Online Appendices for Can risk explain the profitability of technical trading in currency markets?[1]

Yuliya Ivanova	**Christopher J. Neely**	**Paul Weller**	**Matthew T. Famiglietti**
Principal, Promontory Financial Group 801 17th Street, NW Suite 1100 Washington, DC 20006 USA	Vice President, Federal Reserve Bank of St. Louis P.O. Box 442 St. Louis, MO 63166-0442 USA	John F. Murray Professor of Finance Emeritus, The University of Iowa Iowa City, IA 52242 USA	Research Associate, Federal Reserve Bank of St. Louis P.O. Box 442 St. Louis, MO 63166-0442 USA

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[1] Chris Neely is the corresponding author. Federal Reserve Bank of St. Louis, Box 442, St. Louis, MO 63166. e-mail: neely@stls.frb.org; phone: +1-314-444-8568; fax: +1-314-444-8731.

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Appendix A – Computation of Transactions Costs

Any study of trading performance must to pay close attention to transaction costs, especially when using emerging market currencies. The magnitude and the frequency of trades influences the impact of 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) estimated emerging market bid-ask spreads to be two-to-four times bigger than those for developed market currencies over the period 1997 to 2006.

Neely and Weller (2013) used Bloomberg data on one-month forward bid-ask spreads as the basis for estimating transaction costs that vary both over currencies and over time. Correspondence with several foreign exchange traders and with the head of the foreign exchange department of a commercial bank led Neely and Weller to believe that the quoted Bloomberg spreads substantially overestimated the spreads actually available to traders. After comparing spreads from Bloomberg with those on traders' screens and then discussing the size of spreads with traders, the authors concluded that quoted spreads were roughly three times actual spreads. Therefore, Neely and Weller calculated transaction costs as follows: Before December 1995, the start of spread data from Bloomberg, the cost of a one-way trade for advanced countries (UK, Germany, Switzerland, Australia, Canada, Sweden, Norway, New Zealand and Japan) was set at 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 bid-ask observations for all other countries.[2] Once Bloomberg data become available, 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

[2] The costs during the 1970s and 1980s are consistent with triangular arbitrage estimates originally done by Frenkel and Levich (1975, 1977) and McCormick (1979), and used by Sweeney (1986) and Levich and Thomas (1993).

costs, Neely and Weller 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. Figure A1 shows the estimated transaction costs for each currency over time. The greater magnitude and volatility of these emerging market costs is readily apparent.

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

$$R_{t+1}^e = \frac{S_{t+1}(1+i_t^*)^{d_t/365}}{S_t(1+i_t)^{d_t/365}}. \tag{A1}$$

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

$$r_{t+1}^e = \ln(S_{t+1}) - \ln(S_t) + \left(\frac{d_t}{365}\right) * [\ln(1+i_t^*) - \ln(1+i_t)] \tag{A2}$$

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

$$r_{t,t+k}^e = \sum_{i=1}^{k} r_{t+i}^e + \ln(1-c_{t+k}) - \ln(1+c_t).^{3} \tag{A3}$$

A trading strategy may incur transaction costs even when individual trading rules do not, as well as the converse. This will happen if a strategy requires a switch between two rules holding different

[3] 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.

positions but the rules themselves signal no change of position. In this case, the strategy incurs a transaction cost but the individual rules do not. If, on the other hand, a strategy dictates a switch from a rule requiring—let us say, a long position at time t to a different rule requiring a long position in the same currency at time $t + 1$—then no transaction cost is incurred, even though one or both individual rules may have signaled a change of position from time t to $t + 1$.

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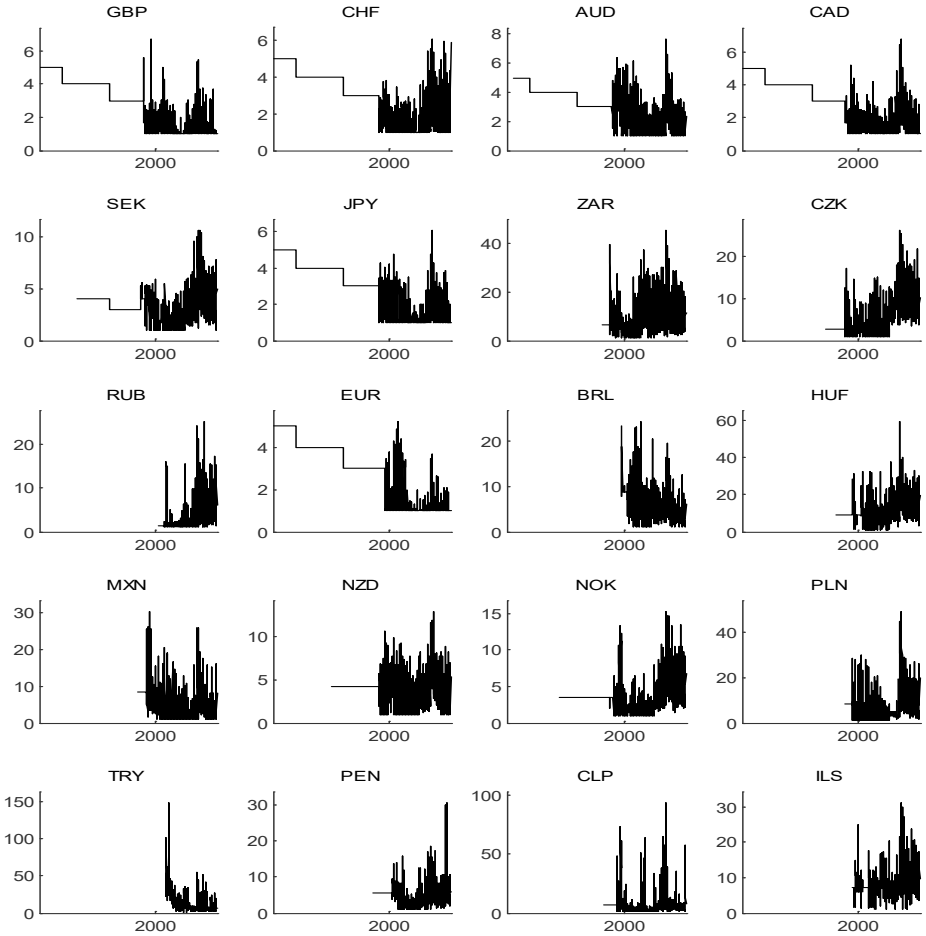
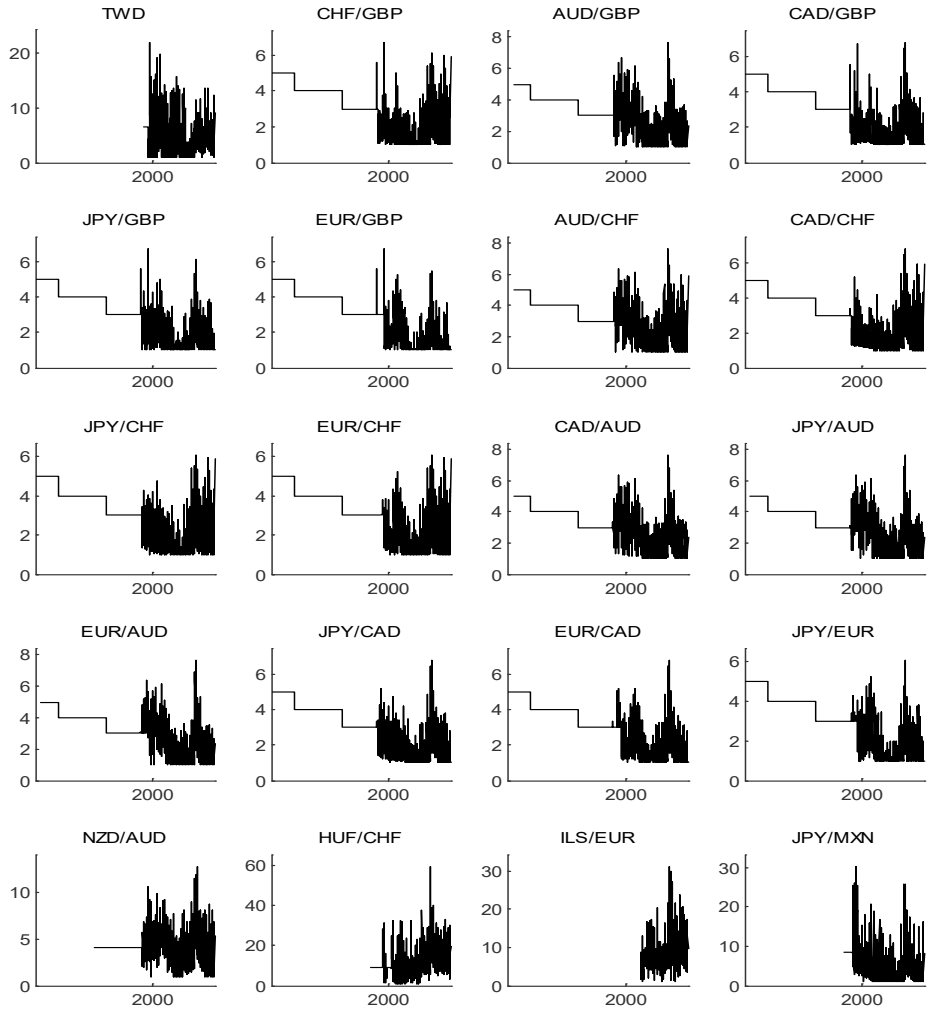
Figure A1
Transaction costs





