

Macroeconomic Conditioning of Momentum Profits: Evidence from 155 Years of UK Equity Markets

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Abstract

This paper provides new evidence on momentum performance conditional on business cycle phases and different levels of geopolitical risk (GPR) regimes using 155 years of UK equity market data from 1869 to 2024. We find that profits are significant in both expansions and recessions, with recessionary profits driven by the underperformance of losers. Momentum performance declines as geopolitical risk rises, suggesting that stable external information environments are essential for sustaining return continuation. We further show that the option-like payoff feature of momentum is regime-dependent and disappears before 1935, when no formal market index existed, indicating that investor awareness of aggregate market conditions is critical for such convex payoff structures. Our results provide further evidence supporting the behavioural nature of the momentum anomaly.

Keywords: Momentum; Business Cycle; Geopolitical Risks; Momentum Crashes; Information Diffusion

JEL: G12, G14, N23, N24

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1. Introduction

Momentum effect, first documented by [Jegadeesh and Titman \(1993\)](#), is widely recognised as one of the most persistent and puzzling financial market anomalies. It is characterised by the tendency for past winners to continue outperforming, and past losers to continue underperforming over short and intermediate horizons. This pattern presents a direct challenge to the Efficient Market Hypothesis (EMH).

While momentum has been extensively documented in global equity markets ([Rouwenhorst, 1998](#); [Griffin et al., 2003](#)), various asset classes ([Moskowitz et al., 2012](#); [Asness et al., 2013](#); [Papailias et al., 2021](#)), stock factors ([Arnott et al., 2023](#)), and even option markets ([Heston et al., 2023](#)), considerable debate remains on its driving mechanisms. Proponents of behavioural finance attribute momentum to investors' short-term underreaction to new information ([Daniel et al., 1998](#)) and conservatism bias ([Barberis et al., 1998](#)). Whereas risk-based explanations posit that momentum profits reflect compensation for exposure to unpriced risks such as liquidity constraints, cross-sectional expected returns, trading volumes or industry-specific effects that are not captured by standard asset pricing models ([Fama and French, 1996](#); [Conrad and Kaul, 1998](#); [Moskowitz and Grinblatt, 1999](#); [Lee and Swaminathan, 2000](#)). Despite the large body of literature, relatively few studies have examined how time-series variation in economic conditions and external shocks affect investor behaviour, and hence affect the formation and persistence of momentum.

This paper revisits the momentum anomaly through the lens of macroeconomic and geopolitical regimes using a long run dataset of UK equities covering the period 1869-2024. We find that momentum strategies behave differently to various macroeconomic conditions. Specifically, momentum strategies remain profitable during both economic states of expansion and recession. However, during recessions, momentum profits are primarily driven by the extreme underperformance of loser portfolios, while winner portfolios exhibit relatively stable returns. We further explore the role of external shocks, proxied by the Geopolitical Risk (GPR) Index, in shaping momentum profitability. We find that momentum performs best under low to moderate levels of geopolitical risk but weakens considerably when geopolitical tensions intensify. Our research offers a conditional explanatory framework for momentum under the joint impact of business cycle and geopolitical risk.

While early empirical research on momentum emphasised its long-term persistence and largely treated the effect as unconditional, more recent studies have highlighted its sensitivity to economic and market states. For example, [Daniel and Moskowitz \(2016\)](#) and [Barroso and Santa-Clara \(2015\)](#) link momentum crashes to macroeconomic and volatility regimes; [Zhang \(2006\)](#) examines information uncertainty as a conditional driver of momentum returns; [Kelly et al. \(2021\)](#) connect momentum with global crash risk. Our paper is related to the abovementioned literature by focusing on macroeconomic business cycles and geopolitical risk as joint sources of time series variation. While business cycle risk captures systematic fluctuations in economic fundamentals tied to aggregate growth and recession phases, geopolitical risk reflects exogenous shocks stemming from political instability and global tensions, representing distinct sources of uncertainty. Our research emphasises that momentum is not purely a static anomaly, but one whose profitability and drivers depend crucially on prevailing economic and external conditions.

In terms of the impact of business cycles on momentum, empirical testing is often constrained by limited data histories. Many stock markets, particularly in developing economies, have only several decades of reliable data. Even the most widely used dataset, CRSP, spans less than a century, beginning in 1926. Given that the average duration of business cycles lasts about 16 years after WWII ([Broadberry et al., 2023](#)), longer historical series are necessary to obtain robust evidence on the relationship between momentum and business cycles. We address this gap by employing a long-run dataset of UK stock and business cycle data covering more than 150 years. The UK market was the world’s largest capital market in the 19th century, offering a representative setting to examine long-term stock market behaviour. The existing literature on constructing the UK momentum factors mostly covers periods after the 1980s, e.g., [Rouwenhorst \(1998\)](#), [Gregory et al. \(2013\)](#), and [Fletcher \(2001\)](#), among others. In contrast, our long-horizon dataset enables us to revisit the debate on the cyclical behaviour of momentum and assess its dynamics under different economic states.

The relationship between momentum and business cycles and market states shows inconsistencies in the existing literature. [Griffin et al. \(2003\)](#) found that traditional macroeconomic indicators cannot explain the persistence of momentum in the US stock market, so the driving mechanisms behind it must be viewed from a more microeconomic perspective. In contrast,

Chordia and Shivakumar (2002), distinguishing between economic expansions and recessions, found that momentum strategies yield significantly positive returns during expansion periods but turn negative and insignificant during recessions. More recently, Goetzmann and Huang (2018) showed that momentum returns are insignificantly higher during recessions than expansions in the imperial Russian stock market over 1865–1914. This is consistent with the risk-based interpretation of momentum as compensation for bearing bad-state risk, although the evidence does not provide statistically robust support. Goyal et al. (2025) found that the momentum effect is more pronounced in rising markets and low-volatility environments, Min and Xiao (2021) divided the business cycle based on turning points and found that momentum returns during the peak phases significantly outperform those in the trough phases.

Based on long-run empirical evidence, we show that momentum strategies remain significantly profitable in both expansions and recessions. Our finding is consistent with Griffin et al. (2003) and Goetzmann and Huang (2018), but different from Chordia and Shivakumar (2002). In particular, we find that momentum strategies remain significantly profitable during recessions periods, often yielding higher returns than during expansions period. For instance, the momentum strategy with a 12-month formation period and 1-month holding period has a mean return of 14.5% per annum in recession periods but only achieves a mean of 11.5% during expansions. This pattern is primarily driven by loser portfolios consistently producing large negative returns in recession periods, and thus leading to stronger momentum profits. Decomposing the realised variance of momentum returns, we find that positive return variation dominates during recessions, while downside semivariance remains relatively stable. This pattern suggests that excess returns in downturns are largely driven by sharp upward price movements, rather than from gradual improvements in underlying fundamentals.

Next, we show that momentum strategies perform best when GPR is at the lowest quartile, and perform worse when GRP level gets higher, implying that stable external information environments are crucial for sustaining return continuation. Dividing the sample into expansions and recessions, we find that the low GPR premium is consistent across the two macroeconomic regimes.

In a further analysis of the momentum crashes, we find that they mostly occur in up-market states and during economic expansions over the 155-year sample period, which is consistent with [Daniel and Moskowitz \(2016\)](#). However, momentum crashes are not necessarily a consequence of recessions or broad market declines. Our evidence suggests that the two-year market returns preceding most crash months are positive, suggesting that severe momentum losses tend to emerge after periods of strong market performance rather than during downturns. Moreover, we find that the asymmetric, option-like payoff of momentum strategies is insignificant over our sample. This is mainly due to the pre-1935 period, when there was no market index in the UK, indicating that the option-like payoff only appears when investors have an unbiased perception of how the market goes.

Our study contributes to the literature in three important aspects. First, the paper systematically examines momentum returns conditional on different macroeconomic states and levels of geopolitical risk. We find that momentum strategies remain profitable in both expansions and recessions, but profits in recessions are primarily driven by the extreme underperformance of prior losers. Our finding adds long run evidence to the existing debate on how the momentum premium varies across different phases of the business cycle. While there has been literature on how momentum is affected by business cycles and market states, studies on the relationship between momentum and GPR are scarce. We find that momentum performance generally declines as geopolitical risk rises, though the relationship is not strictly monotonic and weakens after risk adjustment, indicating that higher geopolitical uncertainty tends to dampen momentum profitability.

Second, we contribute to the growing literature on momentum crash risk by providing new long-run evidence on the conditions under which crashes occur and how their payoff structures evolve. Unlike the U.S. findings of [Daniel and Moskowitz \(2016\)](#) and [Barroso and Santa-Clara \(2015\)](#), which associate momentum crashes primarily with market downturns and volatility spikes, our results show that severe momentum losses in the UK frequently follow up-market conditions rather than down markets. We further document that the option-like payoff pattern is not constant across time but regime-dependent, appearing only in specific macroeconomic and informational environments. This option-like feature becomes largely insignificant before 1935, when no formal market index existed in the UK. This

historical evidence suggests that the option-like behaviour of momentum requires a shared benchmark for market performance; when investors lack a clear perception of aggregate market trends, the convex payoff structure of momentum strategies effectively disappears.

Third, this paper provides the longest and most comprehensive empirical examination of momentum in the UK equity market, using a newly compiled dataset covering the period 1869–2024. By spanning more than 150 years and multiple full business cycles, we show unprecedented historical evidence on the lifecycle and persistence of the momentum effect. Most momentum strategies with different combinations of formation and holding periods exhibit statistically significant abnormal returns over the entire sample period. This extensive dataset also serves as a representative record of the evolution of the UK stock market from manual trading to algorithmic trading, suggesting that the violation of market efficiency persists in the long run.

The remainder of this paper is organised as follows. Section 2 details how we build the long-run UK stock dataset and other macroeconomic variables, and construct the momentum portfolios. Section 3 summarises the performance of various momentum portfolios and their factor exposures. Next, we analyse the heterogeneous performance of momentum under different business cycle phases and geopolitical risk regimes in Section 4. Section 5 examines the relationship between macroeconomic dynamics and the momentum crash risks. Finally, Section 6 concludes.

2. Data and portfolio construction

2.1. UK Stock Market and the momentum portfolio construction

In this paper, we establish a long-term monthly dataset spanning from 1869 to 2024 by integrating historical data from various sources on the UK stock market. First, for stock prices, dividends, and market capitalisations, we compile them from the Investor’s Monthly Manual (1869-1929), Global Financial Data (1930-1956), and the London Share Price Dataset (1957-2024). Stock returns are calculated based on percentage changes in the prices adjusted for dividends. Second, we collect price-to-book ratios from the Cambridge/DTI Databank of the UK Department of Trade and Industry (1955-1990), Datastream (1991-2006), and the Compustat Global database (2007-2024). Lastly, for the risk-free rate used to calculate

excess returns, we collect the prime bank bill rates documented by [Capie and Webber \(2013\)](#) from 1870 to 1978, the three-month interbank rates from the Bank of England interactive database from 1978 to 2016, and the Sterling Overnight Index Average (SONIA) from 2016 to 2024, respectively.

Given that the final dataset was compiled from six different sources, we first performed nomenclature standardisation to ensure consistency. Company identifiers, industry classification labels, and timestamp formats are aligned to maintain structural coherence throughout different periods. During the integration of time series data from various sources, we aligned market data with firm-level accounting data on a temporal basis. For the IMM data (1869–1929), all stocks quoted in US dollars were excluded, retaining only those denominated in British pounds to ensure uniformity in currency units and to eliminate potential distortions arising from exchange rate fluctuations.

Next, to construct the Fama-French three factors for regression analysis, we first build the market factor ($R_m - R_f$) as the value-weighted return of all stocks minus the risk-free rate. For the size factor (SMB), we sort all stocks into deciles based on market capitalisation at the end of June each year, and then compute SMB as the value-weighted return of decile 1 (smallest stocks) minus that of decile 10 (largest stocks). Similarly, for the value factor (HML), we sort all stocks into deciles based on book-to-market ratios (inverse of Price-to-Book) at the end of each June, where decile 1 contains stocks with the highest book-to-market ratios (value stocks) and decile 10 contains stocks with the lowest ratios (growth stocks). HML is calculated as the value-weighted return of decile 1 minus decile 10. For the period prior to 1955, we sort all stocks based on dividend yield percentiles to proxy the HML factor, following the method of [Grossman and Shore \(2006\)](#). The HML factor is computed as the value-weighted return of the high dividend yield group (decile 1) minus that of the low dividend yield group (decile 10).

Finally, we construct the momentum portfolios following the standard approach of [Jegadeesh and Titman \(1993\)](#). At the end of each month, stocks are sorted into deciles in ascending order based on their period returns over the past J -month period (where $J \in \{3, 6, 9, 12\}$). A winner minus loser momentum portfolio is formed by buying the stocks in the top decile (winners) and selling stocks in the bottom decile (losers). We hold the

momentum trading positions for K months, where $K \in \{1, 3, 6, 12\}$. In total, $4 \times 4 = 16$ J - K combinations are formed. In line with [Goetzmann and Huang \(2018\)](#), we construct momentum strategies with and without excluding the most recent month over the formation periods to explore short-term reversal in the long run and ensure comparability with the existing literature. To leave a maximum period of 12-month for the formation and holding period respectively, we start to compare all the portfolio performance from 1871 throughout this paper.

2.2. Business Cycle Data and Geopolitical Risk Index

The business cycle data used in this study spans the period from 1871-2024 and is constructed using a cross-century combination of sources. The core data (1926-2009) we use is the standardised quarterly economic cycle series developed by [Broadberry et al. \(2023\)](#). We classify the UK business cycle into four different phases, namely peak, trough, expansion, and recession. Specifically, we define a peak or a trough as the turning points of the quarterly business cycle data. An expansion period is defined as the interval from the most recent trough to the subsequent peak, while a recession period extends from the most recent peak to the following trough.

To align the temporal coverage of the business cycle data with our stock return dataset, we extend the chronology back to 1871 using the monthly turning point compiled in [Chadha and Nolan \(2002\)](#) for the 1871 to 1925 period. Specifically, for months marked as peaks or troughs in this second dataset, the preceding and following months are also included to form a three-month peak/trough interval, ensuring comparability with the main business cycle data. From 2010 to 2024, we use OECD business cycle data as a supplement for the missing period, as in [Broadberry et al. \(2023\)](#).

For the geopolitical risk measure, we obtain the Geopolitical Risk (GPR) Index developed by [Caldara and Iacoviello \(2022\)](#), selecting data from 1900 to 2024 for the UK as our sample. This index quantifies the frequency of reports on eight categories of geopolitical events, such as threats of war, military conflicts, and terrorism, through systematic analysis of textual data from ten leading newspapers in the UK, the US, and Canada, such as the Chicago Tribune, Financial Times, and The New York Times. The data is measured at a monthly

frequency and includes two-dimensional indicators: “Geopolitical Threat” (GPR Threat) and “Geopolitical Acts” (GPR Acts), capturing signals of risk anticipation and the intensity of actual conflicts, respectively.¹

Figure 1 plots the monthly GPR index from 1871 to 2024, together with shaded areas denoting recession periods as identified by the business cycle dating. The figure illustrates that fluctuations in the GPR index do not coincide perfectly with the phases of the business cycle. For instance, episodes of heightened geopolitical tensions, such as during the two World Wars or the Cold War, do not always align with recessions. Simultaneously, several recessionary periods occurred, during which the GPR index remained relatively reduced. This evidence shows that business cycle dynamics and geopolitical risk capture distinct dimensions of macroeconomic uncertainty. Therefore, it is essential to examine these two factors separately when analysing their impact on the UK momentum strategies.

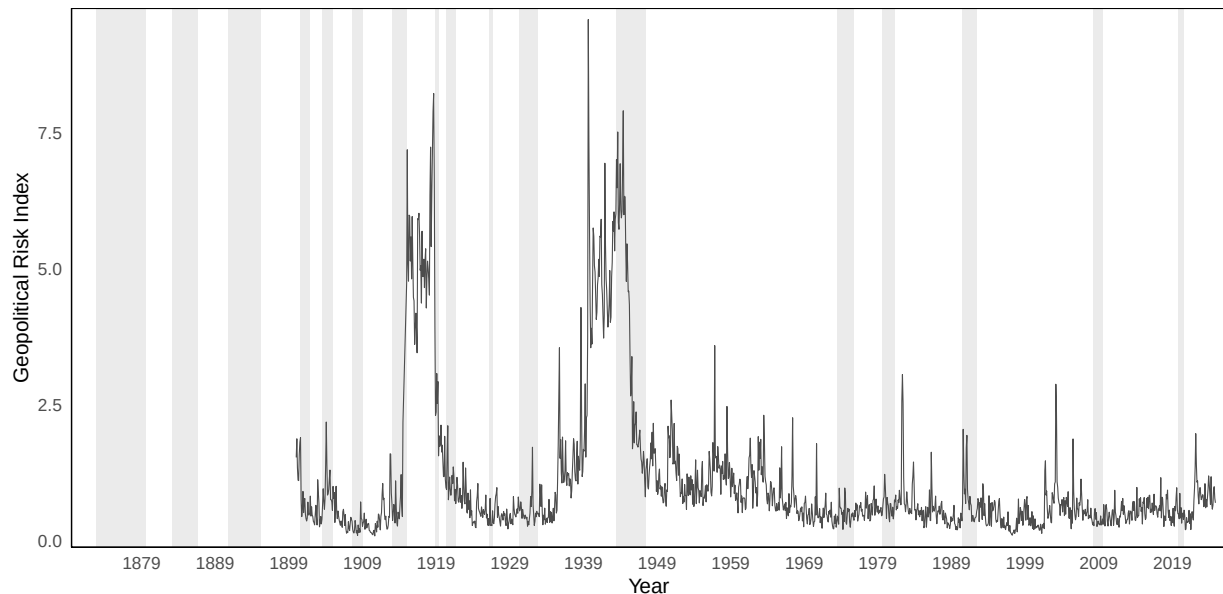


Figure 1: UK Business Cycle and GPR Index

This figure presents an overview of the business cycle and Geopolitical Risk Index (GPR) of the United Kingdom from 1871 to 2024. The solid line represents the GPR index, with higher values indicating greater geopolitical risk. The shaded areas denote recession periods as identified by the business cycle dating, where peak periods are classified as expansions and trough periods are included in recessions.

¹This index has been adopted by the International Monetary Fund (IMF) as a benchmark tool for global financial risk assessment, with data sourced from Matteo Iacoviello’s [official website](#).

