This is a "preproof" accepted article for *Journal of Financial and Quantitative Analysis*.
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DOI:10.1017/S0022109019000887

Good Carry, Bad Carry

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October 16, 2019

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Abstract

We distinguish between "good" and "bad" carry trades constructed from G-10 currencies. The good trades exhibit higher Sharpe ratios and sometimes positive return skewness, in contrast to the bad trades that have both substantially lower Sharpe ratios and highly negative return skewness. Surprisingly, good trades do not involve the most typical carry currencies like the Australian dollar and Japanese yen. The distinction between good and bad carry trades significantly alters our understanding of currency carry trade returns, and invalidates, for example, explanations invoking return skewness and crash risk.

KEY WORDS: currency carry trade, predictability, currency risk factors

JEL CLASSIFICATION CODES: C23, C53, G11,

I Introduction

The currency carry trade, which goes long (short) currencies with high (low) yields continues to attract much research attention, as it has been shown to earn high Sharpe ratios, while its returns are largely uncorrelated with standard systematic risks (e.g., Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov, and Verdelhan (2011)). Prototypical carry currencies among the liquid G-10 currencies are the Swiss franc (CHF) and Japanese yen (JPY), which almost always exhibit the lowest yields and hence a typical G-10 carry trade would short them, and the New Zealand dollar (NZD) and Australian dollar (AUD), which typically have the highest yields and would be held long. These 4 currencies feature prominently in extant explanations of the returns of the carry trade. One such explanation invokes crash risk (e.g., Brunnermeier, Nagel, and Pedersen (2009)) and thus relies implicitly on the fact that JPY and AUD provide the most "skewed" return perspectives from the view point of a U.S. investor. Another is based on the differential exposure to global productivity shocks of producers of final goods, such as Japan and Switzerland, versus commodity producers, such as Australia and New Zealand (Ready, Roussanov, and Ward (2017)).

While the prior literature takes for granted that the prototypical carry currencies[1] drive carry trade profitability, we document the existence of "good" and "bad" currency carry trades.

[1]To clarify terminology, we note that a key component of the return of a carry trade is the interest rate (or forward) differential between the investment and funding currencies that are long and short in the trade, respectively. This component is often, even if perhaps confusingly, referred to as "carry," and we also follow this tradition, for brevity. For the same reason we also sometimes refer to "carry currencies," "carry profitability," "carry returns," etc., instead of "carry trade currencies," "carry trade profitability" and "carry trade returns." The context is clear in all these cases, and should allow no ambiguity.

We consider an investor who sequentially tests whether reducing the set of G-10 currencies improves the historical Sharpe ratio, and then implements equal-weighted carry trades with fewer currencies. We find that such trades improve the return profile (in terms of *both* Sharpe ratio and skewness) relative to the carry trade which employs all G-10 currencies, and denote them as "good" carry trades. Most surprisingly, these good trades almost never include the AUD and JPY, or the NOK - another commodity currency. Next, we construct carry trades using fixed subsets of the G-10 currencies over the full sample, and find that trades involving only the prototypical currencies have lower Sharpe ratios and more negatively skewed returns. We denote them as "bad" carry trades. The trades using the remaining currencies preserve the desirable features of "good" carry trades.

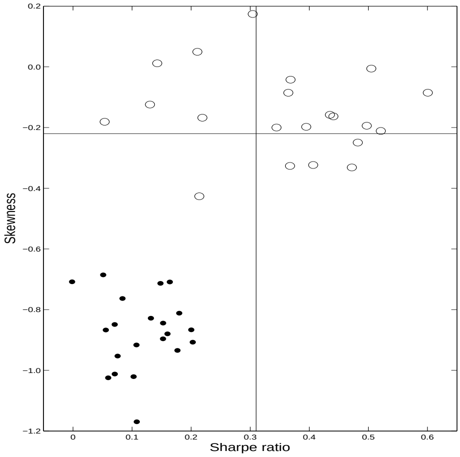
Providing a first glimpse on the issue, Figure 1 contrasts the return properties of carry trades that involve various subsets of the G-10 currencies. In particular, the figure plots (with black dots) the skewness versus Sharpe ratio for all carry trades constructed from *5* currencies that use 3 of the prototypical currencies (AUD, CHF, and JPY), together with any possible pair from the remaining 7 currencies. The currencies enter each trade with equal weights, as is common in the literature and finance industry. Strikingly, these 21 trades show worse Sharpe ratios, and also substantially lower skewness than the strategy that uses all G-10 currencies (denoted with the horizontal and vertical lines in the graph). Therefore, trades constructed predominantly from the prototypical carry currencies appear to be "bad" carry trades. We subsequently refer to the trade from all G-10 currencies as "standard carry" and denote it as SC.

Probing further, Figure 1 also displays (with unfilled circles) the skewness versus Sharpe ratio of the complements of the previous 21 carry trades, which are constructed with the remaining 5 currencies in each case, again with equal weights. It is noteworthy that 14 out of the

FIGURE 1

Good and Bad Carry Trades from Sets of 5 G-10 Currencies

Large black dots plot skewness versus Sharpe ratio of all possible 21 carry trades constructed from 5 G-10 currencies, which include the AUD, CHF, and JPY, together with any possible pair from the remaining 7 currencies. Circles with no fill plot similarly skewness versus Sharpe ratio for the complementary trades, each including the 5 currencies left out of 1 of the previous 21 trades. For each trade, currencies are sorted on their forward differentials (against the USD) at the end of each month over the period Dec. 1984–June 2014, and the 2 currencies with highest differentials are held long over the next month, while the two with the lowest premiums are shorted, all with equal weights. A vertical and horizontal lines indicate the Sharpe ratio and return skewness of the standard carry trade (denoted SC), constructed with all G-10 currencies. Percentage carry trade returns are calculated with spot and forward quotes from Barclays Bank, available via Datastream, and with transaction costs taken into account.



21 complement trades feature higher Sharpe ratios than that of the standard carry (SC) trade (in one case almost double that ratio), and 16 show higher (less negative or positive) skewness. Furthermore, half of the complement trades improve *both* on the skewness and Sharpe ratio of the SC trade, qualifying them as "good" carry trades. These findings cast doubt on efforts to explain carry trade returns by focusing on properties of the prototypical carry currencies, and undermine the practice of associating the carry trade predominantly with such currencies.

In Section IV we investigate the ability of good carry trades to function as risk factors for certain cross sections of currency returns (see, e.g., Lustig et al. (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012)). We find that good carry trades perform at least as well as previously suggested currency market risk factors, and sometimes drive out such factors in a horse race. We also re-examine the predictability findings in Bakshi and Panayotov (2013) and Ready et al. (2017), and find that previously identified carry return predictors strongly predict the returns of bad, but not of good carry trades. In Section V we revisit several interpretations of carry returns that have been advanced in the recent literature, including the explanatory ability of factor models with equity market risk factors, a crash risk explanation of their returns as in Brunnermeier et al. (2009), and the peso problem hypothesis of Burnside et al. (2011). Almost invariably, the results differ greatly across good versus bad carry trades.

In Section VI, we further explore the properties of good and bad carry trades to kindle research on economic models that may explain the strong differences between the two types of trades. We show, for example, that the returns of bad (good) trades derive mostly from the gain that comes from investing at the higher interest rate while borrowing at the lower interest rate, which is partially offset (reinforced) by exchange rate changes. We also examine the relationship between good carry trades and the "dollar carry" trade introduced in Lustig, Roussanov, and

Verdelhan (2014), which goes long (short) all currencies relative to the U.S. dollar when the average foreign interest rate differential relative to the dollar is positive (negative). Because our good carry trades always involve the dollar, they do show substantial return correlation with dollar carry, but we demonstrate that they clearly present a distinct currency and economic risk.

Before introducing “good” and “bad” carry trades in Section III, we describe the data in Section II and discuss some important concepts regarding the design of carry trades. The remainder of the article demonstrates how the good-bad trade distinction fundamentally alters our thinking about carry trades.

II Data and Carry Trade Design

Following previous work, we employ currency spot and forward contract quotes to construct carry trade returns. Using 1-month forward quotes on the last trading day of each month in the sample, and spot quotes on the last day of the following month, we calculate 1-month carry trade returns over the sample period from Dec. 1984 till June 2014 (354 monthly observations). The return calculations take into account transaction costs, exploiting the availability of bid and ask quotes. The data comes from Barclays Bank, as available on Datastream, and have been used in Burnside et al. (2011) and Lustig at al. (2011), (2014), among many others.

Our results are reported for percentage returns and equal (absolute) weights of the currencies entering a trade. On two occasions we report instead results with (natural) logarithmic returns or weights proportional to forward differentials, to facilitate comparability with previous studies.

Let S_t^i (F_t^i) denote the spot (forward) exchange rate of currency i at time t, quoted as foreign currency units per U.S. dollar. That is, the U.S. dollar is the benchmark currency and all trades are implemented relative to the dollar. Then, with t indicating the end of a given month, the percentage excess 1-month return at $t+1$ of one dollar invested at t in a long (short) forward foreign currency contract is:

$$(1) \qquad \mathrm{Rx}_{t+1}^{i,\mathrm{long}} = F_t^{i,\mathrm{bid}}/S_{t+1}^{i,\mathrm{ask}} - 1 \qquad \text{and} \qquad \mathrm{Rx}_{t+1}^{i,\mathrm{short}} = 1 - F_t^{i,\mathrm{ask}}/S_{t+1}^{i,\mathrm{bid}},$$

whereby bid and ask quotes are denoted in the superscript.[2]

We employ the G-10 currencies, which are the New Zealand dollar (NZD), Australian dollar (AUD), British pound (GBP), Norwegian krone (NOK), Swedish krona (SEK), Canadian dollar (CAD), U.S. dollar (USD), euro (EUR), Swiss franc (CHF), and Japanese yen (JPY), whereby prior to 1999 the German mark (DEM) is used instead of the euro. These currencies represent the most liquid traded currencies, and are most often used both in the academic literature and professional practice to construct carry trades.

As indicated previously, the carry trades that we consider go long and short an equal number of currencies relative to the USD, with equal weights. Various alternative weighting schemes are possible, mostly based on the magnitude of the interest rate differentials (see Table 1 for concrete examples from practice and the academic literature), but we prefer to keep the trade as simple as possible. Moreover, the total investment each period is one dollar, that is, the sum of all long and short positions (in absolute value) equals 1. Specifically, when the trade uses all G-10 currencies, the 5 currencies with the lowest interest rates at the end of each month are shorted, and the remaining 5 are held long. In practice, we rank the currencies based on their forward differentials (FD) relative to the U.S. dollar, defined as $\mathrm{FD}_t = F_t/S_t - 1$ at time t and calculated using mid-quotes. The weight of currency i held long (short) is $\omega_t^i = 1/10$ ($\omega_t^i = -1/10$). The

[2]These can also be seen as the payoffs to forward contracts in the foreign currency per "forward" dollar.

percentage excess return of this trade from t to $t+1$ is:

$$\text{(2)} \qquad \mathrm{Rx}_{t+1}^{\mathrm{carry}} = \sum_{i=1}^{10} \left\{ \mathbf{1}_{\omega_t^i > 0} \omega_t^i \, \mathrm{Rx}_{t+1}^{i,\mathrm{long}} - \mathbf{1}_{\omega_t^i < 0} \omega_t^i \, \mathrm{Rx}_{t+1}^{i,\mathrm{short}} \right\},$$

where $\mathbf{1}_{(\cdot)}$ is an indicator function.

When a subset of N currencies is used to construct a carry trade and N is even, we set $\omega_t^i = 1/N$ or $-1/N$ in (2) and substitute N for 10. If N is odd, the currency with the median forward differential is dropped from the trade, and we use $N-1$ instead of N in the definition of ω_t^i and the summation in equation (2).

