-big (SMB) portfolio takes a long position in small firms and a short position in large firms.

of Table 4. As noted above, when the factors are tradable excess returns, factor means are prices of risk. There is no evidence that the CAPM or the 4-factor model explains the excess returns to the TTR strategies.

The quadratic CAPM also exhibits negative coefficients on the market (β_{i,R_m}) but positive, mostly significant coefficients on the quadratic terms (β_{i,R_m^2}). The bottom rows of Panel A show that one can reject equality for these coefficients, identifying the price of risk, which is 0.17 and statistically insignificant (Panel B, Table 4). This value is inconsistent with the theoretically negative price of risk, however, which implies that the quadratic CAPM cannot explain the excess returns of the dynamic portfolio strategies. In addition, the R^2 with no constant is negative.

There are two first stage regressions for the DR-CAPM. The first is the basic CAPM while the second estimates DR-CAPM betas on a sample consisting only of observations in which the market return is at least one standard deviation below its sample mean. The first and third panels of Table 4 display results from these respective first stage regressions. The DR-CAPM betas are generally significant but incorrectly signed, similar to those of the basic CAPM (Panel A). Panel B of Table 4 indicates that the model produces a negative, statistically insignificant price of risk with a negative R^2. Thus, the DR-CAPM fails to explain the dynamic currency portfolio returns.

4.2 *Consumption-based models applied to the returns of portfolios p1 through p12*

We now examine whether consumption-based models of asset pricing can explain the returns to the 12 portfolios of dynamic strategies. The C-CAPM relates asset returns to the real consumption growth of a risk-averse representative agent, as in equation (10). We first consider three variations of the linear approximation of the factor model in (10): the C-CAPM, D-CAPM and EZ-DCAPM (Yogo (2006)).

$$E\left[r_{i,t}^{e}\right] = b_1 cov\left(\Delta c_t, x_{i,t}\right) + b_2 cov\left(\Delta d_t, x_{i,t}\right) + b_3 cov\left(r_{W,t}, x_{i,t}\right), \;\; i = 1, \dots, N \qquad (19)$$

where Δc_t and Δd_t are log nondurable and durable consumption growth, respectively, and $r_{W,t}$ is the log return on the market portfolio. The linear approximation for the most general of these nested models, the EZ-DCAPM, uses nondurables plus services, durables and the market excess return as factors. The beta representation allows us to estimate factor prices, λ, and betas, β.

$$r_{i,t}^e = a_i + \beta_{c,i}\Delta c_t + \beta_{d,i}\Delta d_t + \beta_{W,i} r_{W,t} + \varepsilon_{i,t}, \qquad i = 1, \dots, N \tag{20}$$

$$E(r_i^e) = \beta_{c,i}\lambda_c + \beta_{d,i}\lambda_d + \beta_{W,i}\lambda_W, \qquad i = 1, \dots, N \tag{21}$$

where $\lambda = \Sigma_{ff} b$, $\beta = \Sigma_{ff}^{-1}\Sigma_{fx}$, Σ_{ff} is the factor covariance matrix, Σ_{fx} is the return-factor covariance matrix and equation (19) defines b. The D-CAPM and C-CAPM restrict $\beta_{W,i}$ and the pair, $\{\beta_{d,i}, \beta_{W,i}\}$, to zero, respectively. We can infer the utility parameter values from the linear model coefficient estimates, as in Lustig and Verdelhan (2007) (see equation (4) in that paper).

Panel A of Table 5 shows that the C-CAPM and D-CAPM perform poorly. The betas are generally insignificant or wrongly signed. The prices of consumption risk are negative in Panel B. Most damningly, the second-stage R^2s for models that exclude constants are negative at -1.23 and -0.49, indicating that a simple constant would explain the expected returns better than the model.

The EZ-DCAPM model appears to fit better. The constant is not significant and the second-stage R^2 is sizable at 0.60 and does not change much with the addition of the constant. The price of risk for non-durable consumption in the EZ-DCAPM model is statistically significant but negative, –2.32 percent. This negative price of risk is theoretically implausible, however. Theory predicts that it should be positive in the case where the coefficient of risk aversion is $\gamma > 1$, and the elasticity of substitution in consumption is less than one $(\sigma < 1)$. The estimate of σ in Yogo (2006) for the EZ-DCAPM is 0.210.

The estimated coefficient of risk aversion is significantly negative in all cases, which is also implausible because the dynamic portfolio strategies covary negatively with consumption growth, and thus hedge against consumption risk. To be consistent with the model such strategies should earn negative excess returns.

In summary, the prices of risk are implausibly signed for the C-CAPM, D-CAPM and EZ-DCAPM models, the estimates of risk aversion are implausibly negative and the cross-section regressions fit very poorly without the constant. We conclude that none of these models satisfactorily explains the observed returns to the test assets.

4.3 *Carry-trade models applied to the returns of portfolios p1 through p12*

This failure of consumption-based models has led researchers to look for other risk factors that might proxy for future investment opportunities, such as the Fama and French (1993) and Carhart (1997) factors. Lustig, Roussanov and Verdelhan (2011) have recently applied this idea to construct two currency risk factors. The first factor, which they denote *RX,* is the average currency excess return to going short in the dollar and long in the basket of six foreign currency portfolios. The second factor, HML_{FX}, is the return to borrowing low interest rate currencies (portfolio 1) and investing in high interest rate currencies (portfolio 6), in other words a carry trade.[19]

We examine whether these *RX* and HML_{FX} risk factors explain the cross-sectional variation in expected returns across the 12 technical portfolios. Because the factors are returns to tradable portfolios we can directly test the model by comparing the estimates of the risk premia with the factor means. We reject the model if they differ significantly.

$$r_{i,t}^{e} = \alpha_i + \beta_{i,RX_t} RX_t + +\beta_{i,HML_{FX,t}} HML_{FX,t} + \varepsilon_{i,t}, \qquad i = 1, \dots, N. \quad (22)$$

The "LV factors" subsection of panel A of Table 6 shows that the betas on the *RX* factor are small and almost always insignificant but the HML_{FX} betas are always negative and often significant. The negative betas suggest that the TTR returns tend to be high when carry trade

[19] *RX* and HML_{FX} are very similar to the first two principal components of the returns to the 6 portfolios.

returns are low. The fact that the time series constants are higher than the unadjusted mean returns indicates that accounting for HML_{FX} and *RX* risk actually deepens the puzzle of the profitability of TTRs. In addition, the prices of risk for the HML_{FX} and *RX* factors are negative and the second stage R^2s are negative when the constant is excluded (LV factors, Panel B). These results make it seem unlikely that any carry-trade risk factor could also explain the technical returns.

