Idiosyncratic Carry Trade: Characteristics or Covariances?

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Abstract

This paper investigates the role of idiosyncratic components in currency behavior and their impact on the carry trade strategy. By isolating these components through principal component analysis (PCA) and controlling for common risk factors, we construct idiosyncratic carry trade portfolios that outperform traditional carry strategies. Our findings reveal that controlling for common variation significantly reduces currency volatility while maintaining performance. Our idiosyncratic carry trade approach achieves higher Sharpe ratios and reduces negative skewness, thereby mitigating left tail risk. These results suggest that incorporating idiosyncratic components provides a more robust framework for currency trading, offering valuable insights for investors and policymakers.

Keywords: Carry Trade, international finance, asset pricing, currencies.

JEL Classification: G12, G15, F31.

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1 Introduction

Day by day, we observe that currencies from different countries move in varying patterns. Traditional finance literature often explains these asset movements through their common variations. For instance, Fama (1984) empirically observes the failure of the Uncovered Interest Rate Parity (UIP), showing that while currencies with higher than average interest rates tend to appreciate, those with lower than average interest rates tend to depreciate. Furthermore, Lustig et al. (2011) identify a global risk factor in exchange rate markets that explains currency co-movements. They find that high-interest-rate currencies move positively with this factor, while low-interest-rate currencies move negatively with it.

Despite the importance of these common variations emphasized by the traditional literature, this paper focuses on the idiosyncratic movements in currency behavior to shed new light on the carry trade, a major currency trading strategy. Our approach begins by capturing common currency variation. Following Lustig et al. (2011), we leverage the fact that country-specific and global risk factors can explain the significant co-movement among exchange rates of different currencies. We then isolate the idiosyncratic components of each currency by controlling for these factors. Traditionally, the currency carry trade involves selling currencies with low-interest rate differentials and buying currencies with high-interest rate differentials. Our idiosyncratic version of this trade, however, ranks currencies based solely on the idiosyncratic part of their interest rate differentials.

To highlight the importance of the currency idiosyncratic components, we provide evidence that the idiosyncratic carry trade outperforms the traditional carry strategy. Interestingly, by controlling each currency for its exposure to common variation, we reduce the currency's volatility without significantly affecting its performance. Our portfolios earn economically and statistically significant alphas, doubling Sharpe ratios while reducing the negative portfolio skewness.

Our novel builds on a longstanding debate in the finance literature, particularly within equities research. Common variation reassembling the standard finance literature that seeks to identify sources of systematic risk to explain assets behavior. Consider the standard asset pricing equation expressed in the beta representation of an unconditional asset pricing model:

$$E\left[R_{i,t+1}\right] = \lambda' \beta$$

where $R_{i,t+1}$ is the excess return of any asset i, and $\beta_i = \text{cov}(R_{i,t+1}, -m_{t+1})/\text{var}(m_{t+1})$ where m is the pricing kernel or stochastic discount factor (SDF) that prices all assets. Once a candidate for m is specified, an asset pricing model relies on the covariance with this pricing kernel to determine asset prices. In their influential paper, Fama and French (1996) present a reduced-form factor model $m = -b'[Mkt, SMB, HML]$ with specific weights b. In macro-finance literature, the Stochastic Discount Factor (SDF) is often defined using macroeconomic variables that serve as proxies for marginal utility, such as consumption or economic recessions. These variables represent aggregate risk, indicating that stocks are considered risky because they tend to perform poorly during economic downturns when marginal utility is elevated.

Another strand of finance literature questions whether these factors can represent economically relevant aggregate risks. In another seminal paper, Daniel and Titman (1997) test whether the high returns of high book-to-market and small-size stocks can be attributed to their covariance with the factors identified in Fama and French (1996). The authors find that although high book-to-market stocks do co-move strongly with other high book-to-market stocks, these covariances are not due to specific risks associated with financial distress. Instead, they indicate that high book-to-market firms often share similar traits; for example, they may be involved in related business sectors, belong to the same industries, or be located in the same regions. Furthermore, they highlight that portfolios sorted by similar characteristics but with different betas on the Fama and French (1996) factors do not exhibit different returns. In other words, high book-to-market stocks and small firms have high average returns regardless of their exposure to aggregate risk factors. It is the firm characteristics that primarily determine expected returns.

Characteristics and covariance are both relevant in the currency framework. Lustig et al. (2011) identify a common risk factor in exchange rate determination by constructing monthly portfolios of currencies sorted by their forward premiums. The first two principal components of these portfolio returns account for most of the time-series variation in currency returns. The first component is a level factor, while the second is a slope factor related to changes in global equity market volatility. These factors explain about two-thirds of the cross-sectional variation in exchange rates. Characteristics also play a crucial role in the currency debate. Ranaldo and Söderlind (2010) argue that some currencies are considered safe investments, earning lower risk premiums. In their framework, similar countries can exhibit idiosyncratic behaviors, with one seen as a "safe haven" due to differing risk characteristics. Furthermore, Brunnermeier et al. (2008) show that high-yield currencies are subject to crash risk and varying levels of negative skewness, explaining why they tend to outperform low-yield currencies as investors demand higher returns for the increased risk.

