NBER WORKING PAPER SERIES

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Working Paper 15518
http://www.nber.org/papers/w15518

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2009

Taylor has been supported by the Center for the Evolution of the Global Economy at UC Davis and Jorda by DGCYT Grant (SEJ2007-63098-econ); part of this work was completed whilst Taylor was a Houblon-Norman/George Fellow at the Bank of England; all of this research support is gratefully acknowledged. We thank Travis Berge and Yanping Chong for excellent research assistance. We acknowledge helpful comments from Vineer Bhansali, Richard Meese, Michael Melvin, Stefan Nagel, Michael Sager, Mark Taylor, and seminar participants at The Bank of England, Barclays Global Investors, London Business School, London School of Economics, the 3rd annual JIMF-SCCIE conference, the NBER IFM program meeting, and PIMCO. All errors are ours. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 15518
November 2009
JEL No. C44,F31,F37,G14,G15,G17

ABSTRACT

The carry trade is the investment strategy of going long in high-yield target currencies and short in low-yield funding currencies. Recently, this naive trade has seen very high returns for long periods, followed by large crash losses after large depreciations of the target currencies. Based on low Sharpe ratios and negative skew, these trades could appear unattractive, even when diversified across many currencies. But more sophisticated conditional trading strategies exhibit more favorable payoffs. We apply novel (within economics) binary-outcome classification tests to show that our directional trading forecasts are informative, and out-of-sample loss-function analysis to examine trading performance. The critical conditioning variable, we argue, is the fundamental equilibrium exchange rate (FEER). Expected returns are lower, all else equal, when the target currency is overvalued. Like traders, researchers should incorporate this information when evaluating trading strategies. When we do so, some questions are resolved: negative skewness is purged, and market volatility (VIX) is uncorrelated with returns; other puzzles remain: the more sophisticated strategy has a very high Sharpe ratio, suggesting market inefficiency.

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What is the fate of the efficient markets hypothesis (EMH)? Speaking to *The Economist* after the recent asset market turmoil, Richard Thaler has noted that the hypothesis always had two parts. Part one, the "no-free-lunch part" and part two, the "price-is-right" part. He affirmed that the asset price bubble and bust have effectively demolished part two—and yet, by erasing many cumulative gains and exposing the weakness of many investment strategies, may have bolstered support for part one, at least as a long-run proposition.[1]

In this paper, we re-examine the EMH using one of the most salient and well-trodden testing grounds, the foreign exchange market and the ongoing debate over the carry trade that has reignited once again. Once a relatively obscure corner of international finance, the naïve carry trade (borrowing in low interest rate currencies and investing in high interest rate currencies, despite the exchange rate risk) has drawn increasing attention in recent years, within and beyond academe, and especially as the volume of carry trade activity multiplied astronomically.

Inevitably, press attention has often focused on the personal angle. In 2007, *The New York Times* reported on the disastrous losses suffered by the "FX Beauties" club and other Japanese retail investors during an episode of yen appreciation; one highly-leveraged housewife lost her family's entire life savings within a week.[2] By the fall of 2008 attention was grabbed by an even more brutal squeeze on carry traders from bigger yen moves—e.g., up 60% against the AUD over 2 months, and up 30% against GBP (including 10% moves against both in five hours on the morning of October 24). Money managers on the wrong side saw their funds blowing up, supporting the June 2007 prediction of Jim O'Neill, chief global economist at Goldman Sachs, who had said of the carry trade that "there are going to be dead bodies around when this is over."[3]

Economists have also been paying renewed attention to the carry trade, revisiting old questions: Are there returns to currency speculation? Are the returns predictable? Is there a failure of market efficiency? We are still far from a consensus, but the present state of the literature, how it got there, and how it relates to the interpretations of the current market turmoil, can be summarized in a just few moments, so to speak.[4]

The first point concerns the first moment of returns. There have been *on average* positive returns to naïve carry trade strategies for long periods.[5] Put another way, the standard finding of a "forward discount bias" in the short run means that exchange rate losses will not fully offset

[1] "Efficiency and beyond," *The Economist*, July 16th, 2009.

[2] Martin Fackler, "Japanese Housewives Sweat in Secret as Markets Reel," New York Times, September 16, 2007.

[3] Ambrose Evans Pritchard. "Goldman Sachs Warns of 'Dead Bodies' after Market Turmoil," Daily Telegraph, June 3, 2007.

[4] For a full survey of foreign exchange market efficiency see Chapter 2 in Sarno and Taylor (2002), on which we draw here.

[5] We prefer to focus on the period of unfettered arbitrage in the current era financial globalization—that is, from the mid 1980s on, for major currencies. Staring in the 1960s the growth of the Eurodollar markets had permitted offshore currency arbitrage to develop. Given the increasingly porous nature of the Bretton Woods era capital controls, and the tidal wave of financial flow building up, the dams started to leak, setting the stage for the trilemma to bite in the crisis of the Bretton Woods regime in 1970–73. Floating would permit capital account liberalization, but the process was fitful, and not until 1990s was the transition complete in Europe (Bakker and Chapple 2002). Empirical evidence suggests significant barriers of 100bps or more even to riskless arbitrage in the 1970s and even into the early 1980s (Frenkel and Levich 1975; Clinton 1988; Obstfeld and Taylor 2004). Taking these frictions as evidence of imperfect capital mobility we prefer to exclude the 1970s and the early 1980s from our empirical work. Other work, e.g. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008a,b) includes data back to the the 1970s.

the interest differential gains of the naïve carry strategy.[6] This finding is often misinterpreted as a failure of uncovered interest parity; but UIP is an ex-ante, not an ex-post, condition—and the evidence, albeit limited, shows that average ex-ante exchange rate expectations (e.g., from surveys of traders) are not so far out of line with interest differentials.[7] Rather, expectations themselves seem to be systematically wrong. In this view, ex-post profits appeared to be both predictable and profitable, contradicting the *risk-neutral efficient markets hypothesis*. Indeed, our paper builds on this tradition using both regression and trading-algorithm approaches.[8] However, over periods of a decade or two it is quite difficult to reject ex-post UIP, suggesting that interest arbitrage holds in the long run, and that the possible profit opportunities are a matter of timing.[9]

The second point concerns the second moment of returns. If positive ex-ante returns are not arbitraged away, one way to rationalize them might be that they are simply too risky (volatile) to attract additional investors who might bid them away. This explanation has much in common with other finance puzzles, like the equity premium puzzle. The annual reward-to-variability ratio or Sharpe ratio of the S&P 500, roughly 0.4, can be taken as a benchmark level of risk adjusted return. But anecdotal evidence suggests that investors have little interest in strategies with annual Sharpe ratios below 1, and that this hurdle applies to a currency strategy as much as any other.[10] Historical data show that for all individual currency pairs, this hurdle has not been met using naïve carry trade strategies. Obviously, diversification in a portfolio across many currency pairs can improve performance, since returns on different currencies are not perfectly correlated. But even then, the data show that the hurdle of 1 is hard to beat in the long run for the G10 universe of currencies. Thus, the seemingly excess returns to the naïve carry strategy may be explicable, at least in part, as compensation for volatility.[11,12]

Finally, we turn to the third point of near consensus, on the third moment of returns. Naïve

[6] Seminal studies of the forward discount puzzle include Frankel (1980), Fama (1984), Froot and Thaler (1990), and Bekaert and Hodrick (1993).

[7] Seminal works on survey expectations include Dominguez (1986) and Froot and Frankel (1987, 1989). For an update see Chinn and Frankel (2002).

[8] A standard test of the predictability of returns (the "semi-strong" form of market efficiency) is to regress returns on an ex ante information set. The seminal work is Hansen and Hodrick (1980). Other researchers deploy simple profitable trading rules as evidence of market inefficiency (Dooley and Shafer 1984; Levich and Thomas 1993; Engel and Hamilton 1990).

[9] Support for long-run UIP was found using long bonds by Fujii and Chinn (2000) and Alexius (2001), and using short rates by Sinclair (2005).

[10] Lyons (2001).

[11] It is an open question whether expanding the currency set to include minor currencies, exotics, and emerging markets can add further diversification and so enhance the Sharpe ratio, or whether these benefits will be offset by illiquidity, trading costs, and high correlations/skew. Burnside, Eichenbaum, Kleshchelski and Rebelo (2006) compute first, second, and third moments for individual currencies and portfolio-based strategies for major currencies and some minor currencies. In major currencies the transaction costs associated with bid-ask spreads are usually small, although 5–10 bps per trade can add up if an entire portfolio is churned every month (i.e., 60–120 bps annual). Burnside, Eichenbaum, and Rebelo (2007) explore emerging markets with adjustments for transaction costs. Both studies conclude that there are profit opportunities net of such costs, but the Sharpe ratios are low. Moreover, Sager and Taylor (2008) argue that the Burnside et al. returns and Sharpe ratios may be overstated. Pursuing a different strategy, however, using information in the term structure, Sager and Taylor are able to attain Sharpe ratios of 0.88 for a diversified basket of currencies in back testing.

[12] In this paper we proceed in a risk-neutral framework, a widely-used benchmark, in contrast to the more recent and contentious use of consumption-based asset pricing models in the carry trade context. Lustig and Verdehlan (2007) claimed that the relatively low naïve carry trade returns may be explicable in a consumption-based model with reasonable parameters. Burnside (2007) challenged the usefulness of this approach. Returns to our systematic trading rules have very different moments, however, with mean returns twice as large as the typical naïve strategy, leaving a considerable premium to be explained in either framework.

carry trade returns are negatively skewed. The lower-tail risk means that trades are subject to a risk of pronounced periodic crashes—what is often referred to as a peso problem. Such a description applies to the aforementioned disaster events suffered by yen carry traders in 2007 and 2008 (and their predecessors in 1998). However, many competing investments, like the S&P500, are also negatively skewed, so the question is once more relative. And once again echoing the central limit theorem, this time for higher moments, while individual currency pairs may exhibit high skew, we know that diversification across currency pairs can be expected to drive down skewness in a portfolio. But for naïve strategies some negative skew still remains under diversification, and it is then unclear whether excess returns are a puzzle, or required compensation for skew (and/or volatility).[13]

Returning to Thaler's summary of the EMH, the awful recent performance of naïve carry trades fits with his perspective as applied to the FX market. But we will show that more sophisticated FX trading strategies could, and did, avoid crashes, so the free lunch issue remains open to debate. Specifically, the contribution of our paper is as follows:

- We start from common ground and confirm all of the above findings for our data; naïve carry trades are profitable but, even when diversified, they have low Sharpe ratios and negative skew.[14]

- We show that an important explanatory variable has been omitted from influential prior studies; the deviation from the fundamental equilibrium exchange rate (FEER) is an important predictor of exchange rates.

- Moreover, carry returns may be better explained in a nonlinear model, and our preferred nonlinear model draws together extant ideas from the UIP and PPP literature. The nonlinear model's regimes weigh two signals, a "greed" factor (potential carry trade interest gains plus momentum) and a "fear" factor (potential mean reversion to FEER).

- Inclusion of the FEER control variable improves not only the statistical performance of the model, it also enhances the financial performance of trading rules based on the model, and much more so than diversification alone. For simplicity and comparability we apply the model to equal-weight portfolio strategies among G10 currencies, which is the standard backtesting laboratory. Trading on a long-short directional signal for each currency we achieve Sharpe ratios well in excess of 1 over long periods, and attain zero or even positive skew.

- To support the claim that our directional forecasts beat a coin toss or rival strategies like naïve carry, we do out-of-sample testing using innovative loss functions (Giacomini and

[13] Brunnermeier, Nagel and Pedersen (2008) focus on the "rare event" of crash risk as an explanation for carry trade profits. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008a) argue that peso problems cannot explain carry trade profits, although in a different version of the same paper (2008b), they argue to the contrary.

[14] Note that throughout this article we implicitly assume that the end investor dislikes negative skew, all else equal. Of course, due to well known principal-agent problems arising from asymmetric compensation structures, asset managers may be quite happy to embrace large negative skew if they can obtain larger returns and associated performance fees in the short run before their fund blows up.