Menkhoff, Sarno, Schmeling and Schrimpf (2012a) have used a second category of risk factors, based on global exchange rate volatility, to explain carry trade returns. To investigate volatility's explanatory power for our technical returns, we estimate a global volatility factor in a manner very similar to that of Menkhoff, Sarno, Schmeling and Schrimpf (2012a). We calculate a global foreign exchange volatility factor from the first principal component of the monthly exchange rate return variances. VOL1 is the residual series of an AR(1) process fit to this principal component while VOL2 is the first difference in this principal component. We then estimate a beta representation using these volatility factors and a dollar exposure factor that Menkhoff, Sarno, Schmeling and Schrimpf (2012a) note is very similar to the Lustig, Roussanov and Verdelhan (2011) *RX* factor. Menkhoff, Sarno, Schmeling and Schrimpf (2012a) denote this as the DOL factor while we continue to use the previous RX terminology.

$$r_{i,t}^{e} = \alpha_i + \beta_{i,RX_t} RX_t + \beta_{i,VOL1_t} VOL1_t + \varepsilon_{i,t}, \qquad i = 1, \ldots, N. \tag{23}$$

$$r_{i,t}^{e} = \alpha_i + \beta_{i,RX_t} RX_t + \beta_{i,VOL2_t} VOL2_t + \varepsilon_{i,t}, \qquad i = 1, \ldots, N. \tag{24}$$

Panel A of Table 6 shows that the betas on *RX* are not jointly statistically significant nor significantly different from each other (see the 2 subpanels labeled "VOL factors"). Thus the price of *RX* risk is not identified. In contrast, betas on the volatility factors are positive and highly significant but there is no obvious pattern to the VOL betas from the low to high ranking portfolios. Instead, higher volatility seems to be associated with higher returns to all technical portfolios.

Panel B of Table 6 shows no evidence for the theoretically negative price of volatility risk that one should find when one excludes a constant in the cross-sectional equation. Specifically, if the constant is excluded, the prices of risk on VOL1 and VOL2 are positive but very small and insignificant, and the second-stage R^2s are negative (see VOL factors). In addition, the constant terms are significant. In other words, the volatility factor picks up common time series variation in returns, but the model does not explain the cross-sectional spread in technical returns.

Researchers have also explored skewness as a risk factor for carry trade returns (Rafferty (2012)) and the cross-section of equity returns (Amaya, Christoffersen, Jacobs, and Vasquez (2015)). To investigate whether exposure to skewness can generate the technical trading returns, we form a skewness factor, SKEW, a tradable portfolio that is long (short) currencies in the highest (lowest) skewness quintiles in a given month. We then estimate that factor's beta representation.

$$r_{i,t}^{e} = \alpha_i + \beta_{i,SKEW_t} SKEW_t + \varepsilon_{i,t}, \qquad i = 1, \dots, N. \tag{25}$$

The skewness betas in Panel A of Table 6 are all positive and highly significant. One cannot, however, reject the hypothesis that they are all equal at the 5 percent level, precluding strong identification of risk prices. Also, the constants in the time series regressions ("Skewness factors," Panel A) are generally highly significant and very close in magnitude to the excess returns to the test assets. Thus, the skewness factor is able to account for at most ten percent of the returns to these assets as the time series constants are within 10 percent of the unadjusted means.

4.4 *Macro-based models of currency returns applied to the returns of p1 through p12*

Berg and Mark (2018) relate expected excess carry trade returns to the variance and skewness of SDFs. Currencies of countries whose log SDFs exhibit more variance or positive skewness are "risky" and earn a positive excess return. After testing a number of macro variables as explanatory variables for carry trade returns, Berg and Mark (2018) find that a country's unemployment gap skewness is a risk factor for currency excess returns.

To determine whether this unemployment gap skewness factor could be responsible for the returns to technical trading, we follow Berg and Mark (2018) in constructing such a factor from quarterly macroeocnomic data, and then we estimate its beta representation.

$$r_{i,t}^{e} = \alpha_i + \beta_{i,UR\ GAP\ SKEW_t}\, UR\ GAP\ SKEW_t + \varepsilon_{i,t}, \qquad i = 1, \ldots, N. \tag{26}$$

Panel A of Table 7 shows that none of the unemployment-gap-skewness betas are significantly different from zero at the 5 percent level. Neither are they jointly different from zero or from each other, leaving the risk premium only weakly identified. Panel B shows that the R^2 is small in the model with a constant and negative in the model excluding the constant. In summary, there is no evidence that the unemployment skewness gap explains the returns to technical trading.

4.5 *Liquidity-based model applied to the returns of portfolios p1 through p12*

Finally, we consider the possibility that global FX liquidity may explain technical trading returns. Using three years of intraday data, Mancini, Ranaldo, and Wrampelmeyer (2013) showed that liquidity risk explains carry trade returns; specifically, low interest currencies (with negative carry returns) offer insurance against liquidity risk. Karnaukh, Ranaldo, and Söderlind (2015) extended this work by establishing the accuracy of daily measures of FX liquidity.

We investigate the Karnaukh, Ranaldo and Söderlind (2015) FX liquidity measure as a risk-based explanation of technical returns. We aggregate daily liquidity data to a monthly frequency, and test the factor in the Fama-MacBeth two-stage model, as we have with previous candidates.

$$r_{i,t}^{e} = \alpha_i + \beta_{i,FX\ liquidity_t} FX\ Liquidity_t + \varepsilon_{i,t}, \qquad i = 1, \ldots, N. \tag{27}$$

The right-hand panels of Table 7 show the results of this estimation. Only two of the coefficients on FX liquidity, p1 and p12, are significant at the ten percent level and the test for beta equality is marginal at the 5 percent level. The price of liquidity risk is only significant in the cross-sectional regression with a constant. As discussed previously, sensitivity of the price of risk to the presence/absence of a regression constant indicates poor fit (Burnside (2011)). In addition, the time series constants are again similar to the average returns, indicating minimal factor impact. We conclude that FX liquidity cannot explain technical trading returns.

4.6 *Robustness Checks*

We investigated the robustness of our baseline technical trading results from Neely and Weller (2013) to five variations of the technical rule construction. Specifically, we used the Sortino ratio and average returns to evaluate portfolios instead of the Sharpe ratio. We resorted portfolios every 250-days instead of every 20 days. We considered only USD rates and also only G10 rates. We calculated dynamic technical trading portfolio returns under each of these five alternative rule-construction methods and then we risk-adjusted those returns as in the main results. Appendices *C* and *D* respectively show that inference on the both the raw and risk-adjusted profitability of technical trading results appears robust to reasonable perturbation of the methods.

5. Discussion and Conclusion

Researchers have long documented the profitability of technical analysis in foreign exchange. Such positive studies include Dooley and Shafer (1984), Sweeney (1986), Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Lee, Gleason and Mathur (2001) and Martin (2001).

