Is Carry Trade a Profitable Strategy?

Lorenzo Candotto

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By Lorenzo Candotto

Católica Lisbon School of Business and Economics

Abstract

Uncovered interest parity states that currencies selling at forward premium should appreciate while currencies selling at forward discount should depreciate. In reality the opposite happens, allowing a variety of speculation strategies in the currency markets. In this thesis we implement the carry trade with a sample of 32 currencies including both developed and emerging markets on a time span going from 1976 to 2018. We will show that these strategies offer high Sharpe Ratios even keeping in account the transaction costs. We will then try to explain the results with some equity, bond and forex markets factor models and see how the factors chosen leave unexplained most of the average returns of the carry trade. Finally, we will try to improve the one currency long versus one currency short carry trade, which presents huge drawdowns, by scaling it by volatility and show how this technique improves a lot the Sharpe Ratio of the carry trade.

Resumo

A paridade de juros não coberta estabelece que as moedas que vendem com prêmio a termo devem se valorizar, enquanto as moedas que vendem com desconto a termo devem se depreciar. Na realidade, o oposto acontece, permitindo uma variedade de estratégias de especulação nos mercados cambiais. Neste artigo implementamos o carry trade com uma amostra de 32 moedas, incluindo tanto os mercados desenvolvidos como os emergentes, num período de tempo que vai de 1976 a 2018. Mostraremos que estas estratégias oferecem elevados rácios de Sharpe mesmo tendo em conta os custos de transacção. Em seguida, tentaremos explicar os resultados com alguns modelos de fatores dos mercados de ações, obrigações e forex e ver como os fatores escolhidos deixam inexplicada a maior parte dos retornos médios do carry trade. Finalmente, vamos tentar melhorar a cotação de uma moeda long versus uma moeda short carry trade, que apresenta grandes desvantagens, escalando-a por volatilidade e mostrando como esta técnica melhora muito o Rácio Sharpe do carry trade.

Keywords: Carry Trade, Currencies, Interest Rate Parity, Forward Rates, Spot Rates, Investment Strategies, Empirical Finance

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Table of Contents

List of Tables

List of Figures

1. Introduction

Carry Trade (CT) is a strategy that involves buying high yield currencies and investing in the risk-free asset of the high yield country and selling low yield currencies shorting the risk-free asset of the low yield country without hedging the currency risk. Following the efficient market hypothesis this strategy shouldn't have a positive α as, as we will see, the interest rate parity states that a high yield country should have a depreciating currency that offsets the higher interest rate. From empirical evidence the opposite happens, with high yield currencies that on average appreciate and low yield currencies that on average depreciate and with the CT having a Sharpe Ratio of 0.99 against the 0.70 of the benchmark.

In this thesis we will study the CT strategy with a sample of 32 currencies including developed and emerging markets on a time span going from January 1976 to December 2018. The results we will show, however, are likely to be conservative as many emerging market currencies (and so high yield currencies) were available on average from 1995, forcing us to invest in lower yielding currencies in the time span going from 1976 to 1995.

We will begin by giving a general overview of the performance: we will see how, considering all the sample, a diversified CT gives a better Sharpe Ratio than the benchmark but also how in the last decade the CT saw a worsening risk adjusted return thanks to the Central Banks increasing the liquidity and depressing global interest rates. Furthermore, we will check if some currencies are particulary important in the implementation of the strategy by removing one by one all of them and will see how only the Portuguese Escudo improves significantly the Sharpe Ratio (from 0.85 [*t - stat* of 4.75][1] to 1.04 [*t - stat* of 5.49]) if removed from the sample. Moreover, we will check what are the countries more often bought and sold and will see that the Italian Lira, the Spanish Peseta and the Portuguese Escudo were the top buy for the time span going from 1976 to 1999 and after replaced by the South African Rand, the Mexican Peso and Brazilian Real while on the short side the Japanese Yen and Swiss Franc were the most sold currencies in every decade of the sample. Finally, we will check if the Euro changed the results in some way but we will find that the performance from 1976 to 1999 is not statistically different from the performance going from 1999 to 2018.

Regarding the strategy implementation, we will start by see how the results change by changing the number of currencies traded and find that diversification works also in currency investing with a Sharpe Ratio going from 0.63 [*t - stat* of 3.77], in the case where we just buy and sell

[1] All statistics in this thesis are based on a 5% significance level.

one currency, to 0.99 [*t - stat* of 5.31], in the case where we buy and sell twelve currencies. After that we will check the effect of changing the holding period of the strategy and find that the best risk adjusted return (0.85 [*t - stat* of 4.75]) is obtained with the shorter holding period (one month) while increasing the holding period to twelve months give us a Sharpe Ratio of 0.44 [*t - stat* of 0.79].

We will then try to explain the goodness of the CT results using some factor models on equity, bond and forex markets. Regarding the equity markets we chose the classic Fama and French three factors, for the bond markets we chose the 2-year US government bond yield, the 10-year US government bond yield and the spread between the 10 year and the 2 year US government bonds, for the forex markets we chose the average performance of six currency portfolios obtained from the dataset of H. Lustig, N. Roussanov and A. Verdelhan (2011). We will find that in all the factor models the annualized α is ranges between 4% and 5% and the coefficients pretty small and statistically significant just in few cases, indicating that the factor chosen leave most of the CT results unexplained.

Finally, we will try to improve the CT where we buy and sell just one currency, which presents the biggest drawdowns, by scaling it by volatility. We will implement two strategies: in the first one we will use a volatility target and we will invest in the CT if the if the realized volatility is lower than the target and short the CT if the realized volatility is higher than the target. The results suggest that this strategy doesn't seem an effective way to manage risk as the Sharpe Ratio is basically unchanged: 0.63 [*t - stat* of 3.77] with the usual CT and 0.61 [*t - stat* of 3.75] with the strategy just explained. For the second strategy we also use a volatility target and we leverage the portfolio if the realized volatility is lower than the target and reduce our exposure to the market if the realized volatility is higher than the target. In this case the results are impressive, with a Sharpe Ratio going from 0.63 [*t - stat* of 3.77] to 1.11 [*t - stat* of 5.71].

The thesis is organized as follows: in the section 1 we have the introduction, in section 2 we present the literature review and the CT implementation, in section 3 we explain how we got the data, in section 4 we show the results and in section 5 we write the conclusions.

2. Literature Review

2.1 The Forward Premium Puzzle

The uncovered interest rate parity (UIP) claims that it should not make any difference, for an investor, to invest in a country that offers a high yield rather than in a country that offers a low yield as the currency of the low yield country should appreciate in respect to the currency of the high yield country, therefore offsetting the yield differential. This relationship is represented below:

$$(1 + i_D) = (1 + i_F)\frac{E(S_{t+1})}{S_t}$$

where i_D is the domestic interest rate, i_F is the foreign interest rate, $E(S_{t+1})$ is the expected exchange rate in $t+1$ and S_t is the current exchange rate. If there is the possibility of selling the currency forward, we can eliminate the foreign exchange risk and get the covered interest rate parity (CIP). The formula is the following:

$$(1 + i_D) = (1 + i_F)\frac{F_t}{S_t}$$

where F_t represents the forward exchange rate at which an investor can exchange the foreign currency received from investing in the foreign country at time $t+1$. Unfortunately, this relationship doesn't hold as high yield currencies, that following the interest rate parity should depreciate, on average appreciate, therefore creating the so called "Forward Premium Puzzle". Currency traders and speculators take advantage of this divergence from the standard macroeconomic theory using a variety of strategies of which the most used is probably the CT.

CT is a strategy that involves buying high yielding currencies and shorting low yielding currencies. This is equivalent to borrow at a low yield to lend at a high yield. There is extensive research that shows that this strategy delivers better a Sharpe Ratio than the S&P 500 index: C. Burnside, M. Eichenbaum, I. Kleshchelski and S. Rebelo (2007) show how an equally weighted CT (that keeps in account the transaction costs) have a Sharpe Ratio of 0.52 against the 0.48 of the S&P 500 index for the period going from 1976 to 2005. C. Burnside, M. Eichenbaum and S. Rebelo (2008) show how a well diversificated, equally weighted CT had a Sharpe Ratio of 0.82 from 1976 to 1998 and of 1.11 from 1999 to 2007. C. Burnside, M. Eichenbaum, I. Kleshchelski and S. Rebelo (2007) show how, keeping in account the transaction costs the CT delivers a Sharpe Ratio of 0.51 considering the British Pound as home currency and of 0.69 considering the US Dollar as home currency from 1976 to 2009.