We consider carry trades that are *symmetric*, in that they have an equal number of short and long positions, with equal total weights on the long and short side. Currencies are ranked according to their interest rates, and only the rank determines whether the position taken is short or long, while the signs of the interest rate differentials are irrelevant for the trade design, as these change with the currency perspective (see also Clarida, Davis, and Pedersen (2009)). Importantly, our carry trade design also ensures (approximate) *numeraire independence*, as we do *not* give a special role to the benchmark currency, and hence the positions taken in the various participating currencies are the same, regardless of the benchmark. Numeraire independence is an attractive property, and implies that only one currency trade must be defined for the world at large. Moreover, the returns on such a trade are very similar from any currency perspective, because the translation from one currency to another simply introduces cross-currency risk on currency returns, which is a second-order effect. In fact, the logarithmic returns of our strategies are *exactly* the same from any perspective, by triangular arbitrage (see Maurer, Tô, and Tran (2019) for further discussion). The major commercial investable carry products delivered by the major players in the foreign exchange market, such as Deutsche Bank or Citibank, described in Table 1, are symmetric and numeraire-independent as per our definition. They do not all assign equal weights to all positions however, for example, the well-known tradeable Deutsche Bank carry strategy takes only the 3 highest- and lowest-yielding currencies among the G-10 currencies.

Nonsymmetric trade designs are also possible, and have been considered, for example in a recent well-recognized article by Burnside et al. (2011), where all currencies with interest rates that are higher (lower) than the U.S. dollar interest rate are bought (sold) in equal proportions. Such a strategy is obviously not symmetric, and also may deliver very different results depending on the benchmark currency (see Daniel, Hodrick, and Lu (2017) for further discussion). Another example of a nonsymmetric trade is the "dollar carry" trade, studied in Lustig et al. (2014). These trades are also "dollar-neutral," excluding positions in the benchmark currency (which would generate zero excess returns). In contrast, our symmetric trades are *not* dollar-neutral: positions in the benchmark currency are explicitly included.

III Good and Bad Carry Trades from the G-10 Currencies

In this section we first outline a disciplined approach to create historically attractive symmetric carry trades from subsets of the G-10 currencies, exploiting all available foreign exchange history at each point in time. It evaluates on each trading date whether excluding currencies can improve on the standard carry (SC) trade that uses all G-10 currencies, and if so, which currencies should be excluded. Because of its dynamic implementation, the procedure yields out-of-sample results. Next, we exploit the information garnered in his exercise to create fixed subsets of "good" and "bad" currencies that do not change over time, and use them to construct carry trades over the full sample period.

A Enhancing the Currency Carry Trade

Imagine an investor starting to trade at the end of Dec. 1994 ($t = T_1$). On this date, and at the end of each month going forward till May 2014 ($t = T_2$), he uses all available return information for the period since Dec. 1984 ($t = T_0$) and first calculates the Sharpe ratio (denoted "benchmark Sharpe ratio") of the standard carry (SC) trade that employs all G-10 currencies. The trade ranks these currencies according to their forward differentials at the end of each month between T_0 and $t-1$, for $t = T_1, \ldots, T_2$, and goes long (short) over the following month the 5 currencies with the highest (lowest) forward differentials, all with equal weights.

To create an enhanced carry trade with 9 currencies, on date t the investor excludes one by one each of the G-10 currencies, and computes the Sharpe ratios over T_0 to t of the 10 possible trades that involve only 9 currencies. These trades exclude the currency with the median forward differential at the end of each month between T_0 and $t-1$ and go long (short) the 4 currencies with the highest (lowest) differentials. If the highest of the 10 Sharpe ratios obtained in this way exceeds the benchmark Sharpe ratio, an *enhanced trade* is implemented over the following month (t to $t+1$) using the 9 currencies corresponding to this highest Sharpe ratio, while the one currency left out of the trade is the first to be excluded on date t. If, on the other hand, all 10 Sharpe ratios are lower than the benchmark ratio, then no currency is excluded and the enhanced trade for this date has the return of the standard trade.

Note that the dynamic and real-time nature of this enhanced trade could, in principle, result in a substantially different currency mix used at different points of time. Further, our enhancement rule is intentionally simple and uses an easily understood and popular performance measure, whereas a wide range of sophisticated optimization rules could be applied in this context as well (see, e.g., Barroso and Santa-Clara (2014)). Mimicking the construction of the enhanced trade that uses 9 currencies, we construct analogous enhanced trades that exclude more than one of the G-10 currencies. In particular, on date t when 1 currency has been excluded, we use the remaining 9 currencies to find the highest Sharpe ratio across the 9 possible trades that involve only 8 currencies. Again, if this highest ratio exceeds the benchmark Sharpe ratio, the currency that was omitted to achieve it is the second currency to be excluded for this date, whereas if all Sharpe ratios are lower than the benchmark one, no further currency is excluded and the enhanced trade that uses 8 currencies has the return of the standard trade for that date. Similarly, we attempt to exclude up to 7 of the G-10 currencies on this date t, and thus obtain 7 enhanced trades, which use a decreasing number of currencies. Importantly, we record the exact order in which currencies have been excluded. The above procedure is repeated on each date in the sample to obtain time series of returns of the 7 enhanced carry trades.

For completeness of the search algorithm, we have postulated that if no improvement on the benchmark Sharpe ratio can be achieved for a certain date and number of excluded currencies, then no further currencies are excluded on this date, and all enhanced trades with fewer currencies have the return of the standard trade. In practice, however, this choice is inconsequential.

B Return Patterns for Enhanced Trades

Table 2 presents results for the enhanced carry trades that allow excluding from 1 to as much as 7 currencies on each trading date, and, for comparability, for the standard carry trade. Returns are computed as described in Section II, with equal currency weights and in percentages. Panel A of Table 2 reports the annualized average returns, annualized Sharpe ratios, and return skewness for each carry trade, with interest in skewness justified given its important role in certain explanations for the carry trade returns (e.g., Brunnermeier et al. (2009), Jurek (2014)).

Also reported are p-values for the hypothesis that the respective Sharpe ratio or skewness does not exceed that for the standard trade SC. Because carry returns tend to be negatively skewed, we cannot rely on standard tests for the difference between Sharpe ratios, as for example in Jobson and Korkie (1981) or Memmel (2003), that apply to Gaussian distributions. Therefore, we resort to the bootstrap tests, described in Ledoit and Wolf (2008) for Sharpe ratios, and Annaert, Van Osselaer, and Verstraete (2009) for skewness (see Appendix OA-II for details). Our p-values use 1-sided bootstrap confidence intervals, as the enhanced carry trades are designed with the goal to improve on SC.

The SC trade has an annualized Sharpe ratio of 0.32, and return skewness of -0.33. The benchmark Sharpe ratio is thus close, for example, to the value of 0.31 for the HML trade reported in Lustig et al. (2014) for their set of developed countries, over a similar sample period and using equal weighting and bid and ask quotes. When 1 currency is excluded from the carry trade on each trading day, practically no change is observed, but when 2 currencies are excluded, the Sharpe ratio increases to 0.41, while skewness drops to -0.57. When 3–6 currencies are excluded, the Sharpe ratios remain somewhat higher than the benchmark ratio (between 0.41 and 0.46), with the differences not statistically significant. However, skewness improves sharply in 3 out of these 4 cases and turns positive on 2 occasions (and as high as 0.21 on one), whereby 2 of the associated p-values are below 5% and another one equals 10%. These findings indicate a possible 2-dimensional beneficial effect of excluding 3 or more of the G-10 currencies, given that *both* the Sharpe ratio and skewness improve, albeit not always in a statistically significant way. This effect is further confirmed by the enhanced trade that excludes 7 currencies: the Sharpe ratio is now 0.61, while skewness is positive, and both are marginally significantly different from the benchmark values.

Our findings echo previous results, where significant improvements in skewness are obtained without a substantial change in the Sharpe ratio (e.g., the option-hedged carry trades in Burnside et al. (2011). However, what is surprising in our case is that the improvement of the return profile is i) in both dimensions, and ii) achieved simply by excluding currencies from the symmetric carry trade. Additionally, the 2-dimensional improvement is achieved by a procedure that maximizes the Sharpe ratios alone, without considering the skewness of the returns so obtained.

C Identity of the Excluded Currencies

While on each trading date the enhanced trade re-considers the available return history and thus can potentially deliver a different set of currencies to be excluded, we consistently observe the same currencies to be excluded. Panel B of Table 2 shows the number of months that each G-10 currency is excluded by our enhancement rule over the 234-month sample period of enhanced trading. In particular, it shows how many times the respective currency is the first, or among the first 2, or among the first 3, etc., to be excluded from the carry trade.

The consistency is observed most clearly with respect to the first 3 currencies excluded. Specifically, AUD is the first to be excluded on 135 out of the 234 trading dates in the sample. Furthermore, it is among the first 3 currencies to be excluded on a total of 192 dates. Similarly, NOK is among the first 3 excluded on 219 occasions, and JPY is among them on 214 occasions. These 3 currencies appear to be by far the most detrimental to carry trade Sharpe ratios - no other currency is ever excluded first, and only the EUR has been excluded second or third more than a handful of times.

The next currencies to be the most often excluded are the EUR, NZD, CAD, and CHF, and while the order of their exclusion is somewhat ambiguous, these are the obvious further candidates for exclusion by the enhancement rule. The remaining 3 currencies are clearly found valuable by the rule: GBP and SEK are among the first 7 to be excluded only on about 60 occasions each, and in fact are never among the first 4 excluded. Most conspicuously, however, the USD is never among even the first 7 excluded currencies, reminiscent of previous studies discussing the special role of the USD in the carry trade (e.g., Lustig et al. (2014), Daniel et al. (2017)) from various perspectives.

These findings are surprising, as the enhancement rule consistently excludes from the carry trade precisely the prototypical carry trade currencies, like the JPY and AUD, which have been perpetually among the lowest- or highest-yielding G-10 currencies, and feature commonly as examples in various carry trade discussions. Because the consistency refers to the *entire* period since 1994, the recent financial crisis, which witnessed drastic valuation changes in those currencies, cannot be solely responsible. Likewise, the enhancement rule also tends to exclude the NZD and CHF, which have also been among the few highest- or lowest-yielding currencies over our sample period.

The design of the enhancement procedure, as described in Section III.A, leaves open the possibility that on some date no improvement of the Sharpe ratio can be achieved after certain number of exclusions, whereby no further currencies are excluded and the respective enhanced trades are assigned the SC return for the next trading period. This possibility is of some concern, as it could blur the distinction between enhanced trades that exclude a different number of currencies. However, Panel B in Table 2 reveals that this has never happened in our sample, as evidenced by the fact that the sum of the numbers in the first row equals 234, the sum of those on the second row equals 234 $\times$ 2, and so on. Therefore, on each date in the sample period the enhancement rule has identified 7 currencies to be sequentially excluded, and hence 7 distinct enhanced trades to be implemented.

In sum, Table 2 shows that the enhancement rule consistently excludes the same few currencies from the carry trade, among which are those epitomizing the essential concept underlying carry trades that low (high) yield currencies should be sold (bought). The surprising evidence presented in the table thus calls for a reconsideration of this concept and/or its implementation.

D Good and Bad Carry Trades from Fixed Subsets of the G-10 Currencies

Prompted by the finding that the dynamic enhancement rule excludes the same currencies over and over, we now examine carry trades constructed with fixed subsets of the G-10 currencies. While staying close to the spirit of the enhanced trades, the fixed subsets allow for better comparison with previous carry trade results, which are similarly obtained using fixed sets of currencies over fixed sample periods. Our choice of the fixed subsets is informed by the order of exclusion implied by Panel B of Table 2, which shows that i) the 3 currencies that are the least often excluded by the enhancement rule are the GBP, SEK, and USD, ii) the next 3 least often excluded are the CAD, NZD, and CHF, whereas iii) the AUD, NOK, and JPY are the most often excluded currencies.