Despite such a substantial record of gains, the reasons for this success remain mysterious. The findings of Neely (2002) appear to rule out the central bank intervention explanation suggested by LeBaron (1999). To investigate the possibility of data snooping, data mining and publication bias, Neely, Weller and Ulrich (2009) analyze rule performance in true out-of-sample tests that occur long after important studies. They conclude that data snooping, data mining and publication bias are unlikely explanations. Instead, Neely, Weller and Ulrich (2009) argued that the data were consistent with an adaptive markets explanation.

It remains possible, however, that exposure to some sort of risk generates TTR profitability. Recently, several authors have explained carry trade and/or cross-sectional momentum returns with modern techniques for risk adjustment. If these risk-based explanations for the carry trade also explain the returns to technical trading in foreign exchange markets, it would appear very likely that these factors represent genuine sources of risk. With that in mind, this paper has applied an exhaustive range of risk adjustment techniques to evaluate the evidence that exposure to risk plausibly explains the profitability of ex ante, dynamically selected, foreign exchange portfolios.

We examine many types of risk adjustment models, including variants of the CAPM and equity factors, consumption-based models, and factors motivated by the carry trade puzzle, including a dollar factor, a carry trade factor, foreign exchange volatility, foreign exchange skewness, unemployment gap skewness, and liquidity risk. We find that no model of risk adjustment can plausibly explain the very robust findings of profitability of technical analysis in the foreign exchange market.[20] Instead, we believe that this utter failure of risk adjustment is consistent with other explanations, such as adaptive markets or limits to arbitrage.

[20] The VOL1 and VOL2 factors have some marginal power to explain as much as 10 or 15 percent of portfolio returns for the USD-only and G10-only returns, while the SKEW measure has similar power to explain returns in the Baseline, Returns-sorting and Sortino-sorting scenarios.

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Table 1: Data description

Currency Group	Country	Currency abbreviation versus the USD	# of trading obs	Start Date	End Date	Mean TC	STD of Annualized FX Return
Advanced	Australia	AUD	9008	4/7/1976	12/31/2012	3.1	11.6
Advanced	Canada	CAD	9344	1/2/1975	12/31/2012	2.9	6.7
Advanced	Euro Area	EUR	9717	4/3/1973	12/31/2012	3.0	10.6
Advanced	Japan	JPY	9599	4/3/1973	12/28/2012	3.0	10.5
Advanced	New Zealand	NZD	6027	8/3/1987	12/31/2012	3.9	12.4
Advanced	Norway	NOK	6515	1/2/1986	12/31/2012	3.4	11.6
Advanced	Sweden	SEK	7278	1/3/1983	12/28/2012	3.3	11.4
Advanced	Switzerland	CHF	9697	4/3/1973	12/31/2012	3.1	12.0
Advanced	UK	GBP	9338	1/2/1975	12/31/2012	2.9	9.9
Dev. Europe	Czech Republic	CZK	5049	1/5/1993	12/31/2012	5.2	12.4
Dev. Europe	Hungary	HUF	4466	1/2/1995	12/28/2012	10.3	14.3
Dev. Europe	Hungary/Switzerland	HUF/CHF	4165	1/3/1996	12/28/2012	10.5	12.0
Dev. Europe	Poland	PLN	3918	2/24/1997	12/31/2012	7.1	14.6
Dev. Europe	Russia	RUB	3055	8/1/2000	12/28/2012	3.6	7.4
Dev. Europe	Turkey	TRY	2769	1/2/2002	12/31/2012	12.9	15.4
Latin America	Brazil	BRL	3330	5/3/1999	12/31/2012	6.0	16.8
Latin America	Chile	CLP	4359	6/1/1995	12/28/2012	5.9	9.5
Latin America	Japan/Mexico	JPY/MXN	3887	1/4/1996	12/28/2012	4.6	16.9
Latin America	Mexico	MXN	4220	1/4/1996	12/31/2012	4.6	10.5
Latin America	Peru	PEN	4252	4/1/1996	12/31/2012	5.3	5.0
Other	Israel	ILS	3750	7/20/1998	12/31/2012	8.1	7.8
Other	Israel/Euro Area	ILS/EUR	2552	1/2/2003	12/31/2012	8.5	10.2
Other	South Africa	ZAR	4394	4/3/1995	12/31/2012	8.7	16.4
Other	Taiwan	TWD	3605	1/5/1998	12/28/2012	5.0	5.3
Adv. Cross Rates	Switzerland/UK	CHF/GBP	9169	1/3/1975	12/31/2012	3.0	9.8
Adv. Cross Rates	Australia/UK	AUD/GBP	8920	4/7/1976	12/31/2012	3.2	12.4
Adv. Cross Rates	Canada/UK	CAD/GBP	9217	1/2/1975	12/31/2012	3.0	10.3
Adv. Cross Rates	Japan/UK	JPY/GBP	8982	1/2/1975	12/28/2012	3.0	12.2
Adv. Cross Rates	Euro Area/UK	EUR/GBP	9187	1/2/1975	12/31/2012	3.0	8.1
Adv. Cross Rates	Australia/Switzerland	AUD/CHF	8848	4/7/1976	12/31/2012	3.2	14.4
Adv. Cross Rates	Canada/Switzerland	CAD/CHF	9150	1/3/1975	12/31/2012	3.1	12.4
Adv. Cross Rates	Japan/Switzerland	JPY/CHF	9338	4/3/1973	12/28/2012	3.2	11.7
Adv. Cross Rates	Euro Area/Switzerland	EUR/CHF	9602	4/3/1973	12/31/2012	3.2	5.9
Adv. Cross Rates	Canada/Australia	CAD/AUD	8894	4/7/1976	12/31/2012	3.2	10.3
Adv. Cross Rates	Japan/Australia	JPY/AUD	8633	4/7/1976	12/28/2012	3.2	15.3
Adv. Cross Rates	Euro Area/Australia	EUR/AUD	8861	4/7/1976	12/31/2012	3.2	12.8
Adv. Cross Rates	Japan/Canada	JPY/CAD	8968	1/2/1975	12/28/2012	3.1	12.7
Adv. Cross Rates	Euro Area/Canada	EUR/CAD	9158	1/2/1975	12/31/2012	3.1	10.7
Adv. Cross Rates	Japan/Euro Area	JPY/EUR	9347	4/3/1973	12/28/2012	3.1	11.3
Adv. Cross Rates	New Zealand/Australia	NZD/AUD	6224	8/3/1987	12/31/2012	3.9	8.5

Notes: The table depicts the 21 exchange rates versus the USD and 19 non-USD cross rates used in our sample along with the number of trading dates, the starting and ending dates of the samples, average transaction cost, and standard deviation of annualized daily, log excess returns.