CT, however, is often compared to "picking up pennies in front of a truck" as it has a good performance in times when the volatility is low but tend to perform really bad when the volatility spikes. This characteristic also has extensive literature behind. C. Burnside, M. Eichenbaum, I. Kleshchelski and S. Rebelo (2011) try to improve the results of the CT by buying out of the money options that hedge the risk of big drawdowns (even though the experiment show the Sharpe Ratio of the unhedged CT is slightly better than the hedged CT). L. Menkhoff, L. Sarno, M. Schmeling and A. Schrimpf (2012) show how the performance of high yielding currencies are negatively correlated with the volatility in global markets.

We will show, however, that it is true that the CT perform really bad in bad times, but we will also show that this only happens if the portfolios of long and short currencies are not sufficiently diversificated: increasing the number of currencies improves the Sharpe Ratio and makes the distribution of the returns really close to the Normal distribution. Moreover, P. Barroso and P. Santa-Clara (2015) show how is possible to improve the Sharpe Ratio of the Momentum strategy by reducing the exposure to the market when volatility increases and increase it when volatility decrease. Since Momentum has similar caratheristics to the CT strategy that we are studying (that is, good performance on low volatility periods and very bad performance when the volatility increases), we will also show how to scale our strategy by volatility to improve the results.

2.2 How Is the Carry Trade Implemented?

As described before, CT involves buying high yield currencies and investing in the risk-free asset of the high yield country and selling low yield currencies shorting the risk-free asset of the low yield country without hedging the currency risk. The investor receives the difference between the two risk-free assets (high yield minus low yield) plus the currency performance. This strategy is profitable until the return coming from difference between the risk-free assets is higher than the high yield currency depreciation. Not considering transaction costs the payoff is the following:

$$(1 + r_t^H) - (1 + r_t^L) + \frac{S_{t+1}}{S_t} - 1$$

where r_t^H is the interest rate in the high yield currency, r_t^L is the yield in the low yield currency and S is the exchange rate.

This strategy can also be implemented by buying forward currencies that are at forward discount (Spot > Forward) and selling forward currencies that are at forward premium (Spot < Forward). The strategy is implemented as follows. We infer the level of interest rates from the forward exchange rate. Specifically, the forward exchange rate is calculated as follows:

$$F = Se^{(r_f - r)t}$$

from which we get:

$$r_f - r = \ln\left({}^{F}/_{S}\right)/t$$

note that in the formula of the forward price we subtract the US interest rate, r, from the foreign interest rate, r_f, when usually the opposite is done. This happens because the exchange rate we use, S, is expressed as amount of foreign currency units for one US Dollar and not as US Dollars for a foreign currency unit.

We then sort all the available currencies based on the level of interest rates and we buy the currencies more at discount and sell the currencies more at premium. What does it mean exactly to buy currencies more at discount and selling currencies more at premium? We said we have the exchange rates expressed as amount of foreign currency for one US Dollar so an increase in the exchange rate expressed in this way means that the US Dollar is appreciating. From that follows that to be long on a high yield currency we have to short the forward on the exchange rate US Dollar / High Yield Currency and to be short on a low yield currency we have to buy the forward on the exchange rate US Dollar / Low Yield Currency. We have available only the data for the one-month forward exchange rate so, in case the holding period is higher than one month, the strategy is implemented by rolling over the forward position. As an example, assuming that the holding period is two months, we will buy the forward at t_0, calculate the return between the forward exchange rate in t_0 and the spot exchange rate in t_1, buy another one month forward (in t_1) and calculate the return between the forward exchange rate in t_1 and the spot exchange rate in t_2. Once we choose a holding period, the currencies we will buy and sell will be the same for all the holding period even if the ranking in another month is different: if, for example, the holding period is three months and in the first of these three months the highest and lowest yielding currencies are the Italian Lira and the Japanese Yen, we will buy the Italian Lira and sell the Japanese Yen for all the three months even if in the second month the highest yielding currency is the Spanish Peseta. At the end of the three months we rank again the currencies and repeat the process. We also consider the bid and ask spread so every time we roll over the forward position we buy the forward at the ask price and sell the spot, at expiration, at the bid price or viceversa. These results are likely to be conservative as, if when we hold the investment for n months we would buy and sell the n months forward, we would avoid to pay the transaction costs stemming from the rolling over of the one month forward position for n months.

We use the S&P 500 index as a benchmark for our strategy. The readers may wonder why, if we operate with currencies, we chose the US stock market as benchmark. The reasons are two:

the first one is that, while nowdays we have indexes to compare our strategy with (such as the Deutsche Bank G10 Currency Future Harvest Index ETF), we don't have the data of these benchmarks available since the beginning of our strategy in 1976, making impossible a comparison with older results. The second reason is that the S&P 500 index is the most common benchmark used to evaluate investment strategies and, since the return of the strategy is expressed in US dollars, we decided to use it as well.

2.3 How Should We Evaluate an Investment Strategy?

How should we evaluate the performance of an investment strategy? We know that return alone is not a measure of performance but it also has to be adjusted by risk. But is the risk adjusted return a good indicator when we evaluate the performance of an investment strategy? Only partially. When the distribution of the returns of an investment strategy fall out of the Normal distribution, the strategy will have a skewness different from 0 (which is the skewness of the Normal distribution) and a kurtosis different from 3 (which is the kurtosis of the Normal distribution). More in detail, skewness, which is the third moment of the distribution, measures the asymmetry in a distribution. It can be positive (when the mean exceeds the mode), indicating that there is a higher probability of getting a positive return rather than a negative return, or negative (when the mode exceeds the mean), indicating a higher probability of negative returns. Kurtosis measures instead how much a distribution is more or less peaked than the Normal distribution: a kurtosis higher than 3 indicates that the values are more distributed around the mean (the distribution is more "sharp") and therefore there is a lower probability of getting tail events, a kurtosis lower than 3 indicates that the values are less distributed around the mean (the distribution is more "flat") and therefore there is an higher probability of having tail events. Both negative skewness and negative excess kurtosis are therefore not desiderable features of the return distribution of an investment strategy as they indicate there is a higher probability of getting negative results and that these results are tail events.

There are many ways to adjust the return by the risk and we will present the three most widely used indicators. The first measure is the Sharpe Ratio, which consists in dividing the excess return of the strategy over the risk-free rate by its standard deviation. The ratio is calculated as follow:

$$Sharpe\ Ratio = \frac{E(r_p) - r_f}{\sigma}$$

The second indicator is the Treynor ratio, which consists in dividing the excess return over the risk-free rate of the strategy by the β of the portfolio. The ratio is calculated as follow:

$$Treynor\ Ratio = \frac{E(r_p) - r_f}{\beta}$$

The difference between the Treynor Ratio and the Sharpe Ratio is that the former just considers the systematic risk, while the second considers both the systematic and non-systematic risk.

The last indicator of performance we present is the Jensen's Alpha which was originally used by Micheal Jensen to evaluate the perfomance of Mutual Funds. The Jensen's Alpha is the average return over the risk adjusted return predicted by the CAPM. From the CAPM we have the following relationship:

$$r_p = \alpha + r_f + \beta[E(r_p) - r_f]$$

from which we can get:

$$\alpha = r_p - r_f - \beta[E(r_p) - r_f]$$

Concluding, is worth to mention that even though these measures are widely used, they have their own limitations. The most important one is that usually the parameters needed to calculate these ratios (such as the expected returns and volatility) are inferred looking at the past. Assuming that the past predicts the future may be a reasonable assumption in times when the volatility is low but may produce results that don't reflect reality when the market environment is less clear.

Another important limitation of these ratios comes when the payoff of a strategy is not linear. We will use an example to explain this critic: assume the only strategy an investor pursues consists in selling put options on the S&P 500 index. If the market doesn't crash, this strategy would score good on the measures we presented. However, when the crash happens, the investor is likely to lose most of his capital even though the measures presented suggested he had a good risk adjusted return.

3. Data

In this section we describe the data we use. We took monthly observations from Datastream for the spot and the one-month forward exchange rates for the 32 following currencies: Austrian Schilling, Belgian Franc, Canadian Dollar, Danish Krone, French Franc, German Mark, Irish Punt, Italian Lira, Japanese Yen, Netherlands Guilder, Norwegian Krone, Portuguese Escudo, Spanish Peseta, Swedish Krona, Swiss Franc, US Dollar, Euro, Australian Dollar, New Zealand Dollar, South African Rand, Korean Won, Indian Rupee, Brazilian Real, Mexican Peso, Chinese Yuan, Russian Ruble, Thai Baht, Hong Kong Dollar, Taiwan Dollar and Singapore Dollar. Refer to Appendix A for the list of the codes used to download the currencies from Datastream.

