Momentum and the Cross-section of Stock Volatility[⋆,⋆⋆]

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Abstract

Recent literature shows that momentum strategies exhibit significant downside risks over certain periods, called "momentum crashes". We find that high uncertainty of momentum strategy returns is sourced from the cross-sectional volatility of individual stocks. Stocks with high realised volatility over the formation period tend to lose momentum effect. We propose a new approach, generalised risk-adjusted momentum (GRJMOM), to mitigate the negative impact of high momentum-specific risks. GRJMOM is proven to be more profitable and less risky than existing momentum ranking approaches across multiple asset classes, including the UK stock, commodity, global equity index, and fixed income markets.

Keywords: Cross-sectional momentum; Momentum crashes; Generalised risk-adjusted momentum; Excess volatility; Volatility timing

JEL: G11, G12, G13

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1. Introduction

Despite that momentum strategies (XSMOM) exhibit persistent profitability, their returns are volatile and face crash risks during specific periods.[1] Grundy and Martin (2001) found that momentum returns experience negative beta following bear markets. More recently, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) showed that stock market momentum strategies suffer from infrequent and persistent strings of negative returns, called momentum crashes. Daniel and Moskowitz (2016) argued that momentum crashes are caused by the outperformance in losers returns over winners returns when markets rebound from panic states.

One commonality between Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) is that both papers attributed momentum risks to time-varying volatility of the winner minus loser (WML) series. According to Barroso and Santa-Clara (2015), this is called the momentum-specific risk which cannot be diversified away, as "momentum is a well-diversified portfolio and all its risk is systematic". Therefore, both papers proposed different approaches to scale the position size of the WML returns and allow it to be time-varying. Since the WML series is not known until the constituents of the momentum strategy are determined, their work essentially adjusts momentum returns after the portfolio is constructed.

We argue that the uncertainty of WML returns is not only determined by the time-varying volatility of the WML series, but also the cross-sectional volatility of individual stocks. The core mechanism of momentum is to allocate buy (sell) signals to assets with the highest (lowest) formation period returns. Stocks with high returns are usually associated with high volatility over the formation period. Therefore, the probability of an instrument being selected by a momentum portfolio is highly related to its realised volatility. In the UK market, the number of stocks with the highest (top 10%) realised volatility over the formation period and later selected into the momentum portfolio is

[1]Evidence of momentum has been investigated in international stock markets, see, e.g., Fama and French (1998), emerging markets, see, e.g., Rouwenhorst (1999), commodity market, see, e.g., Miffre and Rallis (2007), Narayan et al. (2015), Bianchi et al. (2015), regional equity indices, see, e.g., Asness et al. (1997), Balvers and Wu (2006), Bhojraj and Swaminathan (2006), foreign exchange, see, e.g., Menkhoff et al. (2012*b*), industries, see, e.g., Moskowitz and Grinblatt (1999), size and B/M factors, see, e.g., Lewellen (2002), Kwon and Satchell (2018), and global asset classes, see, e.g., Asness et al. (2013). In the financial industry, momentum has been incorporated in sorting decisions by the mutual fund manager, see, e.g., Grinblatt and Titman (1989, 1993).

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8.3 times the number of stocks with the lowest (bottom 10%) realised volatility.[2] This clustering of high volatility stocks leads to leads to highly volatile momentum portfolios, or momentum-specific risks. Therefore, we conclude that the momentum risks originate from the ranking procedure at the signalling stage, before the portfolio is constructed.

More interestingly, we find that stocks with high realised volatility over the formation period tend to lose momentum effect, while stocks with low and medium realised volatility show strong momentum effect. Based on our four samples consisting of the UK stock, commodity, equity index, and fixed income markets, we decompose each of them into ten deciles according to the stocks' realised volatility over the formation period.[3] Panel regressions are performed to examine the momentum effect for each of these ten deciles. We find that none of the momentum effect is statistically significant (reflected in the t-statistics of the coefficients) for the three deciles associated with the highest levels of realised volatility. By contrast, most assets in the bottom three deciles with the lowest realised volatility show significant positive momentum effect.

Our findings relate to Grinblatt and Moskowitz (2004) and Da et al. (2014), who documented that stocks creating extreme monthly returns in a few months over the formation period demonstrate weaker return consistency than the ones with a steady price path.[4] The stocks showing extraordinary price movement yield high variation of returns over the formation period. Therefore, the cross-sectional momentum effect ceases to hold in the high volatility deciles as they contain stocks with weak return continuation.

To measure the momentum risks, we calculate the spread between the volatility of a momentum strategy and that of a randomly selected portfolio. The randomly selected portfolio is sampled from the market and has the same number of assets as the momentum strategy. We call this measure the excess volatility of momentum strategies.[5] We calculate

[2]This ratio is 5.2 times for winners and 11.9 times for losers. Consistent with Daniel and Moskowitz (2016) who claimed that loser portfolio is the main cause of momentum crashes, we find that the problem of high volatility stock clustering is more severe in losers.

[3]The idea of dividing the portfolio into ten deciles according to asset realised volatility is similar to Ang et al. (2006).

[4]Li and Liu (2019) also indicated that the assets with hump-shaped price path (upward at early stage of formation period but downward later) tend to lose positive momentum, and assets with rebound price path (downward over the early formation period but upward later) tend to lose negative momentum. Li (2021) further justified this finding from the sentiment aspect.

[5]The concept of excess volatility differs from the one that was first defined by Shiller (1981) and LeRoy and Porter (1981). We use this term here as it measures momentum strategy risks in excess of a benchmark (the market portfolio).

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this excess volatility based on our sample consisting of four markets, namely the UK stock, commodity, equity index, and fixed income markets. The results suggest that the excess volatility of momentum strategies is statistically significant in all asset classes. Hence, confirming the existence of momentum-specific risks.

An intuitive approach to reduce this excess volatility is to consider risk-adjusted returns at the momentum ranking stage. Pirrong (2005) and Rachev et al. (2007) formed their momentum strategies by ranking the Sharpe ratios (SRMOM) instead of period returns in the commodity futures market and U.S stock market, respectively. They have found that their risk-adjusted momentum strategies tend to outperform the original XS-MOM. However, neither paper focused on economic rationales for using a risk-adjusted ranking method. Our paper fills this gap by providing evidence that using risk-adjusted momentum is related to the excess volatility specific to momentum strategies. In a risk-adjusted momentum ranking system, an asset with higher past volatility is less likely to be selected into the winner or loser portfolio. The idea is also consistent with the volatility timing theory in improving portfolio performance, see, e.g., Fleming et al. (2001), Fleming et al. (2003), Kirby and Ostdiek (2012) and Moreira and Muir (2017).[6]

Our empirical results suggest that simply using the Sharpe ratio ranking of Pirrong (2005) and Rachev et al. (2007) eliminates part of the excess volatility of momentum strategies. However, it is far from optimal. Consider, for instance, an asset that has high past absolute returns but at the same time is extremely volatile, simply adjusting its return by one standard deviation is not sufficient to prevent the asset to be selected as momentum winner or loser. Therefore, it is natural to ask the question: is there a generalisation of risk-adjusted momentum that allows investors to change the degree of aggressiveness to adjust returns? Ideally, this generalised method can remove those instruments that are less attractive in terms of reward-to-risk trade-off, while still keeping the high profitability of momentum strategies.

In this paper, we propose such a solution, called generalised risk-adjusted momentum (GRJMOM). GRJMOM sorts momentum winners and losers based on ranking asset risk-adjusted returns in order to mitigate the clustering problem in high volatility stocks. GRJMOM trading strategy leads to substantial statistical and economic superiority com-

[6]The core idea of volatility timing is to construct future portfolios based on the conditional/realised volatility or the conditional covariance matrix of asset returns.

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pared to XSMOM which ranks the absolute returns. In the UK stock market, GRJMOM yields an annualised return of 22.4% compared to the XSMOM return of 17.9%, with the Sharpe ratio improving from 0.67 (XSMOM) to 1.18 (GRJMOM). More importantly, GRJMOM significantly reduces momentum risks from an annualised standard deviation of 27% (XSMOM) to 19% (GRJMOM) and performs much better in periods of momentum crashes.

More specifically, the assets are ranked based on the ratio between period returns and the Nth power of their realised volatility, $\widehat{R}^k_{t-12,t-1} = \frac{R^k_{t-12,t-1}}{(\sigma^k_t)^N}$, where $R^k_{t-12,t-1}$ is the period returns of asset k over the formation period; σ^k_t is the realised volatility over the same period; the parameter N measures how aggressively the period return is adjusted by its realised volatility. The GRJMOM ranking scheme is structurally similar to a generalised volatility timing trading strategy proposed by Kirby and Ostdiek (2012), who also assigned an exponential parameter to the realised volatility in determining portfolio weights. GRJMOM provides a flexible ranking system allowing for risk-focused adjustment during recessions and market crashes.

The tuning parameter N can be of any value greater than or equal to zero. For example, if $N = 0$, then we remove the risk-adjustment from the returns. In such a case, the target GRJMOM is equivalent to the original XSMOM. If $N = 1$, then the Sharpe ratios (return-to-standard deviation) are ranked, which is similar to Pirrong (2005) and Rachev et al. (2007). If $N = 2$, then the return-to-variance ratios are ranked where the risks are more aggressively adjusted.

The optimum N can be calculated using a grid search method based on different degrees of risk aversions. A risk seeker focuses on the relationship between N and portfolio returns; a risk averse investor finds the optimum N where portfolio volatility is minimised; a risk-neutral investor looks for the best N where Sharpe ratio is maximised. In each of the above three cases, we can find one single optimum value for this parameter N using our entire sample. For instance, if we plot the N versus the Sharpe ratios of the corresponding risk-adjusted momentum strategies, we find that the relationship looks like a parabola. This means that we can always find the peak (or trough for minimising volatility problems) by changing the value of N.

Furthermore, we propose a cross-validation method to allow the parameter N to be timing-varying, responding to the market dynamics over the period. Using an expanding

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window, the N that leads to the maximised portfolio Sharpe ratio is defined as the optimum. This method does not require any additional assumptions, allowing all the parameters to be generated automatically. Overall, we find that the optimal N increases over time, for all four asset classes. This means that the role of volatility is becoming more important in momentum strategies over the past decades.

One benefit of GRJMOM is that it performs a cross-sectional adjustment to momentum signals before the portfolio is constructed. Like the plain momentum strategy, it also has a symmetric structure, where the long and short side investments are equal. Hence, the GRJMOM strategy can be compared directly to XSMOM. By contrast, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) conducted the time-series adjustment after the construction of momentum portfolios. Their volatility scaling approaches lead to a time-varying position size of their strategies.[7] According to Goyal and Jegadeesh (2017), our GRJMOM strategy is a "zero net-investment strategy with the total active position being two dollars". By applying the same scaling factor as in Barroso and Santa-Clara (2015) to the GRJMOM strategy, we find that GRJMOM shows substantial outperformance to their constant target volatility scaled momentum strategy.

Finally, we evaluate the risk exposure of GRJMOM using the 4-factor model (Fama and French, 1992, Carhart, 1997) and value & momentum everywhere model (Asness et al., 2013). According to the regression results of the 4-factor model, the GRJMOM strategies report outperforming abnormal returns across multiple markets. In UK stocks, for example, the abnormal profit of GRJMOM is 116% and 30% higher than those of XSMOM and SRMOM strategies, respectively. In the global asset markets, GRJMOM also shows superior alphas compared to XSMOM and SRMOM. Similar performance is observed in the results of the value & momentum everywhere model.

The remainder of this study is organised as follow. Section 2 details the data sources and construction of momentum portfolios. In Section 3, we present our main research motivation and analyse the sources of momentum risks. Section 4 demonstrates how the generalised risk-adjusted momentum strategy is constructed. In Section 5, we focus on analysing the relationship between GRJMOM and momentum crashes. In Section 6, we employ factor models to evaluate the risk exposure of GRJMOM. Finally, we conclude

[7] Although these strategies are still zero net-investment strategies, they are exposed to more market risks over certain periods when the past volatility is low.

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our findings in Section 7.

2. Data and portfolio construction

2.1. Data

Our dataset contains two major samples. First, we base our research on all the stocks traded on the London Stock Exchange from January 1965 to July 2018. Second, we obtain a global sample consisting of 70 investable instruments in three asset classes, including commodity, equity indices and fixed income. Among them, 27 are commodity index futures; 24 are global equity indices; 19 are sovereign bond or short-term deposit. The summary statistics of these three asset classes are available in Appendix A. The following sub-sections detail the data sources.

2.1.1. UK stock market

Our UK stock market sample consists of all the stocks traded on the London Stock Exchange available on Datastream. The entire sample consists of 8,195 stocks, whereas the number of available assets dynamically ranges between 1,231 and 2,205 over the period spanning from January 1965 to July 2018. We obtain the daily closing price of the total return index of these stocks. These type of indices take into account corporate actions, e.g., dividend payment, mergers and acquisitions, stock buyback, and therefore, is less biased. We first calculate the daily percentage returns and aggregate them in to raw monthly returns. Then, we calculate the excess returns by subtracting the UK risk-free rate from the raw returns. The UK one-month treasury yield is downloaded from Datastream as the risk-free rate.

2.1.2. Global asset classes

We obtain the daily closing prices of 27 constituents of the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) from Datastream. Such a dataset is also employed by Bianchi et al. (2015) and Koijen et al. (2018). The advantages of using the S&P GSCI indices are that they reflect the real returns of investing in the underlying futures, incorporating the impact of term structure, can be directly invested in, and use continuous price series which are not affected by price spread when the nearest futures contract expires. Due to the number of indices available, the sample period ranges from January 1984 to July 2018.