3. Long-run UK stock momentum strategies

In this section, we examine the performance of momentum strategies in the UK equity market over a sample period spanning more than 150 years. We assess the performance of momentum strategies from three angles: the portfolio’s excess returns, risk-adjusted performance, and cumulative performance.

Following [Goetzmann and Huang \(2018\)](#), we start by investigating whether the momentum profits are affected by the short-term reversals and market microstructure effects, as documented by [Bandi and Russell \(2008\)](#). We implement two different types of momentum strategies: 1) strategies constructed without a gap between the formation and holding periods; 2) the standard approach of [Jegadeesh and Titman \(1993\)](#) that excludes the most recent month from the formation window to mitigate potential short-term reversal effects.

Table 1 reports the average monthly returns of momentum portfolios under various formation (J) and holding (K) period combinations. In Panel A, for short holding periods ($K = 1$), the momentum effect is weak or even negative, such as -0.85% for $J = 3$ and -0.03% for $J = 9$. In contrast, momentum returns improve as the holding period increases to $K = 3$ or $K = 6$, before flattening or slightly declining at $K = 12$.

Panel B, which skips the most recent month in the formation window, exhibits stronger and more stable momentum profits across all (J, K) combinations. All WML returns are positive and statistically significant at the 1% level, except for the 3-1 strategy. More specifically, the 12-1 momentum strategy yields the highest WML return, achieving 1.16% per month. These results confirm that skipping the last month of the formation period helps mitigate the influence of transitory price reversals and enhances the reliability of the momentum signal.

The above results illustrate positive and persistent momentum returns across various parameter settings. However, documenting excess returns alone does not explain whether these profits can be attributed to exposure to other risk factors. Therefore, we further estimate the risk-adjusted return, also known as the abnormal return (α), based on the Capital Asset Pricing Model (CAPM) and the Fama-French Three-Factor Model (FF3) of [Fama and French \(1993\)](#). Table 2 presents the risk-adjusted performance of momentum portfolios. Panels A and B report results from the CAPM, while Panels C and D correspond

Table 1: Price momentum portfolios return

This table shows the average monthly returns of the value-weighted momentum portfolios formed based on J -month formation and K -month holding periods. The corresponding t -statistics, based on the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#), are in parentheses. Loser/Winner refers to a short/long portfolio with stocks with the lowest/highest formation period returns, and WML denotes the winner minus loser portfolio. The momentum portfolios in Panel A are formed using returns over the entire portfolio formation period. Strategies in Panel B exclude the most recent month from the formation period to avoid the short-term reversal. The sample period ranges from May 1869 to November 2024.

		Panel A					Panel B				
J		$K=$	1	3	6	12	$K=$	1	3	6	12
3	Winner	0.0038	0.0074	0.0088	0.0097		0.0075	0.0089	0.0093	0.0096	
		(2.73)	(5.65)	(7.22)	(8.21)		(5.50)	(6.91)	(7.58)	(8.09)	
	Loser	0.0123	0.0082	0.0060	0.0056		0.0063	0.0057	0.0054	0.0056	
		(7.17)	(5.10)	(3.90)	(3.82)		(3.80)	(3.85)	(3.68)	(4.02)	
	WML	-0.0085	-0.0007	0.0028	0.0040		0.0012	0.0032	0.0039	0.0039	
		(-5.81)	(-0.63)	(2.83)	(5.15)		(0.94)	(3.43)	(5.02)	(6.20)	
6	Winner	0.0074	0.0099	0.0105	0.0103		0.0107	0.0113	0.0112	0.0104	
		(5.45)	(7.72)	(8.45)	(8.78)		(8.07)	(8.98)	(9.10)	(8.86)	
	Loser	0.0102	0.0067	0.0054	0.0053		0.0041	0.0038	0.0041	0.0050	
		(5.46)	(3.84)	(3.24)	(3.38)		(2.42)	(2.34)	(2.62)	(3.34)	
	WML	-0.0028	0.0032	0.0051	0.0051		0.0066	0.0075	0.0071	0.0055	
		(-1.77)	(2.30)	(4.03)	(4.98)		(4.95)	(5.91)	(6.20)	(5.94)	
9	Winner	0.0089	0.0109	0.0118	0.0105		0.0115	0.0117	0.0121	0.0103	
		(6.51)	(8.47)	(9.31)	(8.71)		(8.58)	(9.07)	(9.53)	(8.50)	
	Loser	0.0093	0.0056	0.0041	0.0055		0.0039	0.0033	0.0033	0.0054	
		(4.89)	(3.06)	(2.38)	(3.45)		(2.11)	(1.94)	(1.99)	(3.49)	
	WML	-0.0003	0.0053	0.0076	0.0050		0.0076	0.0084	0.0088	0.0049	
		(-0.19)	(3.63)	(5.65)	(4.43)		(5.23)	(6.14)	(6.94)	(4.63)	
12	Winner	0.0105	0.0120	0.0115	0.0099		0.0132	0.0128	0.0118	0.0099	
		(7.67)	(9.22)	(9.05)	(8.02)		(10.02)	(9.79)	(9.27)	(7.93)	
	Loser	0.0063	0.0042	0.0043	0.0063		0.0017	0.0022	0.0035	0.0062	
		(3.41)	(2.31)	(2.48)	(3.81)		(0.97)	(1.27)	(2.09)	(3.89)	
	WML	0.0042	0.0077	0.0071	0.0037		0.0116	0.0106	0.0082	0.0037	
		(2.64)	(5.51)	(5.31)	(3.05)		(8.66)	(8.24)	(6.41)	(3.16)	

to the FF3 model. Within each model, Panels B and D report the results of momentum strategies incorporating the skip-month adjustment.

The intercepts of the asset pricing models remain largely positive and statistically significant, particularly for skip-month strategies (Panels B and D). Under the CAPM (Panel B), the 12-1 strategy yields the highest α of 1.08% per month ($t = 7.04$). It also yields the highest α of 1.17% per month ($t = 6.18$) under the FF3 model (Panel D). The results from both the CAPM and FF3 models demonstrate that, after controlling for standard risk factors, substantial and statistically significant alphas remain across many momentum strategies, particularly when recent formation-period returns are excluded.

Table 2: Price momentum risk-adjusted performance

This table reports the risk-adjusted performance of momentum strategies based on two asset pricing models. The momentum portfolios are formed based on J -month lagged returns and held for K months. The stocks are ranked into deciles in ascending order based on their lagged returns. A value-weighted portfolio of stocks in the lowest past return decile is referred to as the sell portfolio, and a value-weighted portfolio of stocks in the highest return decile is referred to as the buy portfolio. The values of J and K for different strategies are indicated in the first column and row, respectively. Panel A and Panel B present the CAPM risk-adjusted excess returns. Panel C and D present the Fama-French three-factor model risk-adjusted excess returns. The results in Panel B and Panel D are estimated based on momentum strategies with a one-month gap between the formation and holding periods. The sample period ranges from January 1871 to November 2024. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#) to account for potential autocorrelation in the time series.

J	Panel A: CAPM Model					Panel B: CAPM Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0097 (-6.00)	-0.0019 (-1.56)	0.0013 (1.24)	0.0020 (2.50)		-0.0004 (-0.33)	0.0013 (1.31)	0.0018 (2.24)	0.0014 (2.26)
6		-0.0033 (-2.04)	0.0024 (1.65)	0.0039 (3.06)	0.0032 (3.11)		0.0057 (3.87)	0.0062 (4.79)	0.0055 (4.73)	0.0033 (3.54)
9		-0.0008 (-0.48)	0.0046 (3.00)	0.0066 (4.74)	0.0033 (2.83)		0.0067 (4.32)	0.0072 (5.05)	0.0073 (5.66)	0.0029 (2.69)
12		0.0036 (2.10)	0.0071 (4.60)	0.0062 (4.32)	0.0022 (1.80)		0.0108 (7.04)	0.0095 (6.64)	0.0069 (5.06)	0.0019 (1.61)
J	Panel C: FF Three-Factor Model					Panel D: FF Three-Factor Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0107 (-6.17)	-0.0025 (-1.74)	0.0015 (1.16)	0.0027 (2.69)		-0.0012 (-0.85)	0.0009 (0.70)	0.0020 (1.90)	0.0019 (2.48)
6		-0.0033 (-1.69)	0.0027 (1.56)	0.0049 (3.15)	0.0045 (3.76)		0.0056 (3.02)	0.0067 (4.07)	0.0065 (4.50)	0.0045 (4.07)
9		-0.0004 (-0.21)	0.0057 (3.05)	0.0081 (4.84)	0.0053 (4.01)		0.0072 (3.83)	0.0084 (4.82)	0.0088 (5.67)	0.0049 (3.93)
12		0.0048 (2.34)	0.0086 (4.62)	0.0083 (4.93)	0.0047 (3.42)		0.0117 (6.18)	0.0111 (6.27)	0.0089 (5.58)	0.0043 (3.28)

Both excess return and risk-adjusted performance indicate that the short-term noise and partial reversals significantly affect the momentum strategies over the long run in the UK stock market. The impacts are more visible with short holding periods, but intermediate horizons tend to capture more persistent trends in returns. This pattern is consistent

with evidence from other long-run momentum studies in markets such as the United States (Linnainmaa and Roberts, 2018) and Imperial Russia (Goetzmann and Huang, 2018). In line with this evidence, we adopt the skip-month approach for constructing all momentum portfolios in our subsequent analyses to mitigate potential short-term reversal effects.

We next visually assess the long-run dynamics of the momentum performance via the cumulative performance. Figure 2 plots the cumulative return performance of the momentum strategies with various J and K combinations throughout the entire sample period. Each panel displays the momentum strategies with four holding periods based on a given formation period, J . All cumulative returns are plotted on a logarithmic scale to emphasise long-run growth differentials.

Across the various formation periods, momentum strategies generally display upward-sloping cumulative return paths over the whole sample period, indicating the persistence of momentum profits, except for the 3-1 strategy. Notably, the best-performing strategy in each panel tends to have a combined formation and holding period of at least 12 months. Specifically, the 3-12, 6-6, 9-6, and 12-1 strategies exhibit the highest cumulative returns in their respective panels. These results suggest that the long-run UK momentum effect shares a feature with the existing momentum studies of Jegadeesh and Titman (1993) and Carhart (1997): the optimal proxy for capturing the momentum effect is a strategy for which $J + K \geq 12$.

More importantly, the long-run UK momentum strategies experience several substantial drawdowns over the 150-year sample period. Consistent with patterns observed in the US market, all UK momentum strategies suffer pronounced losses following the Great Depression in the 1930s and the 2007–2008 financial crisis, episodes widely recognised as (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). However, in contrast to their US counterparts, UK momentum portfolios also endure significant drawdowns during additional periods marked by macroeconomic turbulence, such as around 1950 and in the 1970s.

4. Macroeconomic status and momentum in the UK

The previous section indicates that the UK long-run momentum strategies yield persistent positive returns that remain significant even after controlling for standard risk factors using

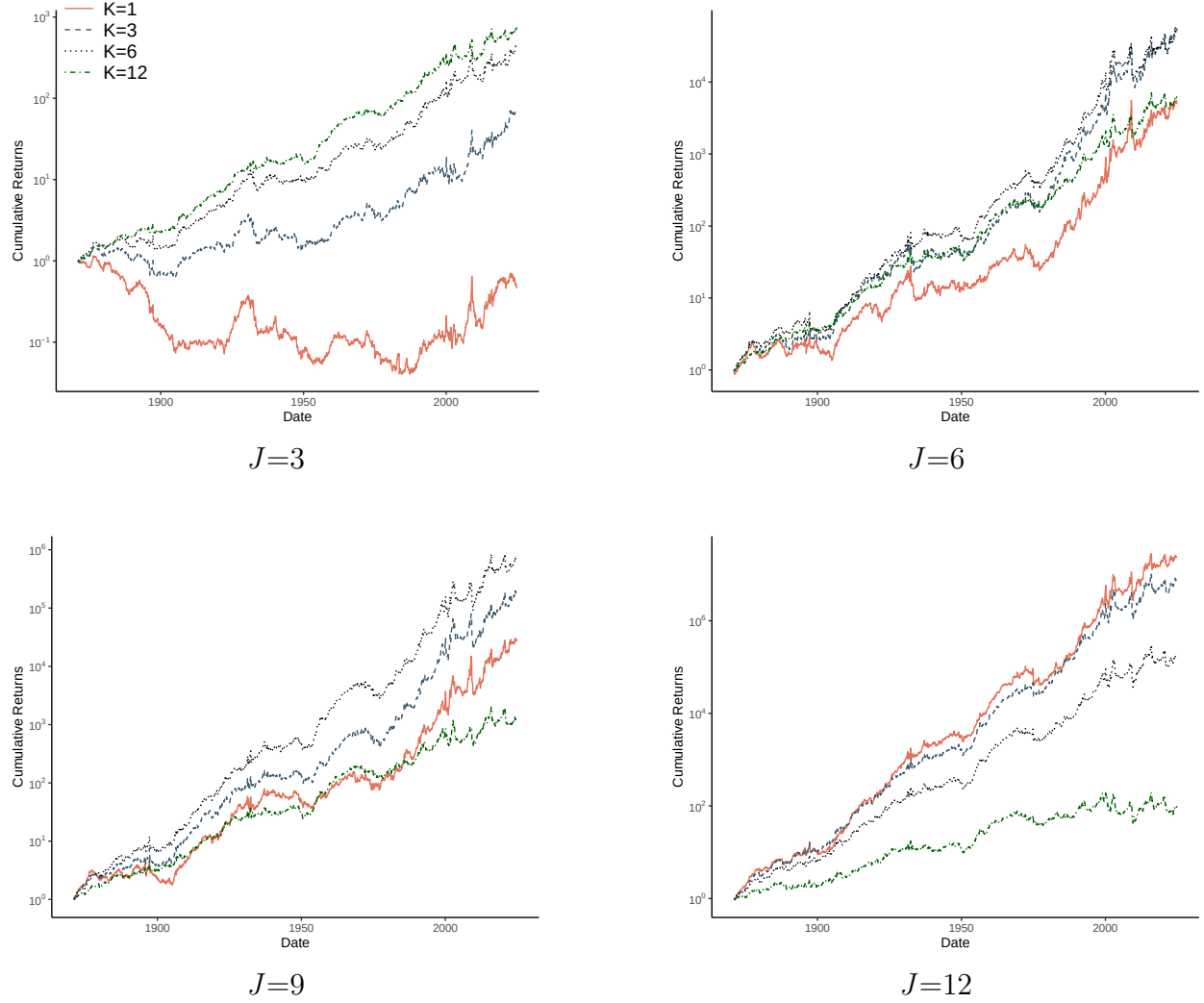


Figure 2: Price momentum portfolios cumulative performance

This figure plots the cumulative returns of price momentum portfolios constructed with skip-months. Portfolios are formed based on J -month lagged returns and held for K months, where $J \in \{3, 6, 9, 12\}$ and $K \in \{1, 3, 6, 12\}$. The Winner portfolio consists of stocks in the top decile of past returns, while the Loser portfolio contains stocks in the bottom decile. The WML (Winner-minus-Loser) strategy captures the return spread between the two. All portfolios are value-weighted and rebalanced monthly. The sample period ranges from May 1869 to November 2024.

CAPM and FF3 models. Notably, the analysis of cumulative performance reveals that macroeconomic shocks have a significant impact on UK momentum returns.

In this section, we investigate how macroeconomic conditions shape the performance of UK momentum strategies by examining their relationship with two key macroeconomic indicators. From a domestic perspective, we consider the role of the business cycle, following the approach of [Chordia and Shivakumar \(2002\)](#) and [Griffin et al. \(2003\)](#). We examine whether momentum returns vary systematically across different phases of the business cycle, and whether their persistence is linked to changes in investor behaviour under different macroeconomic conditions. The analysis first compares momentum profits across expansions, peaks, recessions, and troughs, focusing on whether the momentum effect remains persistent across various stages of the business cycle. We further decompose the sources of momentum profits by separately examining the contributions of prior winners and losers within each cycle phase, allowing us to assess whether return differentials are primarily driven by the continued outperformance of winners or by the disproportionate underperformance of losers. In addition, we investigate whether return-generating volatility differs across cycles, distinguishing periods in which positive price movements dominate from those in which downward volatility prevails. Finally, we assess whether momentum strategies tend to weaken or reverse following business cycle troughs, where abrupt shifts in macroeconomic expectations may offset prior price trends.

Additionally, motivated by the pronounced drawdowns observed during the 1970s oil crisis and 2014-2015 oil price crashes, we assess the impact of international macroeconomic dynamics through measures of geopolitical risk. This analysis aims to provide deeper insights into the macroeconomic status driving long-run momentum profitability in the UK equity market.

4.1. Business cycle and investor short-term underreaction

We begin by outlining the theoretical framework linking the business cycle to momentum profits. Under a risk-compensation channel, momentum returns are expected to rise during recessionary periods when aggregate risk is elevated and risk premia expand ([Campbell and Cochrane, 1999](#); [Campbell and Viceira, 2002](#)). Differently, based on the behaviour analysis,

if momentum profits primarily reflect behavioural forces, such as delayed information processing or trend extrapolation, their variation across business cycle phases may not align with standard measures of risk exposure. [Lagerborg et al. \(2023\)](#) provide further implications by establishing a causal connection between autonomous shifts in public sentiment and fluctuations in the business cycle. If macroeconomic conditions are themselves influenced by these psychological waves, then investor behaviours underpinning momentum strategies could plausibly vary in tandem with economic regimes. Analysing momentum returns across different phases of the business cycle thus offers a tractable setting for assessing whether the persistence of momentum profits is better explained by time-varying risk compensation or by stage-dependent behavioural responses.

Existing literature has examined some similar research questions in other stock markets, but has paid less attention to the UK long-run stock markets. [Chordia and Shivakumar \(2002\)](#), by distinguishing between economic expansions and recessions, found that momentum strategies yield significantly positive returns during expansion periods but turn negative or insignificant during recessions. Drawing on extensive cross-sectional and time-series evidence, they demonstrate that momentum returns exhibit a strong sensitivity to shifts in macroeconomic regimes and argue that these profits are closely tied to dynamic variations in investor expectations and economic conditions, rather than static risk premia. In contrast, [Griffin et al. \(2003\)](#) documented that momentum profits remain robust across both expansions and recessions across global markets, even after controlling for conditional macroeconomic factor exposures, suggesting that traditional risk-based models fail to account for the observed persistence of momentum returns. More recently, [Goetzmann and Huang \(2018\)](#) further observed that momentum returns during recessions are numerically higher (although not statistically significant), challenging the conventional view that momentum effects are driven by compensation for risk.