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

Appendix B– Variable Definitions

Variable	Definition
$R_{m,t}$	Market excess return (used in CAPM) measured by the excess return of the S&P 500 Equity Index
$R_{m,t}^2$	Squared market excess return (used in the squared CAPM) calculated by squaring the excess return of the S&P 500 Equity Index
$R_{m,t}$ (FF)	Fama-French market return is the excess return on the market as measured by the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates).
$R_{SMB,t}$	Small Minus Big is the Fama- French size factor. The Fama-French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market. SMB is the average return on the three small portfolios minus the average return on the three big portfolios. The portfolios, which are constructed at the end of each June, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in t-1 divided by market equity for December of t-1. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. $\text{SMB} = \frac{1}{3}(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - \frac{1}{3}(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$
$R_{HML,t}$	High Minus Low is the Fama- French value factor. The Fama-French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market. HML is the average return on the two value portfolios minus the average return on the two growth portfolios. For more details about the construction of the portfolios refer to the description of the SMB factor. $\text{HML} = \frac{1}{2}(\text{Small Value} + \text{Big Value}) - \frac{1}{2}(\text{Small Growth} + \text{Big Growth})$

Variable	Definition
$R_{UMD,t}$	Up Minus Down is the Fama- French momentum factor. Fama – French use six value-weight portfolios formed on size and prior (2-12) returns to construct the momentum factor. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. UMD is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. $$\text{UMD} = \frac{1}{2}(\text{Small High} + \text{Big High}) - \frac{1}{2}(\text{Small Low} + \text{Big Low})$$
$R_{m,t}$ *Down*	Downside market return. The market excess return used is the same as in $R_{m,t}$ (FF). The downside factor is constructed as Rm Down = Rm if Rm ≤ μ – σ where μ and σ are the sample time series average and standard deviation of the market excess return.
Δc_t	Log nondurable (plus services) consumption growth. Nondurable consumption is the sum of the nominal ND series (deflated by the Price Index for Personal Consumption Expenditures for Nondurables Goods) and the nominal S series (deflated by the Price Index for Personal Consumption Expenditures for Services). ND is the Personal Consumption Expenditures: Goods: Nondurable Goods series divided by the number of households. S is the Personal consumption expenditures: Services series divided by the number of households.
Δd_t	Log durable consumption growth. Durable consumption is calculated as the Durable Chain-Type Quantity Indexes for Net Stock of Consumer Durable Goods divided by number of households.
$r_{W,t}$	Log return on the market portfolio. It is measured by the value-weight return of all CRSP firms including dividends minus the return of the Consumer Price Index.
RX	LRV dollar factor. It is the average currency excess return to going short in the dollar and long in a basket of six foreign currency portfolios. The six currency portfolios are formed on the basis of interest rates. Portfolio 1 contains the currencies with the lowest interest rates and portfolio 6 - the currencies with the highest interest rates. RX is the mean of the returns of the six currency portfolios.
HML_{FX}	LRV carry trade factor. It is the return to a strategy that borrows low interest rate currencies and invests in high interest rate currencies, namely a carry trade. LRV forms six currency portfolios on the basis of interest rates. Portfolio 1 contains the currencies with the lowest interest rates and portfolio 6 - the currencies with the highest interest rates. HML_{FX} is the return of portfolio 6 minus the return of portfolio 1.

