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Dissecting currency momentum☆

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ABSTRACT

This paper shows the cross-sectional and time series momentum in currencies, which cannot be explained by carry and dollar factors, summarize the autocorrelation of these factors. These momentum strategies long currency factors following positive factor returns and short them following losses. Carry and dollar factors are strongly autocorrelated and only earn significantly positive excess returns following positive factor returns. By contrast, idiosyncratic currency returns contain little momentum. Consequently, factor momentum not only outperforms the cross-sectional and time series momentum but also explains them. Limits to arbitrage and time-varying risk premium help explain factor momentum.

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1. Introduction

Past currency returns contain information predictive of future currency returns. In the cross section, past winner currencies earn higher returns than loser currencies, as summarized by Burnside et al. (2011b) and Menkhoff et al. (2012b). This phenomenon is known as "momentum." In the time series, the individual currency's own past returns also positively and strongly predict its future returns (Moskowitz et al., 2012), known as "time series momentum." This predictability violates the weak form of market efficiency and challenges the standard risk-based view of asset prices. In particular, currency momentum and time series momentum exhibit different properties from existing currency strategies, and the excess returns cannot be explained by the factors, such as the carry and dollar. This paper documents that the cross-sectional and time series momentum originate from the momentum in these factors after all.

To analyze the relation between momentum strategies and factors, I first decompose currency returns to systematic returns explained by the carry and dollar factors and unexplained idiosyncratic returns (Verdelhan, 2018). The momentum strategy sorting on past systematic returns generates significant and large excess returns, but sorting on idiosyncratic returns generates little spreads. Similarly, only systematic returns contain momentum in the time series. In short, the momentum returns and factor returns are closely related, despite the low unconditional correlation between them.

Intuitively, currency factors underlie the currency momentum strategies. Following positive carry returns, high-interest-rate currencies are more likely to be sorted into

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the long leg of cross-sectional and time series momentum strategies, and the strategies long the carry factor. Analogously, following negative carry returns, the momentum strategies short the carry factor. Similar predictions hold for the dollar factor. The predictions are strongly supported in the data for both factors and various momentum strategies. For example, the correlation between the momentum and carry return is 0.36 following three months of positive carry returns and −0.62 following three months of losses. The corresponding correlations with the dollar factor are 0.53 and −0.43, respectively. The results suggest currency momentum and time series momentum stem from the momentum embedded in factors.

Next, the analysis formally tests the momentum in currency factors. Regression analysis shows that past currency factor returns strongly predict future factor returns. One percent increase in the past 3-month average carry return predicts an average increase of 0.2% in the carry factor next month. The corresponding coefficient is 0.21% for the dollar factor. This result is impressive, because currency returns are stubbornly difficult to predict. Alternatively, the analysis can be conducted conditioning on the sign of past factor returns. The carry and dollar factors only earn positively significant returns following positive factor realizations and but earn negative or insignificant returns following losses. These predictive results cannot be summarized by existing currency predictors, such as the average forward discount, industrial production growth and output gap.

Consider a time series momentum strategy on factors building on the predictability results. The investor longs the individual factor when the past corresponding factor return is positive and shorts when its past return is negative. The strategy with the 3-month portfolio formation period generates Sharpe ratios as high as 0.85 for the carry and 0.55 for the dollar, ratios that are higher than those of the unconditional carry and dollar. The carry and dollar factors cannot explain the strategy returns. Furthermore, an equal-weighted factor momentum strategy with both factors generates Sharpe ratios of 0.84, 0.94 and 0.69 for 1, 3, and 12-month portfolio formation periods, higher than the Sharpe ratios of the momentum and time series momentum strategies. I refer to this strategy as factor momentum.

Next, I compare factor momentum to momentum and time series momentum strategies. Factor momentum spans both the cross-sectional and time series momentum and the momentum alphas are no longer significant at any conventional level. In particular, factor momentum can explain most time series momentum currency by currency. However, the momentum strategy returns cannot span factor momentum and the factor momentum alphas are large and significant. In sum, both momentum and time series momentum originate from factor momentum and only summarize the autocorrelation in currency factors.

Broadly, factor momentum could reflect mispricing or time-varying risk premium. Empirically, carry momentum is related to currency characteristics and is stronger from less tradable currencies, such as those of emerging markets and countries with less capital account openness as well as more volatile currencies. In contrast, dollar momentum exhibits little correlation with currency characteristics. Overall, limits to arbitrage help partially account for factor momentum (Shleifer and Vishny, 1997).

I next study a model with two global shocks, which govern the carry-sorted cross section and the average foreign currency return, as well as country-specific shocks. The carry and dollar factor premia capture the expected return premium associated with the two global shocks, respectively. In the model, the risk exposure of currency factors to the global shocks varies with the realized volatility shocks, generating time-varying risk premium in the form of autocorrelation. The calibration shows the model can further generate factor momentum quantitatively as in the data.

The remainder of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 explains the data and benchmark momentum strategies. Section 4 decomposes the cross-sectional and time series momentum strategies. Section 5 studies factor momentum and explains the momentum strategies. Section 6 examines the sources of factor momentum and presents the interpretive model. Finally, Section 7 concludes.

2. Related literature

This paper builds on the voluminous literature on momentum. For example, Okunev and White (2003), Burnside et al. (2011b), and Menkhoff et al. (2012b) study various forms of currency momentum. Currency factors cannot explain the momentum return. This disconnect poses challenges to the factor-based view of currency returns (Lustig and Verdelhan, 2011; Lustig et al., 2011; Menkhoff et al., 2012a; Verdelhan, 2018). Furthermore, other existing risk factors, such as the liquidity factor (Brunnermeier and Pedersen, 2009) or the three Fama and French equity factors (Fama and French, 1992), cannot explain the momentum return. Filippou et al. (2018) propose that global political risk affects the momentum profitability. Menkhoff et al. (2012b) show currency momentum returns are related to limits to arbitrage. However, these explanations cannot jointly reconcile currency momentum with other currency factors. This paper shows currency momentum originates from the momentum in currency factors.

Momentum is a prominent anomaly in various markets. Moskowitz et al. (2012) document the profitability of time series momentum in various markets. For the cross-section momentum, a large literature studies the momentum strategies in equity markets, starting with Jegadeesh and Titman (1993, 2001). Asness et al. (2013) provide further evidence across various asset classes. Currency momentum is similar to momentum in many markets but differs in a few important ways. For example, the trading strategy conditioning on the past one month return, generates reversals in equity but finds strong momentum in the currency markets. Furthermore, equity momentum is negatively skewed and suffers from crashes (Daniel and Moskowitz, 2016), but currency momentum is slightly positively skewed with no crashes and actually gained profits during the global financial crisis (Burnside et al., 2011b).

Various explanations have been proposed for equity and bond momentum. Fama and French (1996) show equity momentum returns are difficult to rationalize using covariance risk with standard factors. In contrast, equity momentum is shown to be linked to firm-specific characteristics. Hong et al. (2000) and Avramov et al. (2007) uncover that equity momentum returns are related to small firm sizes and lower credit ratings. Momentum strategies do not work for investment-grade bonds (Gebhardt et al., 2005; Asness et al., 2013), but only generate positive excess returns for non-investment-grade corporate bonds (Jostova et al., 2013). Chui et al. (2010) and Hong et al. (2000) propose explanations based on behavioural or cognitive biases, and Korajczyk and Sadka (2004) study the linkage with limits to arbitrage, such as transaction costs.

In related work, Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) uncover autocorrelation in a number of equity anomaly returns. Ehsani and Linnainmaa (2019) and Kelly et al. (2021) propose that accounting for time-varying factor returns can explain the momentum in equities. Because momentum is a common phenomenon across assets, the momentum anomaly can have a common cause. This paper highlights that only systematic currency returns contain momentum. Furthermore, this paper documents factor momentum in currencies and shows it not only outperforms but also explains momentum, pushing toward a unified explanation of momentum across markets. Factor momentum also outperforms and explains time series momentum in currencies, uncovering a common cause of various momentum strategies.

The intriguing question is what drives factor momentum across markets. Ehsani and Linnainmaa (2019) suggest that if sentiment trading generates equity factors (Kozak et al., 2018), persistent sentiment trading can generate theoretically equity factor momentum. This paper contributes to the literature by proposing a model that generates factor momentum through time-varying risk premium.

Finally, this paper documents a new form of predictability for carry and dollar factors, adding to the literature on currency predictability. The evidence on currency predictability is scarce, as repeatedly documented by the large literature (Meese and Rogoff, 1983; Engel et al., 2007; Rossi, 2013). Among the few predictors, Lustig et al. (2014) show average forward discount and U.S. industrial production growth rates have strong forecasting power for dollar returns.

3. Data and preliminary analysis

This section describes the data, currency factors, currency momentum, and time series momentum.

3.1. Data

The data for spot exchange rates and one-month forward exchange rates cover the sample period from March 1976 to November 2020 and are obtained from Barclays Bank International (BBI) and Reuters via Datastream. I use Reuters data quoted against the British Pound to extend the sample back to 1976 following Burnside et al. (2011a) and Menkhoff et al. (2012b). Both the spot and the forward rates are determined at the end-of-month date (last trading day in a given month).

The total sample consists of a comprehensive list of developed and emerging-market currencies, including Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, the euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the U.K. Individual European countries are excluded from the sample because the inception of the euro occurred in January 1999. Note that the actual sample period of the individual currencies varies, depending on the data availability of the spot and forward rates. The sample covers 48 currencies and contains 16 currencies at the beginning of the sample.

I calculate monthly excess returns to a U.S. investor for holding foreign currency i as

$$rx_{i,t+1} := r_{it} - r_t - \Delta s_{i,t+1} \approx f_{it} - s_{i,t+1}, \tag{1}$$

where rx denotes the excess return of currency i, r_i and r are the one-month interest rates in country i and in the U.S., and s and f are the (log) spot and one-month forward rates, respectively. Exchange rates are denoted as their foreign currency unit per U.S. dollar. If covered interest rate parity (CIP) holds, interest-rate differentials $i_t^k - i_k$ equal forward discounts defined as $fd_t = f_t^k - s_t^k$.[1]

3.2. Currency factors

My analysis focuses on two benchmark currency factors, the carry and dollar. Lustig et al. (2011) and Verdelhan (2018) show that these two factors explain most variations in the currency cross section. Because the currency sample has a limited cross section, I use the entire cross section of currencies to minimize the impact of outliers following Asness et al. (2013) and Koijen et al. (2018). The dollar factor is calculated as the average excess return of all foreign currencies against the U.S. dollar,

$$\text{dollar}_t = \sum_i rx_{it}/N, \tag{2}$$

where N is the number of foreign currencies at time t.

I construct the carry factor by weighting currencies in proportion to their cross-sectional rank based on the forward discount minus the cross-sectional average rank of the forward discount. Specifically, the weight on currency i at time t is

$$w_{it} = c_t(\text{rank}(fd_{it}) - \sum_i \text{rank}(fd_{it})/N), \tag{3}$$

and the weights across all currencies sum to zero, representing a dollar-neutral long-short portfolio. The scaling

[1] Akram et al. (2008) show that prior to the global financial crisis, CIP holds fairly well even during short time intervals. Du et al. (2018) find larger deviations from CIP after the crisis.

Table 1
Systematic and idiosyncratic momentum.
This table presents the monthly raw returns and alphas of currency momentum (MOM) and time series momentum (TSM). The alphas are obtained by regressing the raw returns on the carry and dollar factors. All returns and alphas are in percentage points. The sample period is April 1976 to November 2020.

