



Are carry, momentum and value still there in currencies?☆

Mark C. Hutchinson^{a,b,*}, Panagiotis E. Kyziropoulos^c, John O'Brien^a, Philip O'Reilly^{a,d},
Tripti Sharma^e

^a Cork University Business School, University College Cork, Ireland

^b Abu Dhabi University, United Arab Emirates

^c Boole Centre for Research in Informatics, University College Cork, Cork, Ireland

^d University of New South Wales, Australia

^e Queen's Management School, Queen's University Belfast, Northern Ireland, UK

ARTICLE INFO

JEL classification:

F31

G14

G19

Keywords:

Currency return predictability

Carry

Momentum

Time series momentum

Cross sectional momentum

Value

ABSTRACT

We show that carry, momentum and value predictability in currencies is associated with mispricing. Specifically, investment performance disappears subsequent to published evidence showing portfolio returns are not fully explained by risk. Replicating these studies, we show that the average out-of-sample Sharpe ratio decreases from +0.39 to −0.32. Cross sectional tests show that currencies no longer respond to interest rate and real exchange rate differentials. During this period currency excess returns do not exhibit autocorrelation. Our results are consistent with investors learning about mispricing from academic research.

1. Introduction

Extensive recent evidence concludes that currency portfolios have high investment performance based on three main classes of predictor: carry, momentum and value. There are two competing explanations in the literature for high returns to academic predictors: mispricing and rational expectations. If predictor performance is due to mispricing, published evidence showing high returns controlling for risk, will lead sophisticated investors to learn about and trade against mispricing, with returns associated with the predictor disappearing out-of-sample (Fama & French, 2020). In contrast, if the predictor is due to rational expectations, then, as predictability reflects risk, returns should persist out-of-sample even when widely publicized (Cochrane, 1999).

The main hypothesis of this paper is that carry, momentum and value currency predictability is due to mispricing. Investigating this is important for two reasons. First, there is no consensus in the literature

between risk-based and mispricing explanations for currency predictability. Our paper seeks to shed light on why predictability is observed in the first place. Second, our results are especially relevant to practitioners seeking to make investment decisions in currencies. Recent articles in the financial press have highlighted the weak performance of currency hedge funds, pursuing carry and momentum strategies.^{1,2} If prior predictability is due to mispricing, then performance is unlikely to improve.

To test whether observed currency predictability is due to mispricing, we investigate the economic and statistical out-of-sample performance of carry, momentum and value for a large sample of currencies. Our methodology is guided by robustness. We replicate the core specification of the strategies and define out-of-sample periods, following prominent studies showing the returns of each class of strategy cannot be fully explained by risk. These are carry (Kojien, Moskowitz, Pedersen, & Vrugt, 2018), both cross sectional (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012b) and time series momentum (Moskowitz, Ooi, &

☆ We are grateful to seminar participants at Queen's Management School, Queen's University Belfast for helpful comments. This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant number 18/SPP/3459. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

* Corresponding author at: O'Rahilly Building, University College Cork, College Road, Cork, T12 K8AF, Ireland.

E-mail address: m.hutchinson@ucc.ie (M.C. Hutchinson).

¹ See for example, "Years of forex market calm sends currency funds to the wall", Reuters, September 6th 2019.

² Recent academic evidence also shows relatively weak performance for carry and momentum in the period 2013 to 2019 (Ranaldo & Somogyi, 2021).

Pedersen, 2012), and value (Asness, Moskowitz, & Pedersen, 2013). Our evidence shows an absence of out-of-sample investment performance. Findings consistent with the risk adjusted returns reported in these studies being due to mispricing.

Our study is motivated by McLean and Pontiff (2016) who examine equity market predictors post academic publication. Specifically, McLean and Pontiff (2016) show that the majority of cross sectional predictability in equities can be explained by mispricing and statistical bias. They find that continued out-of-sample predictability is associated with stocks which are costly to arbitrage. Building on McLean and Pontiff (2016), we focus on three widely studied predictors in currency markets, reducing the possibility that existing evidence is due to statistical bias. Currencies feature no short selling constraints and low transaction costs, which means arbitrage can fully eliminate mispricing.

Each of the core predictors contains a substantial number of common approximation errors and noise components, so we also form 252 alternative currency portfolio variations, where the portfolios are formed from a range of parameters for each strategy.³ Results from a joint cross sectional test of performance, minimizing the bias from each method, confirms the disappearance of returns out-of-sample.

We further investigate the effect of publication, by studying the mechanics underlying the predictors. Value relies on long term changes in real exchange rates of currencies, information easily available to investors. If it has predictive power due to mispricing, once investors become aware of the mispricing, they will bid up the value of the undervalued currency relative to the overvalued currency, and we expect the measure to lose predictive power. Fama and MacBeth (1973) regressions reveal that changes in real exchange rates lose all forecasting power in the out-of-sample period. These results support the hypothesis that value returns reported in the literature are due to mispricing.

Given the low level of interest rates coincident with our out-of-sample results, we consider the alternative hypothesis that low carry returns are simply due to the changed macroeconomic environment. To test this, we compare the available carry which an investor could have earned, with the returns achieved by the carry portfolio. The available carry remains positive, while the actual returns to the carry portfolio are on average negative. Further, cross-sectional regressions show a discontinuity in the relationship between carry and future returns. The failure of carry is congruous with mispricing, but is not due to the low level of interest rates.

If the performance of momentum based strategies of buying past winners and selling past losers relies on mispricing, then investors responding to evidence reported in academic studies will lead to the disappearance of return serial correlation. In particular, using time series tests we show economically and statistically significant differences in serial correlation over time. There is no serial correlation during the recent period, consistent with investors arbitraging away momentum profits.

Our study contributes to the growing literature seeking to provide risk or mispricing explanations for currency predictability. Rational expectations explanations of carry include macroeconomic risk

(Colacito, Croce, Gavazzoni, & Ready, 2018; Hassan, 2013; Hoffmann & Studer-Suter, 2017; Lustig & Verdelhan, 2007; Zviadadze, 2017), crash risk (Brunnermeier, Nagel, & Pedersen, 2008), volatility risk (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012a), trade network centrality (Richmond, 2019); time varying risk (Lustig, Roussanov, & Verdelhan, 2014) and Peso problems (Burnside, Eichenbaum, Kleshchelski, & Rebelo, 2011). In contrast, Koijen et al. (2018) conclude that risk cannot fully explain carry returns. Currency momentum studies have documented weak evidence for risk based explanations such as volatility, crash risk, country risk and time varying risk (Menkhoff et al., 2012b) while Asness et al. (2013) and Menkhoff, Sarno, Schmeling, and Schrimpf (2017) show macroeconomic risk and liquidity risk only explain a small fraction of value returns. Causes of momentum mispricing include central bank intervention, shifts in monetary policy (Kouwenberg, Markiewicz, Verhoeke, & Zinkels, 2017; Okunev & White, 2003), and hedging (Moskowitz et al., 2012). Value returns are also associated with mispricing, due to noise trading and central bank intervention, with the activity of these market participants pushing currencies away from fundamental values (Okunev & White, 2003).

We also contribute to the replication and out-of-sample literature showing academic anomalies decline or disappear out-of-sample. Studies have documented diminishing equity return predictability for dividend and earnings yields, dividend payout ratios, net issuing ratios, book-to-market ratios, firm size, firm value, interest rates and macroeconomic factors (see for example, Alquist, Israel, & Moskowitz, 2018; Fama & French, 2020; Schwert, 2003; Welch & Goyal, 2008). Similarly, Huang, Li, Wang, and Zhou (2020) replicate Moskowitz et al. (2012), finding a lack of statistical evidence for time series momentum.

We extend this line of research and show that currency predictability, associated with mispricing, disappears once studies are published showing returns are not explained by risk. Our findings are also related to research investigating whether short term increases in investor attention are associated with reduced carry trade profitability (Goddard, Kita, & Wang, 2015). In contrast, our focus is not on proxies for investor attention. Rather, our results show that academic research is an important source of information about mispricing for sophisticated investors.