In particular, we construct 5 carry trades from fixed subsets, which i) exclude only the AUD, NOK, and JPY, ii) include the GBP, SEK, and USD, together with any of the 3 possible pairs from the CAD, NZD, and CHF, and iii) keep only the GBP, SEK, and USD. These carry trades are designed to illustrate the properties of enhanced carry trades, and we denote them by

G1 to G5, a notation we shall clarify shortly. The first column of Table 3 displays the codes of the currencies included in each of these 5 trades. We also consider the trades complementary to G1–G5, which include the currencies that are left out of each of these trades, and denote these complements by B1 to B5, respectively, with currency codes again displayed in the first column of Table 3. For example, only the 3 most often excluded currencies (AUD, NOK, and JPY) enter the B1 carry trade.

In addition, we consider a larger set of trades which can represent more broadly the enhanced carry trades: it consists of 18 trades from 5 currencies each, and is denoted by GC, whereby each trade includes the 3 least often excluded currencies (GBP, SEK, and USD), together with any possible pair from the remaining currencies which has *none or only one* of the 3 most often excluded currencies (AUD, NOK, and JPY). This choice yields a reasonably large cross section of trades which maintains the predominant presence of currencies that are preferred by the enhancement rule. Again, we also consider the 18 complementary trades, and denote them by BC. Despite creating many carry trades from only 5 currencies, the average correlation among the returns of the 18 good trades is 0.66, and thus lower, for example, than the average correlation among the 25 value-weighted Fama–French portfolios sorted on size and book-to-market for the same period, which is 0.80.

Table 3 presents results for the SC trade, the G1–G5 and B1–B5 trades, and the GC and BC trades described above, using the entire sample period from Dec. 1984 till June 2014. Shown are annualized average returns, return standard deviations and Sharpe ratios, as well as skewness. For the GC and BC trades we show *averages* of these quantities. Also reported are p-values for tests of differences between the Sharpe ratios and skewness coefficients, similar to those in Table 2. In the last 2 lines, the first (second) number in parentheses shows how many of the 18 corresponding individual estimates for the GC or BC trades are significant at the 5% (10%) level. Where p-values are (not) in square brackets, the null hypothesis is that the Sharpe ratio or skewness of a G1–G5 trade or GC trade does not exceed that of the corresponding B1–B5 trade or BC trade (SC trade). Note that over the full sample period the benchmark Sharpe ratio and skewness remain close to those reported in Panel A of Table 2 for the shorter period since 1994.

The G1–G5 trades exhibit invariably higher average returns than the SC trade. In addition, their average returns and return standard deviations tend to increase as the number of currencies in a trade decreases. The Sharpe ratios of the G1–G5 trades all exceed the benchmark Sharpe ratio (in 2 cases by a factor of about 2), with the difference statistically significant at the 5% significance level in 3 cases out of 5. Skewness increases in 3 cases for the G1–G5 trades, even though this increase is significant only for G1. Overall, these 5 trades reproduce the features that characterize the enhanced trades in Table 2.

In contrast, the complementary trades B1–B5 fare much worse. The average returns are often 2–3 times lower than those of the SC trade, whereas the standard deviations are on average twice higher, leading to much lower annualized Sharpe ratios, which are between 0.04 and 0.18. In addition, the return skewness is markedly more negative for these complementary trades, averaging -0.77 (vs. -0.11 for the G1–G5 trades). Furthermore, the p-values shown in square brackets, pertaining to tests of the differences in Sharpe ratios and skewness between the corresponding G1–G5 and B1–B5 trades are below 0.02 for 4 out of 5 Sharpe ratios, and show 3 (1) rejections at the 5% (10%) level for skewness.

The relatively high Sharpe ratios and slightly negative or positive skewness of the G1 to G5 trades earn them the label "good" carry trades ("G" for good). Analogously, we refer to the B1 to B5 trades with low Sharpe ratios and strongly negative skewness as "bad" carry trades ("B" for bad), from now on.

Turning to the larger sets of GC and BC trades, each constructed from 5 currencies, the GC average returns (Sharpe ratios) are on average 3 (three and a half) times higher than those for the BC ones, and the GC skewness is on average twice lower (in absolute terms), whereby the differences are statistically significant in about half the cases. The Sharpe ratios for the GC trades are significantly higher than those for the SC trade in one third of the cases, in line with what was observed for the comparable G2–G4 trades.

To further illustrate the properties of the GC and BC carry trades, Figure 2 plots their Sharpe ratios versus skewness, similar to Figure 1, with unfilled circles and black dots, respectively. The distinction is sharp and clear in the Sharpe ratio dimension, where, with *no* exception, the GC trades dominate the BC trades, thus justifying their classification as good trades. On the other hand, a few GC (BC) trades display low (relatively high) skewness, hence the distinction is not as clear in this dimension, even though on average the skewness of the BC trades is still twice lower, consistent with the bad trades classification.[3]

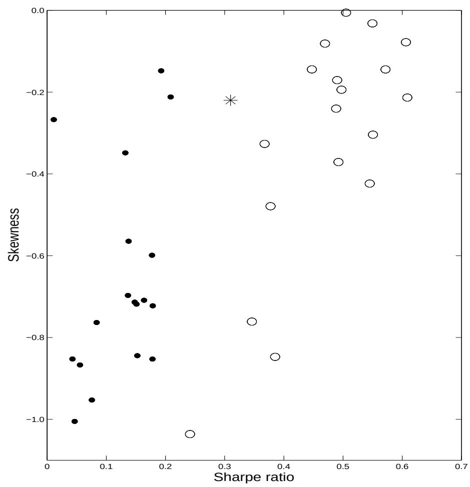
In sum, eliminating some typical carry trade currencies, such as the AUD, JPY, and NOK, from the currency set leads to good carry trades, with Sharpe ratios and skewness mostly higher than those of the SC trade, and the complementary bad carry trades that involve the typical carry

[3]In unreported results we find that when trades from 5 currencies involve the 3 least often excluded currencies (GBP, SEK, and USD) in each case, but are now combined with any other pair that excludes the JPY, the good and corresponding bad trades deliver striking separation in *both* the Sharpe ratio and skewness dimension.

FIGURE 2

Sharpe Ratios versus Skewness for the GC and BC Sets of 18 Carry Trades

Circles with no fill plot skewness versus Sharpe ratio for 18 carry trades, each constructed from 5 of the G-10 currencies, with equal weights. Each of these trades uses the 3 currencies (GBP, SEK and USD) which are least often excluded by the enhancement rule in Section II.A and Table 2. These 3 currencies are combined with any possible pair of the remaining G-10 currencies, which contains *none* or *only 1* of the 3 most often excluded currencies (AUD, NOK, and JPY). Large black dots plot similarly the skewness versus Sharpe ratio for the complementary carry trades, which use the 5 currencies left out of 1 of the previous 18 trades. These 2 sets of 18 trades are denoted in Section II.D and Table 3 and others as GC and BC. Shown also is the standard carry (SC) trade, denoted by a star. The sample period is Dec. 1984–June 2014.



trade currencies. Also, with the exception of the G1 and B1 trades, the correlations between the various trades and SC are always higher for the bad trades (on average 0.80, vs. 0.67 for the good trades).

E Statistical Significance of the Distinction between Good and Bad Carry Trades

Table 3 shows that the distinction between good and bad carry trades is economically and statistically important. However, the statistical evidence must be interpreted with caution. In particular, the reported p-values rely on the block bootstrap procedure under the alternative, developed by Ledoit and Wolf (2008) (see Appendix OA-II). While this procedure accounts for certain finite-sample properties of the distribution of currency returns, it does not reflect two aspects of our good carry trades. First, they are constructed using information from the enhancement procedure, as reported in Panel B of Table 2, and thus the procedure suffers from look-back bias. Second, the enhancement procedure applied to a finite sample is bound to lead to improved Sharpe ratios, even if in population all 10 currencies are necessary to attain optimal results. Therefore, a modified test is needed to assess the statistical contribution as fairly as possible. We emphasize, however, that the results in Table 3 need not be statistically significant to impact carry research: the finding that the prototypical carry trade currencies, if anything, worsen or certainly do not provide a positive contribution to carry returns, suffices.

With respect to the look-back bias, starting the sample in 1994, rather than 1984 weakens the statistical significance somewhat, but we still retain significance at the 10% level for the majority of the trades (not reported). A full correction for this bias would require a much longer sample where we actually let the procedure choose which currencies to exclude ex-ante, before we record trading results.

Incorporating the selection procedure into a test of statistical significance is harder, because it requires creating a benchmark world in which carry trades still have realistic attractive returns, but somehow the identity of the currencies contributing to these returns is randomized. Appendix OA-III describes in detail a procedure creating entirely randomized individual currency returns which nonetheless reproduces exactly the returns of standard carry (SC) in each randomized sample. We then apply our enhancement strategy to 1,000 such randomized samples, finding that the selection procedure biases the Sharpe ratios of the good trades upwards by about 0.15 and that only the G5 (at the 5% level) and G3 (at the 10% level) deliver statistically significant improvements in Sharpe ratios, using proper t-statistics.

Thus, there is no overall strong statistical evidence that the enhancement procedure delivers significantly higher Sharpe ratios. However, it remains the case that the prototypical, "skewed" carry currencies can be removed from the trade without worsening performance.

IV Good Carry Trades as Currency Market Risk Factors

Lustig et al. (2011) suggest as a key currency market risk factor the return of a trading strategy that each month goes long (short) a portfolio with the highest (lowest) forward differentials. This is obviously a symmetric carry trade strategy and is denoted here as "HML^{FX}" (to be distinguished from the Fama–French HML factor used in Section V). Creating test portfolios by ranking currencies on forward differentials, they find that the covariation with HML^{FX} largely explains the difference in average returns between these portfolios. Furthermore, they propose HML^{FX} as a proxy for a global risk factor in a no-arbitrage model explaining the results, and show that it is also related to a measure of aggregate stock market volatility. Menkhoff et al. (2012) conduct a similar exercise using a global exchange rate volatility factor as a proxy for the global risk factor. We now revisit these findings by considering the good carry trades as risk factors and comparing their performance with that of the previously used currency market factors.

A Test Assets and Risk Factors

The test assets in our pricing tests are 5 portfolios of currencies of developed countries (denoted "Developed"), and 6 portfolios which also include emerging market currencies (denoted "All"), created by sorting the respective set of currencies on forward differentials, and taken from Adrien Verdelhan's Web site (http://web.mit.edu/adrienv/www/Data.html) for the period ending in Dec. 2013. We consider these 11 portfolios *together* in our tests, and not the "All" and "Developed" separately, as Lustig et al. (2011) do. The larger cross section poses a higher hurdle to the various risk factors that are examined and compared.[4] Our versions of the 11 portfolios account for transaction costs.

Moving to the risk factors, first we use HML^{FX} ("All" version) as in Lustig et al. (2011) (and available at Verdelhan's site). Next, we use a mimicking portfolio for the innovations in foreign exchange volatility (denoted "FXVol") as in Menkhoff et al. (2012). Finally, we also consider as risk factors the good carry trades G1–G5 to contrast their performance, particularly

[4]While using some currencies twice in each test, the average correlation between the 6 "All" portfolios and 5 "Developed" portfolios is only 0.74, which is just slightly higher than the average correlation among the "Developed" (0.72) or the "All" portfolios (0.68). Moreover, we have verified that the relative performance of the risk factors separately on the "All" and "Developed" portfolios remains largely the same.

with HML^{FX}. Because the correlations between the G1–G5 trades and HML^{FX} (FXVol) are on average 0.39 (−0.29), and do not exceed 0.55 in magnitude multicollinearity concerns do not arise. The respective correlations for the B1–B5 trades average 0.64 (−0.71), suggesting a closer relation between the previously considered currency market factors and our bad carry trades.

B Design of Asset Pricing Tests

We adopt a standard asset pricing framework, following Cochrane ((2005), chaps. 12 and 13), and consider linear factor models, both in their beta representation and stochastic discount factor (SDF) form, assuming SDF's specified as:

$$m_{t+1} = 1 - b' \left(f_{t+1} - E[f] \right). \tag{3}$$

In equation (3) f_{t+1} is a $K \times 1$ vector of risk factors and b is a conformable constant vector of SDF coefficients. Without loss of generality, we set $E\left(m_{t+1}\right) = 1$, given that excess returns of test assets are used.

