Good Carry, Bad Carry

Online Appendix: Not for Publication

OA-I Symmetry and numeraire neutrality of currency trades

This Appendix explains in detail the distinction between several designs of carry trades. Start with a set of N currencies, e.g. the G-10 currencies in our case. A currency trading strategy is a mapping between signals at time t and currency positions taken at this time, whereby positions are defined in terms of the weights of individual currencies. A trading strategy is formulated relative to a benchmark currency, i.e. positions are taken relative to a certain currency in the forward market. From this perspective, two properties seem important:

1. *Symmetry*: the number of short and long positions and their total weights are equal. A stronger version of symmetry would also require equal weights of the individual short or long positions.[1]

2. *Numeraire independence*: the positions taken in the various currencies are the same, regardless of which benchmark currency is considered. As a result, only one currency strategy must be defined for the world at large.

Symmetry and numeraire independence are well-established features of carry trades, and have been both adopted by recent academic studies, and implemented in investable products (see Table 1). Together, these properties imply that the trade's returns will be very similar from any currency perspective. This invariance follows from the fact that the translation of returns from one currency to another simply introduces cross-currency risk on currency returns, which is a second order effect. Conversely, if the ranking of a currency or the signal depends in any way on the identity of the benchmark currency, then defining the same strategy from another currency perspective will yield different currency positions and different currency weights, and this can result in quite different returns. A well-known example is the asymmetric carry strategy in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), which has been shown in Daniel, Hodrick, and

[1] However, if weights are defined relative to a benchmark currency (e.g., based on forward differentials), they may differ on the long and short end, creating weight asymmetry. This would cause the trade to be numeraire-dependent.

Lu (2017) to produce very different (and worse) returns from other, non-USD currency perspectives. In fact, the USD-based version of this strategy is successful (at least partly) due to is its implicit exposure to a dollar-centric currency strategy, the ”dollar carry” trade of Lustig, Roussanov, and Verdelhan (2014).[2]

We now formally show that symmetric, numeraire-independent strategies have largely equivalent returns across the world. Suppose first that the USD is the benchmark currency and define the weight of currency i as w_i. Spot and forward exchange rates are quoted here as USD per one unit of a foreign currency (reversing the notation from Section II above), and denoted as S_t^i and F_t^i. The return of a US-based currency trading strategy over the interval t to $t+1$ is:

$$r_{t+1}^{USD} = \sum_{i=1}^{N} w_i [S_{t+1}^i / F_t^i - 1]. \tag{OA-1}$$

If the strategy is numeraire independent, the weights w_i are *identical* for all currency perspectives. For example, if the trading strategy is based on interest rate signals, these signals should be independent of the benchmark currency.

Defining such a strategy relative, say, to the Japanese yen, with yen exchange rates denoted by $\overline{S}_t^i$ and $\overline{F}_t^i$ (JPY per one unit of currency i), its return (in yen) is:

$$r_{t+1}^{JPY} = \sum_{i=1}^{N} w_i [\overline{S}_{t+1}^i / \overline{F}_t^i - 1] = \sum_{i=1}^{N} w_i \overline{S}_{t+1}^i / \overline{F}_t^i - \sum_{i=1}^{N} w_i \tag{OA-2}$$

With symmetric strategies the weights sum to zero, hence the last term cancels, and we are left with $r_{t+1}^{JPY} = \sum_{i=1}^{N} w_i \overline{S}_{t+1}^i / \overline{F}_t^i$. By triangular arbitrage and symmetry, we can further derive:

$$r_{t+1}^{JPY} \quad = \quad [r_{t+1}^{USD} + \sum_{i=1}^{N} w_i] * \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD} = r_{t+1}^{USD} * F_t^{JPY} / S_{t+1}^{JPY}. \tag{OA-3}$$

[2]The dollar carry weights are 1/(N-1) and are all either positive or negative depending on the average interest rate of the USD relative to other currencies. The weight on the USD itself is zero. The strategy is thus very asymmetric and yields entirely different results for other currency perspectives. That is, a ”British pound carry” or ”Swiss franc carry” need not be anything like dollar carry. Of course, dollar-centric strategies are of interest because of the importance of the dollar in international finance.

Cross-currency risk could drive, in principle, a wedge between the two currency perspectives, but in practice the returns and their properties will be rather similar (barring significant differences in transaction costs), because the forward to spot ratio in (OA-3) is close to one, and applies to returns. We have verified that standard carry strategies (as per our definition in Section II) yield very similar returns from any currency perspective.

It is instructive to repeat the previous calculation, but for *log* returns. In this case:

$$
\begin{aligned}
r_{t+1}^{JPY} &= \sum_{i=1}^{N} w_i \log\left(\overline{S}_{t+1}^{i}/\overline{F}_t^{i}\right) = \sum_{i=1}^{N} w_i \log\left(\frac{S_{t+1}^{i}}{F_t^{i}} \; \frac{\overline{S}_{t+1}^{USD}}{\overline{F}_t^{USD}}\right) \\
&= \sum_{i=1}^{N} w_i \log(S_{t+1}^{i}/F_t^{i}) + \sum_{i=1}^{N} w_i \log(\overline{S}_{t+1}^{USD}/\overline{F}_t^{USD}) \\
&= \sum_{i=1}^{N} w_i \log(S_{t+1}^{i}/F_t^{i}) + \log(\overline{S}_{t+1}^{USD}/\overline{F}_t^{USD}) \sum_{i=1}^{N} w_i \\
&= \sum_{i=1}^{N} w_i \log(S_{t+1}^{i}/F_t^{i}) + 0 = r_{t+1}^{USD}, \qquad \text{(OA-4)}
\end{aligned}
$$

and therefore the log returns of symmetric, numeraire-independent trades are *identical* from any perspective; the differences between their percentage returns from different perspectives are of second order.

In sum, a symmetric carry trade, for any benchmark currency has similar returns for investors across the world. However, symmetry is not a sufficient condition for numeraire independence. It is important to emphasize this point, because a number of recent articles have considered ”currency-neutral” symmetric strategies, where no position is taken with respect the benchmark currency itself, or in other words, the weight assigned to the benchmark currency is always zero (this is implicitly true also for dollar carry). Let’s examine, following Daniel, Hodrick, and Lu (2017), a ”dollar-neutral” carry trade with weights $w_i = 1/(N-1)$ if the interest rate of currency i is in top half of the interest rates of the given set of currencies, and $w_i = -1/(N-1)$ otherwise (if N-1 is odd, the currency with the median interest rate is left out of the trade). This strategy is clearly symmetric. However, it is not numeraire independent because if we define it relative to another benchmark currency, say the yen, the weight function of this ”yen-neutral” trade will change, with now non-zero weights on the USD and zero weights on the JPY. Therefore, such ”currency-neutral” trades will produce different returns for different benchmark currencies, going beyond the differences induced by cross-currency risk.

We recognize that some numeraire-dependent strategies are of obvious interest, but care must be taken to define them in an international context. For example, the HML factor, introduced by Lustig, Roussanov, and Verdelhan (2011, 2014) is a carry trade which is symmetric, but not numeraire-independent as it goes long (short) an extreme portfolio based on an interest rate ranking (as the DB strategy does), but excludes the USD from any portfolio. This dollar neutrality makes the trade numeraire-dependent. Of course, when such a trade is defined for benchmark currencies with non-extreme interest rates, it should often yield similar returns across the different country perspectives.

Our preference for using symmetric, numeraire-independent carry trades is consistent with the best known investable indices, such as the Deutsche Bank (DB) Harvest Indexes. The DB strategy goes long (short) the G-10 currencies with the three highest (lowest) interest rates. Importantly, when the USD interest rate is among the top or bottom three, part of the trade automatically gets a zero return, because a position in the benchmark currency itself is taken, and hence the trade is *not* dollar-neutral. However, it is symmetric and numeraire-independent, which is an advantage for a global currency trading strategy, and may also be an advantage for a global risk pricing factor. In the trades that we consider, all participating currencies are given a non-zero weight, including the benchmark currency, which by design yields a zero return, whether it is held long or short.