Our paper is related to those that explore the failure of the covariance mechanism to explain expected equity returns. By constructing hedging portfolios sorted by their exposures to macroeconomic factors, Herskovic et al. (2019) shows that these portfolios not only hedge against those factors but also hedge against exposure to consumption, GDP, and other reduced-form asset pricing factors such as value, momentum, and profitability. Their portfolio approach methodology closely follows that of Fama and French (1993). Daniel et al. (2020) focus on the fact that factors such as those proposed by Fama and French are not mean-variance efficient (MVE). The authors argue that in the process of building these factors, both priced risk and unpriced sources of common variation in returns are considered. As a result, the factors' Sharpe ratios are lower than the Sharpe ratios of the projection of the risk factor onto the space of returns. By applying an optimization problem that accounts for the covariance matrix of returns, they improve these factors by removing unpriced sources of common variation in returns.

While exploring the failure of the covariance mechanism, our paper differs from these studies in two key ways. First, we apply the hedging concept to currencies. Second, we propose a novel hedging mechanism. Before sorting currencies based on their forward premium, we hedge both the currency excess return and the forward premium. Following the methodology of Lustig et al. (2011), we capture the common variation by applying principal component analysis (PCA) in an expanding window. This approach allows us to isolate the idiosyncratic excess return and idiosyncratic carry. Our idiosyncratic carry trade is then formed based on these variables. Additionally, employing PCA in an expanding window enables us to construct feasible portfolios.

Our approach aims to emphasize the idiosyncratic components within an investment decision framework. By doing so, we seek to enhance the understanding of how different currencies behave and the role of idiosyncratic interest rate differentials in shaping global currency markets. The paper is organized as follows: Section II defines our interest rate differential approach, comparing it to the traditional carry trade strategy. Section III outlines our dataset. Section IV details our methodology, including the application of principal component analysis and the development of our idiosyncratic carry trade strategy. Section V presents the results of our performance and robustness checks. Finally, Section VI provides our conclusions.

2 Currency Carry and Excess Return

To start our analysis is important to keep in mind our interest rate differential approach. This approach involves using forwards and spot currency prices to represent the interest rate differential and it's related with the Covered Interest Rate (CIP), a non-arbitrage argument. Let S_t represent the spot exchange rate using US dollar as the base currency (meaning the amount of foreign currency per US dollar), where s_t is its logarithm and Δs_t represents the depreciation rate (an increase in s_t indicates a depreciation of the foreign currency). Similarly, F_t is the 1-month forward exchange rate against the US dollar, with f_t being its logarithm. Consequently, $f_t - s_t$ denotes the log forward premium or the currency carry.

To clarify the non-arbitrage argument, consider an investor exploring international financial markets, focusing on interest rate differences between two countries. The investor can either invest domestically at the domestic interest rate (i_t^d) or abroad at a potentially higher foreign interest rate (i_t^f). Investing abroad involves currency risk, which the investor hedges using a forward contract to lock in the future exchange rate (F_t). According to Covered Interest Parity (CIP), the returns from foreign and domestic investments should be equivalent once adjusted for the forward exchange rate. This means that the difference in interest rates between the two countries is offset by the difference between the forward and spot exchange rates, eliminating riskless arbitrage opportunities. Mathematically, this is represented as:

$$fp_t = f_t - s_t \approx i_t^f - i_t^d$$

If the same investor commits to buying a foreign currency in the forward market at time t at a specified rate F_t, and then sells it in the spot market at a later time $t+1$ at the prevailing rate S_{t+1}, the difference $f_{i,t} - s_{i,t+1}$ in logarithms quantifies the log excess return ($rx_{i,t+1}$) of currency i, reflecting the gain or loss from this forward-spot strategy. This can also be expressed in terms of the forward premium as: $rx_{i,t+1} = f_{i,t} - s_{i,t} - \Delta s_{i,t+1}$.

2.1 Traditional Carry Trade

In this CIP setting, the log forward premium is commonly used to rank currencies for the traditional carry trade and to calculate the currency excess return. Following the approach of Lustig et al. (2011), at the end of each period t, we categorize all currencies in the sample into six portfolios based on their forward premiums (fp_t) observed at the end of period t. These portfolios are rebalanced monthly. They are ordered from low to high interest rates: portfolio 1 contains currencies with the lowest interest rates or smallest forward premiums, while portfolio 6 contains those with the highest interest rates or largest forward premiums. To compute the log currency excess return (rx^j_{t+1}) for portfolio j, we take the average of the log currency excess returns within each portfolio. The return of the traditional carry trade is then determined by the return difference between the highest and lowest portfolios, $rx^{HML}_{t+1} = rx^6_{t+1} - rx^1_{t+1}$.

3 Data description

We collect monthly data on spot exchange rates and one-month forward rates for 28 economies from Refinitiv/Datastream: Australia (AUD), Brazil (BRL), Canada (CAD), Switzerland (CHF), Czech Republic (CZK), Denmark (DKK), Eurozone (EUR), United Kingdom (GBP), Greece (GRD), Hong Kong (HKD), Hungary (HUF), India (INR), Iceland (ISK), Japan (JPY), South Korea (KRW), Kuwait (KWD), Mexico (MXN), Norway (NOK), New Zealand (NZD), Philippines (PHP), Poland (PLN), Russia (RUB), Sweden (SEK), Singapore (SGD), Slovakia (SKK), Thailand (THB), Turkey (TRY), and South Africa (ZAR). The sample period covered is from June 2004 to December 2023.