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Our equity index sample consists of global major stock indices from both developed and emerging economies. The entire universe includes 24 markets: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Korea, Malaysia, Netherlands, Norway, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, the United Kingdom (UK), the United States (U.S).[8] The daily closing prices of Morgan Stanley Capital International (MSCI) indices are collected from Datastream.[9] The sample ranges from January 1970 to July 2018.

Finally, we collect prices of 19 sovereign bonds or short-term deposits from 8 developed economies with various maturities. They are Australian 3-year bond (AUS 3Y), Australian 10-year bond (AUS 10Y), Canadian 10-year bond (CA 10Y), Euro 2-year bond (EURO 2Y), Euro 5-year bond (EURO 5Y), Euro 10-year bond (EURO 10Y), Euro 30-year bond (EURO 30Y), Eurodollar 1-month time deposit (EuroDollar 1M), Eurodollar 3-month time deposit (EuroDollar 3M), Euro 3-month internal bank deposit (EURIBOR 3M), Japan 5-year bond (JP 5Y), Japan 10-year bond (JP 10Y), Switzerland 10-year bond (SWISS 10Y), United Kingdom 1 year bond (UK 1Y), United Kingdom long gilt (UK 10Y), United States 2-year Treasure (US 2Y), United States 5-year Treasure (US 5Y), United States 10-year Treasure (US 10Y), and United States 30-year Treasure (US 30Y). These contracts are extensively investigated by previous studies, see, e.g., Moskowitz et al. (2012), Asness et al. (2013), Koijen et al. (2018), and are highly liquid. The futures prices are retrieved from Bloomberg for the January 1993 to July 2018 period

Across these three markets, we used the same method as we do in the UK stock market to aggregate daily into monthly returns. For commodities and fixed income, the monthly raw returns are equal to the monthly excess returns since we employ futures prices.[10] For equity indices, we calculate the monthly excess returns by subtracting the U.S one-month T-bill yield from the raw returns. The monthly interest rate of the U.S one-month T-bill is collected from Kenneth French's data library.

[8]Similar datasets are used in prior literature, see, e.g., Balvers and Wu (2006) and Asness et al. (2013).
[9]All price series are measured in USD dollars.
[10]Moskowitz et al. (2012) clarified that excess returns are equivalent to raw returns in futures markets.

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2.1.3. Other dataset

To perform the factor regressions, the monthly percentage returns of the S&P GSCI, MSCI world index, Barclays Aggregate Bond Index, and the Financial Times Stock Exchange (FTSE) all share index are collected as market factors. We also collect the returns series of Fama and French (1996) small market capitalisation minus big (*smb*), high book-to-market ratio minus low (*hml*), and Carhart (1997) premium on winner minus loser (*umd*) from Kenneth French's data library. For the UK stock market, as these factors of Euro area are available from 1991, we splice the European factors with the U.S based factors in January 1991 to cover the entire sample period. Finally, we consider the value & momentum everywhere factors documented by Asness et al. (2013). The monthly percentage returns of these factors are obtained from the website of AQR Capital Management.

2.2. Momentum portfolio construction

We use 12 months as the formation period in our momentum strategies for both the UK stock market and the global assets. 12 months is commonly used in the literature for both stock markets and different asset classes, see, e.g., Jegadeesh and Titman (1993) and Asness et al. (2013). The relative performance is measured based on 12 months period return or risk-adjusted return, depending on different strategies. In each dataset, we buy the assets with the highest past performance (winners) and sell those with the lowest past performance (losers). An equally weighted method is employed and the portfolio is rebalanced monthly.

Given the difference in the size of each sample, we sort winners and losers into different quantiles. First, for the UK stock data, we divide the whole sample into deciles following literature such as Jegadeesh and Titman (1993). Second, in our global samples, the instruments are sorted into quartiles to make sure that the momentum portfolio is well-diversified.[11] For instance, in a momentum strategy in the commodity market, we buy the top performing quartile and sell the bottom performing quartile. In line with other momentum studies in equity markets, we skip the most recent month in the formation period to avoid short-term reversal. To allow for real-world implementation, we screen the firms that are continuously traded over the formation period and are also tradeable

[11] Similar sorting methods are seen in, e.g., Miffre and Rallis (2007) and Bianchi et al. (2015).

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in the following month.

3. The source of high uncertainty momentum strategies

Despite the fact that the momentum strategies have been identified as producing abnormal performance across multiple assets classes, prior literature has also indicated that the volatility of momentum portfolios tend to be much higher than that of a market portfolio. For instance, Barroso and Santa-Clara (2015) showed that the standard deviation of the WML series is 45% higher than that of the market. We argue that this phenomenon is naturally due to the asset selection mechanism of momentum strategies. A momentum strategy invests in stocks with the highest and the lowest relative returns over the formation period. While individual stocks with large absolute period returns are often associated with high volatility, these volatile stocks lead to the high uncertainty of the entire momentum portfolio. In this section, we perform an analysis to support our view and investigate the sources of the high volatility in momentum strategies.

3.1. Excess volatility of momentum strategies

We start by measuring the momentum risks caused by the cluster of high volatility stocks in excess of a market portfolio with the same number of assets. Similar to the idea of abnormal returns in asset pricing models, we define excess volatility as the spread between the volatility of WML returns and that of a market benchmark strategy.[12] The benchmark is a equal-weighted buy-and-hold strategy formed by stochastically investing in m stocks from the samples, where m is equal to the number of assets in the corresponding momentum portfolio. Trading signals are renewed and the portfolio is rebalanced on a monthly level. We repeat the above steps ten thousand times and take the mean of the volatility.

Table 1 summarises the excess volatility of XSMOM strategies across various asset classes. The annualised standard deviations of WML returns are higher than those of the randomly selected market portfolios. The excess volatilities are statistically significant at the 1% level for UK stock, commodity, and fixed income markets. In the global equity

[12]The excess volatility here differs from the concept introduced by Shiller (1981) and LeRoy and Porter (1981). In those papers, excess volatility was the difference between the standard deviation of stock returns in the real world and that predicted by the efficient market hypothesis of Fama (1965).

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index market, the excess volatility is slightly lower, at 0.012, which is still statistically significant at the 10% level.[13]

Table 1: Performance of original momentum strategies across different markets

	Mean	*Vol*	*Skew*	*Kurt*	*MP.vol*	*EX.vol*	*Obs*
UK stocks	0.17	0.26	-0.74	1.75	0.17	0.089***	632
Commodity	0.094	0.23	0.052	0.23	0.17	0.055***	391
Equity Index	0.080	0.19	-0.14	0.44	0.18	0.012*	557
Fixed income	-0.010	0.054	0.076	0.34	0.039	0.015***	247

Mean, *Vol*, *Skew* and *Kurt* denote the annualised XSMOM returns, standard deviation, skewness and kurtosis, respectively. *MP.vol* is the volatility of the market portfolio. *EX.vol* represents the excess volatility of the XSMOM strategy over the market portfolio. *Obs* is the degree of freedom for F-test. '*', '**', '***' represent that the excess volatilities are statistically significant at the 10%, 5% and 1% level.

To understand the causes of this excess volatility, we can assume that the probability of asset k being chosen as either a winner or loser at time t, $P_{t,k}$, is expressed as a function of its period return, $R^k_{t-12,t-1}$, and realised volatility, σ^k_t,[14] over the formation period, as:

$$P^k_t = f(R^k_{t-12,t-1}, \sigma^k_t). \tag{1}$$

Therefore, the return of an equal weighted momentum portfolio, R_t, is given by:

$$R_t = \frac{1}{m}\sum_{k=1}^{m}(signal^k_t|P^k_t) * r^k_t, \tag{2}$$

where m is the number of stocks included in the portfolio; $signal^k_t|P^k_t$ is the trading signal based on the probability P^k_t which takes the value of 1 for winner and -1 for loser. The above equation implies that the total momentum portfolio return is the sum of momentum signals multiplied by their returns, where these signals are dominated by a probability function of asset return and realised volatility. As return and volatility are usually positively related, the higher the mean/volatility, the higher the probability of an

[13] Apart from the above-mentioned asset classes, we also test the excess volatility of momentum strategies in the foreign exchange (FX) market, in which the excess volatility is insignificant. Hence, concluding that the FX market does not require risk-managed momentum adjustment. For more detailed data description and strategy specification in the FX market, see Appendix B.

[14] We assume that each month consists of 21 trading days. For the global asset classes, the realised volatility over the formation period is estimated as: $\sigma^k_t = \sqrt{\frac{21*\sum_{j=0}^{251}(r^k_{d_{t-1-j}})^2}{252}}$, where r^k_d is the daily return of asset k on day d. For the UK stock market, in line with the literature, we skip the most recent month over the formation period, so the realised volatility is estimated as: $\sigma^k_t = \sqrt{\frac{21*\sum_{j=21}^{251}(r^k_{d_{t-1-j}})^2}{231}}$, where all parameters remain the same.

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asset i to be chosen as a constituent of the momentum portfolio. Therefore, we presume that the cluster of high volatility stocks lead to excess volatility in a momentum portfolio.

3.2. Cluster of momentum signals in high volatility stocks

Next, we perform decile portfolios to validate our hypothesis that the cluster of momentum signals are related to individual asset volatility. At the end of each month t, we sort all available instruments into deciles according to their realised volatility over the formation period. Decile one (D_1) consists of the stocks with the lowest volatility, and decile ten (D_{10}) contains those with the highest volatility. This method is also used by Ang et al. (2006), Bali and Cakici (2008) and Fu (2009), who sorted assets into deciles according to the idiosyncratic risks over a given period. Figure 1 reports how many momentum signals are assigned to instruments in each decile. We observe that the number of signals increases gradually from D_1 to D_{10}.[15] In the UK stock market, the number of signals in D_{10} is 8.31 times the number in D_1. In commodity, equity index and fixed income markets, the numbers of signals in D_8-D_{10} are 81.5%, 49.8%, and 49.2% percent higher than those in D_1-D_3, respectively. These results suggest that stocks with high realised volatility during the formation period are more likely to be selected by a momentum strategy.

When comparing the winners and losers, we find that the clustering of momentum signals in high volatility assets is much stronger in losers than in winners. As shown in the UK stock market panel in Figure 1, the loser signals increase more dramatically from D_1 to D_{10} than the winner ones. This means a large proportion of the loser signals are given to those high volatility stocks throughout the investment horizon. Holding high volatility assets in losers might cause large drawdowns in portfolio returns during periods of instability and crises. Our result explains the finding of Daniel and Moskowitz (2016), who suggested that momentum crashes are mainly caused by past losers. In the commodity and equity index panels in Figure 1, the results still hold with the loser signals

[15]The results of global asset portfolios (commodity, equity index and fixed income) do not show monotone increasing pattern. This is because their relative returns are ranked based on quartiles instead of deciles given the number of instruments available in these samples. Therefore, D_8-D_{10} need be considered together and compared to D_1-D_3. In this sense, consistent with the UK stock market sample, the instruments in the high volatility quartile are more likely to appear in a momentum portfolio.

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increasing more from D_1-D_3 to D_8-D_{10}, in comparison with the winners.[16]

3.3. Momentum and the cross-section of stock volatility

To take our analysis a step further, we investigate how the cross-section of stock volatility impacts momentum effect. We implement the XSMOM strategy for each volatility decile in the UK stock market.[17] We sort sub-portfolios into quintiles in order to construct well-diversified portfolios.[18] As seen from the results in Table 2, the momentum mean return in D_{10} is negative and significantly different from zero, whereas the returns in the remaining deciles are all positive. This indicates that stocks with high volatility exhibit reversal instead of return continuation. In D_9, the decile with the second highest volatility, the annualised mean is at least 60% lower than those in other deciles. By contrast, momentum profits are all significantly positive at the 1% level in $D_1 - D_8$. The results imply that the momentum effect vanishes in high volatility stocks, but is strong in low and medium volatility stocks.

Table 2: Performance of momentum strategies by volatility decile (UK stock)

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
Mean	0.130	0.136	0.133	0.138	0.155	0.182	0.184	0.201	0.058	-0.254
t-value	12.20***	12.82***	9.75***	9.09***	9.52***	10.30***	9.17***	8.29***	1.92**	-2.55**
Vol	0.078	0.077	0.100	0.111	0.119	0.130	0.147	0.177	0.223	0.732
SR	1.664	1.749	1.331	1.240	1.299	1.405	1.251	1.131	0.262	-0.348

'D_1' to 'D_{10}' represent the ten deciles constructed by ranking the realised volatility over the formation periods. Decile one contains instruments with the lowest realised volatility, with decile ten consisting of instruments with the highest realised volatility. *Mean*, *t-value*, *Vol*, and *SR* denote the annualised momentum returns, t-values of returns, standard deviations, and Sharpe ratios, respectively.'*', '**', '***' represent that the t-values are statistically significant at 10%, 5% and 1% level.

The poor performance of momentum portfolios in high volatility deciles (D_9 and D_{10}) is consistent with the findings of Grinblatt and Moskowitz (2004) and Da et al. (2014). We contend that this is because the assets with large price changes generate weaker return continuation than the ones with steady returns over the entire formation period. More

[16]In the fixed income market, however, the winner and loser signals increase by a similar rate. We argue this is because the volatility for different fixed income instruments does not vary a lot as in the other three markets. Data summary can be seen in Appendix A.

[17]We only implement the XSMOM strategy in the UK stock market as the sample sizes of the other asset classes are not large enough. A similar double sorted approach is also used by Zhang (2006) in U.S stock markets.

[18]As a robustness check, we also sort stocks into deciles to form the XSMOM strategy. The results show consistent patterns with our quintile approach and are available upon request.

