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INVESTOR SENTIMENT AND THE STATE-DEPENDENT STRUCTURE OF FOREIGN CURRENCY MOMENTUM

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Abstract
This study examines whether investor sentiment conditions the profitability of short-term cross-sectional foreign currency momentum strategies. Using weekly spot and forward exchange-rate data for 63 developed and emerging-market currencies over the period 1997–2015, we construct zero-investment winner–loser portfolios based on excess currency returns across alternative formation and holding horizons ranging from one to four weeks. The empirical results provide strong evidence that short-horizon currency momentum exists at weekly frequencies and that its economic significance depends critically on investor sentiment regimes. Specifically, momentum portfolio returns increase monotonically across ranked portfolios. In contrast, the profitability of the long–short spread portfolio is concentrated primarily during low-sentiment periods, while it weakens substantially during optimistic-sentiment environments. These findings indicate that investor sentiment operates as a state-dependent conditioning variable governing cross-sectional dispersion in currency returns rather than as a uniform predictor of

unconditional momentum profitability. Additional evidence suggests that exchange-rate volatility and macro-financial uncertainty amplify momentum opportunities by widening cross-currency return differentials. Overall, the results highlight the importance of incorporating behavioral indicators into currency allocation strategies and suggest that sentiment-conditioned trading rules improve the timing and risk-adjusted performance of short-term currency momentum portfolios in global foreign exchange markets.

Keywords: Investor sentiment, Currency momentum, Foreign exchange markets, Cross-sectional returns, Behavioral finance

JEL Classification: F31, G11, G14, G41, C58

1. Introduction

Momentum in asset returns represents one of the most robust empirical regularities in financial markets. Evidence from equity markets shows that cross-sectional momentum persists over intermediate horizons ranging from three to twelve months (Jegadeesh and Titman, 1993), appears at weekly frequencies (Pan et al., 2013), and remains stable across international markets and economic conditions (Chan et al., 2000; Griffin et al., 2003). Related research further shows that long-term continuation effects contribute to short-term return dynamics and may coexist with cross-sectional reversals at very short horizons (Gutierrez and Kelley, 2008). These findings suggest that continuation patterns reflect gradual information diffusion and heterogeneous adjustments to expectations rather than purely mechanical price dynamics.

In foreign exchange markets, cross-sectional return predictability has received increasing attention in recent years. Evidence shows that currency momentum strategies generate economically meaningful excess returns across large panels of international currencies (Menkhoff et al., 2012a; Asness et al., 2013). Earlier studies based on moving-average trading rules similarly document substantial momentum profits across both developed and emerging currency markets (Okunev and White, 2003; Chong and Ip, 2009). Despite these advances, relatively little is known about whether continuation patterns persist at short horizons in foreign exchange markets and whether their profitability depends on expectation-driven state variables.

Behavioral asset-pricing theory provides a natural framework for understanding why short-horizon continuation effects may arise. Models based on investor underreaction, conservatism, and overconfidence predict that information is incorporated gradually into asset prices when investors update beliefs imperfectly or face limits to arbitrage (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999). Because exchange-rate expectations reflect heterogeneous beliefs about macroeconomic conditions and relative currency strength, these mechanisms suggest that investor sentiment may influence the timing and magnitude of cross-sectional currency momentum profitability.

Consistent with this interpretation, investor sentiment in foreign exchange markets exhibits substantial variation at weekly frequencies and responds strongly to episodes of global financial stress, including the global financial crisis and the European sovereign debt crisis. These fluctuations indicate that expectations regarding relative currency strength adjust gradually rather than instantaneously to macroeconomic fundamentals and suggest that sentiment represents a potentially important conditioning variable for short-horizon return predictability. Currency returns exhibit systematic cross-sectional predictability linked to momentum and expectation-driven risk premia. Evidence accumulated over the past three decades shows that momentum reflects persistent information-diffusion frictions and remains a core component of systematic investment strategies across asset classes (Wiest, 2023). In foreign exchange markets, the profitability of currency carry and momentum strategies varies with global interest-rate volatility and macro-financial conditions, highlighting the importance of state-dependent return dynamics (Zeng, 2025; Nakagawa & Sakemoto, 2023). Recent research further emphasizes the role of expectations and sentiment in shaping short-horizon exchange-rate behavior. Media sentiment predicts currency reversals (Filippou, Taylor, & Wang, 2024), while investor expectations exhibit persistence at short horizons and respond asymmetrically to political uncertainty (Filippou, Li, Liu, & Taylor, 2024; Filippou, Li, & Liu, 2025). Text-based sentiment factors and survey expectations also improve the measurement of currency risk premia and short-horizon exchange-rate dynamics (Hafez et al., 2024; Kremens & Varela, 2026).

Motivated by these considerations, this paper examines whether investor sentiment conditions the profitability of short-term cross-sectional currency momentum strategies. Specifically, the study addresses three related questions. First, does cross-sectional currency momentum exist at weekly horizons between one and four weeks? Second, does investor sentiment affect the magnitude of continuation patterns across currencies? Third, do conditioning momentum strategies on sentiment regimes improve the measurement of short-horizon currency return predictability? To answer these questions, we construct zero-investment winner–loser portfolios using weekly spot and forward exchange rate data for 63 developed and emerging market currencies over the period from January 1997 to December 2015. Momentum portfolios are formed using alternative combinations of formation and holding horizons ranging from 1 to 4 weeks, yielding 16 strategy specifications. The analysis evaluates whether cross-sectional continuation patterns differ systematically across sentiment regimes, as measured by the Sentix investor sentiment index. Additional robustness tests extend the sample backward to January 1972-October 1997 for a subset of currencies.