In Table 1 we report summary statistics on monthly spot exchange changes and forward premium defined previously as the foreign forward rate minus the currency spot price. Among the developed countries, including Australia, Canada, Switzerland, Denmark, the Euro Area, the United Kingdom, Japan, Norway, New Zealand, Sweden, and Singapore, we observe relatively stable currency behaviors. Developed countries generally exhibit lower and more stable mean exchange rate changes. For instance, Canada, Switzerland, and Singapore have low or negative mean changes, indicating currency stability or appreciation. The forward premia in these countries are also relatively modest, with many exhibiting negative values, such as Switzerland and Japan, reflecting expectations of currency appreciation. The standard deviations are relatively low, indicating less volatility in both exchange rate changes and forward premia.

In contrast, developing countries such as Brazil, the Czech Republic, Hungary, India, Iceland, Mexico, the Philippines, Poland, Russia, South Africa, and Turkey show higher volatility and larger fluctuations in both exchange rate changes and forward premia. Developing economies generally show higher mean exchange rate changes. Turkey, Russia, and Brazil exhibit significant positive mean changes, indicating substantial currency depreciation over the period. Correspondingly, these countries have higher forward premia, with Turkey and Brazil at the top. The standard deviations are also higher, highlighting greater volatility. For instance, Turkey's standard deviation for exchange rate changes is notably high, indicating high uncertainty and risk.

Table 1: Summary statistics of exchange rate changes and forward premia

	FX Changes		Foward Premium	
	Mean	Standard Deviation	Mean	Standard Deviation
Australia	0.27	12.29	1.63	0.55
Brazil	2.53	15.58	7.88	1.13
Canada	-0.21	8.90	-0.02	0.19
Switzerland	-2.21	10.01	-1.82	0.39
Czech Republic	-1.00	11.95	-0.33	0.52
Denmark	0.41	9.21	-0.99	0.39
Euro Area	0.40	9.23	-0.96	0.35
United Kingdom	1.68	9.41	0.03	0.33
Greece	0.40	9.23	-0.96	0.35
Hong Kong	0.01	0.55	-0.47	0.16
Hungary	2.54	14.49	3.01	1.07
India	3.15	7.50	4.66	0.75
Iceland	3.11	14.10	4.69	0.80
Japan	1.24	9.30	-1.89	0.52
South Korea	0.48	11.02	0.29	0.51
Kuwait	0.21	2.43	0.28	0.39
Mexico	2.00	12.17	4.69	0.55
Norway	1.98	11.96	0.21	0.42
New Zealand	-0.06	13.16	2.02	0.50
Philippines	-0.03	5.62	1.92	0.41
Poland	-0.08	13.80	1.65	0.57
Russia	5.72	19.53	8.32	3.49
Sweden	1.40	11.61	-0.72	0.44
Singapore	-1.30	5.68	-0.42	0.26
Slovakia	-1.08	9.77	-0.81	0.38
Thailand	-0.90	6.83	0.58	0.62
Turkey	15.30	17.34	14.38	3.52
South Africa	4.89	16.08	5.56	0.49

Note: The table presents summary statistics of the monthly observations of exchange rate changes and forward premia. Means and standard deviations are annualized by multiplying the variables by 12×100 *and* $\sqrt{12} \times 100$*, respectively.*

4 Common Factors and Idiosyncratic Components

This section clarifies the methodology used to capture the common risk factors and how we utilize it to extract the currency idiosyncratic components used to form the idiosyncratic carry trade.

4.1 Principal Component Analysis

Linear factor models suggest that the average returns of a cross-section of assets can be explained by risk premiums linked to their exposure to a limited number of risk factors. According to the arbitrage pricing theory (APT) from Ross (1976), these factors account for the common variations in individual asset returns. In order to capture this common variation we apply a principal component analysis to the six portfolios formed on forward premiums. Table 2 reports the performance of these six portfolios and the six principal components from the perspective of a U.S investor:

Table 2: Currency Six Portfolios and Principal Components Performance (Monthly Annualized)

Portfolio	1	2	3	4	5	6
	Panel I: Six Portfolios					
Performance	-1.84	-1.09	0.34	0.48	1.59	3.83
SR	(-0.25)	(-0.14)	(0.04)	(0.06)	(0.16)	(0.28)
std	7.27	7.91	7.65	8.34	9.82	13.81
	Panel II: Six Principal Components					
Performance	2.38	3.61	-1.72	0.37	-0.02	0.58
SR	(0.12)	(0.37)	(-0.38)	(0.12)	(-0.01)	(0.22)
std	19.77	9.66	4.56	3.17	2.83	2.7

Note: The table reports the performance (average annualized monthly return), annualized Sharpe ratio (in parentheses), and annualized standard deviation. Panel I presents these metrics for the six portfolios sorted by forward premium ($fp_{i,t}$), while Panel II presents them for the six principal components

Panel I shows that sorting on average forward premiums produces a monotonic pattern in excess returns: currencies with higher average carry tend to earn higher average returns.