Another way to see the fundamental difference between asymmetric, numeraire-dependent trades on the one hand, and numeraire-independent strategies on the other is to examine what would happen if, say, a yen-based investor would try to mimic, for example, dollar carry by taking exactly the same positions, but relative to the yen. That is, she will go long or short in all the currencies (including the yen) as dollar carry does, thus keeping the same weight function as in the original dollar trade, but for a different benchmark currency. This strategy would yield quite different returns as it would face *full* cross-currency risk, and not just profit and loss currency risk.

With the previous notation: $r_{t+1}^{JPY} = [r_{t+1}^{USD} + \sum_{i=1}^{N} w_i] * \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD} - \sum_{i=1}^{N} w_i$. Since for dollar carry these weights add up to one, and not zero as in a symmetric trade, the yen-based return is now:

$$r_{t+1}^{JPY} = [r_{t+1}^{USD} + 1] * \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD} - 1 = r_{t+1}^{USD} F_t^{JPY} / S_{t+1}^{JPY} + [F_t^{JPY} / S_{t+1}^{JPY} - 1], \tag{OA-5}$$

which, compared to the expression in (OA-3), adds a second return term that can well be of similar or even larger magnitude than the first term.

OA-II Tests for differences in Sharpe ratios and return skewness

Sharpe ratios

The statistical significance of the differences between the Sharpe ratio or skewness of the SC trade and those of trades from subsets is evaluated using bootstrap tests that follow Ledoit and Wolf (2008) or Annaert, Van Osselaer, and Verstraete (2009). Skewness difference can be tested in a ”direct” bootstrap that resamples from a distribution which respects the null hypothesis of no difference. In the case of Sharpe ratios, their difference does not easily admit such a distribution, hence the approach followed is ”indirect” and resamples from the observed data. A version of this approach to comparing Sharpe ratios has been applied recently, among others, in DeMiguel, Nogales, and Uppal (2014).

In implementing the test for a difference between Sharpe ratios, we depart in two minor ways from Ledoit and Wolf (2008). First, we only consider the i.i.d. case (their Section 3.2.1). We have verified that our carry trade return series have insignificant autocorrelations for lags up to 10. Furthermore, the suggested block size selection procedure (their Algorithm 3.1) results consistently in a selected block length of one, when using our data. Second, we consider one-sided bootstrap confidence intervals and p-values, since our null hypothesis is that carry trades obtained with the enhancement rule do not *improve* on the Sharpe ratio of the SC trade. We modify accordingly their equation (7).

Following the notation in Ledoit and Wolf (2008), let $\widehat{\mu}_S$ and $\widehat{\mu}_B$ denote the sample average returns of a carry trade from some subset of the G-10 currencies and the SC trade, respectively, while $\widehat{\gamma}_S$ and $\widehat{\gamma}_B$ are the sample second moments (uncentered) of the returns of these trades. Let also $\widehat{v} = (\widehat{\mu}_S, \widehat{\mu}_B, \widehat{\gamma}_S, \widehat{\gamma}_B)$, and assume that $\sqrt{T}(\widehat{v} - v) \xrightarrow{d} (0, \Psi)$, where v is the population counterpart, T is sample length and Ψ is some symmetric positive-definite matrix. The latter assumption holds under mild conditions. For the sample difference $\widehat{\Delta}$ between the Sharpe ratios of the carry trade from a subset of the G-10 currencies and the SC trade, and the deviation of this sample difference from the population value Δ, one can write

$$\text{(OA-6)} \qquad \widehat{\Delta} = f(\widehat{v}) = \frac{\widehat{\mu}_S}{\widehat{\gamma}_S - \widehat{\mu}_S^2} - \frac{\widehat{\mu}_B}{\widehat{\gamma}_B - \widehat{\mu}_B^2} \qquad \text{and} \qquad \sqrt{T}(\widehat{\Delta} - \Delta) \xrightarrow{d} (0, \nabla' f(v) \Psi \nabla f(v)),$$

where $\nabla' f((a,b,c,d)) = \left(\frac{c}{(c-a^2)^{1.5}}, -\frac{d}{(d-b^2)^{1.5}}, -\frac{a}{2(c-a^2)^{1.5}}, \frac{b}{2(d-b^2)^{1.5}} \right)$ and (a, b, c, d) represent the elements in $\widehat{v}$. If $\widehat{\Psi}$ is a consistent estimator of Ψ, then the standard error of $\widehat{\Delta}$ is given by

$$\text{(OA-7)} \qquad s(\widehat{\Delta}) = \sqrt{\frac{\nabla' f(\widehat{v}) \widehat{\Psi} \nabla f(\widehat{v})}{T}}.$$

To test the null hypothesis $\Delta \leq 0$, we bootstrap the returns of the two carry trades that are compared, and consider the studentized random variable $L = \frac{\Delta^* - \widehat{\Delta}}{s(\Delta^*)}$, where Δ^* is a difference in Sharpe ratios computed with bootstrapped returns, and $s(\Delta^*)$ is the corresponding standard error. Even though we bootstrap ”under the alternative”, this procedure generates meaningful sampling variation under the null of no difference between Sharpe ratios. Given the lack of autocorrelation in the carry trade return series, as noted above, we use an i.i.d. bootstrap (5000 samples, with replacement and pairwise, to preserve a possible cross-sectional correlation between the returns of the two carry trades). A p-value for the null is calculated as the proportion of bootstrapped series for which:

$$\widehat{\Delta} - L = \widehat{\Delta} + \frac{\widehat{\Delta} - \Delta^*}{s(\Delta^*)} s(\widehat{\Delta}) \leq 0, \tag{OA-8}$$

similar to equation (7) in Ledoit and Wolf (2008). These p-values are reported in Tables 2 and 3.

Skewness

To test for a difference in skewness, Annaert, Van Osselaer, and Verstraete (2009, page 277) first "symmetrize" the compared return series, by appending to them the mirror images of the original observations in terms of distance to the average return. The skewness (as well as any odd central moment) of these modified returns is thus zero, and a bootstrap that resamples from them conforms to the null of no difference in skewness. Given that autocorrelation does not seem to be an issue in our series, we draw pairwise from the modified series of the compared returns, and compute the p-value as the percentage of draws that yield higher improvement on the benchmark skewness than that observed in the data. All bootstraps are performed with 5000 draws.

OA-III Differences in Sharpe ratios - accommodating the selection

The enhancement procedure described in Section III introduces a possible selection bias, which is not accounted for by the bootstrap-based test described above, following Ledoit and Wolf (2008). To address this issue, we suggest an alternative approach, and instead of bootstrapping the actual carry returns, we adopt the following randomization procedure:

- at the end of month t keep the interest rate differentials as in the data, but assign to each of them *at random* any of the ten returns for the following month $t+1$.
- to *each* of these ten returns for month $t+1$ add the same constant c_{t+1}. We call the returns obtained in this way "randomized" returns.

- the constant c_{t+1} can be positive or negative, and is chosen so that a carry trade that uses all ten "randomized" returns would have exactly the same return as the actual SC trade for month $t+1$. Such a carry trade would choose the currencies to be long or short exactly as the SC trade, based on sorting the same interest rate differentials.

- do this for all months in the sample, and repeat 1000 times, to obtain 1000 sets of ten "randomized" return series, that correspond to the actual interest rate differentials. Given the large number permutations of ten numbers, we do not bootstrap in addition the interest rate differentials.