Variable	Definition
VOL1	Volatility innovations measured by the residuals from AR(1) process fit to the Global FX Volatility factor (VOL). Firstly, we estimate the monthly return variance for each of the available exchange rates at each month in the sample and then calculate the Global Foreign Exchange Volatility factor from the first principal component of the monthly variances. Specifically, VOL is calculated as $$VOL_t = \frac{1}{K_t}\sum_{k\in K_t}\left[\sum_{\tau\in T_t}\frac{\lvert r_{k,\tau}\rvert}{T_{k,t}}\right]$$ where $r_{k,\tau}$ is the return for particular currency k on day τ of month t and K_t and $T_{k,t}$ are the total number of available currencies for month t and the total number of days in month t for currency k. Currencies with fewer than ten observations for a particular month are excluded from the calculation.
VOL2	Volatility innovations measured by first difference of the Global FX Volatility factor (VOL). For detailed description of VOL, refer to the definition of VOL1.
SKEW	Skewness factor. Firstly, we calculate the monthly return skewness for each of the available exchange rates at each month in the sample. Specifically, the return skewness for currency k in month t is calculated as $$SKEW_{k,t} = \frac{\frac{1}{T_t}\sum_{\tau}^{T_t}\left(r_{k,\tau} - \overline{r_{k,t}}\right)^3}{\left(\frac{1}{T_t}\sum_{\tau}^{T_t}\left(r_{k,\tau} - \overline{r_{k,t}}\right)^2\right)^{\frac{3}{2}}}$$ Where $r_{k,\tau}$ is the return for is the return for particular currency k on day τ of month t, $\overline{r_{k,t}}$ is the average return for currency k for month t and T_t is the number of available observations in month t for that currency. Currencies with fewer than ten observations for a particular month are excluded from the calculation. Then for each month, currencies are ranked according to their skewness and separated into quintiles. Quintile 5 is the portfolio with currencies in the highest skewness quintile and Quintile 1 is the portfolio with currencies with the lowest skewness quintile. Lastly, we form the Global FX Skewness factor SKEW as the return of a tradable portfolio that is long the currencies in the highest skewness quintile in a given month and short the currencies in the lowest skewness quintile in a given month. Thus, SKEW is the return of Quintile 5 minus the return of Quintile 1.

Variable	Definition
UR GAP SKEW	Unemployment gap skewness factor. We follow Berg and Mark (2018) in the construction of the factor. Initially, the Hodrick-Prescott (HP) filter is applied to the unemployment rate of each country to induce stationarity, which produces the unemployment rate gap. Then the skewness of the unemployment rate gap is calculated for each country for each quarter based on a back-ward looking moving 20-quarter window. In each quarter, countries are ranked according to their skewness and placed into quartiles: P4 contains the countries with the highest unemployment gap skewness and P1 containing the countries with the lowest skewness. The UR GAP SKEW factor for every quarter is constructed as the average skewness of the unemployment gap of the countries in P4 minus the average skewness of the unemployment gap of the countries in P1.
FX liquidity	Karnaukh, Ranaldo, and Söderlind (2015) compute and publish the systemic FX liquidity factor. This measure is the simple average of bilateral pair liquidity factors, which are constructed from bid-ask spreads and the Corwin and Schultz (2012) bid-ask measure. The following document provides more detailed instructions: https://sbf.unisg.ch/-/media/dateien/instituteundcenters/sbf/ranaldo-research/understanding-fx-liquidity/instructionsdatafxilliquidity.pdf

Appendix C–Technical Trading Performance of 6 Alternative Portfolio Construction Methods

We investigated the robustness of our baseline technical trading results from Neely and Weller (2013) to five variations of the rule construction that alter assumptions about performance metrics for sorting, the rebalancing interval and the set of exchange rates. This appendix first describes the five alternative scenarios and then compares the return performance of the rules constructed under these five methods to the baseline results. We find that the inference on technical trading results is robust to reasonable perturbation of the methods.

Scenario Descriptions

Table C1 in this appendix describes the characteristics of each scenario but we provide a brief description in the text below.

1. Scenario 1 is comprised of the baseline results described in the main text. The Sharpe ratio is used in evaluating past performance of rule/currency combinations, portfolios are rebalanced and rules ranked every 20 days, and the whole universe of currencies described in Table 1 are used.
2. Scenario 2 substitutes the Sortino ratio for the Sharpe ratio in evaluating the past performance of rule/currency combinations and then sorting those combinations. The Sortino ratio is the ratio of an expected excess return to the excess return's "downside deviation." Thus, it is similar to the Sharpe ratio.
3. Scenario 3 investigates the effect of evaluating and sorting rule/currency combinations for portfolios at 250 day intervals instead of 20-day intervals. It uses all exchange rates and the Sharpe ratio as the performance metric.

4. Scenario 4 sorts rule-exchange rate combinations with the average return, rather than the Sharpe ratio, over the whole previous sample. It uses all exchange rates and 20-day rebalancing intervals.
5. Scenario 5 takes the baseline Sharpe performance metric and 20-day rebalancing interval but only considers rules as applied to 21 USD exchange rates. The 21 currencies vs. the USD were as follows: GBP, CHF, AUD, CAD, SEK, JPY, ZAR, CZK, RUB, EUR, BRL, HUF, MXN, NZD, NOK, PLN, TRY, PEN, CLP, ILS, and TWD.
6. Scenario 6 takes the baseline Sharpe performance metric and 20-day rebalancing interval but only considers rules as applied to 6 USD exchange rates constructed from 6 G10 currencies: EUR, CAD, JPY, SEK, CHF, and the GBP. With 16 technical trading rules, the 6 G10 currencies can only produce a maximum of 96 strategies. For this reason, we sorted the 96 G10 strategies into 12 portfolios of 8 strategies each instead of 25 strategies per portfolio as in the other 5 scenarios.

Performance of Alternative Scenarios

We provide basic information with which to evaluate the performance of each scenario. Figure C1 shows the respective Sharpe ratios, mean annual returns and standard deviations for each portfolio return for each of the alternative scenarios. Table C2 provides the same data in tabular format.

A key message from Figure C1 is that for Scenarios 1 through 4, which all used the full set of exchange rates, there was relatively little variation in performance and nothing that was statistically significant. For example, the average Sharpe ratio among the first four portfolio returns for the first four scenarios are 0.54, 0.53, 0.58, and 0.46.[4] The best and worst average Sharpe ratios

[4] These Sharpe ratios are calculated with a correction for autocorrelation. Uncorrected Sharpes are about 50% higher.

(0.58 vs. 0.46) performing portfolios came from using a 250-day rebalancing interval versus those that selected on average return rather than Sharpe ratio. Overall, the inference on technical analysis in the foreign exchange market would be quite similar using the procedures from any of the first four scenarios.

As discussed in the text, there is a good reason to select on Sharpe ratios rather than on average return and it is related to the relation of volatility and leverage. Suppose that two exchange rates, X and Y, had identical directional movements but Y's movements were always twice as big as those of X. Applying the same trading rule to those exchange rates would produce a return for Y that is twice as big as that for X. But Y would not actually be more valuable because one could replicate Y's risk-payoff tradeoff by doubling the leverage of the position in X. The Sharpe ratio would be unchanged by this investment and it would show that trading in X and Y were equally valuable. Thus, it is better to sort based on Sharpe ratios than returns.

The technical portfolio returns from the final two scenarios (USD rates and G10 rates) behave modestly differently because they greatly reduce the universe of exchange rates to 21 and 6 USD rates, respectively. The Sharpe ratios for the top four portfolios for those two scenarios are 0.48 and 0.45, respectively. Even those performances are not greatly (or statistically) different from the baseline case with a Sharpe ratio of 0.54.