The empirical results provide strong evidence that short-horizon cross-sectional currency momentum exists at weekly frequencies and varies systematically across expectation regimes. In particular, continuation patterns are strongest during periods of pessimistic sentiment and weaken substantially during periods of optimistic sentiment. These findings indicate that investor sentiment acts as a conditioning variable governing cross-sectional dispersion in currency returns rather than simply affecting unconditional return levels. To validate these results, the analysis considers alternative formation and holding horizons, examines multiple sentiment regimes, and evaluates momentum profitability across different market environments. The consistency of results across specifications suggests that expectation-driven sentiment variation plays an economically meaningful role in shaping short-horizon continuation patterns in foreign exchange markets.

This paper contributes to the literature in several ways. First, it provides new evidence that cross-sectional currency momentum exists at short horizons using weekly data across a large panel of international currencies. Second, it shows that investor sentiment operates as a state-dependent conditioning variable governing the strength of currency momentum profitability. Third, the results extend behavioral asset-pricing explanations of continuation effects to foreign exchange markets by demonstrating that expectation-driven sentiment variation helps explain time variation in short-horizon currency momentum returns. Together, these findings provide new insights into the role of investor expectations in shaping cross-sectional return predictability in global foreign exchange markets.

2. Literature Review

2.1 Return Momentum in Foreign Currency Markets

A growing body of research documents that foreign exchange returns exhibit a systematic cross-sectional structure that can be exploited using momentum-based trading strategies. Early evidence provided by Okunev and White (2003) shows that moving-average trading rules generate economically meaningful profits across major currency pairs. Chong and Ip (2009) extend this approach to emerging-market currencies and report even stronger return differentials. These findings suggest that continuation patterns in exchange-rate movements may persist across heterogeneous currency markets. Subsequent research confirms that cross-sectional return predictability represents an important feature of currency markets. Moskowitz et al. (2012) show that momentum strategies based on past asset performance generate consistent trading signals across multiple asset classes, including foreign exchange markets. Unlike time-series momentum strategies that rely on the historical performance of individual assets, cross-sectional momentum strategies rank currencies and exploit dispersion in their excess returns. This distinction is particularly important because cross-sectional strategies reflect relative-value opportunities rather than unconditional trends in exchange rates.

Although previous studies document medium-term momentum effects in foreign exchange markets, relatively limited attention has been given to continuation patterns at short horizons. Earlier research on cross-sectional reversals in equity markets (Jegadeesh, 1990; Lehmann, 1990; Lo and MacKinlay, 1990) shows that short-term return dynamics may differ substantially from longer-horizon momentum effects due to market microstructure frictions and the gradual diffusion of information. Extending this perspective to currency markets, the present study examines whether cross-sectional momentum or reversal effects exist at weekly horizons by constructing winner–loser portfolios using backtesting and holding periods ranging from one to four weeks. By focusing on short-horizon continuation patterns, this study contributes new evidence on whether relative currency performance remains predictable at frequencies that reflect expectation adjustments rather than long-run macroeconomic fundamentals.

2.2 Investor Sentiment and Expected Return Dynamics

Investor sentiment plays an important role in shaping asset-price dynamics by influencing expectations, trading behavior, and the speed with which information is incorporated into market prices. Behavioral asset-pricing models suggest that investors frequently rely on heuristics and social interaction when forming expectations, generating predictable return patterns consistent with momentum and reversal effects (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Barberis and Shleifer, 2003). Because investment decisions are often made under conditions of uncertainty, investors with limited private information are particularly likely to follow the behavior of other market participants, thereby reinforcing herd behavior in financial markets (Camerer, 1998; Daniel and Timan, 1999; Barber and Odean, 2008; Kaniel, Saar and Titman, 2008; Li, Rhee and Wang, 2009).

Herding behavior has important implications for market efficiency and asset-price volatility. When investors suppress private information and follow market trends, prices may deviate from their fundamental values, becoming temporarily overbought or oversold (Nofsinger, 2003). Empirical evidence further indicates that investor sentiment is closely related to market volatility and return predictability across financial markets (Brown and Cliff, 2004; Hwang and Salmon, 2008; Barber, Odean, and Zhu, 2006; Zhou, Zhang, and Lin, 2007). Psychological studies also show that optimism, overconfidence, and representativeness bias distort perceptions of risk and expected returns, thereby affecting investment decisions (Forgas, 1995; Gendolla, 2000; Loewenstein et al., 2001; Slovic et al., 2007; Shefrin, 2002).

Additional research shows that sentiment interacts closely with social learning and conformity behavior in financial markets. Analysts often exhibit non-herding behavior by relying on proprietary information rather than following consensus forecasts (Bernhardt, Campello, and Kutsoati, 2006), while broader market participants form expectations through social interaction and information exchange (Ellison and Fudenberg, 1993). When sentiment rises, investors may underestimate systemic risk and increase exposure to risky assets, reinforcing the relationship between sentiment and herd behavior (Hwang and Salmon, 2008). These dynamics contribute to cyclical fluctuations in market sentiment that influence trading activity and return dispersion across assets (Plutchik, 2002; Nofsinger, 2003).

Empirical studies further show that herd behavior can be measured using dispersion-based indicators such as the cross-sectional standard deviation (CSSD) of returns (Christie and Huang, 1995) and the cross-sectional absolute deviation (CSAD) proposed by Chang, Cheng, and Khorana (2000). Subsequent extensions incorporate beta-dispersion measures and residual-based indicators to distinguish between herd and non-herd behavior across international markets (Hwang and Salmon, 2004; Wang, 2008; Luo Jinshui and Li Chun'an, 2009). Evidence from these studies indicates that herding behavior tends to be stronger in emerging markets than in developed markets and exhibits asymmetric responses across bull and bear market conditions (Chang, Cheng, and Khorana, 2000; Li Chun'an and Lai Yiwen, 2005).