- note that the constants c_{t+1} are different for different months, and that each "randomized" return corresponding to a particular interest rate differential is potentially very different from the actual one. This approach may associate, for example, the JPY returns predominantly with the highest interest rates in some randomization trials. However, the returns for each month, and hence the Sharpe ratios of the carry trades with ten currencies (all 1000 with "randomized" returns and the actual SC trade) are exactly the same.

- on each of the 1000 sets of 10 time series reproduce the enhancement procedure described in Section B. Based on the order of exclusion obtained from this procedure, identify for each of the 1000 sets the currencies that would enter "good" and "bad" carry trades.

- in the full sample period construct trades with the least excluded three, five or seven currencies, corresponding to our G1-G5 trades, and similarly with the most often excluded three, five or seven currencies, corresponding to our B1-B5 trades.

For each of 1000 sets of 10 series of randomized carry trade returns, Δ^* denotes the difference between the annualized Sharpe ratio of a good carry trade (from three, five or seven currencies), constructed from this set following the enhancement procedure, and the SC trade or the corresponding bad trade. As in

Appendix OA-II, $\widehat{\Delta}$ denotes the sample difference between the annualized Sharpe ratio of a good carry trade and the SC trade or the corresponding bad trade. We now show $\widehat{\Delta}$ for each good carry trade, the average of the 1000 Δ^*'s for trades from as many currencies as the good trade on the same line, and the proportion of such Δ^*'s exceeding $\widehat{\Delta}$.

	Good trades vs. SC			Good vs. bad trades		
	$\widehat{\Delta}$	avg. Δ^*	% $\Delta^* > \widehat{\Delta}$	$\widehat{\Delta}$	avg. Δ^*	% $\Delta^* > \widehat{\Delta}$
G1	0.20	0.14	0.21	0.42	0.42	0.50
G2	0.18	0.16	0.43	0.31	0.41	0.71
G3	0.30	0.16	0.09	0.57	0.41	0.19
G4	0.20	0.16	0.37	0.45	0.41	0.41
G5	0.39	0.14	0.02	0.56	0.32	0.05

There is substantial bias in the comparison between the G1-G5 carry trades with the SC trade, with the selection procedure adding 14% (for G1 and G5) or 16% (for G2 to G4) to the annualized Sharpe ratio. Yet, in every case the *observed* increases in the Sharpe ratio (denoted by $\widehat{\Delta}$) are even higher, and for two out of the five good trades the observed Sharpe ratio is in the 10% right tail of the distribution of the Sharpe ratios obtained under the selection procedure using the randomized (scrambled) currency returns. When comparing the G1-G5 carry trades to the corresponding B1-B5 trades, the bias is relatively more important, and in fact at least as large as the observed difference in Sharpe ratios for the G1 and G2 trades. Only the G5 versus B5 comparison yields a Sharpe ratio of a good trade in the right tail (5.3%) of the corresponding distribution under scrambled currency returns.

Of course, these observations alone do not constitute a proper test, since the randomization procedure also can change the variability of the returns, and proper testing requires the use of a pivotal test statistic, such as a t-statistic. To create a proper test statistic, we modify the procedure in Ledoit and Wolf

(2008) by bias-correcting our sample Sharpe ratios, and using t-statistics from the empirical distribution as in Appendix OA-II. The results, which also reproduce the relevant portion from Table 3, to facilitate comparison are as follows:

	Good trades vs. SC						Good vs. bad trades				
	av.ret	std.	SR	bstrp.	rand.		av.ret	std.	SR	bstrp.	rand.
SC	1.02	3.30	0.31								
G1	1.67	3.29	0.51	0.02	0.18	B1	0.68	7.50	0.09	[0.01]	[0.50]
G2	1.70	3.47	0.49	0.13	0.44	B2	0.98	5.54	0.18	[0.07]	[0.72]
G3	2.49	4.09	0.61	0.01	0.06	B3	0.21	4.91	0.04	[0.01]	[0.16]
G4	2.22	4.39	0.51	0.12	0.39	B4	0.28	4.96	0.06	[0.02]	[0.42]
G5	3.97	5.71	0.69	0.03	0.04	B5	0.61	4.66	0.13	[0.01]	[0.09]

Let's first focus on the G1 trade. The t-statistic for its Sharpe ratio (0.51) being different from the benchmark Sharpe ratio (0.31) has a p-value of 0.02. When we do the test using the randomized samples, correcting for selection bias, the p-value increases to 0.18, and the difference is no longer statistically significant. The p-values invariably increase for all carry trades, but remain significant at the 5% level for G5, and at the 10% level for G3. For the good vs. bad carry trade comparison, the p-values increase dramatically and only the G5 trade has a significantly higher Sharpe ratio than B5 (at the 10% level).

OA-IV Factor models explaining good and bad carry trades

Tables OA-2 to OA-4 present the results separately for the standard carry trade (SC), the G1-G5 and B1-B5 trades, and the GC and BC trades on average. The first column in Table OA-2 also shows the respective average returns that are to be explained. For the G1-G5 trades these range between 1.7 and 4% (annualized), and are all significantly different from zero at the 1% confidence level (with GMM standard errors); for the GC trades they are on average 2%, and all but two out of 18 are significant at the 5% level. In contrast, the average returns for the bad carry trades never exceed 1%, and are never significant, even at the 10% level.

A. Model with equity volatility

The market factor (denoted MKT) in the model is proxied by the total return of the MSCI-World equity index, in excess of the risk-free rate and expressed in USD. The equity volatility factor (EqVol) reflects innovations in global equity volatilities, as constructed in Lustig, Roussanov, and Verdelhan (2011), and is taken from Verdelhan's website (data until 12/2013). The interaction term (product of MKT and EqVol) is denoted "prod", and exhibits highly negative skewness (-7.6).

The top panel of Table OA-2 reports results from time-series regressions of carry trade returns on the three risk factors. The market betas are significant for both good and bad trades, and of comparable magnitudes. However, the slope coefficient estimates on the product factor are typically negative, albeit rarely significant for good trades, while they are positive, mostly much larger in magnitude, and almost always significant at the 5% significance level for the bad trades. The F-test for no difference between the average slope coefficients across the GC and BC trades rejects only for β_{prod}. Given the high negative skewness of the product factor, the large positive value of β_{prod} implies that the market risk exposure of the bad trades increases substantially in highly volatile times, helping to explain the negative skewness of the bad trades as shown in Table 3.

From the perspective of a time-varying market beta, the large β_{prod} implies, for example, that the effective market beta for bad carry trades ranges between 0.025 and 0.083 for the 10-th and 90-th percentile observations of EqVol (which are -0.67 and 0.59, respectively). This regime dependence is much weaker for good carry trades, due to their smaller β_{prod} estimates. The SC trade resembles the bad trades in this respect, with a β_{prod} that is positive and marginally significant (at the 10% level). Given that increases in volatility tend to characterize periods of market downturns (the correlation between MKT and EqVol is -0.24 in our sample), our findings attribute the under-performance in times of crisis mostly to bad carry trades, while good trades are less affected.

The alpha's obtained in the time-series regressions are difficult to interpret in the presence of non-traded factors. Therefore, we also perform GMM-based cross-sectional tests on the GC and BC return cross sections, and show the results in the last two rows of the table. 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. However, the joint test does not reject for either of the two cross sections, delivering large p-values.

For further clarification, Panels A and B in Figure 4 plot model-predicted vs. actual average returns for the GC and BC trades, where we see practically no relation for the BC trades, but a much better fit for the GC trades, albeit with a few outliers. 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 three-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 Figure 4 show the promise of the model to provide a risk-based interpretation of good carry trades.