Figure C1 shows two minor differences in the behavior of the final two scenarios (USD rates and G10 rates) from the baseline. The first difference is that the lower-ranked USD-rate and G10-rate portfolios tend to have negative Sharpe ratios. The second difference is that the G10-rate portfolios have about 40 percent larger standard deviations than the returns to the other five methods. Both of these are related to the smaller number of exchange rates used in these two scenarios.

The relatively lower returns to the low-ranked USD-rate and G10-rate portfolios are due to the fact that because these methods have far fewer exchange rate-rule combinations, the lower-ranked portfolios dip much lower into their total set of such combinations. For scenarios 1 to 4, which use all exchange rates, the top 12 portfolios only typically use about half the available combinations. But USD-rate and G10-rate methods have far fewer combinations so the lower-ranked portfolios are much nearer the bottom of the distribution of available rules.

Similarly, because there are only 96 exchange rate/rule combinations using only the G10 exchange rates, we constructed smaller portfolios, using only 8 rule-rate combinations in each of the 12 G10 portfolios, instead of the 25 rule-rate combinations in the portfolios for the other five methods. Thus, the standard deviations for the G10-rate portfolios were larger because they were averaging over only 8-rate-rule combinations instead of 25.

A final issue to consider is time variation in returns. Figure C2 shows cumulative returns for the first five portfolios for each of the scenarios. Patterns for the 6 scenarios are generally fairly similar. Around 1990, returns for all portfolios except the top-ranked portfolio drop very low, perhaps to zero. For all scenarios, however, the returns to the top-ranked continue to be positive after 1990. This pattern is consistent with two stylized facts from the technical trading literature: 1) returns to most technical analysis in major currencies declined substantially around 1990 and 2) technical analysis using less commonly studied rules or applied to emerging markets remained profitable.

Since at least Levich and Thomas (1993), researchers have known that technical trading rule profitability in major foreign exchange started to fall off in the late 1980s and early 1990s. Neely, Weller and Ulrich (2009) study reasons for the shift, concluding that an adaptive markets explanation is more convincing than other explanations such as data mining or central bank

intervention or risk. These authors emphasize that low profitability for the most commonly studied MA and filter rules does not mean that technical analysis is generally unprofitable. Returns to less studied or more complex rules, such as channel rules, ARIMA, GP, and Markov models, have also probably declined but have probably not completely disappeared. Neely and Weller (2012) survey the technical literature finding that de Zwart et al. (2009), Pukthuanthong-Le, Levich and Thomas (2007) and Pukthuanthong-Le and Thomas (2008) find that emerging market currencies continue to provide profit opportunities to technical rules.

In summary, we conclude that the performance of the rules using the first four methods (Baseline, Sortino, 250-day and Return) are very similar, with only marginal differences. Those of the last two methods (USD rates and G10 rates) are modestly different from the baseline because their universes of exchanges rates are substantially smaller and include only USD rates.

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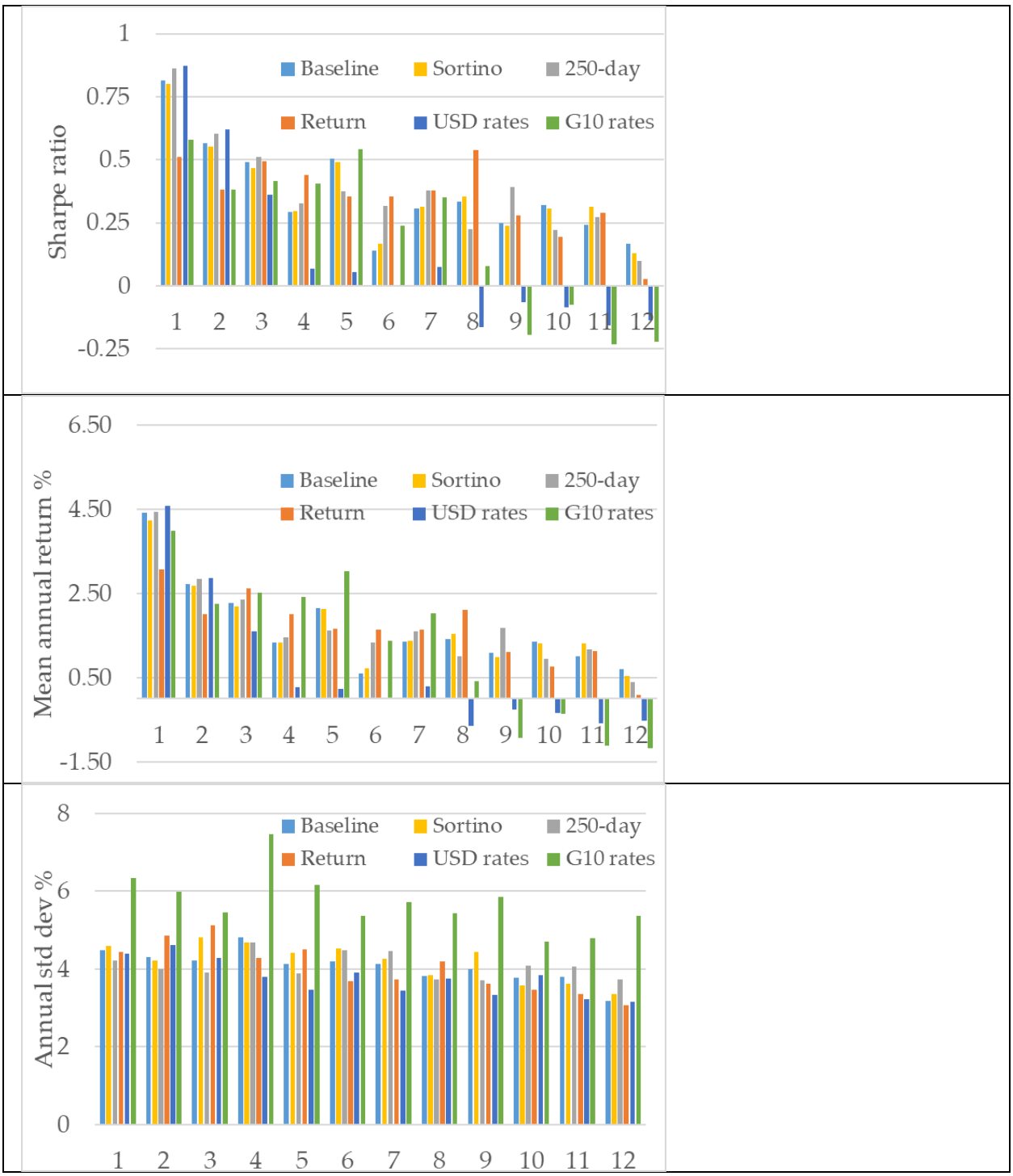
Pukthuanthong-Le, Kuntara, and Lee R. Thomas III. (2008). Weak-form efficiency in currency markets. *Financial Analysts Journal* 64(3), 31–52.

Figure C1: Sharpe ratios, mean annual returns and standard deviations for each portfolio return for each of the alternative scenarios.