White 2006). We also employ (as far as we know, for the first time in economics) a set of powerful tools that have been widely used in other fields, such as medical statistics: the *receiver operating characteristic curve*, or *ROC curve*, and its associated hypothesis tests. For applications in finance we apply an extension of the ROC curve, called ROC* (Jordà and Taylor 2009), which allows for directional predictions to be weighted by on returns, in the spirit of gain-loss performance measures (Bernardo and Ledoit 2000).

- We also compare our approach to rival crash protection strategies. One suggestion is that carry trade skew is driven by market stress and liquidity events (Brunnermeier et al. 2008); but we find that VIX signals provide no additional explanatory or predictive power in our preferred forecasting framework. Another approach suggests that options provide a way to hedge downside risk (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2008ab); but these strategies are very costly to implement compared to our trading rule.

- Finally we perform out-of-sample tests and explore real-world trading strategies for the years up to and including the 2008 financial crisis, looking at our model performance and actual exchange traded funds. The naïve models and crude ETFs crashed horribly in 2008, wiping out years of gains. More sophisticated ETFs resembling our preferred model weathered the storm remarkably well with barely any drawdown.

To conclude, we find that in the past, whilst naïve carry strategies may not have offered adequate compensation for risk (volatility and skew), more sophisticated strategies that accounted for long-run real exchange rate fundamentals could have easily surmounted that hurdle. This provides support for currency strategies that augment carry and momentum signals with a value signal based on real fundamentals. Many sophisticated funds with limited access have pursued such strategies in the past, but the recent arrival of simple, passive ETFs with these same features raises the question of how much "true alpha" active currency managers create. It also begs the question how long any such excess returns might persist before being arbitraged away.[15]

In addition to extending a growing econometric literature on the nature of carry trade dynamics, our paper also provides a touchstone for ongoing theoretical work that attempts to characterize the form and extent of deviations from the efficient markets hypothesis. Our work is sympathetic to a well-established view that asset prices can deviate from their fundamental value for some time, before a "snap back" occurs (Poterba and Summers 1986; Plantin and Shin 2007). Recent theory has focused on what might permit the deviation, and what then triggers the snap. In FX markets, work in this vein includes models of noise traders, heterogeneous beliefs, rational inattention, liquidity constraints, herding, "behavioral" effects, and other factors that may serve to limit arbitrage (e.g., Shleifer and Vishny 1997; Jeanne and Rose 2002; Baccheta and van Wincoop 2006; Fisher 2006; Brunnermeier et al. 2008; Ilut 2008).

[15] Pojarliev and Levich (2007, 2008) argue that active managers deliver less alpha than claimed, and that much of their returns can be described as quasi-beta with respect to style factors like carry, momentum, and value that are now captured in passive indices and funds.

1 Statistical Design

Our primary objectives are to investigate the dynamic links between the excess returns to carry trade and deviations from FEER; to generate forecasts with which to construct out-of-sample formal predictive evaluation; and hence to construct carry trade strategies whose out-of-sample returns can be evaluated for profitability and risk.

The data for the analysis consists of a panel of nine countries (Australia, Canada, Germany, Japan, Norway, New Zealand, Sweden, Switzerland, and the United Kingdom) set against the U.S. over the period January 1986 to December, 2008, observed at a monthly frequency (i.e., the "G10" sample).[16] The variables in this data-set include the end-of-month nominal exchange rate expressed in U.S. dollars per foreign currency units and whose logarithm we denote as e_t; the one-month London interbank offered rates (LIBOR) denoted as i_t for the U.S. and i_t^* for any of the eight counterparty countries; and the consumer price index, whose logarithm is denoted as p_t for the U.S. and p_t^* otherwise. Data on exchange rates and the consumer price index are obtained from the IFS database whereas data on LIBOR are obtained from the British Banker's Association (www.bba.org.uk) and Global Financial Data (globalfinacialdata.com).

The primary variable of interest to us can be thought of as *momentum*, denoted m_t. Momentum refers to the ex-post nominal excess returns of a carry trade, specifically approximated by

$$m_{t+1} = \Delta e_{t+1} + (i_t^* - i_t). \tag{1}$$

In the absence of barriers or limits to arbitrage, and assuming that the efficient markets hypothesis (EMH) holds, the ex-ante value of momentum should be zero, that is $E_t m_{t+1} = E_t \Delta e_{t+1} + (i_t^* - i_t) = 0$.

Momentum can also be expressed in terms of real excess returns as

$$m_{t+1} = \Delta q_{t+1} + (r_t^* - r_t) \tag{2}$$

where $r_t = i_t - \pi_{t+1}$ with $\pi_{t+1} = \Delta p_{t+1}$, and similarly for r_t^* and π_{t+1}^*; and $q_{t+1} = \overline{q} + e_{t+1} + (p_{t+1}^* - p_{t+1})$ so that $\Delta q_{t+1} = \Delta e_{t+1} + \left(\pi_{t+1}^* - \pi_{t+1}\right)$ and the equivalence between (1) and (2) is readily apparent. Under the assumption of (weak) purchasing power parity, $\overline{q}$ is the mean FEER to which q_t reverts, so $q_t - \overline{q}$ is a stationary variable and hence a cointegrating vector. In a more general setting, and in the out-of-sample analysis below, $\overline{q}$ may be time varying, when there is drift in the FEER due to productivity effects or other factors.

The dynamic interactions between nominal exchange rates, inflation and nominal interest rate deviations are the constituent elements of a system whose linear combinations explain the dynamic

[16] Data for the Germany after 1999 are constructed with the EUR/USD exchange rate and the fixed conversion rate of 1.95583 DEM/EUR.

behavior of momentum and FEER conveniently.[17] Specifically, we consider the system

$$\Delta \mathbf{y}_{t+1} = \begin{bmatrix} \Delta e_{t+1} \\ \pi^*_{t+1} - \pi_{t+1} \\ i^*_t - i_t \end{bmatrix}. \tag{3}$$

Under the assumption of purchasing power parity, e_{t+1} and $(p^*_{t+1} - p_{t+1})$ may be $I(1)$ variables, but they are cointegrated; therefore, a natural representation of the dynamics of $\Delta \mathbf{y}_{t+1}$ in (3) is with a vector error correction model (VECM). Although including $(i^*_t - i_t)$ in expression (3) may appear peculiar because it is information known at time $t+1$, expression (3) focuses on forecasting m_{t+1} with the specification for the first equation in the VECM for $\Delta \mathbf{y}_{t+1}$.

2 A Trading Laboratory for the Carry Trade

In this section we construct forecasting models for the returns to carry trades.

2.1 Statistical Properties of Exchange Rates and FEER

Our forecasting model hinges on the error correction representation of the equation for Δe_{it} in the system of expression (3), where we take $q_{t+1} = \overline{q} + e_{t+1} + (p^*_{t+1} - p_{t+1})$ to be a cointegrating vector.[18] A natural impulse is to determine the stationarity properties of the constituent elements of expression (3) so as to verify that q_{t+1} is a proper cointegrating vector. Such steps are natural when the objective of the analysis is to directly examine whether purchasing power parity holds in the data; when one is interested in determining the speed of adjustment to long-run equilibrium; and hence to ensure that the estimators and inference are constructed with the appropriate non-standard asymptotic machinery. However interesting it is to investigate these issues, they are of second order importance for our analysis given our stated focus on predictive ability and derivation of profitable investment strategies—the Beveridge-Nelson representation of the first equation in expression (3) is valid regardless of whether there is cointegration. For this reason, we provide a far less extensive analysis of these issues for our panel data than is customary and refer the reader to the extensive literature on panel PPP testing (e.g., see Taylor and Taylor 2004).

Instead, we investigate the properties of q_{t+1} directly with a battery of cointegration tests that pool the data to improve the power of the tests (while accounting for different forms of heterogeneity in cross-section units) and based on Pedroni (1999, 2004). The results of these tests are summarized in Table 1, with the particulars of each test explained therein. Broadly speaking, while not overwhelming, it seems reasonable to conclude that the data support our thinking of q_{t+1} as a valid cointegrating vector.

While the results of Table 1 are informative regarding the relative strength of PPP, we will show momentarily that there is valuable predictive information contained in real exchange rate

[17] It would be straightforward to augment this model with an order-flow element, as in the VAR system of Froot and Ramadorai (2005).

[18] Note that in all estimations in this paper, $\overline{q}$ is absorbed in country specific intercept terms, so we are testing relative PPP not absolute PPP.

Table 1: Panel Cointegration Tests

	Constant				Constant + Trend			
	Raw		Demeaned		Raw		Demeaned	
Test	stats	p	stats	p	stats	p	stats	p
Panel								
v	2.50**	0.017	3.82**	0.000	0.14	0.395	2.04*	0.050
ρ	-1.68*	0.097	-2.22**	0.034	-0.56	0.340	-1.78*	0.079
PP	-1.59	0.113	1.68*	0.097	-1.09	0.220	-1.71*	0.093
ADF	0.99	0.245	-0.54	0.345	1.27	0.179	-0.39	0.370
Group								
ρ	-0.51	0.350	-1.71*	0.092	0.48	0.356	-2.12**	0.042
PP	-0.98	0.246	-1.65	0.103	-0.40	0.368	-2.06**	0.048
ADF	7.31**	0.000	0.59	0.335	7.16**	0.0009	0.74	0.303

Notes: We use the same definitions of each test as in Pedroni (1999). The tests are residual-based. We consider tests with constant term and no trend, and with constant and time trend. The first 4 rows describe tests that pool along the within-dimension whereas the last 3 rows describe tests that pool along the between-dimension. The tests allow for heterogeneity in the cointegrating vectors, the dynamics of the error process and across cross-sectional units. ** indicates rejection of the null of no-cointegration at the 5% level, or * 10% level. The sample is January 1986 to December 2008.

fundamentals for use in one period-ahead forecasts, which might form the basis of a trading strategy. Hence, we try various forecasting models, from naïve models (e.g., simple carry trades) to more sophisticated models (e.g., nonlinear models of UIP and PPP dynamics). The models are then evaluated in two ways: first from a statistical standpoint, by looking at the in-sample fit and out-of-sample predictive power; and second from a trading standpoint, by examining how implementing these strategies would have affected a currency manager's returns, volatility, Sharpe ratios, and skewness for the sample period.

2.2 Two Naïve Models

Table 2 presents the one-month ahead forecasts of the change in the log nominal exchange rate based on two naïve models. Model 1, denoted "Naïve," imposes the assumption that the exchange rate follows a random walk. All regressors are omitted so there is, in fact, no estimated model. This is simply the benchmark or null model.

However crude it may be, this is still a model that one might use as a basis for trading—long high yield, short low yield—so panels (b)–(d) explore the performance characteristics of the pooled set of trades based on such a strategy, for all 9 currencies against the U.S. dollar and all 276 months (2484 observations). The findings are as expected. Predicted profits are about 20 basis points (bps) per month, positively skewed, but with a similar standard deviation. Monthly forecast errors are a serious problem, with a large standard deviation of 300 bps, and a large negative skew of -0.73 due to "rare event" crashes. As a result actual trading profits are 26 bps per month, with a standard deviation of 300 bps—implying a truly awful monthly Sharpe ratio of less than 0.1. The pooled trades also have a serious negative skew of -0.67.

Model 2, denoted "Naïve ECM," augments the Naïve model: we embrace the idea that real exchange rate fundamentals may have predictive power, in that currencies overvalued (undervalued)

Table 2: Two Naïve Models

Model	(1) Naïve	(2) Naïve ECM
(a) Model parameters		
Dependent variable	Δe_{it}	Δe_{it}
$\log(q_{it} - \bar{q}_i)$	—	-0.0235**
		(0.0047)
R^2, within	-	.0119
F	—	F(1,2447) = 25.39
Fixed effects	—	Yes
Periods	276	276
Currencies (relative to US$)	9	9
Observations	2484	2484
(b) Trading performance †		
Predicted profits		
Mean	0.0022	0.0029
Std. dev.	0.0018	0.0025
Skewness	2.2348	1.5876
C.v.	0.8247	0.8766
Forecast errors		
Mean	0.0005	0.0004
Std. dev.	0.0299	0.0296
Skewness	-0.7278	-0.3705
C.v.	62.1150	71.6838
Actual profits		
Mean	0.0026	0.0033
Std. dev.	0.0299	0.0298
Skewness	-0.6743	-0.0043
C.v.	11.3310	8.9930

† Statistics for trading profits are net, monthly, pooled.