The SDF form of a pricing model is $E[\text{rx}^i_{t+1} m_{t+1}] = 0$, where rx^i_{t+1} are the excess percentage returns of the test assets, indexed by i. The beta representation of the pricing model is $E[\text{rx}^i_{t+1}] = \lambda' \beta^i$, with systematic risk exposures for asset i given by the vector β^i, and λ a vector of factor risk prices. The vectors β^i are estimated by GMM from time-series regressions of returns rx^i_{t+1} on the factors, and λ is estimated from a cross-sectional regression (without a constant) of average returns on the β's. We report the SDF coefficients b and factor risk prices λ with corresponding p-values, as well as p-values for the χ^2 statistic testing if the pricing errors are jointly equal to 0 (see, e.g., Cochrane (2005), p. 237).[5]

C Good Carry Trades in Competition with Other Currency Market Risk Factors

Table 4 shows the results of tests which compare the performance of HML^{FX} and the good carry trades as risk factors. As in Lustig et al. (2011), each test also includes the dollar factor, denoted RX, which is the average excess return of their basket of currencies held long against the USD. In each of the two panels of the table, the first line refers to a model with the RX and HML^{FX} factors alone, the next 5 lines to models with RX and each of the good carry trades

[5]Denoting by Rx_{t+1} the $N \times 1$ vector of the rx^i_{t+1}'s, the moment conditions we use are:

$$g = \begin{bmatrix} E[\text{Rx}_{t+1} m_{t+1}] \\ E[f_{t+1} - E[f_{t+1}]] \end{bmatrix} = \begin{bmatrix} E[\text{Rx}_{t+1} - \text{Rx}_{t+1}(f'_{t+1} - E[f'_{t+1}])b] \\ E[f_{t+1} - E[f_{t+1}]] \end{bmatrix}. \tag{4}$$

The weighting matrix defining which moments are set to 0 is

$$a = \begin{bmatrix} d & 0 \\ 0 & I_K \end{bmatrix},$$

where $d = E[\text{Rx}_{t+1} f'_{t+1} - \text{Rx}_{t+1} E[f'_{t+1}]]$. Further, if $\mu = 1/T \sum_{t=1}^{T} f_t$ and $\overline{\text{Rx}} = 1/T \sum_{t=1}^{T} \text{Rx}_t$, where T is the length of the return time series, then the GMM estimates of b are $(d'd)^{-1} d' \overline{\text{Rx}}$, and that of $E[f_{t+1}]$ is μ. The standard errors of the b estimates are obtained from the covariance matrix $1/T (d'd)^{-1} d' S d (d'd)^{-1}$, where S is an estimator of $\sum_{j=-\infty}^{\infty} E[u_{t+1} u'_{t+1-j}]$ and $u_{t+1} = \begin{bmatrix} \text{Rx}_{t+1} m_{t+1} \\ f_{t+1} - \mu \end{bmatrix}$. As in Lustig et al. (2011), we use 1 Newey–West lag throughout to estimate S.

G1–G5, and the remaining 5 lines to models combining RX, HML^{FX} and each of the G1–G5 trades. The top panel summarizes results from time-series regressions of each of the test assets, and reports average coefficient estimates and (in parentheses) the number of respective estimates that are significant at the 5% or 10% confidence levels. (The regression results for each individual test asset are shown in the Online Appendix, Table OA-6.) The bottom panel reports both the prices of risk λ and the SDF coefficient estimates b. The latter are key in evaluating the relative importance of alternative factors for pricing a given cross section (see, e.g., Cochrane (2005), chap. 13.4).

The top panel of the table does not reveal important differences between HML^{FX} and the good carry trades: the slope coefficients β in the time-series regressions are similarly significant; the R^2 related to HML^{FX} is slightly higher, but so are the respective intercepts α. When entering the regression jointly, the 2 factors also show similar significance, with the HML^{FX} coefficients remaining negative on average, but the coefficients on the good trades turning all positive on average. The RX factor always has a statistically significant slope coefficient of around 1.1. In the bottom panel of Table 4, all 2-factor models (RX with either HML^{FX} or a good carry trade) show significant prices of risk λ for HML^{FX} and the good trades (at the 5% level), but not for the RX factor. However, in the 3-factor models the p-values increase somewhat for HML^{FX}, and in 3 cases become significant only at the 10% level, while the significance remains unaffected for the λ's of the good trades.

An essential difference, however, is observed with respect to the SDF coefficients b. In the 2-factor models, the b-coefficient for HML^{FX} is significant at the 10% level only, but at the 5% level for all good trades. However, in the 3-factor models the b coefficients turn highly insignificant for HML^{FX}, whereas for the good carry trades they remain significant at the 5% level in 3 of the 5 cases, and at the 10% level in 1 case. Moreover, the test for the pricing errors being jointly equal to 0 rejects in this sample for the 2-factor model with RX and $\mathrm{HML}^{\mathrm{FX}}$ with a p-value of 0, while the corresponding p-values for the models with RX and a good trade are all above 0.10, except for G3 where the p-value is 0.09. The test fails to reject the 3-factor models at the 5% level for all specifications. In addition, the b coefficients appear similar across different specifications for the good trades, but not for the $\mathrm{HML}^{\mathrm{FX}}$ factor, where the sign switches across specifications. The results in the bottom panel of Table 4 clearly favor the good carry trades over $\mathrm{HML}^{\mathrm{FX}}$ as risk factors explaining the returns of the interest rate-sorted currency portfolios.

Table OA-1 in the Online Appendix shows results from analogous tests, but with the currency volatility factor FXVol replacing $\mathrm{HML}^{\mathrm{FX}}$. The conclusions remain robust: the good carry trades again win the horse race, with p-values for all their SDF coefficients equal to 0.01 or lower, while these p-values are never below 15% for FXVol.

D Return Predictability of Good and Bad Carry Trades

The cross-sectional tests we have conducted follow the extant literature and assume constant prices of risk and betas. It is surely conceivable that these assumptions are violated and thus that additional factors may affect the unconditional cross section of currency returns (see, e.g., Jagannathan and Wang (1996)). There is, in fact, evidence of carry return predictability. Bakshi and Panayotov (2013) document that commodity index returns and exchange rate volatility strongly predict carry trade returns. Further, Ready et al. (2017) find time-series predictive ability of an index of shipping costs, the Baltic Dry Index (BDI), for carry trade returns. They primarily investigate an unconditional carry strategy that is always long the currencies of commodity exporters (commodity-producing countries) and short those of commodity importers (countries producing final goods), which is a key component of their model.

In Table 5 we reconsider the evidence for time-series predictability from the perspective of good and bad carry trades. To follow closely the empirical design in the two studies cited above, we use *log* returns of equal-weighted good and bad carry trades. The commodity index predictor is defined as the 3-month log change in the CRB index. Exchange rate volatility, σ_t^{avg}, is the cross-sectional average of the annualized standard deviation of the daily log changes over each month t for each of the G-10 spot exchange rates against the USD. The volatility predictor at the end of month t (and used to predict the return for month $t+1$) is then the 3-month log change $\ln\left(\sigma_t^{\text{avg}}/\sigma_{t-3}^{\text{avg}}\right)$. The shipping cost predictor is the 3-month log change in the BDI. As in Bakshi and Panayotov (2013), we show in-sample predictive slope coefficients β and their p-values, using Hodrick (1992) standard errors, adjusted R^2's, and p-values for the MSPE-adjusted statistic of Clark and West (2007).[6] In addition, we show an (out-of-sample) measure of the economic significance of the predictability, using the following strategy: if the predicted carry return for month $t+1$ is positive (negative), the strategy enters a carry trade at the end of month t (no position is taken and the strategy's return for month $t+1$ is 0). The reported measure "ΔSR" of economic significance equals the difference between the Sharpe ratio of the trading strategy,

[6]MSPE stands for "mean squared prediction error". The statistic is obtained using $f_{t+1} = (y_{t+1} - \mu_{t+1})^2 - [(y_{t+1} - \widehat{\mu}_{t+1})^2 - (\mu_{t+1} - \widehat{\mu}_{t+1})^2]$, where $\widehat{\mu}_{t+1}$ is the prediction for month $t+1$ from a predictive regression $y_{t+1} = a + bx_t + \varepsilon_{t+1}$, and μ_{t+1} is the historical average of y. Both $\widehat{\mu}_{t+1}$ and μ_{t+1} are estimated using data up to month t. The null hypothesis is that $\widehat{\mu}_{t+1}$ does not improve on the forecast which uses μ_{t+1} as the predictor. The test statistic is the t-statistic from the regression of f_{t+1} on a constant, for which we report 1-sided p-values.

implemented with the respective subset of G-10 currencies, and the corresponding carry trade as shown in the first column. The predictive regressions use an expanding window with initial length of 120 months.

Table 5 shows clear differences between the return predictability results for good and bad carry trades. Out of 15 possible combinations with the 3 predictors, the G1–G5 trades show a significant predictive slope on 3 occasions, whereas the B1–B5 trades record 13 occasions with p-values not higher than 0.05 and another one with a p-value below 0.10. The average predictive R^2 is 0.7% for the G1–G5 trades and 2.2% for the B1–B5 trades. The MSPE statistics show significant out-of-sample predictability in 1 case (out of 15) for the G1–G5 trades and in 13 cases for the B1–B5 trades. Finally, exploiting the predictability in dynamic trading does not materially impact the Sharpe ratio for the G1–G5 trades (the average change is -0.005), while it mostly improves the Sharpe ratio for the B1–B5 trades, on average by 0.10. The improvement is economically large , because the Sharpe ratios for bad carry trades are often below 0.10 (see Table 3). The above patterns are confirmed by the results from the GC and BC trades, where again the GC trades show insignificant predictive slopes for 2 of the predictors, twice smaller predictive R^2's, rarely significant out-of-sample predictability, and on average a reduction in Sharpe ratios from exploiting predictability by 0.01, in contrast to the BC trades which exhibit an increase by 0.09 in Sharpe ratios on average.

Our predictability results echo some findings in Ready et al. (2017). The CRB commodity index most strongly predicts the returns of the factor that they denote IMX, which is long AUD, NZD and NOK, and short JPY and CHF, as often true for our bad trades.[7] Therefore, our Table 5

[7]They also show that a complement to the IMX trade (denoted CHML) is not predictable at all by the CRB or BDI, and also has practically zero skewness, similar to some of our good trades. However, the

confirms the predictive ability of the CRB and BDI for a "commodity focused" carry trade as implied by their commodity trade model. Our contribution here, however, is to highlight the similarity between the commodity-based trade and our bad carry trades, and the fact that a commodity-based interpretation of carry trade returns reflects mostly features of bad carry trades.

Our results therefore qualify the prevailing carry return predictability story. A carry trade that focuses on the prototypical carry currencies is rather unattractive, but its return properties can be enhanced by exploiting return predictability. In contrast, our good carry trades have attractive properties which, however, cannot be enhanced by the predictors previously identified in Bakshi and Panayotov (2013). It remains, of course, conceivable they are predictable by other variables.

V Good and Bad Carry Trades and Previous Carry Interpretations

This section reconsiders previous studies of carry trades from the good-bad carry trade perspective.

A Explaining Carry Trade Returns with Equity Market Risk Factors

We start by re-examining a key result in the literature stating that standard (linear) equity market factor models cannot explain the time variation in carry returns, which appear uncorrelated with these risk factors in normal times, but correlate highly with them in crisis times (e.g., Melvin and Taylor (2009), Christiansen, Ranaldo and Söderlind (2011)). We examine 3

Sharpe ratio of CHML is still below that of their version of the standard carry trade (0.85 vs. 0.95 in their sample and without transaction costs), hence their orthogonalization procedure fails to identify a good carry trade.

models: i) the Fama–French 3-factor model, following Burnside et al. (2011), ii) a 3-factor model with the market factor, the global equity volatility factor used in Lustig et al. (2011), and their *product*, and iii) a model with 2 factors which explicitly distinguish the down- and up-moves of the equity market, in the spirit of Lettau, Maggiori, and Weber (2015). The latter 2 models effectively exhibit a non-linearity that may capture the time-variation in the correlation mentioned above. To conserve space, we relegate detailed results to the Online Appendix, summarizing the key results here.