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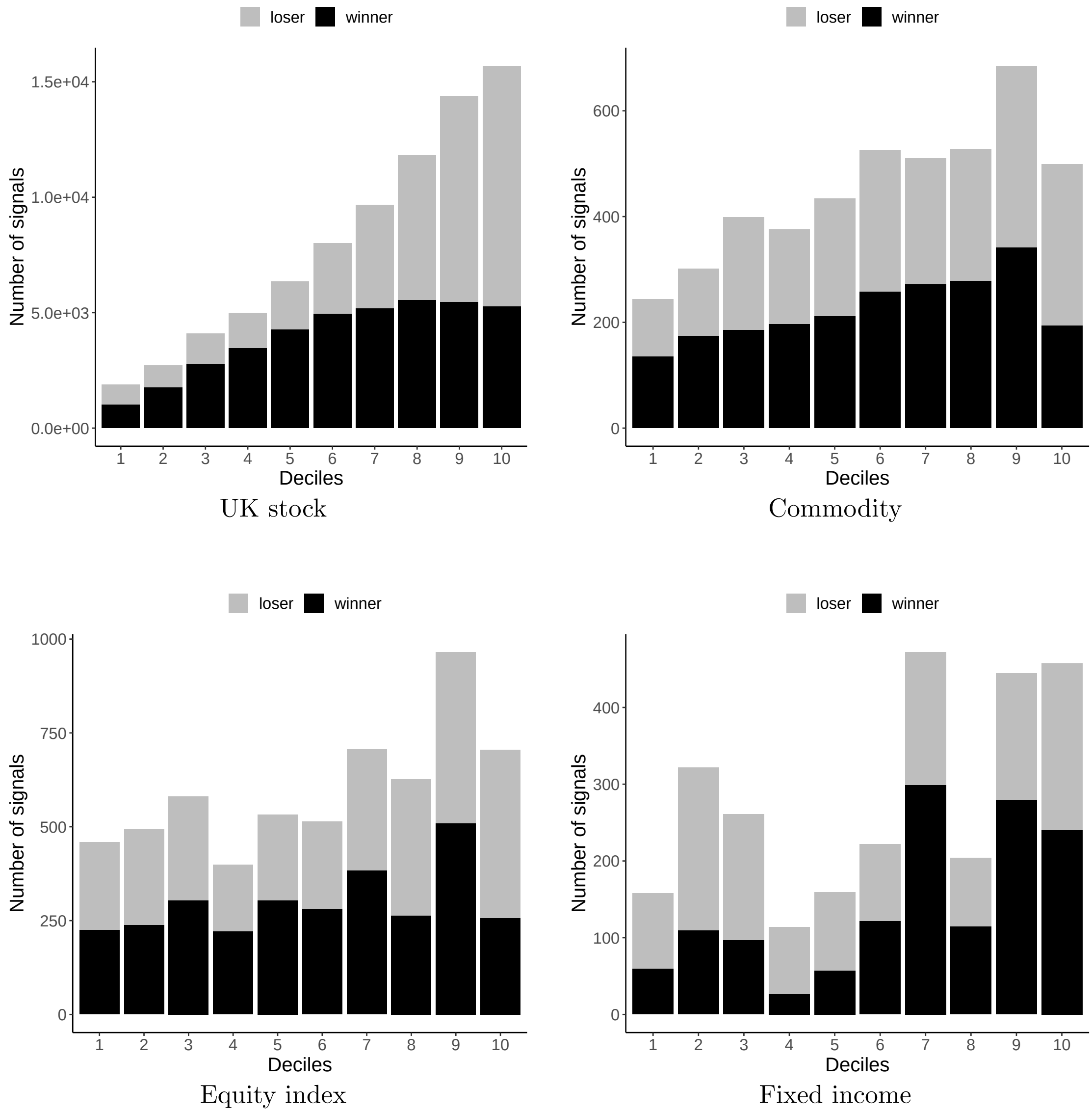
Figure 1: Momentum signal allocation by formation period asset volatility (XSMOM)



This figure summarises the relationship between individual asset volatility and momentum signal allocation. At the end of each month t, we sort all available instruments into deciles according to their realised volatility over the formation period. Decile one consists of the instruments with the lowest volatility over the formation period, with decile ten containing the assets with the highest volatility. Each bar plots how many momentum trading signals are assigned to a given volatility decile.

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recently, Li and Liu (2019) categorised the volatile price movements into hump price path (upward first and later downward) and rebound path (downward at the beginning and upward at the end). The authors found that the assets with hump path (rebound path) cease to hold momentum effect when it is in the winner (loser) portfolio. Therefore, D_9 and D_{10} capture assets with weak return consistency, resulting in lower profits than the portfolios in the remaining deciles.

Interestingly, our finding seems to contradict the results in Zhang (2006) and Bandarchuk and Hilscher (2013), who proposed that the high volatility stocks yield high momentum profits. However, we find that they excluded those stocks with price lower than \$5 which removed around 20% of stocks from the universe. Such a data filtering approach is not a standard way of studying momentum crash risks. Recent momentum studies build portfolios based on all common stocks with available prices and market values, see, e.g., Novy-Marx (2012), Da et al. (2014), Moreira and Muir (2017), Moreira and Muir (2019) and Fama and French (2020). Moreover, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) uncovered the momentum crashes in the sample of all available common stocks. Kim and Lee (2017) claimed that the momentum crash is highly related the penny stock. Therefore, excluding low prices stocks does not benefit our understanding of momentum crashes.

Another possible explanation stems from the perspective of short-sale constraints. Daniel et al. (2018) argued that short-sale is not available for most of the small stocks, causing newswatchers unable to sell momentum losers. Therefore, momentum effect ceases to hold due to the lack of short-term market under-reaction. We contend that this is one of the important reasons for the poor momentum performance in high volatility deciles. Because these deciles mainly consist of small stocks as the returns of the small firms are more volatile than the big ones (Ang et al., 2006, Fu, 2009).

As a robustness check, we further examine the time-series momentum effect in the above-mentioned deciles sorted by realised volatility. In each decile, we regress one-month holding period returns on the returns over the formation period using the pooled panel

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regression.[19] The equitation is as follows:

$$r_t^k = \alpha + \beta R_{t-12,t-1}^k + \epsilon, \qquad in\ Decile\ n. \tag{3}$$

For asset k in D_n, we define $R_{t-12,t-1}^k$ as its return over the formation period.[20] Based on Thompson (2011), we control for both time-varying and cross-sectional fixed effects in our regression. If the β coefficient is positive and significantly different from zero, then holding trading positions consistent with historical trends produces abnormal profits, and therefore, momentum effect exists in this decile.

Consistent with our findings in Table 2, the regression results in Table 3 exhibit that the momentum effect ceases to hold in stocks with high volatility. Across all four markets, the β coefficients are either significantly negative or insignificant from D_8 to D_{10}.[21] We argue that this is because the asset returns are primarily driven by other factors instead of momentum when volatility is high, e.g., macroeconomic factors or sentiment in times of recession. For the UK stock market, only those stocks with intermediate realised volatility (D_3-D_7) show positive betas which are statistically significant. This means that low volatility stocks also do not show return continuation. One possible explanation is that stocks in D_1 and D_2 are illiquid and do not draw enough investors' attention. Therefore, they do not exhibit the momentum effect, as momentum is based on herding behaviour of under-reaction to news.

For the commodity, equity index and fixed income markets, shown in Table 3, the momentum effect is strong in the low volatility deciles (D_1-D_3), but weak in the high volatility deciles (D_8-D_{10}). This indicates that the XSMOM strategies do not work well in these markets, as most of the XSMOM signals are allocated in the high volatility deciles. Given that the momentum effect behaves differently in different markets due to market size and fundamental variation, there is no "one size fits all" solution associated with

[19]This approach is extensively used by time-series momentum studies, e.g., Moskowitz et al. (2012), Huang et al. (2020), and Bianchi (2021).

[20]We skip the most recent month of the formation period in the UK stock market, so the period return of asset k is $R_{t-12,t-2}^k$.

[21]Our finding is similar to Ang et al. (2006) that the high ex-ante volatility reduces asset expected return. In contrast, Bali and Cakici (2008) and Fu (2009) argue that the pattern clarified by Ang et al. (2006) is determined by low liquid stocks. The relationship between asset risks and expect returns differs after excluding the low liquid stocks. However, for our momentum trading scheme we rank all available stocks, so it is rational to see our results as similar to Ang et al. (2006).

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simply applying the XSMOM strategies. A generalised approach is needed to improve the effectiveness of the momentum strategies. In the next section, we introduce such type of generalisation.

Table 3: Coefficients between formation period and holding period returns

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
UK stocks	-0.012	0.003	0.004***	0.002	0.003***	0.006***	0.003***	-0.002*	-0.003***	-0.004
	(-1.36)	(1.48)	(3.03)	(1.19)	(2.61)	(3.68)	(2.89)	(-1.76)	(-3.32)	(-1.23)
Commodity	0.024***	0.023**	0.035**	0.014	0.005	-0.007	0.014*	-0.004	-0.003	-0.011
	(2.62)	(2.59)	(2.59)	(1.07)	(0.39)	(-0.70)	(1.79)	(-0.46)	(-0.34)	(-1.23)
Equity Index	0.009	0.030**	0.024**	0.016*	0.011	0.007	0.020***	0.002	0.011	-0.003
	(1.01)	(2.32)	(2.20)	(1.78)	(1.24)	(0.65)	(2.81)	(0.30)	(1.24)	(-0.48)
Fixed income	0.038***	0.016	0.040**	0.006	-0.005	0.006	-0.016	-0.027	-0.011	-0.031**
	(3.73)	(1.17)	(2.43)	(0.36)	(-0.23)	(0.34)	(-1.04)	(-1.52)	(-0.44)	(-2.51)

'D_1' to 'D_{10}' represent the ten deciles constructed by ranking the realised volatility over the formation periods. Decile one contains instruments with the lowest realised volatility, and decile ten consists of instruments with the highest ones. Four sets of pooled regressions are run, and the t-statistics are estimated based on robust standard error of Thompson (2011). '*', '**', '***' represent that the t-values are statistically significant at the 10%, 5% and 1% level.

4. Generalised risk-adjusted momentum

Given that momentum signals are concentrated in high volatility assets which do not exhibit momentum effect, we propose an improved and generalised version of momentum based on ranking risk-adjusted returns.[22] We call it the generalised risk-adjusted momentum strategy (GRJMOM). This trading rule is superior to XSMOM as it dynamically considers the trade off between asset returns and volatility, and hence, alleviates the negative impact of high volatility clustering. In this section, we show the difference between GRJMOM, XSMOM and SRMOM.

GRJMOM provides a flexible framework to allow investors to weight volatility differently according to market status over time. For example, in times of crisis, one might prefer to put more weight on volatility and focus less on return. Consequently, a GRJMOM strategy selects instruments with lower volatility into winner/loser portfolios. Whereas in periods of a bullish market, one can amplify the impact of return by reducing the weight of volatility. We also introduce a cross-validation approach to find the opti-

[22] Previous studies have shown that controlling for certain level of volatility can improve the momentum performance, e.g., Rachev et al. (2007) and He et al. (2018).

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mal time-varying parameter that yields the best performing GRJMOM strategy in this section.

4.1. Ranking risk-adjusted returns

An intuitive way to form a risk-adjusted momentum strategy is to sort the winners and losers based on relative Sharpe ratios. The Sharpe ratios over the formation period are calculated as:

$$SR^k_{t-12,t-1} = \frac{R^k_{t-12,t-1}}{\sigma^k_t}, \tag{4}$$

where $SR^k_{t-12,t-1}$ is the Sharpe ratio of asset k over the formation period, $R^k_{t-12,t-1}$ denotes the return and σ^k_t is the realised volatility over the same period, as defined in Footnote 14. Similar approaches are also seen in Pirrong (2005), where the daily standard deviations are calculated to scale returns. Both realised volatility and standard deviations are calculated based on the sum of squared daily returns. Therefore, they result in the same ranking for instruments to be selected as momentum winners and losers.

We next consider an alternative risk-adjusted ranking approach based on return-to-variance ratios, where returns are more aggressively scaled by realised volatility. As suggested by its name, we simply calculate the return-to-variance (RV) ratio as follows:

$$RV^k_{t-12,t-1} = \frac{R^k_{t-12,t-1}}{(\sigma^k_t)^2}, \tag{5}$$

where $(\sigma^k_t)^2$ is the realised variance. The momentum strategy based on ranking the return-to-variance ratio shown in Equation 5 is called the return-to-variance momentum (RVMOM). Compared to SRMOM, RVMOM weights volatility more aggressively relative to returns. For instance, Stock A has a return of 5% and realised volatility of 10%; Stock B has a return of 10% and realised volatility of 20%. Under SRMOM, both stocks have Sharpe ratios of 0.5 and hence are ranked the same. However, under RVMOM, the return-to-variance ratios become 5 and 2.5 times for Stock A and B, respectively. This is because the volatility of Stock B is higher than Stock A, and its weight is amplified by the RVMOM ranking system. Hence, reducing its return-to-variance ratio. Therefore, Stock A is considered to be superior and more likely than Stock B to be selected as the winner.

Similar to the plots in Figure 1, we show momentum signal distribution across different volatility deciles under the SRMOM and RVMOM schemes in Figure 2. In each panel, the

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left plot is the momentum signal allocation using SRMOM ranking, while the right plot is the one based on RVMOM ranking. The SRMOM ranking witnesses an improvement from XSMOM shown in Figure 1, where the signals are well-diversified across different deciles in all of the four markets. More specifically, under an SRMOM scheme, in the UK stock and the fixed income markets, only 24% and 20% of the total signals are assigned to $D_8 - D_{10}$, respectively. Whereas in the commodity and equity index markets, the proportions are slighter higher, with both at around 30%.