Note: C.v. = coefficient of variation = ratio of standard deviation to mean. Standard errors in parentheses; ** (*) denotes significant at the 95% (90%) confidence level. Estimation is by ordinary least squares. In column (1), there is no model estimation as coefficients are assumed to be zero and e follows a random walk.

relative to FEER might be expected to face stronger depreciation (appreciation) pressure. Now in panel (a) the one-month-ahead forecast equation has just a single, lone time-varying regressor, the lagged real exchange rate deviation, plus currency-specific fixed effects which are not shown. The coefficient on the real exchange rate term of -0.02 is statistically significant and indicates that reversion to FEER occurs at a convergence speed of about 2% per month on average, which implies that deviations have a half-life of 36 months—well within the consensus range of the PPP literature.

In panel (b) the potential virtues of a FEER based trading approach start to emerge, but only weakly. From a trader's perspective, the results are little better with Model 2: forecast profits are higher and more positively skewed. But we also see the flipside: forecast errors are smaller and the negative skew of the error is reduced, although it is still an irksome -0.37. Thus, although pooled actual ex-post returns in Model 2 have the same mean and volatility (and hence the same feeble Sharpe ratio) as in Model 1, their skewness has been cut from -0.73 to -0.37: a gain, if only a modest one.

By focusing mainly on unconditional naïve carry trade returns, some influential academic papers have concluded that crash risk and peso problems are important features of the FX market. Table 2 may be extremely naïve, but it suffices to launch the start of a counterargument. It shows that an allowance for real exchange rate fundamentals can limit adverse skewness from the carry trade, and it is indeed well known that successful strategies do just that, as we shall see in a moment. However, we do not stop here, since we have the tools to explore superior model specifications that deliver trading strategies with even higher ex post actual returns, lower volatilities, and negligible (or positive) skew.

2.3 Two Linear Models

Table 3 displays the one-month-ahead forecasts from the richer flexible-form exchange rate models discussed in the previous section. Model 3 is based on a regression of the change in the nominal exchange rate on the first lag of the change in the nominal exchange rate, inflation, and the interest rate differentials (this model is labeled VAR since it would correspond to the first equation of a vector autoregressive model for $\Delta \mathbf{y}_{t+1}$ in expression 3). Model 4 extends the specification of Model (3) with the real exchange term and is therefore labeled VECM, by analogy with vector error-correction.

As with the Naïve ECM (Model 2) a plausible convergence speed close to 3% per month is estimated. Other coefficients conform to standard results and folk wisdom. The positive coefficient on the lagged change in the nominal exchange rate of 0.12 suggests a modest but statistically significant momentum effect. The positive coefficient on the lagged interest differential, closer to $+1$ than -1, conforms to the well known forward discount puzzle: currencies with high interest rates tend to appreciate all else equal. The positive coefficient on the inflation differential conforms to recent research findings that "bad news about inflation is good news for the exchange rate" (Clarida and Waldman 2007): under Taylor rules, high inflation might be expected to lead to monetary tightening and future appreciation.

We can see that these models offer some improvement as compared to the Naïve ECM (Model 2). The R^2 is higher and the explanatory variables are statistically significant. They also perform better than either naïve model as judged by actual returns. Their pooled mean forecast and actual returns are about half as high again. For actual returns, the coefficients of variation (the ratio of the sample variance to sample mean) are lower. Hence, their Sharpe ratios are higher, although still very small. For the VAR the monthly Sharpe is 0.15 (0.53 annualized), and for the VECM it is 0.18 (0.63 annualized).

Even more notable, negative skews are much lower. VAR delivers an actual pooled return skew of -0.15 and the VECM actually turns in a slightly positive skew of 0.12. Statistically the VECM is preferred with R^2 and F-statistic twice as large, and the coefficient on the lagged real exchange rate highly significant. From a trading standpoint its performance is also a little better, with mean returns and Sharpe ratio up slightly. Still, 50 bps per month and an annualized Sharpe of 0.63 may be viewed as somewhat disappointing. However, the key finding is that when trades are made conditional on deviations from FEER, actual trading returns have a skew that is zero

Table 3: Two Linear Models

Model	(3) VAR	(4) VECM
(a) Model parameters		
Dependent variable	Δe_{it}	Δe_{it}
$\Delta e_{i,t-1}$	0.1218**	0.1333**
	(0.0267)	(0.0268)
$i_{i,t} - i^*_i, t-1$	0.2889	0.7555**
	(0.3529)	(0.3506)
$\log(\pi_{it} - \pi^*_{it})$	0.2325	0.1690**
	(0.1603)	(0.0047)
$\log(q_{it} - \bar{q}_i)$	–	-0.0277**
		(0.0047)
R^2, within	0.0164	0.0319
F	F(3,2427) = 8.66	F(4,2426) = 14.36
Fixed effects	Yes	Yes
Periods	276	276
Currencies (relative to US$)	9	9
Observations	2484	2484
(b) Trading performance†		
Predicted profits		
Mean	0.0038	0.0047
Std. dev.	0.0033	0.0041
Skewness	1.9779	1.7716
C.v.	0.8566	0.8817
Forecast errors		
Mean	0.0007	0.0005
Std. dev.	0.0294	0.0292
Skewness	-0.2196	0.0297
C.v.	42.3705	53.5159
Actual profits		
Mean	0.0045	0.0052
Std. dev.	0.0295	0.0294
Skewness	-0.1464	0.1195
C.v.	6.5361	5.6245

† Statistics for trading profits are net, monthly, pooled.

Note: C.v. = coefficient of variation = ratio of standard deviation to mean. Standard errors in parentheses; ** (*) denotes significant at the 95% (90%) confidence level. Estimation is by ordinary least squares.

or mildly positive.

2.4 A Nonlinear Model

Are these the best models we can find? We think not, due to the limitations of linear models. We present two arguments that force us to reckon with potential nonlinearities in the exchange rate dynamics.

The first possible reason for still disappointing performance in the VECM (Model 4) is that the model places excessively high weight on the raw carry signal emanating from the interest differential in some risky "high carry" circumstances. This may lead to occasional large losses, even if it is not enough to cause negative skew. Recall that naïve Model (2) placed zero weight on this signal as part of an exchange rate forecast, whereas here the weight is 0.76. We conjecture that the true relationship may be nonlinear. Here we follow an emerging literature which suggests that deviations from UIP are corrected in a nonlinear fashion: that is, when interest differentials are large the exchange rate is more likely to move against the naïve carry trade, and in line with the efficient markets hypothesis (see, inter alia, Coakley and Fuertes 2001; Sarno, Valente and Leon 2006).

The second possible reason for disappointing performance might be related not to nonlinear UIP dynamics, but rather nonlinear PPP dynamics. Here it is possible that VECM places too little weight on the real exchange rate signal in some circumstances, e.g. when currencies are heavily over/undervalued and thus more prone to fall/rise in value. Here again, we build on an increasingly influential literature which point out that reversion to Relative PPP, largely driven by nominal exchange rate adjustment, is likely to be more rapid when deviations from FEER are large (see, inter alia, Obstfeld and Taylor 1997; Michael, Nobay and Peel 1997; Taylor, Peel, and Sarno 2001).

To sum up, past empirical findings suggest that the parameters of the Naïve ECM Model (2) may be expected to differ between regimes with small and large carry trade incentives, as measured by the lagged interest rate differential; and also to differ between regimes with small and large FEER deviations, as measured by the lagged real exchange rate. In addition to these arguments for a nonlinear model, the important role of the third moment in carry trade analyses also bolsters the case, given the deeper point made in the statistical literature that skewness cannot be adequately addressed outside of a nonlinear modeling framework (Silvennoinen, Teräsvirta and He, 2008).

To explore these possibilities we extend the framework further to allow for nonlinear dynamics. We first perform a test against nonlinearity of unknown form and find strong evidence of nonlinearity derived from the absolute magnitudes of interest differentials and real exchange rate deviations. We then implement a simple nonlinear threshold error correction model (TECM). For illustration, we employ an arbitrarily partitioned dataset with thresholds based on median absolute magnitudes.

Table 4 presents the nonlinearity tests using Model (4) in Table 3, the VECM model, where the candidate threshold variables are the absolute magnitudes of the lagged interest differential $|i_{i,t-1} - i^*_{i,t-1}|$ and the lagged real exchange rate deviation $|q_{i,t-1} - \bar{q}_i|$. Although more specific nonlinearity tests tailored to particular alternatives would be more powerful, we are already able to forcefully reject the null with generic forms of neglected nonlinearity by simply taking a polynomial expansion of the linear terms based on the threshold variables. This type of approach is often used in testing against linearity when a smooth transition regression (STAR) model is specified but it is clearly not limited to this alternative hypothesis (see Granger and Teräsvirta 1993). The regression test takes the form of an auxiliary regression involving polynomials of each variable, up to the fourth power.

The results in Table 4 show the hypothesis of linearity can be rejected at standard significance levels for specifications based on whether either or both threshold variables are considered simultaneously. Thus our VECM Model (4) in Table 3 appears to be misspecified, and so we are

Table 4: Nonlinearity Tests

Hypothesis tests	Test statistic
H_0: Nonlinear in $\|i_{i,t} - i_i^*, t-1\|$ and $\|\log(q_{it} - \bar{q}_i)\|$ versus:	
(a) H_1: Nonlinear in $\|\log(q_{it} - \bar{q}_i)\|$ and	$F(44{,}2337) = 4.28$
linear in $\|i_{i,t} - i_i^*, t-1\|$	$p = 0.0000$
(b) H_2: Nonlinear in $\|i_{i,t} - i_i^*, t-1\|$ and	$F(52{,}2337) = 1.42$
linear in$\|\log(q_{it} - \bar{q}_i)\|$	$p = 0.0262$
(c) H_3: Linear in $\|i_{i,t} - i_i^*, t-1\|$ and	$F(96{,}2337) = 28.04$
linear in $\|\log(q_{it} - \bar{q}_i)\|$	$p = 0.0000$

Notes: p refers to the p-value for the LM test of the null of linearity against the alternative of nonlinearity based on a polynomial expansion of the conditional mean with the selected threshold arguments. See Granger and Teräsvirta (1993).

moved to develop a more sophisticated yet parsimonious nonlinear model. For illustration, we use a simple four-regime TECM, where the regimes are delineated by thresholds values taken to be the median levels of the absolute values of the regressors $I_{it} = |i_{i,t-1} - i^*_{i,t-1}|$ and $Q_{it} = |q_{i,t-1} - \bar{q}_i|$, which for simplicity will be denoted by θ_i and θ_q respectively.

Estimates of this model, denoted Model (5) in Table 5, show that from both an econometric and a trading standpoint, the performance of the nonlinear model is outstanding. It also accords with many widely recognized state-contingent FX market phenomena.

We see from Panel (a) in Table 5 that the estimated model coefficients differ sharply across the four regimes. The null of no differences across regimes is easily rejected. In Column 1 of Table 5 we see that the model performs rather poorly in the regime where both interest differentials and real exchange rate deviations are small. Still, there is weak evidence for a self-exciting dynamic with a very strong forward bias: the coefficient on the interest differential is large (+2.5) consistent with traders attracted by carry incentives bidding up the higher yield currency. However, for small interest differentials, we can see from Column 3 in Table 5 that this effect disappears, once large real exchange rate deviations emerge. Still, the fit of the model remains quite poor in Column 3 also.

In Column 2 of Table 5, where the interest differential is above median, this self-exciting property is also manifest clearly, with a coefficient of +1.8 that is statistically significant at the 5% level. The results strongly suggest that wide interest differentials take exchange rates "up the stairs" on a gradual appreciation away from fundamentals.