NOTES: The top, center and bottom panels show the Sharpe ratios, annual return and standard deviations for each of the 12 ex ante sorted portfolios for each of the 6 scenarios.

Figure C2: Cumulative returns for the first five portfolios for each of the 6 scenarios

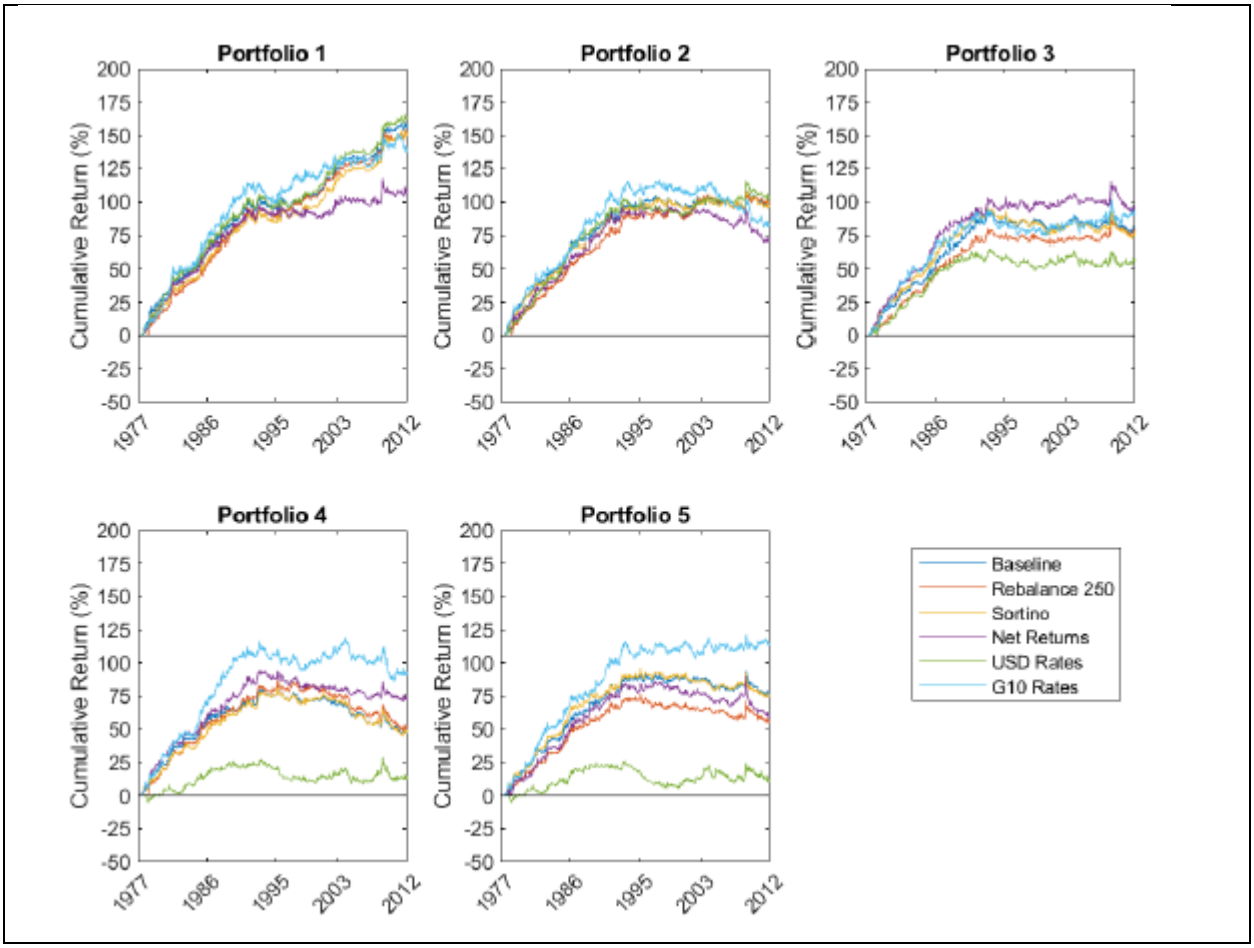


Table C1: Scenario descriptions

Scenario #	Name	Rule/currency peformance metric	Rebalancing interval (days)	FX rates
1	Baseline	Sharpe ratio	20	All rates
2	Sortino	Sortino ratio	20	All rates
3	250-day	Sharpe ratio	250	All rates
4	Return	Average return	20	All rates
5	USD rates	Sharpe ratio	20	Only USD rates
6	G10 rates	Sharpe ratio	20	Only G10 rates

Table C2: Sharpe ratios, mean annual returns and standard deviations for each portfolio return for each of the alternative scenarios.

Sharpe Ratio	1	2	3	4	5	6	7	8	9	10	11	12
Baseline	0.81	0.57	0.49	0.29	0.50	0.14	0.31	0.33	0.25	0.32	0.24	0.17
Sortino	0.80	0.55	0.47	0.30	0.49	0.17	0.31	0.35	0.24	0.31	0.31	0.13
250-day	0.86	0.60	0.51	0.33	0.38	0.32	0.38	0.23	0.39	0.22	0.27	0.10
Return	0.51	0.38	0.50	0.44	0.36	0.36	0.38	0.54	0.28	0.19	0.29	0.03
USD rates	0.87	0.62	0.36	0.07	0.06	0.00	0.07	-0.16	-0.07	-0.09	-0.16	-0.14
G10 rates	0.58	0.38	0.41	0.41	0.54	0.24	0.35	0.08	-0.19	-0.08	-0.23	-0.22
Mean Return												
Baseline	4.41	2.73	2.26	1.34	2.15	0.60	1.36	1.42	1.08	1.36	1.01	0.69
Sortino	4.23	2.68	2.19	1.33	2.13	0.73	1.38	1.55	0.99	1.31	1.31	0.54
250-day	4.44	2.84	2.35	1.45	1.62	1.33	1.61	1.00	1.68	0.95	1.18	0.39
Return	3.08	2.02	2.62	2.01	1.66	1.64	1.63	2.12	1.11	0.76	1.14	0.09
USD rates	4.58	2.87	1.59	0.27	0.22	0.01	0.30	-0.65	-0.25	-0.34	-0.60	-0.52
G10 rates	3.99	2.25	2.53	2.42	3.03	1.38	2.03	0.41	-0.93	-0.37	-1.11	-1.17
Std Deviation												
Baseline	4.48	4.31	4.23	4.83	4.13	4.20	4.14	3.82	3.99	3.78	3.80	3.19
Sortino	4.60	4.23	4.82	4.68	4.42	4.53	4.27	3.84	4.44	3.57	3.61	3.35
250-day	4.23	4.00	3.90	4.69	3.88	4.50	4.47	3.74	3.71	4.10	4.07	3.73
Return	4.44	4.85	5.12	4.29	4.52	3.69	3.73	4.20	3.62	3.48	3.37	3.06
USD rates	4.40	4.63	4.30	3.81	3.46	3.91	3.45	3.75	3.34	3.84	3.22	3.17
G10 rates	6.33	5.98	5.45	7.47	6.16	5.38	5.73	5.43	5.85	4.71	4.79	5.36

NOTES: The top, center and bottom panels of the table show the Sharpe ratios, annual return and standard deviations for each of the 12 ex ante sorted portfolios for each of the 6 scenarios.

