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Currency Momentum: An Emerging Market Issue?

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ABSTRACT

Three main currency strategies have been established in the literature: carry, value, and momentum. We investigate momentum using data on 27 currencies (10 developed countries and 17 emerging markets). We find that momentum returns are driven by emerging market currencies, while the currencies of developed countries have no impact. An emerging market-specific dollar risk factor can partly explain these momentum returns. We carry out permutation tests and find support for our hypothesis that momentum returns are driven by emerging markets. However, we show that transaction costs reduce momentum returns considerably. We also show that the returns are time-varying and have been unattractive recently. The implications of this study for financial practitioners are to focus on emerging market currencies and optimise transaction costs when executing momentum strategies.

Introduction

The core of momentum strategies is to buy those currencies that have risen the most in the past and sell those currencies that have fallen the most. Numerous studies show that momentum strategies lead to significant excess returns (Asness et al., 2013; Burnside et al., 2011b; Filippou et al., 2018; Menkhoff et al., 2012b). In this study, we examine momentum returns of 17 emerging and 10 developed markets both separately and combined. In particular, using permutation tests and emerging market-specific risk factors, we investigate the impact of emerging market currencies on momentum returns.

Our research confirms that currency momentum provides significant outperformance. For the combined dataset covering all 27 currencies, we find that monthly excess returns range from 0.24% to 1.24%, with Sharpe ratios between 0.28 and 0.54 depending on the momentum strategy setting. One key finding of our research is that performance is driven by emerging market currencies. Indeed, after running permutation tests, we confirm that the selection of emerging market currencies leads to higher momentum returns.

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Our findings are in line with those of Menkhoff et al. (2012b). They study 48 currencies and find that momentum returns are higher in countries with high idiosyncratic volatility than in countries with low idiosyncratic volatility. In addition, returns are related to country risk. Menkhoff et al. (2012b) show that momentum strategies generate excess returns in countries with a poor rating, which is not the case for countries with a good rating.

One possible explanation for the importance of emerging market currencies in momentum strategies may be initial underreaction to news (Hong & Stein, 1999). The depreciation of a currency would result in depreciation in the following month, as the information that led to the depreciation in the first period has not yet been fully processed in this period.

Analogous to Brunnermeier et al. (2008), a further explanation for momentum returns lies in funding constraints. Market participants are forced to liquidate positions if they cannot provide a sufficient margin. If, for example, they can no longer meet their margin requirements due to currency devaluation, they must close out their positions by selling the currency. This sell-off exacerbates the existing trend, which is a good setting for momentum strategies. Emerging market currencies are expected to be more affected by funding constraints than currencies of developed countries, as the former are the target of speculators such as hedge funds (Patel & Xia, 2019). Brunnermeier et al. (2008) show that the skewness of currency returns is related to funding constraints and crash risk (i.e. sudden exchange rate movements). Currencies with high interest rates have negative skewness and high crash risk.

Our research contributes to the body of research on this topic by focusing on emerging markets. We use permutation tests and show that emerging markets are the driving force of currency momentum returns. In addition, in line with Lustig et al. (2011), we use dollar risk factors to explain momentum returns. Through linear regressions, we find that an emerging-market specific risk factor can partly explain momentum returns. Moreover, the regression coefficient for an emerging-market specific risk factor is significant, whereas it is not so for a developed-market specific risk factor.

The rest of this paper is organised as follows. Section 2 provides an overview of the existing literature on currency momentum. The research design is presented in Section 3, and the results in Section 4. The findings on risk factors and permutation tests are detailed in Section 5. Section 6 deals with limits of arbitrage, and Section 7 concludes.

Literature review

In the scientific context, but also in practice, three currency strategies have become established: carry, value, and momentum. As described in the Introduction, under the momentum strategy, investors buy currencies with the best past performance and sell currencies with the worst past performance (Burnside et al., 2011b; Filippou et al., 2018; Menkhoff et al., 2012b). By contrast, carry trades are related to the interest rate differentials between countries. This strategy involves buying currencies with high interest rates and selling currencies with low interest rates (Barroso & Santa-Clara, 2015; Brunnermeier et al., 2008; Burnside et al., 2011a). Finally, currency value addresses the overvaluation and undervaluation of currencies based on economic fundamentals (Asness et al., 2013; Menkhoff et al., 2017). Some studies examine momentum, carry, and value strategies in combination (Burnside et al., 2011b; Kroencke et al., 2014).

Since our work relates to momentum, we limit our discussion of the existing literature to momentum strategies. In their widely cited paper, Jegadeesh and Titman (1993) showed that momentum strategies lead to abnormal returns of up to 12 % per annum for equity markets. For currency markets, Okunev and White (2003) were one of the first to document that momentum strategies are profitable.

Momentum strategies are divided into cross-sectional and time-series strategies. The latter strategy examines the time series of a single asset. For currencies as well as other asset classes, this strategy is often shown to lead to excess returns (Hurst et al., 2017; Moskowitz et al., 2012). Moskowitz et al. (2012) investigate time-series momentum in several asset classes and for 58 instruments, finding that the strategy performs well in extreme periods when markets are rising or falling strongly. Additionally, they find evidence that speculators profit at the expense of hedgers when they adopt time-series momentum strategies. An earlier stage of technical trading rules, including momentum, goes back more than 30 years. These studies show that excess returns can be achieved with technical trading rules (Sweeney, 1986; Taylor, 1994).

Menkhoff et al. (2012b) examine currency momentum for 48 currencies between 1976 and 2010 and find that momentum returns are sensitive to transaction costs. Moreover, they show that no systematic risk factor explains momentum returns in the short term. In addition, momentum returns are higher for currencies with high idiosyncratic volatility, in countries with a high risk and thus a poor rating, and for short-term horizons more than long-term ones. Of research that combines the momentum, carry, and value strategies, Barroso and Santa-Clara (2015) show that an optimal currency strategy formed by momentum, carry, and reversal substantially outperforms the carry trade strategy. Specifically, this strategy has a higher Sharpe ratio and outperforms the naive benchmarks proposed in the literature. Asness et al. (2013) investigate value and momentum returns in several asset classes, finding that value and momentum are negatively correlated and deliver significant excess returns.

Burnside et al. (2011b) show that momentum strategies are highly profitable, with observable risk factors explaining only a small proportion of momentum returns. On the contrary, Filippou et al. (2018) find that political risk explains a significant proportion of currency excess returns under the momentum strategy. Further studies have examined the risk factors related to equity markets. Orlov (2016) finds that currency momentum returns depend on equity market illiquidity as well as that currency momentum returns are high after months with low equity market liquidity and vice versa. Turkington and Yazdani (2020) find that recent stock market performance predicts currency performance in the next month.

Research design

Data

We use data from Refinitiv Eikon (formerly Reuters Datastream). In addition to spot rates, we base our analysis on 1-month forward rates. While spot rates have been available since the early 1980s, forward rates have only been available since June 1990. For emerging market currencies, data are primarily available from the mid-1990s. All currencies are quoted against the U.S. dollar. Table 1 shows the availability of the data. We thus analyse data from January 1997 to May 2022.