We move from a Sharpe Ratio of -0.25 in the portfolio sorted on the smallest forward premiums ($fp_{i,t}$) to 0.28 in the portfolio sorted on the largest forward premiums.

Our principal component analysis of currency portfolios is applied at the end of each month in an expanding window[1]. This guarantees the feasibility of our portfolios. Table 3 shows that two factors account for almost 90% of the variation in returns across these six portfolios. As in Lustig et al. (2011), we identify that the first principal component is a level factor that loads positively in all six portfolios, while the second is a slope factor whose weights decrease monotonically from positive to negative, from high to low interest rate currency portfolios. This explains the high performance of the second principal component compared to the other components in Panel II of Table 2. It is important to note that, as in Lustig et al. (2011), we also could not interpret the other principal components.

Table 3: Lustig Six Portfolio Factor loadings (All Countries)

Portfolio	PC1	PC2	PC3	PC4	PC5	PC6
Portfolio 1	0.28	-0.35	0.58	-0.36	-0.53	-0.24
Portfolio 2	0.33	-0.35	0.30	-0.05	0.81	-0.11
Portfolio 3	0.34	-0.28	0.03	0.22	-0.14	0.86
Portfolio 4	0.38	-0.22	-0.22	0.73	-0.18	-0.43
Portfolio 5	0.46	-0.13	-0.69	-0.54	-0.04	-0.07
Portfolio 6	0.58	0.78	0.23	0.02	0.02	0.02
% Var.	73.71	17.58	3.92	1.90	1.50	1.38

Note: The table reports the factor loadings for the six principal components across all six portfolios. The last row (% Var.) represents the percentage of total variance explained by each principal component.

4.2 Idiosyncratic Carry Trade

The main objective of this study is to test whether non-systemic risk (i.e., idiosyncratic components) influences currency pricing and how we can take advantage of it to improve carry trade portfolios. To achieve this, we first identify the common variation,

[1] We start with a training window of 24 months and proceed with re-estimating the PCs at the end of each subsequent month.

represented by the common risk factors, and then control for these components to isolate the idiosyncratic behavior of currencies. In a factor model, we can mathematically express the currency excess return and forward premiums as follows:

$$rx_{i,t} = \alpha_i + \beta_{i,1}PC_1 + \beta_{i,2}PC_2 + \beta_{i,3}PC_3 + \beta_{i,4}PC_4 + \beta_{i,5}PC_5 + \beta_{i,6}PC_6 + \varepsilon_{i,t} \tag{1}$$

$$fp_{i,t} = \gamma_i + \beta_{i,1}PC_1^{fp} + \beta_{i,2}PC_2^{fp} + \beta_{i,3}PC_3^{fp} + \beta_{i,4}PC_4^{fp} + \beta_{i,5}PC_5^{fp} + \beta_{i,6}PC_6^{fp} + \eta_{i,t} \tag{2}$$

By estimating the principal components (PC_k), we gain access to their factor loadings. The factor loadings for principal component k capture the importance of each portfolio in the PC and can be viewed as a portfolio itself. This enables us to capture the carry of each principal component, PC_k^{fp}, which is simply the carry of each portfolio multiplied by the vector of factor loading k. We also aim to identify the factors that determine the behavior of currency components. In this context, betas, which measure exposure, are particularly useful. Since the first principal component (PC) is a level factor, we expect all currencies to have a positive beta relative to it. Additionally, because the second PC is a slope factor, we anticipate that high-yield currencies will have a positive beta, while low-yield currencies will have a low or negative beta.

In order to access the currencies idiosyncratic components we evaluating the residuals in regressions (1) and (2). Since these residuals are controlled for sources of common volatility, we define $rx_{i,t}^{idi}$ as a hedged pair and $fp_{i,t}^{idi}$ as the idiosyncratic forward premium (or carry). If Fama and French (1993) are incorrect, the six principal components used here will fail to price currencies, representing only a source of volatility. In this scenario, rx_t^{idi} will have a lower standard deviation without affecting performance.

Finally, with these idiosyncratic components in hand, we form feasible idiosyncratic carry trade portfolios. We sort currencies into six portfolios based on $fp_{i,t}^{idi}$ and compute the average return for each portfolio j, $rx_{t+1}^{j,idi}$. Then, as in the traditional version, we compute the idiosyncratic carry trade return as the difference between the returns of the highest and lowest portfolios, $rx_{t+1}^{HML,idi} = rx_{t+1}^{6,idi} - rx_{t+1}^{1,idi}$.

5 Hedged Pairs and Idiosyncratic Carry Performance

Having estimated the principal components, we can use regressions (1) and (2) to extract the idiosyncratic currency excess returns and idiosyncratic carry. To understand the importance of each principal component, we add them one at a time. Figure 1 demonstrates that by controlling for up to six principal components, it is possible to reduce the standard deviation of the hedged pairs ($rx^{idi}_{i,t}$), as shown by the bars representing the annualized standard deviation for each country. At the same time Figure 2 shows that the performance is not affect too much by this procedure. Given some exceptions, developed and non-developed countries stay with the same performance on average.