The data was available, against the British Pound, from January 1976 for the European and G10 currencies (excluding the Australian Dollar and New Zealand Dollar), from October 1986 for the Australian and New Zealand Dollar, from December 1996 for the South African Rand, Indian Rupee, Mexican Peso, Thai Baht, Hong Kong Dollar, Taiwan Dollar and Singapore Dollar, from January 1999 for the Euro, from February 2002 for the Korean Won and Chinese Yuan and from March 2004 for Russian Ruble and Brazil Real. The dates described above are the dates where the bid - mid - ask spot and the bid - mid - ask forward exchange rates were available as we are not able to implement the CT if one of these values is missing. Exchange rates against the USD were available for a shorter time span than for the GBP but we could obtain all the exchange rates against the USD dividing the GBP / Foreign Currency Units by GBP / USD.

Regarding the factor models, the data used in the equity markets factor models comes from the Kenneth & French website where we downloaded monthly observations for the three traditional Fama and French factors. The data for the bonds markets factor models comes from St. Louis Federal Reserve Economic Data website[2] where we downloaded monthly observations for the 10-year US government bond, for the 2-year US government bond and for the spread between the 10 years and the 2 years US government bond yield. The data for the forex markets factor models come from the dataset of the paper by H. Lustig, N. Roussanov and A. Verdelhan (2011) where they provide the average performace of the six currency portfolios they constructed.

Finally, the S&P 500 index monthly observations come from Robert Shiller's website[3] as it was the only source with the historical data long enough to cover our sample from 1976.

4. Results

In this section we present the main findings of our study. First, we will show the general performance of the CT strategy and we will give an overview of the countries that are more often included in the strategy considering all the sample or by decade. Second, we will show

[2] Federal Reserve Economic Data website: https://fred.stlouisfed.org/

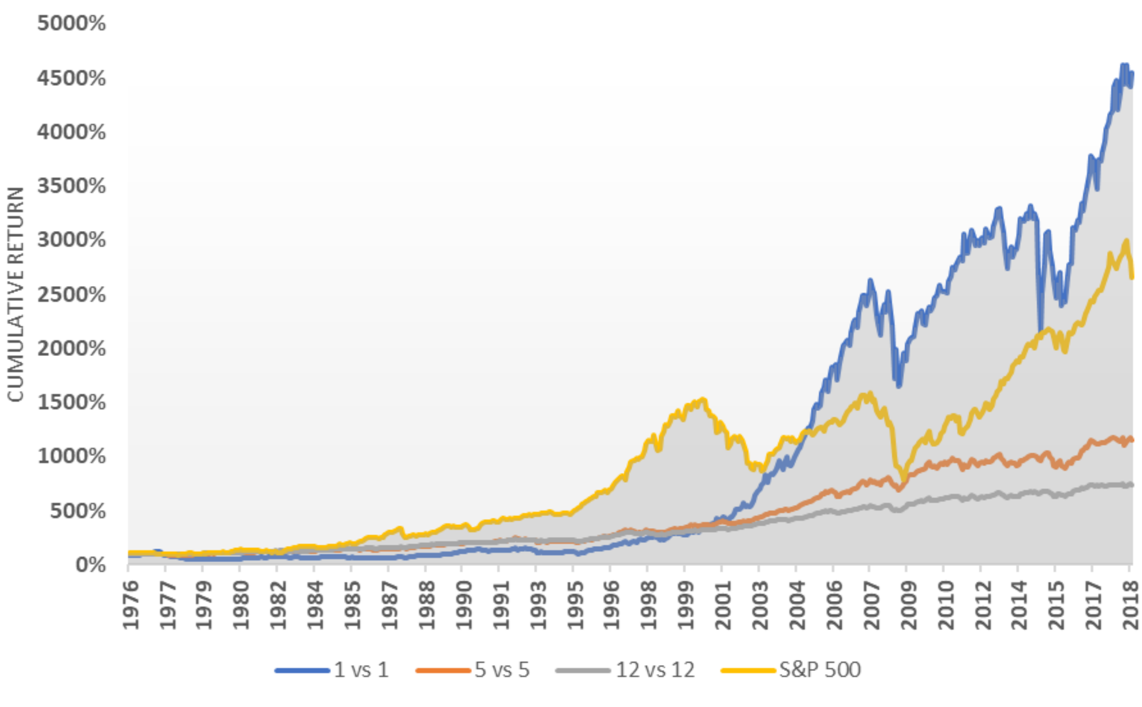
[3] Robert Shiller Online Data Website: http://www.econ.yale.edu/~shiller/data.htm

how the results change if we remove a single currency from the dataset and how the results changed after the Euro came to existence in 1999. Third, we will show the effect of diversification and of different holding periods by changing the number of currencies included in both legs of the strategy (keeping the holding period constant) and changing the holding period (keeping the number of currencies included constant). Fourth, we will use three types of factor models (equity, bonds and forex) to try to explain the performance of the strategy. We will explain why we choose those factors and what we expected the results to be. Finally, we will present two ways to reduce the crash risk in the one long vs one short strategy: the first involves pursuing the opposite strategy (that is buying low yielding currencies and selling high yielding currencies) when volatility is higher than our volatility target, the second involves leveraging the strategy when the 6, 12 or 24 months volatility is lower than the volatility target we chose and reducing the exposure to the market when the volatility is higher than the target.

4.1 Carry Trade: An Overview

In this section we will show the performance of the strategy (compared to the benchmark) in three different cases. The results can be seen in Figure 1.

Figure 1: Cumulative Performance



We present here three types of CT: the first, implemented by buying and selling just the highest and lowest yielding currency. In this case we have a cumulative return of 4,550% from January 1976 but we also have a great volatility, with drawdowns of 37% from October 2007 to

December 2008 and of 34% from March 2014 to January 2015. The second, implemented by buying and selling five currencies. This way of setting up the strategy is more diversified than the previous one: even though the cumulative return is smaller than before (1,152% from 1976 to 2018), the drawdowns are much lower: in the period going from October 2007 to December 2008 the drawdown is 11% and in the period going from March 2014 to January 2015 the drawdown is just 0.3%. The third, implemented by diversifing as much as possible, by buying and selling 12 currencies. In this case the cumulative return is 740% but the drawdowns are even smaller than the previous case: 8% from October 2007 to December 2008 and from March 2014 to January 2015 we have a gain of 1.5%. In all the three cases presented the results are likely to be conservative as, in the period going from 1976 to 1995, we don't have the data for many high yield currencies, forcing us to invest in lower yielding ones. We also split the results by decade and the results can be seen in Table 1.