Despite SRMOM mitigating the signal clustering problem in XSMOM, we argue that it is still not the optimal approach. First, we previously showed that the momentum effect vanishes in high volatility instruments, while SRMOM still has a considerable weight in those deciles. Second, as shown in Table 3, across the three global asset markets, namely commodity, equity index and fixed income markets, low volatility deciles exhibit strong momentum effect. Therefore, it is reasonable to assume that an effective momentum strategy would put more weight in those instruments with low volatility. For this reason, RVMOM is superior to SRMOM as it measures volatility more aggressively. As shown in Figure 2, more RVMOM signals are allocated to low volatility deciles, i.e. $D_1 - D_3$, than SRMOM.

As shown in Equations 4 and 5, both SRMOM and RVMOM employ constant numbers as the exponents of realised volatility in order to scale returns. A generalised version of them can be expressed as:

$$\widehat{R}^k_{t-12,t-1} = \frac{R^k_{t-12,t-1}}{(\sigma^k_t)^N}, \tag{6}$$

where a parameter, N, is introduced as the exponential term. N can be any value greater than or equal to zero. A momentum strategy based on this generalised risk-adjusted ranking approach is called GRJMOM. GRJMOM allows investors to change the degree of volatility exposure relative to return, according to different market properties.

Our GRJMOM is consistent with the idea of volatility timing in portfolio theory, where asset weights are determined by their volatility, see, e.g., Fleming et al. (2001), Fleming et al. (2003) and Moreira and Muir (2017). Specifically, our approach is similar to a generalised volatility timing approach proposed by Kirby and Ostdiek (2012). They suggested that portfolio weights are determined by the conditional variance of risky-asset returns. They further added a tuning parameter to measure how aggressively the weights are adjusted in response to the change in conditional variance. The parameter N in the

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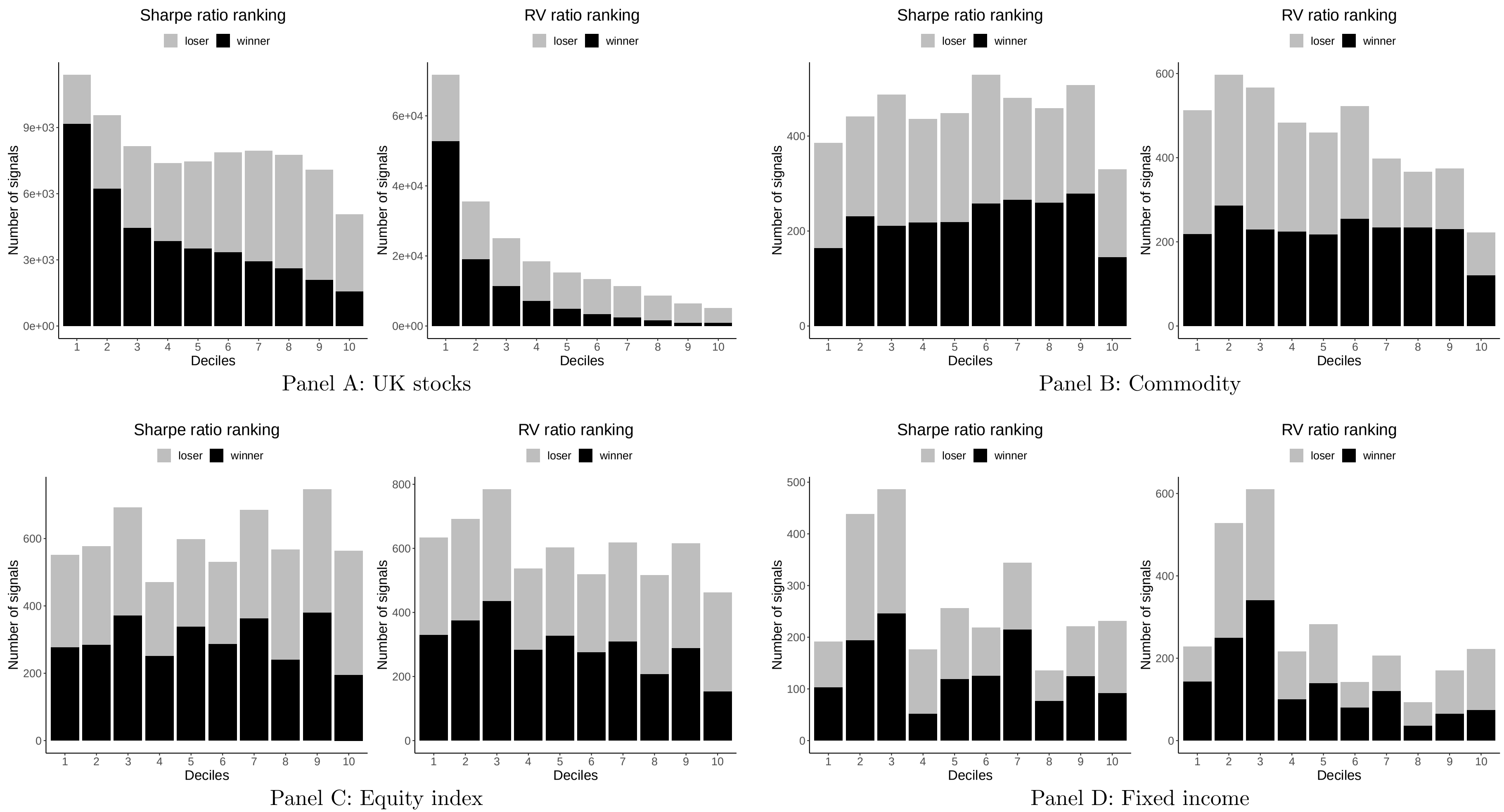
Figure 2: Momentum signal allocation by asset volatility over formation periods (SRMOM and RVMOM)



Decile one contains the lowest volatile instruments, and decile ten contains the highest. The number of signals accounts for how many momentum trading signals are allocated into a given decile. Sharpe ratio ranking means the momentum trading signals are sorted using asset Sharpe ratios over a formation period. RV ranking means the momentum trading signals are sorted using asset return-to-variance ratios over the formation period.

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GRJMOM framework is qualitatively equivalent to their tuning parameter. We discuss the properties of the tuning parameter N and its relation with GRJMOM performance in the next subsection.

4.2. The tuning parameter N

4.2.1. How does N work?

In GRJMOM framework, the tuning parameter N plays an important role in adjusting the returns in response to changing volatility. Similar to Kirby and Ostdiek (2012), we define the tuning parameter N as the degree of aggressiveness about how investors value volatility in risk-adjust returns. Kirby and Ostdiek (2012) set the tuning parameter to be an integer $\eta = \{1, 2, 3, 4\}$ as the exponent of variance. In our case, we let GRJMOM tuning parameter be any value satisfying $N \geqslant 0$, as we assume asset volatility has a continuous impact on return adjustments. The larger the parameter N, the greater the impact volatility has on returns.

Next, we formally show the impact of tuning parameter N on risk-adjusted returns and momentum portfolio selection. We first assume that there are two risky assets a and b in the market, of which the past returns and standard deviations are R_a and σ_a, and R_b and σ_b, respectively. We also assume that the past returns for assets a and b are of the same sign.[23] When comparing the risk-adjusted return, $\widehat{R_a}$ and $\widehat{R_b}$, we simply examine whether the ratio, $\widehat{R_a}/\widehat{R_b}$, is greater than one or not. According to Equation 6, the relationship can be calculated as follows:

$$\frac{\widehat{R_a}}{\widehat{R_b}} = \frac{R_a/(\sigma_a)^N}{R_b/(\sigma_b)^N} \quad = (\frac{R_a}{R_b})(\frac{\sigma_b}{\sigma_a})^N. \tag{7}$$

Given two assets with positive past returns, we list all four possible relationships between return and volatility in Table 4. Scenario 2 and 3 illustrate the case when one asset has a higher return and lower volatility compared to the other. Under GRJMOM system, the asset with the higher return is considered to be superior to the other, and hence, selected for the momentum winner portfolio. According to Equation 7, GRJMOM signals are not affected by the change of N in Scenario 2 and 3. Therefore, GRJMOM

[23]We do not consider the situation that the return of one asset is positive and another is negative. In this case, it does not cause a problem in comparing risk-adjusted returns, as one is likely to be selected as the winner and another as the loser.

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and XSMOM yield exactly the same signals.

In Table 4 Scenario 1 and 4, when one asset has higher return and higher volatility than its rival, the tuning parameter N affects momentum signals. For example, in Scenario 1, both the return and standard deviation of Asset a are lower than those of Asset b. Following Equation 7, R_a/R_b is a constant number smaller than one, while $(\sigma_b/\sigma_a)^N$ is a variable greater than one. The term $(\sigma_b/\sigma_a)^N$ increases when N gets larger. Asset a becomes superior to Asset b, when Equation 7 is greater than one, so that $(\sigma_b/\sigma_a)^N > R_b/R_a$. Otherwise, Asset b is more likely to be selected into the winner portfolio. We can get to a similar conclusion when both assets have negative returns and produce a similar table to Table 4.

Table 4: Return, volatility and momentum investment decisions when both assets have positive past returns

Scenario	*Return*	*SD*	*Signalling decision*
1	$R_a < R_b$	$\sigma_a < \sigma_b$	Depends on N
2	$R_a < R_b$	$\sigma_a > \sigma_b$	Asset b
3	$R_a > R_b$	$\sigma_a < \sigma_b$	Asset a
4	$R_a > R_b$	$\sigma_a > \sigma_b$	Depends on N

Return means the relationship between the returns of two assets; *SD* represents the relationship between the standard deviations of assets; *Decision* means the decisions made by investors.

When both R_a and R_b are negative, the high-ranking assets are the high volatility stocks, which tend not to be selected as losers. Unless in an extreme bear market where almost all the past 12 months stock returns are negative, an asset yielding negative past 12 months return is unlike to be selected as a winner. Throughout the entire investment horizon, the proportion of these extreme situations is as low as 1.2% (8 out of 654 months). The merit of the GRJMOM ranking approach is to assign more trading signals, winners or losers, to low volatility assets. When the parameter N is relatively large, the high volatility assets are more concentrated in the middle of the ranking which are less likely to be selected in the momentum portfolio.

There are a few special cases when N takes certain values. If $N = 0$ and the denominator of Equation 6, $(\sigma_t^k)^N = 1$, the risk-adjusted return $\widehat{R}_{t-12,t-1}^k$ is equal the period return $R_{t-12,t-1}^k$. Hence, GRJMOM ranking scheme is the same as the XSMOM; if $N = 1$, the risk-adjusted return $\widehat{R}_{t-12,t-1}^k$ is the Sharpe ratio of each instrument over

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the formation period, which is equivalent to SRMOM; if $N = 2$, then $\widehat{R}^k_{t-12,t-1}$ becomes the return-to-variance ratio, forming the RVMOM strategy.

Knowing how the tuning parameter N works in GRJMOM system, we next empirically investigate the relationship between N and momentum performance. Using a grid search method, we investigate how N affects momentum portfolio return, volatility and Sharpe ratio by increasing N at intervals of 0.1. Similar to Kirby and Ostdiek (2012), we set the range of N between zero, and four.[24]

Figure 3 plots the above-mentioned relationship with different markets shown in different panels. It can be seen that, across all four markets, both momentum return and Sharpe Ratio monotonically increase with the growth of N until a threshold is reached. After the threshold, the further increase of N decreases the momentum profits. The trend fitted curve looks like a quadratic parabola, where we can always find an optimal point. We pay particular attention to the Sharpe ratio as it is the choice for rational risk-neutral investors. The optimal N, returning the highest Sharpe ratio in the UK stock, commodity, equity index and fixed income markets, are 2.8, 2.3, 2.6 and 2.3, respectively. This result suggests that the existing ranking systems, e.g., the XSMOM ranking ($N = 0$) or SRMOM ranking ($N = 1$), are not optimal. By contrast, the relationship between N and momentum portfolio volatility looks like a parabola which opens upward, where the optimum is when the volatility is at its lowest.[25] Volatility optimisation is preferred by those investors who want to minimise portfolio risks.

4.2.2. Time-varying optimal N

Benefiting from its flexible framework, GRJMOM allows the tuning parameter N to vary across different markets and over time. Distinct from XSMOM and SRMOM, one is free to determine the value of N based on their own risk preferences in a GRJMOM system. Risk lovers are more likely to set the parameter N producing the highest portfolio return; risk-averse investors choose N that generates minimised portfolio volatility; risk-neutral investors prefer to set N when Sharpe ratio of the portfolio reaches the peak. As mentioned above, we focus on the Sharpe ratio in this paper and use it as our parameter

[24] One can certainly explore more by setting a larger range for N with smaller intervals, e.g., 0.01. However, the number of calculations does not add marginal value to this study, as the current setting is adequate to show the pattern.

[25] In the commodity market as shown in Figure 3 Panel B, we do not observe an inflection point as the optimal $N = 7.4$ is greater than four.