B. Model with Up and Down equity market factors

Our interest in such a model is motivated both by the asymmetric patterns in carry trade returns documented above, and the recent work of Lettau, Maggiori, and Weber (2015), who find support for a similar model pricing the joint cross section of several asset classes, including the returns of interest-rate-sorted currency portfolios. Note that their model employs the market factor itself, together with a separate down-market factor, whereas we use uncorrelated down- and up-market factors, which help sharpen the focus on the asymmetric return behavior across good and bad carry trades (see also Ang, Chen, and Xing (2006,

Table 2)). Keeping the notation MKT for the total return of the MSCI-World equity index, in excess of the risk-free rate and expressed in USD, the Down factor is taken to be $min(MKT,0)$, and the Up factor is $max(MKT,0)$.

Table OA-3 shows that in the time-series regressions the slope coefficient estimates on the Down factor are not statistically significant for about 70% of the good carry trades, but are significant for all but one of the bad carry trades. The pattern is *reversed* for the Up factor, where the estimates are significant for most of the good trades, but are in fact never significant for the bad trades, even at the 10% confidence level. The magnitudes of the respective slope coefficients for good versus bad trades also differ largely, by a factor of three or four, and these differences are highly significant, as evidenced by the reported p-values from GMM tests for the equality of the average β_{Down} or β_{Up} across the 18 GC and BC trades. Additional joint tests for pairwise equality between the corresponding coefficients for the GC and BC trades reject with even smaller p-values. As above, the SC trade exhibits mixed features, with both slope coefficients being significant.

The cross-sectional test results resemble those from Table OA-2, in that both risk prices λ_{Down} and λ_{Up} are statistically significant for good trades, and highly insignificant for bad trades, while the tests for the pricing errors being jointly equal to zero fail to reject, with high p-values. Moreover, the plots of model-based versus actual average returns, similar to those in Figure 4) again reveal a reasonable fit for good trades, but no apparent relation for bad trades, indicating that the model with down- and up-market factors more adequately describes the returns of good carry trades. The important additional insight from this model, however, is the striking dichotomy between the returns of good carry trades, which have relatively high Up-market betas but decouple in bad times, and the returns of bad carry trades, which have relatively high Down-market betas.

C. Fama-French three-factor model

Similar to Table OA-2 and in the same format, Table OA-4 illustrates the ability of the Fama-French three-factor model to explain the returns of good and bad carry trades, and the main finding is that the model does not perform well with respect to good carry trades.

The top panel of this table refers to time-series tests, and shows that the betas on the market factor are economically small for these trades (0.05 on average), albeit often significant, while those on the other two factors typically are not significantly different from zero. The adjusted R^2's in the time-series regressions are relatively low, even sometimes negative, whereas the alphas are only about 5 to 30% lower than the unconditional average carry trade returns, and still statistically significant for all G1-G5 trades and 14 of the GC trades. On the other hand, for bad carry trades the betas on all three factors are higher and statistically significant in most cases, and the R^2's are on average 0.12. A test for no difference between the average slope coefficients across the 18 GC and BC trades rejects for β_{MKT} and β_{SMB}, at the 5% confidence level. Interestingly, the model renders all alphas much lower than the respective average returns for the bad carry trades, so that these trades can be qualified as ”negative alpha trades”, from the perspective of this model. The model also explains a large part of the SC trade's average returns, with statistically significant factor loadings and a high R^2. The time-series tests therefore suggest that the good carry trades pose a problem for this model, whereas the SC trade and the bad trades at least are meaningfully exposed to standard risk factors. In addition, a test for alphas being jointly equal to zero does not reject for both the GC and BC sets of carry trades, with p-values above 0.30.

The last two lines of the table show results from GMM-based cross-sectional tests, using the GC and BC trades as test assets. The estimates of the risk prices λ are all statistically insignificant, except for λ_{MKT} for the GC trades, while the tests for the pricing errors being jointly equal to zero exhibit p-values above 0.70. The results for the risk prices thus cast doubt on the explanatory power of the Fama-French three-factor model for the BC trades as well, whereas the joint test results may reflect power issues.

Table OA-1

Currency volatility vs. good carry trades as currency market pricing factors

This table differs from Table 4 only in one aspect: instead of the HML^{FX} factor, we now use the currency volatility factor as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and denote it ”FXVol”. To obtain this factor, our monthly exchange rate volatility proxy is the average across currencies and days in the month of the absolute daily log changes of the exchange rates of the G-10 currencies against the USD, using mid-quotes. Next, we take first differences of the volatility proxy. Finally, we regress these first differences on the percentage monthly returns (in USD) of long positions in the G-10 currencies (except the USD), calculated as in equation (1), but using mid-quotes. The factor we use is the fitted value from this regression (multiplied by 100).

	avg. ret.	p-val		α	p-val	β_{RX}	p-val	β_{FXVol}	p-val	β_{Good}	p-val	R^2	
	2.33	(3/4)		0.04	(5/6)	1.11	(11/11)	0.0000	(6/6)			77.6	
G1				0.06	(0/1)	1.11	(11/11)	0.0001	(6/6)	-0.01	(9/9)	80.8	
G2				0.06	(1/2)	1.11	(11/11)	0.0004	(5/5)	-0.01	(9/9)	78.9	
G3				0.06	(0/1)	1.12	(11/11)	0.0003	(6/7)	-0.01	(8/8)	79.7	
G4				0.01	(1/3)	1.11	(11/11)	0.001	(6/6)	0.02	(8/10)	79.4	
G5				-0.01	(1/4)	1.11	(11/11)	0.001	(6/6)	0.02	(7/7)	78.3	
	λ_{RX}	p-val	λ_{FXVol}	p-val	λ_{Good}	p-val	b_{RX}	p-val	b_{FXVol}	p-val	b_{Good}	p-val	$\chi^2_{pr.err.}$
	2.14	0.10	-0.75	0.06			3.0	0.33	-3.0	0.15			0.00
G1	2.13	0.10	-1.74	0.65	2.43	0.00	4.0	0.17	1.7	0.37	23.6	0.01	0.30
G2	2.14	0.10	-0.04	0.99	4.36	0.00	3.8	0.22	3.1	0.18	37.7	0.00	0.54
G3	2.12	0.10	-1.87	0.63	3.61	0.00	1.6	0.60	2.6	0.21	24.1	0.01	0.08
G4	2.03	0.12	-1.27	0.74	4.34	0.00	-4.5	0.31	0.1	0.94	25.5	0.01	0.00
G5	2.01	0.12	-3.45	0.40	7.44	0.00	-7.4	0.12	-0.9	0.62	26.1	0.00	0.50

Table OA-2

Good and bad carry trades and a three-factor model with market and equity volatility factors

This table reports test results for a three-factor model with a market factor (denoted MKT), an equity volatility factor (EqVol) and the product of MKT and EqVol. MKT is the return of the MSCI-World equity index (total returns in excess of the risk-free rate, in USD). EqVol is the equity volatility factor, used in Lustig, Roussanov, and Verdelhan (2011) and available at Verdelhan's website until 12/2013, and the product of MKT and EqVol is denoted "prod". The test assets are the SC and good and bad carry trades. For the GC and BC trades the "avg. ret." column shows the average of their average returns, and the remaining columns show similarly averages of the regression coefficients and adjusted R^2's (in percent). Standard errors are estimated with GMM and account for one Newey-West lag. The first (second) number in parentheses shows how many of the 18 corresponding individual estimates are significant at the 5% (10%) confidence level. For example, none of the average returns for the 18 BC trades is significant even at the 10% level. In curly brackets are shown p-values for a test of equality of the respective average slope coefficients across the GC vs. BC trades, accounting for heteroskedasticity and one Newey-West lag. The last two lines show, similar to Table 4, results from cross-sectional GMM estimations of the model on the GC and BC carry trades. The sample period is 12/1984 to 12/2013. The reported average returns, α's and λ's are annualized and in percent.