Table 3 reports momentum returns across different business cycle phases. The results show that momentum profits remain positive and statistically significant in both expansion and recession periods across most strategies. For example, the 12-1 strategy yields an average return of 1.45% ($t=4.64$) during recessions, while its corresponding return during expansions is 1.15% ($t=6.83$).

During economic recessions, poor investor performance, particularly the relative underperformance of high-risk assets, is generally considered a rational response, as it reflects heightened risk aversion and deteriorating fundamentals. In contrast, as shown in Table 3, most momentum strategies continue to deliver positive excess returns in both expansionary and recessionary periods. Our findings support the behavioural finance hypothesis: the observed stronger returns during recession periods, relative to expansion periods, suggest that robust market performance in downturns may be driven by irrational investor valuations. This stands in contrast to the results of Chordia and Shivakumar (2002), who document a weakening of momentum profits during the recession period. To explore the mechanism underlying our findings, we analyse how returns from winner and loser portfolios behave across different phases of the business cycle.

Table 4 provides further analysis of the momentum profits by reporting the performance of winner and loser portfolios across expansion and recession phases. The results reveal a distinct difference in the performance of winners and losers under varying macroeconomic conditions. In Panel A, winner portfolios consistently generate significant positive returns at the 1% level during expansions, e.g., the 12-1 strategy yields the highest return at 1.58% per month ($t=10.64$) during expansions. In contrast, winner returns in recessions are much lower and even negative for the 3-1, 3-3, and 3-6 strategies. Panel B shows that loser portfolios experience substantially deeper losses during recessions, which benefits the WML returns during recessions. In contrast, the loser portfolio generates positive returns during the expansion phase, which reduces the WML returns. More specifically, the 12-1 strategy yields the average monthly return of the loser portfolio is -0.96% ($t=-2.17$) in recessions, compared to a positive 0.43% ($t=2.22$) during expansions.

Across most strategies, this pattern is consistent: recessions amplify the underperformance of prior losers far more than they suppress the gains of prior winners. These results show that although both winners and losers are affected by macroeconomic conditions, most of the variation in momentum returns across the business cycle comes from the performance of the loser portfolios. During recessions, the returns of prior losers deteriorate more sharply than those of winners, widening the performance gap that drives overall momentum profits. Therefore, the larger losses of poorly performing stocks during downturns contribute more

Table 3: Momentum profits conditional on different business cycle stages

This table presents momentum profits conditional on different business cycle stages. A business cycle is divided into four stages: Peak, Recession, Trough, and Expansion. Momentum portfolios are formed based on a J -month formation period and K -month holding period. We skipped the most recent month before the holding period to mitigate short-term reversal effects. The numbers reported are momentum returns, calculated as the difference between the winner and loser returns. Columns labelled P-T Diff and E-R Diff represent the differences between returns in the Peak and Trough stages, and between Expansion and Recession stages, respectively. J - K combinations range from 3 to 12 months for both the formation (J) and holding (K) periods. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#). The sample period ranges from January 1871 to November 2024.

Strategy	Peak	Recession	Trough	Expansion	P-T Diff	E-R Diff
3-1	0.0011 (0.24)	-0.0008 (-0.29)	-0.0157 (-1.62)	0.0024 (1.59)	0.0168 (1.49)	0.0032 (0.98)
3-3	0.0038 (1.35)	0.0021 (1.03)	-0.0128 (-1.48)	0.0040 (3.50)	0.0166 (1.62)	0.0020 (0.92)
3-6	0.0018 (1.05)	0.0043 (2.62)	-0.0076 (-0.84)	0.0043 (5.12)	0.0094 (0.88)	0.0001 (0.01)
3-12	0.0018 (0.71)	0.0052 (4.79)	-0.0078 (-1.12)	0.0041 (5.56)	0.0096 (1.10)	-0.0011 (-0.87)
6-1	0.0025 (0.62)	0.0086 (2.57)	-0.0153 (-1.20)	0.0069 (4.92)	0.0178 (1.24)	-0.0017 (-0.47)
6-3	0.0037 (1.00)	0.0081 (3.26)	-0.0122 (-0.87)	0.0081 (5.76)	0.0159 (0.98)	0.0001 (0.01)
6-6	0.0008 (0.19)	0.0088 (3.87)	-0.0109 (-0.89)	0.0075 (5.77)	0.0118 (0.79)	-0.0013 (-0.52)
6-12	0.0018 (0.46)	0.0078 (4.81)	-0.0110 (-1.20)	0.0055 (4.98)	0.0128 (1.12)	-0.0023 (-1.23)
9-1	-0.0018 (-0.33)	0.0101 (3.42)	-0.0096 (-0.73)	0.0078 (4.87)	0.0078 (0.50)	-0.0022 (-0.67)
9-3	-0.0012 (-0.24)	0.0105 (3.88)	-0.0128 (-0.94)	0.0089 (5.78)	0.0116 (0.72)	-0.0016 (-0.54)
9-6	0.0012 (0.22)	0.0117 (4.66)	-0.0106 (-0.84)	0.0090 (5.91)	0.0117 (0.76)	-0.0028 (-1.03)
9-12	0.0027 (0.66)	0.0081 (4.38)	-0.0181 (-1.78)	0.0049 (3.67)	0.0208 (1.64)	-0.0032 (-1.49)
12-1	0.0033 (0.48)	0.0145 (4.64)	-0.0036 (-0.25)	0.0115 (6.83)	0.0069 (0.42)	-0.0030 (-0.95)
12-3	0.0028 (0.46)	0.0134 (5.60)	-0.0100 (-0.70)	0.0108 (6.51)	0.0128 (0.78)	-0.0026 (-0.93)
12-6	0.0027 (0.50)	0.0113 (4.80)	-0.0143 (-1.07)	0.0083 (5.19)	0.0171 (1.07)	-0.0030 (-1.10)
12-12	0.0038 (0.88)	0.0071 (3.69)	-0.0244 (-2.05)	0.0037 (2.51)	0.0281 (2.00)	-0.0033 (-1.30)

to momentum profits than the gains from winners.

We argue that the asymmetry in momentum profit across various business cycle phases aligns with wealth-relative risk aversion. Assuming momentum arises from investors’ short-term underreaction to information, the following mechanism explains this pattern. During recessions—when economic expectations deteriorate—investors become more conservative and risk-averse. This response is consistent with the counter-cyclical rise in risk aversion as wealth nears a “habit” consumption level ([Campbell and Cochrane, 1999](#)) and empirical evidence that poor returns foster lasting pessimism ([Malmendier and Nagel, 2011](#); [Guiso et al., 2018](#)). Consequently, investors view recent winners as fleeting, reducing their underreaction to good news and dampening momentum profits from winners. In contrast, during expansions—driven by positive outcomes—investors grow aggressive and optimistic, often neglecting downside risks ([Gennaioli et al., 2015](#)). This over-extrapolation of recovery prospects encourages belief in rebounds among past losers, diminishing underreaction to their negative signals and allowing loser-driven momentum profits to flourish. Hence, the asymmetric contribution of winners and losers to momentum across the cycle can be traced to cyclical shifts in investor belief formation and risk attitudes.

The abovementioned analysis suggests that momentum profits can be shifted by asymmetric investor reactions across different phases of the business cycle. Besides the sentimental analysis, another potential channel is the various risk compensation demands across business cycle phases. According to [Cooper and Priestley \(2009\)](#) and [Daniel and Moskowitz \(2016\)](#), investors demand greater compensation for downside risk during recessions than in expansions. Thus, for the same level of drawdown, the momentum investors should require a higher rebound during the recess phase, in comparison to the expansions.

To empirically investigate this business cycle related risk compensation, we introduce a state-based variance decomposition model by extending the model of [Barndorff-Nielsen et al. \(2010\)](#) and [Patton and Sheppard \(2015\)](#), which partitions the total variance of strategy returns into upside (good) and downside (bad) components. Positive return variation (good variance) is generally perceived by investors as benign or even beneficial. In contrast, negative return variation (bad variance) captures downside risk, which should be priced. If investors are more averse to downside risk during recessions, the compensation required

Table 4: Momentum profits of winner-loser portfolios conditional on business cycle stages

This table reports momentum profits of winner and loser portfolios during the Recession and Expansion stages of the business cycle from 1871 to 2024. Panels A and B present the average monthly return of the winner and loser portfolios during the Recession and Expansion periods, respectively. The E-R Diff column shows the difference between Expansion and Recession returns, with corresponding Newey-West adjusted t -statistics in parentheses. The momentum portfolios are formed based on J -month lagged returns and held for K months, where J - K combinations range from 3 to 12 months. Newey-West adjusted t -statistics are reported in parentheses beneath each return value.

Strategy	Panel A - Winner			Panel B - Loser		
	Recession	Expansion	E-R Diff	Recession	Expansion	E-R Diff
3-1	-0.0050 (-1.74)	0.0111 (7.15)	0.0161 (4.97)	-0.0043 (-1.01)	0.0087 (5.27)	0.0129 (2.87)
3-3	-0.0022 (-0.70)	0.0119 (8.43)	0.0141 (4.28)	-0.0042 (-1.08)	0.0079 (5.14)	0.0121 (2.91)
3-6	-0.0007 (-0.25)	0.0121 (9.11)	0.0128 (3.91)	-0.0050 (-1.33)	0.0078 (5.25)	0.0128 (3.20)
3-12	0.0008 (0.25)	0.0120 (9.44)	0.0112 (3.47)	-0.0044 (-1.25)	0.0079 (5.47)	0.0123 (3.23)
6-1	0.0001 (0.04)	0.0138 (9.37)	0.0137 (4.13)	-0.0085 (-2.08)	0.0069 (3.89)	0.0154 (3.39)
6-3	0.0009 (0.29)	0.0143 (10.68)	0.0134 (3.96)	-0.0072 (-1.83)	0.0062 (3.57)	0.0134 (3.22)
6-6	0.0015 (0.50)	0.0141 (10.86)	0.0125 (3.80)	-0.0072 (-1.79)	0.0066 (3.90)	0.0138 (3.39)
6-12	0.0021 (0.72)	0.0129 (10.21)	0.0107 (3.38)	-0.0057 (-1.50)	0.0074 (4.59)	0.0130 (3.37)
9-1	0.0015 (0.49)	0.0146 (9.94)	0.0131 (3.92)	-0.0086 (-1.96)	0.0067 (3.54)	0.0153 (3.25)
9-3	0.0020 (0.63)	0.0147 (10.52)	0.0126 (3.68)	-0.0085 (-2.03)	0.0058 (3.16)	0.0142 (3.02)
9-6	0.0032 (1.03)	0.0148 (10.91)	0.0116 (3.44)	-0.0085 (-2.08)	0.0058 (3.30)	0.0143 (3.18)
9-12	0.0024 (0.81)	0.0127 (9.48)	0.0102 (3.15)	-0.0056 (-1.49)	0.0078 (4.67)	0.0135 (3.32)
12-1	0.0049 (1.66)	0.0158 (10.64)	0.0108 (3.35)	-0.0096 (-2.17)	0.0043 (2.22)	0.0138 (2.81)
12-3	0.0043 (1.37)	0.0154 (10.72)	0.0110 (3.23)	-0.0091 (-2.10)	0.0046 (2.35)	0.0136 (2.85)
12-6	0.0036 (1.13)	0.0143 (10.16)	0.0107 (3.09)	-0.0078 (-1.83)	0.0060 (3.18)	0.0137 (2.91)
12-12	0.0022 (0.70)	0.0123 (8.83)	0.0101 (3.01)	-0.0049 (-1.21)	0.0085 (4.85)	0.0134 (3.11)

to bear that risk should increase accordingly. Consequently, we hypothesise that the good variance is relatively higher in recession periods due to stronger rebounds following adverse price movements, consistent with the business cycle dynamic risk compensation hypothesis. The detailed analysis is in the appendix.

These findings indicate that investor reactions to momentum strategies vary across different macroeconomic phases, and such variation is likely driven by irrational valuation behaviour. During recessions, the increase in RSJ values reveals a return structure dominated by upward price jumps, with positive returns (RV_S^+) playing the leading role. This suggests that market price trajectories are driven by a sequence of sharp positive corrections, reflecting investors' delayed responses to information and a partially irrational process of expectation revision. In such downturns, investor overreaction, speculative behaviour, or sluggish adjustment to macroeconomic realities can all contribute to strong market performance or significant positive returns (Daniel et al., 1998; Barberis et al., 1998).

4.2. Geopolitical risks and the momentum performance

While Section 4.1 shows that momentum profits vary across business cycle stages, which is mainly endogenous, momentum strategies may also be impacted by exogenous sources of uncertainty. To capture this dynamic, we utilise the UK Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022), a news-based measure of country-specific geopolitical tensions. Higher values of the GPR index indicate elevated levels of geopolitical risk. This section examines how variations in geopolitical risk impact the performance of momentum strategies in the UK market.

In Table 5, we sort the GPR index into quartiles and report the average monthly returns and FF3 alphas of momentum portfolios for each quartile. Quartile 1 represents the bottom 25% group (most politically stable periods) and Quartile 4 include those months with the top 25% of GPR values (i.e., periods of heightened geopolitical uncertainty). The results show that momentum profitability varies substantially across different levels of geopolitical risk. In high-risk periods (Quartile 4) of Panel A, the momentum returns are low. For instance, short-term formation periods, e.g., 3-1, 3-3, and 6-1 strategies, yield negative or statistically insignificant performance. By contrast, in low-risk periods (Quartile 1) of Panel A, 15 of 16

momentum strategies exhibit statistically significant returns. Taking the example of the most representative momentum strategy, the 12-1 strategy achieves an average monthly return of 1.88% ($t = 5.01$), much higher than the returns of Quartiles 2 to 4. These results suggest that the momentum effect tends to weaken during periods of heightened geopolitical uncertainty, indicating that its profitability relies more on the relative stability and predictability of the external environment rather than simply on compensation for bearing higher risk. Our finding is consistent with the literature where the momentum effect is weakened during high uncertainty periods, see, e.g., [Cooper et al. \(2004\)](#), [Stivers and Sun \(2013\)](#), and [Daniel and Moskowitz \(2016\)](#), among others.

Table 5: Momentum returns across GPR Quartiles

This table reports the average monthly returns and Newey-West t -statistics (in parentheses) for various momentum strategies across different levels of geopolitical risk (GPR), classified into quartiles. Quartile 1 represents the lowest 25% (i.e., most geopolitically stable periods), while Quartile 4 corresponds to the highest 25% of GPR observations (i.e., periods of greatest geopolitical uncertainty). Panel A reports the raw return and Panel B reports the Fama-French three-factor (FF3) alphas. Momentum strategies are denoted as J - K , where J is the formation period and K is the holding period in months. All portfolios skip one month between the formation and holding periods to mitigate microstructure effects. The sample spans from January 1900 to November 2024.

Strategy	Panel A				Panel B			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
3-1	0.0071 (2.72)	0.0035 (0.94)	0.0016 (0.54)	-0.0021 (-0.80)	0.0026 (0.74)	0.0013 (0.37)	-0.0004 (-0.14)	-0.0037 (-1.17)
3-3	0.0068 (3.14)	0.0052 (1.73)	0.0036 (1.70)	0.0008 (0.41)	0.0022 (0.74)	0.0039 (1.35)	0.0025 (1.17)	-0.0008 (-0.30)
3-6	0.0058 (2.67)	0.0044 (1.75)	0.0042 (2.82)	0.0036 (2.62)	0.0023 (0.87)	0.0036 (1.48)	0.0032 (1.83)	0.0021 (0.99)
3-12	0.0059 (3.70)	0.0035 (1.84)	0.0038 (2.61)	0.0039 (3.77)	0.0024 (1.30)	0.0015 (0.84)	0.0027 (1.84)	0.0027 (1.91)
6-1	0.0104 (3.03)	0.0078 (1.78)	0.0076 (2.39)	0.0039 (1.77)	0.0072 (1.65)	0.0100 (2.43)	0.0075 (2.31)	0.0019 (0.52)
6-3	0.0099 (2.91)	0.0083 (2.15)	0.0085 (3.00)	0.0068 (3.45)	0.0075 (1.79)	0.0098 (2.62)	0.0092 (3.19)	0.0055 (1.77)
6-6	0.0103 (3.12)	0.0068 (2.00)	0.0077 (3.19)	0.0064 (3.83)	0.0085 (2.22)	0.0075 (2.16)	0.0081 (3.08)	0.0059 (2.34)
6-12	0.0077 (3.12)	0.0053 (2.11)	0.0050 (2.32)	0.0053 (3.93)	0.0053 (1.85)	0.0048 (1.85)	0.0055 (2.69)	0.0045 (2.46)
9-1	0.0138 (3.64)	0.0093 (1.95)	0.0054 (1.78)	0.0058 (2.39)	0.0126 (2.84)	0.0096 (2.07)	0.0064 (1.93)	0.0055 (1.60)
9-3	0.0131 (3.49)	0.0092 (2.29)	0.0074 (2.49)	0.0072 (3.48)	0.0121 (2.66)	0.0108 (2.61)	0.0089 (2.82)	0.0073 (2.31)
9-6	0.0130 (3.88)	0.0082 (2.21)	0.0080 (2.72)	0.0086 (4.50)	0.0116 (2.95)	0.0094 (2.47)	0.0094 (3.14)	0.0089 (3.26)
9-12	0.0060 (2.22)	0.0054 (1.88)	0.0043 (1.66)	0.0051 (3.26)	0.0047 (1.53)	0.0062 (2.08)	0.0056 (2.37)	0.0047 (2.33)
12-1	0.0188 (5.01)	0.0100 (2.18)	0.0104 (3.16)	0.0109 (4.42)	0.0162 (3.50)	0.0118 (2.70)	0.0133 (3.99)	0.0112 (2.92)
12-3	0.0156 (4.00)	0.0087 (2.19)	0.0104 (3.29)	0.0106 (4.69)	0.0139 (2.99)	0.0103 (2.74)	0.0132 (4.13)	0.0111 (3.47)
12-6	0.0116 (3.27)	0.0068 (1.81)	0.0072 (2.33)	0.0095 (4.66)	0.0104 (2.50)	0.0089 (2.45)	0.0094 (3.23)	0.0101 (3.73)
12-12	0.0042 (1.45)	0.0037 (1.15)	0.0035 (1.25)	0.0046 (2.61)	0.0033 (1.05)	0.0053 (1.64)	0.0053 (2.12)	0.0049 (2.34)

To examine whether the momentum returns expose to risk factors, we further report the alphas of the Fama-French three-factor model regressions in Panel B of Table 5. The results show that, after controlling for market, size, and value factors, the negative relationship between momentum performance and geopolitical risk becomes less consistent. For Quartile 1, most strategies still show significant alphas. However, the difference between Quartiles 2 to 4 becomes less significant. This suggests that part of the sensitivity observed in the raw returns is attributable to common risk exposures rather than pure abnormal performance.