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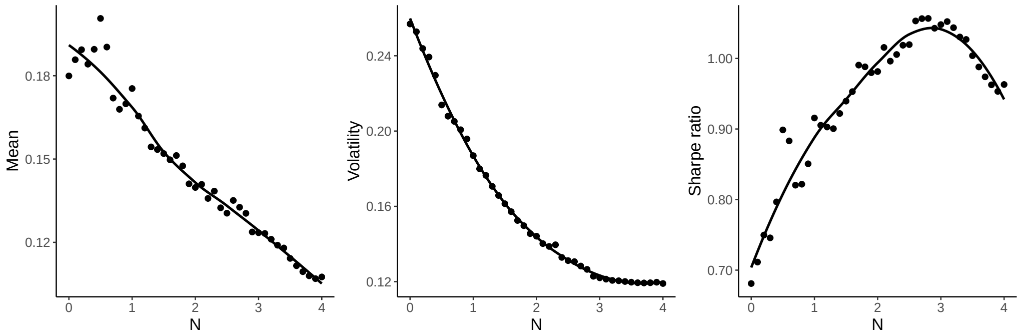
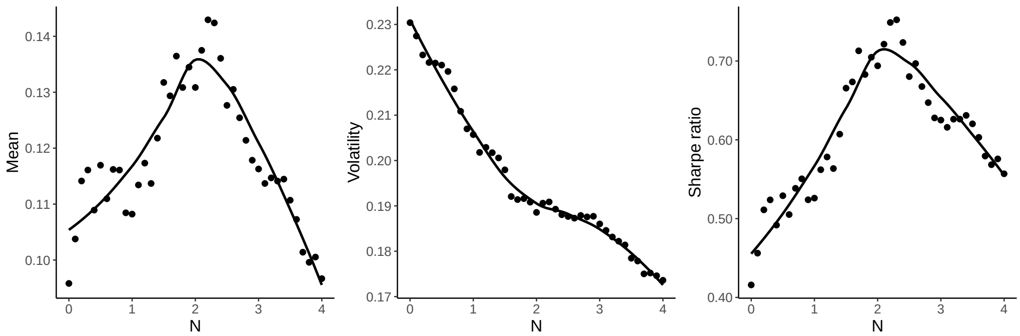
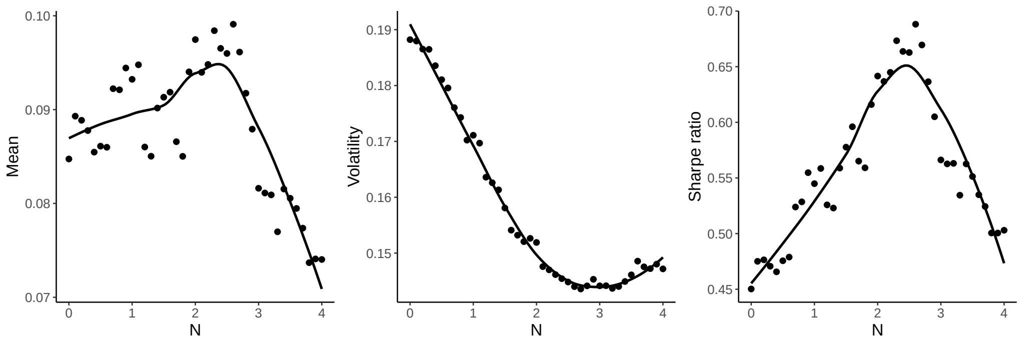
Figure 3: Trade-off between N and the performances of momentum portfolios



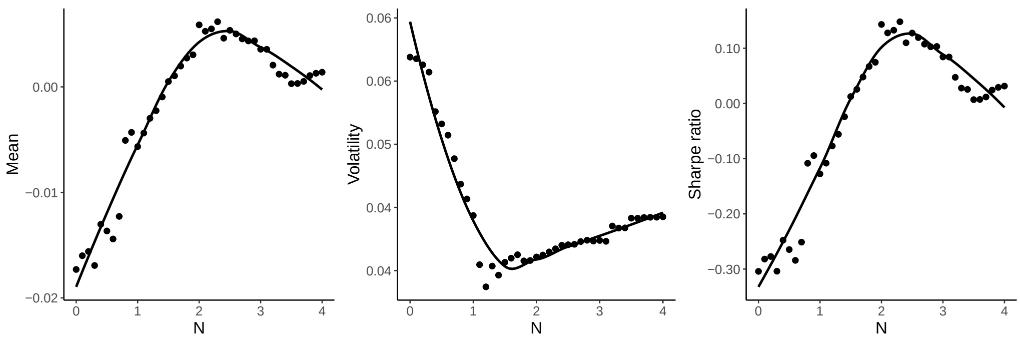
Panel A: UK stocks



Panel B: Commodity



Panel C: Equity index



Panel D: Fixed income

Plots in the first column exhibit the trade-off between the tuning parameter N and the annualised momentum portfolio returns across samples. Plots in the second and third columns display this relationship in terms of volatility and Sharpe ratios. A locally estimated scatter-plot smoothing (LOESS) curve is employed as the trend fitted line in each plot. Different panels show results for different markets.

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selection criteria.

In this sub-section, we investigate how the best parameter N evolves over time. Beginning in month 60, we calculate the optimal N that generates the highest Sharpe ratio for each month, using an expanding window approach. The expanding window prediction (EWP) approach refers to an estimation or modelling method that uses all the observations from the first month to the most recent month, $t-1$, for each period. This approach is extensively implemented in portfolio studies to estimate expected returns, variance and covariance matrix, see, e.g., DeMiguel et al. (2015) and Barroso and Saxena (2021). We employ the expanding estimation window as it considers the market historical performance across the long-term (Gulen and Petkova, 2018).

In Figure 4, we plot the path of optimal N based on the best Sharpe ratio criteria in different markets. Overall, we observe that the optimal N increases over time across all four markets, indicating that volatility becomes an indispensable element to be considered in changing global environment. The paths of N in the UK stock and commodity markets are both volatile at the beginning of the investment horizon and then increase to above two after the 2008 financial crisis. For example, the optimal N in the UK stock market is around 0.8 before 2008 and increases to over 2.1 after the crisis. This makes sense that investors intend to alleviate the cluster of high volatility instruments over crash periods, and hence, consider a more aggressive adjustment by increasing the value of N. By contrast, the N in equity index and fixed incomes markets are more stable but still reach 2.6 and 2 after 2000. Our results show that none of these optimal N reaches zero across different markets or over time, implying XSMOM inefficiency, which does not consider asset volatility. The out-of-sample GRJMOM strategy based on time-varying optimal N is discussed in the next sub-section.

4.3. GRJMOM trading strategy

After introducing the idea of risk-adjusted ranking and the time-varying N, we are able to form the GRJMOM strategy. In it, the winners and losers are sorted by ranking the risk-adjusted return based on Equation 6. To estimate the optimal N, we simply employ a cross-validation method which finds the best N using an expanding window approach. As is mentioned in Section 4.2.2, the optimal N in month $t-1$ is selected when the corresponding GRJMOM portfolio generates the highest Sharpe ratio over the

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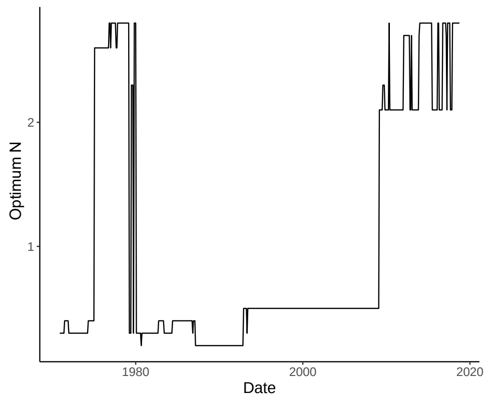
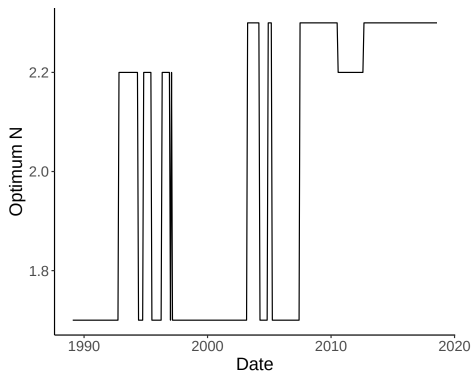
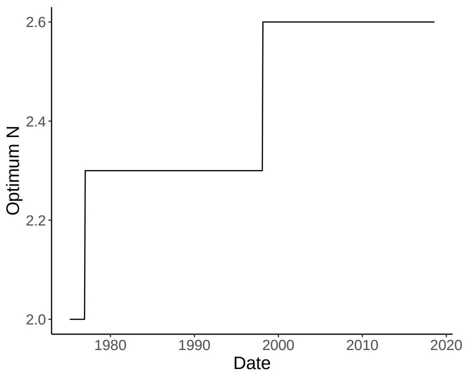
Figure 4: Time-varying optimal N



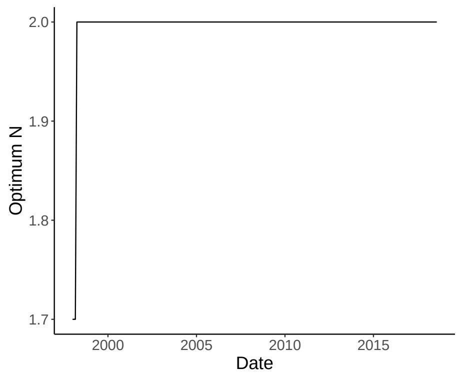
UK stock



Commodity



Equity index



Fixed income

The figure reports the time-varying optimal N over the investment horizon for different markets. The first value of N is available from the 61st month, as an initial window of 60 months is used to calculate the outperformed Sharpe ratio of the momentum portfolio. Parameter N is constrained to lie between 0 and 4 with intervals of 0.1.

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expanding window.[26] Then, we plug this N into Equation 6, in order to sort the winners and losers for the coming month, t.

The GRJMOM strategy holds symmetric long and short legs in terms of winners and losers. Hence, it is a zero net-investment strategy and can be compared directly to XSMOM and SRMOM strategies. Unlike the time-series momentum strategy (Moskowitz et al., 2012) or the constant volatility scaled momentum (Barroso and Santa-Clara, 2015), GRJMOM does not use any leverage or time-varying position size over the investment horizon. The long side and the short side of GRJMOM investment are always equal to \$1. Therefore, the GRJMOM strategy is a "zero net-investment strategy with the total active position being \$2", as is defined by Goyal and Jegadeesh (2017).

We first examine whether the GRJMOM strategy mitigates the excess volatility specific to the original momentum strategies,[27] and compare the results to those shown in Table 3. In Table 5, we measure the excess volatility of the GRJMOM returns across different markets.[28] In all four markets, the excess volatility of GRJMOM returns becomes insignificantly different from zero. It even yields to negative excess volatility compared to the market portfolio in the equity index market. Therefore, we conclude that GRJMOM successfully eliminates the momentum-specific risks caused by the cluster of high volatility instruments.

Table 5: Excess volatility of GRJMOM strategies across multiple markets

	Mean	*Vol*	*Skew*	*Kurt*	*MP.vol*	*EX.vol*	*Obs*
UK stocks	0.22	0.19	-0.12	0.19	0.17	0.02	585
Commodity	0.10	0.19	0.006	0.45	0.17	0.01	343
Equity Index	0.10	0.15	-0.03	0.20	0.17	-0.03	510
Fixed income	0.006	0.040	0.02	0.23	0.039	0.001	236

Mean, *Vol*, *Skew* and *Kurt* denote the annualised GRJMOM returns, standard deviation, skewness and kurtosis, respectively. *MP.vol* is the volatility of the market portfolio. *EX.vol* represents the excess volatility of the GRJMOM strategy over the market portfolio. *Obs* is the degree of freedom for the F-test. None of the excess volatilities reported is significantly different from zero.

For robustness check, we further measure an alternative risk exposure after controlling for asset pricing factors. We capture the standard error of the residuals from two factor

[26] One can use different indicators to determine the value of N such as market volatility or sentiment. We choose to use the cross-validation method as it automatically determines which past information is relevant and which is not (Hall et al., 2004). Moreover, the cross-validation method requires less information and is tractable.

[27] According to Barroso and Santa-Clara (2015), this is also known as momentum-specific risk.

[28] Since the GRJMOM strategy requests a 60-month initial estimation window to determine the first optimal N, the results here are slightly different from what is shown in Table 3.

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models, i.e., the capital asset pricing model (CAPM) of Sharpe (1966) and 3-factor model (FF-3) of Fama and French (1993).[29] The model equations are:

$$
\begin{aligned}
R_i &= \alpha + \beta(mkt - r_f) + \epsilon_t, \\
R_i &= \alpha + \beta_1(mkt - r_f) + \beta_2 smb + \beta_3 hml + \epsilon_t,
\end{aligned} \tag{8}
$$

where R_i is the return series of a single leg (winner/loser) or the entire momentum portfolio for strategy i; mkt is the market factor; r_f is the interest rate of U.S one-month T-bills; smb and hml are the size and value factors; ϵ_t denotes the error term following a normal distribution that $\epsilon_t \sim (0, \sigma_e^2)$. The market factor ($mkt$) varies across markets: FTSE all share index is used for UK stock market; S&P GSCI, MSCI World and Barclays Aggregate Bond indices are employed in commodity, equity index, and fixed income markets, respectively.

Table 6 summarizes the risk exposure of GRJMOM and XSMOM portfolios after controlling for market factors. Panel A reports the standard error of residuals by regressing GRJMOM and XSMOM returns on CAPM and Fama-French three-factor models. Panel B shows the difference in the standard error of residuals (XSMOM minus GRJMOM). We also employ the F-test to examine whether the difference in volatility is statistically significant or not. We observe that GRJMOM significantly reduces the risk after controlling for market factors across different markets. As shown in Panel B, this difference is mainly due to the low volatility of residuals in losers portfolio. In the UK stock market, for example, the GRJMOM winner has slightly higher volatility of residual than the XSMOM winner, while its loser's standard error is only 0.056, which is 24% lower than that of the XSMOM loser. Given the fact that momentum crashes are mainly caused by the losers portfolio (Daniel and Moskowitz, 2016), GRJMOM tends to efficiently control the crash risks.