	avg. ret.	p-val	α	p-val	β_{MKT}	p-vals	β_{EqVol}	p-val	β_{prod}	p-val	R^2
SC	1.02	0.10	0.81	0.19	0.06	0.00	-0.001	0.35	0.02	0.01	10.2
G1	1.67	0.01	1.46	0.02	0.05	0.00	0.000	0.51	0.01	0.28	5.6
G2	1.70	0.01	1.30	0.05	0.05	0.00	0.000	0.84	-0.01	0.18	3.2
G3	2.49	0.00	1.79	0.02	0.09	0.00	-0.001	0.33	-0.01	0.49	10.4
G4	2.22	0.01	1.47	0.10	0.07	0.00	-0.001	0.37	-0.03	0.15	4.8
G5	3.97	0.00	2.63	0.02	0.11	0.00	0.000	0.99	-0.07	0.00	8.4
B1	0.68	0.65	0.51	0.72	0.07	0.06	0.000	0.94	0.04	0.18	3.8
B2	0.98	0.39	0.88	0.40	0.06	0.01	-0.001	0.29	0.04	0.00	7.2
B3	0.21	0.83	0.40	0.66	0.04	0.07	0.000	0.82	0.05	0.00	8.1
B4	0.28	0.78	0.25	0.78	0.07	0.00	-0.001	0.46	0.05	0.01	12.2
B5	0.61	0.52	0.71	0.40	0.05	0.01	-0.001	0.49	0.05	0.00	12.4
GC	1.96	(16/17)	1.37	(6/10)	0.07	(18/18)	-0.001	(0/1)	-0.02	(3/4)	5.8
BC	0.66	(0/0)	0.69	(0/0)	0.06	(14/17)	-0.001	(0/0)	0.05	(17/17)	9.3
GC vs. BC					{0.49}		{0.42}		{0.000}		
					λ_{MKT}	p-val	λ_{EqVol}	p-val	λ_{prod}	p-val	$\chi^2_{pr.err.}$
GC					31.1	0.04	22.0	0.97	7.93	0.74	0.97
BC					6.54	0.57	-289.0	0.48	1.17	0.93	0.76

Table OA-3

Good and bad carry trades and a model with Down- and Up-market factors

This table differs from Table OA-2 only in one aspect: instead of the global market and equity volatility factors we use a Down and Up equity market factors. If MKT denotes the total return of the MSCI-World equity index, in excess of the risk-free rate, the Down factor is taken to be $min(MKT, 0)$, and the Up factor is taken to be $max(MKT, 0)$. The average returns and their p-values are omitted.

	α	p-val	β_{Down}	p-val	β_{Up}	p-val	R^2
SC	1.21	0.22	0.08	0.00	0.05	0.04	9.4
G1	1.68	0.08	0.06	0.00	0.04	0.06	5.5
G2	0.42	0.67	0.02	0.21	0.07	0.00	3.5
G3	1.49	0.20	0.08	0.00	0.10	0.00	10.4
G4	0.56	0.66	0.03	0.28	0.09	0.00	4.2
G5	-1.91	0.25	-0.05	0.20	0.21	0.00	7.9
B1	1.37	0.58	0.13	0.11	0.06	0.36	3.4
B2	2.47	0.15	0.13	0.00	0.03	0.45	5.8
B3	1.73	0.28	0.12	0.03	0.02	0.64	5.3
B4	1.83	0.26	0.15	0.01	0.04	0.32	9.8
B5	2.76	0.06	0.15	0.00	0.01	0.69	9.3
GC	0.49	(0/1)	0.04	(5/6)	0.09	(15/16)	5.9
BC	2.49	(6/8)	0.14	(17/18)	0.02	(0/0)	7.2
GC vs. BC			{0.02}		{0.02}		

	λ_{Down}	p-val	λ_{Up}	p-val	$\chi^2_{pr.err.}$
GC	14.0	0.05	15.5	0.02	0.96
BC	3.83	0.50	5.35	0.56	0.74

Table OA-4

Good and bad carry trades and the three-factor Fama-French model

This table differs from Table OA-2 only in one aspect: instead of the global market and equity volatility factors we use the three-factor Fama-French factors. The average returns and their p-values are omitted.

	α	p-val	β_{MKT}	p-vals	β_{SMB}	p-val	β_{HML}	p-val	R^2
SC	0.36	0.55	0.07	0.00	0.03	0.10	0.03	0.09	10.4
G1	1.24	0.04	0.05	0.00	0.01	0.58	0.01	0.61	4.5
G2	1.44	0.03	0.03	0.01	0.00	0.86	-0.01	0.81	1.6
G3	1.76	0.02	0.07	0.00	0.01	0.79	0.03	0.16	6.4
G4	1.95	0.02	0.02	0.24	0.00	0.94	0.02	0.49	-0.2
G5	3.79	0.00	0.01	0.59	-0.03	0.36	0.00	0.93	-0.4
B1	-0.97	0.51	0.14	0.00	0.08	0.04	0.13	0.00	9.5
B2	-0.21	0.84	0.11	0.00	0.06	0.02	0.08	0.01	10.9
B3	-0.69	0.48	0.09	0.00	0.07	0.00	0.05	0.08	10.6
B4	-0.93	0.34	0.13	0.00	0.05	0.05	0.05	0.09	15.8
B5	-0.43	0.61	0.11	0.00	0.06	0.01	0.05	0.04	14.6
GC	1.45	(11/14)	0.05	(14/15)	0.00	(0/0)	0.03	(3/4)	2.9
BC	-0.40	(0/0)	0.11	(18/18)	0.06	(13/16)	0.05	(10/14)	12.0
GC vs. BC			{0.02}		{0.02}		{0.25}		
			λ_{MKT}	p-val	λ_{SMB}	p-val	λ_{HML}	p-val	$\chi^2_{pr.err.}$
GC			37.2	0.01	-15.5	0.62	2.81	0.89	0.98
BC			0.43	0.96	8.49	0.55	1.43	0.89	0.73

Table OA-5

Economic regressions

The table shows results from multivariate regressions of various carry trade returns on three macro variables: global equity volatility, as in LRV (2011), industrial production growth in the OECD countries, and the residual from regressing the US industrial production growth on that of the OECD. The last three columns show the change in the dependent variable for one standard deviation change in each regressor, all else equal. Intercepts and sensitivities are reported annualized and in percent, and adjusted R^2's are in percent.

	interc.	p-val	β_{EQV}	p-val	β_{IP}	p-val	β_{USres}	p-val	R^2	sensitivity to:		
										EQV	IP	USres
SC	0.71	0.30	-2.23	0.03	0.17	0.08	-0.09	0.51	2.56	-1.72	1.22	-0.55
DC	3.70	0.01	-0.86	0.64	0.27	0.21	0.00	0.99	-0.21	-0.67	1.96	-0.02
G1	1.33	0.05	-1.67	0.08	0.18	0.06	-0.09	0.48	1.84	-1.29	1.34	-0.56
G2	1.28	0.06	-0.50	0.50	0.26	0.00	-0.09	0.47	1.77	-0.39	1.86	-0.54
G3	1.91	0.02	-2.40	0.02	0.32	0.00	-0.25	0.11	4.25	-1.85	2.29	-1.46
G4	1.77	0.05	-1.78	0.16	0.24	0.08	-0.11	0.55	1.26	-1.38	1.71	-0.65
G5	3.69	0.00	0.38	0.78	0.22	0.23	-0.24	0.29	0.30	0.29	1.57	-1.41
B1	-0.05	0.97	-2.85	0.13	0.38	0.13	-0.01	0.98	0.79	-2.20	2.72	-0.04
B2	0.15	0.89	-3.82	0.01	0.40	0.02	-0.14	0.47	3.26	-2.95	2.91	-0.81
B3	-0.21	0.84	-2.69	0.09	0.22	0.17	-0.07	0.74	1.35	-2.07	1.56	-0.42
B4	-0.23	0.83	-3.64	0.03	0.27	0.12	-0.14	0.46	3.07	-2.81	1.92	-0.86
B5	0.04	0.97	-3.45	0.03	0.28	0.04	-0.11	0.52	3.29	-2.66	2.02	-0.68

