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Abstract

This paper examines the role of long-run and cyclical components of interest rate differentials in explaining the returns to currency carry strategies. We show that long-run differentials account for most of the profitability, while cyclical differentials play only a limited role. A simple strategy that goes long currencies above the median long-run differential and shorts those below delivers a statistically and economically significant annualized excess return of 2.48%. Relative to traditional carry, our strategy achieves a higher Sharpe ratio, lower turnover and a less negative skewness. We introduce a new tradable carry factor that explains the cross section of currency returns beyond the benchmark carry factor.

JEL Classification: G12, G15, F31

Keywords: Carry trade, currencies, long-run interest rates, trend-cycle decomposition.

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1. Introduction

The carry trade anomaly is one of the key stylized facts in international finance, reflecting deviations from uncovered interest parity. It refers to a profitable trading strategy that involves borrowing in low interest-rate currencies while lending in high interest-rate currencies being documented, at least, since the 80's (Hansen and Hodrick, 1980; Fama, 1984). The profitability of this strategy arises because the positive returns due to interest rate differentials are only partially offset by currency depreciation. The benchmark empirical representation of this strategy is the carry factor of Lustig et al. (2011), which sorts currencies on nominal short-term interest rates.

Recent work by Hassan and Mano (2019) concludes that sorting countries by interest rate differentials can be well approximated by a static ranking, implying that a country with higher interest rates tends to maintain this position relative to a lower-rate country, even though both may experience rate fluctuations over time. Therefore, understanding long-term interest rate differences across countries is crucial for explaining carry trade profits.

Building on this insight, we decompose long-term nominal interest rate differentials into long-run trends and cyclical components. Sorting on long-run differentials but implementing in short-term bonds represents a middle ground between the traditional carry factor of Lustig et al. (2011) and the static ranking interpretation of Hassan and Mano (2019). Unlike traditional carry, our decomposition isolates the long-run component of interest rate differentials that drives profitability. At the same time, it is more flexible than a purely static ranking, since it allows countries to change positions over time as trends evolve, while still filtering out short-term noise.

Our contribution is threefold. First, we show that long-run trends are the main drivers of the forward premium with cycles playing a limited role. To separate persistent from transitory components of long-term interest rate differentials, we use the Hamilton (2018) filter, a regression-based approach that avoids ad-hoc smoothing and provides a reliable separation between persistent cross-country differences in interest rates and short-run fluctuations. We further show that the estimated trends are closely related to the two main drivers of natural interest rates: productivity and demographics (Carvalho et al., 2016; Cesa-Bianchi et al., 2022; Ferreira and Shousha, 2023; Obstfeld, 2023).

Second, we show that a simple strategy which goes long currencies with above-median long-run differentials and shorts those below delivers a statistically and economically significant annualized excess return of 2.48%. Relative to both the traditional carry of Lustig et al. (2011) and the static ranking carry of Hassan and Mano (2019), our strategy generates higher average and cumulative returns, a higher Sharpe ratio before and after transaction costs, and a return distribution with less excess kurtosis and less negative skewness.

Third, we introduce a new tradable carry factor that captures systematic variation in currency excess returns beyond the carry factor of Lustig et al. (2011). We name this factor $carry^*$, since it is based on the long-run nominal interest rate typically represented by i^*. Fama–MacBeth regressions show that $carry^*$ earns a positive and significant risk premium, while the coefficients on both traditional and static carry are not significant once $carry^*$ is included. Furthermore, the explanatory power of $carry^*$ is robust to controlling for the dollar factor, with the risk premium on $carry^*$ remaining positive and significant. Taken together, these results show that $carry^*$ improves upon existing carry measures, providing incremental explanatory power in the cross section of currency returns.