Table 1. Data availability

Currency	ISO Code	Availability Spot	Availability Forward
Developed Countries			
Euro	EUR	< Jan 1980	May 1990
Great Britain pound	GBP	< Jan 1980	May 1990
Japanese yen	JPY	< Jan 1980	May 1990
Swiss franc	CHF	< Jan 1980	May 1990
Australian dollar	AUD	< Jan 1980	May 1990
Canadian dollar	CAD	< Jan 1980	May 1990
Israeli shekel	ILS	< Jan 1980	Jan 2002
New Zealand dollar	NZD	< Jan 1980	May 1990
Norwegian krone	NOK	< Jan 1980	May 1990
Swedish krona	SEK	< Jan 1980	May 1990
Emerging Countries			
Indian rupee	INR	< Jan 1980	Aug 1996
South Korean won	KRW	Apr 1981	March 2001
Russian rouble	RUB	Sep 1994	Feb 2000
Brazilian real	BRL	Jan 1991	Aug 2000
Indonesian rupiah	IDR	Dec 1987	Nov 1990
Mexican peso	MXN	Nov 1989	Dec 1998
Turkish lira	TRY	Nov 1989	Jul 1995
South African rand	ZAR	< Jan 1980	May 1990
Chilean peso	CLP	Nov 1990	Dec 2002
Colombian peso	COP	Nov 1989	Jan 2004
Polish zloty	PLN	Jun 1993	Aug 1996
Czech koruna	CZK	Jan 1991	Dec 1996
Hungarian forint	HUF	Jun 1993	Sep 1996
Philippine peso	PHP	May 1992	Aug 1996
New Taiwan dollar	TWD	Oct 1983	Oct 2000
Thai baht	THB	Jan 1981	March 1995
Peruvian sol	PEN	Jan 1991	Aug 2003

Note. Table 1 provides an overview of the available spot and forward rates for 10 developed countries and 17 emerging markets.

Our research distinguishes between currencies from developed and emerging markets. We follow MSCI's definition of emerging markets. The following emerging market currencies are or were previously pegged to other currencies for a longer period and these are excluded from the analysis: Chinese renminbi, Egyptian pound, Kuwaiti dinar, Moroccan dirham, Pakistani Rupee, Qatari riyal, Saudi riyal, and United Arab Emirates dirham. Greece is also an emerging market according to MSCI's definition; however, as the country is a member of the Economic and Monetary Union of the EU, it is classified as a developed country. Argentina is considered to be an outlier due to its currency reforms and is also excluded.

MSCI counts 23 nations as developed. The currencies of Denmark, Hong Kong, and Singapore are pegged to other currencies or a basket of currencies and are excluded from the analysis. Of the remaining 20 currencies, 11 belong to the European Monetary Union and are thus subsumed in the euro. This leaves 10 currencies for the developed country sample.

Excess return

All 27 currencies are presented from the perspective of a U.S. investor. An excess return is defined as the return above the risk-free interest rate that a U.S. investor earns by buying a foreign currency within 1 month. The excess return is the difference between the log 1-month forward rate (fw_t) and log spot rate of the respective currency in a month (sp_{t+1}). Sp_t and fw_t are the spot and forward prices in the foreign currency for one U.S. dollar each. A rising sp_t indicates an increase in the value of the U.S. dollar against the foreign currency. All the values are in logs and shown in small letters. The excess return of a U.S. investor is thus

$$rx_{t+1} = fw_t - sp_{t+1}. \tag{1}$$

Our analysis shows that transaction costs are important when adopting the momentum strategy. Therefore, we show the excess return both with and without transaction costs. In the calculations without transaction costs, bid prices are used for both the spot and the forward prices. For the calculations with transaction costs, the excess return in a long position is

$$rx_{t+1} = fw_t^{BID} - sp_{t+1}^{ASK} \tag{2}$$

and that in a short position is

$$rx_{t+1} = fw_t^{ASK} - sp_{t+1}^{BID}. \tag{3}$$

Portfolio construction

For each monthly period, two portfolios are formed based on past excess returns: short and long portfolios. The historical period considered comprises the past 1, 3, 6, and 12 months, analogous to the approach of Menkhoff et al. (2012b). These months are referred to as formation period *f*. In contrast to Menkhoff et al. (2012b), the portfolios are held for 1 month.

The long portfolio comprises the currencies that have risen the most in the past relative to the other currencies. The short portfolio is formed from those currencies that have fallen the most in the past. The momentum returns reported are the differences between the long and short portfolio returns. We apply three settings for the number of currencies included in the long and short portfolios. Both these portfolios include one, three, and five currencies each, where *n* indicates the number of currencies. As we examine only 27 currencies, it makes sense to focus on the portfolios with the highest and lowest changes in value. Our research thus focuses on the high minus low portfolio.

Results

We compute the momentum returns for all 27 currencies in the first step. Table 2 shows the average monthly return of the momentum strategy, defined as the performance of the long portfolio minus the performance of the short portfolio, as well as the standard deviation and skewness values. The annual Sharpe ratio is calculated as the monthly mean return multiplied by 12 divided by the standard deviation multiplied by the square root of 12. We use a two-sided t-test to examine whether the average return differs from 0%. The most significant returns are found for the formation periods of 1, 3, and 6 months, predominantly at the 5% significance level. The Sharpe ratio reaches values between 0.28 and 0.54.

Table 2. Results for the momentum strategies for all 27 currencies

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics (μ = 0)	Standard error
$n = 1, f = 1$	0.00668	0.077781	1.436	0.30	1.5	0.004454
$n = 3, f = 1$	0.004907	0.036494	1.4203	0.47	2.3485*	0.00209
$n = 5, f = 1$	0.003741	0.027686	1.0395	0.47	2.3599*	0.001585
$n = 1, f = 3$	0.012391	0.080152	2.0997	0.54	2.6998**	0.004589
$n = 3, f = 3$	0.00447	0.037735	1.3668	0.41	2.0686*	0.002161
$n = 5, f = 3$	0.003565	0.027079	0.861	0.46	2.299*	0.001551
$n = 1, f = 6$	0.010112	0.071239	2.4379	0.49	2.4788*	0.004079
$n = 3, f = 6$	0.005979	0.040262	1.1151	0.51	2.5935**	0.002305
$n = 5, f = 6$	0.003123	0.028524	0.7597	0.38	1.9122°	0.001633
$n = 1, f = 12$	0.007199	0.077982	1.5133	0.32	1.6122	0.004465
$n = 3, f = 12$	0.004025	0.041346	0.964	0.34	1.7002°	0.002367
$n = 5, f = 12$	0.002392	0.029893	0.5433	0.28	1.3977	0.001712

Note. Table 2 reports the average monthly returns and t-statistics for μ = 0. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively. The formation period is indicated by *f* and the number of currencies in the momentum portfolio by *n*. The Sharpe ratio is the quotient of the monthly mean return multiplied by 12 and the standard deviation multiplied by the square root of 12.

Table 3 shows the results of the momentum strategy when only the 10 currencies of the developed countries are used. For most of the settings, the momentum strategy leads to a negative result for these countries and the returns are not statistically different from 0%. The skewness is much less pronounced and, in some cases, negative. Furthermore, as would be expected, a lower standard deviation can be observed for these developed countries.