The remainder of this paper proceeds as follows. Section 2 details our data. The different currency predictor formulations are described in section 3. Section 4 describes the out-of-sample portfolio analysis results. Section 5 provides cross sectional and time series tests of the determinants of carry, momentum and value profits. We provide robustness results in section 6, before concluding in Section 7.

2. Data

This study initially focuses on the ten most liquid currencies against the US Dollar, the G11 currencies, before examining a broader sample of twenty-four additional peripheral currencies.⁴ The G11 currencies are highly liquid and are widely studied in the literature (see, for example, Bakshi & Panayotov, 2013; Barroso & Santa-Clara, 2015). Spot exchange rates are from MSCI and all other data is from Refinitiv unless otherwise specified. The ICE Benchmark Administration (IBA) one-month LIBOR, or its equivalent, is used as the risk-free rate.

We use OECD Main Economic Indicators Consumer Price Indices to calculate real exchange rates. The US Benchmark 10-Year Government Total Return Index and ICE Bank of America 10–15 Year US Corporate Total Return Index (from the Federal Reserve Economic Data website) are used as proxies for long-term government bond and corporate bond returns respectively. The Fama and French (1993) market, size and value equity factors are from Kenneth French's data library.

We derive daily and monthly excess return series for each currency

³ Related research has focused on dimension reduction where there are a large number of potential indicator parametrisations, such as momentum (Moskowitz et al., 2012). Poncela, Rodríguez, Sánchez-Mangas, and Senra (2011) show that Partial Least Squares (PLS) provides a better forecast than simple averaging across indicators, while Kim and Ko (2020) show that PLS can improve forecasting accuracy by identifying the relevant factors rather than giving weight to all factors in a model. In multivariate models, with a large range of factors, PLS has been shown to improve on Principal Component Analysis (PCA), where there is weak factor structure such as macro-economic models (Groen & Kapetanios, 2016). Machine learning such as SVM or LASSO (itself based on PLS) allows further opportunity to extract value from factors in a multi-variate framework, allowing for extracting non-linear relationships to improve forecasts (for example Paiva, Cardoso, Hanaoka, & Duarte, 2019) and Kita (2021)).

⁴ DEM and the corresponding German risk-free rate and economic variables are used in place of the EUR prior to its inception in 1999.

Table 1
Descriptive statistics.

Country	Start date	Excess return		Interest rate	Inflation rate
		Mean	Std. dev.		
Panel A: G11 currencies					
Australia	Feb-76	1.50	11.20	7.52	4.87
Canada	Feb-75	0.21	7.01	5.79	3.73
Denmark	Feb-75	0.41	10.55	5.35	3.79
Euro Area (Germany)	Feb-75	-0.01	10.67	3.83	2.31
Japan	Sep-78	-0.46	11.34	2.39	1.71
New Zealand	Feb-75	2.26	12.04	8.48	5.55
Norway	Feb-75	-0.01	10.70	6.07	4.24
Sweden	Feb-75	-0.73	10.83	5.73	4.11
Switzerland	Feb-75	0.30	11.75	2.45	1.78
UK	Feb-75	0.63	10.17	6.69	4.90
USA				5.07	3.73
Panel B: Peripheral currencies					
Brazil	Dec-08	0.74	16.03	7.85	5.49
Bulgaria	Dec-08	-0.70	9.90	0.86	3.51
Croatia	Dec-08	-0.68	9.98	1.45	1.90
Czech Republic	Dec-08	-1.15	11.88	0.66	2.08
Egypt	Dec-08	3.14	17.28	11.58	11.60
Hong Kong	Dec-08	-0.15	0.51	0.56	2.88
Hungary	Dec-08	-0.39	14.42	3.22	3.31
Iceland	Dec-08	5.51	12.19	5.65	4.65
India	Dec-08	3.20	8.48	7.35	7.30
Indonesia	Dec-08	4.13	9.71	6.35	6.03
Israel	Dec-08	1.65	7.53	0.93	1.46
Kuwait	Dec-08	-0.51	2.37	1.24	3.59
Malaysia	Dec-08	1.11	8.03	3.02	2.39
Mexico	Dec-08	0.23	12.28	5.45	4.12
Philippines	Dec-08	1.66	5.41	2.45	3.82
Poland	Dec-08	-0.02	13.64	2.62	1.93
Russia	Dec-08	0.06	17.35	8.15	8.19
South Africa	Dec-08	1.45	15.91	6.33	5.31
South Korea	Dec-08	3.76	11.46	2.13	2.16
Saudi Arabia	Dec-08	0.38	0.19	1.09	2.94
Singapore	Dec-08	0.83	6.11	0.73	1.81
Taiwan	Dec-08	1.07	4.88	0.65	1.19
Thailand	Dec-08	2.24	5.71	1.94	2.07
Ukraine	May-10	2.36	18.11	14.60	12.82

Panel A (Panel B) reports annualised mean and standard deviation of excess returns against the US dollar, average interest and inflation rates along with the series start date for G11 (Peripheral) currencies.

pair by combining the spot exchange rate return and the risk free interest rates of the two countries. This is equivalent to the return from holding a long position in a futures or forward contract for the period. Unless otherwise stated, we refer to currency excess returns as returns in the remainder of the paper.

Table 1 reports the mean and volatility (standard deviation) of returns (against the US dollar), interest rates and average inflation rates of the G11 currencies (Panel A) and Peripheral currencies (Panel B). The full sample of portfolio returns for the G11 analyses runs from 1st January 1980 to 30th April 2020, so we include data, where available, from five years prior to construct initial trading signals.

While the variation in mean returns and standard deviation across G11 currencies is low, significant variation occurs in interest rates and inflation rates. The mean return ranges from 2.26% for New Zealand to -0.73% for Sweden. New Zealand also exhibits the highest currency standard deviation of 12.04%, whereas for Canada it is 7.01%. The highest yielding is New Zealand (8.48%), whereas Switzerland has an average rate of 2.45%. Of the countries, Japan has the lowest inflation rate at 1.71% and New Zealand the highest at 5.55%.

For peripheral currencies the variation in returns, interest rates and inflation rates is larger. Returns vary from -0.70% (Bulgaria) to 5.51% for Iceland. The political instability in Ukraine is reflected in its high standard deviation (14.60%). Interest rates and inflation rates in both Egypt and Ukraine are very high at over 10% for both measures in each country, whereas these rates are relatively modest in the remaining peripheral countries.

3. Currency return predictors

In the following subsections, we briefly provide definitions of each return predictor.

3.1. Carry (CAR)

The primary measure of carry, $CAR_{i,t}$, is based on the current yield defined in Kojien et al., (2018). The current carry for currency i against the US dollar is:

$$CAR_{i,t} = \frac{r_t^i - r_t^f}{(1 + r_t^f)} \quad (1)$$

where r_t^f is the risk free rate for the USD and r_t^i is the risk free rate of currency i . We also consider an alternative measure of carry, $\bar{CAR}_{i,t}$, defined as the twelve-month moving average of current carry (Kojien et al., 2018). For both measures the raw value is converted to a trading signal by ranking the raw values of all currencies at time t .

3.2. Cross sectional momentum (MOM)

We specify the Menkhoff et al. (2012b) definition of the cross sectional momentum signal, derived from the cumulative excess return of the currency over the formation period.

$$CR_{i,t,k} = \left(\sum_{l=1}^k \ln(1 + r_{i,t-l,k}) \right) \quad (2)$$

Where $CR_{i,t,k}$ is the cumulative excess return of currency i , at time t , over lag k time periods. The raw value is converted to a trading signal by ranking all currencies at time t .

3.3. Time series momentum (TSM)

We follow Moskowitz et al. (2012) in defining the time series momentum signal,

$$TSM_{i,t,k} = \text{sign}(CR_{i,t,k}) \quad (3)$$

where the signal, $TSM_{i,t,k}$, is the sign of the formation period cumulative excess return, $CR_{i,t,k}$.

3.4. Value (VAL)

We derive the raw value ranking of each currency, following Asness et al. (2013), as the negative of the five-year change in the real exchange rate less the five-year change in the nominal exchange rate (measured in log terms). This is equivalent to the five-year change in purchasing power parity. Following Asness et al. (2013) we specify average values of lagged returns to smooth short term deviations. $VAL_{i,t}$, the value of currency i at time t , is

Table 2
Performance of core strategies.