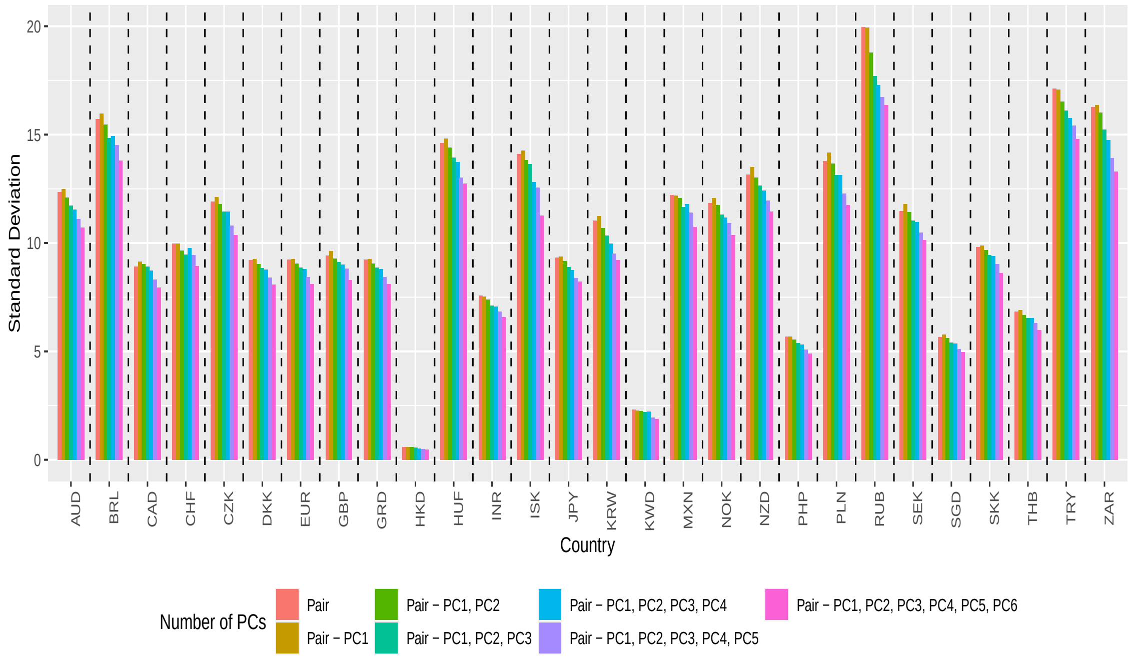

Figure 1: Hedged Pairs Annualized Standard Deviation.

Then, we can use the principal component carry to extract the idiosyncratic carry of every currency pair. Table 4 shows that for developed countries such as Australia, Canada, Switzerland, Denmark, the Euro Area, the United Kingdom, Japan, Norway, New Zealand, Sweden, and Singapore, the carry (forward premium) generally decreases when controlling for up to six principal components. This suggests that the positive carry in these currencies is largely driven by common risk factors. For instance, Australia's carry drops from 1.64 to -0.46, and the United Kingdom's carry falls from 0.03 to -1.31, indicating significant influence from systematic components.

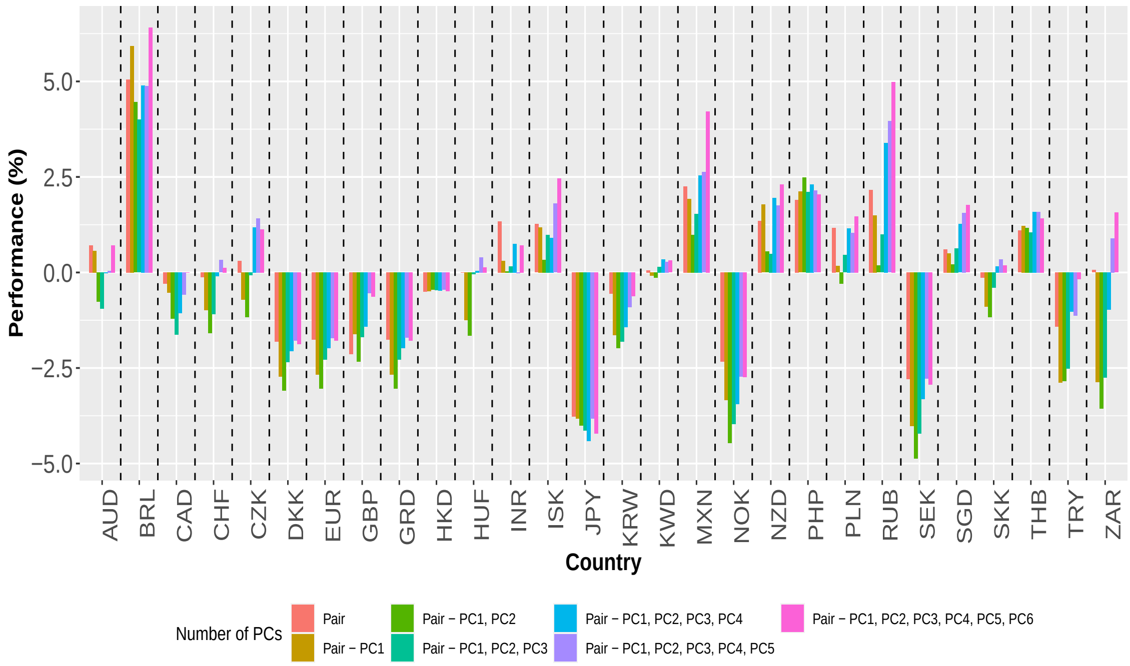

Figure 2: Hedged Pairs Annualized Performance.