Table 3. Results for the momentum strategies for the 10 developed country currencies

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics (μ = 0)	Standard error
n = 1, f = 1	–0.002878	0.033964	0.0991	–0.29	–1.4798	0.001945
n = 3, f = 1	–0.000576	0.021432	0.081	–0.09	–0.46917	0.001227
n = 5, f = 1	0.000252	0.015837	0.4579	0.06	0.27834	0.000907
n = 1, f = 3	–0.001349	0.035188	0.8638	–0.13	–0.66936	0.002015
n = 3, f = 3	–0.001226	0.021245	0.2733	–0.2	–1.0079	0.001217
n = 5, f = 3	–0.001227	0.015575	0.4682	–0.27	–1.376	0.000892
n = 1, f = 6	–0.001685	0.034553	0.1412	–0.17	–0.85148	0.001979
n = 3, f = 6	–0.000904	0.021071	–0.4318	–0.15	–0.74947	0.001207
n = 5, f = 6	–0.000617	0.014884	–0.1609	–0.14	–0.72434	0.000852
n = 1, f = 12	–0.000628	0.03264	–0.2959	–0.07	–0.33577	0.001869
n = 3, f = 12	–0.000045	0.023071	–0.0324	–0.01	–0.034188	0.001321
n = 5, f = 12	–0.000367	0.015575	0.0541	–0.08	–0.41165	0.000892

Note. Table 3 shows the average monthly return for the 10 developed country currencies and t-statistics for μ = 0. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

The lack of success of the momentum strategy when using only the data of the 10 developed countries is the first indication that the success of the momentum strategy is driven by emerging market currencies. Table 4 shows the momentum strategy results when applied exclusively to the 17 emerging market currencies. The returns for the formation periods of 1, 3, and 6 months are significant at 5%, whereas the returns are weakest and not significant at 5% for the formation period of 12 months. The Sharpe ratio reaches values up to 0.72. Thus, momentum with emerging market currencies is attractive even when risk is considered.

Table 4. Results for the momentum strategies for the 17 emerging market currencies

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics (μ = 0)	Standard error
n = 1, f = 1	0.010632	0.077718	1.6049	0.47	2.3891*	0.00445
n = 3, f = 1	0.006662	0.037604	1.2247	0.61	3.0938**	0.002153
n = 5, f = 1	0.005735	0.02766	0.8546	0.72	3.6208***	0.001584
n = 1, f = 3	0.011814	0.08236	2.1491	0.5	2.5051*	0.004716
n = 3, f = 3	0.006026	0.038828	1.3037	0.54	2.7106**	0.002223
n = 5, f = 3	0.00445	0.027981	0.997	0.55	2.7776**	0.001602
n = 1, f = 6	0.010473	0.071852	2.3507	0.5	2.5455*	0.004114

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics (μ = 0)	Standard error
n = 3, f = 6	0.006638	0.038972	1.3033	0.59	2.9746**	0.002232
n = 5, f = 6	0.004229	0.028152	0.9109	0.52	2.6235**	0.001612
n = 1, f = 12	0.007582	0.077977	1.4637	0.34	1.6981°	0.004465
n = 3, f = 12	0.003651	0.040932	1.0826	0.31	1.5578	0.002344
n = 5, f = 12	0.001655	0.026939	0.3559	0.21	1.0729	0.001543

Note. Table 4 presents the average monthly return for the 17 emerging market currencies. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

The results show that the momentum strategy leads to different results depending on which currencies are used. For developed countries, the strategy is unsuccessful. If all 27 currencies are used, we find a significant excess return. However, if only currencies from emerging markets are considered, the returns and their significance increase further. This analysis indicates that emerging market currencies are the major force driving the excess return of momentum strategies. In Section 5 (Risk factors and permutation test), we present the permutation test used to test this hypothesis further.

Our research focuses on the high minus low portfolio of the momentum strategy. In Appendix A, we also show the results separately for the high and low portfolios. We also check the robustness of our results by using the British pound and the euro instead of the US dollar as the base currency. The results for the euro are presented in Appendix A. Our findings are robust for different base currencies.

Risk factors and permutation test

Dollar risk factor

To show the dependence of the momentum strategy on emerging market currencies, we employ the dollar risk factor (DOL) introduced by Lustig et al. (2011) and Verdelhan (2018). Lustig et al. examine the excess returns of currencies and build six portfolios for this purpose. The individual currencies are sorted according to their interest rate differential and then assigned to one of the six portfolios. In a further step, Lustig et al. conduct a principal component analysis to examine which risk factors contribute to the excess return of the six portfolios. They show that the dollar risk factor can explain 70% of the common variation in portfolio returns (Lustig et al., 2011). The dollar risk factor has become established in the literature and is used in numerous studies (e.g., Burnside et al., 2011b; Lettau et al., 2014; Menkhoff et al., 2012a; Verdelhan, 2018). In essence, the dollar risk factor is the average excess return of all foreign currency excess returns from the perspective of a U.S. investor:

$$DOL_{t+1} = \frac{1}{N}\sum_{i} rx_{i,t+1}. \tag{4}$$

The DOL^{ALL} used in this research represents the average monthly returns of all 27 currencies against the U.S. dollar. To highlight the relevance of emerging market currencies, we split this risk factor into DOL^{IND} and DOL^{EM}. DOL^{IND} comprises the monthly returns of the ten developed country currencies against the U.S. dollar, and DOL^{EM} comprises the monthly returns of the 17 emerging market currencies. Table 5 presents the summary statistics of these three risk factors, showing that the largest differences between DOL^{IND} and DOL^{EM} are in the skewness and kurtosis values.

Table 5. Summary statistics of DOL^{ALL}, DOL^{IND}, and DOL^{EM}

	DOL^{ALL}	DOL^{IND}	DOL^{EM}
Mean	–0.000271	–0.000456	–0.000211
Standard deviation	0.021758	0.022343	0.023974
Skewness	–0.503049	–0.139058	–0.669301
Kurtosis	4.597395	4.096367	5.179957
Max	0.059289	0.074484	0.079728
Min	–0.098128	–0.09449	–0.100267

Note. Table 5 reports the summary statistics for DOL^{ALL}, DOL^{IND}, and DOL^{EM}. The risk factors represent the monthly currency returns against the U.S. dollar. Positive DOL values indicate a weaker U.S. dollar.

Using the DOL^{IND} and DOL^{EM} risk factors, we examine whether an emerging market-specific risk factor can explain momentum better than a risk factor compiled without emerging markets. We apply single linear regressions in the following form and then compare the DOL^{EM} and DOL^{IND} values:

$$MOM_t = a + \beta \cdot DOL_t + \varepsilon_t. \tag{5}$$

MOM indicates the monthly returns of the momentum strategy for the individual settings of *n* and *f*. Table 6 shows the results of the two regressions. The adjusted R^2 for DOL^{EM} reaches up to 0.0745, while the maximum value for DOL^{IND} is 0.0167. The betas are mostly significant at the 1% level for the emerging market currencies. By contrast, the betas for DOL^{IND} are predominantly not significant.