	Pre-transaction costs				Net of transaction costs			
	Carry	Cross sectional momentum	Time series momentum	Value	Carry	Cross sectional momentum	Time series momentum	Value
Panel A: Full sample								
Mean	3.67*** (2.72)	1.13 (1.18)	3.01** (2.52)	3.34*** (2.98)	3.38** (2.51)	0.07 (0.08)	2.82** (2.35)	2.99*** (2.70)
Volatility	8.12	6.20	7.04	7.22	8.13	6.16	7.04	7.21
Sharpe ratio	0.45*** (2.81)	0.18 (1.15)	0.43*** (2.67)	0.46*** (2.88)	0.42*** (2.59)	0.01 (0.07)	0.40** (2.50)	0.41*** (2.59)
Alpha	2.41* (1.87)	1.36 (1.37)	3.88*** (3.24)	3.62*** (2.87)	2.12* (1.65)	0.30 (0.31)	3.68*** (3.06)	3.28*** (2.61)
CER	2.99	0.74	2.50	2.80	2.70	−0.31	2.31	2.46
R ²	15.34	1.11	2.52	0.99	15.32	1.10	2.51	0.98
Panel B: In-sample								
Mean	4.03** (2.38)	2.75** (2.44)	3.37** (2.11)	3.78*** (2.81)	3.75** (2.21)	1.48 (1.31)	3.17** (1.97)	3.37** (2.52)
Volatility	8.50	6.46	7.41	7.57	8.51	6.43	7.42	7.56
Sharpe ratio	0.47** (2.49)	0.43** (2.30)	0.45** (2.23)	0.50*** (2.75)	0.44** (2.32)	0.23 (1.25)	0.43** (2.10)	0.45** (2.46)
Alpha	2.31 (1.50)	2.70** (2.21)	4.35*** (2.83)	4.27*** (2.82)	2.03 (1.32)	1.42 (1.17)	4.14*** (2.68)	3.86** (2.57)
CER	3.29	2.33	2.80	3.19	3.00	1.06	2.60	2.79
R ²	15.10	0.08	3.58	1.46	15.08	0.11	3.57	1.44
Panel C: Out-of-sample								
Mean	−0.66 (−0.32)	−3.51** (−2.54)	−0.99 (−0.53)	1.74 (0.97)	−0.70 (−0.33)	−3.95*** (−2.84)	−1.10 (−0.59)	1.61 (0.90)
Volatility	6.86	5.15	6.14	5.77	6.85	5.15	6.14	5.77
Sharpe ratio	−0.10 (−0.27)	−0.68** (−2.20)	−0.16 (−0.52)	0.30 (0.88)	−0.10 (−0.28)	−0.77** (−2.47)	−0.18 (−0.58)	0.28 (0.82)
Alpha	−3.41 (−1.45)	−2.27 (−1.41)	−1.50 (−0.68)	2.99 (1.45)	−3.45 (−1.46)	−2.71* (−1.67)	−1.60 (−0.72)	2.86 (1.39)
CER	−1.13	−3.77	−1.36	1.40	−1.17	−4.20	−1.47	1.28
R ²	42.71	1.39	−1.26	5.72	42.71	1.32	−1.27	5.71

This table reports the performance, before and after transaction costs, of the core strategy portfolios. Performance is reported for three sample periods – full (Panel A), in-sample (Panel B) and out-of-sample (Panel C). The full sample period is January 1980 to April 2020. In-sample and out-of-sample periods vary by strategy. Value and Carry portfolios are constructed using rank-based weights. Cross-sectional momentum has a three-month formation period and one-month holding period. Time series momentum is formed with twelve-month formation and one-month holding period. Mean and Volatility are the annualised portfolio average excess returns and standard deviation. The Sharpe ratio is Mean/Volatility. Alpha is the annualised intercept of the multivariate Fama and French (1993) five-factor model and R² is the adjusted r-square of the model. CER is annualised certainty equivalent return, estimated assuming the risk-aversion coefficient as 2 (Ferreira & Santa-Clara, 2011). The t-statistics (in parentheses) for Mean and Alpha are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors. The t-statistics for the Sharpe ratio are calculated following Lo (2002). The symbols ***, **, and * denote statistical significance of parameter estimates at 1%, 5% and 10% level of significance, respectively.

$$VAL_{i,t} = \ln\left(\frac{CPI_{US,t}}{CPI_{i,t}}\right) - \ln\left(\frac{\bar{S}_{i,t}}{\bar{S}_{i,t-60}}\right) \quad (4)$$

where $\bar{S}_{i,t-60}$ is the average spot exchange rate over the period between $(t - 54)$ and $(t - 66)$, and $\bar{CPI}_{i,t-60}$ and $\bar{CPI}_{US,t-60}$, respectively are the average CPI of country i and the US over the same period.⁵ The raw value is converted to a trading signal by ranking currencies at time t .

4. Portfolio analyses

This section describes the methodologies used to calculate the portfolio returns and measure their out-of-sample investment performance.

4.1. Portfolio specification

The strategies are divided into univariate and relative value for portfolio construction. For the univariate TSM portfolio $w_{i,t}$ the weight

of currency i at time t is:

$$w_{i,t} = \frac{1}{N_t} s_{i,t-1} \quad (5)$$

where $s_{i,t-1}$ is the signal for currency i at time $t - 1$ and N_t is the number of active currencies at t . This weighting results in an unlevered portfolio.

In the case of relative value strategies, the portfolios hold equal sized long and short positions, with no exposure to the base currency (USD). Signals are derived by ranking the raw values and setting the trade signal to 1 (Long) for the top half and -1 (Short) for the bottom half.⁶

For an equal weighted portfolio, the weight of each currency is:

$$w_{i,t} = \frac{2}{N_t} s_{i,t-1} \quad (6)$$

We also consider rank weighting for CAR and VAL (Asness et al., 2013; Koijen et al., 2018) where weights are defined as:

⁶ In the case of an odd number of active currencies, we exclude the mid-ranking currency.

⁵ We lag CPI by six months to control for delayed publication.

Table 3

Out-of-sample versus in-sample multiple strategy performance.

	Average return		Sharpe ratio		Alpha		CER	N
	Mean	Tstat	Mean	Tstat	Mean	Tstat	Mean	
Panel A: All strategies								
In-sample	2.03***	(30.61)	0.39***	(43.42)	2.09***	(25.99)	1.74	252
Out-of-sample	−1.13***	(−17.78)	−0.32***	(−19.29)	−1.00***	(−15.30)	−1.30	252
Out-of-sample – In-sample	−3.10***	(−34.33)	−0.71***	(−37.85)	−3.04***	(−29.78)	−3.00	504
Panel B: Cross sectional momentum								
In-sample	1.55***	(20.21)	0.32***	(26.80)	1.41***	(18.07)	1.30	123
Out-of-sample	−1.40***	(−15.87)	−0.42***	(−17.83)	−1.17***	(−14.94)	−1.54	123
Out-of-sample – In-sample	−2.92***	(−25.20)	−0.74***	(−28.10)	−2.55***	(−23.31)	−2.81	246
Panel C: Time series momentum								
In-sample	2.45***	(26.26)	0.46***	(42.46)	2.76***	(23.87)	2.15	123
Out-of-sample	−0.91***	(−10.46)	−0.23***	(−11.54)	−0.80***	(−8.62)	−1.09	123
Out-of-sample – In-sample	−3.29***	(−26.29)	−0.69***	(−30.49)	−3.48***	(−23.93)	−3.18	246

This table presents results comparing out-of-sample and in-sample performance for all parametrisations of the strategy classes. Reported are the cross sectional portfolio average return (Average Returns), Sharpe ratios (Sharpe Ratios), risk-adjusted alpha (Alphas) and certainty equivalent returns (CER) across all strategies (Panel A) and each strategy (Panels B–C), gross of transaction costs. *Out-of-sample – In-sample* is the mean and the *t*-statistic for a difference of means test, assuming the distributions have equal variance, but unknown population mean. For CER, *Out-of-sample – In-sample* is the difference of mean CER over out-of-sample and in-sample periods. *N* is the number of observations; *Mean* refers to annualised mean and *Tstat* (in parentheses) is *t*-statistics of individual sample two-tailed tests (rows 1 and 2 in each panel) and a difference in means test (row 3). The symbols ***, **, and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

$$w_{i,t} = c_t \left(s_{i,t-1}^{rank} - \frac{N_t + 1}{2} \right) \quad (7)$$

where $s_{i,t-1}^{rank}$ is the rank of the raw signal across all available currencies at time $t - 1$. The function c_t scales the portfolio weight so the sum of both long and short sides equals the capital invested.