	Panel A: Momentum raw return					
	Portfolio 1	2	3	4	5	P5-P1
$h = 1$	-0.27***	-0.20*	-0.06	-0.04	0.15	0.42***
	(-2.61)	(-1.90)	(-0.53)	(-0.36)	(1.25)	(3.86)
SR	-0.39	-0.28	-0.08	-0.05	0.18	0.58
$h = 3$	-0.35***	-0.15	-0.11	0.03	0.15	0.50***
	(-3.35)	(-1.38)	(-0.99)	(0.25)	(1.22)	(4.38)
SR	-0.50	-0.20	-0.14	0.04	0.18	0.65
$h = 12$	-0.28***	-0.14	-0.08	-0.03	0.12	0.40***
	(-2.73)	(-1.35)	(-0.76)	(-0.31)	(0.98)	(3.43)
SR	-0.41	-0.20	-0.11	-0.05	0.15	0.51
	Panel B: Momentum alpha					
$h = 1$	-0.17***	-0.14***	0.01	0.03	0.33***	0.51***
	(-2.99)	(-3.26)	(0.19)	(0.74)	(4.71)	(4.51)
R^2	0.71	0.85	0.87	0.84	0.69	0.02
$h = 3$	-0.21***	-0.08**	-0.08*	0.08*	0.33***	0.54***
	(-3.70)	(-2.18)	(-1.95)	(1.83)	(4.39)	(4.59)
R^2	0.73	0.87	0.88	0.85	0.64	0.01
$h = 12$	-0.14**	-0.08*	-0.06	0.00	0.33***	0.47***
	(-2.46)	(-1.91)	(-1.48)	(0.05)	(4.34)	(3.92)
R^2	0.71	0.86	0.89	0.85	0.64	0.01
Observations	537	537	537	537	537	537
	Panel C: Time series momentum					
	Raw return			Alpha		
	$h = 1$	$h = 3$	$h = 12$	$h = 1$	$h = 3$	$h = 12$
Constant	0.33***	0.35***	0.25***	0.39***	0.38***	0.28***
	(4.37)	(4.62)	(3.20)	(4.95)	(4.79)	(3.39)
R^2				0.01	0.00	0.00
SR	0.65	0.69	0.48			
Observations	537	537	537	537	537	537

number c_t is included such at the overall portfolio is scaled to one dollar long and one dollar short. The scaling merely represents leverage and does not change the profitability of the currencies. The carry factor is then the return on the portfolio,

$$\text{carry}_t = \sum_i w_{it} rx_{it}. \tag{4}$$

3.3. Currency momentum

I define momentum in terms of past returns and use formation periods of 1, 3, and 12 months to be comprehensive. Assume the investor is based in the U.S. Denote past h-month excess returns ending at time t of currency i as $rx^i_{t-h,t}$, $h = 1, 3, 12$. At the end of each month t, currencies are sorted into one of the five portfolios based on $rx^i_{t-h,t}$. Currencies with the lowest one-fifth of past currency returns in a given month $rx^i_{t-h,t}$ are allocated to the first portfolio as past losers. The next one-fifth is allocated to the second portfolio, and so on. The top 20% of all currencies with the highest past currency returns are allocated to the fifth portfolio. The procedure yields a time series for each of the five currency portfolios' excess returns and hence testing portfolios for the cross-sectional momentum. The excess returns are denoted in U.S. dollars.

I construct currency momentum (MOM) from the return of the long-short strategy, which longs the past winner portfolio (portfolio 5) and shorts the past loser portfolio (portfolio 1). I refer to this long-short portfolio return as the momentum return MOM_h, where h denotes the formation period. Although the spot and forward data are denominated in U.S. dollars, the momentum spread portfolios are dollar neutral as the dollar component nets out when taking the difference between the portfolios. The choice of base currency or investor base is also irrelevant for the momentum spread, as long as the base currency does not enter the winner or loser portfolios.

Panel A of Table 1 presents the portfolio returns across various portfolio-formation periods. For example, the returns increase monotonically from −0.35% for portfolio 1 to 0.15% for portfolio 5 with the 3-month momentum. The spread is 50 bps and highly significant. For the 1- and 12-month strategy, the spreads are 42 bps and 40 bps and again highly significant. The upper panel of Fig. 1 plots the three-year moving average of the momentum returns. The three returns exhibit substantial comovement over the sample. For example, all three strategies show strong performance in the early 2000s and underperform in the past five years.

Panel B of Table 1 further examines whether carry and dollar factors can explain the momentum strategy. I find they can explain 80% of variation in individual momentum-sorted portfolio returns, but cannot explain the long-short return variation. The alpha of portfolio 1 for the 3-month momentum is significantly negative at - 0.21% and that

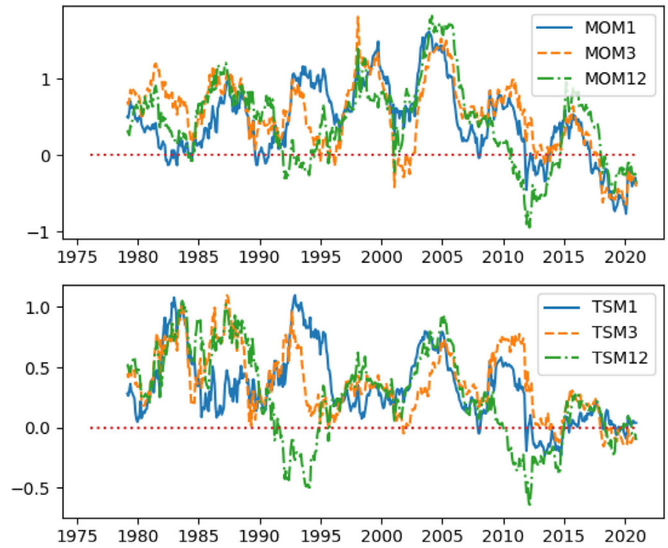

Fig. 1. Currency momentum and time series momentum. This figure plots the 3-year moving-average return of momentum (MOM) and time series momentum (TSM) with portfolio formation periods of 1 month (solid line), 3 months (dashed line), and 12 months (dash-dot line) in percentage points. The sample period is April 1976 to November 2020.

of portfolio 5 is significantly positive at 0.33%. The alphas increase monotonically from portfolios 1 to 5. The monthly alpha spread between these portfolios is 54 bps, higher than the raw returns and highly significant. The R^2 is merely 1%. The 1-month and 12-month momentum earn significant alphas of 51 bps and 47 bps, respectively. In sum, the carry and dollar factors are unable to explain the cross-section of the momentum-sorted portfolio returns.

3.4. Time series momentum

Moskowitz et al. (2012) document autocorrelation in individual asset returns and further propose a time series-momentum strategy exploiting the autocorrelation. The strategy can be constructed for each individual asset or using all assets jointly. First, for each currency at time t, I long 1 U.S. dollar of the currency if the currency return over the past h months is positive and short 1 U.S. dollar of the currency if negative. Because all currencies are denominated in U.S. dollars, time series momentum is also denominated in the dollar. Fig. 2 presents average excess returns by currency. The average return is significantly positive for 17 out of 45 currencies at the 5% level for the 1-month time series and 20 currencies for both the 3-month and 12-month strategies.

Next, I construct time series momentum (TSM) using all currencies jointly. I equal weight the individual-currency TSM following the critique of Kim et al. (2016) and Huang et al. (2020).[2] The strategy longs the currency if the excess return over the past h months is positive and shorts the currency if negative. The portfolio weight of a currency equals $1/N$ if the past return is positive and equals $-1/N$ if negative, where N is the number of currencies at time t. The return is denoted as TSM_h, where h denotes the formation period as defined above. The scaling of the positions is merely leverage and does not profitably affect the strategy.

Panel B of Table 1 presents the average monthly TSM returns. The 1-, 3-, and 12-month time series momentum strategies earn 33 bps, 35 bps and 25 bps, respectively, on average. All excess returns are significant at 1% level. The Sharpe ratios are 0.65, 0.69, and 0.48. Similar to momentum, the carry and dollar factors are unable to explain the TSM excess returns. The R^2 is almost zero and the alphas are 39, 38, and 28 bps, higher than the raw returns. The lower panel of Fig. 1 plots the 3-year moving average of the three strategy returns. The TSM returns comove strongly and comove with momentum. For example, time series momentum experiences strong returns in the 2000s, but lower returns in last few years, similar to momentum.

4. Understanding momentum and time series momentum

The preliminary analysis shows that although currency factors can explain much of the variation of currency portfolios and currency pairs, they cannot explain momentum or time series momentum. This section further examines the relation between the strategies and factors.

4.1. Momentum in systematic and idiosyncratic returns

Because the currencies with high past returns can have higher past systematic returns, idiosyncratic returns, or both, the strong performance of MOM and TSM can come from the predictability of systematic returns, idiosyncratic returns, or both. Formally, the currency return can be decomposed into systematic returns driven by currency

[2] Kim et al. (2016) and Huang et al. (2020) discuss the role of volatility scaling and suggest volatility scaling is a source of potential predictability different from TSM and can overstate TSM. Less volatile currencies tend to be pegged and have dynamics from the free-floating ones. The Internet Appendix studies the volatility scaled TSM as in Moskowitz et al. (2012) as finds similar evidence.

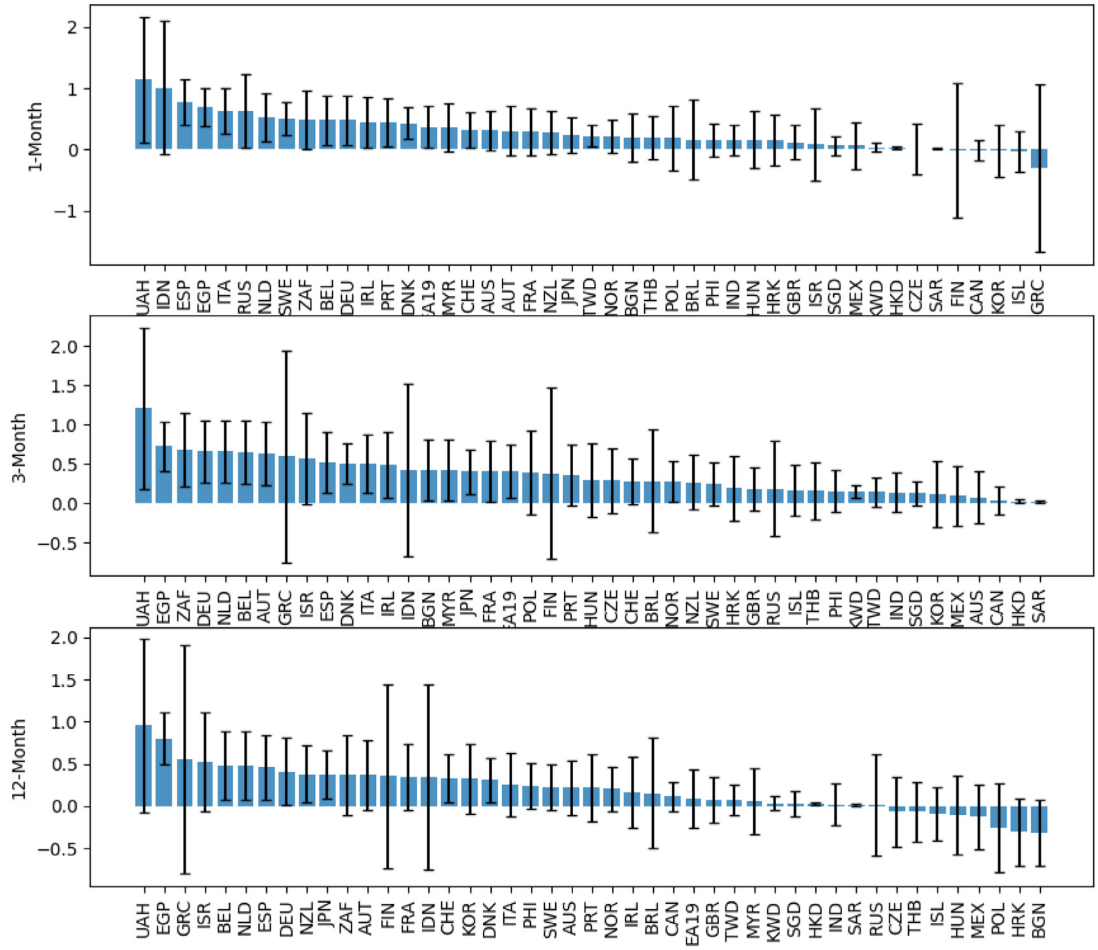

Fig. 2. Time series momentum. This figure plots the average monthly returns of currency time series momentum based on the past 1-month, 3-month and 12-month returns. All returns are in percentage points. The bands denote the 95% confidence interval. The sample period is 1976:04 to 2020:11.