Since previous results demonstrate that both the business cycle and geopolitical risk influence momentum returns, we investigate the joint effect of macroeconomic variables on momentum performance. Specifically, we condition the time series returns of momentum portfolios on both expansion/recession and high/low GPR phases. Table 6 shows that in periods of economic recession combined with low GPR (Recession_Low), most momentum strategies maintain significantly positive returns. This suggests that when macroeconomic fundamentals are weak but the external environment remains relatively stable, the market tends to rely more heavily on past price trends, allowing the momentum effect to persist. In contrast, in periods of economic recession with high GPR (Recession_High), momentum returns decline substantially, with some short-term strategies even turning negative (e.g., the 3-1 strategy records a monthly return of -0.47%, $t=-1.06$). Although most long formation period portfolios still yield positive returns, their magnitude is clearly lower than that of the Recession_Low group. This suggests that geopolitical shocks can erode the ability to leverage past trends during economic downturns, leading to phase-specific breakdowns in the momentum effect. Similarly, during economic expansion phases with low GPR (Expansion_Low), momentum portfolios generally outperform those in the Expansion_High group. This is consistent with our previous finding that momentum performs better in low-GPR periods than in high-GPR periods, independent of business-cycle states. The Recession_Low performance is also generally better than that in the Expansion_Low group, with the highest performance across the four subgroups.

We also find that when GPR is high, short formation period strategies tend to show weak and insignificant returns (e.g., the 3-1 and 3-3 strategies), while portfolios with longer formation periods can still maintain modest positive returns. This implies that external shocks

primarily dampen speculative short-term trend-following behaviour, temporarily weakening the sustainability of the momentum effect under certain market conditions. Finally, when internal and external risks combine, such as a recession coupled with high GPR (Recession_High), most of the short formation period strategies fail to generate significant profits at the 10% level, and the 3-1 and 6-1 strategies even yield losses. Overall, our findings suggest that momentum returns are strongly influenced by how internal and external conditions jointly affect information flow and investor reactions.

Table 6: The joint effect of the business cycles and geopolitical risks

This table presents the average monthly returns and Newey-West t -statistics (in parentheses) for momentum strategies under different economic and geopolitical risk conditions. The sample period is from 1900 to 2024. Portfolio strategies are labelled as J - K , where J represents the formation period (in months) and K represents the holding period (in months). All strategies incorporate a 1-month skip between formation and holding periods to mitigate microstructure biases. The table divides the sample into four distinct regimes: recession periods when GPR is in the bottom 25% interval (Recession_Low), recession periods when GPR falls into the top 25% interval (Recession_High), expansion periods with low GPR (Expansion_Low), and expansion periods with high GPR (Expansion_High).

Strategy	Recession_Low (N = 61)	Recession_High (N = 67)	Expansion_Low (N = 289)	Expansion_High (N = 286)
3-1	0.0157 (1.38)	-0.0047 (-1.06)	0.0067 (2.57)	-0.0019 (-0.60)
3-3	0.0136 (1.59)	0.0007 (0.17)	0.0063 (2.24)	0.0004 (0.19)
3-6	0.0098 (1.53)	0.0019 (0.76)	0.0056 (2.28)	0.0035 (2.12)
3-12	0.0064 (1.65)	0.0059 (2.90)	0.0062 (3.38)	0.0035 (3.03)
6-1	0.0278 (3.49)	-0.0011 (-0.24)	0.0075 (1.79)	0.0049 (1.64)
6-3	0.0168 (3.11)	0.0025 (0.69)	0.0094 (2.30)	0.0075 (3.17)
6-6	0.0123 (2.49)	0.0060 (1.87)	0.0108 (2.78)	0.0066 (3.50)
6-12	0.0090 (2.02)	0.0090 (2.82)	0.0080 (2.63)	0.0049 (3.17)
9-1	0.0216 (2.83)	0.0066 (1.51)	0.0132 (2.92)	0.0057 (2.06)
9-3	0.0167 (5.29)	0.0085 (2.06)	0.0137 (3.00)	0.0071 (3.13)
9-6	0.0151 (3.06)	0.0121 (2.95)	0.0135 (3.32)	0.0082 (3.81)
9-12	0.0072 (1.78)	0.0105 (2.99)	0.0065 (2.01)	0.0045 (2.50)
12-1	0.0279 (3.56)	0.0099 (2.58)	0.0174 (3.46)	0.0116 (3.88)
12-3	0.0186 (3.20)	0.0126 (3.24)	0.0158 (3.30)	0.0107 (4.07)
12-6	0.0135 (1.98)	0.0125 (3.06)	0.0120 (2.66)	0.0092 (3.88)
12-12	0.0043 (0.87)	0.0110 (3.00)	0.0046 (1.31)	0.0038 (1.84)

5. Macroeconomic dynamics and the momentum crash risks

The momentum strategies are profitable but suffer from crash risks. [Barroso and Santa-Clara \(2015\)](#) and [Daniel and Moskowitz \(2016\)](#) propose that momentum crashes can easily eliminate the cumulative profits over two decades in a few months. We argue that, across our long-run UK sample, momentum crash risk is not strongly linked to market states but is instead driven by macroeconomic dynamics.

5.1. Momentum crash in the long run

We first report momentum crashes in the UK stock markets over the 155-year sample period. Table 7 lists the 15 worst-performing months for the average of all momentum strategies, alongside contemporaneous macroeconomic conditions. Notably, only six of these crash months were preceded by negative two-year market returns. This finding contrasts with the U.S. evidence from [Daniel and Moskowitz \(2016\)](#), who report that 14 of the 15 worst momentum returns followed bear markets in the US stock markets. Instead, our results indicate that 11 of the 15 most severe crashes occurred during economic expansion phases.

Table 7: Worst monthly momentum average returns

This table reports the 15 worst monthly average returns and date (Month) for all the momentum strategies of the Table 1 over the full sample period. The table presents all momentum strategies based on different J - K combinations, where J denotes the formation period and K denotes the holding period. $Mkt - 2y$ refers to the two-year market returns leading up to the portfolio formation date, MKT_t denotes the contemporaneous market return, Business cycle represents the phase of the business cycle, the GPR indices and in which quartile are they located are shown in the last two columns. The returns are sorted in ascending order, with the most extreme negative return listed first. The sample period spans from January 1871 to November 2024.

Rank	Month	WML	$MKT - 2y$	MKT_t	Business cycle	GPR	GPR Quartile
1	2009-04	-0.4318	-0.2087	0.1419	Trough	0.4654	2
2	2020-11	-0.2864	0.0391	0.1377	Expansion	0.2237	1
3	1932-08	-0.2553	0.0154	0.0927	Trough	0.4489	2
4	1897-05	-0.2392	0.2463	0.0426	Expansion	-	-
5	2016-02	-0.2354	0.1228	0.0169	Expansion	0.5882	2
6	1975-01	-0.2230	-0.5669	0.5176	Recession	0.5442	2
7	1931-06	-0.2039	-0.2451	0.0937	Recession	0.2760	1
8	2000-03	-0.1936	0.5775	0.0608	Expansion	0.2150	1
9	2003-04	-0.1672	-0.1772	0.0975	Expansion	2.3674	4
10	2000-05	-0.1632	0.5361	0.0160	Expansion	0.4118	1
11	2002-11	-0.1619	-0.1754	0.0507	Expansion	0.7563	3
12	2001-10	-0.1562	0.2065	0.0445	Expansion	1.4775	4
13	1937-04	-0.1504	0.5140	-0.0693	Expansion	1.1312	4
14	2016-04	-0.1500	0.1343	0.0163	Expansion	0.7031	3
15	1949-03	-0.1496	-0.0111	0.0004	Expansion	0.9142	3

Many crashes in the UK can be linked to identifiable macroeconomic shocks. For instance, the crash in May 1897 coincides with the aftermath of the 1893 closure of Indian silver mints,

which collapsed global silver demand and triggered exchange rate volatility between the gold and silver blocs ([Green, 1989](#)), disrupting trade and undermining investor confidence in Indian bonds, a crucial financial instrument in London ([Bordo and Rockoff, 1996](#); [Esteves, 2009](#)). The sharp declines in 1975 followed the October 1973 oil crisis, during which OAPPEC significantly reduced oil production, resulting in a 300% surge in oil prices. The losses in February and April 2016 are likely attributable to the lingering effects of the Eurozone debt crisis and the 2014–2015 global oil price collapse. Finally, the November 2020 crash corresponds to the market turmoil induced by the COVID-19 pandemic.

Next, we present additional evidence linking momentum crash risks to macroeconomic dynamics. Our results in Table 4 show that the returns for momentum loser portfolios shift from negative to positive as the economy transitions from recession to expansion, a pattern observed in the dynamics preceding known momentum crashes. As noted by [Barroso and Santa-Clara \(2015\)](#) and [Daniel and Moskowitz \(2016\)](#), momentum crashes typically occur at market turning points, i.e., from the bear to rebound. In line with this rationale, we hypothesise that momentum strategies can be exposed to increased downside risk during the post-trough phase of the business cycle, similar to the transition from market conditions of contraction to recovery.

To identify the momentum performance after the trough periods, Table 8 shows the quarterly cumulative performance of momentum strategies over the first year after the economic troughs. In the first quarter (Q1), most portfolios still generate positive returns, indicating that the momentum effect remains persistent immediately after the trough, except for the 3-1 strategy, which shows an apparent reversal. By the second quarter (Q2), performance begins to diverge across strategies, with several portfolios—particularly those with formation periods shorter than nine months—showing mixed results. Notably, the third quarter (Q3) emerges as a pivotal period: all portfolios record negative returns, and eight out of sixteen strategies produce statistically significant losses at the 10% level. In the fourth quarter (Q4), most strategies recover to positive territory, although generally weak *t*-statistics suggest only partial recovery and diminished trend persistence. Overall, the results highlight the downside risk associated with momentum strategies during the trough phases.

The negative performance in Q2 and Q3 provides empirical support for the post-trough

Table 8: Post-trough momentum performance

This table reports the quarterly portfolio returns and their corresponding t -statistics following economic troughs. The sample period is from 1871 to 2024. Q1 to Q4 represent the sum of monthly returns in quarters one to four, respectively. Momentum strategies are named as J - K , where J represents the formation period (in months) used to construct the portfolios, and K represents the holding period (in months). For example, 3-1 represents a strategy with a 3-month formation period and a 1-month holding period. All strategies incorporate a 1-month skip between the formation and holding periods to avoid microstructure biases. The t -statistics (shown in parentheses) are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#) to account for potential autocorrelation in the time series of post-trough returns for each strategy.

Strategy	Q1	Q2	Q3	Q4
3-1	-0.0446 (-2.43)	-0.0091 (-0.58)	-0.0359 (-1.13)	-0.0121 (-0.83)
3-3	0.0098 (0.41)	-0.0002 (-0.01)	-0.0261 (-1.22)	0.0013 (0.07)
3-6	0.0184 (1.33)	-0.0092 (-0.54)	-0.0245 (-2.12)	0.0110 (0.99)
3-12	0.0072 (0.91)	0.0009 (0.08)	-0.0158 (-2.05)	0.0127 (1.83)
6-1	0.0033 (0.12)	-0.0260 (-0.94)	-0.0647 (-2.44)	0.0213 (0.98)
6-3	0.0405 (1.60)	-0.0275 (-0.93)	-0.0460 (-2.11)	0.0294 (1.48)
6-6	0.0410 (2.40)	-0.0105 (-0.43)	-0.0235 (-1.55)	0.0296 (2.33)
6-12	0.0191 (1.33)	-0.0043 (-0.29)	-0.0298 (-3.02)	0.0141 (1.51)
9-1	0.0221 (0.93)	-0.0014 (-0.07)	-0.0382 (-1.48)	0.0275 (1.14)
9-3	0.0479 (1.96)	0.0054 (0.24)	-0.0277 (-1.37)	0.0287 (1.54)
9-6	0.0436 (1.96)	0.0066 (0.30)	-0.0170 (-1.15)	0.0280 (1.91)
9-12	0.0239 (1.35)	0.0007 (0.04)	-0.0373 (-3.71)	0.0107 (0.73)
12-1	0.0286 (1.01)	0.0461 (2.66)	-0.0325 (-1.54)	0.0247 (1.48)
12-3	0.0354 (1.41)	0.0351 (1.88)	-0.0309 (-1.59)	0.0283 (1.88)
12-6	0.0277 (1.29)	0.0165 (0.72)	-0.0380 (-2.61)	0.0211 (1.44)
12-12	0.0138 (0.73)	0.0087 (0.48)	-0.0558 (-4.19)	0.0106 (0.59)

momentum downside risk hypothesis. If momentum returns were purely a reward for bearing systematic risk, the most considerable losses would be expected to occur during recessions when aggregate risk is highest. However, the results indicate that momentum strategies are more susceptible to extreme losses during periods of expansion. During the economic regime transition from trough to expansion, signal information reflects both past underperformance and early recovery dynamics. Similar to the market status momentum crashes of [Barroso and Santa-Clara \(2015\)](#) and [Daniel and Moskowitz \(2016\)](#), prior losers tend to rebound more sharply than winners, driving the momentum post-trough drawdown.

Overall, these findings suggest that the downside risk of momentum is not determined solely by market conditions but also by broader macroeconomic regimes. Momentum returns exhibit a cyclical pattern, with strategy breakdowns typically occurring around macroeconomic troughs, as the economy transitions from recession to expansion. Because these post-trough crashes take place early in the expansion phase, they significantly weaken momentum performance during expansions relative to recessions. This evidence highlights the need for a deeper investigation into how macroeconomic dynamics shape the crash risk of momentum strategies.

5.2. Option-like behaviours of the momentum portfolios and the macroeconomic dynamics

[Daniel and Moskowitz \(2016\)](#) attribute momentum crash risks to the mechanism that the momentum portfolio exhibits option-like payoffs, effectively acting as if it were short a call option on the market. That is, when the market declines, the portfolio earns modest gains; but when the market rebounds, it suffers large losses. To test whether this mechanism remain in the long-run, we employ the models as in [Daniel and Moskowitz \(2016\)](#), which regress momentum returns on market returns, augmented with indicator variables for bear markets and contemporaneous up-market months. The key variable is the interaction term that identifies the portfolio's beta in up-market months within bear market periods. We find that the option-like payoffs behaviour of momentum strategies is weak and subject to economic states in the UK stock market over the horizon of 155 years.

In line with [Daniel and Moskowitz \(2016\)](#), we first run the regressions to the most representative momentum strategy, the 12-1 strategy, where the dependent variable $\tilde{R}_{WML,t}$

represents the WML return of the 12-1 strategy in month t . We report results of three OLS regressions in columns 2 to 7 of Table 9.

Regression 1 estimates an unconditional market model:

$$\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\varepsilon}_t \quad (1)$$

where $\tilde{R}_{m,t}$ denotes the excess return of the value-weighted market index in month t , consistent with the standard CAPM. As reported in Panel A, the estimated market beta, $\hat{\beta}_0$, is significantly negative, while the intercept α_0 is significantly positive at the 1% level, consistent with prior studies such as [Grundy and Martin \(2001\)](#).

Regression 2 introduces a conditional CAPM by adding the bear market indicator, $I_{B,t-1}$:

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + \beta_B I_{B,t-1}) \tilde{R}_{m,t} + \tilde{\varepsilon}_t \quad (2)$$

where $I_{B,t-1}$ equals one if the cumulative value-weighted index return over the past 24 months is negative, and zero otherwise. This design isolates expected returns and betas in bear markets. Across three panels, the bear market betas, $\hat{\beta}_B$, are -0.766 ($t = -4.63$), -0.761 ($t = -3.15$), and -0.433 ($t = -1.97$), all statistically significant, consistent with existing literature. [Daniel and Moskowitz \(2016\)](#) further find that the market betas, $\hat{\beta}_0$, become insignificant after extracting the bear market component, so the negative correlation between the market index and the momentum returns is mainly sourced from the bear market. However, for the UK stocks in the long run, such a pattern only appears during expansions, as shown in Panel B of Table 9.

Regression 3 further allows for asymmetric betas in up- and down-markets within bear market periods:

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U})) \tilde{R}_{m,t} + \tilde{\varepsilon}_t \quad (3)$$

where $\tilde{R}_{m,t}$ and $I_{B,t-1}$ are defined as before. $\tilde{I}_{U,t}$ is a contemporaneous up-market indicator equal to one if the excess market return is positive in month t , and zero otherwise. The interaction coefficient, $\beta_{B,U}$, is designed to capture the asymmetric losses of momentum

during rebounds from downturns, which form the basis of the “short call option” analogy in [Daniel and Moskowitz \(2016\)](#).

The results of regression 3 only provide marginal support for the presence of asymmetric option-like payoffs of momentum during bear markets and rebounds in the UK long-run data. Within bear markets, the point estimates of the WML beta are -0.900, -0.858, and -0.782 ($= \hat{\beta}_0 + \hat{\beta}_B$), respectively, when the contemporaneous market return is negative, and -1.032, -1.052, and -0.895 ($= \hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}$), respectively, when the market return is positive. The differences between the betas in down-market and rebound periods are economically small, indicating that the asymmetric payoff of momentum strategies is weak in the UK market. However, $\hat{\beta}_{B,U}$ is -0.453 in the entire sample. It reduces to -0.488 during the expansions and increases to -0.434 during recessions. All three differences in coefficients between the up- and down-market are statistically insignificant at the 10% level, indicating that there is no statistical evidence to support the asymmetric payoffs of momentum during up- and down-market periods after the bear market.

To sum up, the insignificant interaction coefficients, $\hat{\beta}_{B,U}$, and the consistently negative and significant market beta, $\hat{\beta}_0$, suggest that momentum continues to earn returns when the market declines but does not incur substantial losses during market rebounds. Hence, the option-like payoff structure between down- and up-markets identified by [Daniel and Moskowitz \(2016\)](#) is less evident in the UK long-run stock market, particularly during recessions.

Although the 12-1 strategy is widely used as a proxy for the momentum effect, it does not encompass all momentum strategies. To achieve a more comprehensive conclusion, we also added pooled panel regressions to explore whether the asymmetry payoffs exist across all 16 momentum strategies. The results are shown in columns 8 to 13 of Table 9.