A large literature also develops composite sentiment indices based on market activity indicators such as trading volume, margin trading, derivatives activity, IPO issuance, and closed-end fund discounts (Lee, Shleifer, and Thaler, 1991; Neal and Wheatley, 1998; Whaley, 2000; Baker and Wurgler, 2000, 2006; Brown and Cliff, 2004). These indices provide evidence that investor sentiment predicts subsequent asset returns and affects market volatility across multiple financial markets. Additional studies show that uninformed liquidity trading amplifies volatility, whereas informed contrarian trading stabilizes market prices (Avramov, Chordia, and Goyal, 2004). Related research further documents that sentiment dynamics follow cyclical patterns associated with macro-financial conditions and expectation adjustments across market regimes (Poterba and Summers, 1988; Fama and French, 1992; Shiller, 2000; Pagan and Sossounov, 2003; Gonzalez et al., 2005; Powell, Shi, Wei, and Wu, 2007). Taken together, these findings suggest that investor sentiment is an important expectation-driven state variable that influences trading behavior, market volatility, and cross-sectional return dispersion. Building on this literature, the present study investigates whether investor sentiment conditions the profitability of short-term currency momentum strategies by altering the strength of continuation patterns across alternative sentiment regimes.

Previous research shows that foreign exchange returns exhibit systematic cross-sectional predictability that can be exploited using momentum-based trading strategies across developed and emerging currency markets. These continuation patterns suggest that relative currency performance contains useful information for short-term investment decisions. At the same time, behavioral finance theory indicates that investor expectations are often influenced by psychological biases, social interaction, and information frictions, which can generate persistent deviations from fundamental values and affect return dynamics. Empirical evidence further demonstrates that investor sentiment influences market volatility, trading behavior, and the dispersion of asset returns across financial markets. Despite these findings, relatively limited evidence exists on whether investor sentiment conditions the profitability of short-horizon currency momentum strategies. By examining the relationship between sentiment regimes and weekly cross-sectional currency momentum returns, this study contributes new evidence on the role of expectation-driven state variables in shaping short-term return predictability in global foreign exchange markets.

3. Methods and Data

3.1 Calculation of Excess Foreign Exchange Returns

This study uses the calculation model of Menkhoff et al. (2012a) to calculate the excess foreign exchange returns obtained by US investors holding foreign currency (K):

$$rx_{t+1}^{k} \equiv i_t^k - i_t - \Delta s_{t+1} \approx f_t^k - s_{t+1}^k \qquad (1)$$

where s is the current exchange rate after taking the logarithm (log), f is the forward exchange rate, Δs is the logarithmic value of the current exchange rate change, and i^k represents the foreign interest rate level. All exchange rates are quoted in units of US dollars as foreign currency units, where s represents the increase, meaning the US dollar (foreign currency) appreciates (depreciates). As shown in equation (1), the rate of return on foreign currency investment contains two main components: first, the component of appreciation or depreciation; second, the interest income obtained from foreign currency. However, Akram et al. (2008) specifically mentioned that these two return factors can be approximated by the difference between the one-week forward rate and the actual current rate using the covered interest rate valuation relation (CIP). Therefore, this study follows Menkhoff et al. (2012a) and uses Equation (2) to calculate the rate of return for foreign currency investors:

$$rx_{t+1}^{k} = f_t^k - s_{t+1}^k \qquad (2)$$

The above equation is sufficient for calculating the rate of return for holding periods of one week and one month (4 weeks), especially for foreign currency k within one week (month) t, for appropriately buying or selling foreign currency forward rates, and for hedging positions using one-week (one-month) forward contracts in week t+1 (month). Since the use of maturing forward contracts is not immediately available, we calculate the return for holding periods of two or three weeks and use Equations 3 and 4 separately to form buying positions:

$$rx_{t+2}^{k} = (f_t^k - s_{t+1}^k) + (f_{t+1}^k - s_{t+2}^k) \tag{3}$$

$$rx_{t+3}^{k} = (f_t^k - s_{t+1}^k) + (f_{t+1}^k - s_{t+2}^k) + (f_{t+2}^k + s_{t+3}^k) \tag{4}$$

Equations 3 and 4 are quite straightforward, meaning that investors can tend to buy positions for two or three weeks by buying one-week forward contracts (one week) until the end of the relevant holding period. We use a similar method to establish selling positions and conduct an empirical analysis using the medium-term exchange rates we use. We calculate the exchange rate return from last Wednesday to this Wednesday.

3.2 Constructing a Foreign Exchange Portfolio

A contrarian strategy represents the opposite of a momentum strategy, whereby a momentum strategy involves buying (selling) positions in the foreign currency that has appreciated (depreciated) the most relative to the US dollar, and a contrarian strategy involves buying (selling) positions in the foreign currency that has depreciated the most. This study constructs portfolios based on a momentum perspective; if these results show positive returns, this clearly favors a momentum strategy; however, if the returns are negative, this supports a contrarian strategy. This study calculates the excess return on lag each Wednesday, relative to a backtesting period of J weeks (including weeks 1, 2, 3, and 4). The 20% with the largest (smallest) excess return on lag are classified as winners (losers). Next, measuring the returns of winner and loser portfolios over a holding period of K weeks (including weeks 1, 2, 3, and 4), we report on winners, losers, and zero-investment winner-loser (W-L) portfolios across 16 portfolio types. Furthermore, this study multiplies the annualized weekly average return by 52, and similarly, we multiply it by the weekly standard deviation to obtain the annualized volatility value. Finally, the Sharpe ratio is used to measure the annualized volatility of the mean. The above research procedure is very similar to that of Lustig et al. (2011).

3.2.1 Momentum of Foreign Currency Momentum Returns under Different Market Conditions

The Impact of Economic Cycles on Foreign Currency Momentum Returns

First, we examine the characteristics of foreign currency momentum returns under different economic cycles. For this purpose, we use dummy variables of economic expansion and recession in the following regression model setting:

$$MOM(J,K)_t = \beta_{\exp}.D_{\exp} + \beta_{rec}.D_{rec} + \in_{J,K,t} \tag{5}$$

where at time t, represents the time series return of the short-term momentum strategy (J and K vary from 1 to 4 weeks). represents the economic cycle as a dummy variable; the return is 1 during recessions and 0 otherwise.