factors or idiosyncratic returns unexplained by factors:

$$rx_{it} = \underbrace{b_t^{carry} carry_t + b_t^{dollar} dollar_t}_{\text{systematic}} + \underbrace{a_i + e_{it}}_{\text{idiosyncratic}} . \quad (5)$$

I estimate the betas each month using the daily data. The monthly regression allows for time-varying loadings on the currency factors and avoids the look-ahead bias in the estimation. Then, the systematic return is $b_t^{carry} carry_t + b_t^{dollar} dollar_t$, and the idiosyncratic return is difference between the currency return and systematic return. Alternative estimation windows varying from 3 months to 12 months generate similar results and are reported in the Internet Appendix.

4.1.1. Momentum

First, I consider the cross-sectional momentum. The benchmark currency-momentum portfolios are formed by sorting on the past currency returns. For the decomposition, I sort currencies by the past 1-, 3-, and 12-month systematic or idiosyncratic returns into five portfolios to form systematic or idiosyncratic momentum strategies. Panel A of Table 2 reports portfolio returns sorted on systematic past returns. For the 3-month strategy, the average monthly portfolio return increases monotonically from portfolio 1 (−0.35%) to portfolio 5 (0.12%). The high-minus-low return spread is 48 bps, which is significantly positive at the 1% level. The return spreads for the 1-month and 12-month systematic momentum are 45 bps and 30 bps, respectively, and also significantly positive. The return spreads are close to the baseline momentum spreads, which is impressive given that the systematic returns can contain estimation noise.

Panel B reports the idiosyncratic momentum-portfolio returns. Portfolio returns are not monotone from portfolio 1 to 5. The high-minus-low return spreads are −2 bps, −10 bps and 5 bps for 1-, 3-, and 12-month formation period, respectively, which are insignificant at all conventional levels. In short, systematic currency returns experience momentum, and idiosyncratic currency returns do not.

4.1.2. Time series momentum

Next, I examine time series momentum. I now long the individual currency if the past 1-, 3-, and 12-month systematic (or idiosyncratic) return is positive and short if negative. This strategy is the systematic (or idiosyncratic) time series momentum strategy.

Table 2
Systematic and idiosyncratic momentum.
This table presents properties of momentum (MOM) and time series momentum (TSM) based on the past 1-, 3-, and 12-month systematic and idiosyncratic currency returns. Panel A and B report the corresponding monthly portfolio and strategy returns for systematic and idiosyncratic MOM. Panel C reports the strategy returns for systematic and idiosyncratic TSM. All returns are in percentage points. The factor loadings are estimated from a monthly regression with daily data $r_{it} = a_i + b_1 carry_t + b_2 dollar_t + e_{it}$. The systematic currency return is $b_1 carry_t + b_2 dollar_t$, and the idiosyncratic currency return is the $a_i + e_{it}$. The sample period is April 1976 to November 2020.

	Panel A: Systematic MOM					
	Portfolio 1	2	3	4	5	P5-P1
$h = 1$	-0.33***	-0.12	-0.11	0.08	0.12	0.45***
	(-2.84)	(-1.07)	(-0.99)	(0.70)	(0.93)	(3.70)
$h = 3$	-0.35***	-0.15	-0.03	0.01	0.12	0.48***
	(-3.07)	(-1.40)	(-0.32)	(0.05)	(0.98)	(4.11)
$h = 12$	-0.26**	-0.10	-0.08	-0.02	0.04	0.30***
	(-2.38)	(-0.98)	(-0.73)	(-0.20)	(0.32)	(2.71)
	Panel B: Idiosyncratic MOM					
$h = 1$	-0.10	-0.05	-0.09	-0.06	-0.12	-0.02
	(-0.84)	(-0.51)	(-0.83)	(-0.55)	(-0.97)	(-0.22)
$h = 3$	-0.05	-0.08	-0.08	-0.09	-0.15	-0.10
	(-0.46)	(-0.73)	(-0.73)	(-0.85)	(-1.21)	(-0.90)
$h = 12$	-0.15	-0.05	-0.05	-0.09	-0.11	0.05
	(-1.26)	(-0.47)	(-0.48)	(-0.88)	(-0.87)	(0.47)
Observations	537	537	537	537	537	537
	Panel C: Systematic and idiosyncratic TSM					
	Systematic TSM			Idiosyncratic TSM		
	$h = 1$	$h = 3$	$h = 12$	$h = 1$	$h = 3$	$h = 12$
Constant	0.24***	0.31***	0.20***	0.00	0.01	0.01
	(3.04)	(4.09)	(2.71)	(0.08)	(0.36)	(0.24)
Observations	537	537	537	537	537	537

Fig. 3 presents the systematic and idiosyncratic momentum returns by currency. For the systematic TSM, the 1-month average excess return is significantly positive at the 5% level for 10 currencies, the 3-month is significantly positive for 17 currencies, and the 12-month for 9 currencies. By contrast, the average returns are merely significantly positive for 2, 3, and 3 currencies for the 1-, 3-, and 12-month idiosyncratic TSM, and occasionally significantly negative. The result suggests that TSM mostly comes from the systematic returns.

I further construct a systematic and idiosyncratic TSM by equal-weighting all currency positions, similar to the baseline TSM. Panel C shows that the systematic TSM generates an average excess return of 24 bps, 31 bps, and 20 bps per month using 1-, 3-, and 12-month portfolio formation periods. All returns are significantly positive at the 1% level. The return spreads are comparable to the TSM raw returns, 33 bps, 35 bps, and 25 bps. In contrast, the idiosyncratic time series momentum strategy generates small and insignificant return spreads (0, 1, and 1 bps). In sum, only systematic currency returns contains momentum, either in the cross section or time series, and idiosyncratic currency returns do not. Purging factor exposure from the currency returns largely expunges currency momentum and time series momentum.

4.2. Time-varying correlation

The evidence until now shows that currency momentum and time series momentum come from systematic returns driven by factors. Intuitively, the factors underlie the momentum strategies. For example, if the realized carry return is positive, high-interest-rate currencies are more likely to be sorted into winner stocks (portfolio 5) and low-interest-rate currencies into loser stocks (portfolio 1). In other words, currency momentum longs the carry factor when the past carry factor is positive and shorts when negative. If the carry factor exhibits momentum and carry loadings are persistent, high-interest-rate currencies earn higher returns next month again, generating currency momentum.

Next, for time series momentum, if the realized carry return is positive, high-interest-rate currencies are more likely to have positive returns and are in the long leg of the strategy. The low-interest-rate currencies are more likely to have negative returns and are in the short leg of the strategy. As such, time series momentum longs the carry factor when the past carry factor is positive and shorts when negative. Time series momentum would earn positive excess returns next month if the carry factor is more likely to outperform next month again. The relation holds similarly for the role of dollar factor in momentum and time series momentum.

I test these predictions in the data and present the conditional correlation between various momentum strategy returns and factors in Table 3. Panel A shows that the correlations between currency momentum and carry are 0.33, 0.35, and 0.12 following periods of positive carry returns for 1- to 12-month portfolio-formation periods. All coefficients are highly significant. By contrast, the corresponding correlations are −0.58, −0.62, and −0.69 following periods of negative carry returns. For the dollar factor, the correla-

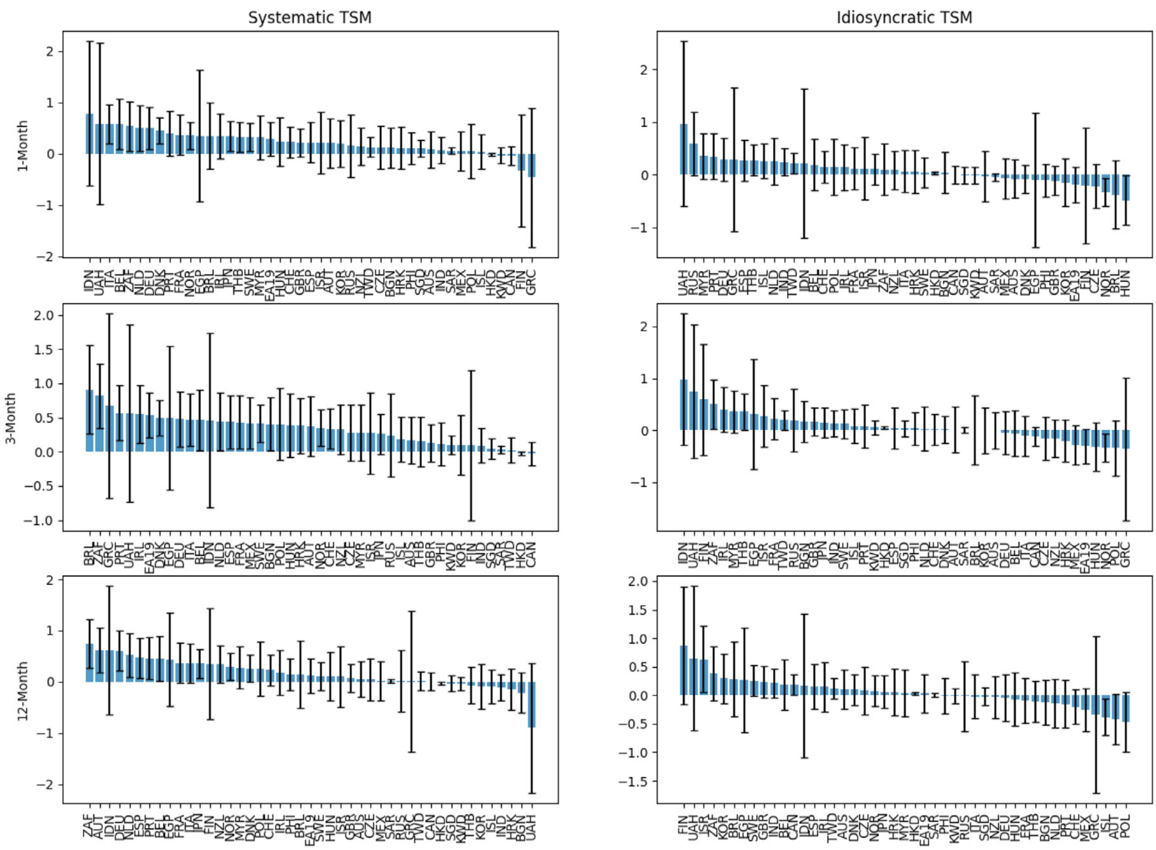

Fig. 3. Systematic and idiosyncratic TSM. This figure plots the time series momentum returns formed on past systematic and idiosyncratic returns. The returns are in percentage points. The bands denote the 95% confidence interval. The sample period is April 1976 to November 2020.