The gross return of a portfolio is given by:

$$r_{s,t} = \sum_{i=1}^{N_t} w_{i,t} \cdot r_{i,t} \quad (8)$$

where $r_{s,t}$ is the return of strategy portfolio s at time t .

Transaction costs are defined by the time dependent transaction cost function of Hurst, Ooi, and Pedersen (2017), measuring cost as a proportion of one-way transaction value.

$$r_{s,t}^{net} = r_{s,t} - tc_t \sum_{i=1}^{N_t} |w_{i,t} - w_{i,t-1}| \quad (9)$$

$r_{s,t}^{net}$ is the net return of strategy portfolio s at time t . tc_t , the transaction cost rate at time t , is a declining function of time. The transaction cost rates are as 0.18% until 1992, 0.06% from 1993 to 2002 and 0.03% thereafter (Hurst et al., 2017).

4.2. Assessing portfolio performance

We use four measures to assess the performance of the trading strategies: mean return, risk-adjusted return, Sharpe ratio and certainty equivalent return. Risk-adjusted returns are the annualised intercepts of the Fama and French (1993) equity and bond five-factor model.

$$R_{s,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 TERM_t + \beta_5 DEF_t + \varepsilon_t \quad (10)$$

$R_{s,t}$ is the return to strategy portfolio s at time t . $RMRF_t$, SMB_t and HML_t are the market, size and value factors for the US stock market respectively. $TERM_t$ is the term factor, the difference in total return between long and short term government bonds, DEF_t is the credit default factor, the difference in total return between corporate and long-term government bonds.

The certainty equivalent return of portfolio s , CER_s is the return for which an investor of a certain risk aversion would be willing to invest into the risky portfolio.

$$CER_s = \bar{R}_s - \frac{\gamma}{2} \sigma_s^2 \quad (11)$$

$\bar{R}_s$ is the sample mean portfolio return for strategy s , σ_s^2 is the sample variance of portfolio s and γ represents the risk-aversion coefficient. We assume $\gamma = 2$, following Ferreira and Santa-Clara (2011).

To analyse out-of-sample economic and statistical significance, we construct a core version of each strategy, before considering 252 portfolios made up of alternative strategy specifications. We define the core strategy and sub-divide our sample period following Kojien et al. (2018) for CAR, Menkhoff et al. (2012b) and Moskowitz et al. (2012) for MOM and TSM, respectively and Asness et al. (2013) for VAL.

The core MOM portfolio is equal weighted with a three-month formation period and one-month holding period. The core portfolios are constructed using rank-based weighting for CAR and VAL. For TSM we specify a twelve-month lookback and one-month holding period.

For CAR the in-sample period is November 1983 to September 2012, for MOM and TSM it is January 1980 to January 2010 and January 1985 to December 2009, respectively, while for VAL the in-sample period runs from January 1980 to July 2011. For all strategy classes the out-of-sample period runs from the end of the in-sample period to April 2020.⁷

4.3. Core strategy performance

Performance statistics, gross and net of transaction costs, are presented in Table 2.

Panel A reports full sample performance. All strategies generate positive returns. The mean return ranges between 1.13% to 3.67% per annum, with CAR being the most profitable, consistent with the literature. The Sharpe ratio of CAR, TSM and VAL are 0.45, 0.43 and 0.46, respectively, whereas MOM is 0.18. Risk-adjusted alphas and CER exhibit similar patterns. In-sample performance across strategy classes in Table 2, Panel B is consistent with the full sample results and prior literature.

The results are very different in the out-of-sample analyses (Table 2,

⁷ To avoid accusations that our results are driven by reverse p-hacking (Harvey, 2017) where the sub-sample cut off is identified to capture the period when the strategy no longer generates positive returns, later in the paper we repeat our analysis using alternative sub-sample cut-offs, and also formally test for a structural break in predictability.

Panel C) where performance disappears across all strategies. Mean returns range from −3.51% to 1.74% per annum, with VAL being the most profitable. The Sharpe ratios range from −0.68 for MOM to 0.30 for VAL, while the CERs are predominantly negative.

Accounting for transaction costs reduces profitability, but most strategies survive transaction costs in the full sample and in-sample periods (Panels A and B). The exception is MOM, which has positive, but not statistically significant returns, in the full and in-sample periods. Out-of-sample (Panel C) none of the core strategy portfolios has statistically significant returns and three (CAR, MOM and TSM) exhibit negative returns, after controlling for transaction costs.

4.4. Testing multiple strategy performance

In this section, we examine the robustness of our findings to a range of parameterizations of each of the strategies. We estimate cross sectional tests across the parametrisations, reducing noise from any one method of constructing the predictor.

We include four specifications of CAR. These are both equal weighted and rank weighted portfolios, formed using either current carry or the average carry over the preceding twelve months. There are two portfolios formed for VAL, using equal weighted and rank weighting schemes.

Momentum portfolios are generated over multiple formation and holding periods and at monthly, weekly and daily trading frequencies. For both cross sectional and time series momentum, each combination of formation and holding period (k, h) produces a distinct portfolio. For monthly trading $h, k \in \{1, 3, 6, 9, 12\}$, generating twenty-five TSM and MOM monthly portfolios (Menkhoff et al., 2012b; Moskowitz et al., 2012). For holding periods greater than one period we form overlapping portfolios.

Following Baltas and Kosowski (2013) we set $h, k \in \{1, 2, 3, 4, 6, 8, 12\}$ for weekly and $h, k \in \{1, 3, 5, 10, 15, 30, 60\}$ for daily trading. This generates forty-nine further portfolios for MOM and TSM at each frequency.

Comparing the Sharpe ratios, net of transaction costs, for the in-sample and out-of-sample periods for MOM and TSM monthly portfolios findings are consistent with our previous results. Of the fifty comparisons, only three perform (marginally) better in the out-of-sample period. Strikingly, thirty-five move from a positive to negative Sharpe ratio in the out-of-sample period.

Next, in Table 3 we report results from testing the difference between out-of-sample and in-sample performance. For each of our performance measures, we report results for cross-sectional tests of statistical significance and a cross sectional difference in means test, comparing in-sample and out-of-sample values.

Panel A reports results for all 252 strategy portfolio variations. In-sample, portfolios generate statistically significant returns of 2.03% per annum, on average, whereas they exhibit a statistically significant average return in the out-of-sample period of −1.13% per annum. Similarly, controlling for risk, the average Sharpe ratio is 0.39 and the abnormal return is 2.09% in the in-sample period. The risk adjusted performance measures decline out-of-sample to become statistically significantly negative (−0.32 Sharpe ratio and −1.00% alpha). Finally, all CERs decline in the out-of-sample period, with differences in CER being uniformly negative. The difference between out-of-sample and in-sample results confirms that the investment performance of trading strategies, overall, has disappeared. The results in Panels B and C for MOM and TSM are consistent. In unreported tests, we repeat this analysis, net of transaction costs, confirming the deterioration in performance.

5. Examining the determinants of carry, momentum and value strategy profits

In this section, we examine the underlying mechanics of strategy

Table 4
Carry Fama-MacBeth regressions.