Momentum Returns During Foreign Exchange Market Booms and Recessions

Following Cooper et al. (2005), we define the average cumulative excess returns (CERs) for all foreign exchange momentum strategies.

$$CER_{t+K2} = \sum_{k=K1}^{K2} r_{k,t+k} \tag{6}$$

where (K1, K2) represent the paired portfolios with holding periods of (one week/two weeks), (one week/three weeks), and (one week/four weeks). This represents the excess return of the MOM(J,K) momentum strategy.

Momentum Returns Under Extreme Market Stress

In this section, we analyze the behavior of short-term foreign exchange momentum returns under market stress. This study defines high foreign exchange market volatility as a period of market stress during recessions; therefore, we calculate foreign exchange market volatility during both foreign exchange market expansions and recessions. We establish a global foreign exchange volatility proxy variable, calculated using data on returns for 63 foreign currencies covered in this study, as follows:

$$\sigma_{FXVOL,t} = \frac{\sum \left| r_t^k \right|}{K_t} \tag{7}$$

where foreign exchange volatility in week t and represent the amount of foreign currency in week t and the absolute return of foreign currency K after taking the logarithm of week t, respectively. We use volatility series in our regression model 8, measuring by taking the first difference of the erroneous volatility time series. This part of the estimation is mainly based on the research design of Menkhoff et al. (2012b), except that the daily foreign exchange return rate is replaced by the weekly return rate:

$$r_{MOM(J,K)_t} = \alpha_0 + \beta_{BOWN}.D_{DOWN} + \beta_{FXVOL}.\sigma^2_{FXVOL,t} + \beta_{\text{int}}.D_{DOWN}.\Delta\sigma^2_{FXVOL,t} + \in_t \tag{8}$$

where $r_{MOM(J,K)t}$ represents the excess return in week *t* under the MOM(J,K) strategy, $\Delta\sigma^2{}_{FXVOL,t}$ is the value of foreign exchange volatility in the same week *t*, β_{DOWN} is a dummy variable representing the market during a recession, and $\beta_{DOWN}\Delta\sigma^2{}_{FXVOL,t}$ represents market pressure in the foreign exchange market.

3.3 Data source

Exchange-rate data are obtained from the Taiwan Economic Journal (TEJ) database, which provides comprehensive coverage of both developed and emerging-market currencies at weekly frequency over the sample period 1997–2015. Excess currency returns are constructed as the difference between the forward exchange rate at time t and the realized spot exchange rate at time t+1, following the standard definition in the international currency momentum literature and ensuring comparability with established cross-sectional foreign exchange return measures. The dataset includes 63 currencies spanning heterogeneous exchange-rate regimes and macroeconomic environments, which allows reliable identification of cross-sectional dispersion in excess returns and supports construction of zero-cost winner–loser momentum portfolios across alternative formation and holding horizons. The use of weekly observations is particularly important because it captures short-horizon expectation adjustments and temporary deviations from fundamentals that are typically obscured at monthly frequencies. This higher-frequency structure provides a suitable empirical framework for isolating sentiment-related variation in exchange-rate dynamics and for evaluating whether investor sentiment operates as a conditioning state variable that amplifies continuation effects in short-term currency momentum strategies across internationally integrated foreign exchange markets.

4. Empirical Analysis

4.1 Investor Sentiment abd Foreign Exchange Returns

Figure 1 presents the time-series variation in investor sentiment in the USD/EUR foreign exchange market over the period 2001–2015 based on the Sentix sentiment index (www.sentix.de). The figure shows substantial short-horizon fluctuations around a relatively stable unconditional mean, indicating that expectations regarding relative currency strength vary persistently over time rather than adjusting smoothly with macroeconomic fundamentals. Sentiment volatility increases noticeably during periods of global financial stress, particularly around the 2008 global financial crisis and the European sovereign debt crisis, suggesting that investor disagreement intensifies during episodes of heightened uncertainty. The persistence of sentiment movements at weekly frequencies implies that expectation shocks are incorporated gradually into exchange-rate dynamics. These features indicate that investor sentiment represents a relevant conditioning variable for short-horizon currency momentum profitability and provide useful information for policymakers seeking to monitor expectation-driven exchange-rate volatility and improve the effectiveness of communication-based stabilization policies in foreign exchange markets.

Figure 2 shows the annual distribution of excess currency returns across the sample period from 1998 to 2015. The figure shows that the cross-sectional dispersion of excess returns remains substantial throughout the sample, though the median return is generally close to zero in most years. This pattern indicates that currency momentum profitability is driven primarily by cross-sectional ranking differences rather than unconditional mean returns. Notably, the dispersion of returns increases during periods of global financial instability, particularly around the early 2000s downturn and the 2008 global financial crisis, suggesting that exchange-rate volatility strengthens opportunities for relative-value trading strategies. The widening interquartile ranges observed during these episodes further indicate that heterogeneity across currencies rises when macro-financial uncertainty intensifies. These findings support the interpretation that excess currency returns exhibit time-varying dispersion that provides the empirical foundation for constructing profitable winner–loser portfolios in weekly currency momentum strategies.