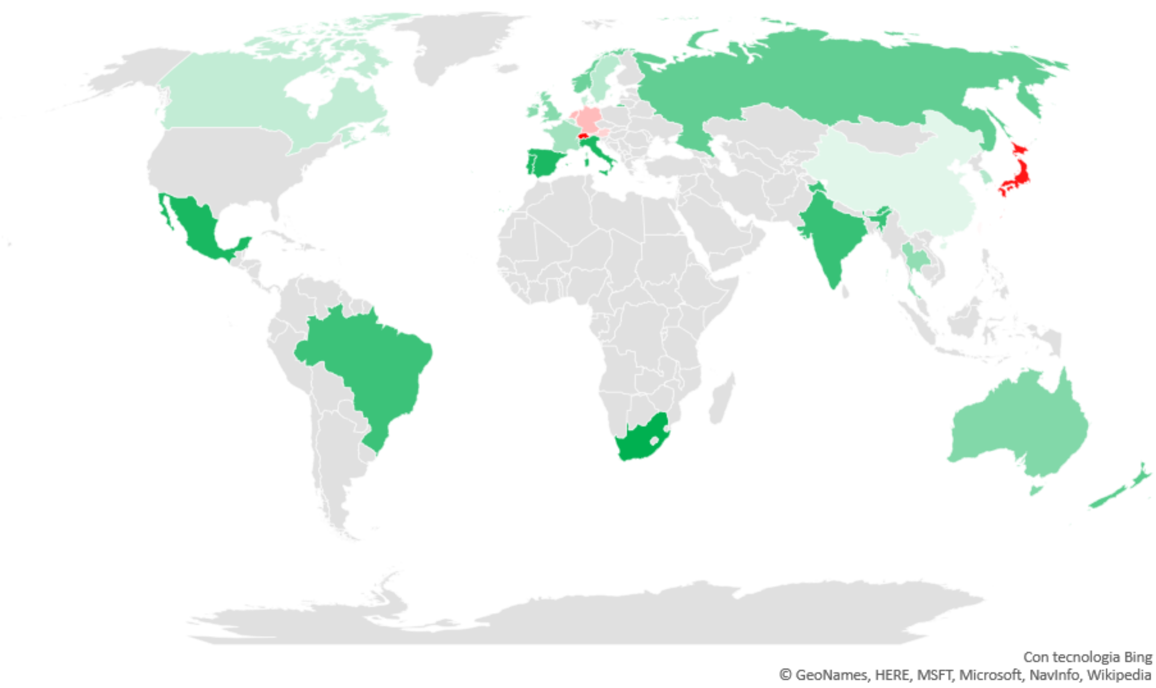
Table 1: Performance by Decade

		Mean (Ann.)	t - stat	St. Dev. (Ann.)	Sharpe Ratio	t - stat	Max	Min	Skewness	Kurtosis
'80s	1 vs 1	8,56%	2.74	9.88%	0.87	2.34	8.20%	- 12.33%	- 1.36	4.65
	5 vs 5	6.05%	4.68	4.09%	1.48	3.23	2.98%	- 3.42%	- 0.71	1.11
	12 vs 12	5.90%	5.28	3.54%	1.67	3.41	4%	- 2.67%	- 0.10	1.31
	S&P 500	12.64%	3.08	12.96%	0.98	2.54	11.58%	- 12.56%	- 0.77	2.31
'90s	1 vs 1	10.86%	2.16	15.90%	0.68	1.95	10.13%	- 14.50%	- 0.72	1.12
	5 vs 5	6.53%	2.59	7.97%	0.82	2.24	5.61%	- 7.81%	- 0.69	1.86
	12 vs 12	4.85%	2.85	5.37%	0.90	2.41	4.45%	- 5.05%	- 0.63	1.46
	S&P 500	14.72%	4.45	10.47%	1.41	3.15	11.30%	- 8.13%	0.27	1.87
'00s	1 vs 1	23.27%	3.85	19.12%	1.22	2.92	15.59%	- 22.34%	- 1.06	3.05
	5 vs 5	9.56%	4.10	7.38%	1.30	3.02	5.32%	- 6.91%	- 0.90	1.50
	12 vs 12	6.58%	4.42	4.71%	1.40	3.14	3.92%	- 5%	- 0.77	1.70
	S&P 500	- 1.41%	- 0.30	14.67%	- 0.10	- 0.30	12.02%	- 20.39%	- 1.12	4.18
'10s	1 vs 1	11.65%	2.16	17.04%	0.68	1.95	18.24%	- 20.64%	- 0.56	4.22
	5 vs 5	5.42%	2.08	8.23%	0.66	1.89	5.32%	- 6.07%	- 0.27	0.12
	12 vs 12	4.03%	2.33	5.47%	0.74	2.07	3.92%	- 4.13%	- 0.18	0.18
	S&P 500	11.36%	3.33	10.77%	1.05	2.67	12.02%	- 10.56%	- 0.48	2.33
All Sample	1 vs 1	10.28%	4.13	16.31%	0.63	3.77	18.24%	- 22.34%	- 0.77	3.10
	5 vs 5	5.96%	5.54	7.04%	0.85	4.75	5.61%	- 7.81%	- 0.57	1.47
	12 vs 12	4.79%	6.49	4.84%	0.99	5.31	4.45%	- 5.05%	- 0.43	1.24
	S&P 500	8.39%	4.58	12.00%	0.70	4.11	12.02%	- 20.39%	- 0.85	3.91

The best decades for the CT were from 2000 to 2010 and from 1980 to 1990 where all the three strategies had a Sharpe Ratio higher than 1 and higher than the benchmark. The worst period for the CT has been the one going from 2010 to 2018 where all the three strategies underperformed the benchmark in terms of risk adjusted return. This under performance is comprensible for two reasons: the first one is that in the last decade the Central Banks poured liquidity in the markets and reduced interest rates which translates in a reduced interest income gained with the CT strategy, the second is that in the past decade the markets increased their efficiency thanks to new players that entered in the market such as high frequency traders and systematic traders that reduced the return of this strategy.

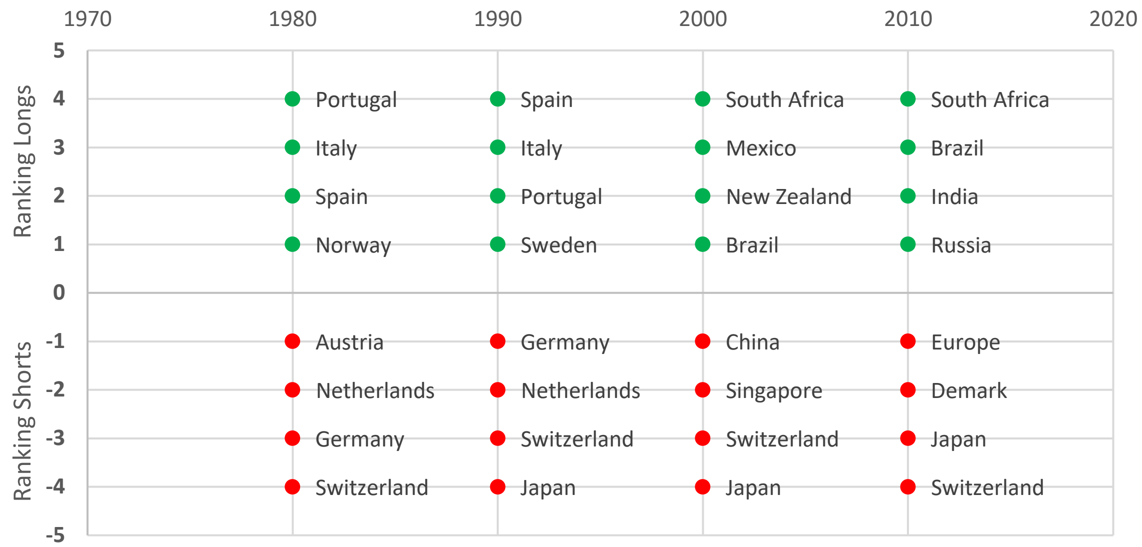
The reader may also wonder what are the countries that are most often included in the strategy. The results are graphically presented in Figure 2. The study is done using 5 currencies on the long leg and 5 currencies on the short leg, the currencies that are present more often in the long leg are shown in green while the ones that are present more often in the short leg are shown in red. The four most bought currencies in all the sample period are the South African Rand, the Portuguese Escudo, the Mexican Peso and the Italian Lira while the most sold currencies are the Swiss Franc, the Japanese Yen, the Netherland Guilder and the Deutsche Mark.

Figure 2: Countries Bought and Sold the Most



However, even though we are confident about the result of the short leg (since the currencies on the short leg are available since the beginning of the sample or are substituted by the Euro), the results for the long leg are likely to not be precise and the reason is the same as above, as the majority of emerging currencies were available from 1995. We tried to provide a solution to this problem in Figure 3. In this study we splitted the dataset by decade and checked what were the five most bought and sold currencies for every decade. In the Figure, 5 and -5 represent the most bought and sold currencies, 4 and -4 the second most bought and sold currencies and so on.

Figure 3: Countries Bought and Sold the Most by Decade[4]



The results give more clarity respect to Figure 2: the currencies of the short leg are the same as before (German Mark, Japanese Yen, Swiss Franc) while on the long leg the Portuguese Escudo, the Italian Lira and the Spanish Peseta were the most bought currencies on the first twenty years and, after the Euro came to existence, the top buys were the South African Rand, the Mexican Peso and the Brazilian Real.