Our panel regression results reinforce and extend the insights from the OLS results, challenging the universality of the asymmetric option-like payoff of momentum. The interaction term, $\hat{\beta}_{B,U}$, is insignificant across the full sample, expansion, and recession periods, indicating that such asymmetry is not a robust feature observed in the UK market over the long run.

A second key result concerns the dependence of momentum’s market beta on prior market

Table 9: Market timing regressions conditional on business cycle

This table reports the results of three specifications of monthly panel regressions estimated over the period from January 1869 to November 2024. Panel A presents results for the full sample, Panel B for expansion periods, and Panel C for recession periods. Columns 2–7 use the returns of the 12-1 strategy as the dependent variable, while columns 8–13 present panel regressions with returns of all momentum strategies as the dependent variable. For the OLS regressions, the t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors of [Newey and West \(1987\)](#). For the panel regressions, we adopt the cluster standard error measure proposed by [Thompson \(2011\)](#) for robust t -statistics. The independent variables include a constant ($\hat{\alpha}_0$); a bear market indicator, $I_{B,t-1}$, equal to one if the cumulative market return over the previous two years is negative (coefficient $\hat{\alpha}_B$); the excess market return, $\tilde{R}_{m,t}$ (coefficient $\hat{\beta}_0$); the interaction term $I_{B,t-1} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_B$); and a contemporaneous up-market indicator, $\tilde{I}_{U,t}$, equal to one if $\tilde{R}_{m,t} > 0$, interacted with the bear market and market return as $I_{B,t-1} * \tilde{I}_{U,t} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_{B,U}$).

Dependents	12-1 momentum strategy						All momentum strategies					
Regression	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}
Panel A: Full Sample												
1	0.014*** (9.20)		-0.345*** (-3.89)			0.041	0.008*** (8.71)		-0.252*** (-5.33)			0.036
2	0.014*** (8.81)	-0.002 (-0.18)	-0.134** (-2.01)	-0.766*** (-4.63)		0.085	0.008*** (8.66)	-0.006 (-1.02)	-0.133*** (-3.18)	-0.424*** (-3.81)		0.059
3	0.014*** (8.81)	0.009 (0.87)	-0.134** (-2.01)	-0.445 (-1.54)	-0.453 (-1.19)	0.087	0.008*** (8.66)	-0.002 (-0.25)	-0.133*** (-3.18)	-0.295* (-1.66)	-0.182 (-0.72)	0.060
Panel B: Expansion												
1	0.013*** (6.91)		-0.168** (-2.11)			0.008	0.008*** (6.94)		-0.140*** (-3.05)			0.010
2	0.013*** (6.95)	-0.003 (-0.33)	-0.097 (-1.35)	-0.761*** (-3.15)		0.028	0.008*** (6.94)	-0.003 (-0.50)	-0.095** (-2.03)	-0.484*** (-2.94)		0.022
3	0.013*** (7.05)	0.006 (-0.47)	-0.097 (-1.37)	-0.467 (-0.81)	-0.488 (-0.69)	0.028	0.008*** (6.94)	0.006 (0.71)	-0.095** (-2.03)	-0.175 (-0.40)	-0.513 (-0.93)	0.023
Panel C: Recession												
1	0.015*** (5.01)		-0.632*** (-4.12)			0.197	0.009*** (4.54)		-0.401*** (-6.04)			0.139
2	0.014*** (5.53)	0.007 (0.40)	-0.349** (-2.22)	-0.433** (-1.97)		0.222	0.008*** (4.90)	0.002 (0.15)	-0.345*** (-3.28)	-0.085 (-0.64)		0.140
3	0.014*** (5.41)	0.022 (1.11)	-0.349** (-2.21)	-0.112 (-0.30)	-0.434 (-1.34)	0.228	0.008*** (4.90)	0.003 (0.25)	-0.345*** (-3.28)	-0.05 (-0.22)	-0.048 (-0.22)	0.141

conditions and the business cycle. In our panel regressions, the indicator for a prior bear market significantly alters momentum’s beta during expansions, with $\hat{\beta}_B = -0.484$ and is strongly significant. By contrast, this effect disappears in recessions, where $\hat{\beta}_B$ is statistically insignificant at -0.085. Taken together with the persistently negative base market beta, $\hat{\beta}_0$, these findings suggest a different risk payoff than the option-like view. Rather than shifting only in times of crisis, the UK momentum strategy exhibits a structural negative correlation with the market, whose sensitivity to past downturns is conditional on the phase of the business cycle. Overall, consistent with the results in Panel A, our panel regression results in Panel B also suggest that the long-run UK stock momentum does not suffer the pronounced asymmetric losses as documented in the U.S. market.

Next, we examine how the option-like payoff is affected by GPR. Table 10 reports the results of the three regressions under different levels of GPR. Columns 2 to 7 present the regression results for the 12-1 strategy. In these baseline specifications, the negative relationship between momentum and the market becomes statistically insignificant only under the highest GPR condition (Quartile 4), indicating that extreme geopolitical uncertainty dampens the inverse link between WML and the market. When GPR is high, common shocks dominate idiosyncratic dynamics, reducing the distinctiveness of factor exposures and weakening the sensitivity of WML to market movements (Morck et al., 2000; Bekaert et al., 2022).

During the bear markets, the negative market exposures become even more pronounced. The bear-market beta ($\hat{\beta}_B$) is significantly negative in Quartile 2 (-0.847 , $t = -4.26$), Quartile 3 (-0.813 , $t = -1.99$), and Quartile 4 (-0.510 , $t = -1.67$), indicating that the negative betas are primarily sourced from bear markets, consistent with the mechanism of Daniel and Moskowitz (2016). By contrast, in the low-GPR regime (Quartile 1), the bear-market beta is statistically insignificant. This suggests that when geopolitical risk is low, investors’ risk aversion is limited, and market downturns are mild (Bekaert et al., 2022; Pástor and Veronesi, 2013). Because market movements are small, the returns of winners and losers are less differentiated by market conditions. As a result, the covariance between WML and the market factor $\tilde{R}_{m,t}$ becomes weak, and the negative market exposure of momentum becomes less pronounced.

The results of Regression 3 are in line with our findings in Table 9 as the interaction terms, $\hat{\beta}_{B,U}$, are negative but statistically insignificant across all four panels. This suggests that there are no significant losses during market rebounds following bear markets, relative to periods when the market remains bearish. Hence, the results of the GPR-based market timing regressions confirm our previous findings that the evidence for the “short call option” mechanism proposed by Daniel and Moskowitz (2016) is weak in the UK market regardless of GPR levels.

The pooled-panel regressions in Columns 8-13, which aggregate across all momentum strategies, largely reinforce the patterns observed for the 12-1 strategy. The results indicate that the negative correlation between momentum and the market is primarily driven by bear-market exposures. Specifically, the coefficient on the bear-market interaction term, $\hat{\beta}_B$, is significantly negative at moderate GPR levels (Quartiles 2 and 3) but becomes insignificant at the lowest and highest GPR levels (Quartiles 1 and 4).

A critical distinction emerges when examining the asymmetric payoff during market rebounds. For the first three GPR quartiles, the interaction terms ($\hat{\beta}_{B,U}$) are statistically insignificant, corroborating the evidence from the 12-1 strategy that momentum does not suffer systematic additional losses when the market recovers within a bear market. In contrast, under the highest level of geopolitical risk (Quartile 4), the interaction term becomes significantly negative at the 10% level ($\hat{\beta}_{B,U} = -0.945$, $t = -1.94$). This result for the aggregate of momentum strategies diverges remarkably from the OLS results for the 12-1 strategy alone, where the coefficient remains insignificant. This finding suggests that the asymmetric payoff materialises only during periods of extreme geopolitical stress.

This pattern reveals that the “short call option” behaviour of momentum is conditional on the high level of geopolitical risk. First, the high GPR precedes periods of heightened market volatility, reduced liquidity, and potential capital constraints (Bekaert et al., 2022; Caldara and Iacoviello, 2022), similar to the market panic states such as the financial crisis. During high GPR periods, investors exhibit a flight-to-quality, aggressively selling off riskier assets, which are the ‘loser’ stocks in the short leg of the momentum portfolio (Pástor and Veronesi, 2013). This selling pressure can push these loser stocks deeper into distress. Consequently, when a market rebound occurs during high-GPR periods, the aggressive shorting positions

Table 10: Market timing regressions conditional on GPR

This table reports the market timing regression results conditional on GPR, with three specifications of monthly panel regressions estimated over the period from January 1869 to November 2024. Panel A presents results for Quartile 1 (lowest GPR), Panel B for Quartile 2, Panel C for Quartile 3, and Panel D for Quartile 4 (highest GPR). Columns 2-7 use the returns of the 12-1 strategy as the dependent variable, while Columns 8-13 present panel regressions with returns of all momentum strategies as the dependent variable. For the OLS regressions, the t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#). For the panel regressions, we adopt the cluster standard error measure proposed by [Thompson \(2011\)](#) for robust t -statistics. The independent variables include a constant ($\hat{\alpha}_0$); a bear market indicator, $I_{B,t-1}$, equal to one if the cumulative market return over the previous two years is negative (coefficient $\hat{\alpha}_B$); the excess market return, $\tilde{R}_{m,t}$ (coefficient $\hat{\beta}_0$); the interaction term $I_{B,t-1} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_B$); and a contemporaneous up-market indicator, $\tilde{I}_{U,t}$, equal to one if $\tilde{R}_{m,t} > 0$, interacted with the bear market and market return as $I_{B,t-1} * \tilde{I}_{U,t} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_{B,U}$). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependents	12-1 momentum strategy						All momentum strategies					
Regression	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}
Panel A: Quartile 1												
1	0.021*** (5.30)		-0.245* (-1.66)			0.017	0.012*** (4.99)		-0.252** (-2.49)			0.029
2	0.018*** (5.25)	0.021 (1.02)	-0.146 (-0.92)	-0.415 (-1.06)		0.030	0.011*** (4.77)	0.007 (0.54)	-0.196* (-1.73)	-0.237 (-0.86)		0.034
3	0.018*** (4.88)	0.047 (1.35)	-0.146 (-0.91)	0.112 (-0.21)	-0.930 (-0.77)	0.034	0.011*** (4.77)	0.015 (0.66)	-0.196* (-1.73)	-0.076 (-0.19)	-0.285 (-0.34)	0.035
Panel B: Quartile 2												
1	0.015*** (3.60)		-0.549*** (-3.89)			0.130	0.010*** (3.90)		-0.343*** (-4.28)			0.086
2	0.015*** (4.14)	-0.018 (-0.84)	-0.186* (-1.93)	-0.847*** (-4.26)		0.217	0.011*** (4.45)	-0.021 (-1.35)	-0.141** (-2.17)	-0.453*** (-2.86)		0.140
3	0.015*** (4.13)	-0.018 (-0.76)	-0.186* (-1.92)	-0.845* (-1.87)	-0.002 (-0.01)	0.217	0.011*** (4.45)	-0.025 (-1.37)	-0.141** (-2.16)	-0.561* (-1.75)	0.132 (0.38)	0.140
Panel C: Quartile 3												
1	0.013*** (3.76)		-0.225* (-1.71)			0.018	0.008*** (3.51)		-0.178** (-2.19)			0.016
2	0.013*** (4.03)	-0.013 (-0.73)	-0.101 (-0.93)	-0.813** (-1.99)		0.055	0.008*** (3.75)	-0.010 (-0.95)	-0.100 (-1.27)	-0.521** (-2.04)		0.040
3	0.013*** (3.95)	0.002 (0.08)	-0.101 (-0.93)	-0.527 (-0.78)	-0.678 (-0.69)	0.057	0.008*** (3.75)	-0.001 (-0.10)	-0.100 (-1.27)	-0.348 (-0.77)	-0.410 (-0.65)	0.041
Panel D: Quartile 4												
1	0.012*** (4.31)		-0.157 (-1.08)			0.012	0.007*** (3.54)		-0.112 (-1.40)			0.010
2	0.013*** (4.52)	-0.008 (-0.91)	-0.064 (-0.40)	-0.510* (-1.67)		0.037	0.007*** (3.82)	-0.007 (-1.15)	-0.054 (-0.63)	-0.311 (-1.49)		0.028
3	0.013*** (4.52)	0.004 (0.23)	-0.064 (-0.40)	-0.100 (-0.28)	-0.679 (-0.93)	0.040	0.007*** (3.82)	0.009 (1.01)	-0.054 (-0.63)	0.260 (0.98)	-0.945* (-1.94)	0.038

result in disproportionately large losses, manifesting as the significant negative $\hat{\beta}_{B,U}$.

5.3. *Dissecting the option-like payoff*

A central question of our study is why the option-like payoff pattern of momentum strategies weakens in the UK stock market over the long run. The structural nature of momentum strategies, driven by trends in past returns, implies that their crash risk should be closely linked to behavioural mechanisms underlying the momentum premium. [Daniel et al. \(1997\)](#), [Barberis et al. \(1998\)](#), and [Hong and Stein \(1999\)](#) argue that momentum profits arise from investors' short-term underreaction to firm-specific information. If the tendency for prices to trend stems from such systematic deviations from full informational efficiency, it follows rationally that the crashes can also originate from behavioural bias. Accordingly, we hypothesise that momentum crashes in the UK market are primarily driven by investor behaviour.

A crucial difference between our work and the existing literature is the sample period. Our sample begins in 1869, when there is no market index published, whereas [Barroso and Santa-Clara \(2015\)](#) and [Daniel and Moskowitz \(2016\)](#) explore momentum crashes when the Standard & Poor's 500 index becomes available for market participants.² Moreover, in the US, the very first official market index, Dow Jones Transportation Average (DJTA), is published in July 1884, and then the well-known Dow Jones Industrial Average (DJIA), is published in May 1896. Unlike US stock markets, the UK equity markets lacked an official market index until the launch of the Financial Times Ordinary Index (FT30) in July 1935. As an essential benchmark for market participants ([Barber and Odean, 2008](#)), the absence of an official market index can reduce the diffusion of market status information and further mislead market participants' expectations of the market ([Veldkamp, 2006](#); [Peng and Xiong, 2006](#)). Our argument is that momentum crash risks rely on processing aggregate public signals. [Bowles et al. \(2024\)](#) support this by showing that anomaly profits are not earned continuously. Instead, profits are highly concentrated around major public macroeconomic announcements. Therefore, the absence of a market index in the pre-1935 sample marks a

²The Standard & Poor's 500 index was officially launched on 4 March 1957. Before that, it was known as the Standard & Poor's 90 index since 1926.

fundamental difference in the efficiency of information acquisition.

We propose that the high visibility of a public market index serves as a crucial focal point for investors, particularly during periods of market distress. In bear market regimes, the index’s decline substantially attracts investor attention, potentially amplifying negative sentiment market-wide ([Andrei and Hasler, 2015](#); [Ben-Rephael et al., 2017](#)). This concentrated attention can lead to an asymmetric behavioural reaction: a collective overreaction to downside expectations of market conditions, coinciding with an underreaction to firm-specific information that could drive stock rebounds, particularly for distressed ‘loser’ equities. In other words, investors overestimate the persistence of market downturns but underestimate the potential for rebounds. This behavioural bias creates conditions in which the pronounced relative outperformance of past losers triggers a momentum crash, consistent with empirical patterns observed by [Barroso and Santa-Clara \(2015\)](#) and [Daniel and Moskowitz \(2016\)](#).

Furthermore, the behavioural bias provides a new channel for explaining the asymmetric payoff documented by [Daniel and Moskowitz \(2016\)](#). The index-catalysed overreaction to adverse news can drive the prices of past losers dramatically below fundamental values, similar to an out-of-the-money call option on firm value. The poor performance of the market index can further amplify the selling pressure of these losers and, therefore, increase the potential for a sharp rebound when the firms’ values are correctly priced, resulting in remarkable asymmetric payoffs of the momentum strategies during the bear market.

Under this framework, the asymmetric payoffs of the momentum strategies should be significant when the market index is visible, but become weak and even disappear when the market index is absent or incomplete. To test this, we separate the entire sample into three sub-samples: 1) pre-index sample, from January 1871 to June 1935, 2) the FT30 sample, from July 1935 to February 1984, and 3) the Financial Times Stock Exchange (FTSE) sample, from March 1984 to November 2024, where the current FTSE indices become available. We apply the regressions of [Daniel and Moskowitz \(2016\)](#), as shown in Equations 1 to 3, in each sub-sample to test how the visibility of the market index affects the momentum asymmetric payoff during the bear markets.