Appendix D —Technical Trading Risk Adjustment for 6 Alternative Portfolio Construction Methods

We investigated the robustness of the risk-adjustment conclusions about baseline technical trading results from Neely and Weller (2013) to five variations of the rule construction that alter assumptions about performance metrics for sorting, the rebalancing interval and the set of exchange rates. The alternative rule construction methods are described in the appendix entitled: "Technical Trading Performance of 6 Alternative Portfolio Construction Methods." We find that the inference on the risk-adjusted performance of technical trading results is robust to reasonable perturbation of the methods of constructing technical rules.

Risk-adjusted Performance of Alternative Scenarios

Table D1 provides a mapping from the names/symbols of the prices of risk in the 15 risk specifications to the generic names (price of risk 1 through 4) which describe them in Tables 2 through 7.

Tables D2 through D7 very briefly describe the results of 2nd stage asset pricing tests, the no-constant estimates of the prices of risk and the accompanying R^2 for each of the 15 specifications. To the extent that a risk measure actually substantially explains the returns to the technical trading rules, the price of risk from that measure should be statistically significant and of the correct sign and the R^2 should be positive and sizable. For a given measure of risk, if the price of risk is of the wrong sign or not statistically significant or the R^2 is very low or negative, then we reject the idea that the measure of risk explains the technical trading rule returns in an important way.

The first model is the CAPM. The CAPM is rejected for the Baseline case and all 5 alternative models because price of risk is of the wrong sign or the R^2 is negative.

We rejected the quadratic CAPM for the Baseline case because the price of risk for volatility was positive. The same holds true for all 5 alternative models, where the price risk of volatility is always positive or insignificant.

The Conditional CAPM (or downside risk CAPM) implies a negative second-stage R^2 for 5 of the 6 scenarios. The sole case in which the R^2 is positive is for the USD-rates. But the price of risk point estimate is incorrectly signed (negative) and statistically insignificant for that case.

As with the Baseline case, for each of the five alternative scenarios, the Carhart model implies statistically significant negative prices of risk for either or both SMB and HML. These negative values are inconsistent with the positive factor means for SMB and HML so we reject this model.

We reject the C-CAPM, D-CAPM and EZ-DCAPM in all 5 alternative cases for exactly the same reasons that we reject them for the Baseline case: Nondurables prices of risk are incorrectly signed and often statistically significant.

Likewise, for the first four scenarios, the LV, Vol1 and Vol2 factors produce insignificant or incorrectly signed prices of risk plus negative R^2 for the second stage regression.

For the USD and G10 rate scenarios, the LV risk measures can be rejected because of statistical insignificance or negative R^2s. Intriguingly, however, there is evidence that the Vol1 and Vol2 factors do have some explanatory power for USD and G10 returns. Their prices of risk are positive and statistically significant and the R^2s are reasonable.

To determine the extent to which these volatility risk factors can explain the excess returns to trading rules in foreign exchange markets, we can examine whether the price of risk is strongly identified by looking at whether we can reject equality of the first stage betas and then we can compare the constants (risk-adjusted return) in the time series regressions to the unconditional

return. Tables D8 and D9 display those statistics for all 6 cases for VOL1 and VOL2, respectively.[5] The two tables show that one cannot reject the equality of the first-stage beta coefficients for either the USD-rate or G10-rate cases with either VOL1 or VOL2. In other words, the prices of volatility risk are not well identified for those cases. In addition, the constants are little different than the sample means of portfolio returns, indicating that volatility factors reduce portfolio excess returns by only a small amount, 10 to 15 percent.

The SKEW measure does appear to have some explanatory power for almost all the cases. The coefficients are positive and statistically significant and the R^2 s are generally positive and sizeable. Again, we can examine the first-stage of the Fama-MacBeth procedure to determine the importance of this finding. Table D10 shows the tests for equality of betas, the risk-adjusted returns (constants) and the sample means of the portfolio returns for all 6 cases. As with the VOL factors, one fails to reject the equality of the estimated betas for four of six cases, the exceptions being Return-sorting and Sortino-sorting. As with the volatility measures, however, the skewness factors can only explain a very modest portion (10-15 percent) of the returns. Although we omit the results for brevity, considering the VOL and SKEW measures together does not improve the explanatory power.

Tables D2 through D7 show that one can reject explanatory power for UR GAP SKEW and FX liquidity measures because they fail to have correctly signed, statistically significant prices of risk and their R^2 s are often negative.

In summary, we find that the VOL1 and VOL2 factors do have some marginal power to explain as much as 10 or 15 percent of USD and G10 returns, while the SKEW measure has similar power to explain returns in the Returns-sorting and Sortino-sorting scenarios.

[5] The short- dollar risk factor (RX) was included in each regression in Tables D8 and D9 but other specifications behaved similarly.

Table D1: Description of the Risk Prices

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	Rm λ	Rm λ	Down λ	Rm λ	Nondurables λ	Nondurables λ	Nondurables λ	R_X λ	R_X λ	R_X λ	SKEW TR λ	VOL2 λ	R_X λ	UR GAP SKEW λ	FX Liquidity λ
Risk Price 2		Rm^2 λ		SMB λ		Durables λ	Durables λ	HML_{fx} λ	VOL1 λ	VOL2 λ		SKEW TR λ	HML_{fx} λ		
Risk Price 3				HML λ			Market λ						VOL2 λ		
Risk Price 4				UMD λ									SKEW TR λ		

Table D2: Risk-adjusted performance of the baseline scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-3.35	-2.02	-3.35	2.43	-3.08	-3.22	-2.32	-1.56	-0.01	-0.41	1.58	-0.05	-1.22	-0.02	0.15
	(1.20)	(-1.42)	(-0.86)	(0.66)	(-2.91)	(-2.02)	(-2.78)	(-1.68)	(-0.03)	(-0.69)	(2.13)	(-1.13)	(-1.45)	(-0.12)	(0.59)
Risk Price 2		0.17		-2.62		-4.89	-1.96	-0.35	0.03	0.03		2.70	1.17		
		(1.92)		(-2.17)		(-1.32)	(-1.52)	(-0.37)	(1.43)	(1.13)		(2.78)	(1.00)		
Risk Price 3				-3.51			-27.07						-0.04		
				(-3.72)			(-1.16)						(-0.97)		
Risk Price 4				5.20									1.85		
				(3.49)									(1.71)		
R^2	-0.16	-0.13	-0.16	0.72	0.50	-0.49	0.60	-0.27	-0.11	-0.18	0.13	0.24	0.38	-2.44	0.10

NOTES: Monthly data 06/1977 – 12/2012. The table displays the prices of risk, t statstics from GMM estimation, and R2s from the second-stage estimation of the 15 Fama-MacBeth asset pricing tests used in the main text. The constant is restricted to equal zero. The return data are the technical trading rule return data constructed using 6 scenarios described in "Appendix C: Technical Trading Performance of 6 Alternative Portfolio Construction Methods." Significance levels of 1%, 5%, and 10% are denoted by cells shaded dark gray, gray and light gray, respectively. These notes apply to Tables D2 through D7.