Table 2: Individual Rule Statistics

Rule Prevalence in the top four portfolios over the full sample

p1 FX rate	p1 rule	p1 % used	p2 FX rate	p2 rule	p2 % used	p3 FX rate	p3 rule	p3 % used	p4 FX rate	p4 rule	p4 % used
CLP	Ch(20,.001,1)	14.7	EUR	Ch(10,.001,1)	15.7	EUR	Ch(10,.001,1)	7.7	EUR	MA(5,20)	10.6
EUR	Ch(10,.001,1)	9.9	CLP	Ch(20,.001,1)	14.3	EUR	mom(20)	6.6	TWD	MA(5,20)	6.6
GBP	Ch(10,.001,1)	9.3	EUR	MA(5,20)	5.6	CLP	Ch(20,.001,1)	6.2	EUR	mom(20)	5.0
EUR	MA(5,20)	7.0	CLP	mom(20)	4.8	EUR	MA(5,20)	5.4	JPY	MA(5,20)	4.6
CAD/GBP	Ch(20,.001,1)	6.8	CLP	filter .03	4.6	CLP	mom(20)	5.2	CLP	mom(20)	4.3

Rule prevalence in portfolio 1 over subsamples

1973-1982 FX rate	1973-1982 rule	1973-1982 % used	1983-1992 FX rate	1983-1992 rule	1983-1992 % used	1993-2002 FX rate	1993-2002 rule	1993-2002 % used	2003-2012 FX rate	2003-2012 rule	2003-2012 % used
GBP	Ch(10,.001,1)	45.9	CAD/GBP	Ch(20,.001,1)	26.4	CLP	filter .02	22.1	CLP	Ch(20,.001,1)	38.8
CAD/GBP	mom(20)	18.4	EUR	Ch(10,.001,1)	26.4	CLP	filter .03	21.4	RUB	filter .005	24.0
EUR	Ch(10,.001,1)	15.3	EUR	MA(5,20)	24.0	CLP	Ch(20,.001,1)	16.0	RUB	MA(5,20)	8.5
EUR	mom(20)	7.1	NOK	MA(1,200)	8.8	EUR/CAD	Ch(10,.001,1)	16.0	RUB	MA(1,200)	5.4
EUR	MA(5,20)	3.1	EUR	mom(20)	4.0	JPY	MA(5,20)	13.0	CLP	Ch(5,.001,1)	4.7

Best individual rule returns over varying samples

FX Rate	Rule	Mean AR	T-Stat Return	Sharpe	Start	End
RUB	filter .005	9.40	4.80	1.19	2000	2012
RUB	MA(1,5)	7.15	3.64	0.93	2000	2012
CLP	Ch(5,.001,1)	8.11	3.69	0.88	1995	2012
TWD	MA(5,20)	4.25	3.30	0.87	1998	2012
TWD	Ch(20,.001,1)	4.02	3.13	0.85	1998	2012
TWD	mom(60)	3.74	2.93	0.83	1998	2012

Notes: The four subpanels of the top panel of the table report the 5 most frequently used rule-exchange rate combinations in portfolios 1-4, respectively, over the whole sample. The four subpanels of the middle panel report the 5 most frequently used rule-exchange rate combinations for portfolio 1 in four subsamples. The bottom panel reports the 5 highest rated ex post individual rules when sorting by Sharpe Ratio over the entire sample available for each currency. These portfolios tend to select more recently introduced currencies because the rules are sorted on their Sharpe Ratio for their entire history. Mean AR denotes mean annual return.

Table 3: Calibration

	CCAPM	DCAPM	EZ-CCAPM	EZ-DCAPM
$std_T[M]/E_T[M]$	0.92	1.22	0.92	1.22
$var_T[M]/E_T[M]$	0.60	0.61	0.59	0.61
MAE (in %)	1.32%	0.95%	1.32%	0.95%
R_2	-1.53	-0.15	-1.54	-0.15

Notes: The sample is 1978–2010 (annual data). The annual excess returns are those to portfolios p1 to p12, as described in the text. The first two rows report the maximum Sharpe ratio (row 1) and the price of risk (row 2). The last two rows report the mean absolute pricing error (in percentage points) and the R^2. Following Yogo (2006), we fixed sigma (σ) at 0.023 (EZ-CCAPM and EZ-DCAPM), alpha (α) at 0.802 (D-CAPM and EZ-DCAPM), delta (δ) at 0.98, and rho (ρ) at 0.700 (D-CAPM, EZ-DCAPM). Gamma (γ) is fixed at 41.16 to minimize the mean squared pricing error in the EZ-DCAPM.

Table 4: Results for CAPM, Quadratic CAPM, Downside risk CAPM and Carhart model for portfolios p1-p12

Panel A: Time Series Regressions

	CAPM Const	Rm β	R^2	**Quad.CAPM** Const	Rm β	Rm^2 β	R^2
p1	***0.40***	**-0.04**	0.01	***0.27***	*-0.03*	***0.57***	0.03
p2	***0.26***	***-0.05***	0.02	**0.18**	**-0.04**	**0.36**	0.03
p3	***0.21***	**-0.04**	0.01	0.11	*-0.03*	***0.46***	0.03
p4	**0.13**	***-0.04***	0.02	0.05	**-0.03**	**0.39**	0.03
p5	***0.20***	**-0.03**	0.01	**0.15**	-0.02	0.22	0.01
p6	0.08	***-0.05***	0.03	-0.02	***-0.04***	***0.45***	0.04
p7	**0.14**	***-0.04***	0.02	0.04	**-0.04**	***0.43***	0.04
p8	**0.14**	***-0.04***	0.02	0.06	**-0.03**	**0.36**	0.03
p9	**0.12**	***-0.06***	0.04	0.01	***-0.04***	***0.52***	0.06
p10	**0.14**	***-0.04***	0.02	0.03	**-0.03**	***0.47***	0.04
p11	*0.10*	**-0.03**	0.01	-0.04	-0.02	***0.63***	0.05
p12	0.08	***-0.04***	0.03	-0.04	**-0.03**	***0.53***	0.06
β1=…=βn=0 p-value		0.01			0.05	0.00	
β1=…=βn p-value		0.22			0.44	0.00	