Table 6. Regressions for DOL^{IND} and DOL^{EM}

	DOL^{IND}				DOL^{EM}			
	Intercept	DOL^{IND}	t-stat	Adj. R^2	Intercept	DOL^{EM}	t-stat	Adj. R^2
$n = 1, f = 1$	0.0066	–0.1932	–0.97	–0.0002	0.0065	–0.6260***	–3.423	0.0341
$n = 3, f = 1$	0.0049	–0.1011	–1.079	0.0005	0.0048	–0.3136***	–3.665	0.0393
$n = 5, f = 1$	0.0037	–0.1041	–1.468	0.0038	0.0037	–0.266***	–4.121	0.05
$n = 1, f = 3$	0.0123	–0.1157	–0.562	–0.0023	0.0123	–0.6331***	–3.357	0.0327
$n = 3, f = 3$	0.0045	0.0330	0.341	–0.0029	0.0044	–0.2202*	–2.459	0.0163
$n = 5, f = 3$	0.0036	0.02034	0.292	–0.003	0.0035	–0.1805**	–2.819	0.0223

	DOL^{IND}				DOL^{EM}			
$n = 1, f = 6$	0.01	–0.30	–1.641	0.0055	0.01	–0.6811***	–4.099	0.0494
$n = 3, f = 6$	0.0059	–0.2545*	–2.483	0.0167	0.0059	–0.4584***	–4.939	0.0715
$n = 5, f = 6$	0.0031	–0.1508*	–2.07	0.0107	0.0031	–0.2736***	–4.113	0.0498
$n = 1, f = 12$	0.0070	–0.3711°	–1.861	0.0080	0.0070	–0.8347***	–4.621	0.0628
$n = 3, f = 12$	0.0039	–0.1908°	–1.805	0.0074	0.0039	–0.4802***	–5.046	0.0745
$n = 5, f = 12$	0.0023	–0.1533*	–2.008	0.0099	0.0023	–0.3358***	–4.868	0.0695

Note. Table 6 compares the results of the linear regressions of DOL^{IND} and DOL^{EM}. The t-value is provided for β. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

The regressions show that an emerging market-specific risk factor has a higher impact on momentum returns than a risk factor derived from developed countries. Although the adjusted R^2 of both risk factors is rather low, the higher impact of DOL^{EM} can be observed. Further, the slope coefficient is negative for most of the values. Negative DOL values indicate a rising U.S. dollar, whereas positive ones indicate an appreciation of the foreign currencies against the U.S. dollar. The negative slope coefficient indicates that a momentum strategy is successful when the U.S. dollar rises.

We perform robustness tests on the above results by replacing the dollar risk factor with the euro and the British pound. For this, we calculate the average excess return of all emerging market currencies against the euro and refer to this risk factor as EUR^{EM}. The average excess return of all currencies from developed countries against the euro represents the EUR^{IND} risk factor. For the British pound, the procedure is identical and enables the calculation of the risk factors GBP^{EM} and GBP^{IND}. Finally, the regression from equation 5 is carried out with the euro and British pound risk factors. The regressions underline the robustness of the findings in Table 6: The returns of the momentum strategy can be better explained by emerging market-specific risk factors than by a risk factor based on currencies from developed countries. The robustness checks are presented in Appendix B.

Permutation tests

Our data covers 27 currencies, of which 17 are emerging market and ten are developed market currencies. In section 4 (Results), we calculated the performance of the momentum strategy for these two different currency groups. The results for the two groups are different (see Tables 3 and 4). From these Tables, the following Figure 1 shows the average monthly returns of the momentum strategy with different settings for n and f.

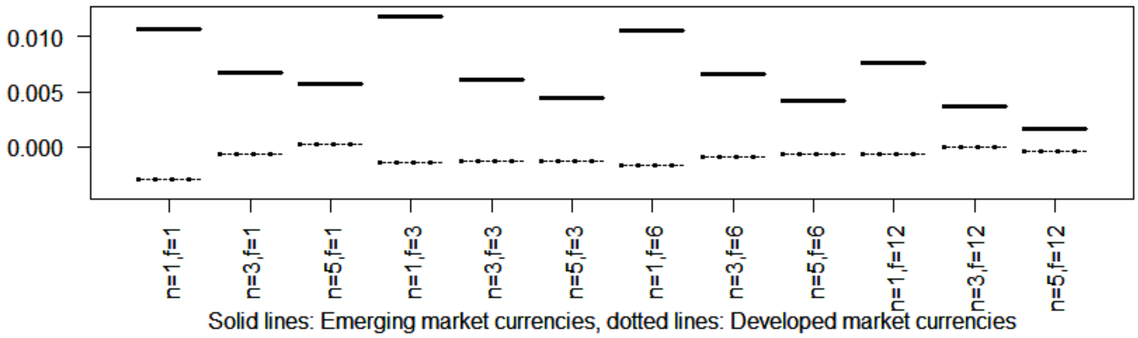

Figure 1. Average monthly returns of the momentum strategy for developed and emerging market currencies.

Note. Figure 1 compares the average monthly returns of the momentum strategy for developed and emerging market currencies with different settings for *n* and *f*.

The group of emerging market currencies dominates the group of developed market currencies. This leads to the assumption that the success of momentum strategies based on a broad bundle of both emerging and developed market currencies is driven by emerging markets. To verify this, we apply a permutation test (Efron & Tibshirani, 1997). In this test, we compare the momentum returns for two groups: One contains 17 currencies and the other ten. The null hypothesis is that the assignment of the 27 currencies to one of the two groups does not matter for the success of the momentum strategy.

The permutation test procedure is as follows: We first define two groups, A and B, and randomly assign 10 of the 27 currencies to group A and the remaining 17 currencies to group B. Second, we apply the momentum strategy for the two groups. We use f = 3 as the formation period and n = 3 as the number of currencies. As a result, we get the average monthly returns r_A and r_B for groups A and B. We run several robustness checks for other settings of n and f than three, leading to comparable results. In the last step, we calculate a test statistic θ, which is the difference between the returns of group B and group A:

$$\theta = r_B - r_A. \tag{6}$$

This procedure of the permutation test is repeated 5000 times. As a result, we obtain a distribution showing the differences between groups B and A's average monthly returns of the momentum strategy.

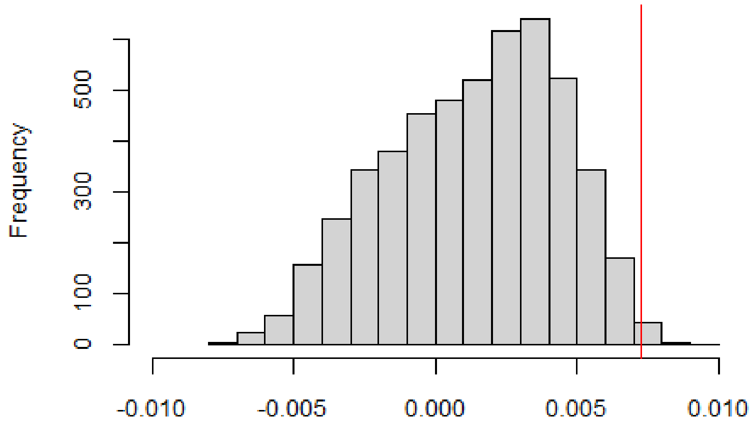

Figure 2. Differences in returns between group B and group A

Note. The histogram shows the differences in momentum returns between groups B and A for the 5000 permutations. Group A contains ten currencies and group B contains 17 currencies. The red line shows the difference between groups B and A for the case in which the 17 emerging market currencies are in group B.