Table 3
Conditional correlation.
This table reports the correlation between momentum (MOM), time series momentum (TSM), and the currency factors conditional on the sign of past factor returns. The formation period $h = 1, 3, 12$ of the momentum strategies matches that of factor momentum. All coefficients are in percentage points, and the t-statistics are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

	Panel A: MOM					
	Carry			Dollar		
	$h = 1$	$h = 3$	$h = 12$	$h = 1$	$h = 3$	$h = 12$
$\text{Factor}_{t-h,t-1} > 0$	0.33***	0.35***	0.12**	0.56***	0.53***	0.61***
	(6.45)	(7.42)	(2.49)	(10.36)	(9.80)	(11.80)
Observations	353	395	431	239	240	240
$\text{Factor}_{t-h,t-1} < 0$	-0.58***	-0.62***	-0.69***	-0.36***	-0.43***	-0.50***
	(-9.74)	(-9.41)	(-9.73)	(-6.65)	(-8.18)	(-9.87)
Observations	184	142	106	298	297	297
	Panel B: TSM					
$\text{Factor}_{t-h,t-1} > 0$	0.07	0.10*	0.05	0.91***	0.87***	0.89***
	(1.34)	(1.96)	(1.03)	(33.21)	(27.02)	(30.12)
Observations	353	395	431	239	240	240
$\text{Factor}_{t-h,t-1} < 0$	-0.38***	-0.35***	-0.45***	-0.85***	-0.85***	-0.89***
	(-5.54)	(-4.38)	(-5.23)	(-28.06)	(-27.81)	(-33.42)
Observations	184	142	106	298	297	297

Table 4
Factor predictability: univariate evidence.
This table presents the regression results for the carry and dollar factors, respectively. The regression equations are $\text{Factor}_t^k = a + bX_{t-1} + e_{i,t}$, where $X_{t-1} = \overline{\text{Factor}}_{t-h,t-1}^k$ for the top panel and $X = \mathbf{1}_{\text{Factor}_{t-h,t-1}^k}$ for the bottom panel. All coefficients are in percentage points, and the t-statistics adjusting for the h month of overlapping windows are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

	Carry			Dollar		
	$h=1$	$h=3$	$h=12$	$h=1$	$h=3$	$h=12$
Panel A: Factor return						
$\text{Factor}_{t-h,t-1}$	0.16***	0.20***	0.22*	0.07	0.21***	0.29**
	(2.82)	(2.98)	(1.75)	(1.13)	(2.83)	(2.40)
Constant	0.40***	0.38***	0.37***	-0.09	-0.08	-0.07
	(4.57)	(4.29)	(4.15)	(-0.91)	(-0.78)	(-0.68)
R^2	0.02	0.02	0.01	0.01	0.02	0.01
Panel B: Sign of factor return						
$\mathbf{1}_{\text{Factor}_{t-h,t-1}}$	0.62***	0.55***	0.15	0.56***	0.68***	0.52**
	(3.48)	(2.82)	(0.81)	(2.81)	(3.58)	(2.44)
Constant	0.06	0.07	0.35**	-0.34***	-0.40***	-0.32***
	(0.38)	(0.37)	(2.08)	(-2.82)	(-3.29)	(-2.59)
R^2	0.03	0.02	0.00	0.02	0.02	0.01
Observations	537	537	537	537	537	537

tions with currency momentum are significantly positively, 0.56, 0.53, and 0.61 following periods of positive dollar returns, but significantly negative at −0.36, −0.43, and −0.50 following periods of negative dollar returns.

Panel B shows that the correlation between time series momentum and carry is low and close to zero following periods of positive carry returns. However, the correlations are significantly negative, −0.38, −0.34 and −0.45, following periods of negative carry returns. For the dollar factor, the conditional correlation varies even more. The correlations are high and significantly positive, 0.91, 0.87 and 0.89, following periods of positive dollar returns and strongly negative, −0.85, −0.85 and −0.89, following underperformance.

In sum, momentum and time series momentum long a currency factor when the past factor return is positive and short when negative. Consequently, momentum in currency factors can potentially drive currency momentum and time series momentum. These conditional correlations differ for the cross-sectional and time series momentum such that these momentum strategies are closely related but not identical. Instead, these momentum strategies can have a common source originating from the factors.

5. Currency factor momentum

This sector formally examines momentum in currency factors and tests the relation between factor momentum and momentum strategies.

5.1. Time-varying factor returns

I regress the factor return on its past return as follows:

$$Factor_t^k = a + b\overline{Factor}_{t-h,t-1}^k + e_t, \tag{6}$$

where $k =$ Carry or Dollar, $\overline{Factor}_{t-h,t-1}^k$ denotes the average return for factor k from $t-h$ to $t-1$, and $h = 1, 3, 12$ matches the portfolio-formation periods studied. Table 4 reports the results. A 1% increase in the average carry return over the past three months is associated with a significant increase of 0.16% for the carry return next month, and a 1% increase for the average dollar factor over the past three months is associated with a significant increase of 0.20% for the dollar return next month. Overall, the predictability is stronger over shorter portfolio formation periods for carry and stronger over longer portfolio-formation periods for dollar.

Another way to examine factor momentum is to simply focus on the sign of past factor returns, minimizing the impact of outliers due to the relatively small cross section. In the next section, I consider a time series factor momentum strategy that conditions on the sign. For the regression analysis, I run the predicative regression similar to Eq. (6), but the independent variable is the sign of past factor returns:

$$Factor_t^k = a + b\mathbf{1}_{Factor_{t-h,t-1}^k} + e_t. \tag{7}$$

The right panel in Table 4 represents the results. Positive factor realizations strongly predict higher factor returns going forward. The expected carry return increases by 62 bps, 55 bps, and 15 bps following 1, 3, and 12 months of positive carry returns, and the expected dollar return increases by 56 bps, 68 bps, and 52 bps following 1, 3, and 12 months of positive dollar returns. The coefficients are highly significant except for 12-month carry regression. By contrast, the factors mostly do not earn significantly positive returns next month following losses. In sum, currency factor returns are time varying, predictable, and significantly higher following positive or higher past factor returns.

Next, I examine whether factor momentum can be explained or summarized by existing predictors. Note that currency predictors are scarce, as highlighted by Meese and Rogoff (1983) and Rossi (2013). I control for the few generic currency predictors proposed in the literature, including the average forward discount (AFD), U.S. indus-

Table 5
Factor predictability: multivariate evidence.
This table presents the regression results of factor momentum for the carry and dollar factors, respectively. The regression equations are $\text{Factor}_t^k = a + bX_{t-1} + c\text{Controls}_{t-1} + e_{i,t}$, where $X_{t-1} = \overline{\text{Factor}}^k_{t-h,t-1}$ for the top panel and $X_{t-1} = \mathbf{1}_{\text{Factor}^k_{t-h,t-1}}$ for the bottom panel. All coefficients are in percentage points, and the t-statistics adjusting for the h month of overlapping windows are reported in the parenthesis below the coefficients. Constants are omitted from the table. The sample period is April 1976 to November 2020.

	Panel A: Factor return					
	Carry			Dollar		
	$h=1$	$h=3$	$h=12$	$h=1$	$h=3$	$h=12$
$\text{Factor}_{t-h,t-1}$	0.15***	0.20***	0.24*	0.03	0.14*	0.20*
	(2.79)	(2.93)	(1.89)	(0.53)	(1.93)	(1.81)
AFD	0.01	-0.04	-0.02	2.02***	1.85***	1.93***
	(0.03)	(-0.08)	(-0.05)	(3.45)	(3.24)	(3.06)
ΔIP	0.04	0.02	0.05	-0.18	-0.16	-0.16
	(0.43)	(0.19)	(0.47)	(-1.16)	(-1.12)	(-1.15)
Output Gap	-0.03	-0.03	-0.04	0.01	0.01	0.02
	(-0.88)	(-1.02)	(-1.23)	(0.27)	(0.26)	(0.35)
Constant	0.40***	0.37***	0.35***	0.33**	0.31**	0.33**
	(3.59)	(3.28)	(2.75)	(2.16)	(2.05)	(2.02)
R^2	0.03	0.02	0.01	0.04	0.05	0.05
Observations	537	537	537	537	537	537
	Panel B: Sign of factor return					
$\mathbf{1}_{\text{Factor}_{t-h,t-1}}$	0.62***	0.55***	0.20	0.44**	0.53***	0.40**
	(3.46)	(2.73)	(1.00)	(2.29)	(2.89)	(2.13)
AFD	0.00	-0.12	-0.02	1.93***	1.79***	1.87***
	(0.01)	(-0.24)	(-0.03)	(3.37)	(3.02)	(2.98)
ΔIP	0.04	0.03	0.05	-0.18	-0.17	-0.17
	(0.45)	(0.25)	(0.47)	(-1.22)	(-1.15)	(-1.23)
Output Gap	-0.03	-0.02	-0.03	0.01	0.02	0.02
	(-0.92)	(-0.86)	(-1.11)	(0.28)	(0.42)	(0.46)
Constant	0.06	0.04	0.30	0.12	0.05	0.12
	(0.32)	(0.20)	(1.44)	(0.66)	(0.27)	(0.70)
R^2	0.03	0.02	0.00	0.05	0.05	0.05
Observations	537	537	537	537	537	537

trial production (ΔIP) (Lustig et al., 2014), and the output gap (Colacito et al., 2020).

Table 5 reports the regression results. The autocorrelation in factor returns is robust to controlling for the existing predictors. The autoregressive coefficient for the carry factor is 0.15, 0.20, and 0.24, similar to the coefficients in the univariate regression. The R^2s also remain comparable to the univariate analysis. For the sign-based specification, the carry return increases by 55 bps next month following positive 3-month carry returns relative to losses. The coefficient is the same as that in the univariate analysis. In short, the carry momentum captures different dynamics than those contained in existing currency-premium predictors. For the controls, the existing predictors have little predictability for the carry factor.

For the dollar factor, the autoregressive coefficients and the sign-based regression coefficients remain largely significant but tend to decrease compared with the univariate coefficients. For example, the dollar return increases by 53 bps next month following positive dollar returns over the past three months relative to losses, compared with 68 bps in the univariate analysis. For the controls, AFD also help predicts dollar fluctuations. Overall, dollar momentum is related to the information contained in existing macroeconomic predictors

The Internet Appendix contains various robustness tests. First, I use the shorter sample starting in April 1983 as in Lustig et al. (2014) for the analysis. Second, I construct the currency factors using portfolio sorting similar to Lustig et al. (2011), instead of using the entire currency cross-section. Results are comparable to the main result.