In contrast, developing countries like Brazil, the Czech Republic, Hungary, India, Iceland, Mexico, the Philippines, Poland, Russia, South Africa, and Turkey exhibit more resilience in their carry values even after controlling for principal components. Brazil's carry remains relatively high, decreasing only from 7.89 to 5.15, while Turkey's carry stays exceptionally high at 13.93, reflecting the strong presence of idiosyncratic factors. These findings highlight that while developed countries' currency carries are more influenced by common factors, developing countries exhibit significant idiosyncratic influences, offering distinct investment opportunities. In the next section, we evaluate whether this new carry measure can improve carry trade portfolios by enhancing returns and reducing their primary source of risk, skewness.

Table 4: Annualized Carry and Idiosyncratic Carry

Countries	Carry	Carry$^{PC:1}$	Carry$^{PC:1,2}$	Carry$^{PC:1,2,3}$	Carry$^{PC:1,2,3,4}$	Carry$^{PC:1,2,3,4,5}$	Carry$^{PC:1,2,3,4,5,6}$
AUD	1.64	1.46	-0.26	-0.46	-0.19	-0.18	-0.46
BRL	7.89	8.22	6.62	5.78	5.87	5.69	5.15
CAD	-0.02	0.24	-0.64	-0.89	-0.82	-1.00	-1.31
CHF	-1.81	-1.93	-2.00	-2.10	-2.18	-2.05	-2.24
CZK	-0.33	0.06	-0.20	-0.21	0.26	0.48	0.29
DKK	-0.99	-0.85	-0.96	-1.01	-0.78	-0.63	-0.78
EUR	-0.95	-0.82	-0.94	-0.99	-0.75	-0.60	-0.75
GBP	0.03	0.08	-1.74	-1.66	-1.28	-1.27	-1.31
GRD	-0.95	-0.82	-0.94	-0.98	-0.75	-0.59	-0.75
HKD	-0.47	-0.45	-0.39	-0.39	-0.39	-0.39	-0.37
HUF	3.01	3.48	3.08	3.19	3.63	3.70	3.35
INR	4.67	4.61	3.61	3.57	3.67	3.71	3.40
ISK	4.70	4.69	3.23	3.19	3.54	3.44	3.55
JPY	-1.87	-2.33	-2.02	-2.22	-2.39	-2.30	-2.02
KRW	0.30	0.26	-0.88	-1.16	-1.13	-0.99	-1.48
KWD	0.30	0.26	0.19	0.23	0.28	0.31	0.23
MXN	4.68	4.53	3.53	3.15	3.45	3.37	2.78
NOK	0.21	0.62	-0.56	-0.86	-0.48	-0.32	-0.63
NZD	2.03	2.29	0.73	0.53	0.46	0.36	-0.08
PHP	1.92	1.95	2.22	2.02	1.94	2.01	1.95
PLN	1.65	1.86	1.58	1.38	1.81	1.90	1.41
RUB	8.26	9.75	7.34	7.31	8.01	8.02	7.70
SEK	-0.71	-0.54	-1.42	-1.65	-1.33	-1.17	-1.46
SGD	-0.42	-0.40	-0.77	-0.74	-0.63	-0.58	-0.68
SKK	-0.80	-0.63	-0.67	-0.73	-0.40	-0.26	-0.31
THB	0.59	0.63	0.71	0.46	0.52	0.54	0.46
TRY	14.32	13.96	14.77	14.35	14.37	14.39	13.93
ZAR	5.57	5.28	4.87	4.82	5.17	5.63	4.83

Note: The table presents the carry (forward premium or $fp_{i,t}$) and the idiosyncratic carry ($fp_{i,t}^{PC1:6}$) controlling up to the six principal component. All variables are annualized by multiplying the variables by 12×100.

5.1 Performance

Finally, Table 5 presents the performance and skewness of carry trades and idiosyncratic carry trades, highlighting the changes when controlling for up to six principal components. The baseline carry trade (sorting currencies by fp_i) has a performance of 5.67 and a negative skewness of -0.56. When sorting while controlling for the first principal component ($fp_i^{PC:1}$), the performance increases to 6.39, with a corresponding improvement in the Sharpe ratio from 0.45 to 0.5. Interestingly, skewness becomes positive, reducing to 0.06, indicating that we are mitigating left tail risk.

Skewness refers to the asymmetry in the distribution of returns, indicating whether returns are more likely to be significantly positive or negative. Negative skewness in carry trades means that while these trades can be profitable on average, they are subject to the risk of sudden and substantial losses. Brunnermeier et al. (2008) finds that this crash risk arises when speculative positions are unwound, leading to abrupt depreciations in the investment currency.