Our paper contributes to the literature seeking to explain the sources of carry trade profitability. Brunnermeier et al. (2008) link carry profits to exposure to global liquidity risk, while Menkhoff et al. (2012) emphasize the role of innovations in global FX volatility. Ready et al. (2017) argue that carry returns reflect the structural dependence of commodity-importing versus commodity-exporting countries. Our contribution is complementary: we show that the profitability of carry trades is primarily associated with persistent cross-country differences in interest rates instead of cycles. To our knowledge, no previous study has systematically decomposed nominal interest rate differentials into long-run and cyclical components in order to explain currency excess returns.

More closely related to our study is Lustig et al. (2019), who examine currency portfolios formed by sorting on the excess returns of long-term bonds while also implementing the carry trade strategy in long-term bonds. They find that the profitability of currency carry trades declines with the maturity of the underlying foreign bonds. Our approach differs in at least three important aspects. First, rather than sorting on excess bond returns, we rank currencies based on long-run interest rate differentials. Second, while their analysis focuses on long-term bonds, we implement the carry trade using short-term bonds. Third, unlike Lustig et al. (2019), we explicitly disentangle the sources of carry trade profitability into trend and cycle components.

This paper also relates to the literature on the asset-pricing implications of long-run trends in nominal interest rates. Kozicki and Tinsley (2001) and Cieslak and Povala (2015) show that persistent inflation trends account for important variation in U.S. treasury yields, while Bauer and Rudebusch (2020) combine inflation and real-rate trends to construct a nominal trend component that subsumes earlier measures and provides a powerful explanation of yield dynamics. Instead of focusing on US treasury yields, we use long-run trends in nominal interest rate differentials to explore FX implications.

The paper is structured as follows. Section 2 presents our data and defines the interest rate decomposition. Section 3 presents the empirical analysis, including portfolio sorting and Fama-MacBeth regressions. Section 4 concludes.

2. Data, interest rate decomposition and portfolio formation

This section describes the currency and interest rate data used in the empirical analysis, the decomposition between long-run trends and cycles, the construction of portfolios and associated excess returns.

2.1. Data

We obtain data for spot exchange rates, 1-month forward exchange rates versus the US Dollar (USD) and 10-year yields, spanning from January 1987 to September 2023, from Reuters via Datastream. Similarly to Lustig et al. (2019), the empirical analysis focuses on G10 countries. Namely, we focus on United States (US), Australia (AU), Canada (CA), Great Britain (GB), Japan (JP), Norway (NO), New Zealand (NZ), Sweden (SE), Switzerland (CH) and Euro Area (EU). Switzerland data starts in February 1994 while Euro Area data starts in January 1999.

We also use macroeconomic and demographic fundamentals from multiple sources. Following Ferreira and Shousha (2023), we measure productivity growth as the trend component of an average of total factor productivity, labor productivity and GDP per capita, drawing on the Long-Term Productivity Database of Bergeaud et al. (2016). The working-age share and birth rate are taken from the United Nations World Population Prospects (2024 revision). The working-age share is defined as the ratio of individuals aged 20–60 to the total population, and the birth rate as the number of live births per 1,000 people per year.

2.2. Interest rate decomposition

We decompose long-term interest rates in trend and cycle using the Hamilton filter (Hamilton, 2018). The Hamilton filter defines the trend as the component of the series that is predictable from its recent past, while the cycle is simply the forecast error. Thus, the cyclical component at time t is measured as how different the actual value of the series at $t + h$ turns out to be from what the data up to t would have predicted. This construction is attractive for interest rates, where predictable, persistent movements reflect secular forces such as productivity and demographics while cyclical deviations arise from transitory shocks like monetary surprises. By directly linking the cycle to deviations from predictable dynamics, the Hamilton filter delivers a decomposition that aligns well with the economic interpretation of trend and cycle.