We test the null hypothesis that a particular allocation of currencies to groups A and B does not affect the differences between the returns of the two groups. In our case, the particular allocation means that group A comprises the ten currencies of the developed countries, and group B comprises the 17 emerging market currencies. The null hypothesis is defined as

$$H_0 : \theta = 0. \tag{7}$$

Tables 3 and 4 in Section 4 (Results) show the values for the case in which all the developed country currencies are in group A and all the emerging market currencies are in group B:

$$r_A | cur_{IND} \in A = -0.001226 \triangleq r_B | cur_{EM} \in B = 0.006026 \tag{8}$$

where cur_{EM} is the vector of the 17 emerging market currencies and cur_{IND} is the vector of the ten developed country currencies. Group B outperforms group A, leading to

$$\hat{\theta} = 0.006026 - (-0.001226) = 0.007252. \tag{9}$$

This encourages us to assume that adopting a momentum strategy for emerging market currencies is more profitable than doing so for developed country currencies. The null hypothesis is rejected if this sample difference is at the edge of the distribution of the differences computed by the permutation test (Figure 2). H_0 provides a single distribution from which we can compute the probability that $\hat{\theta}^*$ is greater than $\hat{\theta}$. The star notation indicates the value for $r_B - r_A$ of a single permutation, while $\hat{\theta}$ denotes the particular case for $r_A | cur_{IND} \in A \triangleq r_B | cur_{EM} \in B$. The p-value is defined as the probability of observing a value greater than or equal to $\hat{\theta}$ under the assumption of the null hypothesis:

$$p - value = Prob_{H_0}\{\hat{\theta}^* \geq \hat{\theta}\}. \tag{10}$$

There are $\binom{10}{27}$ possible permutation replications $\hat{\theta}^*$ and thus about 8.4 million. For this reason, we use a Monte Carlo permutation test with 5000 simulations. The permutation p-value is set as the permutation probability that $\hat{\theta}^*$ is greater than or equal to $\hat{\theta}$:

$$p - value = \#\{\hat{\theta}^* \geq \hat{\theta}\} \,/\, 5000. \tag{11}$$

The result of the permutation test shows that in 23 of the 5000 cases, the differences between the average monthly returns of group B and group A are higher than or equal to 0.007252:

$$p - value = 23 \,/\, 5000 = 0.0046. \tag{12}$$

Hence, we reject the null hypothesis at the 1% level that the particular allocation of emerging market currencies to group B does not affect the difference in returns between groups B and A. The permutation test demonstrates the importance of emerging market currencies for momentum returns. The success of momentum strategies is thus related to emerging market currencies. As emerging market currencies predominantly generate momentum returns, part of the success of the momentum strategy can be derived from the risk associated with holding such currencies.

Limits of arbitrage

Transaction costs

The momentum strategies examined thus far were carried out on the basis of bid prices. However, as noted earlier, transaction costs play a relevant role, especially for emerging market currencies. Indeed, the bid-ask spread is considerably larger for the emerging market currencies than for the currencies of developed countries, as shown in Figure 3, which illustrates that the average spread for the 17 emerging market currencies is 0.20% (standard deviation = 0.14%) compared with 0.07% for the 10 developed countries (standard deviation = 0.02%).

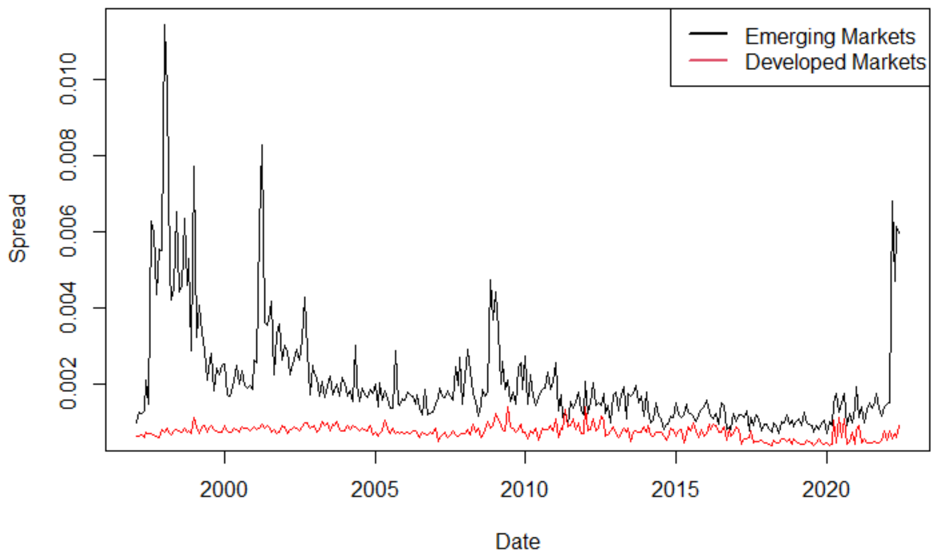

Figure 3. Bid-ask spreads for the emerging and developed markets

Note. This figure shows the average spread of the 17 emerging market currencies and 10 developed country currencies.

If emerging market currencies are indeed the driver of momentum returns, then the high bid-ask spread of these currencies should lower performance. Therefore, we examine the performance of the momentum strategy using bid-ask prices. Table 7 shows the results, with all 27 currencies included in the analysis. The results of the momentum strategies are around 0% for all the settings. No single setup achieves a positive performance at a significance level of 10%. The maximum Sharpe ratio is 0.24 for $n = 1$ and $f = 3$.

Table 7. Momentum strategy using bid-ask prices

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics ($\mu = 0$)	Standard error
$n = 1, f = 1$	0.001996	0.076558	0.8116	0.09	0.45535	0.004384
$n = 3, f = 1$	0.000685	0.034943	0.8118	0.07	0.34253	0.002001
$n = 5, f = 1$	–0.000487	0.026721	0.7231	–0.06	–0.31862	0.00153
$n = 1, f = 3$	0.005276	0.075278	1.6414	0.24	1.2239	0.00431
$n = 3, f = 3$	0.000762	0.037352	0.9904	0.07	0.3564	0.002139
$n = 5, f = 3$	–0.000388	0.025687	0.2991	–0.05	–0.26374	0.001471
$n = 1, f = 6$	0.004529	0.06772	1.9886	0.23	1.1681	0.003878
$n = 3, f = 6$	0.001241	0.037019	0.9949	0.12	0.58552	0.00212
$n = 5, f = 6$	0.000058	0.026845	0.3238	0.01	0.03782	0.001537
$n = 1, f = 12$	0.001774	0.077052	1.0552	0.08	0.40209	0.004412
$n = 3, f = 12$	–0.000601	0.038935	0.6017	–0.05	–0.26979	0.002229
$n = 5, f = 12$	–0.00166	0.0281	0.0321	–0.2	–1.0316	0.001609

Note. Table 7 reports the momentum returns for all 27 currencies and t-statistics for $\mu = 0$. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

Table 7 shows that transaction costs are thus critical to examine whether the returns under momentum strategies can be achieved in practice. Here, transaction costs are applied twice, which is why their effect is so high. On the one hand, n currencies are bought, and the related transaction costs are incurred, which hampers the performance of this long portfolio. On the other hand, n currencies are sold. The bid-ask spread must then also be paid for this portfolio, further lowering performance.