Of course, for given price levels or inflation rates, such dynamics quickly cumulate in ever-larger real exchange rate deviations, moving the model's regime to Column 4 in Table 5, where the fit of the model is best, as shown by a high R^2 and F-statistic. And here the dynamics dramatically change such that the exchange rate can rapidly descend "down the elevator": the lagged real exchange rate carries a highly significant convergence coefficient of 3.6% per month, working against previous appreciation of the target currency, and reverse exchange rate momentum then snowballs, with the lagged exchange rate change carrying a now significant and large coefficient of 0.2.

In addition to being the preferred model based on statistical tests, does the nonlinear TECM Model (5) in Table 5 deliver better trading strategies? Panels (b)–(d) in that table suggest so.

Table 5: Noninear Model

Model	(5) NECM			
(a) Model parameters (by regime)	$Q_{it} < \theta_q$ $I_{it} < \theta_i$	$Q_{it} < \theta_q$ $I_{it} > \theta_i$	$Q_{it} > \theta_q$ $I_{it} < \theta_i$	$Q_{it} > \theta_q$ $I_{it} > \theta_i$
Dependent variable	Δe_{it}	Δe_{it}	Δe_{it}	Δe_{it}
$\Delta e_{i,t-1}$	0.0637	0.1228**	0.1029*	0.2027**
	(0.0417)	(0.0494)	(0.0574)	(0.0567)
$i_{i,t} - i_i^*, t-1$	2.5033**	1.7790**	0.8707	-0.5734
	(1.1577)	(0.6379)	(1.3585)	(0.7811)
$\log(\pi_{it} - \pi_{it}^*)$	0.6731	0.3836	-0.5269	0.1331
	(0.4101)	(0.3880)	(0.3945)	(0.2173)
$\log(q_{it} - \bar{q}_i)$	-0.0572**	-0.0564**	-0.0146**	-0.0364**
	(0.0011)	(0.0265)	(0.0072)	(0.0077)
R^2, within				
F	F(4,642)	F(4,549)	F(4,554)	F(4,641)
	= 4.63	= 4.29	= 1.90	= 8.60
Fixed effects	Yes	Yes	Yes	Yes
Periods	276	276	276	276
Currencies (relative to US$)	9	9	9	9
Observations (by regime)	655	562	567	654
(b) Trading performance †				
Predicted profits				
Mean	0.0057			
Std. dev.	0.0052			
Skewness	2.1205			
C.v.	0.9153			
Forecast errors				
Mean	-0.00002			
Std. dev.	0.0289			
Skewness	0.2573			
C.v.	-1626.59			
Actual profits				
Mean	0.0057			
Std. dev.	0.0293			
Skewness	0.3674			
C.v.	5.1769			

† Statistics for trading profits are net, monthly, pooled.

Note: C.v. = coefficient of variation = ratio of standard deviation to mean. Standard errors in parentheses; ** (*) denotes significant at the 95% (90%) confidence level. Estimation is by ordinary least squares.

Compared to the VECM Model (4) in Table 3, predicted and actual pooled profits are higher still, and nearing 60 bps per month. The pooled actual returns Sharpe ratio is now 0.19 monthly (0.67 annualized). This model's annual Sharpe ratio is the best yet, although it is still well below the annual 1.0 Sharpe ratio benchmark commonly cited as the relevant hurdle for investors. Finally we note that the TECM actual returns are strongly positively skewed: again, crashes are largely avoided.

Table 6: Portfolio Performance

Monthly trading profits for equal-weight portfolios

	(1) Naïve	(2) Naïve ECM	(3) VAR	(4) VECM	(5) TECM
Observations	276	276	276	276	276
Mean	0.0026	0.0034	0.0045	0.0052	0.0057
Std. dev.	0.0154	0.0163	0.0159	0.0169	0.0155
Skewness	-1.8793	0.2472	-0.1019	1.0994	1.0704
Kurtosis	11.3818	3.9371	4.0890	8.1154	8.1316
C.v.	5.8764	4.8622	3.5318	3.2354	2.7357
Sharpe ratio, annualized*	0.5895	0.7125	0.9808	1.0707	1.2663

* Statistics for trading profits are net, monthly, except for annualized Sharpe ratio.

Note: C.v. = coefficient of variation = ratio of standard deviation to mean.

2.5 Portfolio Strategies

The performance of a pooled set of trades for the naïve, linear, and nonlinear models shows how model performance can be improved. But these statistics bear no relation to actual market activity. In reality, traders do not pick a random currency pair each period in which to trade. Instead, currency funds invest in a portfolio of currencies. This allows funds to take advantage of gains from diversification: standard statistical intuition (cf. the Central Limit Theorem) tells us that variance and skewness can be curtailed by taking an average of draws that are imperfectly correlated.[19]

As a practical matter for many trading strategies studied in the academic literature, and some used in practice, the portfolio choice is restricted—for reasons of simplicity, comparability, diversification and transparency. The simplest restriction is to employ simple equal-weight portfolios where a uniform bet of size $\$1/N$ is placed on each of N FX-USD pairs, so that the *only* forecast-based decision is the binary long-short choice for each pair in each period. Granted, lifting this restriction to allow adjustable portfolio weights must, ipso facto allow even better trading performance, at least on backtests. But from our standpoint of presenting a puzzle—rejecting the null of the efficient market hypothesis, and showing a strategy with high returns and Sharpes, and low skewness—meaningful forecasting success even when restricted to an equal-weight portfolio is evidence enough to support our story.

Table 6 illustrates the gains from diversification strategies and shows how these gains deliver very promising returns in cases where our FEER based models are employed. In each panel we report mean, standard deviation, skewness, coefficient of variation, and annual Sharpe ratios for the naïve models, the linear models, and the nonlinear model. The panels cover various portfolio construction rules. In all cases the U.S. dollar is the base currency, as before.

Here we hypothetically wager $1/N on each currency trade, for the N currencies, with the long-short direction for each currency given by the model's predicted return. This is called the equal-weight portfolio. For these portfolios we construct summary statistics as before, plus an annual Sharpe ratio. The performance of the portfolio-based trading strategies is revealing. It is clear that some of the advantage of the VAR and the VECM models (3) and (4) over the naïve

[19] A numerical illustration is provided by Burnside, Eichenbaum and Rebelo (2008).

models starts to wane once many currencies are traded, but the nonlinear TECM retains some clear advantages by better avoiding currencies with high unconditional crash potential.

Consider first the Naïve Model (1) in Table 2 and the VAR Model (3) in Table 3, without any real FEER fundamental. Gains from diversification are obvious right away as compared with the pooled data presented earlier. Under equal-weight portfolios, the Naïve Model attains an annual Sharpe of 0.59 but the VAR now has an annual Sharpe of 0.98. However, these portfolio strategies are still rather undesirable given their low returns of 26–34 bps per month and negative skew.

In contrast, the linear models of the Naïve ECM Model (2) in Table 2 and the VECM Model (4) in Table 3 do a very good job in the portfolio setting in purging unwanted skewness from actual returns. The Naïve ECM has weak positive skew, and VECM has weak negative skew. Returns are 45–52 bps per month, and the annualized Sharpe ratios are 0.71 and 1.07 respectively, thus clearing the mythical 1.0 hurdle.

The superiority of the TECM model is now very clear, as shown by the final column of Table 6. In equal weight form, it outshines all other models on mean return (57 bps per month) and annualized Sharpe (1.27).[20,21]

2.6 Exploring the Performance Improvements

We now start to examine why the proposed model refinements generate improved performance.

We look at both in and out-of-sample evidence, and the sample reserved for out-of-sample evaluation was chosen to run from January 2004 to December 2008. For these purposes, one step-ahead forecasts are generated, one at a time, with a rolling window that begins with the January 1986 observation and finishes with the December 2003 observation. Table 7 shows that the model refinements do very little to increase the ability of the trader to pick a profitable direction for a trade over and above the Naïve carry strategy. In sample, the random walk exchange-rate model gets the direction of 58% of trades right, but what is striking is that the other models do no better. The TECM also achieves 58%. Out of sample, the findings are similar: the Naïve model got the direction right 51% of the time, the TECM 53%. So what is so great about the refined models?

The answer is given in Table 8 and explored in much more detail in the next section. It is not the ability to pick the right direction of trades more often; it is the ability to pick the right direction on trades that are likely to result in large gains or losses. For simplicity, this table compares just the Naïve and TECM models. In-sample (panel a) we find that over 2438 pooled trades, the two models agreed on direction 1547 times and disagreed 891 times. When in agreement, returns were 65 bps per month, Annual Sharpe was 0.83 and skew was -0.23. The worst trade lost 11% in a month, the best gained 12%. But when the models took opposite sides, the differences were stark. The Naïve model collected negative returns of 42 bps, the TECM just the opposite. Annual

[20] Even if the entire portfolio churns once per month, which it does not, and assuming typical G10 bid-ask spreads of 2 bps for a round trip, these returns would be 55 bps and 82 bps, respectively, with miniscule downward revisions in the Sharpe ratios even after allowance for transaction costs.

[21] Further tweaks are possible to enhance performance even further. If equal weights are replaced by weights proportional to the signal strength, the TECM model achieves returns (84 bps per month) and an annualized Sharpe ratios (1.48) that are even more impressive, without negative skew. The improvements occur because the linear weighting allows the model to re-weight towards more high risk/return trades with negative skew, without turning the overall skew significantly negative.

Table 7: Fraction of Profitable Trading Positions Correctly Called (%)

(a) In sample					
	Naïve	Naïve ECM	VAR	VECM	TECM
Australia	62.9	57.5	56.6	55.5	55.9
Canada	57.8	52.0	56.6	55.9	54.8
Germany	52.0	53.1	55.9	54.0	56.3
Japan	58.2	53.8	61.0	59.9	56.3
New Zealand	63.3	59.3	62.1	57.7	58.8
Norway	57.1	55.3	57.4	56.6	58.1
Sweden	62.7	50.6	66.2	66.2	62.4
Switzerland	53.8	54.5	58.1	55.1	58.1
UK	53.1	54.9	49.3	53.3	53.9
Pooled	57.9	54.6	58.1	57.1	57.1
(b) Out of sample					
	Naïve	Naïve ECM	VAR	VECM	TECM
Australia	55.0	48.3	53.3	45.0	58.3
Canada	43.3	51.7	50.0	46.7	51.7
Germany	45.0	46.7	48.3	51.7	45.0
Japan	56.7	56.7	65.0	66.7	56.7
New Zealand	61.7	60.0	60.0	60.0	60.0
Norway	46.7	46.7	58.3	58.3	48.3
Sweden	53.3	53.3	56.7	60.0	60.0
Switzerland	53.3	55.0	53.3	53.3	55.0
UK	45.0	50.0	51.7	51.7	45.0
Pooled	51.1	52.0	55.2	54.8	53.3

Note: In sample is 1987 to 2008, out of sample is 2004 to 2008 recursive.

Table 8: When Does the TECM Model Outperform the Naïve Model?

(a) In sample	N	mean	s.d.	Sharpe	skew	min	max
All trades pooled							
Naïve	2438	0.0026	0.0297	0.3032	-0.6926	-0.1773	0.1180
TECM	2438	0.0057	0.0293	0.6691	0.3674	-0.1100	0.1773
Models agree							
Naïve	1547	0.0065	0.0270	0.8345	-0.2272	-0.1100	0.1180
TECM	1547	0.0065	0.0270	0.8345	-0.2272	-0.1100	0.1180
Models disagree							
Naïve	891	-0.0042	0.0329	-0.4387	-0.9740	-0.1773	0.0744
TECM	891	0.0042	0.0330	0.4427	0.9694	-0.0744	0.1773
(b) Out of sample	N	mean	s.d	Sharpe	skew	min	max
All trades pooled							
Naïve	539	-0.0025	0.0315	-0.2721	-1.0580	-0.1773	0.1038
TECM	539	0.0028	0.0315	0.3033	0.7006	-0.1056	0.1773
Models agree							
Naïve	373	0.0002	0.0278	0.0254	-0.3700	-0.1056	0.1038
TECM	373	0.0002	0.0278	0.0254	-0.3700	-0.1056	0.1038
Models disagree							
Naïve	166	-0.0085	0.0379	-0.7765	-1.4338	-0.1773	0.0736
TECM	166	0.0085	0.0379	0.7765	1.4338	-0.0736	0.1773

Note: In sample is 1987 to 2008, out of sample is 2004 to 2008 recursive. The Sharpe ratio is annualized. Other statistics are monthly.