5.2. Factor momentum strategy

The regression analysis suggests the factor performance can be improved by conditioning on past returns. Consider a time series momentum strategy of factors. An investor can long the currency factor when the past h-month factor return is positive and short when the past h-month factor return is negative. I scale the portfolio weights such that the overall portfolio equivalent to 1 U.S. dollar, either long or short. The scaling in the portfolio weights is merely leverage and changes the raw returns, but does not change the profitability of the strategy. To gauge the profitability of the strategy, I instead focus on the t-statistics of the excess return and Sharpe ratio.

Panel A of Table 6 first presents the strategy raw returns. If an investor only longs the carry factor when the past 3-month carry return is positive and shorts when negative, she earns an excess return of 43 bps per month (t-statistics of 5.59), with an annualized Sharpe ratio of 0.85. A similar 3-month dollar momentum strategy earns an excess return of 35 bps per month with t-statistics of 3.67 and an annualized Sharpe ratio of 0.55. Results are simi-

Table 6
Factor momentum returns.
Panel A reports the average factor momentum return based on the carry, dollar, and both factors (FMOM). The portfolio formation period is denoted at the top of the columns. Panel B reports the results of regressing factor momentum on carry and dollar factors. All coefficients are in percentage points, and the *t*-statistics are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

	Carry			Dollar			FMOM		
Panel A: Raw return									
	1M	3M	12M	1M	3M	12M	1M	3M	12M
Return	0.43***	0.43***	0.33***	0.29***	0.35***	0.27***	0.36***	0.39***	0.30***
	(5.51)	(5.59)	(4.22)	(2.99)	(3.67)	(2.79)	(5.56)	(6.16)	(4.55)
SR	0.82	0.85	0.63	0.45	0.55	0.42	0.84	0.94	0.69
Panel B: Alpha									
Carry	0.08*	0.21***	0.51***	-0.13**	-0.11**	-0.08	-0.02	0.05	0.22***
	(1.93)	(4.88)	(13.14)	(-2.44)	(-2.01)	(-1.44)	(-0.64)	(1.41)	(5.99)
Dollar	0.06*	0.10***	0.08***	-0.02	-0.02	0.02	0.02	0.04	0.05*
	(1.78)	(2.85)	(2.66)	(-0.55)	(-0.55)	(0.39)	(0.67)	(1.29)	(1.73)
Constant	0.39***	0.34***	0.10	0.34***	0.40***	0.30***	0.37***	0.37***	0.20***
	(4.93)	(4.41)	(1.43)	(3.51)	(4.05)	(3.08)	(5.57)	(5.66)	(3.08)
R^2	0.01	0.05	0.25	0.01	0.01	0.00	0.00	0.01	0.06
Observations	537	537	537	537	537	537	537	537	537

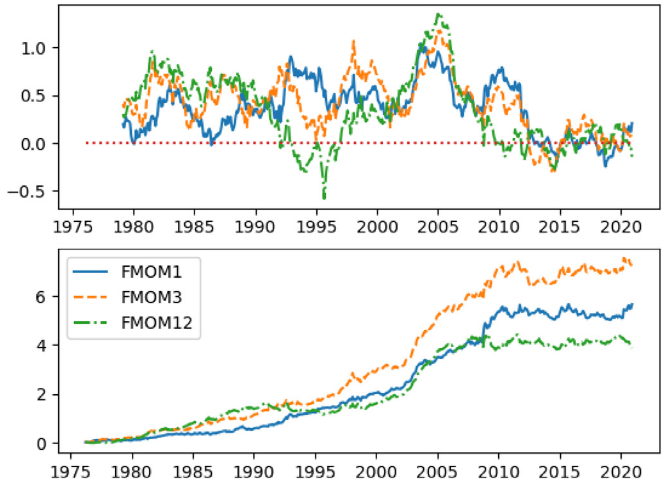

Fig. 4. Factor momentum. This figure plots returns of factor momentum (FMOM) with portfolio formation periods or 1 month (solid line), 3 months (dashed line), and 12 months (dash-dot line). The top panel plots the 3-year moving average return in percentage points, and the bottom panel plots the cumulative return. The sample period is April 1976 to November 2020.

lar across different conditioning horizons. All Sharpe ratios are higher than the corresponding unconditional carry and dollar strategies.

Next, I construct a currency-factor momentum strategy with both factors (FMOM) by equally weighting the individual factor momentum. The 3-month FMOM generates an excess return of 39 bps per month with *t*-statistics of 6.16 and an annualized Sharpe ratio of 0.94. The Sharpe ratios for the 1-month and 12-month factor momentum are 0.84 and 0.69, which are higher than those of both individual factor momentum. These factor momentum Sharpe ratios are higher than those of the corresponding MOM and TSM. Panel B shows the currency factors cannot explain factor momentum in the carry, dollar, or the strategy using both factors jointly. For example, the joint FMOM generates alphas of 37 bps, 37 bps, and 20 bps for 1-, 3-, and 12-month formation periods, comparable to the respective excess returns of 36 bps, 39 bps, and 30 bps.

Fig. 4 plots the 3-year moving-average returns and cumulative returns of FMOM. Factor momentum generates strong positive 3-year moving average returns over most of the sample. The cumulative returns are consistent and impressive, in line with the high Sharpe ratios.

5.3. MOM, TSM or FMOM

The evidence until now shows both the cross-sectional and time series momentum originate from systematic returns and factors exhibit strong momentum. In particular, FMOM generates higher Sharpe ratios than MOM and TSM. Fig. 5 further plots the returns of 3-month MOM, TSM, and FMOM. The strategies are scaled to have the same volatility as the 3-month FMOM. The plot shows the three strategies share very strong comovement. In fact, a visual comparison would suggest returns of these three strategies comove even more than returns of the same strategy with different portfolio-formation periods. For the cumulative return,

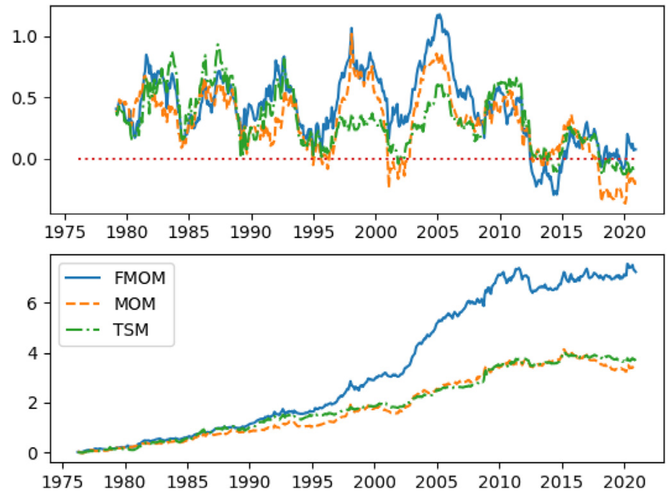

Fig. 5. Factor, cross-sectional and time series momentum. This figure plots returns of the 3-month factor momentum (FMOM, solid line), currency momentum (MOM, dashed line) and time series momentum (TSM, dash-dot line). The top panel plots the 3-year moving average return in percentage points, and the bottom panel plots the cumulative return. For ease of comparison, the MOM and TSM returns are scaled to have the same volatility as FMOM. The sample period is April 1976 to November 2020.

FMOM strongly outperforms MOM and TSM over the past four decades. As such, factor momentum can potentially be the true factor underlying cross-sectional and time series momentum strategies. This section tests the hypothesis.

5.3.1. Momentum

First, I run the following regression to study the relation between momentum and factor momentum:

$$MOM_t = \alpha + \beta X_t + \varepsilon_t, \tag{8}$$

where rx_t is the benchmark anomaly return and X is the vector of factors. Section 4 shows the carry and dollar factors cannot explain currency momentum. Now, I add factor momentum to the factor model, and thus, $X = [\text{Carry}, \text{Dollar}, \text{FMOM}]$.

Panel A of Table 7 presents the regression results for individual momentum-sorted portfolio returns and the long-short return. The carry and dollar loadings are omitted from the table to conserve space. The model's performance dramatically improves compared with the two-factor model, and most momentum alpha is explained away. For example, the loading of the 3-month momentum on factor momentum monotonically increases from −0.53 for portfolio 1 to 0.65 for portfolio 5. The difference is 1.18 and has a t-statistic of 19.91, which is also the loading of 3-month momentum on factor momentum. The portfolio alphas are no longer monotone across the five portfolios, and the long-short alpha is merely 11 bps and insignificant. Whereas the two-factor model can only explain 2% of the variation in momentum, the three-factor model can explain as much as 43%. The alphas decrease to 12 bps, 11 bps, and 24 bps for the three portfolio-formation periods, and the first two are insignificant at any conventional level. In sum, factor momentum possesses a strong ability to explain currency momentum.

The F-test of Gibbons et al. (1989) (GRS) can further evaluate the model's performance. Panel B presents results for a factor model (1) carry and dollar and (2) carry, dollar, and factor momentum. The two-factor model is rejected at the 0.00 p-value level, consistent with the evidence that the carry and dollar factors cannot explain currency momentum. After factor momentum is added to the model, the model cannot be rejected at the 5% level for any portfolio formation period. In short, factor momentum can explain currency momentum.

One can further the analysis and ask whether momentum or factor momentum is the true factor. I run the spanning test for currency momentum and factor momentum:

$$Factor^i_t = \alpha + \beta Factor^j_t + \varepsilon_t, \tag{9}$$

where $i, j =$ MOM or FMOM. Panel A of Table 8 shows factor momentum spans momentum. Currency momentum no longer earns significant alphas at any conventional levels after I control for factor momentum. But momentum doesn't span factor momentum. The remaining factor momentum alphas are more than half of the FMOM raw returns and highly significant at the 1% level for all horizons. In sum, currency momentum stems from and merely summarizes factor momentum.

5.3.2. Time series momentum

This section examines whether factor momentum can explain time series momentum. To conserve space, I only discuss the results of the more compact single-factor model with factor momentum.[3] First, I regress TSM returns for individual currencies on FMOM. Fig. 6 plots the remaining alphas by currency. For the benchmark TSM, 17, 20, and 20 currencies earn significantly positive returns for the 1-, 3-, and 12-month portfolio-formation periods. After controlling for FMOM, the alphas are only significantly positive at the 5% level for two, one, and two currencies and

[3] The Internet Appendix contains results for the three-factor model with carry, dollar, and factor momentum and results are similar.