Table D3: Risk-adjusted performance of the Sortino scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-3.33	-1.27	-3.33	1.57	-2.23	-2.32	-1.69	-1.20	0.68	0.16	1.56	-0.01	-0.95	0.21	0.14
	(-1.96)	(-1.05)	(-0.85)	(0.62)	(-2.52)	(-1.74)	(-1.76)	(-1.66)	(1.09)	(0.27)	(2.09)	(-0.26)	(-1.00)	(1.14)	(0.71)
Risk Price 2		0.22		-0.55		-3.91	-1.63	-0.48	0.04	0.04		1.80	1.04		
		(2.27)		(-0.20)		(-1.44)	(-1.19)	(-0.50)	(1.46)	(1.36)		(2.76)	(1.10)		
Risk Price 3				-3.88			-25.15						-0.01		
				(-1.98)			(-1.26)						(-0.14)		
Risk Price 4				7.05									1.11		
				(1.57)									(1.61)		
R^2	-0.14	-0.03	-0.14	0.83	0.28	-1.08	0.23	-0.25	0.02	-0.10	0.10	0.11	0.17	-2.50	0.10

NOTES: See Table D2.

Table D4: Risk-adjusted performance of the 250-day rebalancing scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-3.53	-1.57	-3.53	-1.66	-3.64	-3.65	-2.07	-0.61	0.57	0.45	1.65	0.01	0.66	0.99	0.17
	(-2.00)	(-0.96)	(-0.86)	(-0.73)	(-2.34)	(-1.54)	(-1.95)	(-1.07)	(1.14)	(0.88)	(2.10)	(0.26)	(0.92)	(1.84)	(0.59)
Risk Price 2		0.20		-0.66		-5.47	-2.15	-0.79	0.04	0.04		1.54	1.71		
		(1.94)		(-0.46)		(-1.24)	(-1.32)	(-1.10)	(1.67)	(1.66)		(2.71)	(1.67)		
Risk Price 3				-2.91			-24.35						0.02		
				(-1.95)			(-0.94)						(0.52)		
Risk Price 4				2.98									1.45		
				(1.47)									(1.63)		
R^2	-0.14	-0.10	-0.14	0.72	0.38	-0.86	0.17	-0.32	0.00	-0.07	-0.02	-0.02	0.29	-2.15	0.11

NOTES: See Table D2.

Table D5: Risk-adjusted performance of the Return-sorted scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-3.22	-0.50	-3.22	-2.64	-4.58	-3.00	-2.16	-0.86	0.01	0.14	1.53	0.00	0.05	-0.36	-0.01
	(-1.95)	(-0.34)	(-0.84)	(-0.87)	(-1.05)	(-1.54)	(-2.07)	(-1.08)	(0.01)	(0.24)	(2.03)	(0.16)	(0.08)	(-1.11)	(-0.03)
Risk Price 2		0.26		-3.20		-5.39	-3.15	-0.57	0.03	0.03		1.49	0.69		
		(2.57)		(-1.38)		(-1.18)	(-2.04)	(-0.88)	(1.55)	(1.53)		(2.11)	(1.09)		
Risk Price 3				-1.12			-14.86						0.03		
				(-0.53)			(-0.65)						(1.08)		
Risk Price 4				-3.33									0.51		
				(-0.76)									(0.85)		
R^2	-0.02	0.26	-0.02	0.39	0.73	-0.27	0.59	-0.54	0.04	0.05	0.36	0.36	0.46	-3.98	-0.07

NOTES: See Table D2.

Table D6: Risk-adjusted performance of the USD-rates scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-1.53	-6.44	-1.53	2.68	-3.67	-3.77	-3.16	1.93	3.30	3.26	1.26	-0.10	-0.67	0.44	-0.10
	(-1.30)	(-2.42)	(-0.79)	(0.78)	(-1.62)	(-1.96)	(-1.88)	(2.12)	(2.46)	(2.41)	(1.34)	(-0.83)	(-0.37)	(0.47)	(-0.32)
Risk Price 2		-0.24		3.64		-3.96	-3.60	-1.25	0.09	0.10		4.16	5.21		
		(-1.30)		(0.75)		(-0.95)	(-0.93)	(-0.83)	(1.03)	(1.02)		(2.60)	(1.49)		
Risk Price 3				-4.93			-8.47						0.14		
				(-1.45)			(-0.31)						(0.96)		
Risk Price 4				13.54									0.91		
				(1.65)									(0.34)		
R^2	0.10	0.38	0.10	0.90	0.75	0.73	0.77	0.05	0.50	0.49	0.23	0.53	0.93	-0.17	-0.10

NOTES: See Table D2.

Table D7: Risk-adjusted performance of the G10-rates scenario

	CAPM	Quad. CAPM	Conditional CAPM	Carhart	C-CAPM	D-CAPM	EZ-DCAPM	LV	VOL1	VOL2	Skewness	Skew+VOL2	Skew+Vol2+LV	UR Gap Skew	FX Liquidity
Risk Price 1	-2.22	-3.32	-2.22	2.18	-1.24	-1.04	-1.50	0.27	0.66	0.67	2.27	-0.07	0.37	0.28	-0.15
	(-1.53)	(-1.97)	(-0.83)	(0.88)	(-1.84)	(-0.89)	(-1.26)	(0.99)	(2.67)	(2.64)	(2.04)	(-0.52)	(1.09)	(1.19)	(-0.62)
Risk Price 2		-0.04		-4.10		-3.50	-3.32	-0.27	0.04	0.04		3.86	0.83		
		(-0.35)		(-1.43)		(-2.09)	(-1.63)	(-0.46)	(1.21)	(1.24)		(2.20)	(1.34)		
Risk Price 3				-0.02			-19.31						0.01		
				(-0.01)			(-0.60)						(0.25)		
Risk Price 4				1.45									1.43		
				(0.77)									(1.65)		
R^2	-0.02	0.01	-0.02	0.53	0.54	0.22	0.79	-0.18	0.24	0.30	0.69	0.84	0.85	-0.41	-0.33

NOTES: See Table D2.