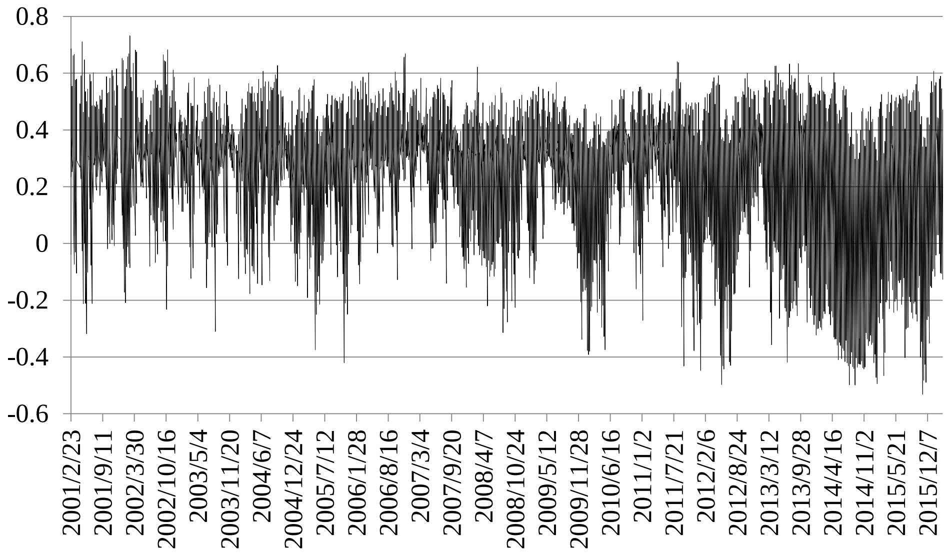

Figure 1

Time-varying investor sentiment in foreign currency markets (2001–2015)

Source: Sentix (www.sentix.de)

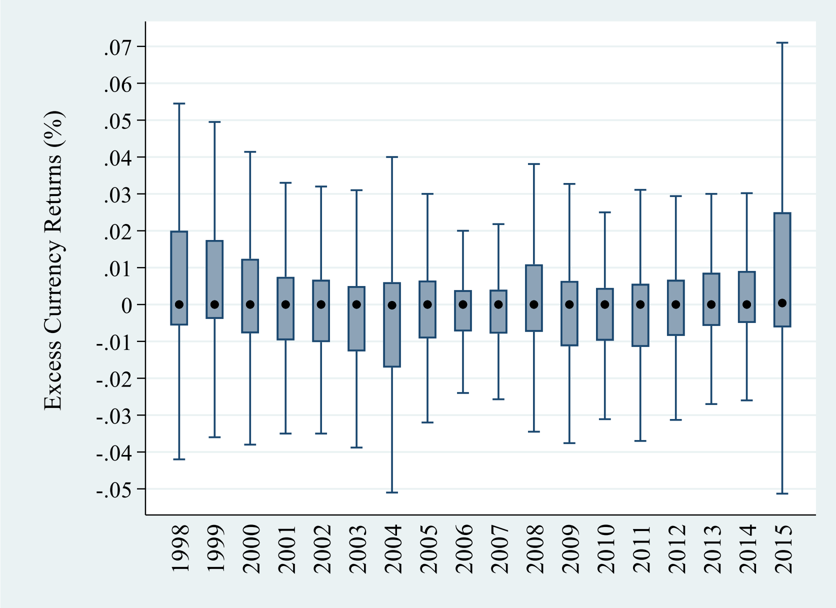

Figure 2

Time trend distribution of excess currency returns (%)

4.2 Portfolio Returns for Foreign Currency Returns

Figure 3 illustrates the time-series evolution of portfolio returns for four foreign currency portfolio strategies (M1–M4) over an event window spanning 36 periods before and 59 periods after the event date (t = 0). Two key patterns emerge. First, portfolio returns display a stable monotonic ordering across strategies throughout the sample window, with M1 consistently delivering the lowest returns and M4 the highest. This ordering suggests that the alternative portfolio constructions capture different degrees of exposure to the underlying currency return premium, with M4 providing the strongest loading on the priced component of currency returns. Importantly, the persistence of this ranking before and after the event indicates that the relative effectiveness of the sorting procedures remains intact across regimes. Second, the figure reveals a pronounced and persistent decline in returns immediately following the event date across all four strategies.

Rather than reverting to pre-event levels, returns stabilize at a lower plateau in the post-event window, consistent with a structural reduction in the profitability of currency-based strategies. The fact that this decline is observed uniformly across M1–M4 suggests that the event reflects a common shift in the economic environment affecting currency risk premia rather than a change specific to any individual portfolio specification. These results have direct implications for investors. Although higher-return specifications such as M4 continue to outperform alternative constructions, the downward shift in return levels implies that historical estimates based on pre-event samples overstate the expected performance of currency strategies in the post-event period. Consequently, investors should adjust portfolio allocations to reflect the lower expected compensation available after the event while continuing to favor portfolio designs that most effectively capture the underlying currency return premium.

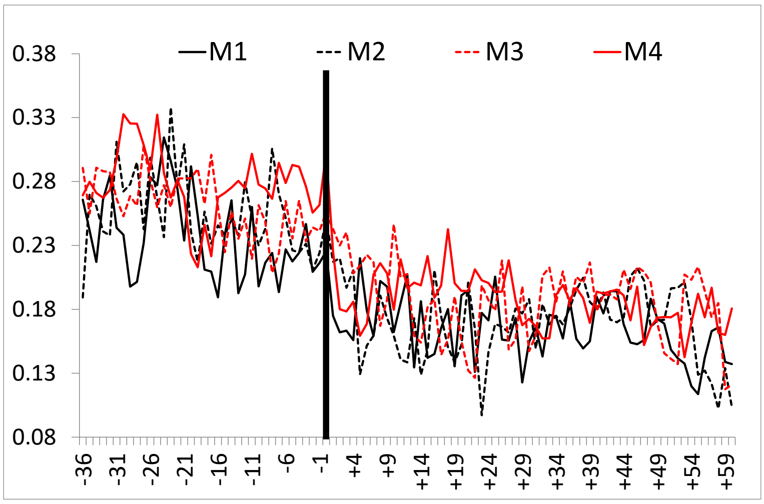

Figure 3

Time trend of portfolio returns for foreign currency returns

4.3 Investor Sentiment and the State-Dependent Structure of Currency Momentum Returns

Table 1 reports the dynamic behavior of foreign currency momentum portfolio returns (M1–M4) across alternative investor sentiment regimes. The results provide strong evidence that investor sentiment operates as a conditioning state variable governing both the level and the cross-sectional dispersion of currency momentum profitability while preserving a stable monotonic ordering of returns from M1 (lowest) to M4 (highest). Importantly, the High–Low difference portfolio (M4–M1) shows that the economic significance of the currency momentum premium is concentrated primarily in pessimistic sentiment environments and largely disappears during optimistic periods.