Table 11 reports the results of sub-sample regressions. Panels A, B, and C show the results based on the pre-index, FT30, and FTSE samples, respectively. For the OLS regres-

Table 11: Sub-period market timing regressions

This table reports the market timing regression results estimated over three sub-periods. Panels A to C present results based on sub-samples January 1871-June 1935, July 1935-February 1984, and March 1984-November 2024, respectively. Columns 2-7 use the returns of the 12-1 strategy as the dependent variable, while columns 8-13 present panel regressions with returns of all momentum strategies as the dependent variable. For the OLS regressions, the t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#). For the panel regressions, we adopt the cluster standard error measure proposed by [Thompson \(2011\)](#) for robust t -statistics. The independent variables include a constant ($\hat{\alpha}_0$); a bear market indicator, $I_{B,t-1}$, equal to one if the cumulative market return over the previous two years is negative (coefficient $\hat{\alpha}_B$); the excess market return, $\tilde{R}_{m,t}$ (coefficient $\hat{\beta}_0$); the interaction term $I_{B,t-1} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_B$); and a contemporaneous up-market indicator, $\tilde{I}_{U,t}$, equal to one if $\tilde{R}_{m,t} > 0$, interacted with the bear market and market return as $I_{B,t-1} * \tilde{I}_{U,t} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_{B,U}$). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regression	12-1 momentum strategy						All momentum strategies					
	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}
Panel A: January 1871 - June 1935												
1	0.015*** (7.95)		-0.864*** (-3.93)			0.120	0.009*** (7.76)		-0.710*** (-6.22)			0.118
2	0.013*** (7.53)	0.011 (1.01)	-0.412** (-2.39)	-1.392*** (-5.09)		0.197	0.008*** (6.65)	0.007 (1.00)	-0.414*** (-3.87)	-0.915*** (-4.20)		0.167
3	0.013*** (7.51)	0.016 (1.13)	-0.412** (-2.38)	-1.225*** (-3.82)	-0.261 (-0.57)	0.198	0.008*** (6.65)	0.008 (0.83)	-0.414*** (-3.87)	-0.866** (-2.41)	-0.078 (-0.14)	0.167
Panel B: July 1935 - February 1984												
1	0.010*** (4.57)		-0.147 (-0.96)			0.017	0.005*** (3.74)		-0.061 (-0.80)			0.005
2	0.009*** (4.45)	0.001 (0.01)	0.060 (0.79)	-0.617*** (-3.11)		0.109	0.005*** (3.46)	-0.004 (-0.86)	0.049 (1.17)	-0.328*** (-3.11)		0.051
3	0.009*** (4.43)	0.015 (1.33)	0.060 (0.80)	-0.231 (-1.28)	-0.529*** (-2.86)	0.118	0.005*** (3.46)	0.002 (0.31)	0.049 (1.17)	-0.166 (-1.31)	-0.222 (-1.13)	0.054
Panel C: March 1984 - November 2024												
1	0.021*** (4.72)		-0.513*** (-3.34)			0.055	0.014*** (5.51)		-0.427*** (-4.17)			0.064
2	0.022*** (4.74)	-0.002 (-0.07)	-0.411*** (-2.97)	-1.494*** (-2.87)		0.121	0.015*** (5.65)	-0.010 (-0.61)	-0.353*** (-3.95)	-0.969** (-2.15)		0.115
3	0.022*** (4.83)	0.066 (1.50)	-0.411*** (-3.04)	0.428 (0.35)	-3.121* (-1.65)	0.139	0.015*** (5.65)	0.040 (1.55)	-0.353*** (-3.95)	0.458 (0.56)	-2.317* (-1.86)	0.131

sions based on the 12-1 momentum strategy, the market betas, $\hat{\beta}_0$, remain negative across three panels. In regression 2, the bear market betas, $\hat{\beta}_B$, are also negative and statistically significant at the 1% level, indicating that the negative market betas are mainly scoured from the bear markets. However, the asymmetric payoff is weak before the market index is launched, but becomes significant after the FT30 is available. The joint coefficient, $\hat{\beta}_{B,U}$ is only -0.261 ($t=-0.57$) in Panel A but -0.529 ($t=-2.86$) and -3.121 ($t=-1.65$) in Panel B and C, respectively. Such results verify our hypothesis that a visible public market index enlarges the asymmetric payoff of the momentum portfolio during bear markets.

For the panel regressions, the results of regressions 1 and 2 align with the OLS results based on the 12-1 strategy. The market betas are all negative across three panels. The negative betas are primarily attributed to the bear market, as indicated by the significantly negative betas during that period. An intriguing divergence emerges within the FT30 sub-period. While the OLS regression for the 12-1 momentum strategy yields a statistically significant coefficient for the asymmetric payoff, the corresponding coefficient in the panel regression is statistically insignificant ($\hat{\beta}_{B,U} = -0.222$, $t = -1.13$).

We attribute this disparity in the significance of the asymmetric payoff ($\hat{\beta}_{B,U}$) between the 12-1 strategy and the panel regressions to the interaction between the information environment and the momentum formation period. The FT30 index provided an incomplete market representation, covering mainly industrial firms but excluding sectors like financials. Furthermore, its publication via newspapers meant that the speed of aggregate information diffusion about the market state was much slower than in later periods. Both incomplete information and reduced information diffusion lead investors to require more time to aggregate market information and synchronise sentiment about market conditions ([Chordia et al., 2005](#); [Veldkamp, 2006](#)). For instance, momentum investors who rely on 3-6 month formations are less likely to explore the two-year market states from archived newspapers.

For the 12-1 strategy, the 12-month formation period provides sufficient time for this slower information aggregation to be completed. Investors utilising this strategy can adequately assess the prevailing market regime (e.g., a bear market) even with a partially covered index ([Hong and Stein, 1999](#)), thereby allowing the asymmetric payoff to emerge, leading to the significant $\hat{\beta}_{B,U}$ in the OLS regression. Conversely, for strategies with shorter formation

periods ($J=3, 6, 9$ months), the slow information diffusion may inhibit the complete synchronisation of investor sentiment within the shorter formation window. The market state may not be fully perceived by momentum investors relying on shorter formation periods, thereby attenuating the collective overreaction and the subsequent sharp rebound dynamics necessary to generate a pronounced asymmetric payoff (Hong et al., 2000).

Consequently, for panel regressions, the statistically insignificant results from the shorter-formation period strategies dilute the significant effect observed for the 12-1 strategy, leading to the insignificant $\hat{\beta}_{B,U}$ in Panel B. This finding supports the proposition that the asymmetric momentum payoff is contingent not only on the market state but also, critically, on the interplay between the efficiency of the information environment and the length of the momentum formation periods.

When the market index is unavailable, macroeconomic indicators serve as proxies of market status, so we next explore how macroeconomic dynamics and the visibility and completeness of the market index jointly affect the asymmetric payoff of momentum strategies. Table 12 presents the results of regression 3, as shown in Equation 3, across three samples. Panels A and B illustrate the results during the expansion and recession phases, respectively. For GPR analysis as shown in Panels C and D, we reform into two groups, high and low GPR, with each group covering half of the sample to avoid biased results from a small sample size.

Across all panels, the results reveal that the asymmetric payoff, $\hat{\beta}_{B,U}$, remains statistically insignificant during the pre-index era. This finding strongly supports the notion that the availability of a public index is an essential condition for synchronised investor behaviour, i.e., the collective overreaction to the bear markets. Without this focal point, macroeconomic distress alone appears insufficient to trigger the pronounced asymmetry.

During the FT30 period (1935-1984), characterised by an incomplete index and relatively slow information diffusion speed, the results show that the asymmetric payoff ($\hat{\beta}_{B,U}$) becomes statistically significant for the 12-1 strategy, during recessions ($\hat{\beta}_{B,U} = -0.660, t = -1.82$) and periods of low GPR ($\hat{\beta}_{B,U} = -1.499, t = -2.06$). However, even under these conditions, the coefficient remains statistically insignificant in the panel regressions pooling across all strategies, $\hat{\beta}_{B,U} = -0.259$ ($t = -0.89$) in Panel B and $\hat{\beta}_{B,U} = -0.156$ ($t = -1.06$) in Panel C.

Table 12: Sub-period market timing regressions conditional on macroeconomic dynamics

This table reports the market timing regression results estimated over three sub-periods. Panels A to C present results based on sub-samples January 1871-June 1935, July 1935-February 1984, and March 1984-November 2024, respectively. Columns 2-7 use the returns of the 12-1 strategy as the dependent variable, while Columns 8-13 present panel regressions with returns of all momentum strategies as the dependent variable. For the OLS regressions, the t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#). For the panel regressions, we adopt the cluster standard error measure proposed by [Thompson \(2011\)](#) for robust t -statistics. The independent variables include a constant ($\hat{\alpha}_0$); a bear market indicator, $I_{B,t-1}$, equal to one if the cumulative market return over the previous two years is negative (coefficient $\hat{\alpha}_B$); the excess market return, $\tilde{R}_{m,t}$ (coefficient $\hat{\beta}_0$); the interaction term $I_{B,t-1} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_B$); and a contemporaneous up-market indicator, $\tilde{I}_{U,t}$, equal to one if $\tilde{R}_{m,t} > 0$, interacted with the bear market and market return as $I_{B,t-1} * \tilde{I}_{U,t} * \tilde{R}_{m,t}$ (coefficient $\hat{\beta}_{B,U}$). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regression	12-1 momentum strategy						All momentum strategies					
	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}
Panel A: Expansion												
Jan 1871 - Jun 1935	0.012*** (4.40)	0.004 (0.29)	-0.219 (-1.01)	-0.537 (-1.03)	0.006 (0.01)	0.017	0.008*** (4.50)	0.003 (0.30)	-0.298** (-2.10)	-0.523 (-1.18)	0.386 (0.82)	0.023
Jul 1935 - Feb 1984	0.009*** (3.63)	-0.005 (-0.40)	0.032 (0.41)	-0.402 (-1.13)	0.029 (0.06)	0.013	0.005*** (3.16)	-0.000 (-0.07)	0.031 (0.65)	-0.050 (-0.19)	-0.285 (-0.84)	0.009
Mar 1984 - Nov 2024	0.021*** (4.30)	0.024 (0.58)	-0.376** (-2.43)	-0.414 (-0.36)	-1.389 (-0.96)	0.083	0.014*** (4.79)	0.016 (0.75)	-0.297*** (-2.88)	-0.233 (-0.32)	-1.045 (-1.12)	0.074
Panel B: Recession												
Jan 1871 - Jun 1935	0.013*** (5.59)	0.019 (0.70)	-1.038*** (-3.29)	-0.647 (-1.13)	-0.693 (-0.65)	0.432	0.007*** (4.34)	0.000 (0.01)	-0.839*** (-4.16)	-0.662 (-1.32)	0.043 (0.06)	0.339
Jul 1935 - Feb 1984	0.008 (1.43)	0.027 (0.67)	0.227** (2.13)	-0.351 (-0.94)	-0.660* (-1.82)	0.465	0.003 (1.20)	0.009 (0.40)	0.192** (2.32)	-0.300 (-1.30)	-0.259 (-0.89)	0.270
Mar 1984 - Nov 2024	-0.016 (-0.44)	0.172 (1.57)	-0.537 (-1.27)	2.497 (0.77)	-4.632 (-0.63)	0.143	0.024** (2.36)	0.070 (1.35)	-0.585*** (-3.18)	2.465 (1.34)	-3.880 (-1.28)	0.169
Panel C: Low GPR												
Jan 1871 - Jun 1935	0.020*** (6.72)	-0.005 (-0.18)	-0.449 (-1.63)	-1.499** (-2.06)	-0.027 (-0.03)	0.413	0.011*** (5.40)	-0.014 (-0.70)	-0.337** (-2.09)	-1.366** (-2.45)	0.233 (0.29)	0.367
Jul 1935 - Feb 1984	0.008** (2.48)	0.026 (1.37)	0.062 (0.73)	-0.181 (-0.68)	-0.642*** (-2.73)	0.187	0.005** (2.22)	0.007 (0.64)	0.040 (0.74)	-0.156 (-1.06)	-0.243 (-1.19)	0.079
Mar 1984 - Nov 2024	0.021*** (3.25)	0.192*** (4.38)	-0.192 (-1.08)	4.245** (2.52)	-8.594*** (-3.46)	0.187	0.013*** (3.65)	0.128*** (3.21)	-0.188 (-1.49)	3.452** (2.18)	-6.457*** (-3.07)	0.159
Panel D: High GPR												
Jan 1871 - Jun 1935	0.014*** (4.32)	0.010 (0.54)	-0.445** (-2.07)	-1.083 (-1.37)	0.175 (0.16)	0.157	0.008*** (3.49)	0.001 (0.13)	-0.416*** (-2.69)	-0.724** (-2.08)	0.549 (1.08)	0.099
Jul 1935 - Feb 1984	0.010*** (3.31)	-0.013 (-0.77)	0.058 (0.44)	-0.565 (-1.29)	0.432 (0.67)	0.014	0.005*** (2.63)	-0.003 (-0.31)	0.067 (0.99)	-0.114 (-0.36)	-0.180 (-0.42)	0.015
Mar 1984 - Nov 2024	0.023*** (4.25)	-0.023 (-0.47)	-0.727*** (-4.33)	-0.52 (-0.41)	-0.427 (-0.24)	0.161	0.017*** (4.82)	-0.015 (-0.69)	-0.590*** (-6.69)	-0.194 (-0.27)	-0.574 (-0.62)	0.165

This difference between the single 12-1 strategy and pooled panel results strongly supports the hypothesis involving the interaction between information diffusion speed and the length of the formation period. It indicates that while certain macroeconomic states act as triggers amplifying sentiment, the translation into a significant asymmetric payoff also requires sufficient time for information aggregation, given the slow diffusion under the partial FT30 index. For strategies with shorter formation periods included in the panel, the slower information flow likely prevents the complete synchronisation of sentiment required for the pronounced asymmetry, even under these triggering macro conditions. This leads to the insignificant finding when averaging across all strategies in the panel regressions during these states.

In the modern FTSE era, with the development of comprehensive indices and communication technologies accelerating the diffusion of information, the pattern shifts. The asymmetric payoff ($\hat{\beta}_{B,U}$) shows strong significance in the panel regressions during periods of Low GPR (Panel C), while being less consistent during other periods. This suggests that while index visibility enables the asymmetric payoff, the specific macroeconomic conditions are the preconditions. Significant asymmetric payoff is more pronounced during periods of low geopolitical risk, reflecting that corrections of behavioural mispricing are more aggressive during low geopolitical uncertainty regimes.

Another interesting pattern is that the asymmetric payoff of the 12-1 strategy is significant in the FT30 sample but no longer evident in the FTSE sample. During the FT30 period, with slower information diffusion under the incomplete market index, the low-frequency business cycle indicators serve as a crucial signal coordinating investor sentiment, making recessions triggers for asymmetry (Hong and Stein, 1999; Veldkamp, 2006). By contrast, the FTSE era, marked by rapid communication technology and comprehensive index visibility, shifts investor focus towards higher-frequency, salient news related to geopolitical events or market shocks, as captured by GPR (Barber and Odean, 2008; Andrei and Hasler, 2015). Consequently, the conditions under which over/under-reaction synchronise sufficiently to generate significant asymmetric payoff appear to have migrated from the business cycle downturns towards the geopolitical risks, suggesting that the interaction between macroeconomic states and the dynamics of information dissemination and investor attention determines the signif-

icance of momentum’s asymmetric payoff.

To conclude, the sub-period analysis across various economic states reveals that the asymmetric momentum payoff is not static but rather dynamically conditioned by both the information environment (the visibility of the market index) and the macroeconomic state. Its absence pre-index underscores the necessity of a visible index. The FT30 period reveals the emergence of asymmetry under specific macroeconomic states, but only for long formation period strategies that are capable of aggregating slower information. Finally, the FTSE era, with faster diffusion, demonstrates that the asymmetry can become a more general feature across formation periods.

6. Conclusion

This paper provides a comprehensive investigation of momentum profitability in the UK equity market, covering more than 150 years from 1869 to 2024. Using an integrated dataset that spans multiple market regimes and trading technologies, we show that momentum remains a persistent but state-dependent phenomenon. Its returns vary systematically with macroeconomic dynamics both domestically (business cycles) and externally (geopolitical risk), revealing that the drivers of momentum profits are far from static.

The results show that momentum strategies generate significant positive returns during both expansions and recessions, with even higher returns observed in some recessionary periods. During recessions, momentum returns are primarily driven by the extreme underperformance of prior losers rather than the continued strength of winners. This asymmetry indicates that momentum gains in downturns often arise from correctional rebounds rather than improvements in fundamentals, reflecting investors’ delayed response to information and heightened sensitivity to downside risk.

Additionally, geopolitical uncertainty emerges as a critical external conditioning variable. Our evidence indicates that momentum strategies perform strongest in periods of low geopolitical risk and weaken substantially as geopolitical tensions intensify. When geopolitical risks rise, the predictability of returns declines, and short-horizon strategies, in particular, lose effectiveness. The results remain broadly consistent after adjusting for standard risk factors, implying that geopolitical uncertainty exerts an independent influence on investor

behaviour and cross-sectional return persistence. When conditioning on both business cycles and geopolitical risks, we find that these two factors are largely independent, suggesting that the impacts of domestic and external risks do not overlap.

The long historical horizon also allows us to reassess the nature of momentum crashes. We find that most severe drawdowns occur during economic expansions and following periods of strong market performance, rather than during recessions. This finding supports the view that momentum crashes are not merely by-products of market downturns but reflect cyclical phases of overextension. We also reveal that the option-like payoff feature of momentum strategies is statistically insignificant in the UK equity market over the 155-year sample period. We find that this divergence is related to investors' perception of the market index, particularly due to the absence of a public market index before 1935. Without a public index as an anchor, sentiment synchronisation is impeded, preventing the collective overreaction required to generate the pronounced asymmetric payoff. Our findings provide further evidence that the momentum effect is essentially an artefact of investors' irrational behaviour and belief formation.

Our study contributes to a deeper understanding of the lifecycle of the momentum effect and its conditional drivers, offering long-run empirical evidence for how such market anomalies persist and evolve dynamically over time. The insights also have practical implications for investment and risk management: the source of momentum profits, the optimal holding period, and portfolio configuration should be adjusted in line with changing macroeconomic conditions and external risks to reduce the likelihood of phase-specific reversals or crashes. From a regulatory perspective, attention should also be paid to how momentum trading may amplify market instability under certain macroeconomic scenarios.

Overall, this study advances the understanding of how long-run macroeconomic and geopolitical regimes shape one of the most enduring puzzles in empirical asset pricing. Future research can extend this analysis by exploring cross-market interactions between global risk factors and domestic momentum dynamics, and extend the comparative analyses to other equity markets. Moreover, there is scope to quantify how information transmission channels affect investor underreaction and to explore new challenges arising in the age of artificial intelligence.

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Appendix A. Momentum and OECD Business Cycle

Table A.1: Momentum profits conditional on business cycle stage with OECD data

This table presents momentum profits conditional on different business cycle stages based on OECD data. A business cycle is divided into four stages: Peak, Recession, Trough, and Expansion. Momentum portfolios are formed based on a J -month formation period and K -month holding period. We skipped the most recent month before the holding period to mitigate short-term reversal effects. J - K combinations range from 3 to 12 months for both the formation (J) and holding (K) periods. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#). The sample period ranges from February 1955 to November 2024.