As we control for more principal components, the performance continues to improve. For $fp_i^{PC:1,2}$, performance increases to 7.34, with a Sharpe ratio rising to 0.59, though skewness slightly worsens to -0.37. Interestingly, controlling for three principal components ($fp_i^{PC:1,2,3}$) results in a performance of 8.15, with the Sharpe ratio at 0.69 and skewness improving to -0.27. Performance peaks when controlling for four principal components ($fp_i^{PC:1,2,3,4}$), reaching 10.13 with the highest Sharpe ratio of 0.91. Importantly, skewness improves significantly to -0.02, indicating a substantial reduction in left tail risk. When controlling for all six principal components ($fp_i^{PC:1,2,3,4,5,6}$), the performance is 8.82, with a Sharpe ratio of 0.86 and skewness stable at -0.37. In Figure 3, we can observe that this improved performance is also reflected in higher cumulative returns as more principal components are controlled for. For example, when currencies are sorted based on $fp_i^{PC:1,2,3,4,5}$, the cumulative return nearly doubles, highlighting the significant benefit of accounting for idiosyncratic factors in enhancing overall returns.

Figure 3: Carry Trade and Idiosyncratic Carry Trade Cumulative Returns in 100-basis point.

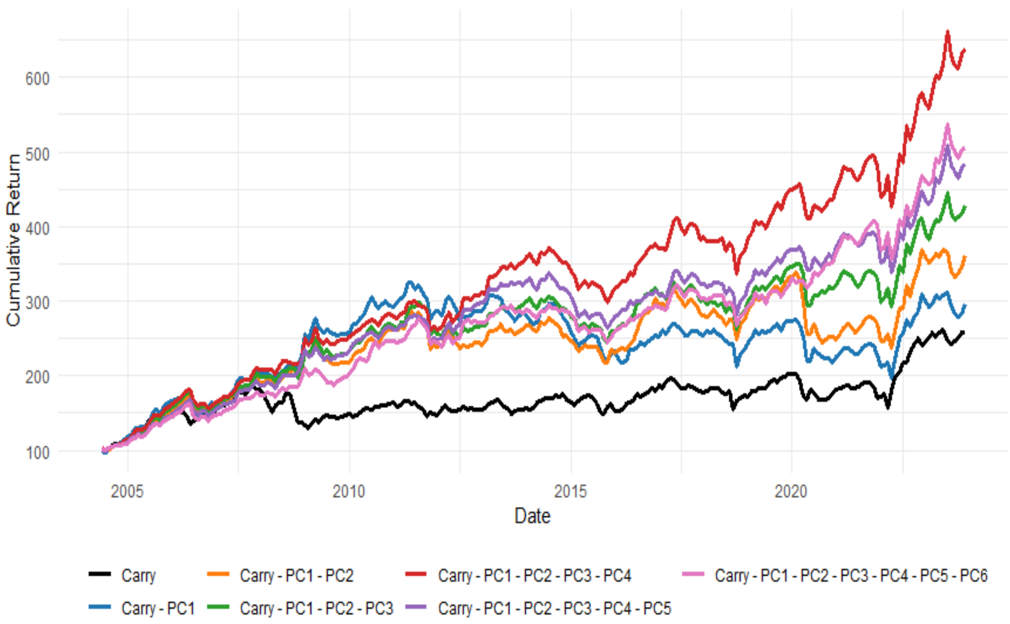

Table 5: Carry Trade and Idiosyncratic Carry Trade Performance and Skewness

Rank	Performance	Skewness
$Carry_i$	5.67	-0.56
	(0.45)	
$Carry_i - PC1$	6.39	0.06
	(0.5)	
$Carry_i - PC1 - PC2$	7.34	-0.37
	(0.59)	
$Carry_i - PC1 - PC2 - PC3$	8.15	-0.27
	(0.69)	
$Carry_i - PC1 - PC2 - PC3 - PC4$	10.13	-0.02
	(0.91)	
$Carry_i - PC1 - PC2 - PC3 - PC4 - PC5$	8.63	-0.35
	(0.82)	
$Carry_i - PC1 - PC2 - PC3 - PC4 - PC5 - PC6$	8.82	-0.37
	(0.86)	

Note: The table presents the performance (monthly average return annualized) and return skewness of the carry trade sorted on the carry/forward premium ($fp_{i,t}$) and idiosyncratic carry/forward premium ($fp_{i,t}^{PC1:6}$) controlling up to the six principal component. Annualized Sharpe ration are in parenthesis.

5.2 Robustness

As a robustness check, we also ran the traditional carry trade (rx_{t+1}^{HML}) on the principal components plus the idiosyncratic carry trade and also do the inverse to test whether the traditional method of sorting currencies outperforms our new approach. Table 6 shows that the traditional carry trade is well explained by the principal components, which is expected by the theory, but does not outperform the idiosyncratic carry strategies. In contrast, Table 7 demonstrates that the idiosyncratic carry trade generates significant alphas, particularly as more principal components are controlled for, highlighting the superior performance of our new approach.