Table 7
Explaining currency momentum.
Panel A reports the results of regressing the momentum portfolio returns on the various factors $r_t^K = \alpha + \beta X_t + \varepsilon_t$. The portfolio formation period h is denoted at the top of the columns. The factor loadings of carry and dollar are omitted from the table. Panel B reports Gibbs-Ross-Shanken test results using the following factors a) Carry and Dollar b) Carry, Dollar and h-month factor momentum (FMOM), where h matches the portfolio formation period. All coefficients are percentage points, and the t-statistics are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

Panel A: Explaining momentum portfolios	Portfolio 1	2	3	4	5	P5-P1
			$h=1$			
FMOM	-0.52***	-0.22***	0.04	0.29***	0.52***	1.04***
	(-17.07)	(-8.35)	(1.44)	(10.97)	(12.95)	(18.05)
Constant	0.02	-0.06	-0.01	-0.07*	0.14**	0.12
	(0.38)	(-1.42)	(-0.15)	(-1.77)	(2.21)	(1.33)
R^2	0.81	0.86	0.87	0.87	0.76	0.39
			$h=3$			
FMOM	-0.53***	-0.23***	-0.01	0.22***	0.65***	1.18***
	(-17.92)	(-9.54)	(-0.45)	(8.41)	(15.61)	(19.91)
Constant	-0.01	-0.00	-0.07*	-0.00	0.09	0.11
	(-0.28)	(-0.02)	(-1.79)	(-0.10)	(1.44)	(1.15)
R^2	0.83	0.89	0.88	0.87	0.75	0.43
			$h=12$			
FMOM	-0.48***	-0.20***	-0.02	0.16***	0.65***	1.13***
	(-15.20)	(-7.57)	(-0.97)	(5.91)	(15.76)	(18.26)
Constant	-0.04	-0.04	-0.05	-0.03	0.20***	0.24**
	(-0.90)	(-0.99)	(-1.34)	(-0.73)	(3.12)	(2.53)
R^2	0.79	0.88	0.89	0.86	0.75	0.39
Observations	537	537	537	537	537	537

Panel B: Gibbs-Ross-Shanken test	$h=1$		$h=3$		$h=12$	
	Test Stat	p-value	Test Stat	p-value	Test Stat	p-value
Carry + Dollar	3.39	0.00	4.58	0.00	3.84	0.00
+ FMOM	1.47	0.15	0.780	0.55	2.08	0.07

Table 8
Spanning test.
This table reports results of the factor spanning tests. Panel A reports results for MOM and FMOM and Panel B reports results for TSM and FMOM. The dependent variable is denoted on top of the columns and the independent variable is the other anomaly return in the pair. The portfolio formation period of MOM and TSM matches that of FMOM. All coefficients are percentage points, and the t-statistics are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

Panel A: MOM versus FMOM	MOM			FMOM		
	1M	3M	12M	1M	3M	12M
Factor	1.05***	1.17***	1.03***	0.36***	0.36***	0.32***
	(18.01)	(19.72)	(16.34)	(18.01)	(19.72)	(16.34)
Constant	0.05	0.04	0.09	0.20***	0.21***	0.17***
	(0.54)	(0.48)	(0.96)	(3.99)	(4.28)	(3.12)
R^2	0.38	0.42	0.33	0.38	0.42	0.33

Panel B: TSM versus FMOM	TSM			FMOM		
	1M	3M	12M	1M	3M	12M
Factor	0.91***	0.91***	0.89***	0.65***	0.63***	0.61***
	(28.05)	(26.76)	(24.96)	(28.05)	(26.76)	(24.96)
Constant	0.01	-0.00	-0.01	0.14***	0.17***	0.14***
	(0.12)	(-0.05)	(-0.20)	(3.38)	(3.99)	(3.21)
R^2	0.60	0.57	0.54	0.60	0.57	0.54
Observations	537	537	537	537	537	537

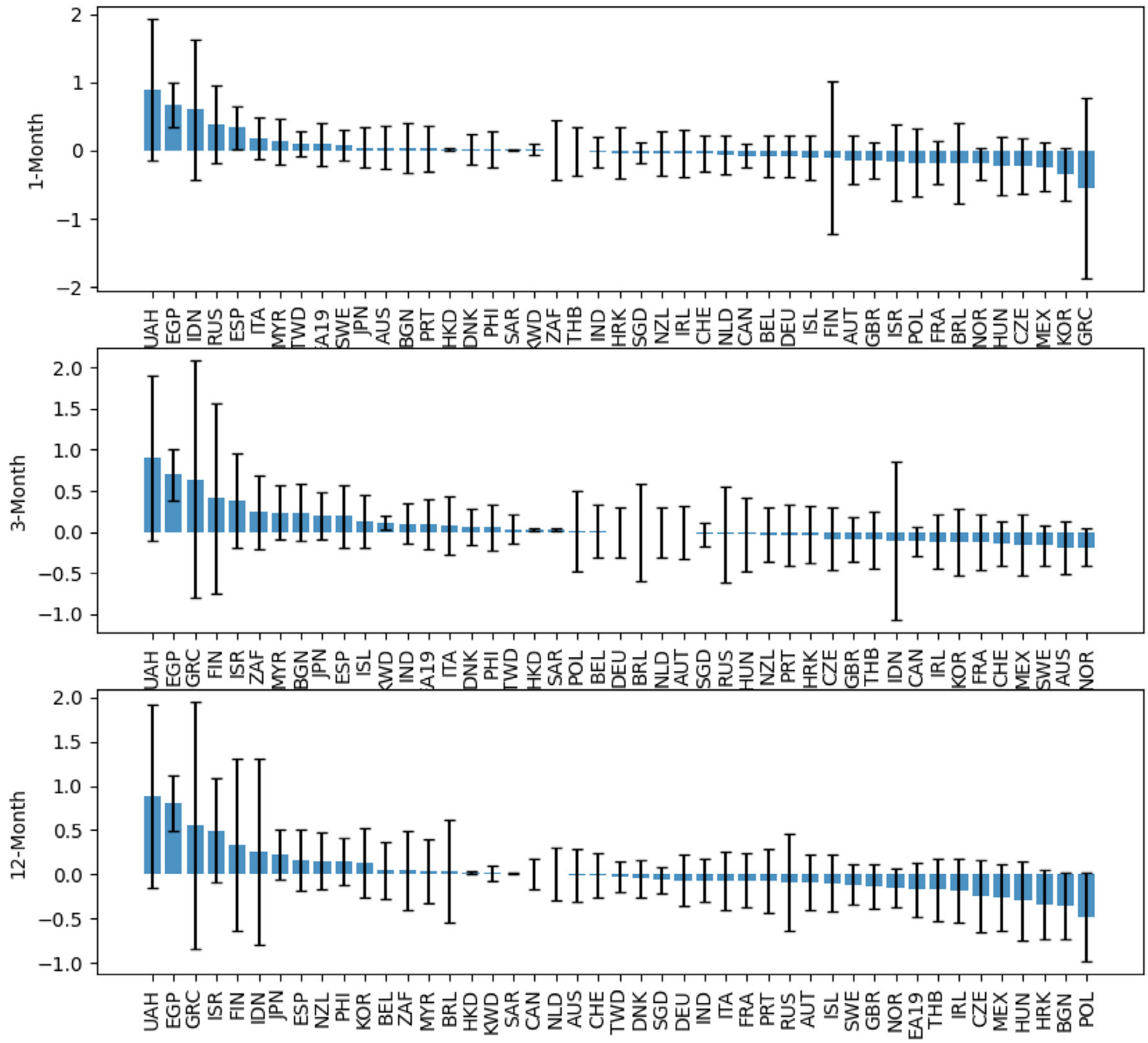

Fig. 6. Time series momentum versus factor momentum. This figure plots the alphas of regressing h-month time series momentum on the corresponding factor momentum. The alphas are in percentage points and the bands denote the 95% confidence interval. The sample period is April 1976 to November 2020.

significantly negative occasionally. In short, factor momentum largely explains time series momentum embedded in currencies.

Second, I conduct spanning tests between equal-weighted TSM and FMOM. Panel B of Table 8 shows TSM loads significantly on FMOM, with t-statistics around 25. The residual alphas are less than 1 bps, which is small and insignificant at any conventional level. By contrast, TSM cannot span FMOM. The FMOM alphas are about half of the raw returns, 14 bps, 17 bps, and 14 bps, and highly significant. In sum, the predictability from past currency returns, either in the cross-section or time series, merely summarizes the momentum embedded in currency factors.

5.4. Robustness

This section conducts robustness checks of the factor momentum strategy. First, I form the strategy based on the past raw returns. The strategy longs the indivual factor when the past h-month factor return is positive and shorts when negative, but the weights are proportional to the past returns. Specifically, the portfolio position of factor k is $\overline{Factor}^{k}_{t-h,t-1}$ in percentage points. Panel A of Table 9 reports the average raw returns. Similar to the baseline strategy, the carry, dollar, and equal-weighted factor momentum all earn significantly positive returns. The Sharpe ratios are slightly lower compared with the sign-based baseline strategy, implying that minimizing the impact of extreme individual returns helps improve the performance. The Internet Appendix further finds the raw-return-based factor momentum again explains and spans the corresponding MOM and TSM, consistent with the baseline evidence.

Second, I consider an alternative refinement of the factor momentum strategy. Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Kim et al. (2016) docu-

Table 9
Factor momentum returns: robustness.
This table reports the average factor momentum returns for robustness analysis. The portfolio formation period is denoted at the top of the columns. Panel A uses past raw return based construction, Panel B studies the volatility scaled strategy, and Panel C reports the returns net of bid-ask spreads. All coefficients are in percentage points, and the *t*-statistics are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

	Carry			Dollar			FMOM		
	1M	3M	12M	1M	3M	12M	1M	3M	12M
Panel A: Return based									
Return	0.71***	0.49***	0.31***	0.36	0.42**	0.19**	0.54***	0.45***	0.25***
	(3.93)	(4.45)	(4.51)	(1.30)	(2.53)	(2.04)	(2.96)	(4.27)	(4.05)
SR	0.58	0.67	0.68	0.19	0.38	0.30	0.45	0.65	0.62
Panel B: Volatility scaled									
Return	0.87***	1.01***	0.79***	0.64***	0.71***	0.54***	0.75***	0.86***	0.66***
	(4.82)	(5.69)	(4.37)	(3.41)	(3.78)	(2.86)	(5.63)	(6.65)	(4.86)
SR	0.72	0.86	0.54	0.51	0.57	0.43	0.84	1.00	0.73
Panel C: Net return									
Return	0.29***	0.28***	0.17**	0.24**	0.31***	0.22**	0.27***	0.29***	0.20***
	(3.82)	(3.67)	(2.24)	(2.50)	(3.20)	(2.32)	(4.16)	(4.64)	(3.03)
SR	0.56	0.57	0.33	0.37	0.48	0.45	0.63	0.71	0.44
Observations	537	537	537	537	537	537	537	537	537

ment that volatility timing improves currency momentum, equity momentum, and time series momentum in various markets. I weight the portfolio position by the inverse volatility now. Specifically, the portfolio weight is the sign of the past factor return times 10% divided by the annualized factor volatility. Note the carry and dollar factors have different volatility, and the volatility scaling can enhance a more equal risk allocation to the factors.

The ex-ante volatility σ_t is estimated at each point in time using an exponentially weighted lagged squared returns in the spirit of a simple univariate GARCH model (Moskowitz et al., 2012). Specifically, the ex-ante annualized variance σ_t^2 for each asset or strategy is calculated as

$$\sigma_t^2 = 12\sum_{\tau=0}^{\infty}(1-\delta)\delta^{\tau}(r_{t-1-\tau}-\bar{r}_t)^2, \tag{10}$$

where the scalar 12 annualizes the variance, the weights $(1-\delta)\delta^{\tau}$ add up to one, and $\bar{r}_t$ is the exponentially weighted average return computed similarly. The parameter is chosen so that the center mass of the weights $\sum_{\tau=0}^{\infty}(1-\delta)\delta^{\tau}\tau = \delta/(1-\delta)$ =60 days. Panel B shows that, measured by the Sharpe ratio, the volatility-scaled carry momentum decreases somewhat, while the dollar momentum and equal-weighted factor momentum improve slightly.[4]

Finally, I study the net return of the factor momentum strategy accounting for transaction costs. Panel C shows that, after accounting for the bid-ask spreads, the excess returns of factor momentum decrease compared with the gross returns, but are still significantly positive. The Sharpe ratios are again consistently high for various portfolio formation periods. The Internet Appendix further shows the past factor returns only correlate significantly with future net factor returns, but do not correlate with future bid-ask spreads.