Let's start with the model featuring a market factor (denoted MKT), proxied by the total return of the MSCI-World equity index, in excess of the risk-free rate and expressed in USD, an equity volatility factor (EqVol) constructed as in Lustig et al. (2011), and the interaction term (the product of MKT and EqVol). Table OA-2 shows that in time-series regressions of carry trade returns on the 3 risk factors the main difference between good and bad trades is in their loadings on the product factor. These are typically negative, albeit rarely significant, for the good trades, while they are positive, much larger in magnitude, and almost always significant at the 5% significance level for the bad trades. Given that increases in volatility tend to coincide with market downturns, the market exposure of the bad trades increases substantially in bad times, making them under-perform in times of crisis.

We also perform GMM-based cross-sectional tests on the GC and BC return cross sections. For the GC trades, the risk price for the MKT factor is significant at the 5% level, while for the BC trades no risk price is significant, although the model is not rejected for either of the 2 cross sections. When we run a simple OLS regression of actual average returns on a constant and the model-based expected returns, we obtain an R^2 of 0.67 for the GC trades, and 0.29 for the BC trades. The combined evidence suggests that this 3-factor model does not adequately describe the returns of the bad carry trades, but still saliently reveals the high exposure of these trades to the equity market during high-volatility periods. In contrast, a significant price of risk for the market factor and tighter link between model expected returns and average returns show the promise of the model to provide a risk-based interpretation of good carry trades.

The Online Appendix further shows quite similar results for the model with an Up- and Down-market factors. Table OA-3 shows that good (bad) carry trades load primarily on the Up (Down)-market factor, with beta exposures being economically and statistically very different across the two types of trades. In the cross-sectional tests, the prices of risk for both factors are significant; the pricing errors are not statistically different from zero and the model generates expected returns highly (weakly) correlated with good (bad) carry trades.

The Online Appendix and Table OA-4 report analogous results for the Fama–French 3-factor model. Here the time-series regressions reveal that good carry trades do not load much on any of the 3 factors, and retain significant alphas relative to the model. In contrast, the bad carry trades feature significantly higher regression slope coefficients on all 3 factors and it is striking that their SMB and HML exposures are positive and economically meaningful (often even above 0.10). However, the Fama–French model fails to fit expected returns cross-sectionally, with all prices of risk being insignificantly different from 0 for both good and bad carry trades.

In sum, the evidence from Tables OA-2 to OA-4 provides (weak) support for the ability of risk factors from the equity market to explain the returns of the good carry trades. Our results are not directly comparable to studies analysing numeraire-dependent carry trades (e.g., Daniel et al. (2017)).

B Currency Crashes as an Explanation for the Carry Return Puzzle

One established explanation for the carry trade's profitability is that it reflects compensation for the negative return skewness or crash risk, inherent to these trades. For example, Brunnermeier et al. (2009) argue that "investment currencies are subject to crash risk, that is, positive interest rate differentials are associated with negative conditional skewness of exchange rate movements.... The skewness cannot easily be diversified away, suggesting that currency crashes are correlated across different countries .... This correlation could be driven by exposure to common, crash-risk factors". If agents exhibit a preference for positive skewness, an equilibrium model may generate negatively skewed returns and high Sharpe ratios for the carry trade.

However, the crash risk hypothesis is not consistent with our findings from good and bad carry trades (see Figure 1 and Table 3): good carry trades have relatively high Sharpe ratios and slightly negative (or even positive) skewness. The assertion in Brunnermeier et al. (2009) that the negative skewness in carry trade returns cannot be diversified away must also be qualified. We have demonstrated that, in fact, skewness can be dramatically improved by judiciously removing currencies from the carry trade, without impairing profitability. Studies relying on option market data (e.g., Burnside et al. (2011), Jurek (2014)) have criticized the crash-risk hypothesis before, because options can essentially hedge away the crash risk without undermining much the carry trade's profitability.

VI Further Exploration of Good and Bad Carry Trades

In this section we embark on a more detailed examination of the good and bad carry trades, trying to set the stage for future work that will hopefully clarify fully the economic interpretation of our findings. First, we reflect on the return components of various carry trades and how they contribute to the differential performance of the good and bad trades. Second, the good carry trades always include the USD (it is never excluded in our selection procedure). There is a burgeoning literature stressing the special nature of the USD in international financial markets: Adrian, Etula, and Shin (2015) associate increased global dollar funding with expected currency depreciations; Hassan (2013) argues that economies representing a larger share of world wealth have low interest rates and low risk premiums, whereas Maggiori (2013) ascribes a low premium to holding the USD to its role as a reserve currency. Lustig et al. (2014) explore a new trade, denoted “dollar carry,” which goes long (short) in all foreign currencies against the USD with equal weights when their average interest rate differential relative to the USD is positive (negative). The dollar carry trade has a very attractive Sharpe ratio, substantially higher than that of SC, raising the issue that we may have simply repackaged dollar carry into our good carry trades. We show that this is not the case, and these two types of trades, while correlated, are economically distinct.

A The Sources of Good and Bad Carry Returns

In Table 6, we decompose carry trade returns into an interest rate (or forward differential) component, and an exchange rate change component. SC derives more than 100% of its returns from the interest rate component, i.e., the investment currencies do depreciate and/or the funding currencies do appreciate, but the exchange rate component is sufficiently small relative to the “carry” to leave an attractive return on the table. Bad carry trades have higher carry return components, both in absolute terms (and the difference is statistically significant) and in relative terms, but even more negative exchange rate components, so that lower returns than those for standard carry are obtained. In contrast, good carry trades derive their returns *both* from the carry and exchange rate components. Their carry component is on average about 20 basis points lower than that of SC in 3 cases (and statistically significant at the 5% level for the G4 trade), while it is significantly higher for the G3 trade (even if still lower than the carry of any bad trade).

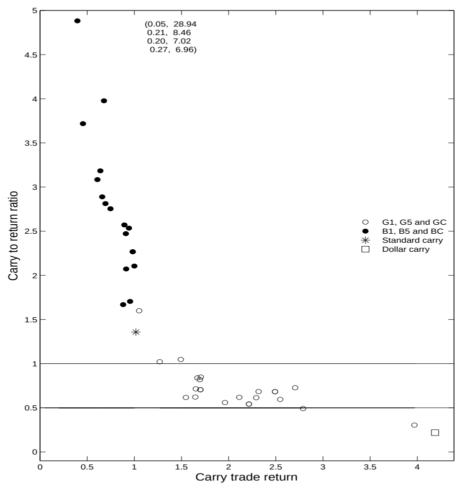
The contrast between the carry contributions to the returns of bad and good trades is illustrated in Figure 3. The graph plots total average return on the horizontal axis, and the ratio of carry to total return on the vertical axis for all trades considered in this paper (18 GC trades, 18 BC trades, as well as the G1 and G5, and B1 and B5 trades). The graph also includes the standard and dollar carry trades. Bad carry trades have lower returns and much higher carry-to-return ratios; good carry trades have higher returns, and derive between 50 and 100% of their returns from carry (the G5 trade being the only exception).

These results suggest that the unbiasedness hypothesis may not be strongly rejected for bad carry currencies, which include the prototypical carry currencies. Recall that a necessary condition for a carry trade to deliver excess returns is that the unbiasedness hypothesis does not hold, at least for some period of time (see Bekaert, Wei, and Xing (2007) for recent tests of the hypothesis). However, when examining standard regressions testing the unbiasedness hypothesis for the 4 pairs containing prototypical carry currencies, AUD/JPY, NZD/JPY, AUD/CHF, and NZD/CHF (see Table 7), we find no strong rejections of the hypothesis. In particular, we regress future exchange rate changes onto a constant and the current forward differential, and the null hypothesis is that the constant is 0 and the slope coefficient is 1. The constants (slope coefficients) in all 4 regressions are insignificantly different from 0 (1). Most saliently, the slope coefficient for the AUD/JPY regression is 0.92, and thus remarkably close to 1. However, our analysis reveals the NOK also to be a "bad" currency, more so than the CHF and the NZD. Interestingly, Table 7 shows that the slope coefficient in unbiasedness regressions of the NOK relative to the CHF and

FIGURE 3

Decomposing Carry Trade Returns

For all trades considered in this paper (18 GC trades, 18 BC trades, as well as G1 and G5, and B1 and B5) the figure plots total average returns (horizontal axis) versus the ratios of average carry to total return (vertical axis). As previously, white (black) dots correspond to good (bad) trades. For visual clarity, 4 outlier points (all referring to bad carry trades) are not shown on this plot, but their coordinates are displayed in the top left corner. Also plotted are the standard and dollar carry trades (SC and DC). Horizontal lines correspond to carry-to-return ratio of one (all average return comes from carry alone), and one half (return comes equally from carry and exchange rate changes).



JPY is either not significantly different from 1, or exceeds 1 by a large amount, indicating an expected depreciation of the NOK relative to the JPY when the NOK interest rate exceeds the JPY one. This is partially counteracted by a positive and significant constant.

The decomposition and the regression results above also suggest that the good carry trades are likely to be more “active” than the bad or standard carry trades (i.e., they likely involve more frequent rebalancing). The insightful paper by Hassan and Mano (2015) decomposes the carry trade into a “static” trade (which goes long (short) currencies with unconditionally low (high) forward differentials) and a dynamic trade, which also helps explain deviations from unbiasedness. Such deviations, driven by the slope coefficient in the unbiasedness regressions being different from 1, lead to dynamic trades when forward premiums are high or low relative to their unconditional means. However, carry trades can also be profitable simply through nonzero constants in the unbiasedness regressions (see Bekaert and Hodrick (2012), chap. 7).

Table 8 provides some evidence on the dynamic nature of the various carry trades. We create a dummy variable that records the proportion of currencies that change position (from long to short or vice versa) at each point of time. For example, for a completely static trade this proportion is 0, whereas a trade where half the currencies switch positions at each point of time would record 50% on this measure. Furthermore, since the dynamic nature may be related to the number of currencies in the trade, it is important to take sampling error into account. The table shows the sample averages of these proportions, together with 95% confidence intervals, computed using the bootstrapped carry trade returns employed in Section E.

Clearly, the good carry trades are more “dynamic” than the bad trades and the SC trade. Note that the average proportions for good trades are invariably above the confidence interval for SC (and vice versa for the bad trades). Yet, the proportions for the good carries and SC are relatively highly correlated in the time series (ranging between 49% and 82%), suggesting that these trades switch currency positions at roughly similar times. For bad carry trades the proportion of switches is typically within the confidence interval of SC, except for the B3 trade.

The last 3 columns in Table 8 report the ratios between the average returns of various static carry trades (which are never rebalanced), and the returns of the corresponding good or bad carry trade, mimicking the Hassan and Mano (2015) methodology.[8] The trades are constructed with all G-10 currencies, as well as with the currencies entering the G1–G5 and B1–B5 trades. The various "static trades" use as weights the average forward differentials over the Dec. 1984–Dec. 1994 period (the first 120 months of our sample), demeaned and normalized to have absolute values that sum to 1. The weights are kept fixed for the entire sample period Jan. 1995–June 2014, without ever rebalancing.

Hassan and Mano (2015) find that static trade returns account for about 70% of carry trade returns (but the standard error on that estimate is substantial), whereas according to Lustig et al. (2011) this proportion is between one third and one half. Analogously, the average return of the static SC trade in Table 8 is about half of that of the original SC trade. Importantly, there is a clear distinction between the relative performance of the static versions of the good and bad carry trades, with the ratios between the corresponding average returns never exceeding 0.30 (and sometimes going negative) for the good trades, but ranging between 0.60 and 1.2 for the bad trades. The distinction is even clearer in terms of Sharpe ratios (see the last 2 columns), which for

[8]We use log returns and currency weights equal to the demeaned and normalized forward differentials at each trading date over Jan. 1995–June 2014.

the good static trades rarely exceed 0.15, much worse than their rebalanced counterparts. In contrast, the Sharpe ratios of the rebalanced and static "bad" trades are close to one another.