	Lag length				
Intercept	1-month	2-month	3-month	6-month	R ²
Panel A: In-sample					
0.10 (0.79)	1.13*** (3.31)				0.13
0.10 (0.83)		1.06*** (3.18)			0.13
0.10 (0.77)			0.98*** (2.99)		0.13
0.10 (0.72)				0.90*** (2.76)	0.12
Panel B: Out-of-sample					
−0.34* (−1.73)	0.11 (0.11)				0.15
−0.37* (−1.81)		−0.07 (−0.07)			0.15
−0.36* (−1.72)			0.05 (0.05)		0.16
−0.32 (−1.47)				−0.34 (−0.34)	0.15

This table shows the results for monthly cross-sectional regressions over the in-sample (Panel A) and out-of-sample (Panel B) periods, respectively. In each month, the dependent variable is individual currencies' excess returns and the explanatory variable is individual currencies' carry in the previous l -month ($CAR_{i,t-l}$). The mean of the time series of coefficients estimated with lag lengths $l = 1, 2, 3$ and 6 months, are presented under Lag length. Intercept represents the mean of monthly time series of constants and are expressed in percent. T-statistics based on Newey and West (1987) standard errors are presented in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

profitability, showing with empirical analyses why investment returns disappear out-of-sample. We group CAR and VAL as their signals are based on relative changes in interest rates and real exchange rates, respectively, whereas MOM and TSM rely on past currency returns.

5.1. Are carry and value still related to future returns?

To examine the impact of the information contained in CAR and VAL conditional variables on future returns, we estimate the relationship between return and lagged predictor variables using Fama and MacBeth (1973) regressions (Kojien et al., 2018; Menkhoff et al., 2017).

$$r_{i,t} = \alpha_t + \beta_l X_{i,t-l} + \varepsilon_t \quad (12)$$

where $r_{i,t}$ is the cross section of currency returns at time t ($i = 1, 2, \dots, N_t$). $X_{i,t-l}$ is the lagged predictor variable corresponding to either carry ($CAR_{i,t-l}$) or value ($VAL_{i,t-l}$) for monthly $l = 1, 2, 3, 6$. The regression is estimated each month, generating time series estimates of α_t and β_t for in-sample and out-of-sample periods.

Table 4 presents the mean intercept and beta coefficients along with Newey and West (1987) t -statistics for carry. In Panel A, the in-sample period, the beta coefficients at each lag length are positively and statistically significant, with t -statistics ranging from 2.76 to 3.31, consistent with Kojien et al. (2018). A predictive coefficient close to one as seen across Panel A implies that the price of high interest rate currency appreciates relative to the low interest rate currency and the investor earns the interest rate differential, on average.

However, we find no statistical evidence for carry predictability in the out-of-sample period. Panel B of Table 4 shows that beta coefficients on the predictor variables are not statistically significant from zero. The price changes of the high and low interest rate currencies are no longer related to interest rate differentials.

To rule out the low level of interest rates post 2008 as the main cause of the disappearance of carry returns, we examine the relationship between exchange rate movements and interest rate differentials.

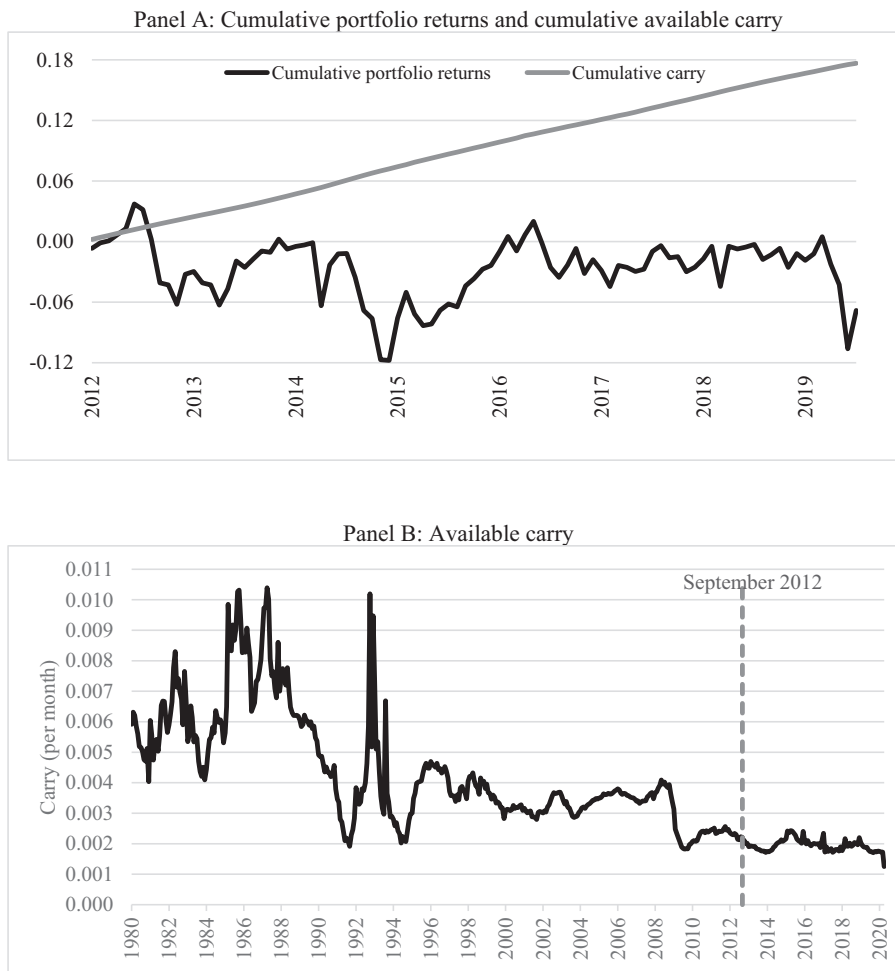


Fig. 1. Portfolio returns and available carry.

Notes: Available carry is the average carry of the high carry currencies minus the average carry among the low carry currencies, in the portfolio. Panel A shows the cumulative gross portfolio returns and the cumulative available carry for the out-of-sample period (October 2012 to April 2020). Panel B presents the available carry for the full sample period beginning January 1980 and ending April 2020.

The available carry to be earned at time t , $ACAR_{portfolio,t}$ is defined, following [Kojen et al. \(2018\)](#), as the weighted average carry of the high carry currencies minus the weighted average carry among the low carry currencies.

$$ACAR_{portfolio,t} = \sum_{w_{i,t} > 0} w_{i,t} CAR_{i,t} - \sum_{w_{i,t} < 0} abs|w_{i,t}| CAR_{i,t} \quad (13)$$

Where $w_{i,t}$ are the weights used to construct the CAR core strategy portfolio, and $CAR_{i,t}$ is the carry of currency i at time t . We plot cumulative portfolio gross returns and the cumulative available carry for the out-of-sample period in Panel A of [Fig. 1](#). As cumulative portfolio returns are below cumulative carry, portfolio returns have been affected by unfavourable spot exchange rate movements, rather than low interest rates.

To understand the evolution of available carry through time, Panel B of [Fig. 1](#) plots the series for the full sample period beginning January 1980. During the in-sample period overall interest rate differentials are high, and the available carry averages 0.42% per month. However, available carry declines significantly after the global financial crisis in 2008. In the out-of-sample period, the monthly average value of $ACAR_{portfolio,t}$ reduces, but is still positive 0.19%. These findings indicate that while the overall low interest rate environment in G11 currencies contributed to the negligible performance, changes in exchange rate behaviour are responsible for the elimination of carry returns, in the out-of-sample period.

We repeat Fama and MacBeth regressions for value, reporting results in [Table 5](#). In Panel A, the currency value predictor is positively related to the cross-section of future returns during the in-sample period. For a

one-month lag, we find a statistically significant slope coefficient of 0.01 with t-statistic of 2.71. The relative value of currencies, based on changes in five-year purchasing power parity, are strong predictors of returns, with lags of up to six months exhibiting a positive relationship with current returns in the in-sample period.

However, in Panel B, out-of-sample slope coefficients are statistically insignificant. The value measure has no predictive power in the out-of-sample period, explaining the poor performance of the VAL strategy portfolio. The results in Panel B show a discontinuity in the relationship between currency returns and changes in real exchange rates, implying a correction of mispricing.