Estimation of the Hamilton filter is straightforward and can be carried out using ordinary least squares (OLS) regressions. In particular, we consider the following specification

$$i_{c,t} = \delta_0 + \sum_{j=1}^{12} \delta_j i_{c,t-j} + v_{c,t}. \tag{1}$$

where $i_{c,t}$ represents the nominal interest for country c based on 10-year bond yields. We use a rolling 24-month window to estimate Equation 1 every month[1]. We measure the trend component, $i^*_{c,t}$, as the fitted value and the cyclical component as the forecasting residuals $\tilde{i}_{c,t} = i_{c,t} - i^*_{c,t}$. Hamilton (2018) provides a quantitative analysis of the main drawbacks of the HP filter such as end-point bias, the creation of spurious cycles and introduction of artificial persistence. Although Hamilton (2018) focus is to improve on the HP filter out of sample, the analysis and criticisms are relevant for several other filters commonly used for trend-cycle decomposition such as Baxter and King (1999) and Christiano and Fitzgerald (2003) filters. Therefore, we use Hamilton's procedure in our empirical analysis.

2.3. Carry*, carry$^\sim$ and portfolio formation

We use the decomposition detailed in Section 2.2 to compute two signals. Our first variable captures trend differentials in nominal interest rates with respect to the US

$$carry^*_{c,t} = i^*_{c,t} - i^*_{US,t} \tag{2}$$

while the second captures cycle differentials in nominal interest rates with respect to the US

$$carry^{\sim}_{c,t} = \tilde{i}_{c,t} - \tilde{i}_{US,t} \tag{3}$$

We describe the allocation procedure for the $carry^*$ signal with the case of $carry^\sim$ being analogous. At the end of each month t, we allocate currencies to two portfolios based on their long-run trend differential with respect to the US at the end of period t. Currencies are ranked from low to high values of our sorting variable. Therefore, portfolio 1 (P1) contains currencies with the lowest values of $carry^*_c$ and portfolio 2 (P2) contains currencies with the highest values of $carry^*_c$. We compute the (log-)excess currency return, $rx_{c,t+1}$, as the

[1]While our empirical analysis is based on 24-month windows, our results are robust to different window sizes as well as to an expanding window alternative.

value of buying a foreign currency in the (log-)forward market, $f_{c,t}$, and then selling it in the (log-)spot market after one month, $s_{c,t+1}$. Since covered interest parity holds closely in the data at the monthly frequency as shown, for example, in Akram et al. (2008), our excess return corresponds to

$$rx_{c,t+1} = f_{c,t} - s_{c,t+1} = f_{c,t} - s_{c,t} - \Delta s_{c,t+1}$$

We compute the currency excess return for portfolio p, $rx_{p,t+1}$, by taking the equally weighted average of the log currency excess returns in each portfolio. We rebalance portfolios at the end of each month. In this paper, we report Sharpe ratio with and without taking transaction costs into account given the substantial turnover employed in currency strategies as exemplified in Burnside et al. (2007) and Menkhoff et al. (2012). We assume transaction costs of 15 basis points proportional to the two-way portfolio turnover. Our assumption implies an annualized mean cost of about 1.5% for the traditional carry portfolio. This can be view as conservative relative to the 0.34% cost reported by Filippou et al. (2024). Portfolio turnover[2] is computed as

$$TO_{p,t} = \sum_{c=1}^{N} \left| w_{c,t} - w_{c,t-1} \frac{1 + rx^{l}_{c,t-1}}{1 + rx^{l}_{p,t-1}} \right|,$$

where w_c is the weight of currency c in the portfolio p.

3. Empirical results

In this section we analyze the performance of *carry** to price the cross section of currency returns. First, we show that trend differentials, captured by *carry**, not cycle differentials, represented by *carry*$^\sim$, are the main drivers of forward premiums. Second, we highlight the predictive ability of *carry** using univariate portfolio sorting. Thirdly, we use Fama-MacBeth regressions to show the distinguishing pricing ability of the *carry** factor when compared to other established currency factors.