	Conditional CAPM Down Const	Rm Down β	Const	Rm β	Down R^2	R^2
p1	***0.27***	**-0.10**	***0.40***	**-0.04**	0.03	0.01
p2	***0.14***	***-0.09***	***0.26***	***-0.05***	0.03	0.03
p3	***0.11***	**-0.08**	***0.21***	**-0.04**	0.03	0.01
p4	**0.04**	***-0.07***	**0.13**	***-0.04***	0.02	0.02
p5	***0.13***	**-0.05**	***0.20***	**-0.03**	0.01	0.01
p6	-0.04	***-0.09***	0.08	***-0.05***	0.04	0.03
p7	**0.04**	***-0.08***	**0.14**	***-0.04***	0.03	0.02
p8	**0.04**	***-0.07***	**0.14**	***-0.04***	0.03	0.02
p9	**-0.01**	***-0.10***	**0.12**	***-0.06***	0.05	0.04
p10	**0.03**	***-0.08***	**0.14**	***-0.04***	0.03	0.02
p11	*0.00*	**-0.08**	*0.10*	**-0.03**	0.03	0.01
p12	-0.03	***-0.09***	0.08	***-0.04***	0.05	0.03
β1=…=βn=0 p-value		0.01		0.01		
β1=…=βn p-value		0.13		0.22		

	Carhart Const	Rm β	SMB β	HML β	UMD β	R^2	Mean R
p1	**0.41**	*-0.04*	**-0.05**	*-0.06*	0.03	0.04	0.37
p2	***0.27***	*-0.05*	-0.04	-0.03	0.01	0.03	0.23
p3	**0.21**	-0.03	-0.04	-0.02	0.02	0.02	0.19
p4	**0.13**	-0.04	-0.02	-0.02	0.02	0.02	0.11
p5	0.17	-0.02	-0.02	**0.01**	0.03	0.02	0.18
p6	***0.07***	-0.04	-0.03	*-0.01*	0.02	0.04	0.05
p7	**0.13**	-0.03	-0.03	0.01	0.02	0.03	0.11
p8	**0.13**	-0.03	-0.03	0.01	0.02	0.03	0.12
p9	***0.11***	*-0.05*	-0.04	*0.01*	0.02	0.05	0.09
p10	**0.12**	*-0.03*	-0.04	**0.01**	0.03	0.04	0.11
p11	0.08	-0.02	-0.03	**0.02**	0.03	0.03	0.09
p12	**0.08**	***-0.03***	-0.05	0.00	0.01	0.05	0.06
β1=…=βn=0 p-value		0.03	0.50	0.18	0.26		
β1=…=βn p-value		0.15	0.95	0.16	0.69		

Panel B: Cross Sectional Regressions

	Const	Rm λ	R^2	Const	Rm λ	Rm^2 λ	R^2	Const	Down λ	R^2
Coefficient	**0.21**	*1.53*	0.02	**0.21**	1.45	-0.05	0.02	0.01	-3.93	0.18
t statisic	(2.48)	(-1.99)		(2.31)	(1.00)	(-0.44)		(0.02)	(-0.75)	
Coefficient		*-3.35*	-0.16		-2.02	0.17	-0.13		-3.35	-0.16
t statisic		(-1.99)			(-1.30)	(1.68)			(-0.86)	

	Const	Rm λ	SMB λ	HML λ	UMD λ	R^2
Coefficient	0.08	3.26	-1.89	-3.76	3.95	0.74
t statisic	(0.30)	(1.05)	(-0.49)	(-1.87)	(1.05)	
Coefficient		2.43	-2.62	-3.51	5.20	0.72
t statisic		(0.66)	(-0.95)	(-1.67)	(1.53)	

Notes: Monthly data 06/1977 – 12/2012. Factors are the excess return on the U.S. stock market (R_m), the excess return on the U.S. stock market in downturn ($R_m\ Down$), the size factor (SMB), the value factor (HML) and the momentum factor (UMD). The DR-CAPM has two first stage regressions. The first is identical to the basic CAPM. These results are in the first subpanel. The second first-stage DR-CAPM regression is performed only on observations in which the market return is at least one standard deviation below its sample mean. These results are in the third subpanel (DR-CAPM). ( ) denotes t-statistics based on GMM standard errors. *Italic*, **bold**, and ***bold italic*** fonts indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 5: Results for C-CAPM, D-CAPM and EZ-DCAPM model for portfolios p1-p12

Panel A: Time Series Regressions

	C-CAPM			D-CAPM				EZ-DCAPM					
	Const	ND β	R^2	Const	ND β	Durables β	R^2	Const	ND β	Durables β	Market β	R^2	Mean R
p1	***5.87***	*-0.97*	0.11	***4.72***	**-1.50**	0.54	0.14	***5.64***	*-1.29*	0.35	-0.06	0.19	4.52
p2	***3.35***	-0.43	0.03	***4.63***	0.16	-0.60	0.07	***5.42***	0.33	-0.75	-0.05	0.12	2.75
p3	**2.55**	-0.28	0.01	*2.92*	-0.11	-0.17	0.01	**3.56**	0.03	-0.30	-0.04	0.04	2.16
p4	1.10	0.11	0.00	*3.16*	1.06	*-0.96*	0.09	***4.77***	*1.42*	**-1.28**	**-0.11**	0.23	1.25
p5	**2.11**	0.10	0.00	**3.83**	0.89	*-0.80*	0.09	***5.18***	*1.19*	**-1.07**	**-0.09**	0.21	2.25
p6	0.88	-0.04	0.00	1.37	0.18	-0.23	0.01	2.36	0.40	-0.42	-0.07	0.08	0.82
p7	1.19	0.20	0.01	**2.74**	0.91	-0.72	0.08	**3.47**	*1.07*	*-0.87*	-0.05	0.12	1.46
p8	**2.36**	-0.64	0.07	***3.70***	-0.02	-0.62	0.13	***4.29***	0.11	*-0.74*	-0.04	0.16	1.47
p9	1.13	-0.10	0.00	1.83	0.22	-0.32	0.02	2.10	0.28	-0.38	-0.02	0.02	0.99
p10	0.95	0.19	0.01	1.35	0.38	-0.19	0.01	1.94	0.51	-0.31	-0.04	0.04	1.21
p11	0.31	0.46	0.03	0.35	0.48	-0.02	0.03	1.49	0.73	-0.24	**-0.08**	0.15	0.95
p12	0.74	-0.12	0.00	0.37	-0.29	0.17	0.01	0.92	-0.17	0.06	-0.04	0.05	0.57
β1=…=βn=0 p-value		0.00			0.00	0.03			0.00	0.00	0.00		
β1=…=βn p-value		0.00			0.00	0.03			0.00	0.00	0.00		