Table 1

Impact of Investor Sentiment on the Returns of Foreign Currency Momentum Portfolios

Holding Periods (Weeks)	M1 (Low)		M2		M3		M4 (High)		**Difference (M4-M1) (High- Low))**	
Panel A：All periods										
0	0.226***	(2.845)	0.251***	(3.185)	0.256***	(3.247)	0.303***	(3.619)	0.077	(1.468)
+1	0.175**	(2.202)	0.217***	(2.776)	0.243***	(3.052)	0.226***	(2.677)	0.051	(0.923)
+2	0.162**	(2.027)	0.220***	(2.911)	0.230***	(2.890)	0.180**	(2.256)	0.018	(0.339)
+3	0.163**	(2.079)	0.197**	(2.521)	0.240***	(3.066)	0.178**	(2.257)	0.015	(0.275)
+4	0.156*	(1.953)	0.211***	(2.884)	0.208***	(2.671)	0.186**	(2.343)	0.030	(0.565)

+5	0.220***	(2.876)	0.129	(1.616)	0.214***	(2.760)	0.159*	(1.966)	-0.061	(-1.169)
+6	0.179**	(2.266)	0.152*	(1.900)	0.223***	(3.027)	0.169**	(2.048)	-0.010	(-0.200)
+7	0.159**	(1.969)	0.159**	(2.037)	0.217***	(2.728)	0.207***	(2.632)	0.048	(0.936)
+8	0.202**	(2.529)	0.191**	(2.353)	0.167**	(2.182)	0.216***	(2.684)	0.014	(0.267)
+9	0.198**	(2.505)	0.173**	(2.319)	0.188**	(2.439)	0.208**	(2.508)	0.010	(0.207)
+10	0.162**	(2.123)	0.159**	(2.013)	0.247***	(3.197)	0.180**	(2.245)	0.017	(0.360)
+11	0.185**	(2.476)	0.141*	(1.842)	0.205**	(2.537)	0.219***	(2.747)	0.034	(0.727)
+12	0.207***	(2.623)	0.139*	(1.788)	0.208***	(2.600)	0.197**	(2.536)	-0.010	(-0.214)
Panel B：Higher Investor's Sentiment Periods										
0	0.265*	(1.665)	0.230	(1.606)	0.230	(1.444)	0.236	(1.480)	-0.029	(-0.298)
+1	0.030	(0.193)	0.192	(1.353)	0.141	(0.813)	0.156	(0.901)	0.125	(1.154)
+2	-0.069	(-0.366)	0.105	(0.632)	0.136	(0.754)	0.069	(0.358)	0.138	(1.438)
+3	-0.071	(-0.461)	0.013	(0.082)	0.014	(0.091)	-0.147	(-0.906)	-0.076	(-0.802)
+4	0.136	(0.986)	0.215	(1.560)	0.155	(1.119)	0.144	(0.975)	0.008	(0.062)
+5	0.042	(0.250)	-0.034	(-0.183)	0.101	(0.609)	-0.070	(-0.372)	-0.112	(-1.105)
+6	-0.039	(-0.223)	-0.055	(-0.258)	0.053	(0.264)	-0.112	(-0.571)	-0.073	(-0.694)
+7	0.053	(0.328)	0.151	(0.949)	0.199	(1.186)	-0.002	(-0.010)	-0.054	(-0.492)
+8	0.043	(0.303)	0.122	(0.919)	0.023	(0.160)	0.004	(0.027)	-0.039	(-0.364)
+9	0.037	(0.256)	0.054	(0.421)	0.010	(0.074)	-0.030	(-0.181)	-0.067	(-0.648)
+10	0.065	(0.500)	-0.022	(-0.163)	0.147	(1.099)	0.116	(0.747)	0.051	(0.486)
+11	0.009	(0.065)	-0.075	(-0.542)	0.166	(1.014)	0.091	(0.561)	0.082	(0.835)
+12	0.340	(1.644)	0.197	(0.901)	0.281	(1.355)	0.333	(1.610)	-0.007	(-0.068)
Panel C：Stable Investor's Sentiment Periods										
0	0.172	(1.291)	0.119	(0.777)	0.161	(1.236)	0.314**	(2.049)	0.142	(1.328)
+1	0.157	(1.158)	0.090	(0.646)	0.147	(1.179)	0.161	(1.064)	0.005	(0.045)
+2	0.157	(1.182)	0.169	(1.426)	0.117	(0.968)	0.154	(1.155)	-0.003	(-0.033)
+3	0.161	(1.119)	0.134	(0.905)	0.261**	(2.020)	0.328**	(2.221)	0.167	(1.506)
+4	0.163	(0.977)	0.202	(1.410)	0.192	(1.153)	0.175	(1.064)	0.011	(0.114)
+5	0.281**	(2.208)	0.244*	(1.692)	0.303**	(2.318)	0.198	(1.361)	-0.084	(-0.750)
+6	0.209	(1.558)	0.154	(1.280)	0.263**	(2.463)	0.242*	(1.694)	0.033	(0.305)
+7	0.096	(0.616)	0.044	(0.303)	0.099	(0.720)	0.230*	(1.686)	0.135	(1.487)
+8	0.271	(1.620)	0.235	(1.363)	0.153	(0.977)	0.155	(0.967)	-0.116	(-1.158)
+9	0.408**	(2.511)	0.231	(1.540)	0.341**	(2.270)	0.326**	(2.017)	-0.081	(-0.758)
+10	0.404**	(2.386)	0.450**	(2.592)	0.460***	(2.723)	0.423**	(2.383)	0.019	(0.194)
+11	0.606***	(3.869)	0.528***	(3.064)	0.506***	(2.874)	0.543***	(3.182)	-0.063	(-0.653)
+12	0.359**	(2.546)	0.220*	(1.684)	0.315**	(2.147)	0.290**	(2.151)	-0.070	(-0.704)