Table OA-6: **Detailed version of the top panel of Table 4**

Good	port.	avg. ret.	p-val	α	p-val	β_{RX}	p-val	$\beta_{HML^{FX}}$	p-val	β_{Good}	p-val	R^2
	1	-1.63	0.25	-1.74	0.00	1.02	0.00	-0.39	0.00			90.3
	2	-0.19	0.88	-1.15	0.08	0.88	0.00	-0.13	0.00			75.8
	3	0.79	0.54	-0.28	0.65	0.95	0.00	-0.13	0.00			78.4
	4	2.80	0.05	1.12	0.10	1.01	0.00	0.00	0.94			78.4
	5	3.68	0.02	1.62	0.03	1.11	0.00	0.05	0.11			80.0
	6	4.65	0.01	0.43	0.35	1.03	0.00	0.61	0.00			93.8
	7	-0.18	0.92	-0.38	0.67	1.24	0.00	-0.46	0.00			80.5
	8	1.04	0.57	-0.14	0.87	1.27	0.00	-0.23	0.00			77.6
	9	2.76	0.12	1.16	0.14	1.28	0.00	-0.14	0.00			81.7
	10	2.77	0.14	0.39	0.66	1.28	0.00	0.05	0.19			79.7
	11	4.79	0.02	1.55	0.13	1.27	0.00	0.27	0.00			75.2
G1	1			-2.27	0.00	0.99	0.00			-0.61	0.00	76.5
	2			-0.85	0.15	0.89	0.00			-0.50	0.00	78.8
	3			-0.29	0.63	0.94	0.00			-0.30	0.00	77.7
	4			0.87	0.18	1.00	0.00			0.16	0.03	78.9
	5			1.15	0.10	1.10	0.00			0.41	0.00	82.3
	6			1.40	0.16	1.08	0.00			0.85	0.00	71.0
	7			-0.97	0.38	1.21	0.00			-0.75	0.00	69.4
	8			0.34	0.66	1.28	0.00			-0.87	0.00	81.7
	9			0.71	0.38	1.26	0.00			-0.05	0.62	80.1
	10			-0.06	0.94	1.27	0.00			0.41	0.00	81.4
	11			0.78	0.36	1.25	0.00			1.14	0.00	82.4
G2	1			-2.34	0.00	0.99	0.00			-0.56	0.00	76.0
	2			-1.10	0.08	0.88	0.00			-0.34	0.00	76.0
	3			-0.57	0.37	0.93	0.00			-0.13	0.08	76.2
	4			0.72	0.25	0.99	0.00			0.24	0.00	79.6
	5			1.34	0.06	1.10	0.00			0.28	0.00	81.1
	6			1.94	0.07	1.10	0.00			0.50	0.00	65.9
	7			-1.09	0.33	1.20	0.00			-0.66	0.00	68.6
	8			-0.31	0.73	1.25	0.00			-0.45	0.00	75.6
	9			0.59	0.47	1.26	0.00			0.03	0.74	80.1
	10			-0.09	0.92	1.27	0.00			0.42	0.00	81.7
	11			1.67	0.12	1.28	0.00			0.56	0.00	73.5
G3	1			-2.14	0.00	1.04	0.00			-0.50	0.00	76.2
	2			-0.88	0.16	0.92	0.00			-0.34	0.00	76.9
	3			-0.35	0.57	0.96	0.00			-0.19	0.00	76.9
	4			0.97	0.14	0.99	0.00			0.06	0.30	78.5
	5			1.21	0.09	1.07	0.00			0.27	0.00	81.4
	6			1.19	0.23	1.01	0.00			0.70	0.00	70.8
	7			-0.80	0.47	1.27	0.00			-0.61	0.00	69.2
	8			0.11	0.89	1.31	0.00			-0.52	0.00	77.5
	9			0.87	0.28	1.28	0.00			-0.11	0.16	80.3
	10			-0.02	0.98	1.24	0.00			0.28	0.00	80.7
	11			0.59	0.52	1.16	0.00			0.90	0.00	81.2
G4	1			-2.80	0.00	1.05	0.00			-0.26	0.00	71.4
	2			-1.10	0.09	0.98	0.00			-0.33	0.00	76.3
	3			-0.48	0.44	0.99	0.00			-0.18	0.00	76.7
	4			0.91	0.17	0.96	0.00			0.13	0.04	78.8
	5			1.35	0.05	1.03	0.00			0.27	0.00	81.2
	6			2.12	0.06	1.00	0.00			0.38	0.00	64.8
	7			-1.83	0.10	1.23	0.00			-0.19	0.19	63.8
	8			-0.23	0.80	1.39	0.00			-0.49	0.00	76.6

	9	0.72	0.37	1.28	0.00			-0.05	0.55	80.1
	10	0.31	0.72	1.23	0.00			0.17	0.08	79.9
	11	1.26	0.19	1.04	0.00			0.80	0.00	78.0
G5	1	-2.68	0.00	1.03	0.00			-0.17	0.00	71.0
	2	-0.93	0.16	0.95	0.00			-0.22	0.00	75.5
	3	-0.83	0.19	0.92	0.00			0.02	0.66	75.8
	4	0.57	0.37	0.94	0.00			0.16	0.00	79.6
	5	1.33	0.06	1.06	0.00			0.14	0.00	80.5
	6	2.53	0.03	1.11	0.00			0.06	0.48	62.8
	7	-1.96	0.07	1.19	0.00			-0.05	0.64	63.3
	8	-0.41	0.65	1.30	0.00			-0.19	0.00	74.0
	9	0.40	0.63	1.23	0.00			0.07	0.22	80.2
	10	-0.03	0.97	1.21	0.00			0.19	0.02	80.4
	11	1.99	0.07	1.24	0.00			0.18	0.05	70.8
G1	1	-1.69	0.00	1.02	0.00	-0.38	0.00	-0.06	0.39	90.3
	2	-0.79	0.19	0.89	0.00	-0.04	0.15	-0.44	0.00	79.0
	3	-0.15	0.81	0.95	0.00	-0.10	0.00	-0.16	0.06	78.7
	4	0.94	0.15	1.00	0.00	-0.05	0.18	0.22	0.01	79.0
	5	1.23	0.08	1.10	0.00	-0.05	0.11	0.48	0.00	82.5
	6	0.47	0.31	1.03	0.00	0.61	0.00	-0.04	0.49	93.8
	7	-0.30	0.74	1.25	0.00	-0.44	0.00	-0.11	0.34	80.6
	8	0.47	0.55	1.28	0.00	-0.09	0.04	-0.75	0.00	82.1
	9	0.99	0.21	1.28	0.00	-0.18	0.00	0.21	0.05	82.1
	10	0.00	1.00	1.27	0.00	-0.04	0.33	0.47	0.00	81.4
	11	0.69	0.42	1.24	0.00	0.06	0.16	1.05	0.00	82.6
G2	1	-1.57	0.00	1.03	0.00	-0.36	0.00	-0.17	0.00	90.8
	2	-0.91	0.15	0.89	0.00	-0.09	0.00	-0.25	0.00	77.0
	3	-0.29	0.64	0.95	0.00	-0.13	0.00	0.01	0.88	78.3
	4	0.83	0.20	1.00	0.00	-0.05	0.16	0.29	0.00	79.8
	5	1.34	0.07	1.10	0.00	0.00	0.98	0.28	0.00	81.1
	6	0.60	0.19	1.03	0.00	0.63	0.00	-0.17	0.00	94.1
	7	-0.18	0.84	1.25	0.00	-0.43	0.00	-0.21	0.02	80.9
	8	0.10	0.90	1.27	0.00	-0.19	0.00	-0.25	0.02	78.2
	9	0.95	0.22	1.28	0.00	-0.17	0.00	0.21	0.03	82.2
	10	-0.05	0.96	1.27	0.00	-0.02	0.65	0.44	0.00	81.6
	11	1.21	0.23	1.26	0.00	0.21	0.00	0.34	0.00	76.1
G3	1	-1.69	0.00	1.03	0.00	-0.38	0.00	-0.04	0.41	90.3
	2	-0.80	0.20	0.92	0.00	-0.07	0.02	-0.27	0.00	77.4
	3	-0.21	0.73	0.96	0.00	-0.12	0.00	-0.05	0.39	78.3
	4	1.00	0.14	0.99	0.00	-0.02	0.51	0.09	0.22	78.5
	5	1.23	0.09	1.07	0.00	-0.02	0.42	0.30	0.00	81.3
	6	0.47	0.31	1.03	0.00	0.61	0.00	-0.03	0.52	93.8
	7	-0.27	0.76	1.26	0.00	-0.44	0.00	-0.08	0.44	80.6
	8	0.30	0.72	1.31	0.00	-0.15	0.00	-0.33	0.00	78.9
	9	1.05	0.18	1.27	0.00	-0.16	0.00	0.08	0.34	81.8
	10	0.00	1.00	1.24	0.00	-0.02	0.69	0.30	0.00	80.7
	11	0.49	0.59	1.16	0.00	0.08	0.09	0.80	0.00	81.5
G4	1	-1.72	0.00	1.03	0.00	-0.39	0.00	-0.02	0.75	90.3
	2	-0.83	0.18	0.97	0.00	-0.10	0.00	-0.27	0.00	77.8
	3	-0.15	0.80	0.98	0.00	-0.12	0.00	-0.10	0.06	78.6
	4	0.95	0.15	0.96	0.00	-0.02	0.57	0.14	0.04	78.8
	5	1.31	0.07	1.03	0.00	0.02	0.54	0.26	0.00	81.2
	6	0.44	0.34	1.03	0.00	0.61	0.00	-0.01	0.90	93.8
	7	-0.52	0.55	1.21	0.00	-0.47	0.00	0.11	0.38	80.6
	8	0.30	0.72	1.38	0.00	-0.19	0.00	-0.37	0.00	79.4
	9	1.11	0.15	1.27	0.00	-0.14	0.00	0.04	0.65	81.7