Panel B: Cross-sectional Regressions

	Const	ND λ	γ	R^2	Const	ND λ	Durables λ	γ	σ	R^2	Const	ND λ	Durables λ	Market λ	γ	σ	α	R^2
coefficient	1.45	**-1.93**	**-83.78**	0.50	1.49	**-1.90**	*-1.79*	**-82.22**	-0.05	0.50	0.57	**-2.10**	-1.69	-19.29	*-94.73*	*-0.08*	0.02	0.63
t stat	(1.59)	(-3.03)	(-2.77)		(1.71)	(-3.21)	(-2.01)	(-2.92)	(-0.14)		(0.43)	(-2.43)	(-1.44)	(-1.58)	(-2.36)	(-1.97)	(0.06)	
coefficient		**-3.08**	**-133.15**	-1.23		*-3.22*	-4.89	*-140.10*	0.53	-0.49		**-2.32**	-1.96	-27.07	**-106.16**	-0.11	0.12	0.60
t stat		(-2.91)	(-2.62)			(-2.02)	(-1.32)	(-2.20)	(1.03)			(-2.78)	(-1.52)	(-1.16)	(-2.60)	(-1.58)	(0.26)	

Notes: Annual data 1978 – 2010. Nondurables (Δc_t) and Durables (Δd_t) are log nondurables (plus services) and durable consumption growth, respectively, and Market ($r_{W,t}$) is the log return on the market portfolio. ( ) denotes t-statistics based on GMM standard errors. *Italic*, **bold**, and ***bold italic*** fonts indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 6: Results for FX-based models for portfolios p1-p12

Panel A: Time Series Regressions

	LV factors				**VOL factors (2)**							
	Const	Rx β	HMLfx β	R^2	Const	Rx β	VOL1 β	R^2	Const	Rx β	VOL2 β	R^2
p1	***0.35***	-0.02	-0.03	0.00	***0.29***	0.00	**2.36**	0.03	***0.32***	-0.01	**1.88**	0.02
p2	**0.20**	-0.03	**-0.07**	0.02	0.12	-0.02	***2.15***	0.03	*0.15*	-0.03	**1.92**	0.03
p3	*0.16*	-0.04	-0.05	0.01	0.11	-0.03	**1.71**	0.02	0.13	-0.03	**1.66**	0.03
p4	0.06	-0.02	*-0.05*	0.01	-0.01	-0.01	***2.52***	0.05	0.02	-0.01	***2.40***	0.06
p5	0.12	-0.02	-0.03	0.01	0.08	-0.01	**1.74**	0.03	0.10	-0.01	***1.75***	0.03
p6	0.04	-0.03	**-0.08**	0.03	-0.05	-0.01	***2.95***	0.07	-0.02	-0.01	***2.84***	0.08
p7	0.10	0.01	***-0.09***	0.04	0.01	0.01	***1.95***	0.03	0.04	0.02	***2.22***	0.05
p8	0.09	-0.02	**-0.07**	0.02	0.03	-0.02	**1.78**	0.03	0.05	-0.02	**1.64**	0.03
p9	0.12	-0.06	***-0.09***	0.05	0.02	-0.05	***2.65***	0.07	0.05	-0.05	***2.76***	0.08
p10	*0.15*	-0.04	***-0.10***	0.06	0.04	-0.04	***2.69***	0.08	0.08	-0.03	***2.68***	0.09
p11	0.11	-0.02	***-0.09***	0.04	0.02	-0.02	***2.02***	0.04	0.05	-0.02	***1.77***	0.03
p12	0.10	0.00	***-0.09***	0.04	0.01	0.01	2.68	0.07	0.04	0.01	2.20	0.05
β1=…=βn=0 p-value		0.27	0.22			0.27	0.00			0.28	0.01	
β1=…=βn p-value		0.18	0.19			0.23	0.01			0.23	0.02	

	Skewness factor (3)									
	Const	SKEW β	R^2	Const	Rx β	HMLfx β	VOL2 β	SKEW β	R^2	Mean R (06/77-12/12)
p1	***0.35***	***0.10***	0.05	***0.30***	***-0.02***	***0.00***	1.90	0.11	0.08	0.32
p2	**0.20**	***0.11***	0.08	***0.15***	***-0.03***	***-0.03***	1.73	0.12	0.13	0.15
p3	**0.17**	***0.10***	0.06	***0.12***	***-0.03***	***-0.02***	1.46	0.10	0.09	0.12
p4	0.09	***0.09***	0.06	0.02	***-0.01***	***-0.01***	2.23	0.09	0.11	0.02
p5	**0.16**	***0.09***	0.06	***0.08***	***-0.02***	***0.01***	1.77	0.09	0.10	0.10
p6	0.02	***0.10***	0.08	-0.02	***-0.02***	***-0.03***	2.59	0.10	0.16	-0.03
p7	0.09	***0.10***	0.07	0.07	***0.01***	***-0.06***	1.85	0.09	0.14	0.04
p8	0.10	***0.10***	0.08	0.06	***-0.03***	***-0.04***	1.46	0.10	0.13	0.05
p9	0.07	***0.07***	0.04	0.08	***-0.05***	***-0.05***	2.45	0.07	0.14	0.04
p10	0.10	***0.08***	0.05	0.11	***-0.04***	***-0.06***	2.38	0.07	0.16	0.07
p11	0.07	***0.07***	0.05	0.08	***-0.03***	***-0.07***	1.42	0.07	0.09	0.04
p12	0.03	***0.10***	0.09	0.06	***0.00***	***-0.05***	1.84	0.10	0.16	0.04
β1=…=βn=0 p-value		0.00			0.01	0.00	0.03	0.07		
β1=…=βn p-value		0.32								
					0.00	0.00	0.00	0.07		

Panel B: Cross-sectional regressions

	Const	R_X λ	HML_{fx} λ	R^2	Const	R_X λ	VOL1 λ	R^2	Const	R_X λ	VOL2 λ	R^2
coefficient	*0.22*	-0.20	2.07	0.34	*0.19*	0.15	-0.05	0.06	**0.27**	-0.39	*-0.09*	0.21
t stat	(1.86)	(-0.27)	(1.80)		(1.91)	(0.23)	(-1.55)		(2.48)	(-0.50)	(-2.19)	
coefficient												
t stat		-1.56	-0.35	-0.27		-0.01	0.03	-0.11		-0.41	0.03	-0.11
		(-1.68)	(-0.37)			(-0.03)	(1.43)			(-0.69)	(1.13)	

	Const	SKEW λ	R^2	Const	R_X λ	HML_{fx} λ	VOL2 λ	SKEW λ	R^2
coefficient	-0.14	*3.11*	0.18	0.10	-1.04	1.41	-0.05	1.20	0.39
t stat	(-0.76)	(1.86)		(0.47)	(-1.17)	(1.37)	(-1.37)	(0.68)	
coefficient									
t stat		*1.58*	0.13		-1.22	1.17	-0.04	1.85	0.38
		(2.13)			(-1.45)	(1.00)	(-0.97)	(1.71)	

Note: LV and VOL factors - monthly data 11/1983 – 12/2012. Skewness factor - monthly data 06/1977 – 12/2012. Rx- the average currency excess return to going short in the dollar and long in the basket of six foreign currency portfolios. HML_{FX} - the return to a strategy that borrows low interest rate currencies and invests in high interest rate currencies, in other words a carry trade. VOL1 - volatility innovations measured by the residuals from AR(1). VOL2 - volatility innovations measured by first difference. SKEW – return of a portfolio that is long currencies in the highest skewness (positive) quintile and short currencies in the lowest (negative) skewness quintile for a given month. ( ) denotes t- statistics based on GMM standard errors. *Italic*, **bold**, and ***bold italic*** fonts indicate statistical significance at the 10, 5 and 1 percent levels, respectively. Rows labeled “Mean R” in panel A show the mean monthly returns for each portfolio.