Next, we examine the profitability of GRJMOM strategies. Table 7 summarises the performance metrics of GRJMOM strategies, in which the existing momentum strategies, XSMOM and SRMOM, are added as benchmarks. Each panel shows the strategy performance in a different market. We first focus on the performance of GRJMOM strategies in UK stock, commodity and equity index markets, since the annualised portfolio re-

[29] We also implement Fama-French-Carhart 4-factor model, by Fama and French (1996) and Carhart (1997), and find the results are similar with those of the 3-factor model.

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Table 6: Conditional risks of original and GRJMOM strategies

Portfolios	UK stock		Commodity		Equity index		Fixed income	
	CAPM	FF-3	CAPM	FF-3	CAPM	FF-3	CAPM	FF-3
Panel A: Standard error of residuals								
XSMOM winner	0.044	0.041	0.043	0.043	0.043	0.038	0.016	0.016
XSMOM loser	0.075	0.074	0.044	0.044	0.038	0.041	0.010	0.010
XSMOM WML	0.074	0.073	0.065	0.065	0.041	0.054	0.017	0.017
GRJMOM winner	0.038	0.035	0.040	0.040	0.054	0.034	0.005	0.005
GRJMOM loser	0.056	0.056	0.037	0.037	0.034	0.035	0.007	0.007
GRJMOM WML	0.054	0.053	0.054	0.053	0.034	0.046	0.008	0.008
Panel B: Differences between XSMOM and GRJMOM (XSMOM minus GRJMOM)								
Winner	0.006***	0.006***	0.003	0.003	-0.011***	0.004***	0.011***	0.011***
	(1.34)	(1.36)	(1.16)	(1.17)	(0.63)	(1.25)	(10.63)	(10.02)
Loser	0.019***	0.018***	0.007***	0.007***	0.004***	0.006***	0.003***	0.003***
	(1.78)	(1.76)	(1.39)	(1.39)	(1.26)	(1.38)	(2.14)	(2.17)
WML	0.020***	0.021***	0.012***	0.012***	0.006***	0.009***	0.008***	0.008***
	(1.89)	(1.94)	(1.48)	(1.49)	(1.39)	(1.41)	(4.30)	(4.39)

This table summarises the risk exposure of GRJMOM and XSMOM portfolios after controlling for market factors. Panel A reports the standard error of residuals by regressing GRJMOM and XSMOM returns on CAPM and Fama-French three factor models. Panel B shows the difference in standard error of residuals (XSMOM minus GRJMOM). The degrees of freedom for the F-test here are consistent with those in Table 5. '*', '**', '***' represent that the F-values are statistically significant at 10%, 5% and 1% level, respectively.

turns are positive and significantly different from zero in these samples. In UK stocks, the annualised return of GRJMOM is 22.4%, significantly outperforming XSMOM and SRMOM with annualised returns of 17.9% and 17.7%, respectively. The Sharpe ratio of GRJMOM strategy is 1.18 per annual, whereas those of the XSMOM and SRMOM are 0.67 and 0.92. Similar patterns are observed in commodity and equity index markets, where the returns and Sharpe ratios of GRJMOM strategies are significantly higher than those of the other two benchmarks.

When looking at winner and loser portfolios separately, GRJMOM outperforms the benchmarks mainly because of the significant improvement of the losers. Ideally, a loser portfolio should create negative returns as it is a short position. However, we find the losers of XSMOM and SRMOM strategies generate positive returns across UK stock and equity index markets, reducing the momentum profits. After the GRJMOM ranking, the positive returns are reduced to 2.9% in the UK stock market, -3.5% in the commodity market and -0.9% in the equity index market. Moreover, the GRJMOM strategy significantly decreases the maximum drawdown. As shown in Panel A, the maximum drawdown of GRJMOM in the UK stock market is 0.47, while those of the XSMOM and SRMOM are 0.9 and 0.71, respectively.

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In the fixed income market, as shown in Table 7 Panel D, the annualised returns of all three momentum strategies are insignificantly different from zero. This pattern is consistent with the findings in previous literature, see, e.g., Asness et al. (2013), that the momentum effect fails to create significant abnormal profits in the fixed income asset class. However, GRJMOM still generates a positive annualised return of 0.6%, whereas the other two benchmarks produce negative returns. We further investigate the performance of momentum winner and loser portfolios. In contrast with the other two approaches where winner does not show significant outperformance, the GRJMOM winner yields a statistically significant return (t=2.4) in the fixed income market.

As a robustness check, we conduct a regression test to examine the outperformance of GRJMOM with respect to other existing momentum strategies, i.e. XSMOM and SRMOM. Following Daniel and Moskowitz (2016), we regress the monthly returns of GRJMOM on a variety of factors containing the market, Fama and French (1993) size and value factors (FF factors), and the XSMOM/SRMOM returns. Table 8 reports the alphas and their t-statistics of GRJMOM compared to other benchmarks and factors.

Panel A of Table 8 reports the results based on the regressions of our GRJMOM portfolio on the market factors plus XSMOM and FF factors plus XSM. For the market plus XSMOM model, the alphas of GRJMOM are at 1.0%, 0.5%, and 0.3% per month (t=6.72, 2.87, 2.39) in UK stock, commodity and equity index markets, respectively. After adding the size and value factors of Fama and French (1993) as control variables, the intercepts are still statistically significant at 1.1%, 0.5%, and 0.3% per month (t=7.07, 2.95, 2.45) in UK stocks, commodities and equity indices, respectively. However, the alphas of GRJMOM are insignificant at 0.1% per month in the fixed income market. In Panel B of Table 8, we repeat the regressions by examining the alphas of GRJMOM with respect to SRMOM. The alphas are statistically significant at at least a 10% level in all four markets. These results suggest that the abnormal performance of GRJMOM is not captured by XSMOM, SRMOM or other market factors.

To conclude, across all asset classes, our results indicate that the GRJMOM strategies produce higher profits and alphas, lower volatility and maximum drawdown than the XS-MOM and SRMOM. Therefore, we consider GRJMOM as an effective and implementable investment strategy.

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Table 7: Performance of momentum strategies across different asset types

Strategies	*Portfolios*	*Mean*	*T-value*	*SD*	*SR*	*MaxDD*	*Skew*	*Kurt*
Panel A: UK stock								
	winner	0.260***	9.08	0.20	1.31	0.48	-0.12	0.35
XSMOM	loser	0.079*	1.66	0.33	0.24	0.97	0.49	1.04
	WML	0.179***	4.61	0.27	0.67	0.90	-0.73	1.63
	winner	0.228***	9.82	0.16	1.42	0.47	-0.14	0.35
SRMOM	loser	0.048	1.36	0.24	0.20	0.96	0.076	0.26
	WML	0.177***	6.32	0.19	0.92	0.71	-0.16	0.22
	winner	0.255***	9.86	0.18	1.43	0.45	-0.19	0.38
GRJMOM	loser	0.029	0.79	0.25	0.11	0.97	0.025	0.19
	WML	0.224***	8.16	0.19	1.18	0.47	-0.14	0.22
Panel B: Commodity								
	winner	0.060	1.57	0.20	0.29	0.62	-0.011	0.53
XSMOM	loser	-0.014	-0.41	0.19	-0.076	0.76	0.19	0.57
	WML	0.074*	1.72	0.23	0.32	0.55	0.006	0.45
	winner	0.073**	2.01	0.19	0.38	0.53	-0.046	0.49
SRMOM	loser	-0.013	-0.45	0.16	-0.084	0.66	0.041	0.35
	WML	0.086***	2.26	0.20	0.42	0.45	0.073	0.31
	winner	0.069**	2.05	0.18	0.38	0.52	-0.028	0.55
GRJMOM	loser	-0.035	-1.30	0.15	-0.24	0.78	-0.035	0.40
	WML	0.10***	2.99	0.19	0.56	0.37	0.038	0.30
Panel C: Equity index								
	winner	0.079***	2.70	0.19	0.41	0.62	-0.35	0.50
XSMOM	loser	0.009	0.28	0.21	0.04	0.83	-0.074	0.22
	WML	0.070***	2.59	0.18	0.40	0.64	-0.027	0.20
	winner	0.091***	3.15	0.19	0.48	0.65	-0.37	0.58
SRMOM	loser	0.004	0.14	0.19	0.021	0.82	-0.13	0.20
	WML	0.087***	3.49	0.16	0.53	0.38	-0.013	0.18
	winner	0.088***	3.11	0.18	0.48	0.66	-0.29	0.46
GRJMOM	loser	-0.009	-0.31	0.18	-0.048	0.87	-0.10	0.13
	WML	0.096***	4.25	0.15	0.65	0.42	-0.034	0.18
Panel D: Fixed income								
	winner	0.002	0.13	0.054	0.029	0.16	0.070	0.17
XSMOM	loser	0.015	1.63	0.042	0.37	0.11	-0.25	0.97
	WML	-0.014	-1.09	0.056	-0.25	0.30	0.13	0.35
	winner	-0.002	-0.32	0.030	-0.071	0.12	0.021	0.23
SRMOM	loser	0.005	0.58	0.037	0.13	0.12	-0.32	1.67
	WML	-0.007	-0.73	0.042	-0.16	0.22	0.39	1.07
	winner	0.011***	2.40	0.020	0.54	0.041	0.23	0.30
GRJMOM	loser	0.005	0.56	0.038	0.13	0.077	0.29	1.03
	WML	0.006	0.65	0.040	0.15	0.15	-0.17	0.66

Mean denotes the annualised portfolios returns. The portfolio returns are calculated by going long the selected assets. *Vol*, *Skew* and *Kurt* are the annualised standard deviation, skewness and kurtosis of portfolio returns. *MaxDD* denotes the annualised maximised drawdown. *T-value* is measured as $t = \frac{\mu * \sqrt{n/12}}{\sigma}$, where μ is annualised portfolio return; n is sample size at a monthly level; σ is annualised standard deviation of portfolio returns. '*', '**', '***' represent that the t-values are statistically significant at 10%, 5% and 1% level, respectively.

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Table 8: Alphas of GRJMOM with respect to XSMOM and SRMOM

	UK stock		Commodity		Equity index		Fixed income	
Panel A: GRJMOM and XSMOM								
	mkt+XSM	FF+XSM	mkt+XSM	FF+XSM	mkt+XSM	FF+XSM	mkt+XSM	FF+XSM
alpha	0.010***	0.011***	0.005***	0.005***	0.003***	0.003***	0.001	0.001
t	(6.72)	(7.07)	(2.87)	(2.95)	(2.39)	(2.45)	(1.13)	(1.05)
Panel B: GRJMOM and SRMOM								
	mkt+SRM	FF+SRM	mkt+SRM	FF+SRM	mkt+SRM	FF+SRM	mkt+SRM	FF+SRM
alpha	0.005***	0.005***	0.003**	0.003**	0.002*	0.002*	0.001*	0.001*
t	(3.94)	(3.89)	(2.23)	(2.26)	(1.72)	(1.92)	(1.84)	(1.72)

This table presents the regression results of the GRJMOM returns with respect to the market (mkt), Fama-French size and value factors (FF) and XSMOM/SRMOM (XSM/SRM) portfolios captured in each asset class. '*', '**', '***' represent that the t-values are statistically significant at 10%, 5% and 1% level, respectively.

5. GRJMOM and crash risks

In this section, we investigate the relationship between GRJMOM and momentum crashes. First, for each asset class, we identify crash periods by calculating the worst month of momentum strategies and compare the performance of GRJMOM to the XSMOM and SRMOM over these crash periods. Second, we compare the GRJMOM strategy to the risk-managed WML portfolio, i.e. constant volatility scaling approach (CVS) of Barroso and Santa-Clara (2015) to identify the outperformed risks management method. GRJMOM exhibits statistically significant alphas, lower volatility and maximum drawdown compared to the CVS approach.

5.1. Performance of GRJMOM over crash periods

Figure 5 plots the cumulative performance of different momentum strategies over the entire investment horizon in each market. We highlight that the GRJMOM strategy (solid black line) produces the highest cumulative performance in all asset classes. We observe that the dollar investment of GRJMOM is more stable than XSMOM and SRMOM with the smallest maximum drawdown, as confirmed in the results of Table 7. We also add shaded areas in Figure 5 indicating the worst periods of the plain momentum strategy in each asset class, or momentum crashes. Our GRJMOM exhibits substantial improvements compared to XSMOM and SRMOM during these periods.

In the UK stock market, the GRJMOM strategy mitigates the crash of XSMOM after the 2007-2008 financial crisis. Without risk management, the momentum investors suffered from a loss of 84.6% over a six month period between 2009-2010, as shaded in Panel A of Figure 5. By contrast, our GRJMOM reduces this drawdown to 19.7%. In

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1971, a dollar invested in the GRJMOM strategy would be worth over $10,000 by July 2018, whereas the same investment in XSMOM and SRMOM strategies would be worth only $557 and $1,877, respectively.

The GRJMOM strategies also show dominant performance in the global asset classes, followed by the SRMOM and XSMOM. In the commodity market (Figure 5 Panel B), we identify a similar crash period during 2009-2010 after the global financial crisis. Although our GRJMOM approach faces a small crash at the beginning of the shaded period, it later makes a strong rebound, leading to an overall gain during the crash period. In the equity index market (Figure 5 Panel C), we observe a similar pattern where GRJMOM gains profits during the crash periods. Finally, in the fixed income sample (Figure 5 Panel D), neither the XSMOM nor SRMOM strategies generate positive cumulative profits. In this case, our GRJMOM still realises a profit and mitigates the momentum crashes.

For a more in-depth analysis of the performance of GRJMOM over crash periods, we select the periods when momentum performs the worst over the entire investment horizon. We first find the ten worst single month's returns of XSMOM strategy in the UK market. Among them, the worst momentum crash occurred in April 2009, leading to a single month's return of -75.9%. Then, following Gulen and Petkova (2018), we compare the GRJMOM returns to the XSMOM and SRMOM over these months in Panel A of Table 9. The GRJMOM outperforms XSMOM in nine out of the ten months, the rest of the one month returns being virtually the same. In April 2009, GRJMOM generated a return of -17.9%, which is 58% higher than that of XSMOM. We also conduct the same analysis in the global asset classes samples and arrive at the same conclusion. These results are presented in Appendix C.