5.2. Are past returns still related to future returns?

In this section, we investigate the relationship between historical and future currency returns for trading strategies dependent on past returns. If momentum is due to mispricing then we anticipate sophisticated investors learning about and trading against momentum mispricing, will correct serial correlation in currency excess returns. Using Principal Component Analysis (PCA) and regression analysis we first show that MOM and TSM share time series return autocorrelation as a common source of returns. We then examine the evolution of return autocorrelation using pooled time series regressions.

Panel A of [Table 6](#) presents the results for PCA carried out using gross portfolio return series of all TSM and MOM variations over the full sample period. The cumulative percentage of variance explained by the first three principal components for each strategy class is over 70%. These results indicate that MOM shares a common source of returns with

Table 5
Value Fama-MacBeth regressions.

	Lag length				
Intercept	1-month	2-month	3-month	6-month	R ²
Panel A: In-sample					
0.10 (0.73)	0.01*** (2.71)				0.10
0.11 (0.83)		0.01*** (2.66)			0.10
0.14 (1.04)			0.01*** (2.95)		0.10
0.15 (1.08)				0.02*** (3.25)	0.10
Panel B: Out-of-sample					
−0.43** (−2.44)	0.00 (0.68)				0.10
−0.33* (−1.83)		0.00 (0.19)			0.09
−0.32* (−1.71)			0.00 (−0.02)		0.09
−0.23 (−1.15)				0.00 (0.13)	0.07

This table shows the results for monthly cross-sectional regressions over the in-sample (Panel A) and out-of-sample (Panel B) periods, respectively. In each month, the dependent variable is individual currencies' excess returns and the explanatory variable is individual currencies' value in the previous l -month ($VAL_{i,t-l}$). The mean of the time series of coefficients estimated with lag lengths $l = 1, 2, 3$ and 6 months, are presented under Lag length. Intercept represents the mean of monthly time series of constants and are expressed in percent. T-statistics based on Newey and West (1987) standard errors are presented in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Table 6
Times series momentum relationship with cross sectional momentum.

Panel A: Principal component analysis				
	% Variance explained	Time series momentum factor correlation		
		First	Second	Third
Time series momentum	77.47	1.00	1.00	1.00
Cross sectional momentum	72.30	0.55	0.55	0.49
Panel B: Regression analysis				
	α	β_{TSM}	R ²	
Cross sectional momentum	0.00	0.48***	0.30	

Panel A presents the results of principal component analysis conducted on all specifications of the time series momentum and cross sectional momentum portfolios. The cumulative percentage of variance explained by the first three common factors for each strategy is shown in column (1). Column (2–4) presents time series momentum factors' correlation with cross sectional momentum factors. Panel B shows the results of a regression showing the relationship between average time series momentum portfolios and average cross sectional momentum portfolios. The dependent variable MOM are equal weighted portfolios, rebalanced monthly, formed from all available cross sectional momentum portfolios. The independent variable, TSM is an equal weighted portfolio, rebalanced monthly, formed from all available time series momentum portfolios. All returns are gross of transaction costs. *** denotes statistical significance at 1% level of significance.

TSM.

While PCA provides insights to common latent factors underlying the time series of variables, an alternative is to test the economic and

statistical significance of the MOM alpha, after controlling for TSM, and the relationship between their returns, in a regression analysis.⁸ To do this we form equal weighted portfolios, rebalanced monthly, for time series momentum, and cross sectional momentum, using all available portfolios for each strategy class. We then regress the cross sectional momentum equal weighted portfolio on the time series momentum equal weighted portfolio.

If time series momentum explains the returns to cross sectional momentum then we would expect to see an intercept which is not statistically significant from zero, as reported in Panel B. The time series momentum portfolio beta is positive and highly significant with an R² of 30%, confirming the PCA findings.

From these results, we infer that time series momentum and cross sectional momentum share time series return predictability as their underlying source of returns. To test whether there is a change in time series return predictability in the out-of-sample period, we specify pooled panel regressions of serial correlation following Moskowitz et al. (2012). For each formation period, k , we estimate

$$r_{i,t} = \alpha + \beta_k \text{sign}(r_{i,t-k}) + \varepsilon_k \quad (14)$$

where the explanatory variable is the sign of the return on currency i at time $t - k$.

Panel A and B of Fig. 2 present beta coefficients by month lag and the corresponding t -statistics over the in-sample and out-of-sample periods, respectively. The out-of-sample results show no relationship between past and future returns, explaining why the investment performance of these strategies is weak in the out-of-sample period.

6. Robustness tests

6.1. Peripheral currency portfolio results

The results above suggest that the investment returns of carry, momentum and value portfolios disappear out-of-sample. Recall, that so far our analyses have focused on the G11 currencies. If it's the case that the power of these predictors has dissipated, then the evidence should be consistent for other currencies. Testing using a broader sample of currencies is particularly important for carry as prior research shows that carry returns are mainly generated from peripheral currencies (Richmond, 2019).

To test the robustness of our main results to this view, we repeat the analysis measuring the out-of-sample investment returns of peripheral currency portfolios formed on carry, momentum and value. For consistency, we use identical strategy specific out-of-sample periods and core strategy parametrisations as our analysis for G11 currencies, reporting results for twenty-four peripheral currencies and a combined portfolio of G11 and peripheral currencies. We measure the average return as well as risk-adjusted performance measures, reporting results both before and after transaction costs. Results reported in Table 7 are qualitatively identical to those reported in Table 3 for G11 currencies.

6.2. Predictability breakpoint

Our selection of out-of-sample period start date is based on the end of the sample period of recent studies assessing the risks of the strategy. The argument could be made for alternative studies and corresponding out-of-sample periods, or a single uniform period. To address this issue here we provide results for a common extended period, and specify

⁸ See, for example, Moskowitz et al. (2012) and Goyal and Jegadeesh (2018).

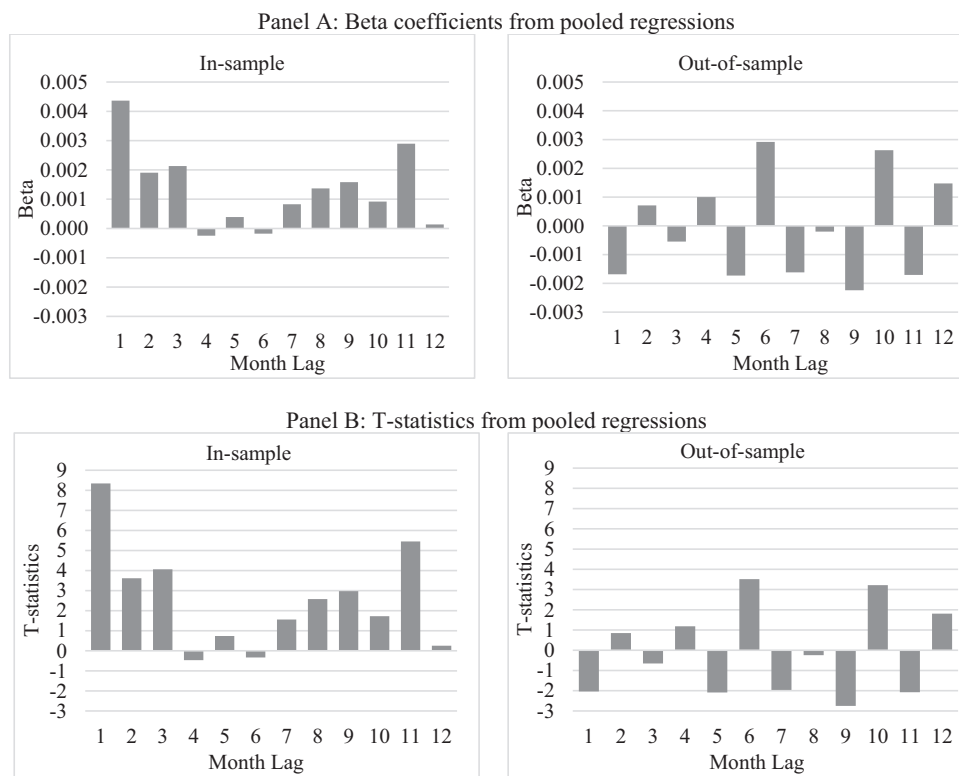


Fig. 2. Autocorrelation in currency excess returns.