Hence, good carry represents a dimension of standard carry that is not well explained by its static component. This is intuitive, because good carry trades tend to exclude currencies with either the highest or lowest forward differentials, and thus do not have stable short and long positions. In contrast, and as shown above, the currencies involved in bad carry trades typically switch less often from long to short positions and vice versa. Our results thus confirm the Hassan and Mano (2015) decomposition for "bad carry trades," but not for "good carry trades". Hassan and Mano (2015) split up carry trades in the static carry trade we studied above and a "dynamic" trade, which essentially exploits time-variation in the relative ranking of currencies in terms of their forward differentials, relative to their unconditional counterparts. This dynamic trade must necessarily be relatively more important for good trades, which feature currencies with less extreme interest rate differentials relative to the dollar, and for which the unbiasedness hypothesis does not hold. The dynamic trade therefore also contributes positively to the trade exploiting deviations from unbiasedness (what they called the "forward premium trade"). Do note that our results are not entirely comparable to Hassan and Mano (2015) because they do not impose symmetry on their carry trade, while we do.

B Good Carry versus Dollar Carry

In this section, we characterize the differences and similarities between the dollar carry trade and our good carry trades. First, note that dollar carry (hereafter DC for short) does not satisfy the standard conditions for a carry trade as discussed in Section II. Carry trades go long (short) high (low) yield currencies, whereas DC combines high and low yield currencies on one side of the trade. Going back to Table 6, the last column reports the carry (i.e., interest rate) and exchange rate change components for DC, and the last row of the table reports p-values for a test of equality between the carry components of the trade in the respective column and DC. The DC trade derives most of its substantial returns from currency appreciation, and only 22% from interest rate differentials. This proportion is significantly lower than that of any other carry trade. Perhaps not surprisingly, the G5 trade, only featuring 3 currencies which include the USD comes closest to DC. In Figure 3, the DC trade also represents somewhat of an outlier. Furthermore, when constructing versions of DC from "good" and "bad" currencies separately, we find that their Sharpe ratios are very similar.

Second, DC is much less dynamic than the good trades: the last row of Table 8 shows that it switches positions more rarely (despite any switch involving all currencies). The switching proportions are also not very correlated with those for the good trades (at most 39%) or the SC trade (47%). Furthermore, Table 8 (column "days w/o switch") shows that while the typical proportion of days when no currency switches position from long to short or vice versa ranges between 0.60 and 0.80 in carry trades, it is 0.93 for DC.

Third, because good carry trades eliminate some non-dollar exposure, they should be more correlated with DC than SC or the bad carries are. Table 9 confirms this intuition, showing in Panel A that DC has the highest correlation with good trades. However, for the G1, G2 and G3 trades the correlation is less than 50%, and it does not exceed 70% for the G5 trade. Moreover, the correlations between the good trades (except G5) and SC are higher than those for DC. Good carries thus preserve their close link with the SC trade, and remain distinct from DC.

In Panel B of Table 9 we report on regressions which have the returns of SC, DC or good carries either as dependent or independent variables. Both SC and good carries have explanatory power for the DC trade, but SC is insignificant in two specifications. The R^2's are relatively low, being less than 40% in all but one case. The DC trade mostly delivers significant alphas relative to these 2 factors, which is not surprising, given its very attractive return profile. Next, both SC and DC have explanatory power for good carry trades, with almost all slope coefficients featuring p-values below 1% and R^2's ranging from 43% to 75%. The coefficients on SC, however, are typically much larger than the coefficients on DC. The G2, G3 and G5 trades still show significant alphas with respect to these 2 factors. Finally, the return of SC is explained with R^2s between 18 and 75% and all intercepts are insignificantly different from 0. The explanatory power in this case comes predominantly from the good carries, as evidenced by the small coefficients and some high p-values on DC.

Table 9 shows that neither good carries, nor DC can be perfectly spanned by other trades, despite being correlated with them. In contrast, SC *is* spanned, and this is mostly due to the good carry trades. Being proper carry trades, the good carries should therefore be viewed, unlike DC, as better versions of SC.[9] We also investigate the explanatory power of 3 economic factors for various carry trades, including DC, namely, the global equity market volatility, global industrial production growth, proxied by the OECD total growth,[10] and the residual from regressing the

[9]For further validation of this claim, in unreported results we consider creating a mean-variance efficient portfolio from DC, SC and one of the G1–G5 portfolios. When we do so, the good carries invariably get a large positive weight, always exceeding that of DC, sometimes by factor of 2 or 3, and SC is always shorted (except if paired with the G5 trade, when its weight is close to 0). In other words, good carries dominate DC and SC is pushed out.

[10]From stats.oecd.org, Monthly economic indicators, Production of total industry excluding construction, growth rate over the previous month, seasonally adjusted

U.S. industrial production growth onto the global growth variable (see Online Appendix Table OA-5 for the results). We find that the various carry trades are similarly related to the macro factors considered, but that DC appears to have no significant link to these factors. Hence, an economic interpretation of the carry trade returns remains elusive.

Finally, DC and good carry trades both exhibit little skewness, but use very different mechanisms to eliminate the impact of bad carry currencies in this respect. While the good trades simply remove the currencies, DC puts such naturally "long" and "short" currencies on the same side of the trade. To see this more clearly, consider the small table underneath, which shows average forward differentials against the USD for the remaining G-10 currencies over our full sample period Dec. 1984–June 2014 (together with the first 3 moments of the percentage returns of long positions in each currency against the USD, not adjusted for transaction costs).

	NZD	AUD	NOK	GBP	SEK	CAD	EUR	CHF	JPY
Avg. forw. differ.	4.40	3.26	1.98	2.19	1.63	0.83	-0.41	-1.58	-2.51
Avg. return	7.23	4.42	3.82	4.11	3.27	1.81	2.85	2.76	1.21
Std. dev.	12.40	11.88	10.24	10.83	11.31	7.10	10.92	11.82	11.46
Skewness	-0.137	-0.585	-0.374	-0.048	-0.321	-0.331	-0.139	0.109	0.497

All numbers are annualized and in percentages, except for skewness. The bad carry currencies (JPY, AUD, and NOK) do not only have among the highest forward differentials, they also are the most skewed. The good carry trades essentially remove these currencies and thereby do not worsen and mostly improve the return-risk properties of the trade. Therefore, this skewness must be idiosyncratic and not priced, or it must be endogenously generated by carry traders. Why this is the case remains an important open question for further research, but it surely undermines any explanation of attractive carry returns based on priced "crash" risk.

C Revisiting the Factor Pricing of Currency Returns

We now compare the performance of DC and good carries as pricing factors for the interest rate-sorted portfolios, discussed in Section C above. Table 10 reports results from pricing tests, which juxtapose DC with the G1–G5 trades, but do not include the RX factor (which only shorts the USD and has correlation of 0.53 with DC).[11] The top panel summarizes, as in previous tables, results from time-series regressions on individual portfolios, while the bottom panel presents results from cross-sectional tests. (The first-pass regression results for each individual test asset are shown in the Online Appendix, Table OA-7.)

DC alone explains reasonably well the time-series behavior of the test assets - none of the intercepts and all slope coefficients are significant, even at the 5% confidence level, with a relatively high R^2 of 21%. The performance of the good trades alone is similar with respect to the intercepts, while the slopes are not always significant and the R^2's are much lower in 3 out of 5 cases. Moving to the cross-section, however, we observe that the price of risk for DC is significant only with a p-value of 0.07, while 3 of the good trades show significance at the 5% level. In addition, the test for the pricing errors being jointly equal to zero rejects with a p-value of 0.03 for DC, but never rejects for individual good carries, even at the 10% confidence level.

We also perform cross-sectional tests which include both DC and a good trade, as reported at the bottom of Table 10. The price of risk λ is now statistically significant for DC at the 5% level in only 2 out of 5 cases, whereas 4 out of the 5 p-values for the good carries are at 2% or below.

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[11]DC is short the dollar about 70% of the time in our sample, and its profitability is entirely driven by these short dollar positions. Note that this is not true for the good carry trades, which gain both when the dollar is short and long.

The *p*-values for the SDF coefficients b, which provide the proper horse race test, are all above 0.20 for DC. In contrast, 4 of these *p*-values for the good trades are below or equal to 0.10. The relatively high correlation between DC and the G5 trade may be the source of insignificant coefficients in this specification. Also note that the *b*-coefficients for the good trades are quite stable (see also Table 4), whereas the *b*-coefficients for DC switch sign across specifications. While the statistical significance in favor of good trades is borderline, the conjecture that good trades may be simply reflecting features of DC is thus not supported here.

VII Conclusion

This paper introduces "good" and "bad" carry trades, which are all constructed from subsets of the G-10 currencies, but exhibit markedly different return properties, in terms of Sharpe ratios and skewness. Surprisingly, trades that just exclude some of the typical carry trade currencies *do* perform better than the benchmark SC trade, while trades that only include the typical carry currencies have inferior return profiles. These findings challenge the conventional wisdom on the construction of carry trades from an investor's view point. Furthermore, the trades from subsets also challenge some of the available conceptual interpretations of the carry trade. We document that several of these interpretations appear to be mostly consistent with the bad carry trades, but are less applicable to good trades.

We find that good carry trades can serve as risk factors, able to explain a cross section of currency portfolio returns, and in this role can drive out previously suggested risk factors, such as the HML^{FX} factor of Lustig et al. (2011). Further, the returns of good carry trades can be explained to a certain extent with risk factors from the global equity market. While good carry trades are more strongly correlated with the "dollar carry" trade of Lustig et al. (2014) than is the standard carry trade, good trades remain symmetric carry trades, deriving the bulk of their returns from carry (i.e., interest rate differentials), and offer a distinct return profile.

The results in this paper, even though largely focused on the statistical properties of carry trade returns, should impact the study of carry trades in various directions. First, exploring crash risk or differentiating fundamental risks of commodity producers versus exporters are unlikely fruitful avenues of research. Second, our reported asset pricing tests can inform further risk-based interpretations of carry trade returns. Finally, it can be promising to explore, in the spirit of Koijen, Moskowitz, Pedersen, and Vrugt (2015), the notion of good and bad carry trades from financial assets other than currencies.

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TABLE 1

Some Recent Approaches to Carry Trade Construction

Table 1 summarizes three aspects of carry trade constructions, as adopted in recent studies. It shows which currencies are employed in the trade, are currencies given equal weights (possibly among other weighting schemes), and whether the total weights of the long and short sides of the trade are equal. The bottom part of the table provides similar details on several investable carry trade indexes (source: FX Week (Feb. 2008)).