As a robustness check, we also report the six-month cumulative returns of different momentum strategies over the three worst crash periods. As shown in Panel B of Table 9, the results remain unchanged from the single month. GRJMOM shows its superiority in mitigating crash risks. In the 2009 crash, GRJMOM only loses 11.1% over the six months, while SRMOM and XSMOM lose 20.5% and 86.6%, respectively. These results are consistent with above-mentioned findings based on Figure 5, indicating that GRJMOM is an effective risk-managed approach and profitable strategy.

According to Grundy and Martin (2001), Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), momentum crashes appear after the market panics when the

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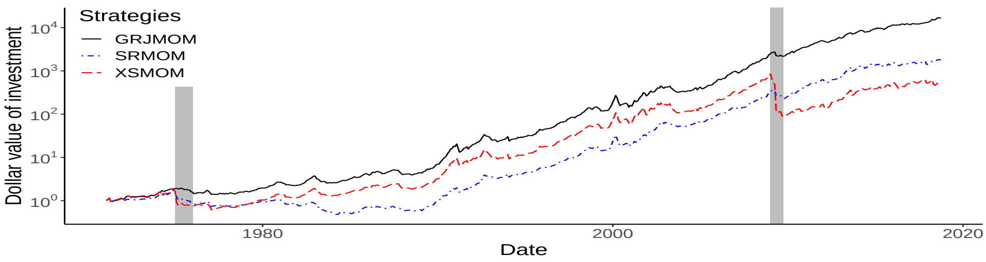
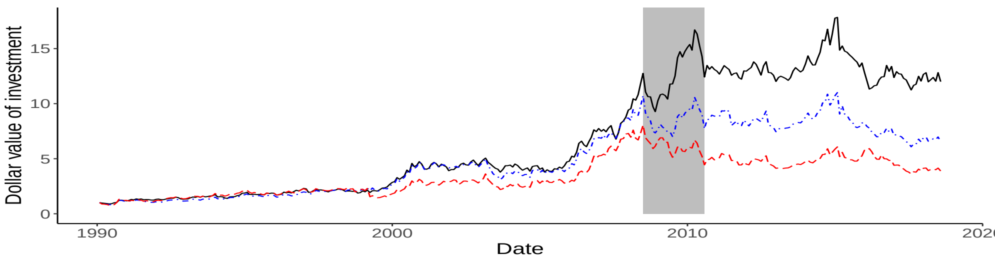
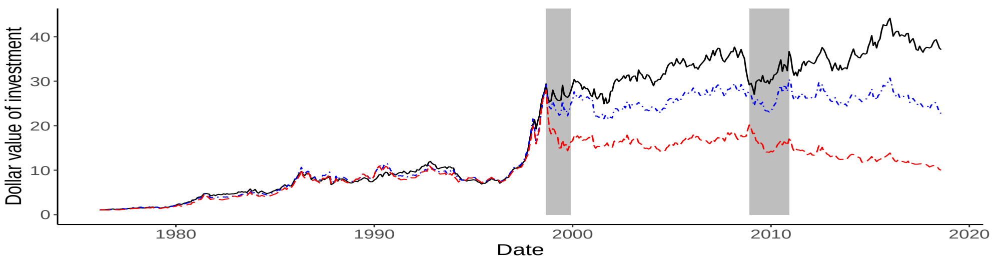
Figure 5: Cumulative performance of risk-adjusted momentum strategies across markets



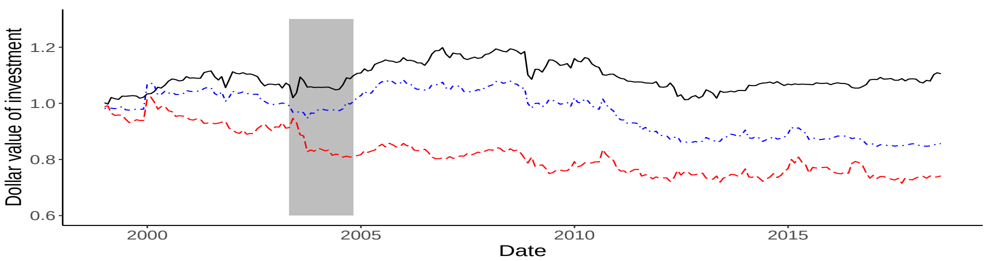
UK stock



Commodity



Equity index



Fixed income

These plots exhibit the cumulative performance of XSMOM, SRMOM and GRJMOM strategies across asset classes throughout the whole sample period. The dollar value of investment (y-axis) is logarithmically scaled in the UK stock market, given the huge difference across the three strategies. The shaded areas indicate the worst periods of the plain momentum strategy in each asset class or momentum crashes.

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Table 9: Performance of GRJMOM and momentum crashes (UK stock market)

Order	Date	Strategy			Difference	
		XSMOM	SRMOM	GRJMOM	GRJ-XS	GRJ-SR
Panel A: Single month return						
1	2009-04	-0.759	-0.244	-0.179	0.580	0.065
2	1975-01	-0.437	-0.253	0.010	0.447	0.263
3	2013-08	-0.246	-0.173	-0.063	0.184	0.110
4	2009-01	-0.241	0.075	0.076	0.317	0.001
5	2000-04	-0.221	-0.199	-0.213	0.008	-0.013
6	2018-04	-0.219	-0.028	-0.028	0.191	0.000
7	2009-08	-0.213	-0.098	-0.058	0.155	0.040
8	1994-01	-0.210	-0.157	-0.214	-0.004	-0.057
9	2001-10	-0.209	0.039	-0.038	0.172	-0.076
10	2009-03	-0.202	0.008	0.019	0.221	0.012
Panel B: Six months cumulative return						
1	2009-06	-0.866	-0.205	-0.111	0.755	0.094
2	1975-03	-0.538	-0.328	-0.001	0.537	0.327
3	2003-09	-0.390	-0.173	-0.286	0.104	-0.112

Panel A reports the ten worst single month returns of the XSMOM strategy in the UK stock market. Panel B reports the six-month cumulative returns over the three worst crash periods, where the date indicates the last month. GRJ-XS (GRJ-SR) denotes the difference between GRJMOM and XSMOM (SRMOM), which is calculated by subtracting one from another.

momentum losers reverse from the trough faster than the winners. In this case, the profits generated by the winners are not enough to cover the losses caused by the losers. Without considering these reversals of losers, the plain momentum ranking system fails to allocate the 'real losers' into the portfolio after the market panics. Our GRJMOM approach incorporates asset realised volatility over the formation periods at the ranking stage so that these 'false losers' are excluded from the portfolio as they exhibit high volatility. This explains why GRJMOM yields profitable short legs, avoiding the reversals in losers during the crash periods.

5.2. GRJMOM versus volatility scaling approach

Barroso and Santa-Clara (2015) argued that the momentum-specific risk is the main cause of momentum crashes. In order to mitigate momentum-specific risks, they proposed a simple but effective scaling approach based on past realised volatility of the WML series, called the constant volatility scaling (CVS) approach. In this study, we compare our GRJMOM performance to the CVS approach to check which one is better in managing momentum risks.

As mentioned in the introduction, GRJMOM is structurally the same as a plain

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momentum strategy which invests \$1 in both the long and short leg. The position size taken when following the GRJMOM strategy is constant over time. By contrast, the CVS approach creates a time-dynamic momentum portfolio size, where the momentum return is inversely scaled by its six months ex-ante volatility. The CVS WML returns are calculated as:

$$r^*_{WML,t} = \frac{\sigma_{target}}{\sigma_{WML,t}} r_{WML,t}, \tag{9}$$

where $r_{WML,t}$ is the WML return; $r^*_{WML,t}$ is the scaled WML return; $\sigma_{WML,t}$ is the realised volatility of $r_{WML,t}$ over the past six months; and σ_{target} is a constant target volatility. In order to make the two strategies comparable with to each other, we apply the same scaling factor $\sigma_{target}/\sigma_{WML,t}$ to our GRJMOM, so that both strategies have the same risk exposure.[30]

Barroso and Santa-Clara (2015) defined the target volatility σ_{target} as the annualised volatility of the market index in the long-run. Following their approach, we obtain the target volatility by calculating the annualised volatility of each market index at, 18.50% (FTSE all share), 18.56% (S&P GSCI), 13.11% (MSCI world) and 6.21% (Barclays Aggregate Bond).

Table 10 presents the performance metrics of GRJMOM and CVS strategies across the four markets. The scaled GRJMOM exhibits higher means and Sharpe ratios in each market, indicating strong profitability. In terms of risk management, the scaled GRJMOM shows a lower standard deviation than the CVS in three of the four markets, with the exception being fixed income, where the two are virtually the same. We also regress the return of scaled GRJMOM on the market risk premium and the CVS return. Alphas are at least statistically significant at a 5% level in UK stocks, commodities and equity indices, while in the bond market the difference is relatively small.[31] These improvements imply that the GRJMOM ranking is a more efficient risk-adjusted approach than the CVS approach in momentum investing.

[30] It is unfair to directly compare the GRJMOM and CVS approach as the average position size of the latter is greater than \$1. In the UK stock market, for example, for each one dollar invested in the GRJMOM strategy, the average investment in CVS is \$1.61 over time.

[31] We also estimate the alphas through the FF-3 model, and the results are indifferent from those of the CAPM.

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Table 10: Scaled GRJMOM versus CVS

	Mean	*T-value*	*SD*	*SR*	*MaxDD*	*Skew*	*Kurt*
Panel A: CVS							
UK stock	0.317	6.851	0.320	0.991	0.744	-0.295	0.321
Commodity	0.087	2.167	0.212	0.409	0.428	-0.021	0.155
Equity index	0.111	3.188	0.227	0.492	0.620	-0.012	0.197
Fixed income	-0.003	-0.267	0.045	-0.061	0.181	0.279	0.367
Panel B: Scaled GRJMOM							
UK stock	0.355	9.169	0.267	1.327	0.566	-0.091	0.148
Commodity	0.101	3.064	0.174	0.578	0.377	-0.029	0.029
Equity index	0.127	4.143	0.199	0.639	0.536	-0.079	0.226
Fixed income	0.004	0.327	0.047	0.075	0.211	-0.107	0.373

Panel C: Alphas of scaled GRJMOM (benchmark: CVS)				
	UK stock	Commodity	Equity index	Fixed income
alpha	0.010***	0.004**	0.003**	0.0004
t	(5.52)	(2.57)	(2.16)	(0.46)

The reported statistics contain annualised mean (*Mean*), T-value of mean (t), standard deviation (*SD*), Sharpe Ratio(*SR*), maximize drawdown (*Maxdd*), skewness (*Skew*), and kurtosis (*Kurt*). Panel A and B summarise the performance metrics of the CVS and GRJMOM portfolios. Panel C reports the alphas and t-statistics of the regression: $R_{Scaled.GRJMOM} = \alpha + \beta_1(R_{mkt} - R_{rf}) + \beta_2 R_{CVS}$. '*', '**', '***' represent t-statistics that are statistically significant at 10%, 5%, and 1% levels, respectively.

6. Factor analysis

To understand the superiority and risk exposure of the GRJMOM strategy, we now focus on examining the abnormal performances of GRJMOM by running different asset pricing models. We employ two extensively used multi-factor regressions: i) the four factor model documented by Fama and French (1996) and Carhart (1997), and ii) the value & momentum everywhere factors of Asness et al. (2013).

Table 11 shows the factor loading of GRJMOM returns by running Fama-French-Carhart four-factor models. In it, *mkt*, *smb*, *hml*, and *umb* denote the market, size, value, and momentum factors, respectively. The GRJMOM strategy exhibits alphas of 1.7%, 0.8%, 0.7%, and 0.09% per month in the UK stock, commodity, equity index and fixed income markets, respectively. The alphas are statistically significant at a 1% level for the UK stock, commodity and equity index markets, whereas they are positive but insignificant in the fixed income markets. As discussed previously, this makes sense because fixed income markets do not exhibit strong momentum effects. Across the four markets, the alphas of GRJMOM are at least 14% higher than those of other momentum trading schemes. The largest spread appears in the UK stock market, where the alpha of GRJMOM is 0.6% higher than that of the XSMOM.

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We next examine the risk exposures of these strategies against risk factors. We find that GRJMOM, in most cases, is significantly positively related to the movement of the market factors, except for the fixed income market where the relationship is negative. GRJMOM has no relation to the size effect but is negatively related to the value effect. More importantly, we show that GRJMOM greatly reduces its exposure to the momentum factor, *umd*. By contrast, XSMOM has beta coefficients of 0.82 in the UK stock market, indicating that this strategy is highly exposed to the momentum factor.