3.1. Carry**, not carry*$^\sim$*, drives the forward premium*

We decompose long-term nominal interest rates into trend and cyclical components for each country following the procedure described in Section 2.2. Based on the decomposition,

[2] We use linear returns, $rx^{l}_{c,t}$, instead of log-returns, $rx_{c,t}$, when computing portfolio turnover. For most cases, the difference between $rx^{l}_{c,t}$ and $rx_{c,t}$ is negligible

we construct the long-run trend differential, $carry^*$, and the cyclical differential, $carry^\sim$, for each country as described in Section 2.3 using Equations 2 and 3. To assess which component is the primary driver of the forward premium, we estimate the following time-series regression:

$$f_{c,t} - s_{c,t} = a + b_1 carry^*_{c,t} + b_2 carry^\sim_{c,t} + \varepsilon_{c,t} \tag{4}$$

Our findings, detailed in Panel A of Table 1, reveal that for all countries, both $carry^*$ and $carry^\sim$ significantly explain the forward premium. However, Panel B shows that almost all of the explained component of the forward premium is driven by $carry^*$, while $carry^\sim$ plays only a small role. Thus, $carry^*$, not $carry^\sim$, drives the forward premium. Therefore, we focus our analysis on the pricing properties of $carry^*$.

Table 1: The table reports time-series regressions of log-forward premium on interest rate trend and cycle for each country c represented by Equation 4 (Panel A) and the proportion of log-forward premium variance explained by each component (Panel B). We compute the proportion of variance explained by each component using the relative LMG method (Lindeman et al., 1980). While both trend and cycle differentials are significant, almost all forward premium variance is explained by $carry^*$. We report robust standard errors in parenthesis and use $*$ to denote p-values following the usual notation: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

	Dependent variable:								
	$f_{c,t} - s_{c,t}$								
	AU	CA	GB	JP	NO	NZ	SE	CH	EU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$carry^*_{c,t}$	0.128***	0.087***	0.118***	0.128***	0.203***	0.118***	0.131***	0.144***	0.108***
	(0.011)	(0.008)	(0.007)	(0.013)	(0.009)	(0.007)	(0.005)	(0.009)	(0.005)
$carry^\sim_{c,t}$	0.105***	0.108***	0.131***	0.170***	0.244***	0.126***	0.161***	0.175***	0.146***
	(0.033)	(0.017)	(0.018)	(0.036)	(0.024)	(0.019)	(0.022)	(0.015)	(0.014)
T	406	406	406	406	406	406	406	332	273
R^2	0.256	0.260	0.450	0.195	0.566	0.392	0.619	0.459	0.641
B: Proportion of variance explained by each component									
$carry^*_{c,t}$	0.96	0.83	0.92	0.88	0.89	0.91	0.95	0.75	0.88
$carry^\sim_{c,t}$	0.04	0.17	0.08	0.12	0.11	0.09	0.05	0.25	0.12

In Appendix A, we show that our decomposition is not merely a statistical device but also carries macroeconomic content: the estimated trends, i^*, are closely linked to the fundamental drivers of long-run interest rate trends, namely productivity growth and demographics.

3.2. Carry commands a positive excess return*

We use the standard methodology of univariate portfolio sorting to assess the unconditional pricing ability of the $carry^*$ signal. Table 2 shows the summary statistics of the one-month ahead excess returns of these median portfolios (columns one and two), as well as the return on the self-financing portfolio that buys currencies above the median long-run differential and shorts those below.

Table 2: The table presents summary statistics for portfolios sorted according to the *carry** measure over the sample January 1992 to September 2023. Sharpe ratios are annualized mean excess returns (Mean) over annualized standard deviations (Std. Dev.). Robust t-statistics (t-statistic) for mean excess returns are also reported.

	P1	P2	P2 - P1
Mean (%)	-1.403	1.074	2.477
Std. Dev. (%)	7.406	9.229	6.627
Sharpe Ratio	-0.189	0.116	0.374
t-statistic	-1.040	0.630	2.030

The results in Table 2 indicate a strong positive relationship between the *carry** measure and future excess returns: the annualized average return spread between the high (P2) and low (P1) portfolios is 2.48%. This spread is also statistically significant with a t-statistic of 2.03. The performance of *carry** cannot be attributed to a single portfolio leg. In fact, the short leg delivers negative average returns while the long delivers positive average returns. The spread portfolio also obtains a smaller volatility than either P1 or P2, again highlighting the usefulness of the long-short strategy. Consequently, the Sharpe ratio of the spread high minus low (P2 - P1) portfolio is higher than either of its components. We refer to the high minus low portfolio as the *carry** factor.