	Which Currencies?	Weights Equal?	Long and Short Equal?
Brunnermeier et al. (2009)	G-10	Yes	Yes
Clarida et al. (2009)	G-10	Yes	Yes
Jorda and Taylor (2009)	G-10 ex SEK	Yes	No
Ang and Chen (2010)	G-10 plus 13 other	Yes	Yes
Burnside et al. (2011)	20 developed	Yes	No
Lustig et al. (2011)	9 to 34, plus a smaller subset of 15 developed	Yes	Yes
Lustig et al. (2014)		Yes	No
Menkhoff et al. (2012)		Yes	Yes
Ready et al. (2013)		Yes	Yes
Bakshi and Panayotov (2013)	G-10	Yes	Yes
Hassan and Mano (2015)	9 to 39, plus a smaller subset of 15 developed	No (deviations of forward differentials from their mean)	Yes
Daniel et al. (2017)	G-10	Yes and no (various weighting schemes)	Yes and no
Jurek (2014)	G-10	Yes and no (various weighting schemes)	Yes and no
Barroso and Santa-Clara (2014)	27 developed	No (vol. scaled deviations of forward differentials from their mean)	Yes
Some investable carry trade indexes:			
Barclays Capital: Intelligent Carry Index	G-10	No (portfolio optimization)	Yes
Citigroup: Beta1 range	G-10	Yes (uses 9 or 13 most liquid tradeable pairs)	Yes
Credit Suisse: Rolling Optimized Carry Indices	G-10 and G-18	No (portfolio optimization)	Yes
Deutsche Bank: G-10 Harvest Index	G-10	Yes (3 highest- and lowest-yielding)	Yes
JP Morgan: IncomeFX	G-10	Yes and no (4 pairs selected each month to optimize the risk-return ratio)	Yes

TABLE 2

Carry Trades Constructed by Sequentially Excluding G-10 Currencies

Using mid-quotes for spot (S_t) and 1-month forward (F_t) exchange rates of the G-10 currencies against the USD (Euro spliced with DEM before 1999) from Datastream, in Table 2 we calculate forward differentials as $F_t/S_t - 1$. With these we construct carry trades either using all G-10 currencies, or excluding 1 up to 7 of these currencies, as explained in Section A. Panel A reports their averages (denoted "avg. ret.," annualized and in percentages) and SR's (both annualized), as well as skewness (denoted "skew"). The first column of the table shows how many currencies have been excluded. The columns denoted "*p*-val" are obtained using bootstrap confidence intervals for the hypothesis that the respective SR or skewness does not exceed the benchmark one (see Appendix OA-II). The sample period is Dec. 1984–June 2014 (354 months), and the initial window for calculating SR's that are used to decide which currencies should be excluded is 120 months. Each column in Panel B shows how many months, out of the 234 months in which we search for the highest SR's, was a currency with code displayed in the first row, the first to be excluded (row starting with "1"), or among the first 2 excluded (row starting with "2"), etc.

TABLE 2 (continued)

	Panel A. Average Returns, Sharpe Ratios, Skewness					*Panel B. Frequency and Order of Exclusion*									
	Avg. Ret.	SR	*p*-Val	Skew	*p*-Val	NZD	AUD	NOK	GBP	SEK	CAD	USD	EUR	CHF	JPY
SC	1.00	0.32		-0.33											
1	1.05	0.32	0.51	-0.26	0.24	0	135	50	0	0	0	0	0	0	49
2	1.23	0.41	0.22	-0.57	0.87	0	184	219	0	0	0	0	15	0	50
3	1.25	0.41	0.25	0.01	0.03	0	192	219	0	0	0	0	74	3	214
4	1.34	0.46	0.21	0.21	0.01	14	224	234	0	0	82	0	152	10	220
5	1.56	0.40	0.32	-0.01	0.10	106	224	234	0	41	82	0	230	19	234
6	1.47	0.44	0.29	-0.35	0.53	171	234	234	36	58	175	0	230	32	234
7	3.17	0.61	0.10	0.04	0.10	172	234	234	63	58	175	0	234	234	234

TABLE 3

Carry Trades Constructed with Fixed Subsets of the G-10 Currencies

Table 3 shows averages (denoted "avg. ret.," in percentages), standard deviations ("std. dev.," in percentages) and Sharpe ratios ("SR"), all annualized, as well as skewness (denoted "skew") for the monthly excess returns of several carry trades, all with equal weights. "SC" denotes the standard carry trade constructed with all G-10 currencies. The G1 to G5 trades are constructed using the currencies with the displayed codes, and represent combinations of currencies that are less often excluded by the enhancement rule discussed in Section A and Table 2. B1 to B5 are the complementary trades, each using the currencies that have been left out of one of the G1–G5 trades. "GC" denotes the set of 18 carry trades, each constructed from the 3 least often excluded currencies (USD, GBP, and SEK), combined with any possible pair of the remaining G-10 currencies that contains *none* or *only 1* of the 3 most often excluded currencies (AUD, NOK, and JPY). "BC" denotes the set of 18 complementary carry trades, each using the 5 currencies left out of 1 of the 18 trades in GC. The rows corresponding to the GC and BC trades show *averages* of the average returns, standard deviations, Sharpe ratios and skewness across the respective 18 carry trades. The columns denoted "*p*-val" show *p*-values obtained using bootstrap confidence intervals (see Appendix OA-II). The first (second) number in parentheses shows how many of the 18 corresponding individual estimates are significant at the 5% (10%) confidence level. Where *p*-values are not in square brackets, the null hypothesis is that the respective SR or skewness does not exceed the one of the SC trade. Where *p*-values are in square brackets, the null is that the SR or skewness of a G1–G5 trade or GC trade does not exceed that of the corresponding B1–B5 trade or BC trade. The sample period is Dec. 1984–June 2014 (354 months).

TABLE 3 (continued)

		Avg. Ret.	Std. Dev.	SR	*p*-Val	Skew	*p*-Val
SC		1.02	3.30	0.31		-0.22	
G1	NZD, GBP, SEK, CAD, USD, EUR, CHF	1.67	3.29	0.51	0.02	0.07	0.02
G2	GBP, SEK, CAD, USD, CHF	1.70	3.47	0.49	0.13	-0.17	0.41
G3	NZD, GBP, SEK, USD, CHF	2.49	4.09	0.61	0.01	-0.21	0.48
G4	NZD, GBP, SEK, CAD, USD	2.22	4.39	0.51	0.12	-0.01	0.19
G5	GBP, SEK, USD	3.97	5.71	0.69	0.03	-0.23	0.50
B1	AUD, NOK, JPY	0.68	7.50	0.09	[0.01]	-0.92	[0.01]
B2	NZD, AUD, NOK, EUR, JPY	0.98	5.54	0.18	[0.07]	-0.60	[0.06]
B3	AUD, NOK, CAD, EUR, JPY	0.21	4.91	0.04	[0.01]	-0.85	[0.04]
B4	AUD, NOK, EUR, CHF, JPY	0.28	4.96	0.06	[0.02]	-0.87	[0.04]
B5	NZD, AUD, NOK, CAD, EUR, CHF, JPY	0.61	4.66	0.13	[0.01]	-0.63	[0.17]
GC		1.96	4.11	0.47	(6/7)	-0.33	(0/0)
BC		0.66	5.13	0.13	[(8/12)]	-0.66	[(5/11)]

TABLE 4

Currency HML versus Good Carry Trades as Currency Market Pricing Factors

Several factor pricing models are estimated with GMM, as described in Section IV, over Dec. 1984 to Dec. 2013. In Table 4, the 11 test assets (6 "All" and 5 "Developed" interest-rate sorted currency portfolios (net returns)) and the RX (dollar) and currency HML (denoted "HML^{FX}") factors ("All" version, net) are as in Lustig et al. (2011), and kindly made available at Adrian Verdelhan's Web site. The good carry trades G1–G5 are as in Table 3. All models include the RX factor, and either the HML^{FX} or a good carry trade (as indicated in the first column), or both. The top panel reports *averages* of the 11 annualized average returns, time-series regression coefficients and adjusted R^2s (in percentages). Standard errors are estimated with GMM and account for 1 Newey–West lag. The first (second) number in parentheses shows how many of the 11 corresponding estimates are significant at the 5% (10%) confidence level. The bottom panel shows, for the same models, factor risk prices λ and SDF coefficients b with p-values, as well as p-values for the χ^2 statistic testing that the pricing errors are jointly equal to 0. Average returns, α's and λ's are reported annualized and in percentages. β_{Good}, λ_{Good} and b_{Good} refer to the good carries G1–G5, as shown in the first column.

TABLE 4 (continued)

	Avg. Ret.	p-Val		α	p-Val	β_{RX}	p-Val	$\beta_{HML^{FX}}$	p-Val	β_{Good}	p-Val	R^2	
	2.33	(3/4)		0.21	(1/2)	1.12	(11/11)	-0.05	(8/8)			81.1	
G1				0.06	(1/1)	1.11	(11/11)			-0.01	(10/10)	78.3	
G2				0.06	(1/1)	1.11	(11/11)			-0.01	(9/10)	75.9	
G3				0.06	(0/1)	1.12	(11/11)			-0.01	(9/9)	77.3	
G4				0.01	(1/1)	1.11	(11/11)			0.02	(8/9)	75.3	
G5				-0.01	(0/3)	1.11	(11/11)			0.02	(7/7)	74.0	
G1				0.15	(0/1)	1.12	(11/11)	-0.06	(5/6)	0.08	(6/8)	83.0	
G2				0.16	(0/1)	1.12	(11/11)	-0.05	(8/8)	0.05	(10/10)	81.9	
G3				0.12	(0/1)	1.11	(11/11)	-0.06	(7/8)	0.07	(5/5)	82.2	
G4				0.15	(0/1)	1.1	(11/11)	-0.05	(8/8)	0.06	(5/6)	82.1	
G5				0.13	(0/0)	1.11	(11/11)	-0.05	(8/8)	0.03	(7/7)	81.6	

	λ_{RX}	p-Val	$\lambda_{HML^{FX}}$	p-Val	λ_{Good}	p-Val	b_{RX}	p-Val	$b_{HML^{FX}}$	p-Val	b_{Good}	p-Val	$\chi^2_{pr.err.}$
	2.29	0.08	4.24	0.03			4.03	0.18	4.75	0.06			0.00
G1	2.13	0.10			2.09	0.02	3.43	0.24			17.80	0.03	0.17
G2	2.13	0.10			2.90	0.03	3.08	0.30			22.47	0.04	0.50
G3	2.12	0.10			2.91	0.02	1.70	0.59			15.91	0.03	0.09
G4	2.03	0.12			4.29	0.01	-4.38	0.35			24.98	0.02	0.22
G5	1.99	0.13			8.64	0.01	-8.54	0.13			29.83	0.01	0.47
G1	2.13	0.11	3.23	0.08	2.10	0.01	3.42	0.25	-0.08	0.98	18.03	0.03	0.27
G2	2.17	0.10	3.68	0.05	2.46	0.05	3.24	0.27	1.11	0.71	18.10	0.12	0.27
G3	2.11	0.11	3.29	0.07	3.03	0.01	1.49	0.64	-0.55	0.86	17.45	0.06	0.05
G4	2.09	0.11	3.31	0.07	3.74	0.00	-2.85	0.50	1.31	0.60	20.26	0.02	0.24
G5	2.13	0.10	3.88	0.04	6.18	0.01	-4.57	0.30	2.66	0.25	20.05	0.01	0.97

TABLE 5

Carry Return Predictability

Table 5 shows results from univariate predictive regressions for the log returns of the SC trade, the G1–G5 and B1–B5 trades, and the GC and BC trades as described in Table 3. The 3 predictors shown in the first row of the table have been found to predict carry trade returns in (Bakshi and Panayotov, 2013, Table 2) and (Ready et al., 2017, Table 10), and are designed as in those studies (see also Section D). The table displays the in-sample estimates of the predictive slope coefficients β, 2-sided p-values, based on the Hodrick (1992) 1B covariance matrix estimator, and adjusted R^2's (in percentages). Next are shown 1-sided p-values (denoted "MS") for the MSPE-adjusted statistic (Clark and West (2007), see also footnote 6), obtained with an expanding window with initial length of 120 months. The columns denoted "Δ SR" report a measure of the economic significance of predictability, based on a prediction-based trading strategy, which enters into a carry trade at the end of month t only if the trade's return predicted for month $t+1$ is positive (if a negative return is predicted, the carry trade return for month $t+1$ is 0). Specifically, the measure equals the difference between the Sharpe ratio of the prediction-based strategy, implemented with the respective subset of G-10 currencies, and the corresponding unconditional carry trade (using an expanding window with initial length of 120 months). For the GC and BC trades the table shows averages of the respective 18 predictive slope coefficients β, adjusted R^2's, and changes in Sharpe ratios. The first (second) number in parentheses shows how many of the 18 corresponding individual estimates are significant at the 5% (10%) confidence level. The sample period is Dec. 1984–June 2014.