Strategy	Peak	Recession	Trough	Expansion
3-1	-0.0016 (0.13)	0.0030 (0.69)	-0.0019 (0.22)	0.0078 (2.62)
3-3	0.0021 (0.20)	0.0029 (0.85)	0.0040 (0.59)	0.0079 (3.65)
3-6	-0.0013 (0.17)	0.0049 (1.80)	0.0013 (0.25)	0.0059 (3.27)
3-12	0.0035 (0.61)	0.0048 (2.29)	-0.0026 (0.50)	0.0049 (3.68)
6-1	-0.0066 (0.53)	0.0117 (2.27)	-0.0005 (0.06)	0.0105 (3.41)
6-3	-0.0018 (0.16)	0.0122 (2.78)	0.0001 (0.01)	0.0109 (3.90)
6-6	-0.0028 (0.31)	0.0116 (3.02)	-0.0033 (0.35)	0.0093 (3.78)
6-12	0.0013 (0.17)	0.0086 (2.94)	-0.0074 (0.88)	0.0066 (3.51)
9-1	-0.0082 (0.55)	0.0132 (2.69)	-0.0067 (0.55)	0.0119 (3.60)
9-3	-0.0046 (0.42)	0.0134 (2.96)	-0.0079 (0.68)	0.0120 (3.99)
9-6	0.0001 (0.01)	0.0125 (3.09)	-0.0095 (0.87)	0.0110 (3.94)
9-12	0.0035 (0.47)	0.0072 (2.18)	-0.0131 (1.27)	0.0055 (2.40)
12-1	0.0022 (0.17)	0.0153 (2.81)	-0.0067 (0.60)	0.0148 (4.34)
12-3	0.0041 (0.35)	0.0136 (2.77)	-0.0134 (1.13)	0.0135 (4.30)
12-6	0.0035 (0.36)	0.0111 (2.50)	-0.0143 (1.24)	0.0102 (3.45)
12-12	0.0045 (0.66)	0.0044 (1.18)	-0.0185 (1.78)	0.0043 (1.69)

The momentum profits conditional on business cycle stages based on OECD data are reported in Table A.1. All strategies continue to exhibit significantly positive returns during expansionary periods. For example, the 12-1 strategy yields a return of 0.0148 ($t = 4.34$), which is highly statistically significant. During recessions, all strategies also deliver positive returns; the 6-9 strategy, for instance, achieves a return of 0.0111 ($t = 3.36$). Seven strategies show negative returns during the peak phase, while only two generate positive returns during

the trough phase. These findings are consistent with the stage-specific momentum patterns reported in Table 3 of the main text.

Appendix B. Semivariances analysis

Previous studies have shown that bad variance, captured by downside risk, exhibits the strongest correlation with asset pricing factors (Patton and Sheppard, 2015), whereas good variance is generally perceived by investors as acceptable, or even desirable. The fact that momentum strategies generate positive returns under both expansionary and recessionary regimes suggests that these profits may not be driven by exposure to systematic risk. Instead, these strategies may benefit from the tendency to capture sharp upward price adjustments following periods of mispricing or market stress.

Building on the work of Bollerslev et al. (2020), we decompose the realised variance of the momentum returns into upside and downside semivariances (denoted as RV^+ and RV^-) in a given business cycle phase, corresponding to good and bad variance, respectively.

$$\begin{aligned} RV_S^+ &= \frac{1}{n_S} \sum_{i=1}^{n_S} r_i^2 \mathbf{1}_{\{r_i > 0\}}, \\ RV_S^- &= \frac{1}{n_S} \sum_{i=1}^{n_S} r_i^2 \mathbf{1}_{\{r_i < 0\}}, \end{aligned} \tag{B.1}$$

where r_i denotes the momentum strategy return in month i , and n_S represents the number of months during the business cycle phase, where $S \in \{\text{Expansion}, \text{Recession}\}$. We add a standardised term $\frac{1}{n_S}$ as the number of monthly momentum returns varies across business cycle states.

Then, we defined the state-based return jump (RJ_S) as $RV_S^+ - RV_S^-$, and the normalised version (RSJ_S) as:

$$RSJ_S = \frac{RV_S^+ - RV_S^-}{RV_S^+ + RV_S^-}, \tag{B.2}$$

The value of RSJ lies within the interval $[-1, 1]$: a value closer to 1 indicates that upside volatility dominates; conversely, a value closer to -1 suggests that downside shocks are the primary source of portfolio volatility. Unlike Bollerslev et al. (2020), who adopt these two terms as the cross-sectional return predictors. Our state-based RJ_S and RSJ_S have different economic meanings, measuring the positive momentum returns generated to compensate for momentum downside risks during a given sample period. In other words, for a given level

of downside risks, RV_S^- , the higher RJ_S and RSJ_S show more aggressive rebounds in the momentum returns.

If the positive returns reported in both recession and expansion phases, as shown in Table 3, reflect a homogenous risk premium, we would expect RSJ to exhibit minimal variation across business cycles. Conversely, if momentum profits rely more heavily on positive price jumps during recessions and on smoother trends during expansions, RSJ should show a distinct cyclical pattern.

Table B.1: Decomposition of momentum realised variance across business cycles

This table reports the normalised realised variance decomposition for momentum strategies during recession ($N=396$) and expansion ($N=1347$) periods. RV^+ (RV^-) represents the average squared returns for positive (negative) returns. RV is the sum of RV^+ and RV^- . RSJ measures the relative difference between good and bad variance. Numbers in parentheses are Newey-West t -statistics. The sample period is from January 1871 to November 2024.

Strategy	Recession Period (N = 396)				Expansion Period (N = 1347)			
	RV^+	RV^-	RV	RSJ	RV^+	RV^-	RV	RSJ
3-1	0.0015	0.0014	0.0029	0.0575	0.0016	0.0016	0.0032	0.0037
3-3	0.0008	0.0007	0.0015	0.0205	0.0010	0.0009	0.0018	0.0515
3-6	0.0005	0.0004	0.0009	0.1360	0.0006	0.0006	0.0012	0.0439
3-12	0.0003	0.0002	0.0006	0.1550	0.0004	0.0003	0.0007	0.0789
6-1	0.0023	0.0016	0.0038	0.1794	0.0020	0.0015	0.0036	0.1379
6-3	0.0013	0.0011	0.0024	0.1144	0.0017	0.0013	0.0030	0.1425
6-6	0.0011	0.0008	0.0019	0.1985	0.0013	0.0010	0.0023	0.1105
6-12	0.0007	0.0005	0.0012	0.2036	0.0008	0.0006	0.0014	0.1217
9-1	0.0021	0.0015	0.0036	0.1812	0.0022	0.0017	0.0040	0.1354
9-3	0.0017	0.0012	0.0029	0.1993	0.0019	0.0014	0.0033	0.1419
9-6	0.0016	0.0010	0.0025	0.2341	0.0016	0.0012	0.0028	0.1224
9-12	0.0010	0.0007	0.0017	0.1772	0.0010	0.0009	0.0019	0.0336
12-1	0.0024	0.0018	0.0042	0.1501	0.0025	0.0017	0.0042	0.1777
12-3	0.0020	0.0014	0.0035	0.1680	0.0021	0.0015	0.0036	0.1405
12-6	0.0017	0.0013	0.0030	0.1356	0.0017	0.0014	0.0031	0.0891
12-12	0.0011	0.0010	0.0020	0.0455	0.0011	0.0012	0.0022	-0.0340

Table B.1 presents the decomposed realised variance of 16 momentum strategies for both expansionary ($N = 1,347$) and recessionary ($N = 396$) periods. The results show that, in 13 out of the 16 strategies, RSJ is higher during recessions than during expansions. For instance, in the 9-6 momentum portfolio, RSJ equals 0.2341 in recessions and only 0.1224 in expansions. Similar patterns of relative contraction are observable in most strategies, such as 6-12 and 12-6.

In other words, when $RSJ_{Rec} > RSJ_{Exp}$, it indicates that the sum of squared positive returns (RV_S^+) increases disproportionately in recessions, while RV_S^- does not rise in tandem. This implies a jagged price trajectory in recessions, characterised by slight drawbacks

followed by large upward jumps. Each substantial jump contributes significantly to RV_S^+ , pushing up the value of RSJ . By contrast, price paths in expansions tend to be smoother and more gradual, with both positive and negative returns being relatively mild and symmetrically distributed, resulting in lower RSJ values. Meanwhile, RV shows minimal variation between macroeconomic regimes, suggesting that overall volatility remains broadly stable. What changes, instead, is the internal composition of volatility with respect to direction.

Appendix C. Performance of momentum crashes

To verify the impacts of the post-trough crashes during the expansion periods, we follow [Daniel and Moskowitz \(2016\)](#) and present the ten worst months for each momentum strategy under different economic phases in Table C.1. The results show that the momentum strategies suffer from higher crash risks during the expansions. Panel A shows results in recessions, the average losses ranging from -0.077 to -0.197 . In contrast, Panel B shows that the worst-month losses are uniformly more severe during expansions, with average losses ranging from -0.121 to -0.264 . Therefore, the worst month analysis confirms the existence of post-trough crashes, and the extreme losses surely reduce the momentum performance during the expansion period.

Table C.1: Performance of momentum crashes

This table reports the performance of momentum crashes under different business cycle conditions. Panel A and Panel B correspond to recession and expansion periods, respectively. For each panel, we identify the 10 worst monthly returns for each momentum strategy during the respective cycle stage. Momentum strategies are constructed using J - K combinations, where J and K denote the formation and holding periods (in months), ranging from 3 to 12. The entries in each panel represent the ten most negative returns, sorted in ascending order. The final row in each panel reports the mean of the ten worst returns, serving as a summary indicator of downside risk during crashes. The sample period spans from January 1871 to November 2024.

	3-1	3-3	3-6	3-12	6-1	6-3	6-6	6-12	9-1	9-3	9-6	9-12	12-1	12-3	12-6	12-12
Panel A: Recession																
1	-0.243	-0.212	-0.144	-0.137	-0.288	-0.214	-0.206	-0.174	-0.291	-0.274	-0.258	-0.199	-0.501	-0.437	-0.399	-0.283
2	-0.170	-0.160	-0.135	-0.088	-0.232	-0.199	-0.145	-0.132	-0.214	-0.174	-0.229	-0.178	-0.302	-0.259	-0.237	-0.177
3	-0.164	-0.134	-0.102	-0.083	-0.187	-0.158	-0.137	-0.126	-0.188	-0.171	-0.167	-0.141	-0.191	-0.179	-0.171	-0.164
4	-0.152	-0.126	-0.089	-0.081	-0.187	-0.151	-0.137	-0.105	-0.178	-0.153	-0.142	-0.125	-0.181	-0.157	-0.163	-0.138
5	-0.140	-0.113	-0.086	-0.078	-0.177	-0.147	-0.130	-0.103	-0.173	-0.149	-0.141	-0.120	-0.149	-0.156	-0.148	-0.130
6	-0.140	-0.102	-0.085	-0.074	-0.174	-0.141	-0.122	-0.091	-0.168	-0.145	-0.133	-0.109	-0.140	-0.137	-0.145	-0.122
7	-0.138	-0.101	-0.083	-0.069	-0.172	-0.140	-0.117	-0.089	-0.164	-0.145	-0.118	-0.107	-0.139	-0.136	-0.142	-0.119
8	-0.137	-0.090	-0.072	-0.060	-0.163	-0.135	-0.113	-0.076	-0.163	-0.142	-0.114	-0.101	-0.128	-0.120	-0.122	-0.115
9	-0.136	-0.089	-0.070	-0.053	-0.160	-0.129	-0.106	-0.071	-0.149	-0.120	-0.105	-0.098	-0.123	-0.114	-0.102	-0.114
10	-0.127	-0.087	-0.069	-0.049	-0.154	-0.125	-0.103	-0.071	-0.140	-0.120	-0.096	-0.094	-0.122	-0.108	-0.099	-0.114
Mean	-0.155	-0.121	-0.093	-0.077	-0.189	-0.154	-0.132	-0.104	-0.183	-0.159	-0.150	-0.127	-0.197	-0.180	-0.173	-0.148
Panel B: Expansion																
1	-0.436	-0.239	-0.239	-0.161	-0.297	-0.300	-0.340	-0.196	-0.327	-0.339	-0.376	-0.280	-0.403	-0.383	-0.377	-0.282
2	-0.280	-0.216	-0.223	-0.159	-0.271	-0.281	-0.304	-0.192	-0.312	-0.270	-0.304	-0.221	-0.316	-0.355	-0.327	-0.252
3	-0.250	-0.214	-0.219	-0.152	-0.267	-0.254	-0.271	-0.166	-0.264	-0.252	-0.276	-0.197	-0.292	-0.272	-0.232	-0.227
4	-0.221	-0.203	-0.197	-0.125	-0.247	-0.248	-0.207	-0.161	-0.255	-0.251	-0.209	-0.191	-0.266	-0.237	-0.222	-0.205
5	-0.216	-0.198	-0.159	-0.122	-0.241	-0.248	-0.191	-0.147	-0.246	-0.250	-0.205	-0.178	-0.261	-0.233	-0.204	-0.205
6	-0.212	-0.185	-0.150	-0.121	-0.231	-0.212	-0.187	-0.141	-0.244	-0.240	-0.199	-0.174	-0.256	-0.231	-0.196	-0.195
7	-0.205	-0.175	-0.144	-0.100	-0.220	-0.205	-0.185	-0.140	-0.240	-0.233	-0.193	-0.174	-0.222	-0.202	-0.195	-0.180
8	-0.197	-0.170	-0.134	-0.097	-0.219	-0.195	-0.181	-0.140	-0.220	-0.231	-0.185	-0.173	-0.213	-0.200	-0.193	-0.177
9	-0.194	-0.164	-0.131	-0.088	-0.210	-0.189	-0.180	-0.135	-0.212	-0.203	-0.183	-0.170	-0.208	-0.187	-0.191	-0.172
10	-0.182	-0.156	-0.123	-0.085	-0.201	-0.183	-0.164	-0.132	-0.208	-0.201	-0.178	-0.153	-0.203	-0.185	-0.189	-0.164
Mean	-0.239	-0.192	-0.172	-0.121	-0.240	-0.231	-0.221	-0.155	-0.253	-0.247	-0.231	-0.191	-0.264	-0.249	-0.233	-0.206

Appendix D. Sub-period analysis

In the previous empirical analysis, we systematically examined the performance characteristics and risk-adjusted returns of momentum strategies using the full sample and demonstrated their sensitivity to internal business cycles and external geopolitical risks. However, whether this effect can persist across different stages of financial market development remains an open empirical question. From a long-term historical perspective, financial markets have undergone significant structural shifts from the era of manual trading, through the period of institutionalisation and financial innovation, to the current phase of electronic and algorithmic trading. According to behavioural finance theory, as market efficiency improves and information transmission accelerates, investors’ short-term underreaction and trend-following biases may gradually diminish, thereby weakening the persistence of the momentum effect (Chordia et al., 2001; Griffin et al., 2010; Chordia et al., 2014). Based on this expectation, this section further divides the sample period into three sub-periods: the “Manual Trading Era” before 1949, the “Institutionalisation and Financial Innovation Era” from 1950 to 1996, and the “Electronic and Algorithmic Trading Era” from 1997 onward. For each sub-period, we replicate the baseline analyses of momentum returns and risk-adjusted performance to assess their robustness under different market conditions, and to examine whether the behavioural drivers of momentum have attenuated or shifted as market structures have evolved.

Tables D.1 through D.3 report the results for the manual trading era (1869–1949), the institutionalisation and financial innovation period (1950–1996), and the electronic and algorithmic trading era (1997–2024), respectively.

As shown in Table D.1, during the early manual trading period (1869–1949), momentum portfolios still generate significant excess returns that align with the full-sample benchmark results. The skip-month adjustment continues to improve the performance of medium- and long-term formation strategies (e.g., $J = 6, 12$), whereas short formation–short holding combinations (such as $J = 3, K = 1$) yield negative and statistically significant WML returns. This pattern echoes earlier findings that short-term strategies are more prone to noise trading and signal reversals in markets with slower information transmission and limited liquidity.

In the institutionalisation and financial innovation era (1950–1996, Table D.2), most momentum strategies display higher return levels, and the skip-month adjustment further

enhances WML significance. This suggests that improvements in trading systems, information disclosure, and financial intermediation strengthened the market's responsiveness to past price trends, allowing behavioural biases to sustain momentum effects over medium and long horizons.

In the electronic and algorithmic trading era (1997–2024, Table D.3), the return levels of momentum portfolios decline compared to earlier periods, particularly for long formation strategies ($J = 12$), whose significance weakens or approaches zero in some configurations. Additionally, short formation strategies exhibit greater volatility and more inconsistent performance. This is consistent with behavioural finance predictions that as market efficiency improves and algorithmic trading accelerates information absorption, the room for investor underreaction and trend-following behaviour diminishes, gradually eroding momentum profits.

Table D.1: Price momentum portfolios return from 1869 to 1949

This table shows the momentum portfolios formed based on J -month lagged returns and held for K -month. The stocks are ranked in ascending order on the basis of the lagged returns. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. This table presents the average monthly returns of these portfolios. The values of J and K for the different strategies are indicated in the first column and row, respectively. The momentum portfolios in Panel A are formed using returns over the entire portfolio formation period, while those in Panel B have the most recent month in the formation period skipped. t -statistics are in parentheses. The sample period ranges from 1869 to 1949.

		Panel A					Panel B				
J		$K=$	1	3	6	12	$K=$	1	3	6	12
3	Winner	-0.0013 (-0.76)	0.0034 (2.26)	0.0056 (4.12)	0.0071 (5.59)		0.0033 (2.17)	0.0055 (3.81)	0.0065 (4.94)	0.0071 (5.67)	
	Loser	0.0118 (7.80)	0.0076 (5.17)	0.0050 (3.45)	0.0043 (3.14)		0.0050 (-2.96)	0.0044 (-2.96)	0.0036 (-2.52)	0.0039 (-2.89)	
	WML	-0.0131 (-8.91)	-0.0042 (-3.64)	0.0005 (0.53)	0.0027 (3.77)		-0.0017 (-1.15)	0.0011 (0.99)	0.0028 (3.29)	0.0032 (5.19)	
6	Winner	0.0030 (1.86)	0.0063 (4.26)	0.0076 (5.79)	0.0079 (6.11)		0.0070 (4.78)	0.0080 (5.94)	0.0083 (6.62)	0.0080 (6.34)	
	Loser	0.0086 (4.99)	0.0054 (3.29)	0.0041 (2.56)	0.0037 (2.48)		0.0029 (1.70)	0.0030 (1.79)	0.0030 (1.88)	0.0036 (2.42)	
	WML	-0.0056 (-3.64)	0.0009 (0.69)	0.0035 (3.06)	0.0042 (4.69)		0.0041 (2.73)	0.0050 (3.83)	0.0053 (4.73)	0.0044 (5.08)	
9	Winner	0.0049 (3.12)	0.0075 (5.49)	0.0090 (6.79)	0.0080 (6.25)		0.0076 (5.16)	0.0087 (6.54)	0.0096 (7.33)	0.0080 (6.24)	
	Loser	0.0083 (4.98)	0.0051 (3.15)	0.0033 (2.02)	0.0039 (2.59)		0.0022 (1.35)	0.0024 (1.50)	0.0021 (1.33)	0.0037 (2.47)	
	WML	-0.0034 (-2.04)	0.0024 (1.80)	0.0058 (4.79)	0.0041 (4.24)		0.0054 (3.61)	0.0063 (4.93)	0.0075 (6.32)	0.0043 (4.70)	
12	Winner	0.0078 (5.06)	0.0094 (6.61)	0.0091 (6.53)	0.0078 (5.96)		0.0107 (7.35)	0.0104 (7.34)	0.0094 (6.82)	0.0077 (5.91)	
	Loser	0.0056 (3.16)	0.0035 (2.01)	0.0032 (1.89)	0.0044 (2.77)		0.0008 (0.45)	0.0014 (0.82)	0.0023 (1.40)	0.0043 (2.75)	
	WML	0.0022 (1.44)	0.0059 (4.79)	0.0059 (5.04)	0.0033 (3.33)		0.0099 (7.47)	0.0091 (7.67)	0.0071 (6.33)	0.0035 (3.66)	

Table D.2: Price momentum portfolios return from 1950 to 1996

This table shows the momentum portfolios formed based on J -month lagged returns and held for K -month. The stocks are ranked in ascending order on the basis of the lagged returns. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. This table presents the average monthly returns of these portfolios. The values of J and K for the different strategies are indicated in the first column and row, respectively. The momentum portfolios in Panel A are formed using returns over the entire portfolio formation period, while those in Panel B have the most recent month in the formation period skipped. t -statistics are in parentheses. The sample period ranges from 1950 to 1996.