	10	0.21	0.81	1.23	0.00	0.03	0.41	0.15	0.15	79.9
	11	0.73	0.43	1.05	0.00	0.19	0.00	0.68	0.00	80.3
G5	1	-1.49	0.00	1.06	0.00	-0.39	0.00	-0.08	0.01	90.5
	2	-0.58	0.36	0.96	0.00	-0.11	0.00	-0.19	0.00	77.6
	3	-0.42	0.49	0.93	0.00	-0.13	0.00	0.05	0.19	78.4
	4	0.62	0.35	0.94	0.00	-0.01	0.64	0.17	0.00	79.5
	5	1.22	0.09	1.06	0.00	0.04	0.18	0.13	0.01	80.6
	6	0.65	0.16	1.06	0.00	0.61	0.00	-0.07	0.02	93.9
	7	-0.53	0.53	1.22	0.00	-0.46	0.00	0.05	0.53	80.5
	8	0.27	0.74	1.32	0.00	-0.22	0.00	-0.14	0.03	78.0
	9	0.85	0.29	1.24	0.00	-0.14	0.00	0.10	0.11	82.0
	10	-0.15	0.86	1.21	0.00	0.04	0.34	0.18	0.02	80.5
	11	1.19	0.25	1.22	0.00	0.26	0.00	0.12	0.12	75.4

Table OA-7: **Detailed version of the top panel of Table 10**

Good	port.	avg. ret.	p-val	α	p-val	β_{DC}	p-val	β_{Good}	p-val	R^2
	1	-1.63	0.25	-3.23	0.02	0.38	0.00			12.6
	2	-0.19	0.88	-1.37	0.27	0.28	0.00			8.7
	3	0.79	0.54	-0.98	0.41	0.42	0.00			17.6
	4	2.80	0.05	0.18	0.88	0.63	0.00			34.3
	5	3.68	0.02	0.81	0.54	0.69	0.00			33.8
	6	4.65	0.01	2.27	0.18	0.57	0.00			17.7
	7	-0.18	0.92	-2.64	0.12	0.59	0.00			18.1
	8	1.04	0.57	-1.24	0.45	0.54	0.00			16.1
	9	2.76	0.12	0.17	0.91	0.62	0.00			21.7
	10	2.77	0.14	-0.18	0.91	0.70	0.00			26.5
	11	4.79	0.02	1.53	0.35	0.78	0.00			27.5
G1	1	-1.63	0.25	-1.02	0.48			-0.36	0.04	2.1
	2	-0.19	0.88	0.28	0.83			-0.28	0.04	1.6
	3	0.79	0.54	0.90	0.50			-0.07	0.66	-0.2
	4	2.80	0.05	2.13	0.15			0.40	0.01	2.7
	5	3.68	0.02	2.54	0.11			0.69	0.00	6.8
	6	4.65	0.01	2.77	0.12			1.12	0.00	14.4
	7	-0.18	0.92	0.56	0.76			-0.45	0.03	1.9
	8	1.04	0.57	1.96	0.30			-0.55	0.00	3.2
	9	2.76	0.12	2.31	0.20			0.27	0.26	0.6
	10	2.77	0.14	1.55	0.41			0.73	0.00	5.7
	11	4.79	0.02	2.36	0.20			1.45	0.00	20.0
G2	1	-1.63	0.25	-1.07	0.46			-0.33	0.02	1.9
	2	-0.19	0.88	0.04	0.98			-0.13	0.33	0.2
	3	0.79	0.54	0.64	0.63			0.09	0.51	-0.1
	4	2.80	0.05	2.00	0.17			0.47	0.00	4.3
	5	3.68	0.02	2.76	0.08			0.54	0.00	4.6
	6	4.65	0.01	3.36	0.07			0.76	0.00	7.2
	7	-0.18	0.92	0.46	0.80			-0.38	0.05	1.5
	8	1.04	0.57	1.31	0.49			-0.16	0.41	0.0
	9	2.76	0.12	2.21	0.22			0.32	0.11	1.1
	10	2.77	0.14	1.54	0.39			0.72	0.00	6.2
	11	4.79	0.02	3.32	0.09			0.86	0.00	7.7
G3	1	-1.63	0.25	-1.61	0.28			-0.01	0.95	-0.3
	2	-0.19	0.88	-0.41	0.76			0.09	0.37	0.0
	3	0.79	0.54	0.14	0.92			0.26	0.02	2.0
	4	2.80	0.05	1.48	0.31			0.53	0.00	7.7
	5	3.68	0.02	1.76	0.26			0.77	0.00	13.7
	6	4.65	0.01	1.71	0.29			1.18	0.00	24.7
	7	-0.18	0.92	-0.15	0.94			-0.01	0.93	-0.3
	8	1.04	0.57	0.79	0.68			0.10	0.50	-0.1
	9	2.76	0.12	1.52	0.40			0.50	0.00	4.3