Table 6: Traditional Carry Trade Regression o PCs and Idiosyncratic Carry Trade

	Dependent variable:						
	rx_{t+1}^{HML}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.023	0.024	0.022	0.016	0.010	0.021	0.025
	(0.040)	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)
PC1	0.303***	0.303***	0.303***	0.302***	0.302***	0.303***	0.303***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PC2	1.128***	1.128***	1.128***	1.128***	1.130***	1.128***	1.127***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
PC3	−0.351***	−0.351***	−0.351***	−0.349***	−0.347***	−0.351***	−0.351***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
$rct_t^{PC:1}$		−0.002					
		(0.011)					
$rct_t^{PC:1,2}$			0.001				
			(0.011)				
$rct_t^{PC:1,2,3}$				0.011			
				(0.012)			
$rct_t^{PC:1,2,3,4}$					0.016		
					(0.012)		
$rct_t^{PC:1,2,3,4,5}$						0.002	
						(0.013)	
$rct_t^{PC:1,2,3,4,5,6}$							−0.003
							(0.014)
Observations	235	235	235	235	235	235	235
R^2	0.973	0.973	0.973	0.973	0.973	0.973	0.973
Adjusted R^2	0.973	0.973	0.973	0.973	0.973	0.973	0.973
Residual Std. Error	0.607 (df = 231)	0.608 (df = 230)	0.608 (df = 230)	0.607 (df = 230)	0.606 (df = 230)	0.608 (df = 230)	0.608 (df = 230)
F Statistic	2,77*** (df = 3; 231)	2,07*** (df = 4; 230)	2,07*** (df = 4; 230)	2,08*** (df = 4; 230)	2,08*** (df = 4; 230)	2,07*** (df = 4; 230)	2,07*** (df = 4; 230)

Note: *p<0.1; **p<0.05; ***p<0.01. $rct_t^{PC1:6}$ denotes the idiosyncratic carry trade return controlling up to five PCs. In parenthesis are standard errors.

Table 7: Idiosyncratic Carry Trade Regression on PCs

	Dependent variable:					
	$rct_t^{PC:1}$	$rct_t^{PC:1,2}$	$rct_t^{PC:1,2,3}$	$rct_t^{PC:1,2,3,4}$	$rct_t^{PC:1,2,3,4,5}$	$rct_t^{PC:1,2,3,4,5,6}$
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.508**	0.555**	0.652***	0.811***	0.726***	0.770***
	(0.244)	(0.237)	(0.225)	(0.211)	(0.201)	(0.195)
PC1	0.078*	0.055	0.035	0.056	0.017	0.037
	(0.042)	(0.041)	(0.039)	(0.037)	(0.035)	(0.034)
PC2	0.035	0.065	−0.055	−0.101	−0.121*	−0.159**
	(0.086)	(0.084)	(0.080)	(0.075)	(0.071)	(0.069)
PC3	−0.090	−0.200	−0.173	−0.242	−0.094	0.004
	(0.183)	(0.178)	(0.169)	(0.158)	(0.151)	(0.146)
PC4	−0.560**	−0.203	−0.173	−0.042	−0.050	−0.072
	(0.263)	(0.256)	(0.243)	(0.228)	(0.217)	(0.210)
PC5	0.394	0.179	0.330	0.313	−0.027	−0.075
	(0.295)	(0.287)	(0.272)	(0.255)	(0.244)	(0.236)
PC6	0.079	0.075	0.359	0.394	0.295	0.177
	(0.309)	(0.300)	(0.285)	(0.267)	(0.255)	(0.246)
Observations	235	235	235	235	235	235
R^2	0.043	0.020	0.025	0.043	0.021	0.031
Adjusted R^2	0.017	−0.005	−0.0003	0.018	−0.005	0.005
Residual Std. Error (df = 228)	3.688	3.585	3.401	3.190	3.040	2.942
F Statistic (df = 6; 228)	1.694	0.791	0.987	1.707	0.825	1.205

Note: **p<0.1;* ***p<0.05;* ****p<0.01.* $rct_t^{PC1:6}$ *denotes the idiosyncratic carry trade return controlling up to six PCs. In parenthesis are standhard errors.*

6 Conclusion

This study has examined the importance of idiosyncratic components in currency behavior and their impact on the carry trade strategy. By isolating these idiosyncratic components, we were able to construct feasible idiosyncratic carry trade portfolios that outperform traditional carry trade strategies. Our approach involved capturing the common variation through principal component analysis (PCA) and controlling for these factors to isolate the idiosyncratic behavior of currencies.

The results indicate that by controlling for common risk factors, we significantly reduce currency volatility without adversely affecting performance. Our portfolios achieved economically and statistically significant alphas, doubling the Sharpe ratios while reducing negative skewness, thereby mitigating left tail risk.

Our principal component analysis revealed that two factors account for nearly 90% of the variation in returns across the six currency portfolios. The first principal component, a level factor, and the second principal component, a slope factor, are crucial in explaining the common variation. However, our findings suggest that while developed countries' currency carries are heavily influenced by these common factors, developing countries exhibit significant idiosyncratic influences, offering unique investment opportunities.

Additionally, our robustness checks confirmed that the traditional carry trade is well explained by the principal components but does not outperform the idiosyncratic carry strategies. The idiosyncratic carry trade generated significant alphas, particularly as more principal components were controlled for, highlighting the superior performance of our new approach.

In conclusion, this paper demonstrates that considering idiosyncratic components in currency behavior provides a more robust framework for currency trading strategies. By leveraging these insights, investors can enhance returns and reduce risks, contributing to a deeper understanding of global currency markets. This approach offers valuable guidance for both investors and policymakers navigating the complexities of international finance.

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