Table D8: Time-series results for the VOL1 variable for all 6 scenarios

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	β1=…=βn =0 p-value	β1=…=βn p-value
Baseline														
Constant	0.29	0.12	0.11	-0.01	0.08	-0.05	0.01	0.03	0.02	0.04	0.02	0.01	0.00	0.01
Mean R	0.32	0.15	0.12	0.02	0.10	-0.02	0.04	0.04	0.04	0.07	0.04	0.04		
Sortino Sorting														
Constant	0.28	0.12	0.08	0.01	0.07	-0.06	0.03	0.03	0.01	0.04	0.04	0.00	0.00	0.01
Mean R	0.31	0.15	0.10	0.03	0.09	-0.03	0.06	0.05	0.04	0.06	0.06	0.03		
250-day Rebalancing														
Constant	0.31	0.16	0.12	0.01	0.03	0.02	0.04	-0.01	0.06	0.01	0.00	-0.02	0.00	0.10
Mean R	0.34	0.18	0.14	0.03	0.07	0.04	0.07	0.02	0.10	0.03	0.03	0.01		
Net Returns Sorting														
Constant	0.15	0.09	0.09	0.05	0.03	0.04	0.06	0.08	0.04	-0.01	0.02	-0.04	0.00	0.02
Mean R	0.19	0.09	0.13	0.07	0.06	0.07	0.07	0.11	0.06	0.01	0.05	-0.01		
USD Rates														
Constant	0.31	0.15	0.06	0.00	-0.01	-0.04	-0.02	-0.11	-0.07	-0.08	-0.11	-0.09	0.01	0.12
Mean R	0.33	0.17	0.08	0.00	0.00	-0.02	0.01	-0.09	-0.05	-0.06	-0.09	-0.08		
G10 Rates														
Constant	0.23	0.08	0.11	0.10	0.13	0.06	0.05	-0.04	-0.10	0.02	-0.10	-0.11	0.47	0.65
Mean R	0.27	0.09	0.12	0.12	0.17	0.08	0.07	-0.03	-0.11	0.01	-0.07	-0.08		

NOTES: The table displays the constants (risk-adjusted return) from the first-stage time series regressions, sample mean returns and statistics on equality of first stage betas for all 6 scenarios. The risk factors in each regression were the short- dollar factor (RX) and VOL1. Significance levels of 1%, 5%, and 10% are denoted by cells shaded dark gray, gray and light gray, respectively.

Table D9: Time-series results for the VOL2 variable for all 6 scenarios

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	β1=…=βn =0 p-value	β1=…=βn p-value
Baseline														
Constant	0.32	0.15	0.13	0.02	0.10	-0.02	0.04	0.05	0.05	0.08	0.05	0.04	0.01	0.02
Mean R	0.32	0.15	0.12	0.02	0.10	-0.02	0.04	0.04	0.04	0.07	0.04	0.04		
Sortino Sorting														
Constant	0.32	0.15	0.10	0.04	0.09	-0.03	0.06	0.05	0.04	0.08	0.07	0.03	0.00	0.09
Mean R	0.31	0.15	0.10	0.03	0.09	-0.03	0.06	0.05	0.04	0.06	0.06	0.03		
250-day Rebalancing														
Constant	0.34	0.18	0.15	0.04	0.07	0.05	0.06	0.02	0.10	0.04	0.03	0.01	0.00	0.05
Mean R	0.34	0.18	0.14	0.03	0.07	0.04	0.07	0.02	0.10	0.03	0.03	0.01		
Net Returns Sorting														
Constant	0.19	0.10	0.13	0.08	0.06	0.07	0.08	0.11	0.07	0.02	0.05	-0.01	0.00	0.03
Mean R	0.19	0.09	0.13	0.07	0.06	0.07	0.07	0.11	0.06	0.01	0.05	-0.01		
USD Rates														
Constant	0.34	0.18	0.08	0.02	0.01	-0.01	0.02	-0.07	-0.04	-0.04	-0.08	-0.06	0.07	0.47
Mean R	0.33	0.17	0.08	0.00	0.00	-0.02	0.01	-0.09	-0.05	-0.06	-0.09	-0.08		
G10 Rates														
Constant	0.26	0.10	0.13	0.12	0.16	0.08	0.07	-0.02	-0.09	0.05	-0.07	-0.09	0.16	0.76
Mean R	0.27	0.09	0.12	0.12	0.17	0.08	0.07	-0.03	-0.11	0.01	-0.07	-0.08		

NOTES: The table displays the constants (risk-adjusted return) from the first-stage time series regressions, sample mean returns and statistics on equality of first stage betas for all 6 scenarios. The risk factors in each regression were the short- dollar factor (RX) and VOL2. Significance levels of 1%, 5%, and 10% are denoted by cells shaded dark gray, gray and light gray, respectively.

Table D10: Time-series results for the skewness variable for all 6 scenarios

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	β1=…=βn=0 p-value	β1=…=βn p-value
Baseline														
Constant	0.35	0.20	0.17	0.09	0.16	0.02	0.09	0.10	0.07	0.10	0.07	0.03	0.00	0.32
Mean R	0.38	0.23	0.19	0.12	0.18	0.05	0.12	0.12	0.09	0.12	0.08	0.06		
Sortino Sorting														
Constant	0.33	0.20	0.16	0.09	0.16	0.03	0.09	0.11	0.06	0.09	0.09	0.02	0.00	0.02
Mean R	0.36	0.23	0.19	0.11	0.18	0.06	0.12	0.14	0.08	0.11	0.11	0.04		
250-day Rebalancing														
Constant	0.36	0.23	0.18	0.10	0.12	0.09	0.12	0.06	0.13	0.06	0.08	0.01	0.00	0.31
Mean R	0.38	0.25	0.20	0.13	0.14	0.11	0.14	0.09	0.14	0.08	0.11	0.03		
Net Returns Sorting														
Constant	0.24	0.15	0.20	0.14	0.11	0.10	0.12	0.16	0.07	0.05	0.08	-0.01	0.00	0.02
Mean R	0.27	0.17	0.23	0.17	0.14	0.13	0.14	0.18	0.09	0.07	0.10	0.01		
USD Rates														
Constant	0.37	0.22	0.11	0.00	0.01	-0.02	0.01	-0.07	-0.04	-0.05	-0.06	-0.06	0.00	0.22
Mean R	0.39	0.24	0.13	0.02	0.02	-0.01	0.02	-0.06	-0.03	-0.04	-0.05	-0.04		
G10 Rates														
Constant	0.31	0.16	0.18	0.19	0.23	0.10	0.16	0.02	-0.09	-0.05	-0.09	-0.10	0.02	0.13
Mean R	0.34	0.18	0.21	0.21	0.26	0.12	0.17	0.04	-0.08	-0.05	-0.09	-0.09		

NOTES: The table displays the constants (risk-adjusted return) from the first-stage time series regressions, sample mean returns and statistics on equality of first stage betas for all 6 scenarios. The risk factor in each regression was the skewness factor. Significance levels of 1%, 5%, and 10% are denoted by cells shaded dark gray, gray and light gray, respectively.