Sharpes were -0.44 versus 0.44. Skew was -0.97 versus 0.97. Naïve suffered a worst trade of 17%, but the TECM had that on the plus side. TECM's worst month was only a 7% loss, and that was Naïve's best. These results explain why overall, the TECM did better: it avoided crashes, and when extreme returns were likely it was better able to pick the right side of the trade. Overall returns in TECM were 57 versus 26 bps per month for Naïve, Annual Sharpe was 0.67 versus 0.30, and skew was $+0.37$ versus -0.69.

The out-of-sample results in Table 8 panel (b) apply to the period of the credit crunch and great carry trade crash of 2008. These results only amplify the point further. Mean returns were not that different here, 28 versus -25 bps per month but they were at least up for TECM. Sharpe was $+0.30$ versus -0.27. Skew was the dramatically different factor in the crisis period: $+0.70$ for TECM versus -1.17 for the Naïve model.

To sum up, after several stages of refinement, our preferred TECM model surmounts the objections usually raised to justify excess returns to carry trades. The crudest, naïve long-short carry trade strategies, even with currency diversification, deliver Sharpe ratios well below investors' benchmark 1.0 threshold and crash-ridden returns displaying marked negative skew. But by conditioning on the real exchange rate and allowing for nonlinearity, our TECM portfolios deliver high returns with a Sharpe ratio 25%–50% above the conventional hurdle for an unexploited risky arbitrage opportunity.

3 Predictive Ability Evaluation

Is this all too good to be true? Out-of-sample predictive ability testing is the gold standard by which the success or failure of many models in economics is judged. The literature on the ability to predict exchange rates spawned by Meese and Rogoff (1983) has been particularly savage on the field: time and again the invincible random walk has emerged victorious against an onslaught of ever more sophisticated economic/econometric models of the exchange rate. The models investigated in the previous section are promising suitors but they must now face rigorous scrutiny.

The approach that we pursue in this section builds on some standard predictive ability measures and brings in other techniques that are quite new in economics. Moreover, rather than just evaluating the ability to predict exchange rates per se, we are interested in evaluating a model's ability to generate attractive profits that have high Sharpe ratios and low skewness.

Recall our definition of ex-post nominal excess returns of a long FX position,

$$m_{t+1} = \Delta e_{t+1} + (i_t^* - i_t)$$

which we labeled *momentum* and let $\widehat{m}_{t+1}$denote the one-period ahead forecast. Since $(i_t^* - i_t)$ is known at time t, then the only source of uncertainty comes from the prediction of Δe_{t+1}. In practice, the position an actual trader takes (i.e., determining which currency to borrow in and which to invest in) depends on the sign of $\widehat{m}_{t+1}$ for which we define the dichotomous variable $\widehat{d}_{t+1}$. This variable takes the value of 1 if $\widehat{m}_{t+1} > 0$ and -1 otherwise, so that realized returns can be defined as

$$\widehat{\mu}_{t+1} = \widehat{d}_{t+1} m_{t+1}.$$

Setting the forecasting problem up as a binary choice or direction problem makes sense on a couple of dimensions. First, as a statistical matter, making successful continuous exchange rate (and hence, return) forecasts is a harder challenge, as those working in the Meese-Rogoff tradition have shown; but a directional forecast sets a lower bar, one that recent work suggests could be surmountable (Cheung, Chinn, and Garcia Pascual 2005). Second, it is all that is needed even in the case of equal-weight currency portfolios. Thirdly, directional forecasting is important for traders. Like other funds, currency strategies face the risk of redemptions or closure if negative returns are frequent and/or large. It is nice to pick the bigger winners, rather than just small ones, but not if the strategy risks blowing up. The point is only amplified when funds are leveraged. Thus from a trader's point of view, what is often most important is the ability to correctly predict the profitable direction of the carry trade and for this reason we introduce methods designed to evaluate a model's ability to correctly classify the data according to direction.

In this section we examine the directional predictive ability of our preferred models in two ways. First, we evaluate the quality of the binary signal itself using new techniques from signal detection theory. We then evaluate the performance of trading strategies based on the binary signal, using loss-function methods that can go beyond the prevalent RMSE criterion and instead be adapted to metrics of investment performance of interest to traders, like returns, Sharpe, and skewness.

3.1 Hits and Misses: The ROC Curve

Forecasts of a binary outcome are called *classifiers.* The biostatistics and engineering literatures provide techniques, rarely used in economics, for the statistical evaluation of models for classification (see Pepe, 2003 for a survey). Specifically, the *receiver operating characteristic* (ROC) curve characterizes the quality of a forecasting model and its ability to anticipate correctly the occurrence and non-ocurrence of pre-defined events.[22] For greater detail, we refer readers to another paper where we discuss and develop ROC techniques to evaluate investment performance (Jordà and Taylor 2009).

In our problem the directional outcome variable is $d_{t+1} = sign(m_{t+1}) \in \{-1, 1\}$, the ex-post profitable direction of the currency investment. Let the variable $\widehat{\delta}_{t+1}$ to be a scoring classifier such that for a given threshold c, $\widehat{\delta}_{t+1} > c$ is taken to indicate $\widehat{d}_{t+1} = 1$, and $\widehat{\delta}_{t+1} \leq c$ corresponds to $\widehat{d}_{t+1} = -1$ instead. Our classifier will be the predictions of the conditional means obtained with the models in Tables 2–5, so that $\widehat{\delta}_{t+1} = \widehat{m}_{t+1}$ but in what follows we maintain the more generic notation $\widehat{\delta}_{t+1}$.

Let $TP(c)$ denote the true positive rate defined as $P[\widehat{\delta}_{t+1} > c | d_{t+1} = 1]$, sometimes also called *sensitivity* or *recall rate,* and in the more familiar Neyman-Pearson nomenclature, 1 minus the

[22] The origin of the ROC curve can be traced back to radar signal detection theory developed in the 1950s and 1960s (Peterson and Birdsall, 1953), and its potential for medical diagnostic testing was recognized as early as 1960 (Lusted, 1960). More recently, ROC analysis has been introduced in psychology (Swets, 1973), in atmospheric sciences (Mason, 1982), and in the machine learning literature (Spackman, 1989).

Type II error, or the power of the test (the test here being the ability to correctly identify d_{t+1} with $h(\widehat{\delta}_{t+1})$, for any strictly monotonic function $h(.)$). Let $FP(c)$ denote the false positive rate defined as $P[\widehat{\delta}_{t+1} > c | d_{t+1} = -1]$ which is 1 minus the *specificity* or the Type I error, or the size of the test. Then the ROC curve is defined as the plot of $TP(c)$ against $FP(c)$ for values of $c \in (-\infty, \infty)$. Notice that when $c = \infty$, $TP(c) = FP(c) = 0$ and when $c = -\infty$ then $TP(c) = FP(c) = 1$ so that the ROC curve can be displayed in $[0, 1] \times [0, 1]$ space.

The 45-degree diagonal line corresponds to the ROC curve of a *uninformative classifier*, where, for any given observation, at any threshold, there is a 50-50 chance of correctly classifying the direction of trade. In this context, the 45-degree line corresponds to the natural null of the efficient markets hypothesis: on average, profitable trades cannot be predicted better than a coin toss and the classifier contains no information at any threshold. This is a natural benchmark in our analysis. Intuitively, the "better" a classifier is, the closer the ROC curve is to the *ideal classifier* that hugs the left and top edges of the unit square (and the further away it is from the 45-degree line). We now apply a formal test based on this intuition.

The *area under the curve* (AUC) measures the probability that the classifier for an observation whose outcome is $d_{t+1} = 1$ attains a higher value than that for an observation whose outcome is $d_{t+1} = -1$, that is $P[\widehat{\delta}^{+}_{t+1} > \widehat{\delta}^{-}_{t+1}]$ and where the superscript denotes the sign of the true outcome. Thus, the AUC ranges from 0.5 to 1, since for a simple coin toss the probability described previously would be 0.5. (Should any classifier deliver an AUC less than 0.5, its forecast could simply be inverted!)[23]

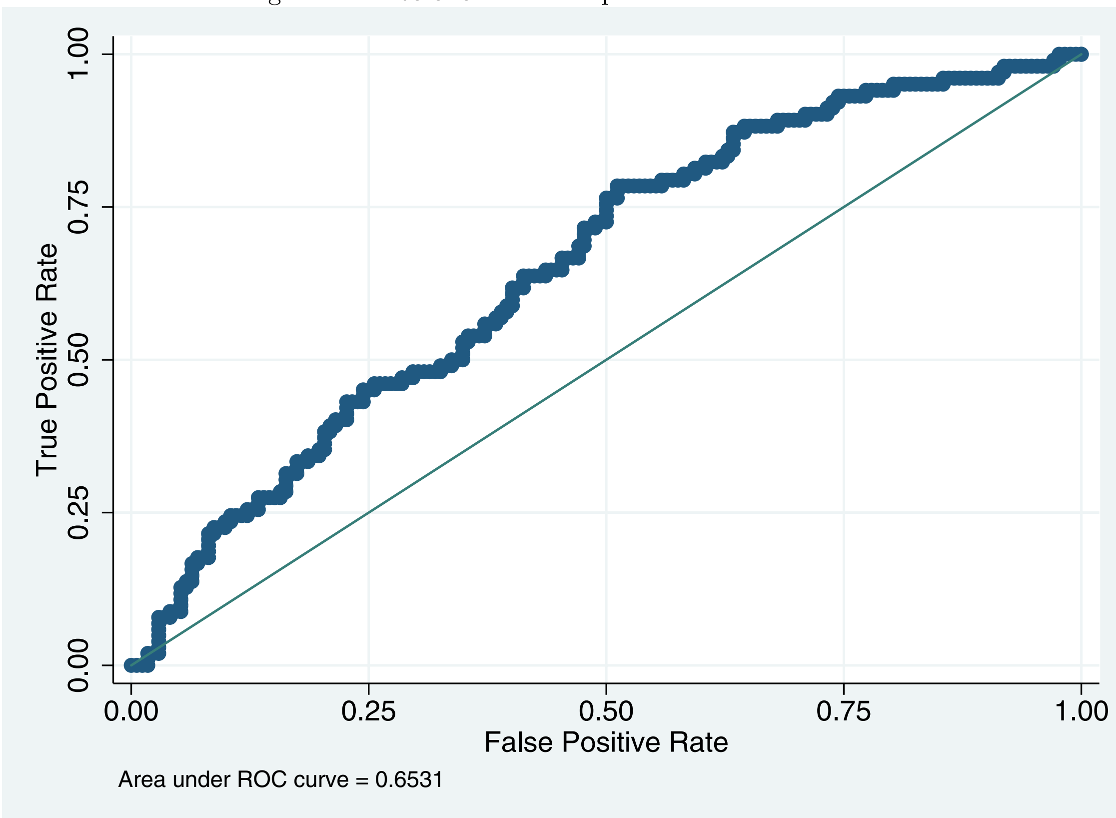
As an illustration using our data, Figure 1 shows a ROC graph. The ROC is displayed for the case of directional forecasts for the New Zealand dollar only, for the preferred TECM model, with in-sample predictions. In this case, the AUC is about 0.65 and statistically significantly different from the coin toss with a p-value of 0.0000. Obviously, we could generate a ROC graph for each model, country and sample—90 graphs in all—but this is clearly impractical. Instead we pool the data, and Table 9 shows the pooled AUC, in- and out-of-sample, for a concise summary. All models appear informative for the in sample case; but the results are weaker for the naïve models in the out-of-sample case. However, the VAR, VECM and TECM all deliver impressive out-of-sample z-scores that exceed 2 surmount the 5% significance level to reject the efficient markets null. By these criteria, G10 currency returns are clearly forecastable at a one month horizon, in a directional sense, at very high levels of statistical significance using our modeling approach.