The bid-ask quotes are from Refinitiv Eikon and they are indicative only. Lyons (2001) states that traded spreads are lower than quoted spreads in practice. Gilmore and Hayashi (2011) argue that rolling forward contracts using foreign exchange swaps can significantly reduce transaction costs. We thus conduct an additional analysis for all the currencies in which we halve the bid-ask spread, following Menkhoff et al. (2012b), Barroso and Santa-Clara (2015), and Goyal and Saretto (2009). Mancini et al. (2013) also show that the effective trading costs in the spot market are less than half the bid-ask quotes. Table 8 shows the results of the momentum strategy when the bid-ask spread is halved.

Table 8. Momentum strategy with a halved bid-ask spread

	Monthly mean return	Standard deviation	Skewness	Sharpe ratio	t-statistics (μ = 0)	Standard error
n = 1, f = 1	0.004338	0.076593	1.1487	0.2	0.98918	0.004386
n = 3, f = 1	0.002796	0.03541	1.0972	0.27	1.3792	0.002028
n = 5, f = 1	0.001627	0.027046	0.8782	0.21	1.0505	0.001549
n = 1, f = 3	0.008833	0.075997	1.8523	0.4	2.0298*	0.004352
n = 3, f = 3	0.002616	0.037176	1.2009	0.24	1.2289	0.002129
n = 5, f = 3	0.001588	0.026154	0.5717	0.21	1.0606	0.001498
n = 1, f = 6	0.00732	0.068356	2.2598	0.37	1.8703°	0.003914
n = 3, f = 6	0.00361	0.038185	1.0755	0.33	1.6511°	0.002186
n = 5, f = 6	0.001591	0.027326	0.5551	0.2	1.0166	0.001565
n = 1, f = 12	0.004486	0.075891	1.2554	0.2	1.0324	0.004345
n = 3, f = 12	0.001712	0.039541	0.796	0.15	0.75606	0.002264
n = 5, f = 12	0.000366	0.028613	0.2999	0.04	0.22356	0.001638

Note. Table 8 shows the momentum returns for the 27 emerging market currencies when the bid-ask-spread is halved. The t-statistic is provided for H_0: μ = 0. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

Table 8 shows a positive excess return for all 12 settings. However, only one value reaches significance at the 5% level and the highest Sharpe ratio is 0.4. Transaction costs are thus a relevant factor when implementing a momentum strategy in practice. Our results align with the findings of Menkhoff et al. (2012b) and Barroso and Santa-Clara (2015), with the latter showing that momentum and reversal strategies do not outperform after accounting for transaction costs. However, transaction costs can be optimised in combination with other currency strategies such as carry.

Time-varying excess return

A key factor in putting a momentum strategy into practice is the stability of returns over time. Investors prefer strategies with stable returns unless the investment horizon is very long. However, risk aversion and risk premiums in currency markets are time-varying (Demirer et al., 2022) and countercyclical (Lustig et al., 2014), leading to time-varying returns under currency momentum. Hence, following Menkhoff et al. (2012b), we examine the momentum strategy for rolling investment periods with a maturity of 36 months. Figure 4 shows the rolling momentum strategy with a formation period of three months (f = 3) and three currencies (n = 3). The strategy is presented for all 27 currencies as well as for the 17 emerging market currencies and 10 developed country currencies separately.

Figure 4. 36-month rolling returns

Note. Figure 4 presents the returns for an investment horizon of 36 months. The values show the monthly mean returns at different entry points.

The rolling strategy delivers positive returns for the emerging markets and all 27 currencies until 2008. Since the global financial crisis, returns have been lacklustre and predominantly negative. Indeed, if the momentum strategy is based solely on the currencies of developed countries, the 36-month rolling return fluctuates around zero.

Conclusion

Our analyses demonstrate that the returns of momentum strategies are based on emerging market currencies. We find that the momentum strategy for all 27 currencies (10 belonging to developed countries and 17 to emerging markets) leads to significant outperformance, with Sharpe ratios of up to 0.54. If the momentum strategy is only applied to emerging market currencies, the returns and Sharpe ratios rise further. Moreover, risk factors such as DOL indicate that emerging market currencies rather than developed country currencies drive these momentum returns. The linear regressions show significant β values for DOL^{EM}. Furthermore, the adjusted R^2 of DOL^{EM} is higher than that of DOL^{IND}.

The permutation test underlines that emerging market currencies are the driving force for momentum. A momentum strategy executed solely with emerging market currencies outperforms all other combinations of currencies at the 1% significance level. However, transaction costs play an important role in collecting returns. If the quoted bid-ask spread is applied, momentum returns disappear. If only half the quoted bid-ask spread is traded, which seems to be typical in practice, a positive result is still observed for currency momentum, partly at the 5% significance level, depending on the formation period and number of currencies. Another aspect of using momentum in practice is the variance in returns over time. Until 2008, momentum strategies were consistently successful, whereas investment performance with a horizon of 36 months has been mixed since then.

The implications of this study hold special relevance for financial practitioners. When applying the momentum strategy to currencies, it is sufficient to focus only on emerging market currencies. This saves resources and avoids unnecessary transactions. However, transaction costs play a significant role. Therefore, portfolio managers should focus on optimising transaction costs, for example by using innovative financial products such as non-deliverable forwards or by combining momentum with other strategies.

This article also contributes to the field of academic research. Momentum has been the subject of numerous studies and has been found not only in currencies but also in other markets. Our findings shed light on the key elements of currency momentum. Emerging markets are the crucial source of momentum returns, not developed countries. Future research could take this as an opportunity to focus more decisively on emerging market currencies rather than a broad bundle of both developed and emerging market currencies.

The results of this study are limited by the selected data, models, and assumptions. We distinguish between developed and emerging markets using MSCI's definition and thus follow a specific allocation. Further, our data are based on end-of-month exchange rates. An important limit to arbitrage is the magnitude of transaction costs. An interesting direction for future research could therefore be to evaluate the difference between quoted and actual bid-ask spreads, with a focus on emerging markets.