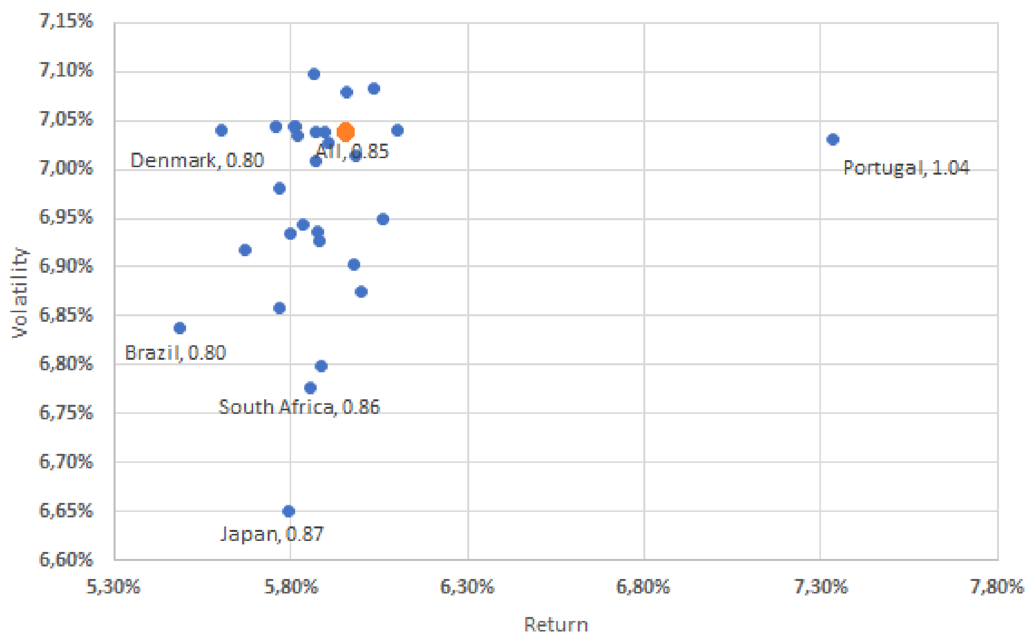
4.2 Are Some Countries Particularly Important?

In our analysis we wondered if some countries give significant contribution to the strategy performance. To conduct this study we contructed portfolios of 5 currencies both on the long and short leg, with a holding period of 1 month. We then removed the currencies one by one (reintroducing in the dataset, at every step, the currency previously removed) and saw how the results changed. Figure 4 shows the results. It doesn't seem that removing a single currency has a big impact on the overall Sharpe Ratio of the strategy, with the return changing at most 0.45%

[4] In this Figure, 5 represents the higher ranking (meaning the currency is the most bought) and -5 the lowest ranking (meaning the currency is the most sold).

and the volatility changing at most 0.39% compared to the case where no currency is removed. The only exception is the Portuguese Escudo that, if removed, significantly improves the results, with a Sharpe Ratio going from 0.85 [*t - stat* of 4.75] (in the case where no currencies are removed) to 1.04 [*t - stat* of 5.49] (in the case the Portuguese Escudo is removed).

Figure 4: Change in Results by Removing a Country[5]



4.3 Did the Euro Change the Game?

The Euro, that came in existence in 1999, took the place of both many high yielding currencies (such as the Italian Lira or the Portuguese Escudo) and low yielding currencies (such as the Deutsche Mark and the Netherlands Guilder). How did the common currency change the results? To find out we considered two periods of time: the first going from January 1976 to December 1998 and the second going from January 1999 to December 2018. We also had to remove from the dataset many currencies because, to have two comparable samples, we needed currencies data available in both periods of time. The first sample include the Austrian Schilling, the Belgian Franc, the Canadian Dollar, the Denmark Krone, the French Franc, the Deutsche Mark, the Irish Punt, the Italian Lira, the Japanese Yen, the Netherlands Guilder, the Norvegian Krone, the Swedish Krone, the Portuguese Escudo, the Spanish Peseta, the Swiss Franc and the British Pound. The second sample include the Canadian Dollar, the Denmark Krone, the Japanese Yen, the Norvegian Krone, the Swedish Krone, the Swiss Franc, the Euro

[5] The numbers in the figure represents the Sharpe Ratios of the strategy that we get by removing the country.

and the British Pound. The results can be seen in Table 2: the Sharpe Ratio for the period going from 1976 to 1998 is 0.74 [*t - stat* of 2.92] while the Sharpe Ratio for the period going from 1999 to 2018 is 0.39 [*t - stat* of 1.69]. However, after running a t-test (where we impose the null hypothesis that there is no difference in the results) we find that the difference is not statistically significant [*t - stat* of -1.15] so the 1976 – 1998 performance is not statistically different from the 1999 – 2018 one.

Table 2: Performance Before and After the Euro

	Before The Euro	After The Euro
Mean (Ann.)	5.12%	2.39%
t - stat	3.29	1.75
St. Dev. (Ann.)	6.94%	6.07%
Sharpe Ratio	0.74	0.39
t - stat	2.92	1.69
Max	6.10%	4.42%
Min	- 7.58%	- 6.75%
Skewness	- 1.08	- 0.71
Excess Kurtosis	2.87	1.59

4.4 Does Diversification Improve the Results?

In this section we present what happens if we increase the number of currencies bought and sold in the strategy. To conduct this study we kept the holding period constant at 1 month and changed the number of traded currencies to 1, 3, 5, 9 and 12. It is common knowledge that diversification increase the Sharpe Ratio in stock investing and we wanted to check if the same is true for currency investing. Results are presented in Table 3: as we can see, diversification plays an important role in currency markets as well. The Sharpe Ratio goes from 0.63 [*t - stat* of 3.77] in the case where we buy and sell just the highest and lowest yielding currencies to 0.99 [*t - stat* of 5.31] in the case where we buy and sell 12 currencies on both the legs of the trade. We can also see how the third and fourth moments of the distribution get closer to normality as we diversificate by adding currencies to the portfolio: even though skewness, which measures the degree of asymmetry of a distribution around its mean, is negative (which is not a desiderable feature for an investor as it means the probability of having bad results is higher than the probability of having good results), it goes from -0.77 (in the 1 vs 1 currencies case) to -0.43 (in the case of 12 vs 12 currencies case). The excess kurtosis, that measure the degree to which a distribution is more or less peaked than a Normal distribution, goes from 3.10 (in the 1 vs 1 case) to 1.11 (in the 12 vs 12 case), getting closer to normality. Finally, we can see an improvement also in the maximum drawdown that goes from -22.34% in the 1 currency vs 1 currency case to -5.05% in the 12 currencies vs 12 currencies case. The same is true if we consider just the G10 currencies where we also kept the holding period constant at 1 month and changed the number of traded currencies from 1 to 5. Results are presented in Table 4. The Sharpe Ratio goes from 0.73 [*t - stat* of 4.27] in the case where we buy and sell just the highest and lowest yielding currencies to 0.86 [*t - stat* of 4.82] in the case where we buy and sell 5 currencies on both the legs of the trade. If we look at the third and fourth moments we can also see considerable improvements gained by diversificating: the skewness goes from -1.06 in the 1 long vs 1 short case to -0.36 in the 5 long vs 5 short case while the excess kurtosis goes from 3.19 to 1.15, getting closer to normality. Also in this case we were able to reduce the maximum drawdown from -19.37% to -8.02%.

Table 3: Results of Diversification Considering All the Currencies

	C = 1, HP = 1	**C = 3, HP = 1**	**C = 5, HP = 1**	**C = 9, HP = 1**	**C = 12, HP = 1**
Mean (Ann.)	10.28%	6.46%	5.96%	5.00%	4.79%
t - stat	4.13	4.55	5.54	6.48	6.49
St. Dev. (Ann.)	16.31%	9.31%	7.04%	5.06%	4.84%
Sharpe Ratio	0.63	0.69	0.85	0.99	0.99
t - stat	3.77	4.08	4.75	5.31	5.31
Max	18.24%	8.50%	5.61%	4.45%	4.45%
Min	- 22.34%	- 12.65%	- 7.81%	- 5.21%	- 5.05%
Skewness	- 0.77	- 0.52	- 0.57	- 0.41	- 0.43
Excess Kurtosis	3.10	2.23	1.47	1.11	1.24

Table 4: Results of Diversification Considering Just the G10 Currencies

	C = 1, HP = 1	**C = 2, HP = 1**	**C = 3, HP = 1**	**C = 4, HP = 1**	**C = 5, HP = 1**
Mean (Ann.)	9.40%	7.81%	6.50%	5.89%	5,89%
t - stat	4.81	5.41	5.52	5.64	5.64
St. Dev. (Ann.)	12.80%	9.45%	7.71%	6.84%	6.84%
Sharpe Ratio	0.73	0.83	0.84	0.86	0.86
t - stat	4.27	4.67	4.74	4.82	4.82
Max	10.20%	11.09%	8.61%	7.45%	7.45%
Min	- 19.37%	- 10.18%	- 10.65%	- 8.02%	- 8.02%
Skewness	- 1.06	- 0.36	- 0.53	- 0.36	- 0.36
Excess Kurtosis	3.19	1.26	1.97	1.15	1.15