Table 1 (Continued)

Panel D：Lower Investor's Sentiment Periods										
0	0.647***	(3.135)	0.599***	(2.982)	0.714***	(3.568)	0.706***	(3.352)	0.059	(0.441)
+1	0.638***	(3.216)	0.767***	(3.788)	0.745***	(3.601)	0.714***	(3.816)	0.076	(0.581)
+2	0.716***	(3.670)	0.898***	(4.689)	0.799***	(3.618)	0.734***	(4.000)	0.019	(0.132)
+3	0.807***	(4.085)	0.836***	(4.652)	0.862***	(4.208)	0.728***	(3.916)	-0.079	(-0.515)
+4	0.511**	(2.538)	0.711***	(4.081)	0.604***	(3.405)	0.670***	(3.850)	0.160	(1.255)
+5	0.702***	(3.424)	0.592***	(3.032)	0.633***	(3.066)	0.685***	(3.613)	-0.017	(-0.128)
+6	0.658***	(3.195)	0.597***	(3.071)	0.590***	(3.311)	0.760***	(3.859)	0.102	(0.880)
+7	0.663***	(3.223)	0.686***	(3.776)	0.775***	(3.764)	0.768***	(3.951)	0.105	(0.980)
+8	0.608***	(2.892)	0.598***	(3.057)	0.584***	(2.954)	0.721***	(3.815)	0.113	(0.958)
+9	0.333*	(1.690)	0.498***	(2.811)	0.484**	(2.426)	0.555***	(2.834)	0.222**	(2.236)
+10	0.259	(1.577)	0.330**	(2.050)	0.436***	(2.790)	0.255	(1.604)	-0.004	(-0.042)

+11	0.088	(0.522)	0.025	(0.168)	0.173	(1.038)	0.144	(0.887)	0.056	(0.663)
+12	0.130	(0.852)	0.161	(1.186)	0.195	(1.240)	0.232	(1.612)	0.102	(1.035)

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A presents unconditional estimates over the full sample period. Consistent with the existing literature on currency momentum, portfolio returns increase monotonically from M1 through M4 across most holding horizons, indicating that higher-ranked portfolios capture progressively stronger exposure to continuation patterns embedded in cross-sectional currency returns. However, the High–Low spread remains modest and statistically insignificant across most horizons, suggesting that unconditional estimates understate the strength of the momentum premium because averaging across sentiment regimes compresses cross-sectional dispersion. This result indicates that the absence of a strong unconditional spread reflects regime aggregation rather than weak underlying momentum predictability.

Panel B reports results for high-sentiment periods and shows that momentum profitability weakens substantially in optimistic market environments. Returns across individual portfolios decline sharply in magnitude and lose statistical significance across most horizons. More importantly, the High–Low spread collapses toward zero and becomes statistically insignificant, indicating that optimistic sentiment compresses cross-sectional dispersion between high- and low-momentum currencies. This compression suggests that elevated sentiment strengthens arbitrage capacity and accelerates the incorporation of information into exchange rates, thereby limiting the persistence of cross-sectional continuation patterns captured by the long–short momentum strategy.

Panel C presents results for stable sentiment periods and reveals intermediate behavior between optimistic and pessimistic regimes. Momentum portfolio returns remain positive across most holding horizons and become statistically significant primarily at medium- and longer-term horizons. The High–Low spread gradually widens at longer horizons in this regime, indicating that cross-sectional return dispersion re-emerges as sentiment stabilizes. This pattern suggests that neutral sentiment environments represent transitional states in which continuation effects persist but have not yet been fully amplified by shifts in aggregate risk tolerance or market frictions.

Panel D provides the strongest evidence of regime-dependent momentum profitability. During low-sentiment periods, returns are economically large and statistically significant across nearly all portfolios and holding horizons. Most importantly, the High–Low spread becomes both economically meaningful and statistically significant, indicating that cross-sectional differences between high- and low-momentum currencies widen substantially when aggregate sentiment deteriorates. The strengthening of the spread portfolio in this regime implies that the profitability of long–short currency momentum strategies is concentrated primarily in pessimistic environments characterized by reduced investor risk tolerance and tighter funding conditions.

Comparing the High–Low spread across Panels A to D further clarifies the asymmetric contribution of sentiment regimes to overall momentum profitability. While the unconditional spread in Panel A appears weak, this reflects the offsetting effects of strong spreads during low-sentiment periods and negligible spreads during high-sentiment periods. Stable sentiment regimes contribute to intermediate dispersion, which becomes more pronounced at longer horizons. Together, these results indicate that investor sentiment governs when cross-sectional continuation in currency returns translates into economically meaningful long–short momentum profits rather than whether such continuation exists. The concentration of high–, such as M4, during low-sentiment states, rather than relying exclusively on symmetric long–short strategies, is consistent with counter-cyclical variation in currency risk premia. When aggregate sentiment declines, investors become more sensitive to downside risk and require greater compensation for holding currencies exposed to global risk factors. At the same time, tighter intermediary balance-sheet constraints and reduced capital mobility may slow arbitrage activity, allowing cross-sectional continuation patterns to persist.