6. Sources of factor momentum

The currency market is a market with huge transaction volume and no natural short-selling constraints. The market is also dominated by professional traders. Hence, the currency market considerably raises the hurdle for generating significant excess returns from factor momentum as documented above. This section examines the sources of currency factor momentum. First, I examine whether exploiting the factor strategy return involves substantial arbitrage costs. Second, I study a model with time-varying risk premium.

6.1. Limits to arbitrage

The currencies exhibit different properties for different countries in accessibility, trading cost, and idiosyncratic risk. This section studies whether factor momentum correlates with arbitrage costs and whether significant limits to arbitrage prevent investors from trading sufficiently to drive away the apparent profits.

First, I split the sample to developed-market (DM) and emerging-market (EM) currencies. The developed markets include Australia, Austria, Belgium, Canada, Estonia, the euro area, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, and the U.K., but most currencies only span part of the sample. Then, I construct the carry and dollar factor for each subsample and regress the factor returns on the average past factor returns as in Eq. (6). I focus on the autoregressive regression instead of the regression with signs

[4] The Internet Appendix further studies the impact of volatility scaling. The volatility scaled time series momentum and factor momentum significantly load on each other, but cannot fully span each other. The results imply that the volatility scaling is a source of excess returns different from autocorrelation, consistent with Kim et al. (2016) and Huang et al. (2020).

Table 10
Factor momentum and limits to arbitrage.
This table presents the regression results of factor momentum for subsets of currencies. Panel A reports results for developed market (DM) and emerging market (EM) currencies. Panel B to D study currency subsets split by capital account openness (KA), idiosyncratic volatility (IVOL), and volatility (Vol). The regression equations are $\text{Factor}_t^k = a + b\overline{\text{Factor}}_{t-h,t-1}^k + e_{i,t}$, where the factors are formed within each subset of currencies. The portfolio formation period h is denoted on top of the columns. All coefficients are in percentage points, and the t-statistics adjusting for the h month of overlapping windows are reported in the parenthesis below the coefficients. The sample period is April 1976 to November 2020.

	Carry			Dollar		
Panel A: Developed and emerging markets						
	$h = 1$	$h = 3$	$h = 12$	$h = 1$	$h = 3$	$h = 12$
DM	0.11	0.20**	0.39***	0.09	0.25***	0.30**
	(1.59)	(2.42)	(2.76)	(1.16)	(2.83)	(2.32)
EM	0.07	0.19**	0.06	0.05	0.19**	0.25**
	(1.19)	(1.99)	(0.46)	(0.93)	(2.57)	(1.97)
Panel B: Capital account openness						
High KA	0.15**	0.13*	0.09	0.07	0.23***	0.32***
	(2.13)	(1.67)	(0.60)	(1.10)	(2.86)	(2.62)
Low KA	0.13***	0.25***	0.31*	0.07	0.20***	0.23**
	(2.81)	(3.62)	(1.95)	(1.08)	(2.65)	(2.04)
Panel C: Idiosyncratic volatility						
Low IVOL	0.12**	0.10	-0.14	0.03	0.17*	0.28**
	(2.45)	(1.57)	(-1.35)	(0.49)	(1.94)	(2.34)
High IVOL	0.09*	0.13*	0.25*	0.11*	0.24***	0.31**
	(1.70)	(1.71)	(1.75)	(1.84)	(3.35)	(2.31)
Panel D: Volatility						
Low Vol	0.17***	0.11	-0.02	0.03	0.17**	0.34***
	(2.66)	(1.42)	(-0.15)	(0.38)	(1.97)	(3.02)
High Vol	0.11**	0.18***	0.25**	0.10*	0.23***	0.26**
	(2.13)	(2.64)	(2.16)	(1.70)	(3.24)	(1.97)

of past factor returns such that the levels of factor returns within the subsample do not affect the coefficients.

Panel A of Table 10 reports that the coefficients for carry tend to be smaller and less significant for DM currencies than those of the EM currencies. For example, the autocorrelation coefficient is insignificant within developed markets for the 12-month horizon and highly significant in the emerging markets. The result shows less tradable or less liquid currencies, such as EM currencies, experience less factor momentum, especially in the longer horizon. The dollar autocorrelation is comparable for DM and EM currencies.

Second, I use the capital account openness index (KA) in Chinn and Ito (2008) and split the currencies into those with above- and below-the-median KA at the time of portfolio formation $t-1$. Using the median as the cutoff helps generate a sufficiently large subsample cross-section, although the capital openness is relatively high in the later sample. Panel B shows that, for currencies of high-KA countries, the carry factor tends to be less autocorrelated than those of low-KA countries, especially over longer portfolio-formation periods. By contrast, the dollar autocorrelation is comparable between currencies with different KA levels and even tends to be higher for the more tradable currencies.

Third, I consider the implicit cost associated with limits to arbitrage. An investor has to bear idiosyncratic currency risks when he tries to bet on factor momentum. The risk can be more prominent for currencies, because the currency cross-section is relatively small. Consequently, he may wish to hedge the idiosyncratic risks or would prefer to avoid the more volatile currencies. Factor momentum may not be fully arbitraged away due to these limits. I split the sample into currencies with lower-than-median and higher-than-median idiosyncratic volatility or currency volatility during the portfolio formation period $t-1$. The idiosyncratic return is estimated each month using the daily data in Eq. (5), and the idiosyncratic and currency volatility are calculated as in Eq. (10).

Panel C and D of Table 10 report the results of the autoregressive regressions. Consistent with limits to arbitrage, carry exhibits more autocorrelation among the currencies with higher idiosyncratic volatility or currency volatility, especially over the longer horizons. In fact, carry momentum is mostly small and insignificant over the 3- and 12-month portfolio-formation periods for the less volatile currencies, but is significant and sizeable for the more volatile currencies. By contrast, currencies with different levels of volatility exhibit dollar momentum of largely similar magnitude and significance.

In sum, limits to arbitrage can help explain carry momentum, especially at the longer portfolio-formation periods. However, the more liquid and less volatile currencies still experience carry momentum. Dollar momentum does not correlate with the currency characteristics and thus cannot be explained by limits to arbitrage. The evidence is also consistent with the existing evidence that limits to arbitrage can partially account for currency momentum (Menkhoff et al., 2012b).

6.2. Time-varying risk premium

This section studies a model to interpret factor momentum as time-varying risk premium. The economy has multiple countries and a representative agent populates in each country, following Brennan and Xia (2002) and Backus et al. (2001). The log nominal stochastic discount factor (SDF) process of the representative agent in each country i follows Cox et al. (1985):

$$\begin{aligned} -m_{i,t+1} &= \alpha + \xi_i\sigma_{it}^2 + \tau\sigma_{wt}^2 + \sqrt{\gamma}\sigma_{it}u_{i,t+1} \\ &\quad - \sqrt{\delta_{it}}v_{w,t+1} + \sqrt{\kappa}\sigma_{it}u_{g,t+1}. \end{aligned} \tag{11}$$

Consistent with the empirical analysis, the model features two global shocks, v_w and u_g. The first global shock, v_w, is related to the carry factor (Lustig and Verdelhan, 2011), and the second global shock, u_g, is related to the dollar factor. Verdelhan (2018) documents that the two factors explain most of the bilateral exchange rate variations. The model also features a country-specific idiosyncratic shock u_i. The shocks v_w, u_g, and u_i are i.i.d, and follow the standard normal distribution.

The volatility evolves as follows,

$$\begin{aligned} \sigma_{i,t+1}^2 &= \phi_i\sigma_{it}^2 + v_{i,t+1}, \\ \sigma_{w,t+1}^2 &= \phi_w\sigma_{wt}^2 + v_{w,t+1}, \end{aligned} \tag{12}$$

where v_i and v_w follow the gamma distribution. The shape and scale parameters for v_i are k and ζ. Then, the mean of the random variable v_i is $k\zeta$ and the variance is $k\zeta^2$. The shape and scale parameters for v_w are k_w and ζ_w. The Gamma distribution ensures the resulting volatility process is always positive.

The SDFs have time-varying loading on the global shock v_w,

$$\delta_{it} = \delta_i\left(1 + \frac{\chi}{2} - \frac{\chi}{1 + e^{\overline{v}_{w,t-h,t}}}\right), \tag{13}$$

where $\overline{v}_{w,t-h,t}$ denotes the moving average of the v_w shock from $t-h$ to t. The loading varies around the unconditional loading and χ governs the loading sensitivity to realized v_w shocks. By contrast, the loading on the global shock u_g is transient and determined by the country-specific volatility.

The U.S. SDF follows a similar process and I omit the subscripts to be concise:

$$\begin{aligned} -m_{t+1} &= \alpha + \xi\sigma_t^2 + \tau\sigma_{wt}^2 + \sqrt{\gamma}\sigma_t u_{t+1} \\ &\quad - \sqrt{\delta_{US}}v_{w,t+1} + \sqrt{\kappa}\sigma_t u_{g,t+1}, \\ \sigma_{t+1}^2 &= \phi_i\sigma_t^2 + v_{t+1}. \end{aligned} \tag{14}$$

The volatility shock v again follows the gamma distribution. The shape and scale parameters are again k and ζ. I further assume $\delta_{US} = (\delta_H + \delta_L)/2$, where the subscripts H and L denote high- and low-interest-rate currencies. As such, the U.S. dollar is a currency with average interest rates.

6.2.1. Interest rates and exchange rates

The risk-free rate for country i can be solved as

$$\begin{aligned} r_{it} &= -E_t m_{i,t+1} - \frac{1}{2}var_t(m_{i,t+1}) \\ &= \alpha + \left(\xi - \frac{1}{2}\gamma - \frac{1}{2}\kappa\right)\sigma_{it}^2 + \left(\tau - \frac{1}{2}\delta_{it}\right)\sigma_{wt}^2. \end{aligned} \tag{15}$$

To focus on the intuition, I assume

$$\begin{aligned} \xi_i &= \frac{1}{2}(\gamma + \kappa) \text{ for all countries except the U.S.} \\ \xi &< \frac{1}{2}(\gamma + \kappa) \text{ for the U.S.,} \end{aligned} \tag{16}$$

so that the carry and dollar factors are uncorrelated. Following Backus et al. (2001), when markets are complete, the log spot rate changes can be written as

$$\Delta s_{i,t+1} = -m_{i,t+1} + m_{t+1}. \tag{17}$$

The excess return of currency i thus equals

$$\begin{aligned} rx_{i,t+1} &= r_{it} - r_t - \Delta s_{it+1} \\ &= -\frac{1}{2}(var_t(m_{i,t+1}) - var_t(m_{t+1})) \\ &\quad + (E_{t+1} - E_t)(m_{i,t+1} - m_{t+1}). \end{aligned} \tag{18}$$

6.2.2. Carry and carry momentum

Assume law of large number holds and the idiosyncratic risks net out for the currency factors. The carry return is defined as the excess return difference between high- and low-interest-rate countries,

$$\begin{aligned} carry_{t+1} &= \lim_{N_H\to\infty}\frac{1}{N_H}\sum_{i\in H} rx_{i,t+1} - \lim_{N_L\to\infty}\frac{1}{N_L}\sum_{i\in L} rx_{i,t+1} \\ &= \frac{1}{2}(\overline{\delta_{it}}^L - \overline{\delta_{it}}^H)\sigma_{wt}^2 \\ &\quad + (\overline{\sqrt{\delta_{it}}}^H - \overline{\sqrt{\delta_{it}}}^L)(E_{t+1} - E_t)v_{w,t+1}. \end{aligned} \tag{19}$$

The superscripts H and L denote high- and low-interest-rate countries, and the overline denotes the average for this group of currencies. Eq. (15) shows high-δ_i countries have, on average, low interest rates and low-δ_i countries have, on average, high interest rates:

$$\overline{\delta_{it}}^H < \overline{\delta_{it}}^L. \tag{20}$$

In the model, the carry return has negative exposure to the volatility shock v_w and earns positive expected returns, consistent with Menkhoff et al. (2012a). The expected carry premium is then proportional to the loading difference, $\overline{\delta_{it}}^L - \overline{\delta_{it}}^H$, and the expected variance of v_w, σ_{wt}^2.