4.5 Do Different Holding Periods Change the Results?

In this section we present what happens if we change the holding period of our investment (with the holding period going from 1 to 12 months) keeping the number of currencies on both the long and short side equal to 5. The results are presented in Table 5. The results for a holding period of 6, 9 and 12 months are not statistically significant but as we can see, shortening the holding period has an effect similar to diversification: the Sharpe Ratio is at its highest when the holding period is just 1 month, at 0.85 [*t - stat* of 4.75] while with a 12-months holding period is 0.44 [*t - stat* of 0.79]. The skewness improves as well if we shorten the holding period, going from -0.75 when the holding period is 12 months to -0.57 when the holding period is 1 month. Regarding the excess kurtosis there seem to be no clear pattern: it is 1.47 with a 1-month holding period, it reaches 5.20 with a 6-months holding period and decreases back to 1.78 with a 12-months holding period. Regarding the maximum drawdown we can see some improvements by increasing the holding period: we have a maximum drawdown of -7.81% with a 1-month holding period and a maximum drawdown of just -1.96% with a 12-months holding period.

Table 5: Results of Changing the Holding Period Considering All the Currencies

	HP = 1, C = 5	**HP = 3, C = 5**	**HP = 6, C = 5**	**HP = 9, C = 5**	**HP = 12, C = 5**
Mean (Ann.)	5.96%	1.67%	0.81%	0.46%	0.31%
t - stat	5.54	4.19	3.78	3.06	2.86
St. Dev. (Ann.)	7.04%	2.61%	1.40%	0.98%	0.70%
Sharpe Ratio	0.85	0.64	0.58	0.47	0.44
t - stat	4.75	2.20	1.43	0.97	0.79
Max	5.61%	3.46%	2.39%	1.88%	1.52%
Min	- 7.81%	- 6.48%	- 4.25%	- 2.87%	- 1.96%
Skewness	- 0.57	- 1.19	- 1.55	- 0.98	- 0.75
Excess Kurtosis	1.47	4.35	5.20	2.84	1.78

If we consider just the G10 currencies we get similar results. Results are presented in Table 6. Also in this case the results for a holding period of 6, 9 and 12 months are not statistically significant but as we can see, shortening the holding period has an effect similar to diversification: we have the highest Sharpe Ratio when the holding period is 1 month, at 0.86 [*t - stat* of 4.82], while with a 12-months holding period it is 0.67 [*t - stat* of 1.14]. Also in this case the skewness has the lowest value, -0.36, with a holding period of 1 month and decreases to -0.75 with 12 months as holding period. The excess kurtosis is at its closest point to normality with a holding period of 1 month at 1.15. In line with the previous case, increasing the holding period reduces the maximum drawdown as well, going from -8.02% with 1 month holding period to -1.57% with a 12-months holding period.

Table 6: Results of Changing the Holding Period Considering Just the G10 Currencies

	HP = 1, C = 5	HP = 3, C = 5	HP = 6, C = 5	HP = 9, C = 5	HP = 12, C = 5
Mean (Ann.)	5.89%	1.91%	0.90%	0.64%	0.41%
t - stat	5.64	5.39	4.48	4.42	4.35
St. Dev. (Ann.)	6.84%	2.31%	1.31%	0.95%	0.61%
Sharpe Ratio	0.86	0.82	0.69	0.68	0.67
t - stat	4.82	2.69	1.65	1.33	1.14
Max	7.45%	3.61%	2.46%	2.24%	1.64%
Min	- 8.02%	- 4.49%	- 3.55%	- 2.26%	- 1.57%
Skewness	- 0.36	- 0.48	- 0.92	- 0.51	- 0.54
Excess Kurtosis	1.15	1.57	3.53	1.70	1.46

4.6 Factor Models

In this section we will check if the goodness of the results we got so far can be explained by some factor models. We chose to differentiate between three types of factor models: Equity Factor Models, Bond Factor Models, Forex Factor Models and additional three models obtained by mixing the previous factors. In each case we run a regression of the CT returns obtained by buying and selling the 12 highest and lowest yielding currencies, $R_{CT,t}$, on the returns of the factors we chose, F_t, that represent the sources of risks, as in the following equation:

$$R_{CT,t} = \alpha + \beta F_t + \varepsilon_t$$

Since we use returns as risk factors, the constant term in the regression, α, measures the average performance of the carry trade that is not explained by the exposure of the carry trades to the market risks included in the regression.

4.6.1 Equity Factor Models

The factors we chose in this category are the Fama and French Three Factors: "Market Excess Return" defined as the return of the market over the risk-free rate, "Small Minus Big" defined as the return on a portfolio built by buying stocks with a low market capitalization and shorting stocks with a high market capitalization and "High Minus Low" defined as the return on a portfolio built by buying stocks with a high book to market value and shorting stocks with a low book to market value. We chose them to see if the strategy performance can be explained by three of the most famous and traditional factors. The results are presented in Table 7.

Table 7: Equity Markets Factor Models Results

	Alpha (Ann.)	t - stat Alpha	Beta	t - stat Beta	R Squared
Market Excess Return	4.31%	5.9928	0.0836	6.1455	0.0691
Small Minus Big	4.86%	6.5811	0.0304	1.4716	0.0042
High Minus Low	4.91%	6.6194	0.0080	0.3708	0.0003

As we can see, even though the "Market Excess Return" present some modest explanatory power, it doesn't seem that these equity factors are succesful in explaining the CT results: just one of them is statistically significant, with a small coefficient that allows the annualized α to be 4.31% [*t - stat* of 5.99]. Moreover, the biggest R^2 is just 0.069.

4.6.2 Bond Factor Models

The factors we chose in this category include: the 10-year rate on US government bond, the 2-year rate on US government bond and the spread between the 10 year and 2 year US government bonds. We choose those factors because the 10-year rates usually respond more to concerns regarding growth and inflation, the 2-year rates are more responsive to the Central Bank monetary policy and the 10 – 2 years spread is one of the most common recession predictor. By including those three factors we think we incorporate well the dynamics of the bond markets

Table 8: Bond Markets Factor Models Results

	Alpha (Ann.)	t - stat Alpha	Beta	t - stat Beta	R Squared
10 Year Rate	3.58%	2.2044	0.0178	0.9310	0.0017
2 Year Rate	3.93%	3.0626	0.0156	0.9545	0.0018
10Y Minus 2Y	5.43%	5.1024	- 0.0439	- 0.6543	0.0008

In this case the results are less esplicative than before: none of the factors are statistically significant, indicating that the bond market factors don't explain at all the performance of the CT.

4.6.3 Forex Factor Models

The factor used in our Forex factor model is the average performance of six portfolios of currencies created by H. Lustig, N. Roussanov and A. Verdelhan (2011). The construction of these portfolios is structured in the following way: 35 currencies are divided in six portfolios, the portfolio 1 includes the lowest yielding currencies (compared to the US Dollar) while the portfolio 6 includes the highest yielding currencies (compared to the US Dollar). Results are presented in Table 9.

Table 9: Forex Markets Factor Models Results

	Alpha (Ann.)	t - stat Alpha	Beta	t - stat Beta	R Squared
Average FX	5.01%	6.1027	0.0758	2.1648	0.0110

As we can see, even though the average return of the forex portfolios present some modest explanatory power, it doesn't seem that this FX factor is succesful in explaining the CT results: a small coefficient that allows the annualized α to be 5.01% [t - *stat* of 6.10]. Moreover, the R^2 is just 0.011.

4.6.4 Some More Models

Finally, we tried to combine some factors. Specifically, we built a model combining the Market Excess Return, Big Minus Small and High Minus Low factors, a model combining the 10-year rate, the 2-year rate and the spread between the 10 year and the 2 year and a model combining the Market Excess Return and the Average FX Portfolios Performance. Results are presented in Table 10.