		Panel A					Panel B				
J		$K=$	1	3	6	12	$K=$	1	3	6	12
3	Winner		0.0091 (3.08)	0.0129 (4.73)	0.0145 (5.48)	0.0154 (6.00)		0.0133 (4.64)	0.0145 (5.24)	0.0152 (5.63)	0.0156 (5.94)
	Loser		0.0196 (6.28)	0.0130 (4.41)	0.0108 (3.68)	0.0104 (3.63)		0.0109 (3.72)	0.0101 (3.72)	0.0106 (3.86)	0.0105 (3.81)
	WML		-0.0105 (-4.33)	-0.0001 (-0.03)	0.0037 (2.45)	0.0050 (4.29)		0.0023 (1.19)	0.0044 (3.04)	0.0046 (3.70)	0.0050 (5.53)
6	Winner		0.0125 (4.38)	0.0156 (5.61)	0.0163 (6.04)	0.0161 (6.17)		0.0158 (5.45)	0.0171 (6.11)	0.0172 (6.31)	0.0162 (6.15)
	Loser		0.0156 (4.73)	0.0122 (3.88)	0.0102 (3.53)	0.0101 (3.48)		0.0091 (2.85)	0.0082 (2.72)	0.0085 (2.88)	0.0096 (3.32)
	WML		-0.0031 (-1.18)	0.0034 (1.54)	0.0061 (3.32)	0.0060 (4.07)		0.0067 (3.03)	0.0088 (4.50)	0.0087 (5.32)	0.0067 (5.01)
9	Winner		0.0149 (4.94)	0.0173 (6.13)	0.0179 (6.66)	0.0163 (6.13)		0.0184 (6.38)	0.0180 (6.41)	0.0182 (6.63)	0.0161 (5.96)
	Loser		0.0159 (4.91)	0.0111 (3.63)	0.0089 (2.93)	0.0103 (3.42)		0.0108 (3.50)	0.0086 (2.87)	0.0082 (2.75)	0.0103 (3.43)
	WML		-0.0010 (-0.39)	0.0062 (2.84)	0.0090 (4.25)	0.0060 (3.45)		0.0076 (3.29)	0.0094 (4.53)	0.0100 (4.93)	0.0058 (3.50)
12	Winner		0.0152 (5.06)	0.0177 (6.26)	0.0172 (6.27)	0.0154 (5.64)		0.0188 (6.84)	0.0189 (6.77)	0.0179 (6.48)	0.0154 (5.63)
	Loser		0.0111 (3.57)	0.0091 (2.95)	0.0087 (2.74)	0.0106 (3.38)		0.0062 (1.97)	0.0064 (2.11)	0.0080 (2.62)	0.0106 (3.41)
	WML		0.0042 (1.66)	0.0086 (3.94)	0.0086 (4.23)	0.0048 (2.57)		0.0126 (5.36)	0.0126 (6.03)	0.0099 (4.86)	0.0048 (2.65)

Table D.3: Price momentum portfolios return from 1997 to 2024

This table shows the momentum portfolios formed based on J -month lagged returns and held for K -month. The stocks are ranked in ascending order on the basis of the lagged returns. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. This table presents the average monthly returns of these portfolios. The values of J and K for the different strategies are indicated in the first column and row, respectively. The momentum portfolios in Panel A are formed using returns over the entire portfolio formation period, while those in Panel B have the most recent month in the formation period skipped. t -statistics are in parentheses. The sample period ranges from 1997 to 2024.

J		Panel A					Panel B				
		$K=$	1	3	6	12	$K=$	1	3	6	12
3	Winner	0.0085	0.0092	0.0081	0.0072		0.0096	0.0090	0.0072	0.0063	
		(2.20)	(2.51)	(2.34)	(2.15)		(2.35)	(2.41)	(2.10)	(1.85)	
	Loser	0.0002	0.0011	0.0008	0.0013		0.0013	0.0015	0.0016	0.0024	
6		(0.04)	(0.18)	(0.13)	(0.24)		(0.22)	(0.26)	(0.29)	(0.48)	
	WML	0.0082	0.0082	0.0073	0.0058		0.0083	0.0076	0.0056	0.0039	
		(1.46)	(1.61)	(1.63)	(1.57)		(1.59)	(1.66)	(1.65)	(1.32)	
9	Winner	0.0100	0.0098	0.0085	0.0072		0.0120	0.0102	0.0088	0.0071	
		(2.74)	(2.83)	(2.52)	(2.22)		(3.31)	(2.97)	(2.67)	(2.22)	
	Loser	0.0048	0.0007	0.0012	0.0017		-0.0009	-0.0016	0.0003	0.0013	
12		(0.65)	(0.11)	(0.18)	(0.28)		(-0.14)	(-0.25)	(0.05)	(0.24)	
	WML	0.0052	0.0091	0.0073	0.0055		0.0128	0.0117	0.0085	0.0059	
		(0.78)	(1.51)	(1.28)	(1.19)		(2.24)	(2.24)	(1.69)	(1.45)	
15	Winner	0.0096	0.0094	0.0086	0.0071		0.0105	0.0093	0.0087	0.0068	
		(2.77)	(2.64)	(2.39)	(2.08)		(2.95)	(2.54)	(2.41)	(1.98)	
	Loser	0.0006	-0.0022	-0.0014	0.0023		-0.0030	-0.0027	-0.0013	0.0025	
18		(0.08)	(-0.31)	(-0.21)	(0.39)		(-0.42)	(-0.40)	(-0.20)	(0.43)	
	WML	0.0090	0.0116	0.0100	0.0048		0.0134	0.0120	0.0099	0.0043	
		(1.29)	(1.77)	(1.62)	(0.95)		(2.11)	(2.00)	(1.75)	(0.92)	
21	Winner	0.0089	0.0088	0.0078	0.0061		0.0103	0.0085	0.0076	0.0059	
		(2.30)	(2.44)	(2.18)	(1.70)		(2.59)	(2.20)	(2.09)	(1.60)	
	Loser	-0.0005	-0.0021	0.0006	0.0044		-0.0031	-0.0023	0.0000	0.0046	
24		(-0.07)	(-0.29)	(0.09)	(0.70)		(-0.46)	(-0.33)	(0.00)	(0.77)	
	WML	0.0095	0.0110	0.0072	0.0017		0.0134	0.0108	0.0076	0.0013	
		(1.24)	(1.58)	(1.10)	(0.31)		(2.12)	(1.71)	(1.31)	(0.26)	

While the momentum effect generally maintains positive portfolio returns across different market phases, consistent with the full-sample results, simply observing raw returns is not sufficient to rule out the possibility of risk premium explanations. Therefore, we further examine the risk-adjusted performance of momentum portfolios within each sub-period using the CAPM and Fama-French three-factor models, focusing on whether the alphas remain robust and whether they exhibit signs of attenuation as market structures evolve. This additional analysis helps clarify whether the persistence of the momentum effect relies on behavioural drivers that are not captured by standard risk factors, and whether such drivers have weakened over time as financial markets have developed.

From Table D.4, it can be seen that during the earliest manual trading era, the risk-adjusted performance of momentum portfolios differs substantially from the full-sample results. For example, the short formation–short holding strategy ($J=3$, $K=1$) yields a WML alpha of -1.34% ($t=-8.38$) under the CAPM, not only significantly negative but also lower than the full-sample result, indicating that in a low-efficiency market, short-term momentum strategies are more vulnerable to noise trading and return reversals. In contrast, longer formation and holding periods (e.g., $J=12$, $K=6$) still generate a significant positive alpha (0.68% , $t=4.21$), consistent with the full-sample findings. This suggests that even in manually matched markets with extremely slow information diffusion, trend-following behaviour remains effective over longer horizons. Overall, momentum profits in this stage rely more on the accumulation of longer-term trends, while short-term reversal risk is pronounced (Hong and Stein, 1999).

In Table D.5, most momentum strategies show weaker alpha returns, especially for short-term configurations, which perform similarly to or even worse than in the full sample. For example, the $J=3$, $K=1$ WML alpha under the CAPM is -1.61% ($t=-6.53$), still negative and lower than the baseline (-0.97%). Mid- and long-term strategies are also less robust than in the full sample: for instance, the $J=9$, $K=6$ portfolio has an FF3 alpha of only 0.50% ($t=2.07$). This indicates that during the era of institutionalisation and financial innovation, with more standardised trading rules and improved disclosure, behavioural biases began to converge and the significance of momentum alpha diminished.

Compared with the previous two periods, the electronic and algorithmic trading stage

(Table D.6) shows a clear divergence in momentum alphas. On the one hand, short-formation-period alphas are generally higher than in the full sample. For example, the J=3, K=1 FF3 alpha reaches 1.11% (t=2.37). On the other hand, medium- and long-term strategies (e.g., J=12, K=6) still deliver significant positive alphas under both CAPM and FF3, at levels comparable to or stronger than the full sample (FF3: 1.58% vs. full sample 0.83%). This suggests that with the rise of algorithmic trading, higher trading frequency and faster information transmission have dampened short-term noise trading, allowing some short-term momentum opportunities to be captured more effectively under liquidity shocks, while long-term momentum remains as persistent as during the baseline period.

Table D.4: Risk adjusted performance of momentum portfolios from 1869 to 1949

This table reports the alpha results from asset pricing model regressions. The momentum portfolios are formed based on J -month lagged returns and held for K -month. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. The values of J and K for different strategies are indicated in the first column and row, respectively. Panel A and Panel B present the CAPM risk-adjusted excess returns. Panel C and D present the Fama-French three-factor model risk-adjusted excess returns. The returns in Panel B and Panel D are calculated by skipping one month between the formation and holding periods. The sample period ranges from 1869 to 1949. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by Newey and West (1987) to account for potential autocorrelation in the time series.

J	Panel A: CAPM Model					Panel B: CAPM Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0134 (-8.38)	-0.0043 (-3.31)	0.0004 (0.31)	0.0021 (2.25)		-0.0026 (-1.68)	0.0005 (0.41)	0.0021 (2.24)	0.0021 (2.85)
6		-0.0048 (-2.51)	0.0016 (0.93)	0.0039 (2.66)	0.0040 (3.35)		0.0047 (2.57)	0.0056 (3.65)	0.0055 (3.98)	0.0040 (3.56)
9		-0.0028 (-1.47)	0.0032 (1.88)	0.0063 (3.96)	0.0042 (3.11)		0.0060 (3.35)	0.0069 (4.14)	0.0078 (4.99)	0.0042 (3.31)
12		0.0033 (1.81)	0.0069 (4.12)	0.0068 (4.21)	0.0038 (2.76)		0.0107 (5.98)	0.0097 (5.86)	0.0076 (4.86)	0.0037 (2.78)
J	Panel C: FF Three-Factor Model					Panel D: FF Three-Factor Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0140 (-8.08)	-0.0046 (-3.15)	0.0003 (0.20)	0.0025 (2.11)		-0.0028 (-1.80)	0.0002 (0.15)	0.0021 (1.75)	0.0023 (2.68)
6		-0.0049 (-2.33)	0.0012 (0.63)	0.0039 (2.14)	0.0043 (2.99)		0.0042 (1.92)	0.0051 (2.64)	0.0056 (3.16)	0.0044 (3.13)
9		-0.0029 (-1.36)	0.0031 (1.50)	0.0066 (3.32)	0.0050 (2.92)		0.0056 (2.72)	0.0069 (3.35)	0.0081 (4.24)	0.0050 (3.14)
12		0.0034 (1.55)	0.0073 (3.44)	0.0074 (3.64)	0.0050 (2.81)		0.0107 (4.84)	0.0101 (4.93)	0.0083 (4.33)	0.0049 (2.92)

Robustness tests across different stages of financial market development show that the momentum effect has not disappeared despite the continuous evolution of trading systems, information transmission, and algorithmic trading. Although the performance of short-term strategies has shown some convergence and even reversal risk as market efficiency has improved, medium-term and long-term momentum portfolios have continued to deliver stable

Table D.5: Risk adjusted performance of momentum portfolios from 1950 to 1996

This table reports the alpha results from asset pricing model regressions. The momentum portfolios are formed based on J -month lagged returns and held for K -month. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. The values of J and K for different strategies are indicated in the first column and row, respectively. Panel A and Panel B present the CAPM risk-adjusted excess returns. Panel C and D present the Fama-French three-factor model risk-adjusted excess returns. The returns in Panel B and Panel D are calculated by skipping one month between the formation and holding periods. The sample period ranges from 1950 to 1996. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#) to account for potential autocorrelation in the time series.

J	Panel A: CAPM Model					Panel B: CAPM Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0161 (-6.53)	-0.0052 (-2.96)	-0.0019 (-1.28)	-0.0010 (-0.87)		-0.0029 (-1.47)	-0.0011 (-0.71)	-0.0014 (-1.05)	-0.0013 (-1.37)
6		-0.0081 (-3.20)	-0.0019 (-0.86)	0.0003 (0.16)	-0.0002 (-0.14)		0.0015 (0.67)	0.0031 (1.52)	0.0026 (1.46)	0.0003 (0.19)
9		-0.0063 (-2.48)	0.0006 (0.24)	0.0034 (1.66)	0.0000 (-0.01)		0.0018 (0.77)	0.0033 (1.53)	0.0038 (2.00)	-0.0006 (-0.37)
12		-0.0014 (-0.56)	0.0033 (1.46)	0.0030 (1.44)	-0.0011 (-0.57)		0.0076 (3.14)	0.0071 (3.22)	0.0041 (1.95)	-0.0013 (-0.70)
J	Panel C: FF Three-Factor Model					Panel D: FF Three-Factor Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		-0.0167 (-6.23)	-0.0057 (-2.87)	-0.0015 (-0.85)	-0.0005 (-0.38)		-0.0037 (-1.88)	-0.0012 (-0.72)	-0.0010 (-0.66)	-0.0010 (-0.86)
6		-0.0081 (-2.85)	-0.0013 (-0.50)	0.0014 (0.62)	0.0012 (0.71)		0.0016 (0.63)	0.0039 (1.65)	0.0034 (1.65)	0.0013 (0.89)
9		-0.0051 (-1.69)	0.0022 (0.80)	0.0050 (2.07)	0.0020 (1.06)		0.0032 (1.20)	0.0051 (2.05)	0.0054 (2.45)	0.0014 (0.84)
12		-0.0001 (-0.03)	0.0047 (1.76)	0.0049 (2.13)	0.0012 (0.64)		0.0088 (3.23)	0.0088 (3.57)	0.0060 (2.70)	0.0010 (0.52)

Table D.6: Risk adjusted performance of momentum protfolios from 1997 to 2024

This table reports the alpha results from asset pricing model regressions. The momentum portfolios are formed based on J -month lagged returns and held for K -month. A value-weighted portfolio of stocks in the lowest past return decile is the sell portfolio, and a value-weighted portfolio of the stocks in the highest return decile is the buy portfolio. The values of J and K for different strategies are indicated in the first column and row, respectively. Panel A and Panel B present the CAPM risk-adjusted excess returns. Panel C and D present the Fama-French three-factor model risk-adjusted excess returns. The returns in Panel B and Panel D are calculated by skipping one month between the formation and holding periods. The sample period ranges from 1997 to 2024. The t -statistics are computed using the heteroskedasticity- and autocorrelation-consistent (HAC) standard errors described by [Newey and West \(1987\)](#) to account for potential autocorrelation in the time series.

J	Panel A: CAPM Model					Panel B: CAPM Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		0.0144 (3.16)	0.0128 (3.02)	0.0116 (3.35)	0.0087 (3.01)		0.0119 (2.65)	0.0099 (2.73)	0.0081 (3.11)	0.0053 (2.53)
6		0.0121 (2.40)	0.0151 (3.16)	0.0131 (2.92)	0.0090 (2.35)		0.0185 (3.88)	0.0167 (3.89)	0.0133 (3.33)	0.0084 (2.50)
9		0.0179 (3.41)	0.0194 (4.03)	0.0162 (3.40)	0.0087 (2.02)		0.0208 (4.36)	0.0183 (4.01)	0.0150 (3.39)	0.0074 (1.84)
12		0.0169 (2.81)	0.0178 (3.20)	0.0132 (2.47)	0.0058 (1.19)		0.0193 (3.56)	0.0163 (3.11)	0.0125 (2.50)	0.0045 (0.96)
J	Panel C: FF Three-Factor Model					Panel D: FF Three-Factor Model with Skip				
	$K=$	1	3	6	12	$K=$	1	3	6	12
3		0.0111 (2.37)	0.0104 (2.22)	0.0109 (2.70)	0.0090 (2.78)		0.0094 (1.91)	0.0081 (1.87)	0.0077 (2.29)	0.0058 (2.32)
6		0.0105 (1.73)	0.0146 (2.57)	0.0138 (2.69)	0.0106 (2.53)		0.0171 (2.97)	0.0166 (3.19)	0.0144 (3.09)	0.0099 (2.66)
9		0.0162 (2.61)	0.0197 (3.48)	0.0177 (3.30)	0.0113 (2.52)		0.0196 (3.46)	0.0191 (3.51)	0.0166 (3.33)	0.0099 (2.37)
12		0.0177 (2.62)	0.0193 (3.08)	0.0158 (2.72)	0.0091 (1.86)		0.0196 (3.15)	0.0177 (2.95)	0.0151 (2.73)	0.0076 (1.64)

and significant excess returns.