To understand the drivers of factor momentum, I calculate the 1-month carry autocorrelation. Assume the variables are stationary, and the following relation arises

$$corr(carry_t, carry_{t+1}) = corr\left(\frac{1}{2}(\overline{\delta_{i,t-1}}^{L} - \overline{\delta_{i,t-1}}^{H})\sigma^2_{w,t-1} - (\overline{\sqrt{\delta_{i,t-1}}}^{L} - \overline{\sqrt{\delta_{i,t-1}}}^{H})\upsilon_{wt}, \quad \underbrace{\frac{1}{2}(\overline{\delta_{it}}^{L} - \overline{\delta_{it}}^{H})}_{=\frac{1}{2}(\delta_L - \delta_H)\left(1+\frac{\chi}{2} - \frac{\chi}{1+e^{\overline{\upsilon}_{w,t-h,t}}}\right)} \cdot \underbrace{\sigma^2_{wt}}_{=\phi_w \sigma^2_{w,t-1} + \upsilon_{wt}} \right). \tag{21}$$

The loading on the global shock, $\overline{\delta_{it}}^{L} - \overline{\delta_{it}}^{H}$, and the volatility level, σ^2_{wt}, further affect carry momentum. For the volatility term, first, the volatility process has a persistence of ϕ_w, introducing a positive autocorrelation into the expected carry premium. Second, the volatility shock υ_w reduces the carry return contemporaneously and pushes up the expected carry premium next period, generating a negative autocorrelation for carry returns. The Internet Appendix shows that, consistent with the model, the carry return does not correlate with heightened financial market volatility or economic uncertainty. The volatility effect is overall muted for generating the carry autocorrelation.

For the loading, $\overline{\delta_{it}}^{L} - \overline{\delta_{it}}^{H}$, the volatility shock υ_w reduces the contemporaneous carry return and increases the loading on the global shock through χ and further increases the expected carry premium. This loading variation generates a positive autocorrelation in carry returns. If the impact of the loading variation dominates the volatility dynamics, the carry return becomes autocorrelated as in the data.

6.2.3. Dollar and dollar momentum

The dollar factor is the average excess return of all foreign currencies against the dollar,

$$\begin{aligned} dollar_{t+1} &= \lim_{N\to\infty} \frac{1}{N} \sum_i rx_{i,t+1} \\ &= -\frac{1}{2}(\gamma+\kappa)\left(\overline{\sigma^2_{i,t}}^{Non-USD} - \sigma^2_t\right) + \sqrt{\gamma}\sigma_t u_{t+1} \\ &\quad + \sqrt{\kappa}\left(\sigma_t - \overline{\sigma_{i,t}}^{Non-USD}\right) u_{g,t+1}. \end{aligned} \tag{22}$$

The equation above shows that, the expected dollar excess returns is determined by the variance difference between the U.S. and other countries, $\overline{\sigma^2_{i,t}}^{Non-USD} - \sigma^2_t$. The variance difference is time-varying and also corresponds to the risk exposure to the global shock u_g.

Then the 1-month autocorrelation of the dollar factor can be calculated as

$$corr(dollar_t, dollar_{t+1}) = \frac{\phi_i(\gamma+\kappa)^2 E\sigma^4_{t-1}}{4var(dollar)}. \tag{23}$$

The equation suggests that the volatility persistence ϕ_i translates into not only persistent volatility and loading differences, but also autocorrelation in dollar factor returns. The Internet Appendix shows that the dollar return correlates with higher expected financial volatility and economic uncertainty empirically, consistent with the model.

6.2.4. Quantitative evidence

This section calibrates the model and conducts quantitative analysis. I calibrate the subset of parameters pertinent to the carry and dollar factor returns. The target moments include the mean, standard deviation, Sharpe ratio, and autocorrelation of the currency factors as well those of the forward-discount components in the currency factors. Panel A of Table 11 presents baseline parameters. First, because the level of loading and volatility are fungible, I set κ, δ_H and δ_L to 3, 0.01, and 0.64 to help pin down the model. Next, the persistence of the volatility process, ϕ_i and ϕ_w, is set to 0.89 and 0.8, respectively, matching the overall autocorrelations of the forward-discount components in currency factors. The parameters of the volatility processes, k, ζ, k_w and ζ_w, are then calibrated to match the mean, volatility, and Sharpe ratio of the carry and dollar factors. I set γ to a very small number, 0.005, to make the global dollar risk a large part of the dollar factor and boost dollar autocorrelation. The parameter ξ for all countries except the U.S. is calibrated to 0.95, matching the volatility of average forward discount. Finally, the loading on the global shock υ_w is calibrated to vary with the 6-month moving average of the z_w shocks, with a sensitivity χ of 19 to match the overall carry autocorrelations.

The model moments are estimated from 10,000 simulations. Panel B shows the model replicates patterns in the data well. In the baseline calibration, the carry factor earns a positive monthly return of 0.50% with a volatility of 1.89%, close to the empirical estimates, 0.48% and 1.87%. The Sharpe ratio is 0.92, versus 0.89 in the data. Furthermore, the simulated carry autocorrelations match the overall autocorrelation in the data. The coefficients, estimated using past 1-, 3-, and 12-month returns, are 0.12, 0.20, and 0.23 (0.16, 0.20, and 0.22 in the data). Regarding the term structure, the calibrated correlation is higher for the 12-month case, consistent with the data. The corresponding autocorrelations of the forward-discount components in the carry factor are consistently high, namely, 0.86, 0.82, and 0.62, close to the corresponding coefficients in the data.

For the dollar factor, the baseline model generates small and smooth returns with a monthly average of - 0.04% and a low standard deviation of 2.26%, close to the empirical counterparts, - 0.09% and 2.22%. The Sharpe ratio is close to zero, - 0.07, matching - 0.14 in the data well. The average forward discount has a mean of - 0.01% and a low volatility of 0.20%, in line with the data moments (- 0.20% and 0.20%). The dollar factor is autocorrelated with coefficients of 0.06, 0.15, and 0.27 for estimations using the 1-, 3-, and 12-month past returns, respectively, comparable to the empirical estimates of 0.07, 0.21 and 0.29. The autocorrelations for average forward discount are high, 0.89, 0.88, and 0.76, comparing with 0.82, 0.86, and 0.83 in the data.

Next, I use comparative statics to examine the channels in the model. For the carry factor, Eq. (21) shows that because the risk exposure to the global shock υ_w varies with the shock realization, the expected carry premium

Table 11
Quantitative results.
This table reports the quantitative results of the model. Panel A presents the baseline parameters. Panel B presents empirical estimates in the data (Data), the corresponding standard errors (S.E.), and the quantitative results for the baseline case and the alternative cases, in which the alternative parameters are in the top of the column. The model moments are calculated from 10,000 simulations.

Panel A: Parameters

ξ_i	γ	κ	ϕ_i	ϕ_w	δ_H	δ_L
0.95	0.005	3	0.89	0.8	0.01	0.64
χ	h	k	ζ	k_w	ζ_w	
19	6	3.5	0.0009	0.025	0.12	

Panel B: Moments

	Carry Factor				
	Data	S.E.	Baseline	$\chi = 0$	$\phi_i = 0$
Mean (%)	0.48	0.08	0.50	0.47	0.50
Standard Deviation (%)	1.87	0.08	1.89	1.74	1.89
Sharpe Ratio (%)	0.89		0.92	0.93	0.92
Mean Forward Discount (%)	0.89	0.02	0.50	0.47	0.50
SD of Forward Discount (%)	0.48	0.04	1.31	1.08	1.31
AR_{1M}	0.16	0.05	0.12	0.00	0.12
AR_{3M}	0.20	0.07	0.20	0.02	0.20
AR_{12M}	0.22	0.12	0.23	0.05	0.23
AR_{1M} of Forward Discount	0.83	0.03	0.86	0.82	0.86
AR_{3M} of Forward Discount	0.89	0.04	0.82	0.81	0.82
AR_{12M} of Forward Discount	0.85	0.07	0.62	0.64	0.62
	Dollar factor				
Mean (%)	-0.09	0.10	-0.04	-0.04	-0.03
Standard Deviation (%)	2.22	0.09	2.26	2.26	2.63
Sharpe Ratio (%)	-0.14		-0.07	-0.07	-0.04
Mean Forward Discount (%)	-0.20	0.01	-0.01	-0.01	0.00
SD of Forward Discount (%)	0.20	0.01	0.20	0.20	0.09
AR_{1M}	0.07	0.06	0.06	0.06	-0.01
AR_{3M}	0.21	0.07	0.15	0.15	0.00
AR_{12M}	0.29	0.12	0.27	0.27	-0.03
AR_{1M} of Forward Discount	0.82	0.02	0.89	0.89	-0.01
AR_{3M} of Forward Discount	0.86	0.03	0.88	0.88	-0.01
AR_{12M} of Forward Discount	0.83	0.08	0.76	0.76	-0.01

also varies with the realized carry return, generating carry momentum. Column $\chi = 0$ instead assumes that the risk exposure is constant. The carry autocorrelation decreases from 0.12, 0.20, and 0.23 to zero, 0.02, 0.05, respectively, none of which are significant in the large simulated sample. For the dollar factor, Eq. (23) shows that when the volatility σ_i is persistent, the dollar loading on u_g is also autocorrelated, generating autocorrelated dollar returns. To test the channel, column $\phi_i = 0$ assumes away the autocorrelation in the volatility process. The autocorrelation of the dollar factor decreases from 0.06, 0.15, and 0.21 to - 0.01, zero, and - 0.03, respectively. In sum, the model replicates the empirical autocorrelation in currency factors through time-varying exposure to the global shocks, and currency factor momentum can represent time-varying risk premium.

7. Conclusion

This paper documents that momentum and time series momentum in currencies, which cannot be explained by currency factors, only summarize the autocorrelation of currency factors. In fact, only systematic currency returns contain momentum in the cross section and time series, and idiosyncratic currency returns do not. The momentum strategies long currency factors following positive factor returns, but short following losses.

Further analysis shows that carry and dollar factors are autocorrelated. They earn significantly positive returns following positive past returns, but not following losses. A factor momentum strategy, which longs the individual factor when past performance is positive and shorts the individual factor when past performance is negative, earns significantly positive excess returns. Factor momentum not only outperforms the cross-sectional and time series momentum, but also explains and spans them. As such, the cross-sectional and time series momentum are closely related but not identical, and they have a common cause rooted in factor momentum. Because momentum is a prevalent phenomenon across various markets, this paper pushes toward a unified explanation for the cross-sectional and time series momentum across markets.

This paper further documents that limits to arbitrage can help partially explain factor momentum. I next propose a model with two global shocks and country-specific shocks. The currency factor exhibits time-varying risk exposure to the global shocks, generating time-varying risk premium and factor momentum observed in the data.

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