3.3. Carry* *improves upon traditional carry*

A natural question is whether the *carry** factor is distinct from, and improves upon, the traditional carry factor of Lustig et al. (2011) or the static rank approach of Hassan and Mano (2019). To this end, we assess its performance in univariate sorts and evaluate its risk-pricing ability through Fama–MacBeth regressions. Our results highlight that *carry** outperforms the benchmark carry factor as well as the static carry both as a trading strategy and as a priced risk factor in currency markets.

Table 3 shows the summary statistics of the one-month ahead excess returns of *carry**, traditional carry and the static carry factors. Carry sorts currencies based on their nominal interest rates. Static Carry sorts currencies on the initial five-year average forward premium, reflecting the static rank of Hassan and Mano (2019). The trading strategy based on *carry** delivers superior returns compared to both the traditional and static carry. *Carry** yields higher average excess returns and Sharpe ratio, distancing itself from traditional carry even more when accounting for transaction costs due to its lower turnover. Moreover, the return distribution of *carry** exhibits a less negative skewness, which is an important improvement given the well-documented downside risks associated with carry trades (Brunnermeier et al., 2008). Finally, *carry** exhibits a lower excess kurtosis which indicates less extreme losses. Taken together, these results highlight that isolating the long-run component of interest rate differentials not only enhances profitability but also improves the risk-return tradeoff of carry strategies.

Table 3: The table presents summary statistics for portfolios sorted according to three different measures: Carry*, Carry and Static Carry. *Carry** reflects long-run trends differential relative to the U.S. as detailed in Section 2.3. Carry is the traditional carry signal that sorts currencies based on their nominal interest rates. Static Carry is the initial five-year average forward premium reflecting the static rank of Hassan and Mano (2019). Sharpe ratios are annualized mean excess returns (Mean) over annualized standard deviations (Std. Dev.). Robust t-statistics (t-statistic) for mean excess returns are also reported. To assess the importance of transactions cost, we report average annualized turnover (Turnover) and the Sharpe ratio net of transaction cost (Sharpe Ratio (net)). Finally, we show the higher-moments of the portfolios: Skewness and Kurtosis.

	Carry*	Carry	Static Carry
Mean (%)	2.477	1.966	1.373
Std. Dev (%)	6.627	6.374	6.258
Sharpe Ratio	0.374	0.308	0.219
t-statistic	2.030	1.710	1.230
Turnover	5.416	10.092	0.622
Sharpe Ratio (net)	0.251	0.071	0.205
Skewness	-0.318	-0.706	-0.391
Kurtosis	0.746	1.962	1.247

Our results are also economically significant. Figure 1 shows the cumulative profit of a one dollar initial investment in the three strategies. Our *carry** strategy yields a cumulative return of 104.6% over the sample period, higher than 74.9% from carry and 45.3% from static rank. The strategy appears to perform well throughout the sample with the exception of the 2008 crisis and the 2010's where all carry versions struggled. Appendix B corroborates this finding by showing that the *carry** strategy delivers the highest Sharpe ratio across the three strategies when averaged over 12-month rolling windows.