3.2 Gains and Losses: The Return-Weighted ROC* Curve

The ROC analysis shows that our model is a good classifier of optimal direction. However, correctly classifying the direction of the trades without regard for the returns or losses generated by the classification is insufficient. For example, Tables 7 and 8 showed that although the TECM model

[23] The AUC statistic is closely related to the Wilcoxon-Mann-Whitney (WMW) U statistic of equality between classifiers by the relation: $U = n_{+}n_{-}(1 - AUC)$ where n_{+} refers to those observations for which $d_{t+1} = 1$, n_{-} refers to those observations for which $d_{t+1} = -1$, and U is asymptotically normal. Thus, AUC provides a second and more convenient non-parametric test for the quality of a classifier with respect to the coin toss and, in practice, it is the summary statistic commonly reported in ROC analysis. The U statistic is also known to be robust to heteroskedasticity (Conover 1999).

Figure 1: A ROC Curve Example: New Zealand Dollar



Notes: In-sample predictions using TECM Model. Sample: Apr. 1986 to Dec. 2008. Area under the curve for this case: AUC = 0.6531 (s.e.=0.0335, z=4.5673, p=0.0000).

does not pick winners any better than some simpler specifications, it is able to avoid large losses responsible for negative skewness in the distribution of returns. Thus, a classifier that correctly pinpoints 10 trades with low returns but misses a key trade that generates a devastating loss will be less desirable than a classifier that is equally accurate on average but correctly classifies the large events.

For this reason, Jordà and Taylor (2009) introduce a novel refinement to the construction of the ROC curve that accounts for the relative profits and losses of the classification mechanism.[24] We proceed in the spirit of gain-loss measures of investment performance (Bernardo and Ledoit 2000) by attaching weights to a given classifier's upside and downside outcomes in proportion to observed gains and losses. This alternative performance measure will give little weight to right or wrong bets when the payoffs are small; but when payoffs are large it will penalize classifiers for picking trades that turn out to be big losers, and reward them for picking big winners.

To keep the new curve normalized to the unit square, consider all the trades where "long FX" was the ex-post correct trade to have made. The maximum gain from classifying all these trades

[24] A similar improvement to ours is the instance-varying ROC curve described in Fawcett (2006).

Table 9: Area Under the ROC Curve

Model	AUC	s.e.	z-score	p-value
(a) In Sample				
Naïve	0.5905	0.0115	7.85	0.0000
Naïve ECM	0.5604	0.0116	5.19	0.0000
VAR	0.5996	0.0115	8.67	0.0000
VECM	0.5935	0.0115	8.11	0.0000
TECM	0.6084	0.0114	9.47	0.0000
(b) Out of sample				
Naïve	0.5170	0.0249	0.68	0.4949
Naïve ECM	0.5245	0.0249	0.99	0.3236
VAR	0.5654	0.0247	2.65	0.0081
VECM	0.5778	0.0246	3.17	0.0015
TECM	0.5541	0.0247	2.19	0.0284

Notes: In sample is 1987 to 2008, out of sample is 2004 to 2008 with recursive estimation. The AUC statistic is a Wilcoxon-Mann-Whitney U-statistic with asymptotic normal distribution and its value ranges from 0.5 under the null to a maximum of 1 (an ideal classifier). See Jordà and Taylor (2009).

correctly with $\widehat{d}_{t+1} = 1$ would be

$$B_{\max} = \sum_{d_{t+1}=1} m_{t+1}.$$

Now consider all the trades where "short FX" was the ex-post correct trade to have made. Similarly, the maximum loss from misclassification of these trades, and going long in them, would be

$$C_{\max} = \sum_{d_{t+1}=-1} m_{t+1}.$$

We can now redefine, or rescale, the true positive and false positive rates $TP(c)$ and $FP(c)$ in terms of the upside and downside returns m actually achieved, relative to the maximally attainable gains and losses thus defined. For any given threshold c, this leads to new statistics as follows:

$$TP^*(c) = \frac{\sum_{\widehat{d}_{t+1}=1|d_{t+1}=1} m_{t+1}}{B_{\max}}; \quad \text{and} \quad FP^*(c) = \frac{\sum_{\widehat{d}_{t+1}=1|d_{t+1}=-1} m_{t+1}}{C_{\max}}$$

The plot of $TP^*(c)$ versus $FP^*(c)$ is then, by construction, limited to the unit square, and generates what we term a *returns-weighted ROC curve*, which is denoted the ROC* curve. Associated with the ROC* curve is a corresponding return-weighted AUC statistic, denoted AUC*. Intuitively, if AUC* exceeds 0.5 this is evidence that the classifier outperforms the coin toss null from a return-weighted or gain-loss perspective. Detailed derivation of these statistics and their properties are provided in Jordà and Taylor (2009), along with techniques for inference.

Using these return-weighted statistics strongly reinforces our argument that classifiers based on our more refined models (VECM/TECM) are informative; in contrast the performance of the more naïve models are not statistically distinguishable from the coin-toss null. Table 10 collects summary AUC* statistics for the same in- and out-of-sample periods discussed in Table 9.

The AUC* statistics are higher than the corresponding AUC statistics reported in Table 9, and the z-scores attained are much higher too. The VECM and TECM appear to perform better

Table 10: Area Under the Return-Weighted ROC* Curve

Model	AUC*	s.e.	z-score	p-value
(a) In Sample				
Naïve	0.5690	0.0116	5.94	0.0000
Naïve ECM	0.6060	0.0114	9.26	0.0000
VAR	0.6291	0.0113	11.42	0.0000
VECM	0.6496	0.0112	13.41	0.0000
TECM	0.6769	0.0109	16.21	0.0000
(b) Out of sample				
Naïve	0.4355	0.0246	-2.62	0.0087
Naïve ECM	0.4961	0.0249	-0.16	0.8747
VAR	0.5720	0.0246	2.92	0.0034
VECM	0.6052	0.0243	4.37	0.0000
TECM	0.5912	0.0244	3.73	0.0002

Notes: In sample is 1987 to 2008, out of sample is 2004 to 2008 with recursive estimation. The AUC* statistic is a Wilcoxon-Mann-Whitney U-statistic with asymptotic normal distribution and its value ranges from 0.5 under the null to a maximum of 1 (an ideal classifier). See Jordà and Taylor (2009).

than the other less refined models, with TECM ahead in sample, and VECM slightly ahead out of sample, although the confidence intervals for the AUC measures are overlapping in these cases so there is not much to distinguish them.

Clearly, both of these models are unambiguously better than the coin toss, with a p-value of 0.0001 or less in all cases. This is perhaps to be expected: as we have shown earlier, the major benefit of the models presented here is not the better overall fit, but enhanced ability to get on the right side of big moves—and the weighted ROC* measure is ideally suited to provide evidence for this advantage. For completeness, Figure 2 shows the ROC* curve for New Zealand that complements the ROC curve in Figure 1. There are no substantive differences—the curves have a similar, slight asymmetric pattern, although in this case as well the AUC* attains a higher value than the AUC in Figure 1.

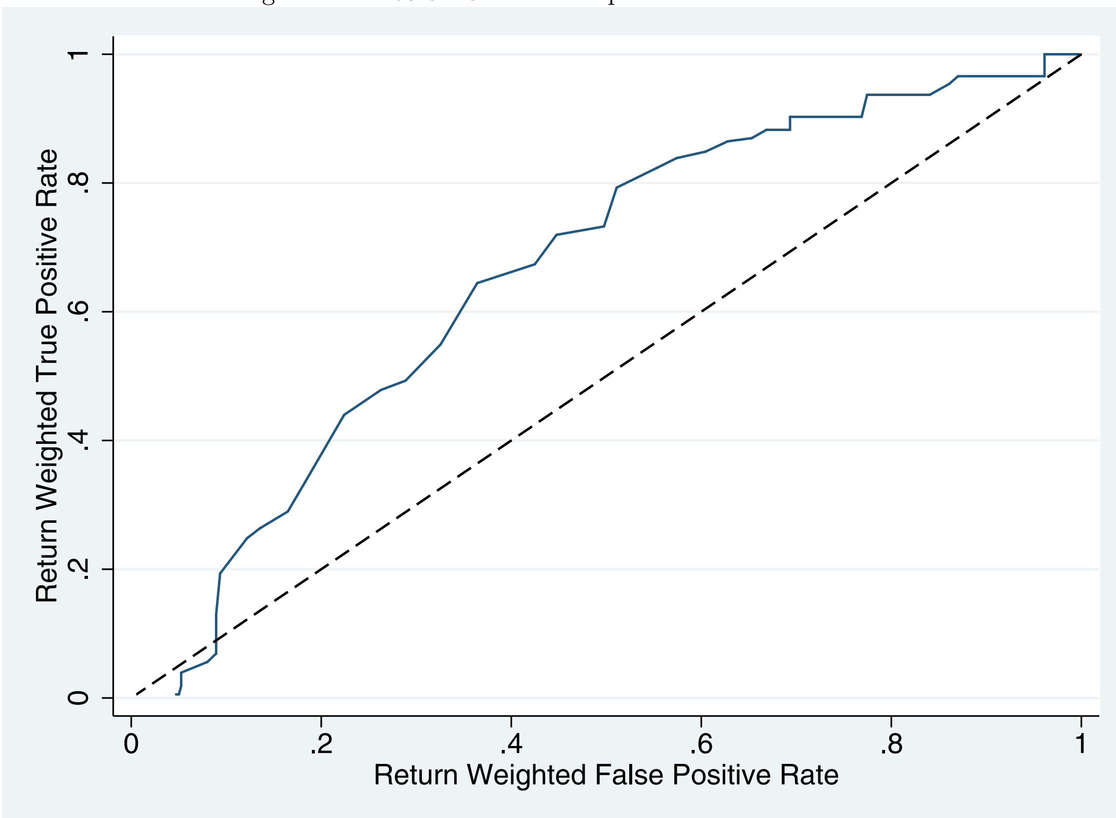
3.3 Beyond RMSE: Trading-Based Predictive Ability Tests

The ROC-based tests suggest that our preferred directional models are informative, at least in terms of getting the sign correct more often than a coin toss. But this is not the only performance metric of interest. Do any of our models generate meaningful improvement from a trader's perspective? And are some better than others in this regard? In this section we propose some flexible tests of predictive ability for use in this setting.

Extant tests designed to assess the marginal predictive ability of one model against another are based, generally speaking, on a comparison of the forecast loss function from one model to the other. Such is the approach proposed by the popular Diebold and Mariano (1995) and West (1996) frameworks and subsequent literature, with the usual choice of loss function being the root-mean squared error (RMSE).

The approach that we pursue is to consider a variety of loss functions and use a framework that naturally extends our ROC based analysis. For this purpose we generate a series of out-of-

Figure 2: A ROC* Curve Example: New Zealand Dollar



Notes: In-sample predictions using TECM Model. Sample: Apr. 1986 to Dec. 2008. Area under the curve for this case: AUC* = 0.6631 (s.e.=0.0347, z=4.6941, p=0.0000)

sample, one-period ahead forecasts from a rolling sample of fixed length. It is clear that in this type of set-up, estimation uncertainty never vanishes and for this reason we adopt the conditional predictive ability testing methods introduced in Giacomini and White (2006). These tests have the advantage of permitting heterogeneity and dependence in the forecast errors, and their asymptotic distribution is based on the view that the evaluation sample goes to infinity even though the estimation sample remains of fixed length.