Table 7: Results for macro and FX liquidity models for portfolios p1-p12

Panel A: Time Series Regressions

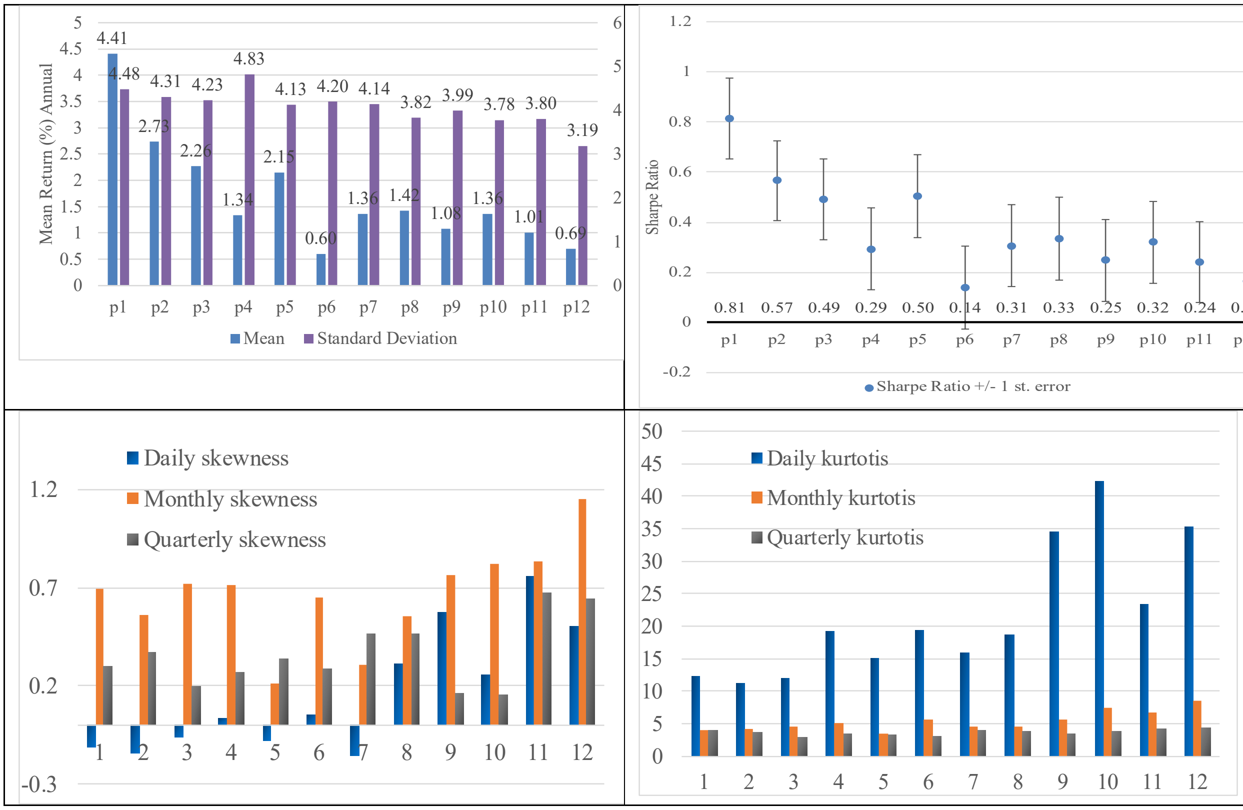
	Unemployment Rate Gap Skew Factors				**FX Liquidity Factors**			
	Const	UR GAP SKEW	R^2	Mean R	Const	FX Liquidity	R^2	Mean R
p1	***0.93***	0.14	0.001	1.03	**0.25**	*0.34*	0.0139	0.24
p2	**0.72**	-0.19	0.002	0.58	0.04	0.26	0.0093	0.04
p3	0.44	0.09	0.001	0.51	0.00	0.04	0.0003	0.00
p4	0.19	0.08	0.000	0.25	-0.08	0.17	0.0050	-0.08
p5	0.51	-0.06	0.000	0.47	0.00	0.00	0.0000	0.00
p6	0.26	-0.21	0.003	0.11	-0.10	0.14	0.0033	-0.11
p7	0.28	0.01	0.000	0.29	-0.07	-0.09	0.0016	-0.07
p8	**0.58**	*-0.37*	0.009	0.32	-0.01	0.22	0.0095	-0.02
p9	0.18	*0.11*	0.001	0.25	-0.05	0.05	0.0005	-0.05
p10	0.28	0.05	0.000	0.31	-0.01	0.05	0.0005	-0.01
p11	0.04	0.22	0.003	0.20	-0.03	0.10	0.0018	-0.03
p12	0.30	*-0.20*	0.003	0.16	0.00	**0.33**	0.0241	0.00
β1=…=βn=0 p-value		0.36				0.01		
β1=…=βn p-value		0.35				0.06		

Panel B: Cross-sectional regressions

	Const	UR GAP SKEW	R^2	Const	FX Liquidity	R^2
coefficient	**0.38**	*0.32*	0.05	-0.05	**0.36**	0.30
t stat	(2.60)	(1.97)		(-0.79)	(2.79)	
coefficient						
t stat		-0.02	-2.44		0.15	0.10
		(-0.12)			(0.52)	