To formally evaluate whether *carry** contains independent pricing information beyond established currency return factors, we employ the two-pass methodology of Fama and MacBeth (1973). Since Lustig and Verdelhan (2007), this approach has become standard in currency asset pricing directly linking returns to risk factors through the stochastic discount factor (SDF) m_t. In the first pass, we estimate β_c from time-series regressions of each asset's

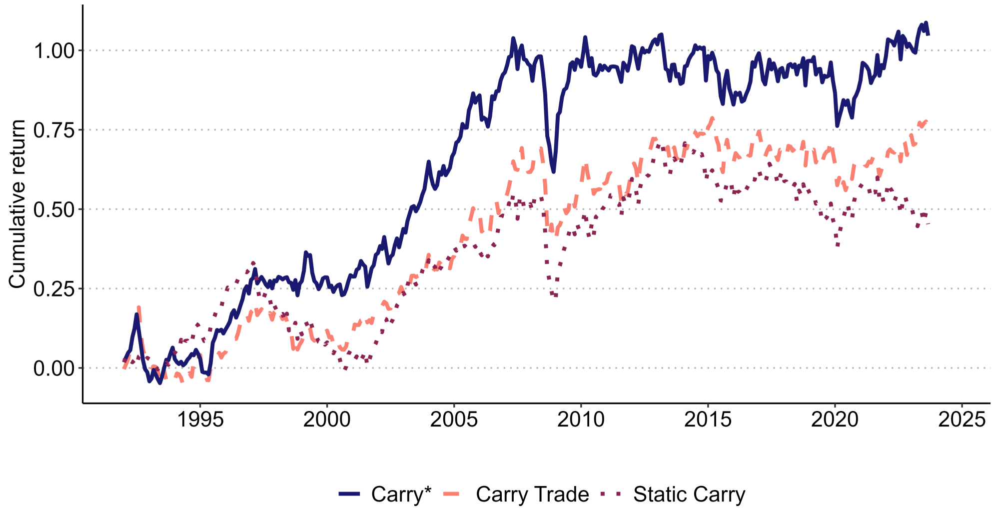

Figure 1: Cumulative excess returns of long–short, equal-weighted currency portfolios. Each month, currencies are sorted by the previous month's value of the characteristic. We go long those above the cross-sectional median and short those below, rebalancing monthly. Series are initialized at 0 (wealth = 1).

excess return on the factors f_t:

$$rx_{c,t} = \alpha_c + f_t \beta_c^\top + \epsilon_{ct}, \quad c = 1, \ldots, N, \quad t = 1, \ldots, T,$$

with α_c capturing the risk-adjusted average excess return. In the second step, expected returns are proxied by average realized returns, $\overline{rx}_c = \frac{1}{T}\sum_{t=1}^{T} rx_{c,t}$, and regressed on the estimated betas:

$$\overline{rx}_c = \hat{\beta}_c \lambda^\top + a_c, \quad c = 1, \ldots, N,$$

where a_c denotes the pricing error and $\hat{\beta}_c\lambda^\top$ the model-implied risk premium. The risk prices are estimated as

$$\hat{\lambda} = (\hat{\beta}^\top \hat{\beta})^{-1} \hat{\beta}^\top \overline{rx},$$

with $\hat{\beta}$ the $N \times K$ matrix of estimated factor loadings and $\overline{rx}$ the $N \times 1$ vector of average excess returns.

We consider four factors: *carry**, carry, static carry and the dollar factor of Lustig et al. (2011). The *carry** factor is simply the return on the High-Low portfolio as defined in Section 3.2. The carry and static carry factors are created analogously to the *carry** factor, based on the spread between the top and bottom single-sorted median portfolios using nominal interest rates and the average forward-premium of the first five-years as the sorting variable. The dollar factor is simply the excess return on the equal-weighted portfolio of all currencies.

Table 4 reports estimated annualized risk premia, along with their associated standard

Table 4: The table presents results from second stage Fama-MacBeth regressions using different specifications. *Carry**, Carry, Static carry and Dollar factors are defined in Section 3.3. The coefficients presented are the estimated risk prices $\hat{\lambda}$. Robust standard errors are shown in parenthesis. We use $*$ to denote p-values following the usual notation: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	$\overline{rx}_c$					
	(1)	(2)	(3)	(4)	(5)	(6)
Carry*	0.015**			0.018**	0.021***	0.023***
	(0.006)			(0.008)	(0.005)	(0.004)
Carry		0.012**		0.007		
		(0.006)		(0.020)		
Static Carry			0.005		0.007*	
			(0.005)		(0.004)	
Dollar						−0.002
						(0.003)
R^2	0.467	0.369	0.210	0.521	0.640	0.779

errors. The first column in Table 4 shows that the *carry** factor alone commands a positive and significant annualized risk premium, with an estimate of 1.5%. This implies that currencies with higher exposure to *carry** are compensated with higher expected returns, consistent with the portfolio-sorting evidence in Section 3.2. The second and third columns show that carry and static carry also command positive risk premia, albeit not significant for the static case.