Table 10: Other Factor Models Results

	Alpha (Ann.)	t - stat Alpha	Beta	t - stat Beta	R Squared
(MKT - RF) + SMB + HML	4.08%	5.6259	0.0909 | 0.0103 | 0.0496	6.3317 | 0.4929 | 2.2477	0.0783
10Y + 2Y + (10Y - 2Y)	3.95%	1.6547	0.0048 | 0.0106 | -0.0057	0.1344 | 0.4591 | -0.1032	0.0018
(MKT - RF) + Average FX	4.23%	5.4158	0.1099 | 0.0259	7.2731 | 0.7682	0.1219

As we can see, the best result is achieved by combining the Market Excess Return and the Average FX Portfolios Performance but, again, it doesn't seem enough to explain the carry trade results: of the two factors, just the Market Excess Return is statistically significant but the coefficient is still small enough to allow the annualized α to be 4.23% [t - *stat* of 5.41]. Moreover, even tough the R^2 is almost double than the highest we had before (0.069 for the Market Exces Return), is still just 0.122.

Concluding, even tought we thought the factors choosen incorporated well the risks of the CT, our study demonstrated the opposite, with few of the factors choosen being statistically significant and deludent results for the statistically significant factors.

4.7 Additional Strategies

4.7.1 How to Improve the Results? Volatility Scaling!

We saw that the one currency long vs one currency short CT is the one that has the biggest drawdowns and in this section we will present two ways to reduce the drawdown risk in this strategy. The first one comes from the simple logic that if a strategy perform bad during a certain period, then the opposite of this strategy must perform well. The first step in implementing this strategy was calculating the realized six months rolling standard deviation of the returns of the one vs one CT. We then set an annualized volatility target of 16% (which is the annual average volatility of the strategy) and checked if the annualized standard deviation in the past six months was higher than the target. If the realized volatility was lower that the target we implemented the CT in the usual way, otherwise we implemented it in the opposite way, by buying the lowest yielding currency and selling the highest yielding one. We can see the results in Table 11: the usual CT delivers a Sharpe ratio of 0.63 [*t - stat* of 3.77] while the strategy described above delivers a slightly lower Sharpe ratio of 0.61 [*t - stat* of 3.75] so it doesn't seem then that this way of managing the drawdown risk is succesful.

Table 11: Results of Going Short on the Carry Trade in High Volatility Periods

	Carry Trade	Carry Trade Reversed
Mean (Ann.)	10.28%	9.90%
t - stat	4.13	3.97
St. Dev. (Ann.)	16.31%	16.33%
Sharpe Ratio	0.63	0.61
t - stat	3.77	3.65
Max	18.24%	18.24%
Min	- 22.34%	- 22.34%
Skewness	- 0.77	- 0.73
Excess Kurtosis	3.10	3.04

The idea for the second strategy that we will show comes from the paper by P. Barroso and P. Santa-Clara (2015). The Momentum strategy involves buying assets that recently performed well and selling assets that recently performed bad. The authors could improve the Sharpe ratio of the strategy from 0.53 (obtained implementing the Momentum as described above) to 0.97

by scaling it by volatility. They implemented the scaled Momentum as follows: they chose a volatility target and calculated a realized rolling window volatility. They then levered the momentum strategy by $\sigma_{Target}/\sigma_{Realized}$ if the σ_{Target} was higher than the $\sigma_{Realized}$ and reduced their exposure to the market by $\sigma_{Target}/\sigma_{Realized}$ if the σ_{Target} was lower than the $\sigma_{Realized}$.

Since the CT presents some similarities with the Momentum strategy (that is, both the strategies perform good in good times and extremely bad in bad times), we decided to also try to scale the one long vs one short CT. We chose an annual target volatility of 16% and calculated a realized 6, 12 and 24 months rolling standard deviation of the returns of the one vs one CT. Then we levered our portfolio or reduced our exposure following the same principle explained above. The results are presented in Table 12.

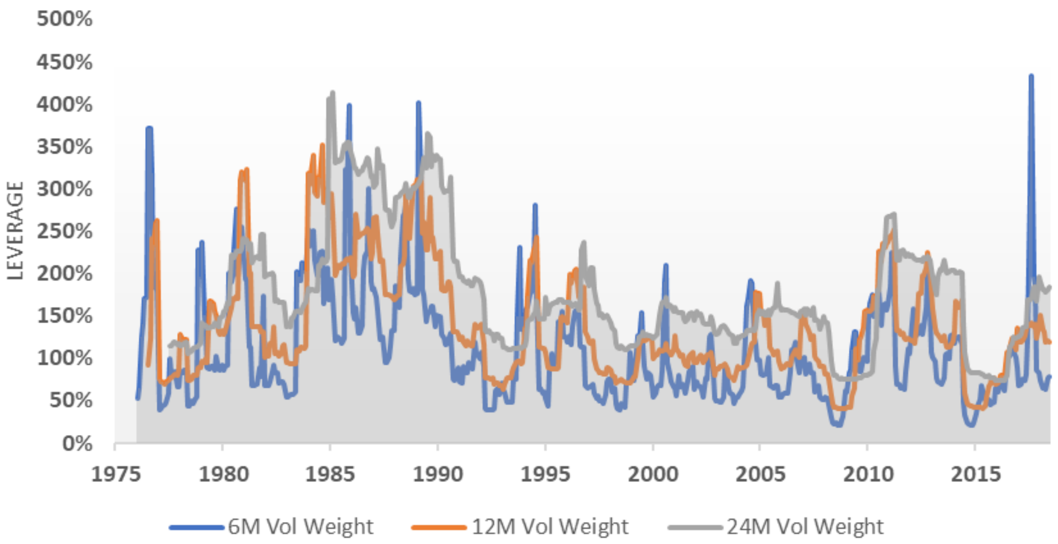
Table 12: Results of the Scaled Carry Trade

	Not Scaled	6M Scaled	12M Scaled	24M Scaled
Mean (Ann.)	10.28%	14.19%	16.17%	20.62%
t* - *stat	4.13	7.26	6.13	5.52
St. Dev. (Ann.)	16.31%	12.73%	17.11%	23.91%
Sharpe Ratio	0.63	1.11	0.95	0.86
t* - *stat	3.77	5.71	5.09	4.71
Max	18.24%	15.09%	16.18%	20.92%
Min	- 22.34%	- 7.95%	- 13.59%	- 22.11%
Skewness	- 0.77	0.05	- 0.24	- 0.42
Excess Kurtosis	3.10	0.18	0.26	0.78

Also in the case of currency investing, the Sharpe Ratio almost doubles in the case where we scale the strategy using the realized 6-months volatility, going from 0.63 [*t* - *stat* of 3.77] in the not scaled CT to 1.11 [*t* - *stat* of 5.71] in the scaled CT. Looking at the third and fourth moments of the distribution we can see how the returns are distributed almost normally, with a slightly positive skweness of 0.05 and an excess kurtosis of 0.18. Scaling the strategy using the 12-months and 24-months realized volatility also improves the results even if not as much as we have using the realized 6-months volatility: the Sharpe Ratios of these two strategies are respectively 0.95 [*t* - *stat* of 5.09] and 0.86 [*t* - *stat* of 4.71] and the third and fourth moments of the distribution are also closer to normality than in the case without scaling with a skewness of respectively -0.24 and -0.42 and an excess kurtosis of respectively 0.26 and 0.48.

The results obtained suggest that volatility is “volatile”, increasing and decreasing quickly, making a wider volatility rolling window less useful to react in time to market movements. This effect can also be seen in Figure 5 where we show the leverage of the strategy during the 1976 – 2018 span.

Figure 5: Leverage of the Strategy



As expected, a shorter rolling window corresponds to a more volatile leverage that allow to adjust the leverage of the strategy more quickly to the market environment. Moreover, out of the 510 observations we have, scaling with the 6-months realized volatility allowed to reduce the exposure to the market on 288 months (56% of the time), using the 12-months realized volatility reduced the exposure to the market 167 months (33% of the time) and using the 24-months realized volatility allowed to reduce the exposure just on 48 months (9% of the time). Finally, the better results obtained by using the 6-months volatility can also be explained by the average leverage used, that is 110% for the 6-months case, 138% for the 12-months case and 177% for the 24-months case.