Notes: We regress the monthly excess return of each currency on the sign of its own lagged excess return over various horizons. Reported are the pooled regression estimates across G11 currencies. Panel A shows the beta coefficients and Panel B reports the corresponding T-statistics. The in-sample period is January 1980 to December 2009. The out-of-sample period is January 2010 to April 2020.

Table 7
Performance of peripheral currency portfolios.

	Pre-transaction costs				Net of transaction costs			
	Carry	Cross sectional momentum	Time series momentum	Value	Carry	Cross sectional momentum	Time series momentum	Value
Panel A: Peripheral currencies								
Mean	1.79 (0.78)	0.70 (0.46)	0.10 (0.07)	2.87 (1.19)	1.72 (0.75)	0.32 (0.21)	0.02 (0.01)	2.77 (1.14)
Volatility	6.56	5.17	4.44	6.31	6.56	5.18	4.44	6.31
Sharpe ratio	0.27 (0.74)	0.14 (0.43)	0.02 (0.07)	0.46 (1.32)	0.26 (0.71)	0.06 (0.20)	0.00 (0.01)	0.44 (1.27)
Alpha	0.64 (0.28)	0.65 (0.38)	0.01 (0.01)	3.00 (1.32)	0.25 (0.25)	0.25 (0.15)	-0.07 (-0.04)	2.90 (1.27)
CER	1.35	0.43	-0.10	2.47	1.28	0.05	-0.18	2.36
R ²	21.40	5.22	-3.75	3.65	21.37	5.12	-3.76	3.64
Panel B: Combined G11 and peripheral currencies								
Mean	2.35 (1.14)	-0.63 (-0.51)	-0.23 (-0.15)	2.23 (1.06)	2.30 (1.11)	-1.02 (-0.82)	-0.32 (-0.21)	2.12 (1.01)
Volatility	5.89	4.51	4.72	5.44	5.89	4.51	4.72	5.44
Sharpe ratio	0.40 (1.08)	-0.14 (-0.45)	-0.05 (-0.16)	0.41 (1.20)	0.39 (1.06)	-0.23 (-0.73)	-0.07 (-0.22)	0.39 (1.14)
Alpha	1.14 (0.54)	-0.11 (-0.07)	-0.44 (-0.26)	2.64 (1.40)	1.09 (0.51)	-0.50 (-0.35)	-0.53 (-0.32)	2.54 (1.35)
CER	2.00	-0.83	-0.45	1.93	1.95	-1.22	-0.54	1.82
R ²	24.31	3.78	-3.18	6.04	24.28	3.69	-3.18	6.03

This table reports the out-of-sample performance, before and after transaction costs, of the core trading strategies for a portfolio of twenty-four peripheral currencies (Panel A) and a portfolio of thirty-four G11 and peripheral currencies (Panel B). Carry and Value portfolios are constructed using rank-based weights. Cross-sectional momentum has a three-month formation period and one-month holding period. Time series momentum is formed with a twelve-month formation and one-month holding period. Mean and Volatility are the annualised portfolio average excess returns and standard deviation. The Sharpe ratio is mean excess return divided by standard deviation. Alpha is the annualised intercept of the multivariate Fama and French (1993) five-factor model and R² is the adjusted r-square of the model. CER is annualised certainty equivalent return estimated assuming the risk-aversion coefficient as 2 (Ferreira & Santa-Clara, 2011). The t-statistics (in parentheses) for Mean and Alpha are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors. The t-statistics for the Sharpe ratio are calculated following Lo (2002). The symbols ***, **, and * denote statistical significance of parameter estimates at 1%, 5% and 10% level of significance, respectively.

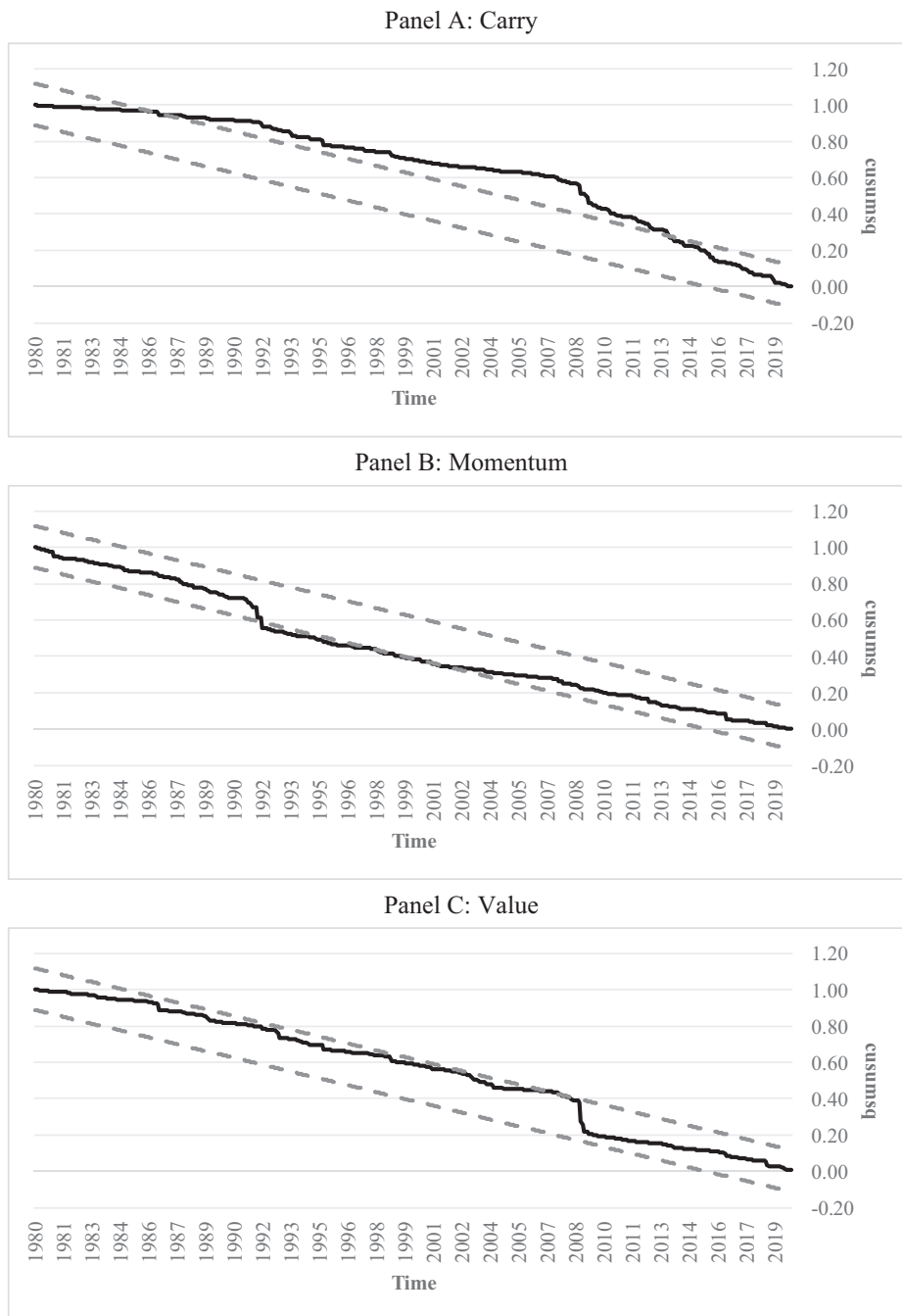


Fig. 3. Cusum test for the predictability break-point.

Notes: We estimate a backwards Cusum of squares test of coefficient stability using the time series of beta coefficients from Fama-MacBeth regressions for carry (Panel A), momentum (Panel B) and value (Panel C). Test statistics are denoted by the solid black line. Critical bands at the 10% significance level are denoted by broken grey lines.

statistical analysis to formally test when the relationship between carry, momentum and value and future currency returns ceased.⁹

We identify September 2009 as a reasonable out-of-sample start point as [Burnside et al. \(2011\)](#) and [Menkhoff et al. \(2012a\)](#) sample periods end on July 2009 and August 2009, respectively. The out-of-sample investment returns (not tabulated to save space) from September 2009 to April 2020 of the G11 core currency portfolios formed on carry, momentum and value, are qualitatively identical to those reported previously.