Columns 4–6 report results from specifications that jointly include *carry** with other factors. When both *carry** and traditional carry are included, only *carry** remains significant, with an annualized risk premium estimate of 1.8%. When accounting for the static carry, the annualized risk premium of *carry** is slightly higher, at 2.1%. Finally, when we include the dollar factor, *carry** not only remains significant but also becomes even stronger, with an annualized risk premium estimate of 2.3%.

Overall, the Fama–MacBeth regressions confirm that the *carry** factor remains statistically and economically significant, earning a positive risk premium in the cross-section of currency returns, even after accounting for other versions of the carry factor or for the dollar factor. This evidence suggests that carry trade strategies based on long-run trend differentials of nominal interest rates improve upon traditional carry strategies.

4. Conclusion

This paper shows that the profitability of currency carry strategies is primarily driven by long-run interest rate differentials rather than short-term cyclical fluctuations. By applying the Hamilton (2018) filter, we isolate persistent cross-country trends in interest rates that are closely linked to structural economic forces such as productivity and demographics. Our results show that these long-run differentials account for the bulk of the forward premium and command a positive and significant risk premium in the cross-section of currency returns.

A simple strategy that goes long currencies with above-median long-run differentials and shorts those below delivers economically meaningful and statistically significant excess returns, with higher Sharpe ratios, lower turnover, and reduced downside risk compared to both traditional and static carry strategies. Furthermore, we introduce a tradable $carry^*$ factor that improves upon existing benchmarks, providing incremental explanatory power in asset-pricing tests and earning a robust positive risk premium even after controlling for other well-established currency factors.

Our findings highlight the central role of persistent cross-country interest rate differences in driving carry trade profitability. By focusing on long-run fundamentals rather than transitory fluctuations, investors can obtain a more reliable and robust source of currency returns.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to check for grammar errors and improve readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix

Appendix A. Macroeconomic determinants of *carry**

We show that the components of $carry^*$, the estimated trends i_t^*, are connected to secular forces by estimating the following annual panel regression:

$$\bar{i}^*_{c,y} = a_c + \sum_{p=1}^{P} b_c X_{c,y} + \varepsilon_{c,t} \tag{A.1}$$

$\bar{i}^*_{c,y}$ is the annual-average of the long-run trend, $i^*_{c,t}$, and $X_{c,y}$ are macroeconomic or demographic variables potentially related to $i^*_{c,t}$.

Our findings, detailed in Table A.1, show that the decomposition is not just a statistical tool to de-noise interest rate data. The estimated long-run trends are related to productivity growth, working-age share and birth rate, which are commonly emphasized in the macroeconomic literature as the main drivers of long-run rates (Carvalho et al., 2016; Cesa-Bianchi et al., 2022; Ferreira and Shousha, 2023; Obstfeld, 2023).

Table A.1: The table reports panel regressions of the annual-average of the long-run interest rate, $\bar{i}^*_{c,y}$, into productivity growth, birth rate and working-age share for each country c as shown in Equation A.1. Our estimated long-run trends are related to the secular drivers of long-run rates. We report standard errors in parenthesis and use $*$ to denote p-values following the usual notation: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	$\bar{i}^*_{c,y}$			
	(1)	(2)	(3)	(4)
Productivity growth	0.079***			0.039***
	(0.014)			(0.010)
Birth rate		1.543***		1.394***
		(0.076)		(0.089)
Working-age share			0.663***	0.248***
			(0.093)	(0.072)

The first column of Table A.1 shows a positive relation between our estimated long-run trend and productivity growth. There are at least two reasonable economic explanations for this connection as pointed, e.g., in Lunsford and West (2019) and Ferreira and Shousha (2023). First, when productivity growth slows down, it reduces investment opportunities, decreasing investment demand. Second, lower productivity growth also lowers expected income for households, increasing their precautionary savings. Thus, within a savings-and-investment framework, lower productivity growth should drive down long-run interest rates trends because of both lower investment demand and higher savings.