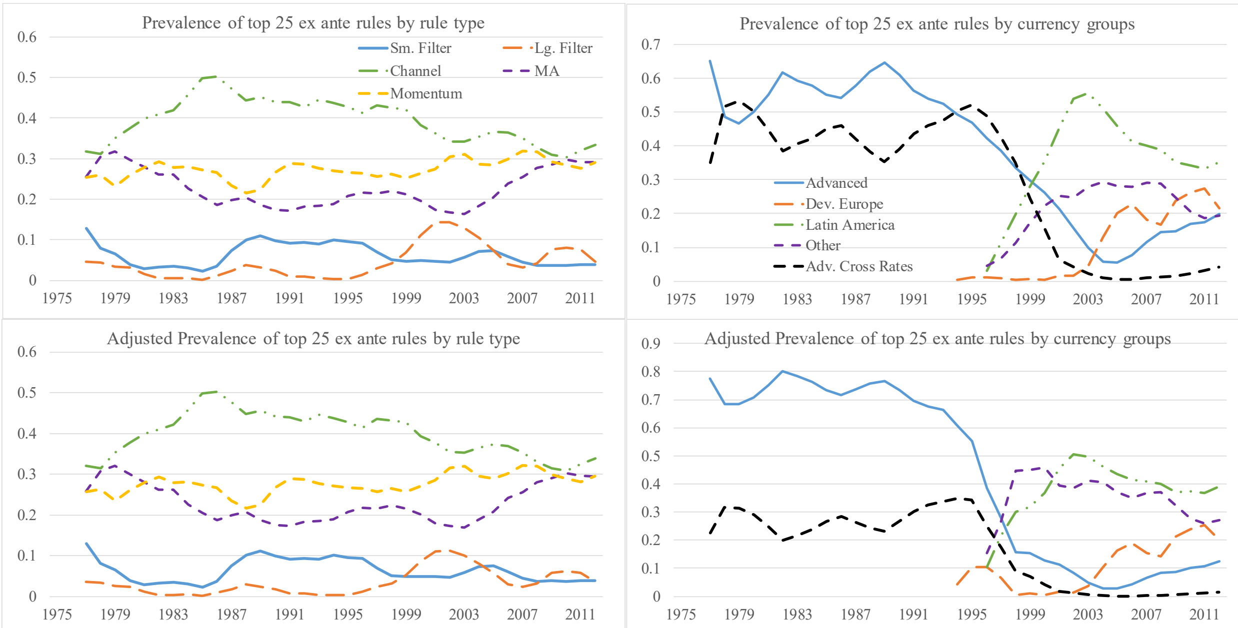
Note: Unemployment skewness data: Quarterly data Q4/1978 – Q4/2012. UR GAP SKEW (unemployment rate gap skewness) is an HML (high-minus-low) macro factor composed as the average skewness in Q1 minus the average skewness in Q4. Q1 and Q4 are the quartiles of currencies with the highest and lowest skewness of the unemployment rate gap for a given quarter. FX Liquidity model: Monthly data 01/1991 – 12/2012. The FX Liquidity factor is the systematic FX liquidity (FX syst) factor from Karnaukh, Ranaldo, and Söderlind (2015). The authors thank Angelo Ranaldo for posting these data. Excess portfolio returns are quarterly and monthly, respectively. ( ) denotes t- statistics based on GMM standard errors. *Italic*, **bold**, and ***bold italic*** fonts indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Figure 1: Summary excess return statistics from sorted portfolios p1 to p12 (mean, standard deviation, Sharpe ratio, skewness, kurtosis)



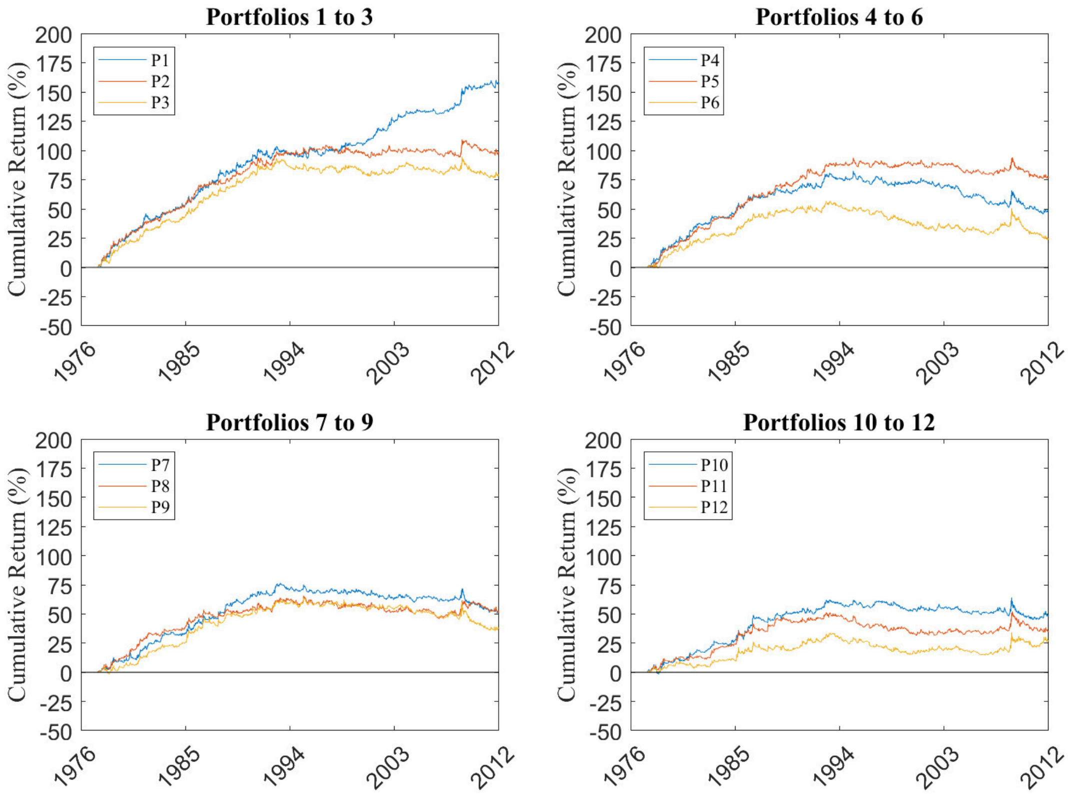
Notes: The four panels of the figure show summary return statistics from sorted portfolios p1 to p12. Clockwise from top left, the panels depict annualized means and standard deviations of the 12 daily portfolio returns, the Sharpe ratios of the 12 daily portfolio returns with 1-standard error bands, the skewness coefficients of the daily, monthly and quarterly portfolio returns, and the kurtosis coefficients of the daily, monthly and quarterly portfolio returns.

Figure 2: Trading rule and exchange rate prevalence in the top-ranked, ex ante portfolio over time



Notes: The left-hand panels denote the 3-year moving average prevalence of types of trading rules in the ex ante top-ranked portfolio of strategies. The right-hand panels denote the 3-year moving average prevalence of exchanges rates (by currency group) in the ex ante top-ranked portfolio of strategies. The panels on the top denote the raw frequency of the rule groups, whereas those on the bottom adjust for group size. Small filters are those less than or equal to 0.02; large filters are those greater than 0.02.

Figure 3: Cumulative portfolio returns over time



Notes: The panels depict cumulative returns for the 12 technical portfolios from 1977 through 2012.