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Appendix A

Average monthly momentum returns for the high, low, and high minus low (HML) portfolios with the US dollar and euro as base currencies

Table A1. Average monthly returns of the momentum strategy for all 27 currencies with the US dollar and euro as base currencies

	USD high	USD low	USD HML	EUR high	EUR low	EUR HML
n = 1, f = 1	0.00387	-0.002811	0.006681	0.00516°	-0.001831	0.006991
	(1.3202)	(-0.72729)	(1.5)	(1.8164)	(-0.49645)	(1.5698)
n = 3, f = 1	0.001465	-0.003442	0.004907*	0.002777°	-0.00222	0.004997*
	(0.84858)	(-1.6076)	(2.3485)	(1.7504)	(-1.1368)	(2.4024)
n = 5, f = 1	0.000992	-0.002749	0.003741*	0.002072	-0.001366	0.003438*
	(0.67139)	(-1.5439)	(2.3599)	(1.5829)	(-0.88724)	(2.1429)
n = 1, f = 3	0.005541°	-0.00685	0.012391**	0.007441**	-0.005405	0.012846**
	(1.9475)	(-1.6209)	(2.6998)	(2.7929)	(-1.3336)	(2.7726)
n = 3, f = 3	0.001391	-0.003078	0.00447*	0.00289°	-0.001659	0.004548*
	(0.75548)	(-1.4012)	(2.0686)	(1.7212)	(-0.8163)	(2.0828)
n = 5, f = 3	0.001827	-0.001737	0.003565*	0.003214*	-0.000933	0.004147**
	(1.198)	(-0.98689)	(2.299)	(2.3453)	(-0.58902)	(2.627)
n = 1, f = 6	0.001304	-0.008808*	0.010112*	0.002654	-0.0078*	0.010454*
	(0.52089)	(-2.3025)	(2.4788)	(1.088)	(-2.186)	(2.5781)
n = 3, f = 6	0.002193	-0.003786	0.005979**	0.003806*	-0.002548	0.006353**
	(1.269)	(-1.6126)	(2.5935)	(2.2618)	(-1.228)	(2.7389)
n = 5, f = 6	0.001161	-0.001963	0.003123°	0.00248°	-0.00095	0.003429*
	(0.77929)	(-1.0671)	(1.9122)	(1.7653)	(-0.61216)	(2.0741)
n = 1, f = 12	0.003284	-0.003915	0.007199	0.004354°	-0.001844	0.006199
	(1.276)	(-0.98115)	(1.6122)	(1.6565)	(-0.48165)	(1.3829)
n = 3, f = 12	0.000949	-0.003076	0.004025°	0.002183	-0.001728	0.003911
	(0.55477)	(-1.3041)	(1.7002)	(1.3444)	(-0.79528)	(1.6279)
n = 5, f = 12	0.000903	-0.00149	0.002392	0.002301°	-0.00018	0.002481
	(0.61095)	(-0.79095)	(1.3977)	(1.711)	(-0.1095)	(1.4269)

Note. Table A1 presents the average monthly returns of the momentum strategy. The analysis includes all 27 currencies. The results are shown for the high, low, and high minus low (HML) portfolios. Numbers in brackets show the t-statistics for $\mu = 0$. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively. The formation period is indicated by *f*, and the number of currencies in the momentum portfolio by *n*.

Table A2. Average monthly returns of the momentum strategy for ten developed country currencies with the US dollar and euro as base currencies

	USD high	USD low	USD HML	EUR high	EUR low	EUR HML
n = 1, f = 1	-0.003561*	-0.000683	–0.002878	-0.001832	0.000703	-0.002535
	(-2.1227)	(-0.40653)	(-1.4798)	(-1.2776)	(0.45772)	(-1.3427)
n = 3, f = 1	-0.001025	-0.000449	–0.000576	0.000381	0.000595	-0.000214
	(-0.73203)	(-0.30158)	(-0.46917)	(0.3447)	(0.5519)	(-0.16211)
n = 5, f = 1	-0.000255	-0.000508	0.000252	0.00094	0.000872	0.000068
	(-0.19395)	(-0.3642)	(0.27834)	(0.99328)	(0.85781)	(0.072929)
n = 1, f = 3	-0.000271	0.001078	–0.001349	0.000958	0.001772	-0.000814
	(-0.16162)	(0.61311)	(-0.66936)	(0.64088)	(1.1749)	(-0.41287)
n = 3, f = 3	-0.001218	8.57e-06	–0.001226	0.00028	0.001106	-0.000825
	(-0.84439)	(0.005897)	(-1.0079)	(0.24192)	(0.99583)	(-0.63381)
n = 5, f = 3	-0.001033	0.000195	–0.001227	0.000556	0.001314	-0.000758
	(-0.77144)	(0.14112)	(-1.376)	(0.5709)	(1.3578)	(-0.82316)
n = 1, f = 6	-0.001772	-0.000088	–0.001685	0.000414	0.001139	-0.000725
	(-1.0231)	(-0.049905)	(-0.85148)	(0.25691)	(0.78581)	(-0.35995)

	USD high	USD low	USD HML	EUR high	EUR low	EUR HML
n = 3, f = 6	-0.000714	0.000191	–0.000904	0.000845	0.000678	0.000167
	(-0.50972)	(0.12865)	(-0.74947)	(0.78395)	(0.62578)	(0.13341)
n = 5, f = 6	-0.000691	-0.000074	–0.000617	0.000875	0.000967	-0.000092
	(-0.52663)	(-0.053588)	(-0.72434)	(0.88874)	(1.0156)	(-0.099248)
n = 1, f = 12	-0.001478	-0.00085	–0.000628	0.000575	0.000382	0.000193
	(-0.9436)	(-0.47491)	(-0.33577)	(0.38721)	(0.25119)	(0.099304)
n = 3, f = 12	-0.000158	-0.000113	–0.000045	0.001064	0.000906	0.000158
	(-0.11612)	(-0.074157)	(-0.034188)	(0.94524)	(0.79099)	(0.11691)
n = 5, f = 12	-0.000579	-0.000212	–0.000367	0.000701	0.001055	-0.000354
	(-0.44159)	(-0.15151)	(-0.41165)	(0.71711)	(1.0604)	(-0.3559)

Note. Table A2 shows the average monthly returns of the momentum strategy. The analysis comprises ten developed country currencies. The results are given for the high, low, and high minus low (HML) portfolios. Numbers in brackets show the t-statistics for $\mu = 0$. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively. The formation period is indicated by f, and the number of currencies in the momentum portfolio by n.