Specifically, let $\{L^i_{t+1}\}^{T-1}_{t=R}$ denote the loss function associated with the sequence of one step-ahead forecasts, where R denotes the fixed size of the rolling estimation-window from $t = 1$ to $T - 1$, and let $i = 0, 1$ (with the index 0 indicating forecasts generated with the unit root null model and the index 1 indicating the alternative model). Then, the test statistic

$$GW_{1,0} = \frac{\Delta \overline{L}}{\widehat{\sigma}_L/\sqrt{P}} \xrightarrow{d} N(0,1) \tag{4}$$

provides a simple test of predictive ability, where

$$\Delta\overline{L} = \frac{1}{P}\sum_{t=R}^{T-1}\left(L_{t+1}^{1} - L_{t+1}^{0}\right);$$

and

$$\widehat{\sigma}_L = \sqrt{\frac{1}{P}\sum_{t=R}^{T-1}\left(L_{t+1}^{1} - L_{t+1}^{0}\right)^2}$$

(since $E(\Delta L) = 0$ under the null. See theorem 1 in Giacomini and White, 2006); and where $P = T - R + 1$.

The flexibility in defining the loss function permitted in the Giacomini and White (2006) framework is particularly useful for our application. The framework extends naturally to a panel context, where the forecasts for N different currencies over P periods are pooled together. In that case, assuming independence across units in the panel we may implement the above test with the observation count P replaced by NP. Because one may suspect that the panel units are not independent, we implement a cluster-robust covariance correction however.

The traditional summary statistic of predictive performance is the well-known root-mean squared error

$$RMSE_i = \sqrt{\frac{1}{P}\sum_{t=R}^{T-1}(\widehat{m}_{t+1}^{i} - m_{t+1})^2}; i = 0, 1$$

where $\widehat{m}_{t+1}^{i} = E_t(m_{t+1}|\text{Model}= i)$ for $i = 0, 1$. Thus, one can assess whether differences in RMSE between models are statistically significant by choosing

$$L_{t+1}^{i} = \left(\widehat{m}_{t+1}^{i} - m_{t+1}\right)^2; i = 0, 1.$$

But even if $RMSE$ is a major focus of the academic literature, it is of little interest to those in financial markets, since models with good (poor) fit measured by $RMSE$ could still generate poor (respectively, good) returns. So what about investors' preferred performance criteria? Fortunately, the flexibility of the framework allows one to consider loss functions based on alternative metrics. Three natural ways to assess the advantages of different models from the perspective of the trades they generate are as follows:

First, the average return, defined for the evaluation sample as

$$RTN_i = \frac{1}{P}\sum_{t=R}^{T-1}\widehat{\mu}_{t+1}^{i}; i = 0, 1.$$

Second, the Sharpe ratio, defined for the evaluation sample as

$$SR_i = \frac{\frac{1}{P}\sum_{t=R}^{T-1}\widehat{\mu}_{t+1}^{i}}{\sqrt{\frac{1}{P}\sum_{t=R}^{T-1}\left(\widehat{\mu}_{t+1}^{i} - \overline{\mu}^{i}\right)^2}}; i = 0, 1.$$

Table 11: Forecast Evaluation: Loss-Function Statistics for Pooled Data

	RMSE ($\times$100)	RTN (annual %)	SR (annual)	SK (monthly)
(a) In sample, 1987–2008				
Naïve	2.93	3.23	1.08	-0.77
NECM	2.91	4.16	1.32	0.06
VAR	2.89	5.42	1.83	-0.26
VECM	2.87	6.46	2.19	0.24
TECM	2.83	7.35	2.42	0.34
(b) Out of sample, 2004–2008				
Naïve	2.23	-2.84	-1.01	-1.00
NECM	2.22*	-0.80	-0.21	-0.36
VAR	2.21	2.23*	0.72	-0.17*
VECM	2.20	3.70*	1.22	0.44*
TECM	2.20	3.27*	0.92	0.64*

Notes: * indicates the GW statistic against the Naïve null based on the corresponding loss function, is significant at the 95% confidence level. To correct for cross-sectional dependence, a cluster-robust covariance correction is used. See text.

Third, and finally, the skewness of realized returns

$$SK_i = \frac{\sqrt{P(P-1)}}{P-2} \frac{\frac{1}{P}\sum_{t=R}^{T-1}\left(\widehat{\mu}_{t+1}^{i} - \overline{\mu}^{i}\right)^3}{\left(\frac{1}{P}\sum_{t=R}^{T-1}\left(\widehat{\mu}_{t+1}^{i} - \overline{\mu}^{i}\right)^2\right)^{3/2}}; i = 0, 1.$$

where $\overline{\mu}^i = \frac{1}{P}\sum_{t=R}^{T-1}\widehat{\mu}_{t+1}^i$ for $i = 0, 1$. Thus, this Sharpe ratio measures the out-of-sample risk/return profile of the carry trade strategies implied by competing forecasting models, whereas the skewness coefficient allows us to assess the models' ability to avoid infrequent but particularly large negative returns. The associated loss functions are derived as in the case of the $RMSE$ and summarized in the appendix for completeness.

Table 11 summarizes the full in-sample and the out-of-sample loss functions: RMSE (in percent); Annualized Return (in percent); Annualized Sharpe Ratio; and the monthly Skewness coefficient for each of the models in Tables 2, 3, and 5; that is the Naïve (null); the Naïve ECM; the VAR, the VECM; and the TECM models. For panel (b), which contains the out-of-sample results, an asterisk indicates that the Giacomini-White (2006) statistic associated to the loss function in that column is significant at the conventional 95% confidence level (as compared to the Naïve model in row 1). Results for pooled month-year observations are shown. The results in column 1 show that the difference in the models as judged by RMSE are miniscule. However, measured by metrics that matter to traders, the differences are considerable. For example, in our preferred model, in-sample the difference in annual mean returns is +3.23 for Naïve versus +7.35 percent for TECM. Out-of-sample the period includes the period of carry trade crashes, and the difference is -2.84 versus +3.45 percent (panel b). Annual Sharpe Ratios for pooled returns are boosted from +1.08 to +2.42 in-sample, and from -1.01 to +0.92 in the turbulent out-of-sample period. Skewness improves from -0.77 to +0.34 in-sample, and from -1.0 to +0.64 out-of-sample. There is little doubt which of these returns a currency hedge fund manager would have preferred.

The GW tests also show that, with the exception of skewness, these performance improvements are statistically significant, out-of-sample, relative to the Naïve model.

4 Alternative Crash Protection Strategies

In this section we compare the merits of our fundamentals-based model with the recent literature, where two alternative crash protection strategies have emerged. The first is a contract-based strategy: Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008ab) explore a crash-free trading strategy where FX options are used to hedge against a tail event that takes the form of a collapse in the value of the high-yield currency. The second is a model based strategy: Brunnermeier et al. (2008) argue that an important cause of carry trade crashes is the arrival of a state of the world characterized by an increase in market volatility or illiquidity.

4.1 Options

In Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008ab) a naïve carry trade strategy is the starting point. Traders go long the high yield currencies and short the low yield currencies. The focus is also on major currencies, as here, although the sample window goes back to the 1970s era of capital controls, and applies to a larger set of 20 currencies. Returns may be computed for individual currencies, portfolios, of for subsets of currencies (e.g., groups of 1, 2 or 3 highest yield currencies against similar groups of lowest yield currencies). However, each naïve strategy can be augmented by purchase of at-the-money put options on the long currencies.[25]

This augmentation leads to positive skew by construction. It averts tail risk, but at a price. How large is that price? For the 1987/1 to 2008/1 period a naïve unhedged equally-weighted carry trade had a return of 3.22% per annum with an annualized Sharpe ratio of 0.54 and a skewness of -0.67. This compares with the U.S. stock market's 6.59% return, 0.45 Sharpe ratio, and skewness of -1.16 over the same period. Normality of returns is rejected in both cases.

Implementing the options-based hedged carry trade boosts the Sharpe ratio a little, eliminates the negative skew, but at a significant cost. Added insurance costs of 0.71% per annum mean that the hedged strategy lowers returns to only 2.51% annually, has a Sharpe of 0.71, and a significant positive skew of 0.75. Thus on an annualized basis the hedged strategy costs 80 bps, and still fails to bring the Sharpe close to the mythical 1.0 hurdle.

In contrast, let us now compare our similar equal-weight naïve carry trading strategy with our nonlinear fundamentals-based return-forecast strategy, in Table 6, panel (a). Comparing Models (1) and (5), our strategy increases returns from 29 to 46 bps per month, and still eliminates negative skew. For comparison, on an annualized basis, the return rises from 3.45% to 5.55%, a gain of 210 bps, with a Sharpe ratio of 1.34. Unlike the options-based strategy, our approach can increase returns and lower skew at the same time.

We make some further observations. To be fair, we recognize that the strategies implemented by Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008ab) are crude and mainly illustrative.

[25] This strategy is also studied by Bhansali (2007).

The options they employ are at-the-money, and push skew into strong positive territory. In reality, investors might purchase option that are more out-of-the-money; at much lower costs, this could protect against only the large crashes, yet still eliminate the worst of the negative skew (Jurek 2008). Nonetheless, even if lower cost option strategies are found, our results suggest that there is a better no-cost way to hedge against crashes by using data on deviations from long-run fundamentals, and this information also serves to boost absolute returns and Sharpe ratios too. Moreover, options contracts have other drawbacks, many of which were shown to be salient issues after the financial crash of 2008. Option prices embed volatility, so in periods of turmoil the price of insurance can rise just when it is most needed, depending on the implied FX volatility (Bhansali 2007). And as with all derivatives, options carry counterparty risk. In addition, options price and position data from exchanges may not be representative, since this activity represents only a tiny fraction of FX option trading, the vast majority being over-the-counter. Also, like forwards and futures derivatives, options carry bid-ask spreads that can explode such as to make markets dysfunctional in crisis periods. Finally, whilst Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008ab) show the viability of an options-based strategy for 20 widely-traded major currencies, FX derivative markets are thin to nonexistent for many emerging market currencies, and bid-ask spreads can be wide, so in those markets currency strategists may have to seek alternative plain-vanilla approaches, like ours, that might help avert currency crash risk.

4.2 VIX Signal

In Brunnermeier et al. (2008) it is argued that various forms of generalized asset market distress, by reducing risk appetite, may be significant contributors to carry trade crashes. The logic of the argument is that such conditions may prompt a pull back from all risky asset classes, leading to short-run losses via order flow effects, or the price impact of trades. To provide empirical support for this proposition the authors show that, on a weekly basis, changes in the VIX volatility index (a proxy for distress) correlate with the returns to naïve carry trade strategies—that is, trading strategies which do not condition on any information except the interest differential. An increase in VIX was found to correlate with lower carry trade returns, all else equal, suggesting that liquidity risk might partially explain the excess returns. However, lagged changes in VIX had little or no predictive power for next periods returns. This prompts us to explore whether the same arguments hold true in our sample, and if we detect any difference when we use our preferred trading strategy. We found that in our data, using the same 1992–2006 sample period, at a *monthly frequency*, there was no evidence that the change in VIX was correlated with returns contemporaneously, nor that it helped predict next period's returns.

Specifically, in the spirit of Brunnermeier et al. (2008), we computed loadings of the returns on the contemporaneous and lagged change in VIX. We first regressed the actual (signed) returns of trades based on the naïve model on the contemporaneous change in VIX for all months and all currencies in our data over their sample period 1992–2006. We then did the same for the lagged change in VIX. We then re-ran both regressions using the actual (signed) returns of our preferred TECM model. In none of the four regression was the slope coefficient significant, and in all cases it actually had the "wrong" positive sign, suggesting that rising VIX was slightly positively correlated with profits this month, or next month.

We make some further observations. To be fair, we should note that Brunnermeier et al. (2008) present these results at a weekly frequency. In our dataset, we have to work at monthly frequency given the underlying price index data used to construct the real exchange rate fundamental signal. We conjecture that the VIX signal may have stronger correlations with current or future returns at weekly or even fortnightly frequency, even when placed in a model like ours augmented to account for real exchange rate fundamentals, although further research is warranted in this area.

If the sample is extended using our full dataset, including through the volatile crisis period in 2007–2008, the coefficients are not stable and we do sometimes find a statistically significant role for VIX signals in predicting negative actual (signed) returns of the naïve Model 1, although this episode is outside the window considered by Brunnermeier et al. (2008). But this result disappears, and the sign even reverses, when we include the real exchange rate term and use our preferred TECM model, suggesting that the real exchange rate deviation alone may serve as an adequate crash warning. In fact, in these models the sign of the coefficient on the change in VIX was often positive and significant, suggesting potentially the opposite interpretation: when VIX is rising, arbitrage capital may be being withdrawn, but this has a tendency to leave more profits on the table for the risk tolerant, or "patient capital," and for traders pursuing profitable fundamental-based strategies with inherent skew protection of the sort developed here.