The second and third columns of Table A.1 capture the relation between long-run interest rate trends and demographic transition. Column 2 shows a positive relation between interest rate trends and birth rate. Lower birth rate implies lower population growth leading to a higher capital–labor ratio, which depresses the marginal product of capital being similar to a permanent slowdown in productivity growth, pushing down long-run interest rates (Carvalho et al., 2016). The third column shows a positive relation between interest rate trends and working-age share. While this is plausible, given that a decrease in the working-age can act similarly to reducing the population growth, the sign of this relation is not as clear cut. The decrease in the working-age share can imply an increase in retirees making the aggregate savings fall and pushing real interest rates up (Carvalho et al., 2016). For our sample, the first channel seems to dominate the second.

Appendix B. Additional *carry**, carry and static carry analysis

Figure B.1 supports the robustness of the *carry** performance. The *carry** strategy delivers the highest Sharpe ratio across the three strategies when averaged over 12-month rolling windows, indicating that its superior performance is not confined to the full sample but extends across a wide range of subsample periods. Averaging over rolling windows mitigates the impact of isolated episodes and shows that the performance of *carry** is a robust and persistent feature of the data.

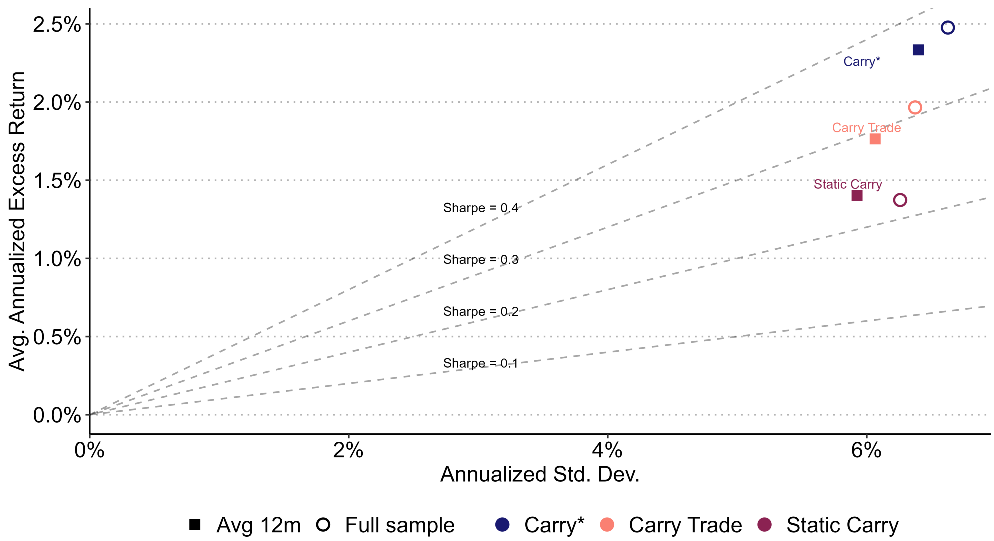

Figure B.1: Risk–return comparison: average rolling year vs. full sample. For each strategy, the filled square marks $(\bar{\mu}^{(12)}, \bar{\sigma}^{(12)})$, the average across all complete 12-month windows of annualized excess return and annualized volatility, while the hollow circle marks the full-sample pair $\big(12\,\overline{rx},\, \sqrt{12}\,\mathrm{sd}(rx)\big)$. Dashed rays from the origin are iso-Sharpe lines.