Table A3. Average monthly returns of the momentum strategy for 17 emerging market currencies with the US dollar and euro as base currencies

	USD high	USD low	USD HML	EUR high	EUR low	EUR HML
n = 1, f = 1	0.005145°	-0.005487	0.010632*	0.006328*	-0.004304	0.010632*
	(1.7465)	(-1.3787)	(2.3891)	(2.2167)	(-1.1383	(2.3891)
n = 3, f = 1	0.002529	-0.004132°	0.006662**	0.003712*	-0.002949	0.006662**
	(1.4373)	(-1.8493)	(3.0938)	(2.3221)	(-1.4302)	(3.0938)
n = 5, f = 1	0.002725°	-0.00301	0.005735***	0.003908**	-0.001826	0.005735***
	(1.7928)	(-1.6438)	(3.6208)	(2.7849)	(-1.1068)	(3.6208)
n = 1, f = 3	0.005046°	-0.006768	0.011814*	0.00623*	-0.005584	0.011814*
	(1.7445)	(-1.5996)	(2.5051)	(2.2749)	(-1.3773)	(2.5051)
n = 3, f = 3	0.002447	-0.003579	0.006026**	0.003631*	-0.002396	0.006026**
	(1.3105)	(-1.5706)	(2.7106)	(2.1331)	(-1.1058)	(2.7106)
n = 5, f = 3	0.002343	-0.002107	0.00445**	0.003527*	-0.000924	0.00445**
	(1.5196)	(-1.1803)	(2.7776)	(2.5008)	(-0.54116)	(2.7776)
n = 1, f = 6	0.001689	-0.008784*	0.010473*	0.002872	-0.007601*	0.010473*
	(0.66141)	(-2.2715)	(2.5455)	(1.148)	(-2.1132)	(2.5455)
n = 3, f = 6	0.002582	-0.004056°	0.006638**	0.003765*	-0.002872	0.006638**
	(1.5408)	(-1.7182)	(2.9746)	(2.248)	(-1.3549)	(2.9746)
n = 5, f = 6	0.001819	-0.00241	0.004229**	0.003003*	-0.001226	0.004229**
	(1.2041)	(-1.2806)	(2.6235)	(2.0731)	(-0.72187)	(2.6235)
n = 1, f = 12	0.00346	-0.004122	0.007582°	0.004643°	-0.002939	0.007582°
	(1.2958)	(-1.0202)	(1.6981)	(1.7492)	(-0.76155)	(1.6981)
n = 3, f = 12	0.001288	-0.002363	0.003651	0.002472	-0.001179	0.003651
	(0.72516)	(-0.98854)	(1.5578)	(1.4556)	(-0.53059)	(1.5578)
n = 5, f = 12	0.000705	-0.00095	0.0016551	0.001889	0.000234	0.0016551
	(0.45144)	(-0.5021)	(1.0729)	(1.3044)	(0.13727	(1.0729)

Note. Table A3 reports the average monthly returns of the momentum strategy. The analysis includes 17 emerging market currencies. The results are presented for the high, low, and high minus low (HML) portfolios. Numbers in brackets show the t-statistics for $\mu = 0$. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively. The formation period is indicated by f, and the number of currencies in the momentum portfolio by n. The results for USD HML and EUR HML are identical by construction. USD HML refers to selling the US dollar and buying n currencies (high portfolio). At the same time, the US dollar is bought, and n currencies are sold (low portfolio). By construction, the long and short positions in the US dollar balance each other out. The principle is identical for EUR HML, i.e. the long position in n currencies (short position in the euro) and the short position in n currencies (long position in the euro) levels out the euro position.

Appendix B

Regressions of the monthly momentum returns on risk factors based on the euro and British pound

Table B1. Linear regressions of the monthly momentum returns MOM_t on euro-based risk factors EUR^{IND} and EUR^{EM}: $MOM_t = a + \beta \cdot EUR_t^{IND} + \varepsilon_t$ and $MOM_t = a + \beta \cdot EUR_t^{EM} + \varepsilon_t$

	EUR^{IND}				EUR^{EM}			
	Intercept	EUR^{IND}	t-stat	Adj. R^2	Intercept	EUR^{EM}	t-stat	Adj. R^2
n = 1, f = 1	0.0065	0.164	0.547	–0.0023	0.0072	–0.4872*	–2.436	0.016
n = 3, f = 1	0.0049	0.2279	0.162	–0.0032	0.0052	–0.2648**	–2.832	0.0226
n = 5, f = 1	0.0037	0.0381	0.357	–0.0029	0.0039	–0.2002**	–2.821	0.0224
n = 1, f = 3	0.0123	0.0932	0.302	–0.003	0.013	–0.5978**	–2.913	0.024
n = 3, f = 3	0.0043	0.1576	1.085	0.0006	0.0047	–0.2247*	–2.314	0.141
n = 5, f = 3	0.0035	0.1069	1.025	0.0002	0.0037	–0.1872**	–2.696	0.0202
n = 1, f = 6	0.0096	0.5492*	2.013	0.0099	0.0104	–0.2971	–1.613	0.0052
n = 3, f = 6	0.0058	0.2157	1.394	0.0031	0.0062	–0.2145*	–2.067	0.011
n = 5, f = 6	0.003	0.1957°	1.788	0.0072	0.0032	–0.1017	–1.378	0.0029
n = 1, f = 12	0.0068	0.4083	1.362	0.0028	0.0077	–0.4694*	–2.34	0.0145
n = 3, f = 12	0.004	0.0644	0.404	–0.0028	0.0044	–0.3615***	–3.433	0.0343
n = 5, f = 12	0.0024	0.0434	0.376	–0.0028	0.0026	–0.2352**	–3.078	0.027

Note. Table B1 compares the results of the linear regressions of EUR^{IND} and EUR^{EM}. The t-value is provided for β. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.

Table B2. Linear regressions of the monthly momentum returns MOM_t on British pound-based risk factors GBP^{IND} and GBP^{EM}: $MOM_t = a + \beta \cdot GBP_t^{IND} + \varepsilon_t$ and $MOM_t = a + \beta \cdot GBP_t^{EM} + \varepsilon_t$

	GBP^{IND}				GBP^{EM}			
	Intercept	GBP^{IND}	t-stat	Adj. R^2	Intercept	GBP^{EM}	t-stat	Adj. R^2
n = 1, f = 1	0.0067	–0.1692	–0.75	–0.0014	0.0069	–0.5219**	–2.984	0.0254
n = 3, f = 1	0.0049	–0.0777	–0.735	–0.0015	0.0050	–0.2548**	–3.109	0.0277
n = 5, f = 1	0.0038	–0.0426	–0.531	–0.0024	0.0038	–0.1901**	–3.056	0.0267
n = 1, f = 3	0.0124	0.0251	0.108	–0.0033	0.0126	–0.4766**	–2.637	0.0192
n = 3, f = 3	0.0044	0.1266	1.159	0.0011	0.0045	–0.152°	–1.775	0.007
n = 5, f = 3	0.0035	0.1018	1.3	0.0023	0.0036	–0.121*	–1.971	0.0094
n = 1, f = 6	0.0101	–0.0275	–0.133	–0.0032	0.0103	–0.4185**	–2.604	0.0187
n = 3, f = 6	0.006	0.0676	0.58	–0.0022	0.0061	–0.1957*	–2.146	0.0117
n = 5, f = 6	0.0031	0.0218	0.263	–0.0031	0.0032	–0.1282*	–1.983	0.0095
n = 1, f = 12	0.00724	–0.1299	–0.575	–0.0022	0.0075	–0.5642**	–3.226	0.03
n = 3, f = 12	0.0041	–0.152	–1.271	0.002	0.0042	–0.3844***	–4.192	0.0517
n = 5, f = 12	0.0024	–0.1121	–1.296	0.0022	0.0025	–0.2579***	–3.875	0.0044

Note. Table B2 compares the results of the linear regressions of GBP^{ND} and GBP^{EM}. The t-value is provided for β. Numbers annotated with °, *, **, and *** are significant at the levels of 10%, 5%, 1%, and 0.1%, respectively.