From an investor perspective, these findings imply that the effectiveness of currency momentum strategies depends critically on conditioning portfolio exposure on sentiment regimes rather than implementing static long–short allocations. In particular, the regime-specific behavior of the High–Low spread suggests that the expected return to the momentum strategy is strongly time varying and predictable using investor sentiment as a conditioning variable. For institutional investors implementing currency momentum as part of a multi-factor allocation framework, these results support dynamically increasing exposure to the High–Low portfolio during pessimistic sentiment periods, when cross-sectional dispersion and compensation for currency risk are largest, while scaling back exposure during optimistic sentiment regimes when arbitrage activity compresses continuation effects. Moreover, because the monotonic ranking from M1 through M4 remains stable across regimes, investors seeking directional exposure to currency momentum signals may further enhance performance by tilting allocations toward higher-ranked portfolios such as M4 during low-sentiment states rather than relying exclusively on symmetric long–short implementations. More broadly, the evidence suggests that investor sentiment contains economically meaningful information about the conditional opportunity set available to currency investors. Incorporating sentiment into tactical allocation rules, therefore, provides a practical mechanism for improving both expected returns and risk-adjusted performance relative to unconditional currency momentum strategies.

4.4 Investment Implications

The regime-dependent behavior of currency momentum returns documented in empirical analysis has several important implications for investors implementing cross-sectional currency strategies. Most importantly, the results indicate that the profitability of currency momentum strategies is strongly conditional on investor sentiment rather than constant across time. In particular, the High–Low momentum spread (M4–M1) is economically meaningful primarily during periods of pessimistic sentiment. It becomes negligible during optimistic regimes, suggesting that unconditional implementations of currency momentum strategies may substantially underestimate the time variation in expected returns. First, the evidence supports a timing-based allocation interpretation, in which investor sentiment serves as a conditioning variable for expected currency-momentum profitability. Because the High–Low spread is largest and most persistent during low-sentiment periods, investors can improve expected performance by increasing exposure to currency momentum strategies when aggregate sentiment deteriorates and reducing exposure during optimistic sentiment environments when continuation effects weaken.

Second, the results have direct implications for the implementation of long–short currency momentum strategies. The statistical insignificance of the unconditional High–Low spread masks the fact that economically meaningful long–short profits are concentrated almost entirely in pessimistic sentiment regimes. This finding suggests that regime-conditioned implementations of the momentum spread portfolio are likely to deliver superior performance relative to static strategies that maintain constant exposure across sentiment states.

Third, the stability of the monotonic ranking from M1 through M4 across sentiment regimes implies that investors can further enhance performance by adopting cross-sectional tilting strategies within the momentum portfolio universe. In particular, allocating relatively greater weight to higher-ranked portfolios, such as M4, during low-sentiment periods allows investors to capture better the portion of the momentum signal that becomes most strongly priced when aggregate risk tolerance declines. Finally, the results suggest broader implications for multi-factor portfolio construction involving currency strategies. Because investor sentiment governs both the level and dispersion of currency momentum returns, incorporating sentiment indicators into tactical allocation rules provides a practical mechanism for improving the conditional efficiency of currency exposures within diversified portfolios. More generally, the evidence indicates that investor sentiment contains economically meaningful information about the time-varying opportunity set available to currency investors and therefore represents a useful conditioning variable for dynamic portfolio allocation decisions involving cross-sectional currency strategies.

5. Conclusion, Implications, and Limitations

This paper examines whether investor sentiment conditions the profitability of short-horizon cross-sectional currency momentum strategies. Using weekly spot and forward exchange-rate data for 63 developed and emerging-market currencies over the period 1997–2015, we document that continuation patterns exist at horizons between one and four weeks and vary systematically across sentiment regimes. In particular, the profitability of momentum spread portfolios is concentrated primarily during pessimistic sentiment environments and weakens substantially during optimistic periods. These findings indicate that investor sentiment operates as a conditioning state variable governing cross-sectional dispersion in currency returns rather than simply affecting unconditional return levels. The results contribute to the literature on currency return predictability by showing that expectation-driven variation in investor sentiment helps explain time-varying short-horizon momentum profitability. While prior research documents the existence of medium-term currency momentum premia, the evidence presented here shows that continuation effects remain economically meaningful even at weekly horizons when evaluated within a regime-dependent framework. More broadly, the findings support conditional asset-pricing models in which heterogeneous expectations and limits to arbitrage generate predictable variation in cross-sectional currency returns.

The results also have important implications for investors and policymakers. For institutional investors implementing currency momentum strategies, conditioning portfolio exposure to sentiment regimes provides a practical mechanism to improve risk-adjusted performance and to time long–short currency allocations. Because sentiment captures expectation-driven variation in market-wide risk tolerance and disagreement about future exchange-rate movements, incorporating sentiment into tactical currency allocation frameworks improves the measurement of the conditional opportunity set available to global investors. From a policy perspective, the evidence further suggests that sentiment indicators contain useful information about expectation-driven exchange-rate volatility, particularly during periods of global financial stress when disagreement about macroeconomic fundamentals increases.

Despite these contributions, several limitations remain. First, the sentiment measure used in this study is based on a specific survey-based indicator. It may not fully capture alternative dimensions of expectation heterogeneity reflected in media-based, textual, or market-implied sentiment measures. Second, although the weekly frequency of the data allows identification of short-horizon continuation patterns, higher-frequency expectation adjustments may occur at daily or intraday horizons that remain outside the scope of the present analysis. Third, the sample period ends in 2015 and therefore does not incorporate more recent developments in foreign exchange markets associated with unconventional monetary policy spillovers and post-pandemic global financial conditions. Future research may extend the analysis by incorporating alternative sentiment proxies, higher-frequency expectation measures, and intermediary balance-sheet constraints to examine in greater detail the mechanisms linking expectation dynamics to short-horizon currency momentum premia.

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