4.7.2 Derivatives as a Way to Manage Risk

Another way to manage the risk in the CT strategy would be to use options to limit the potential downside of the strategy. As explained before, we implement the CT by doing two operations: buying a high yield currency and sell the US Dollar (that means selling a forward on the exchange rate expressed as US Dollar / High Yield Currency) and buy the US Dollar and sell a low yield currency (that means buying a forward on the exchange rate expressed as US Dollar / Low Yield Currency). Considering the single legs of the trade we can see two sources of risk:

in one leg, the high yield currency could depreciate toward the US Dollar, in the other leg the low yield currency could appreciate toward the US Dollar. Currently the strategy payoff is as follows:

$$\left(S_{HYC,t+1} - F_{HYC,t}\right) + \left(F_{LYC,t} - S_{LYC,t+1}\right)$$

where $F_{HYC,t}$ and $S_{HYC,t+1}$ are the forward rate at time t and the spot rate at time $t+1$ for the high yield currency and $F_{LYC,t}$ and $S_{LYC,t+1}$ are the forward rate at time t and the spot rate at time $t+1$ for the low yield currency. In a strategy implemented in this way the losses can be potentially unlimited. How can we limit the potential downside coming from the depreciation of the high yield currency? A possible solution is to buy a put on the high yield currency and a call on the low yield currency. The payoff of the put would be as follows:

$$Put\ Payoff = MAX(0, K_t - S_{t+1}) - P_t\left(1 + r_f\right)$$

where K_t is the strike price of the put and P_t is the put premium. And the payoff of the call would be:

$$Call\ Payoff = MAX(0, S_{t+1} - K_t) - C_t\left(1 + r_f\right)$$

where K_t is the strike price of the put and C_t is the call premium. Breaking down the single legs of the trade we can see how it is possible to limit the downside stemming from the depreciation of the high yield currency by buying a put on the high yield currency. The long leg unhedged payoff is:

$$Long\ Leg\ Unhedged\ Payoff{:}\ \left(S_{HYC,t+1} - F_{HYC,t}\right)$$

and by buying a put we have:

$$Long\ Leg\ Hedged\ Payoff{:}\ \left(S_{HYC,t+1} - F_{HYC,t}\right) + \left(K_t - S_{HYC,t+1}\right) - P_t\left(1 + r_f\right)$$

that simplifies into:

$$Long\ Leg\ Hedged\ Payoff{:}\ \left(K_t - F_{HYC,t}\right) - P_t\left(1 + r_f\right)$$

The same is true considering the short leg: in this case the risk comes from the appreciation of the low yield currency and to hedge this risk we need to buy a call on the low yield currency. As before we have:

$$Short\ Leg\ Unhedged\ Payoff{:}\ \left(F_{LYC,t} - S_{LYC,t+1}\right)$$

and by buying a call we have:

$$Short\ Leg\ Hedged\ Payoff: \left(F_{LYC,t} - S_{LYC,t+1}\right) + \left(S_{LYC,t+1} - K_t\right) - C_t\left(1 + r_f\right)$$

that simplifies into:

$$Short\ Leg\ Hedged\ Payoff: \left(F_{LYC,t} - K_t\right) - C_t\left(1 + r_f\right)$$

As we can see, in both cases the maximum loss is defined by the difference between the forward price and the strike price of the options plus the options premium. Note that if we would be able to trade directly the exchange rates (as an example: buy directly the exchange rate Indian Rupee / Japanese Yen) instead of doing two trades against the US Dollar (as an example: buy Indian Rupee and sell US Dollar and buy US Dollar and sell Japanese Yen), we wouldn't need to buy two options. However, for how the CT is implemented we need to buy both a put on the high yield currency and a call on the low yielding currency and the reason is the following: if we would just buy a put on the high yield currency, we would be hedged in the case of a high yield currency depreciation but we would be still exposed to a low yield currency appreciation, on the other hand, if we would just buy a call on the low yield currency, we would be hedged in the case of a low yield currency appreciation but we would be still exposed to a high yield currency depreciation.

It would have been interesting to study the effect of the option hedging on the strategy but we didn't have access to the two databases (Chicago Mercatile Exchange and J. P. Morgan) from where the historical data is available. We can get a hint of the result from the paper of C. Burnside, M. Eichenbaum, I. Kleshchelski, S. Rebelo (2011) where the authors pursued a similar study and getting to the result that the hedged CT perform slightly worse in terms of Sharpe Ratio than the unhedged CT (0.449 against 0.476).

5. Conclusions

The saying that the CT resembles "picking up pennies in front of a truck" seems appropriate if the strategy in implemented using few currencies: we saw that building the CT with just one currency on the long leg and one on the short leg gives a maximum drawdown of -22.34% and a Sharpe Ratio of 0.63 (against the Sharpe Ratio of the benchmark which is 0.70 considering all the sample). However, the more we diversificate, the more this tail risk seems to disappear: using twelve currencies on both legs reduce the maximum drawdown to -5.05%, the distribution moves closer to normality and the Sharpe Ratio increases to 0.99. Moreover, scaling the strategy by volatility improves the results of the one long vs one short CT in all the three cases we studied: scaling using the realized 6-months volatility produces the best result, with a Sharpe

Ratio going from 0.63 (in the case where no scaling is applied) to 1.11, using the realized 12-months increase the Sharpe Ratio to 0.95 and using the realized 24-months volatility increase the Sharpe Ratio to 0.86.

We also saw that the goodness of the CT strategy is not explained by standard risk factors: at the beginning of our analysis we thought the equity markets, bond markets and forex markets factors we chose incorporated well the risks of the CT but we were proved wrong: in all the factor models used the annualized α is ranging between 4% and 5% and the coefficients pretty small and statistically significant just in few cases, indicating that the factor choosen leave most of the CT results unexplained.

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Appendix A: Currency Codes

	Pound Spot Code	Pound Forward Old Code	Pound Forward New Code	Dollar Spot Code	Dollar Forward Old Code	Dollar Forward New Code
Austrian Schilling	AUSTSCH	AUSTS1F		AUSTSC$		USATS1F
Belgian Franc	BELGLUX	BELXF1F		BELGLU$		USBEF1F
Canadian Dollar	CNDOLLR	CNDOL1F	UKCAD1F	CNDOLL$		USCAD1F
Danish Krone	DANISHK	DANIS1F	UKDKK1F	DANISH$		USDKK1F
French Franc	FRENFRA	FRENF1F		FRENFR$		USFRF1F
German Mark	DMARKER	DMARK1F		DMARKE$		USDEM1F
Irish Punt	IPUNTER	IPUNT1F		IPUNTE$		USIEP1F
Italian Lira	ITALIRE	ITALY1F		ITALIR$		USITL1F
Japanese Yen	JAPAYEN	JAPYN1F	UKJPY1F	JAPAYE$		USJPY1F
Netherlands Guilder	GUILDER	GUILD1F		GUILDE$		USNLG1F
Norwegian Krone	NORKRON	NORKN1F	UKNOK1F	NORKRO$		USNOK1F
Portuguese Escudo	PORTESC	PORTS1F		PORTES$		USPTE1F
Spanish Peseta	SPANPES	SPANP1F		SPANPE$		USESP1F
Swedish Krona	SWEKRON	SWEDK1F	UKSEK1F	SWEKRO$		USSEK1F
Swiss Franc	SWISSFR	SWISF1F	UKCHF1F	SWISSF$		USCHF1F
US Dollar	USDOLLR	USDOL1F	UKUSD1F	USDOLLR		USGBP1F
Euro	ECURRSP		UKEUR1F	EUDOLLR		USEUR1F
Australian Dollar	AUSTDOL		UKAUD1F	AUSTDO$	MBAUD1F	USAUD1F
New Zealand	NZDOLLR		UKNZD1F	NZDOLL$	MBNZD1F	USNZD1F
South Africa	COMRAND		UKZAR1F	COMRAN$		USZAR1F
Korean Won	KORSWON		UKKRW1F	KORSWO$		USKRW1F
Indian Rupee	INDRUPE		UKINR1F	INDRUP$		USINR1F
Brazilian Real	BRACRUZ		UKBRL1F	BRACRU$		USBRL1F
Mexican Peso	MEXPESO		UKMXN1F	MEXPES$		USMXN1F
Chinese Yuan	CHIYUAN		UKCNY1F	CHIYUA$		USCNY1F
Russian Ruble	CISRUBM		UKRUB1F	CISRUB$		USRUB1F
Thai Baht	THABAHT		UKTHB1F	THABAH$		USTHB1F
Honk Kong Dollar	HKDOLLR		UKHKD1F	HKDOLL$		USHKD1F
Taiwan Dollar	TAIWDOL		UKTWD1F	TAIWDO$		USTWD1F
Singapore Dollar	SINGDOL		UKSGD1F	SINGDO$		USSGD1F

Here above we present the codes used to dowload the data from Datastream. For the Forward Rates can have two codes as in 1996 the codes changed for all the forward rates and we needed to merge the two datasets: one got with the old code (that usually gives us the data from 1976 to 1996) and one got with the new code (that gives us the data from 1996 to 2018).