	10	2.77	0.14	0.61	0.73			0.86	0.00	12.8
	11	4.79	0.02	1.18	0.49			1.45	0.00	30.9
G4	1	-1.63	0.25	-2.94	0.03			0.59	0.00	11.1
	2	-0.19	0.88	-1.22	0.33			0.47	0.00	8.8
	3	0.79	0.54	-0.61	0.62			0.63	0.00	14.6
	4	2.80	0.05	0.78	0.53			0.91	0.00	27.1
	5	3.68	0.02	1.22	0.38			1.11	0.00	33.0
	6	4.65	0.01	1.99	0.21			1.20	0.00	29.6
	7	-0.18	0.92	-1.99	0.25			0.82	0.00	12.9
	8	1.04	0.57	-0.41	0.82			0.65	0.00	8.6
	9	2.76	0.12	0.55	0.73			1.00	0.00	20.9
	10	2.77	0.14	0.15	0.93			1.18	0.00	27.9
	11	4.79	0.02	1.13	0.44			1.65	0.00	46.5
G5	1	-1.63	0.25	-3.33	0.01			0.43	0.00	9.9
	2	-0.19	0.88	-1.54	0.23			0.34	0.00	7.9
	3	0.79	0.54	-1.41	0.23			0.56	0.00	19.3
	4	2.80	0.05	-0.02	0.98			0.71	0.00	28.0
	5	3.68	0.02	0.65	0.65			0.76	0.00	26.2
	6	4.65	0.01	1.83	0.27			0.71	0.00	17.4
	7	-0.18	0.92	-2.72	0.12			0.64	0.00	13.5
	8	1.04	0.57	-1.24	0.47			0.57	0.00	11.3
	9	2.76	0.12	-0.38	0.81			0.79	0.00	22.4
	10	2.77	0.14	-0.81	0.60			0.90	0.00	27.4
	11	4.79	0.02	1.20	0.49			0.90	0.00	23.4
G1	1	-1.63	0.25	-2.48	0.05	0.54	0.00	-0.83	0.00	23.0
	2	-0.19	0.88	-0.81	0.50	0.40	0.00	-0.63	0.00	16.2
	3	0.79	0.54	-0.51	0.66	0.52	0.00	-0.52	0.00	22.1
	4	2.80	0.05	0.34	0.78	0.66	0.00	-0.17	0.19	34.6
	5	3.68	0.02	0.72	0.59	0.67	0.00	0.10	0.54	33.7
	6	4.65	0.01	1.59	0.34	0.43	0.00	0.75	0.00	22.9
	7	-0.18	0.92	-1.61	0.31	0.80	0.00	-1.14	0.00	30.0
	8	1.04	0.57	-0.14	0.93	0.77	0.00	-1.22	0.00	30.5
	9	2.76	0.12	0.47	0.77	0.68	0.00	-0.33	0.13	22.5
	10	2.77	0.14	-0.31	0.85	0.68	0.00	0.14	0.51	26.5
	11	4.79	0.02	0.70	0.66	0.61	0.00	0.92	0.00	34.2
G2	1	-1.63	0.25	-2.55	0.04	0.55	0.00	-0.80	0.00	23.1
	2	-0.19	0.88	-0.98	0.43	0.38	0.00	-0.46	0.00	13.0
	3	0.79	0.54	-0.69	0.56	0.49	0.00	-0.33	0.01	19.5
	4	2.80	0.05	0.25	0.84	0.64	0.00	-0.08	0.46	34.2
	5	3.68	0.02	0.86	0.51	0.70	0.00	-0.07	0.64	33.7
	6	4.65	0.01	1.99	0.24	0.50	0.00	0.32	0.06	18.6
	7	-0.18	0.92	-1.72	0.29	0.81	0.00	-1.08	0.00	29.7
	8	1.04	0.57	-0.59	0.72	0.70	0.00	-0.76	0.00	22.1
	9	2.76	0.12	0.39	0.80	0.67	0.00	-0.26	0.16	22.2
	10	2.77	0.14	-0.29	0.85	0.68	0.00	0.13	0.48	26.5
	11	4.79	0.02	1.34	0.42	0.73	0.00	0.23	0.20	27.8

G3	1	-1.63	0.25	-2.66	0.05	0.50	0.00	-0.43	0.00	16.3
	2	-0.19	0.88	-1.11	0.38	0.33	0.00	-0.19	0.07	9.4
	3	0.79	0.54	-0.82	0.49	0.45	0.00	-0.12	0.30	17.7
	4	2.80	0.05	0.17	0.89	0.62	0.00	0.01	0.95	34.1
	5	3.68	0.02	0.46	0.73	0.62	0.00	0.26	0.04	34.8
	6	4.65	0.01	1.04	0.51	0.32	0.01	0.91	0.00	29.0
	7	-0.18	0.92	-1.75	0.30	0.76	0.00	-0.65	0.00	23.5
	8	1.04	0.57	-0.62	0.70	0.67	0.00	-0.46	0.00	18.8
	9	2.76	0.12	0.21	0.90	0.63	0.00	-0.03	0.87	21.4
	10	2.77	0.14	-0.66	0.68	0.61	0.00	0.35	0.04	28.0
	11	4.79	0.02	0.14	0.93	0.50	0.00	1.03	0.00	39.6
G4	1	-1.63	0.25	-3.45	0.01	0.26	0.03	0.33	0.02	14.6
	2	-0.19	0.88	-1.57	0.21	0.17	0.11	0.29	0.01	10.7
	3	0.79	0.54	-1.20	0.31	0.30	0.01	0.33	0.01	20.0
	4	2.80	0.05	-0.12	0.92	0.46	0.00	0.46	0.00	38.5
	5	3.68	0.02	0.36	0.78	0.43	0.00	0.68	0.00	41.4
	6	4.65	0.01	1.60	0.30	0.19	0.13	1.01	0.00	30.7
	7	-0.18	0.92	-2.88	0.09	0.45	0.00	0.37	0.03	19.5
	8	1.04	0.57	-1.36	0.41	0.48	0.00	0.18	0.31	16.3
	9	2.76	0.12	-0.23	0.88	0.39	0.01	0.60	0.00	26.3
	10	2.77	0.14	-0.68	0.64	0.42	0.00	0.76	0.00	33.7
	11	4.79	0.02	0.62	0.66	0.26	0.08	1.39	0.00	48.3
G5	1	-1.63	0.25	-3.55	0.01	0.28	0.02	0.19	0.13	13.4
	2	-0.19	0.88	-1.68	0.18	0.18	0.08	0.18	0.08	9.7
	3	0.79	0.54	-1.59	0.17	0.23	0.03	0.36	0.00	21.8
	4	2.80	0.05	-0.37	0.75	0.45	0.00	0.33	0.00	37.3
	5	3.68	0.02	0.26	0.84	0.51	0.00	0.32	0.00	36.2
	6	4.65	0.01	1.56	0.33	0.34	0.01	0.42	0.00	20.7
	7	-0.18	0.92	-3.07	0.07	0.45	0.00	0.25	0.06	19.0
	8	1.04	0.57	-1.58	0.34	0.44	0.00	0.20	0.15	16.7
	9	2.76	0.12	-0.66	0.67	0.35	0.01	0.49	0.00	26.0
	10	2.77	0.14	-1.12	0.44	0.40	0.00	0.55	0.00	31.9
	11	4.79	0.02	0.78	0.63	0.54	0.00	0.44	0.00	30.3

Figure 4: **Average vs. model-based expected returns**

Circles with no fill (large black dots) plot model-based expected monthly returns versus average monthly returns (annualized and in percent) for the GC (BC) set of 18 carry trades, as described in Table 3. The model based returns refer to the three-factor model with a market factor (MKT), an equity volatility factor (EqVol) and the product of MKT and EqVol, and are estimated, for each trade, as the product of its time-series slope estimates (β) with respect to the factors in the model, and the corresponding estimates of the factor risk prices λ, as shown in Table OA-2. The bottom right corner of each plot shows the R^2 obtained in regressing average returns on model-based returns (with a constant). The sample period is 12/1984 to 12/2013.