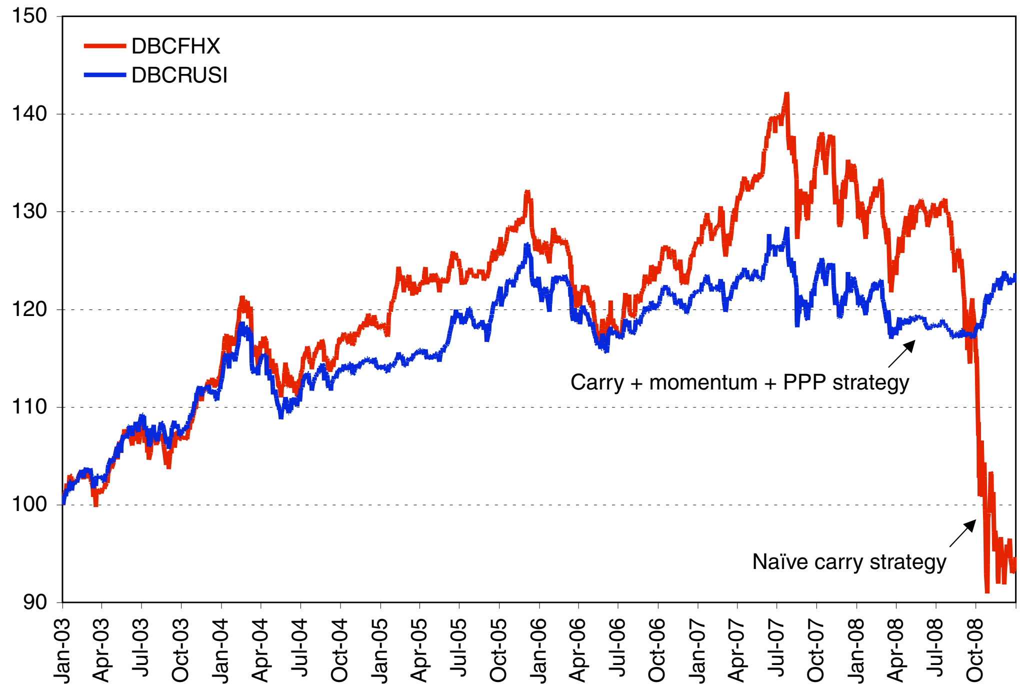
5 Reality Check: Exchange Traded Funds

Beyond out-of-sample forecasting, an alternative way to judge our preferred modeling and trading strategies against the naïve benchmark is to compare the recent performances of different currency funds in the real world. When comparing the merits of naïve versus fundamentals-based strategies, the relative performance of these funds in the financial crisis 2008 proves to be very revealing.

First, we seek a fund representative of the naïve long-short approach, the basic carry strategies of Burnside, Eichenbaum, and Rebelo (2008), and the same authors with Kleshchelski (2008ab), henceforth BER/K. For this purpose we focus on the Deutsche Bank G10 Currency Harvest USD Index (AMEX: DBCFHX, Bloomberg: DBHVG10U). This index has been constructed back to March 1993 using historical data. Since April 2006 this index has been made available to retail investors—in the United States, for example, it trades as the Powershares DB G10 Currency Harvest Fund (AMEX: DBV). These indices track a portfolio based on 2:1 leveraged currency positions selected from ten major "G10" currencies with the U.S. dollar as a base. For every \$2 invested, the index goes long (+\$1) in the three currencies with the highest interest rates, and short (\$-1) in the three with the lowest interest rates, and with 0 invested in the other three, with \$1 placed in Treasuries for margin. The portfolio is reweighted only every quarter and is implemented via futures contracts. If the U.S. dollar is one of the long or short currencies, that position makes no profit in the base currency and is dropped, so leverage falls to 1.66.

This ETF's naïve approach to forecasting any currency pair via the carry signal matches the BER/K approach. The main differences are that the index is not equal weight and tries to pick

Figure 3: Naïve Carry ETF versus Augmented Carry ETF, 2003–08



Notes: The ETFs are based the Deutsche Bank G10 Currency Harvest USD Index (DBCFHX) and Deutsche Bank Currency Returns USD Index (DBCRUSI). The indices predate the ETF inception dates.

6 winners out of 9, the fund's leverage is finite and so this fund has to pay the opportunity costs of satisfying the margin requirement, and the fund also changes a 0.75% per annum management fee. The performance of the index in the period 2003 to 2008 is shown in Figure 3, where the starting value of the index is rebased to 100. The first four years, up to mid/late 2007 were a golden age for naïve strategies: the index return was about 10% per year, and the index peaked over 140 in mid-2007. Even after some reversals, as late as the middle of 2008 the index stood at 130, and was up 30% on January 2003 levels.

Based on a similar, strong performance by their trading strategy through mid-2007, the virtues of a naïve carry trade strategy, protected only by cross-currency diversification, were praised by Burnside, Eichenbaum, and Rebelo (2008, 588):

> It is much less obvious what particular peso problem can explain the high Sharpe ratio associated with the equally weighted carry trade. That strategy seems to involve "picking up pennies in front of an unknown truck that has never been seen."

Unfortunately, in the second half of 2008 the Naïve-BER/K type of carry trade strategies were hit by the financial equivalent of a runaway eighteen-wheeler. The index gave up about 10% in the third quarter and a further 20% in October in a major unwind. After all that the index stood below its January 2003 level of 100, and four and a half years of gains had been erased.

Could a more sophisticated carry trade strategy have avoided this carnage, whilst still preserving positive returns overall? Yes. To see this we now look for a different index which matches better with our more sophisticated trading strategy. We focus on the Deutsche Bank Currency Returns USD Index (Bloomberg: DBCRUSI). This investible index operates on the same set of "G10" currencies but amalgamates three different trading signals for each currency, where again the signals are +1 (long), 0 (no position), and –1 (short). The first signal is the same as before: the naïve carry trade signal based purely on the interest rate, the 3-month LIBOR rate (The "Carry Index"), updated every three months. The second signal is based a calculation of the deviation of that currency from its FEER level, based on continuously updated common-currency price levels from the OECD (The "Valuation Index") updated every three months. The third signal is based on momentum, and takes into account the USD return to holding that currency in the previous period (The "Momentum Index") updated every month. Clearly this *augmented carry* strategy is much closer in spirit to our augmented models, given its mix of signals. In our model "carry" corresponds to the lagged interest differential; "momentum" corresponds mostly to the lagged exchange rate change (given persistence in the interest differential); and "valuation" corresponds to our monthly real exchange rate deviation.

The Deutsche Bank Currency Returns index is not currently available as an exchange traded fund in the U.S., but it is traded as an ETF in Frankfurt. A test of our approach is to ask: did investors in this more sophisticated fund fare better in 2008 than those invested in the naïve DBV fund. As Figure 3 shows, they did much better. On the 2003–07 upswing this index was less volatile, but returns were still strong, up about 28% at the peak. Momentum signals got the money quickly out of crashing currencies (and back in when they rose), and valuation signals hedged against dangerously overvalued currencies (and jumped in otherwise), tempering the naïve carry signal. The real test was in 2008. The index did remarkably well: performance was absolutely flat returns, and kept 20% of the cumulative gains locked in. Looking at the three components of this strategy, a 30%+ loss on the carry signal in 2008, was offset by a 10% gain on the PPP signal and a 20% gain on the momentum signal.

Notice how the relative performance of these ETFs closely matches the results of our trading strategies as shown back in Table 7. In the out of sample results the Naïve-BER/K type model showed a loss of 2.84% per year from 2004 to 2008. Our more sophisticated VECM showed a gain of 4.15% per year. That differential of 7% per year would cumulate to a roughly 30% divergence in index values over a four year period. Despite some differences in methods between our model simulations and the ETFs, this is almost exactly the cumulative divergence seen for the real-world ETFs in Figure 3.

Fundamentals matter. Comparing the two ETFs makes clear the gains from using a more sophisticated currency strategy incorporating a FEER measure. Although academic research has focused on the naïve strategies, it is no secret in the financial markets that more refined models, taking into account the signals discussed here and many others, are actively employed by serious fund managers and are now leaking out into traded products.[26]

[26] For example, in addition to the Deutsche Bank ETs, see also the FX Currents from Goldman Sachs.

6 Conclusion

The international financial crisis of the second half of 2008 effectively undid the majority of the persistent carry trade returns observed during the previous five to ten years. Strategies based on arbitraging interest rate differentials across countries under the belief that it was equiprobable for exchange rates to appreciate or depreciate displayed consistently positive average returns. But these returns were volatile and subject to occasional crashes (negative skewness). It can be argued then, that the observation of persistent carry trade returns does not violate the efficient markets hypothesis.

This paper instead shows that more sophisticated strategies that incorporate information about the fundamental equilibrium exchange rate can deliver positive returns with high Sharpe ratios and zero or even mildly positive skewness. We do not claim to be better at forecasting exchange rates than the ubiquitous random walk model in Meese and Rogoff (1983). We claim that we can predict better than the toss of a coin the direction of the carry trade that will produce positive returns. Our results indicate that this is no in-sample fluke and in fact, a thorough out-of-sample analysis that includes the turbulent period of the second-half of 2008, reaffirms the robustness of our claims. Moreover, the historical performance of real-world ETFs during this period (discussed in the previous section) corroborates our findings.

In addition to these findings, our paper makes two contributions to the empirical assessment of the directional predictive potential of alternative investment strategies. On the one hand, we adapt formal predictive ability tests with loss functions that better represent those characteristics that are most important to an investor, which do not necessarily correspond with those that have been traditionally important to an econometrician. Moreover, we introduce in this paper new techniques commonly used in biostatistics, the ROC curve and associated statistics, that are of considerable utility for investors. In a companion paper we have extended the discussion of the techniques introduced here in several dimensions. For instance, among some of the topics we cover, we discuss how to evaluate more sophisticated trading strategies that allow for long-short-cash positions (Jordà and Taylor 2009).

We believe that there is more work to be done that builds on the foundations of this paper. In this paper we have considered simple portfolio strategies based on equal- or return-tuned-weights, but clearly strategies that exploit the time-varying correlation structure across countries beg for more sophisticated portfolio designs. Similarly, a lesson from the ROC analysis introduced in this paper is that directional prediction can be fine-tuned to reflect the marginal trade-offs between return, volatility, and skew encapsulated in each investor's preferences.

However, both of these extensions naturally beg the question: Whither the efficient markets hypothesis?

Appendix

The loss functions of the Giacomini-White (2006) statistic in expression (4) corresponding to each of the three trading-based metrics are, for returns:

$$L_{t+1}^{i} = \widehat{\mu}_{t+1}^{i}; i = 0, 1;$$

for the Sharpe ratio

$$L_{t+1}^{i} = \frac{\widehat{\mu}_{t+1}^{i}}{\sqrt{\frac{1}{P}\sum_{t=R}^{T-1}\left(\widehat{\mu}_{t+1}^{i} - \overline{\mu}^{i}\right)^{2}}}; i = 0, 1;$$

and for skewness, we use Pearson's second definition of skewness to provide a comparable scale with the returns- and Sharpe ratio-based loss functions, specifically

$$L_{t+1}^{i} = \frac{3\left(\widehat{\mu}_{t+1}^{i} - \mu^{i}(0.50)\right)}{\sqrt{\frac{1}{P}\sum_{t=R}^{T-1}\left(\widehat{\mu}_{t+1}^{i} - \overline{\mu}^{i}\right)^{2}}}; i = 0, 1$$

where $\mu^{i}(0.50)$ refers to the median of $\widehat{\mu}_{t+1}^{i}$ for $t = R, ..., T-1$. The cluster correction that we use for the panel consists in computing the covariance matrix of the loss function difference across countries and standardizing by the inverse of its Cholesky decomposition.

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