TABLE 5 (continued)

	Commodity Returns					Change in Exchange Rate Volatility					Change in BDI				
	β	*p*-val	R^2	MS	Δ SR	β	*p*-val	R^2	MS	Δ SR	β	*p*-val	R^2	MS	Δ SR
SC	0.015	0.12	0.8	0.45	-0.04	-0.005	0.00	2.4	0.01	0.10	0.003	0.15	1.0	0.18	0.08
G1	0.006	0.53	0.1	0.99	-0.04	-0.003	0.12	0.8	0.22	-0.04	0.003	0.16	0.9	0.21	0.10
G2	0.013	0.19	0.5	0.85	-0.05	-0.003	0.21	0.6	0.30	0.00	0.002	0.39	0.3	0.79	0.00
G3	0.008	0.50	0.1	0.82	0.01	-0.005	0.05	1.6	0.13	-0.05	0.005	0.02	2.3	0.02	0.09
G4	0.012	0.52	0.3	0.88	-0.03	-0.006	0.04	1.9	0.21	-0.03	0.002	0.48	0.4	0.71	-0.01
G5	-0.005	0.82	0.0	0.94	0.00	-0.003	0.35	0.4	0.60	0.03	-0.002	0.68	0.1	0.97	-0.05
B1	0.069	0.01	3.3	0.02	0.29	-0.010	0.02	1.7	0.01	0.22	0.010	0.05	2.3	0.04	-0.14
B2	0.043	0.04	2.3	0.06	0.15	-0.008	0.01	2.1	0.01	0.13	0.010	0.01	4.2	0.01	0.09
B3	0.032	0.04	1.6	0.10	-0.02	-0.007	0.01	2.3	0.01	0.32	0.004	0.15	1.0	0.13	-0.15
B4	0.040	0.03	2.5	0.06	0.12	-0.007	0.02	1.9	0.02	0.23	0.007	0.06	2.3	0.05	0.09
B5	0.029	0.05	1.4	0.12	-0.01	-0.006	0.01	1.9	0.01	0.14	0.007	0.02	2.8	0.01	0.06
GC	0.010	(0/3)	0.5	(0/0)	-0.04	-0.005	(11/14)	1.4	(3/5)	0.00	0.002	(2/3)	0.8	(2/3)	-0.02
BC	0.033	(7/14)	1.7	(1/9)	0.03	-0.007	(15/17)	1.8	(17/18)	0.17	0.008	(12/14)	2.9	(12/15)	0.07

TABLE 6

Carry Components in Carry Trade Returns

Table 6 shows the average returns, and the components of these returns due to carry and exchange rate changes, for the standard (SC) trade, the good and bad carry trades G1–G5 and B1–B5, and the dollar carry (DC) trade of Lustig et al. (2014), which we consider in more detail in Section B. The respective values are shown annualized and in percentages. Also shown are in curly brackets *p*-values from a test for equality of the respective average carry component to that of the SC and DC trades (Newey–West standard errors, with 12 lags).

	SC	B1	B2	B3	B4	B5	G1	G2	G3	G4	G5	DC
Avg. total ret.	1.02	0.68	0.98	0.21	0.28	0.61	1.67	1.70	2.49	2.22	3.97	4.19
Avg. deprec.	-0.37	-2.02	-1.25	-1.58	-1.65	-1.28	0.26	0.50	0.78	1.01	2.76	3.27
Avg. carry	1.38	2.70	2.23	1.78	1.92	1.88	1.40	1.20	1.70	1.20	1.20	0.92
Carry to total ret.	1.36	3.98	2.27	8.46	6.96	3.08	0.84	0.70	0.68	0.54	0.30	0.22
Comparing Carry Components (*p*-values)												
to that of SC		{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.63}	{0.08}	{0.00}	{0.04}	{0.32}	{0.01}
to that of DC		{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.01}	{0.04}	{0.00}	{0.04}	{0.01}	

TABLE 7

Unbiasedness Hypothesis Regressions for Pairs of Prototypical Carry Trade Currencies

In Table 7, for each of the 6 currency pairs NZD/CHF, AUD/CHF, NOK/CHF, NZD/JPY, AUD/JPY and NOK/JPY monthly log changes in spot rates are regressed against the corresponding forward differentials (all mid-quotes): $\ln(S_{t+1}/S_t) = \alpha + \beta \ln(F_t/S_t) + \varepsilon_{t+1}$. Estimates of α and β are shown, together with 2-sided p-values, based on the Hodrick (1992) 1B covariance matrix estimator, for the null hypotheses $\alpha = 0$ and $\beta = 1$. The sample period is Dec. 1984–June 2014, and the data source is Barclays Bank, via Datastream.

	CHF				JPY			
	α	p-Val	β	p-Val	α	p-Val	β	p-Val
NZD	0.001	0.74	0.46	0.31	0.003	0.45	0.63	0.49
AUD	-0.002	0.58	0.15	0.30	0.002	0.57	0.92	0.92
NOK	-0.001	0.72	0.43	0.17	0.007	0.03	2.22	0.10

TABLE 8

Dynamic Nature of Carry Trades

Table 8 characterizes the dynamic behavior of the the standard carry (SC) trade, the G1–G5 and B1–B5 trades, and, in the last row, the dollar carry (DC) trade of Lustig et al. (2014), which we consider in more detail in Section B. The first column of the table shows, for each trade, the time-series average of the proportion of currencies that change (switch) position, from long to short or vice versa, at each point of time. The average proportion is given in percentages. The next 2 columns show bootstrapped 95% confidence intervals for these average proportions. The column denoted "days w/o switch" shows the proportion of dates in the sample when not a single currency changed position from short to long or vice versa. Next the table shows the correlation between the proportions for the G1–G5 and B1–B5 trades, and those for standard carry (SC). The last 3 columns aim to compare static and dynamic versions of our various trades. *Static* trades have been defined in Hassan and Mano (2015), and, to keep close to their setup, we use as weights the average forward differentials of the respective currencies over Dec. 1984–Dec. 1994, demeaned and normalized to have absolute values that sum to 1. These weights are kept fixed for the rest of the sample period for the static trades, without ever rebalancing. *Dynamic* trades are the usual (dynamically rebalanced) trades, as considered throughout this paper, but with weights again equal to the cross-sectionally demeaned forward differentials, normalized to have absolute values that sum to 1. Shown are the ratios between the average returns of the respective static and dynamic carry trade, and the corresponding Sharpe ratios. Average returns and Sharpe ratios are calculated for the period Dec. 1994–June 2014.

TABLE 8 (continued)

	Switch (%)	95%. Conf. Int.		Days w/o Switch	Correl. with SC	Ratio of Static to Dynamic Avg. Ret.	Sharpe Ratios	
							Dynamic	Static
SC	8.22	[5.72	11.05]	0.68		0.45	0.41	0.21
G1	12.75	[9.27	16.47]	0.66	0.82	0.23	0.51	0.14
G2	12.97	[9.35	16.88]	0.73	0.75	-0.23	0.34	-0.10
G3	11.90	[8.73	15.18]	0.75	0.59	0.24	0.55	0.14
G4	17.22	[13.20	21.25]	0.63	0.63	0.28	0.50	0.13
G5	16.34	[11.99	20.96]	0.78	0.49	-0.01	0.69	-0.01
B1	9.82	[5.67	14.64]	0.86	0.53	1.07	0.21	0.23
B2	9.97	[6.35	13.94]	0.78	0.56	1.16	0.22	0.29
B3	12.18	[8.44	16.60]	0.73	0.59	0.75	0.25	0.22
B4	10.14	[7.25	13.20]	0.78	0.50	0.61	0.24	0.16
B5	10.12	[6.92	13.60]	0.71	0.65	0.82	0.27	0.24
DC	6.80	[3.40	11.05]	0.93	0.47			

TABLE 9

Correlations and Spanning

Panel A of Table 9 shows return correlations between SC and DC and the G1–G5 and B1–B5 carry trades. In Panel B, "Good" refers to the good carries G1–G5 shown in the first column, the LHS variable is that for which no regression coefficient is reported on the respective row. Intercepts are reported annualized and in percentages.

Panel A. Correlations

	DC	G1	G2	G3	G4	G5	B1	B2	B3	B4	B5
SC	0.40	0.87	0.63	0.77	0.62	0.41	0.72	0.84	0.84	0.78	0.88
DC		0.41	0.42	0.48	0.61	0.68	0.17	0.15	0.15	0.07	0.09

Panel B. Return Regressions

	Interc.	p-Val	β_{SC}	p-Val	β_{DC}	p-Val	β_{Good}	p-Val	R^2
G1	-0.50	0.10			0.03	0.05	0.85	0.00	0.75
G2	-0.20	0.67			0.07	0.00	0.54	0.00	0.42
G3	-0.56	0.16			0.02	0.36	0.61	0.00	0.59
G4	-0.03	0.94			0.01	0.56	0.45	0.00	0.37
G5	0.02	0.97			0.10	0.00	0.14	0.00	0.18
G1	2.91	0.02	0.42	0.05			0.51	0.01	0.16
G2	2.71	0.02	0.47	0.00			0.59	0.00	0.20
G3	2.18	0.07	0.15	0.36			0.75	0.00	0.22
G4	1.97	0.06	0.07	0.56			0.97	0.00	0.37
G5	0.74	0.44	0.31	0.00			0.79	0.00	0.48
G1	0.69	0.03	0.84	0.00	0.03	0.02			0.75
G2	0.70	0.15	0.58	0.00	0.10	0.00			0.43
G3	1.13	0.02	0.86	0.00	0.12	0.00			0.63
G4	0.50	0.37	0.59	0.00	0.27	0.00			0.53
G5	1.63	0.03	0.27	0.00	0.49	0.00			0.48

TABLE 10

Dollar Carry versus Good Carry Trades as Currency Market Pricing Factors

Table 10 differs from Table 4 only in one aspect: instead of the RX and HML^{FX} factors, we now use the dollar carry factor (denoted “DC”), as in Lustig et al. (2014) and Hassan and Mano (2015), calculated for the G-10 currencies. The test assets are again the 11 interest rate-sorted portfolios as in Lustig et al. (2011). “Good” refers to the good carries G1–G5.

	Avg. Ret.	*p*-Val	α	*p*-Val	β_{DC}	*p*-Val	β_{Good}	*p*-Val	R^2
	2.33	(3/4)	-0.04	(0/0)	0.56	(11/11)			21.2
G1			1.88	(0/0)			0.26	(9/9)	5.3
G2			1.89	(0/2)			0.25	(7/7)	3.1
G3			1.02	(0/0)			0.52	(7/7)	8.6
G4			0.26	(0/0)			0.93	(11/11)	21.9
G5			-0.41	(0/0)			0.67	(11/11)	18.8
G1			0.21	(0/0)	0.55	(11/11)	-0.27	(7/7)	26.8
G2			0.23	(0/0)	0.56	(11/11)	-0.29	(5/6)	24.5
G3			-0.12	(0/0)	0.49	(11/11)	0.06	(7/8)	24.7
G4			-0.43	(0/0)	0.31	(8/9)	0.58	(10/10)	27.2
G5			-0.67	(0/0)	0.34	(10/11)	0.34	(7/9)	23.8

	λ_{DC}	*p*-Val	λ_{GC}	*p*-Val	b_{DC}	*p*-Val	b_{Good}	*p*-Val	$\chi^2_{pr.err.}$
	0.45	0.07			8.3	0.07			0.03
G1			0.32	0.01			28.4	0.01	0.99
G2			0.46	0.03			37.0	0.02	0.32
G3			0.35	0.04			21.6	0.02	0.13
G4			0.27	0.07			13.7	0.06	0.14
G5			0.37	0.07			11.1	0.06	0.95
G1	4.85	0.05	2.27	0.01	6.3	0.21	14.5	0.09	0.77
G2	5.19	0.04	2.93	0.02	5.8	0.27	18.1	0.10	0.99
G3	4.04	0.12	2.95	0.01	3.7	0.52	13.6	0.09	0.15
G4	1.15	0.75	3.49	0.01	-6.8	0.53	24.5	0.10	1.00
G5	3.12	0.31	3.88	0.13	-3.4	0.81	15.5	0.37	0.16