⁹ In unreported tests we also investigate whether academic publication can be linked to changes in investor attention. We replicate the [Goddard et al. \(2015\)](#) Google Search Volume Index methodology but find no evidence to explain our findings.

Next, we are interested in trying to identify the point when the change occurred for each of the predictors. To do this, first we estimate a series of [Fama and MacBeth \(1973\)](#) first stage cross-sectional regressions to capture a time series of betas for each conditioning variable. Then for each time series of betas we apply a Cusum of squares test for parameter stability ([Brown, Durbin, & Evans, 1975](#)). We backward estimate the test to more precisely identify the most recent structural break point, when there is a change in the regression regime.¹⁰

Results reported in [Fig. 3](#) show the break in coefficient stability occurs at different points in time for the three predictors. Note, it is unlikely that the structural break occurs exactly on these dates, since the

¹⁰ [Fung and Hsieh \(2004\)](#) take a similar approach to identify structural breaks in hedge fund risk exposure.

effect will show up gradually in the regression coefficients. The break in carry is most recent, with a breakpoint in June 2013. Value has a breakpoint in September 2007 whereas the momentum breakpoint occurs much earlier, in August 2001. The earlier breakpoint for momentum is consistent with our portfolio results, where the in-sample performance of the cross sectional portfolio is not statistically significant, net of transaction costs.

7. Conclusions

In this paper, motivated by recent evidence showing that the returns of currency predictability portfolios cannot be explained by risk, we have tested to see if predictability is due to mispricing. Our evidence is consistent with sophisticated investors learning about and trading against the mispricing, leading to it disappearing out-of-sample.

None of the strategies generate meaningful performance, with mean returns ranging from -3.51% to 1.74% per annum, and statistically insignificant risk adjusted returns. These findings are insensitive to the choice of out-of-sample start point and the sample of currencies. A joint test of 252 strategy variations, minimizing predictor estimation error, confirms the decrease in performance, with the average Sharpe ratio dropping from 0.39 to -0.32 out-of-sample.

For value strategies, Fama and MacBeth (1973) regressions confirm a breakdown in the relationship between changes in real exchange rates and future returns. Interest rate differentials have remained positive, despite the relatively low level of rates, but cross-sectional regressions show carry is no longer correlated with future currency returns. We find no out-of-sample evidence of serial correlation, leading to the negative investment performance of momentum strategies.

In future work, it would also be interesting to examine whether incorporating dimension reduction techniques, such as partial least squares or machine learning, to these predictors improves out-of-sample return forecasts.

CRediT authorship contribution statement

Mark C. Hutchinson: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition. **Panagiotis E. Kyziropoulos:** Methodology, Software, Formal analysis. **John O'Brien:** Conceptualization, Methodology, Writing – review & editing. **Philip O'Reilly:** Supervision, Project administration, Funding acquisition, Writing – review & editing. **Tripti Sharma:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

References

- Alquist, R., Israel, R., & Moskowitz, T. (2018). Fact, fiction, and the size effect. *Journal of Portfolio Management*, 45(1), 34–61.
- Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, 68(3), 929–985.
- Bakshi, G., & Panayotov, G. (2013). Predictability of currency carry trades and asset pricing implications. *Journal of Financial Economics*, 110(1), 139–163.
- Baltas, N., & Kosowski, R. (2013). Momentum strategies in futures markets and trend-following funds. In *Paper Presented at the Paris December 2012 Finance Meeting EUROFIDAI-AFFI Paper*.
- Barroso, P., & Santa-Clara, P. (2015). Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis*, 50(5), 1037–1056.
- Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society*, 37(2), 149–192.
- Brunnermeier, M. K., Nagel, S., & Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual*, 23(1), 313–348.
- Burnside, C., Eichenbaum, M., Kleshchelski, I., & Rebelo, S. (2011). Do peso problems explain the returns to the carry trade? *Review of Financial Studies*, 24(3), 853–891.
- Cochrane, J. H. (1999). Portfolio advice for a multifactor world. *Economic Perspectives*, 23(3), 59–61.
- Colacito, R., Croce, M. M., Gavazzoni, F., & Ready, R. (2018). Currency risk factors in a recursive multicountry economy. *Journal of Finance*, 73(6), 2719–2756.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.
- Fama, E. F., & French, K. R. (2020). The value premium. *Review of Asset Pricing Studies*, 11(1), 105–121.
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636.
- Ferreira, M. A., & Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, 100(3), 514–537.
- Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, 60(5), 65–80.
- Goddard, J., Kita, A., & Wang, Q. (2015). Investor attention and FX market volatility. *Journal of International Financial Markets, Institutions and Money*, 38, 79–96.
- Goyal, A., & Jegadeesh, N. (2018). Cross-sectional and time-series tests of return predictability: What is the difference? *Review of Financial Studies*, 31(5), 1784–1824.
- Groen, J. J., & Kapetanios, G. (2016). Revisiting useful approaches to data-rich macroeconomic forecasting. *Computational Statistics & Data Analysis*, 100, 221–239.
- Harvey, C. R. (2017). Presidential address: The scientific outlook in financial economics. *Journal of Finance*, 72(4), 1399–1440.
- Hassan, T. A. (2013). Country size, currency unions, and international asset returns. *Journal of Finance*, 68(6), 2269–2308.
- Hoffmann, M., & Studer-Suter, R. (2017). Systematic consumption risk in currency returns. *Journal of International Money and Finance*, 74, 187–208.
- Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? *Journal of Financial Economics*, 135(3), 774–794.
- Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2017). A century of evidence on trend-following investing. *Journal of Portfolio Management*, 44(1), 15–29.
- Kim, H., & Ko, K. (2020). Improving forecast accuracy of financial vulnerability: PLS factor model approach. *Economic Modelling*, 88, 341–355.
- Kita, A. (2021). *Machine learning predictions of credit and equity risk premia*. Working Paper.
- Kojen, R. S., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. *Journal of Financial Economics*, 127(2), 197–225.
- Kouwenberg, R., Markiewicz, A., Verhoeks, R., & Zinkels, R. C. J. (2017). Model uncertainty and exchange rate forecasting. *Journal of Financial and Quantitative Analysis*, 52(1), 341–363.
- Lo, A. W. (2002). The statistics of Sharpe ratios. *Financial Analysts Journal*, 58(4), 36–52.
- Lustig, H., & Verdelhan, A. (2007). The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review*, 97(1), 89–117.
- Lustig, H., Roussanov, N., & Verdelhan, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, 111(3), 527–553.
- McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1), 5–32.
- Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012a). Carry trades and global foreign exchange volatility. *Journal of Finance*, 67(2), 681–718.
- Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012b). Currency momentum strategies. *Journal of Financial Economics*, 106(3), 660–684.
- Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2017). Currency value. *Review of Financial Studies*, 30(2), 416–441.
- Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228–250.
- Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703–708.
- Okunev, J., & White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis*, 38(2), 425–447.
- Paiva, F. D., Cardoso, R. T. N., Hanaoka, G. P., & Duarte, W. M. (2019). Decision-making for financial trading: A fusion approach of machine learning and portfolio selection. *Expert Systems with Applications*, 115, 635–655.
- Poncela, P., Rodríguez, J., Sánchez-Mangas, R., & Senra, E. (2011). Forecast combination through dimension reduction techniques. *International Journal of Forecasting*, 27(2), 224–237.
- Ranaldo, A., & Somogyi, F. (2021). Asymmetric information risk in FX markets. *Journal of Financial Economics*, 140(2), 391–411.
- Richmond, R. J. (2019). Trade network centrality and currency risk premia. *Journal of Finance*, 74(3), 1315–1361.
- Schwert, W. G. (2003). Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of the economics of finance* (pp. 939–974). North Holland, Amsterdam: Elsevier Science B.V.
- Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21(4), 1455–1508.
- Zviadadze, I. (2017). Term structure of consumption risk premia in the cross section of currency returns. *Journal of Finance*, 72(4), 1529–1566.