Table 11: Factors loading of GRJMOM versus XSMOM and SRMOM strategies (FF-4)

Strategies	*alpha*	*mkt*	*smb*	*hml*	*umb*
Panel A: UK stock					
XSMOM	0.012***	-0.308***	0.0010	-0.175*	0.820***
	(4.30)	(-5.99)	(0.11)	(-1.80)	(12.62)
SRMOM	0.015***	-0.318***	0.085	-0.305***	0.421***
	(7.23)	(-8.37)	(1.25)	(-4.24)	(8.76)
GRJMOM	0.017***	-0.145***	0.107	-0.239***	0.434***
	(8.07)	(-3.68)	(1.52)	(-3.21)	(8.76)
Panel B: Commodity					
XSMOM	0.005	0.187***	0.046	0.018	0.313***
	(1.62)	(3.30)	(0.42)	(0.15)	(4.36)
SRMOM	0.007**	0.261***	0.083	-0.049	0.243***
	(2.35)	(5.22)	(0.86)	(-0.47)	(3.83)
GRJMOM	0.008***	0.230***	0.115	-0.075	0.194***
	(3.15)	(4.92)	(1.28)	(-0.77)	(3.27)
Panel C: Equity index					
XSMOM	0.004*	-0.003	-0.013	0.117	0.357***
	(1.89)	(-0.06)	(-0.17)	(1.46)	(6.76)
SRMOM	0.005**	0.060	0.038	0.101	0.242***
	(2.54)	(1.18)	(0.56)	(1.35)	(4.94)
GRJMOM	0.007***	0.082*	0.049	-0.002	0.099**
	(3.54)	(1.71)	(0.75)	(-0.02)	(2.15)
Panel D: Fixed income					
XSMOM	-0.002*	0.139**	-0.006	0.002	0.049***
	(-1.88)	(2.41)	(-0.20)	(0.06)	(2.68)
SRMOM	-0.0004	-0.040	0.011	-0.004	0.008
	(-0.43)	(-0.87)	(0.47)	(-0.18)	(0.54)
GRJMOM	0.001	-0.152***	0.008	0.023	-0.021
	(1.37)	(-3.52)	(0.35)	(0.98)	(-1.50)

Panels in this table display the results of OLS regressions based on Fama-French-Carhart four-factor model in different markets. The dependent variables are the monthly returns of XSMOM, SRMOM and GRJMOM strategies. The independent variables include: the market (*mkt*), size (*smb*), value (*hml*), momentum (*umd*) factors. Each panel exhibits the regression results of a given asset class. The alpha represents the monthly abnormal returns after controlling for risk factors. '*', '**', '***' represent statistically significant t-values at 10%, 5% and 1% levels, respectively.

In addition, we run similar regressions using the value & momentum everywhere

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factors of Asness et al. (2013). These factors provide a common global generalisation of risk premia which work in both stock markets and different asset classes. Table 12 presents the results of the following regression:

$$R_{WML} = \alpha + \beta_1(mkt - r_f) + \beta_2 val + \beta_3 mom + \epsilon_t, \tag{10}$$

where mkt is the market factor that is consistent with above-mentioned market factor in Equation 8; val and mom denote the value and momentum factor constructed by the corresponding asset class as provided in Asness et al. (2013). As shown in Table 12, the GRJMOM strategies produce the highest abnormal returns across all asset classes. Consistent with the results in Table 11, the alphas of GRJMOM are significantly different from zero at the 1% level, except for the fixed income market. In the UK stock market, the alpha of GRJMOM is 0.6% and 0.2% per month higher than those of the XSMOM and SRMOM, respectively.

Consistent with the results in FF-4 factor regressions, GRJMOM exposes more of its risk to the movement of the market but less to the momentum factors. In the UK stock market, SRMOM and GRJMOM returns are significantly negatively related to the value effect, while XSMOM does not show statistically significant coefficients.. For commodities, the SRMOM strategy implementation results in insignificant intercepts in the value & momentum everywhere model (Panel B of Table 12), while it generates a signficant positive alpha in the FF-4 model (Panel B of Table 11). The insignificant alpha implies that the SRMOM strategy is not an efficient risk-adjusted ranking approach, at least for commodities.

To sum up, according to the results from the two multi-factor, the abnormal return of our innovation is at least 40% higher than that of the XSMOM strategy, and at least 14% better than that of the SRMOM strategy. The results of the factor loadings strongly support the superiority of GRJMOM across asset classes. Hence, we conclude that our innovation is an appropriate risk-adjusted momentum ranking approach that manages risk exposures and returns significant alpha.

7. Conclusion

In this study, we found that the high uncertainty of momentum strategies is driven by the cross-sectional realised volatility of individual assets. Instruments with high volatility

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Table 12: Factors loading of GRJMOM versus XSMOM and SRMOM strategies (value & momentum everywhere)

Strategies	*alpha*	*mkt*	*val*	*mom*
XSMOM	0.012***	-0.190***	-0.090	1.003***
	(3.69)	(-2.71)	(-0.93)	(11.617)
SRMOM	0.016***	-0.213***	-0.170**	0.614***
	(7.08)	(-4.21)	(-2.43)	(9.876)
GRJMOM	0.018***	-0.101**	-0.147**	0.666***
	(7.65)	(-1.97)	(-2.08)	(10.56)
Panel B: Commodity				
XSMOM	0.0003	0.019	-0.034	1.046***
	(0.15)	(0.62)	(-0.98)	(29.32)
SRMOM	0.003	0.118***	-0.076**	0.813***
	(1.61)	(3.56)	(-2.08)	(21.41)
GRJMOM	0.005***	0.113***	-0.066*	0.670***
	(2.64)	(3.15)	(-1.67)	(16.38)
Panel C: Equity index				
XSMOM	0.003*	-0.007	-0.371***	0.821***
	(1.70)	(-0.15)	(-4.93)	(13.14)
SRMOM	0.005**	0.055	-0.344***	0.682***
	(2.49)	(1.29)	(-4.75)	(11.34)
GRJMOM	0.006***	0.123***	-0.307***	0.489***
	(3.22)	(3.00)	(-4.41)	(8.45)
Panel D : Fixed income				
XSMOM	-0.001	0.075	-0.079	0.515***
	(-1.41)	(1.35)	(-0.81)	(5.57)
SRMOM	-0.0003	-0.070	0.016	0.264***
	(-0.26)	(-1.52)	(0.19)	(3.47)
GRJMOM	0.001	-0.144***	-0.029	-0.079
	(1.31)	(-3.27)	(-0.38)	(-1.08)

Panels in this table display the results of OLS regressions based on value & momentum everywhere factors across different markets. The dependent variables are the monthly returns of XSMOM, SRMOM and GRJMOM strategies, respectively. The factors include: the market factor (*mkt*); value everywhere factor (*smb*); momentum everywhere factor (*mom*). '*', '**', '***' represent t-values that are statistically significant at 10%, 5%, and 1% levels, respectively.

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over the formation period are more likely to be selected into a momentum portfolio. Therefore, momentum portfolios usually display high excess volatility compared to a randomly selected portfolio with the same number of assets. The empirical results in the paper strongly support our argument based on evidence from various asset classes including UK stock, commodity, equity index and fixed income markets.

We show that stocks with high realised volatility over the formation period tend to lose momentum effect, while stocks with low realised volatility show strong momentum. The plain momentum strategy which focuses on high volatility stocks, does not perform well when market is in a state of high uncertainty. Our results indicate that a risk-adjusted momentum strategy is needed to reduce the risks of momentum strategies, and hence improve the performance.

We develop a generalised risk-adjusted ranking procedure to alleviate the excess risks momentum strategies, called GRJMOM. It provides a flexible and generalised framework to rank risk-adjusted returns when sorting momentum winners and losers. Distinct from the existing risk-adjusted ranking method, GRJMOM allows investors to switch the aggressiveness of returns scaled by their realised volatility, in responding to different market conditions.

Evidence shows that our innovation can diversify the clustering of high volatility instruments present in the original momentum portfolios, and alleviate both conditional and unconditional risks present in WML returns. This diversification further improves the performance of momentum strategies across all asset classes. The GRJMOM strategies show higher returns and Sharpe ratios, and lower volatilities and maximised drawdown compared to other momentum trading rules. This outperformance is further supported by the high abnormal profits when running multi-factor regressions.

The study contributes to the literature in risk-managed momentum and momentum crashes, as seen in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). It provides a different view on the mitigations of momentum risk, which is sourced from cross-sectional ranking instead of time-series scaling. As suggested by our results, GRJMOM is a better approach than the existing CVS approach of Barroso and Santa-Clara (2015) due to its significantly higher performance.

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Appendix A. Summary statistics

Our global sample includes three asset classes: 27 commodity future indices, 24 stock indices and 19 fixed income futures. We obtain end of day prices for commodities and stock indices from Datastream, with those from fixed income markets being sourced from Bloomberg. The available dates vary across assets, but all the price series end in July 2018. Table A.1 reports the summary statistics and sample start dates of our global samples.

As shown in the table, the return variation is significant across commodities. Panel A presents a summary of our commodity sample which consists of 27 constituents of the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) from Datastream. The sample period is from January 1984 to July 2018. Brent produces the highest annualised return at 17.70% per annual, with Copper generating the best Sharpe ratio at 0.4835, whereas Natural gas creates the lowest return at -22.97% per annual and the worst risk-adjusted performance at -0.4073. Panel B reports the statistics of our equity index universe which consists of 24 markets. All the price series in this sample are measured in U.S. dollars. Not surprisingly, all stock indices create positive returns over the entire sample period. The annualised return and Sharpe ratio of Portugal are only 1.82% and 0.0727, respectively, which are much lower than those of the remaining markets. In contrast, the Hong Kong market generates the highest annualised return at 18.88%. Panel C presents the statistics of the fixed income sample which contains 19 sovereign bonds or short-term deposits futures with various maturities. The annualised returns of fixed income are all positive and quite low. The highest return is only 3.96% for Euro 30 year sovereign bond future, whereas the Japanese five year sovereign bond future earns only 0.09% per annul.

Annualised volatilities also vary across instruments in each asset class. In the commodity class, Natural gas reports the highest annualised volatility at 56.41%, and Live cattle is the lowest at 17.04%. In our equity index sample, the annualised volatility of U.S stock index is 19.81% which is the only equity index lower than 20%, whereas the Thai stock index reports the highest volatility at 35.77%. The Australian 10 year sovereign bond future presents the lowest volatility at 1.49% per annum, and the Euro 30 years bond future shows the highest volatility at 15% per annum.

Overall, the annualised average returns of commodity futures are more volatile than

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others; equity indices all demonstrate positive average returns and slightly lower volatility than commodities; fixed income futures report the smallest annualised returns and standard deviations.

Table A.1: Summary statistics of global asset classes

Instrument	*Mean*	*SD*	*SR*	*Start.Date*
Panel A: Commodity				
Brent	0.1770	0.3862	0.4583	1999-01-11
WTI Crude oil	0.1143	0.4040	0.2830	1987-01-08
Gas oil	0.1619	0.3577	0.4525	1999-01-07
Heating oil	0.1010	0.3815	0.2648	1984-01-31
Natural gas	-0.2297	0.5641	-0.4073	1994-01-10
RBOB gas	0.1869	0.3956	0.4724	1988-01-08
Gold	0.0150	0.1901	0.0786	1984-01-31
Platinum	0.0568	0.2614	0.2175	1984-01-31
Silver	0.0211	0.3331	0.0634	1984-01-31
Lean.hogs	-0.0619	0.2697	-0.2296	1984-01-31
Live cattle	0.0240	0.1704	0.1406	1984-01-31
Feeder cattle	0.0296	0.1847	0.1603	2002-01-08
Aluminum	-0.0349	0.2344	-0.1489	1991-01-08
Copper	0.1431	0.2960	0.4835	1984-01-31
Lead	0.1023	0.3522	0.2904	1995-01-09
Nickel	0.1135	0.4000	0.2838	1993-01-11
Tin	0.1467	0.4366	0.3360	2007-03-16
Zinc	0.0237	0.3100	0.0764	1991-01-09
Cocoa	-0.0468	0.3380	-0.1385	1984-01-31
Coffee	-0.0357	0.4122	-0.0867	1984-01-31
Corn	-0.0793	0.2790	-0.2844	1984-01-31
Cotton	0.0259	0.2801	0.0926	1984-01-31
Soybean	0.0405	0.2600	0.1558	1984-01-31
Soybean.oil	-0.0068	0.2743	-0.0248	2005-01-10
Sugar	0.0257	0.4034	0.0637	1984-01-31
Wheat Chicago	-0.0591	0.3096	-0.1910	1984-01-31
Wheat Kansas	-0.0651	0.3219	-0.2023	1999-01-07
Panel B: Equity index				
Australia	0.0944	0.2510	0.3760	1970-01-01
Austria	0.1073	0.2527	0.4247	1970-01-01
Belgium	0.1066	0.2266	0.4704	1970-01-01
Canada	0.1026	0.2106	0.4874	1970-01-01
Denmark	0.1567	0.2252	0.6959	1970-01-01
France	0.1167	0.2537	0.4601	1970-01-01
Germany	0.1231	0.2548	0.4832	1970-01-01
Hong Kong	0.1888	0.3306	0.5711	1970-01-01
Italy	0.0704	0.2867	0.2457	1970-01-01
Japan	0.1303	0.2445	0.5330	1970-01-01
Netherlands	0.1293	0.2392	0.5407	1970-01-01

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Table A.1 – continued from previous page

Instrument	*Mean*	*SD*	*SR*	*Start.Date*
Norway	0.1404	0.3067	0.4577	1970-01-01
Portugal	0.0182	0.2498	0.0727	1988-01-01
Spain	0.0770	0.2647	0.2908	1970-01-01
Sweden	0.1668	0.2821	0.5914	1970-01-01
Switzerland	0.1374	0.2129	0.6452	1970-01-01
United Kingdom	0.1030	0.2451	0.4201	1970-01-01
United States	0.1143	0.1981	0.5769	1970-01-01
Korea	0.1503	0.3978	0.3777	1988-01-01
Malaysia	0.1030	0.2918	0.3528	1988-01-01
Singapore	0.1381	0.2582	0.5348	1970-01-01
South Africa	0.1435	0.3266	0.4393	1993-01-01
Taiwan	0.1178	0.3384	0.3481	1988-01-01
Thailand	0.1330	0.3577	0.3719	1988-01-01
Panel C: Fixed income futures				
AUS 3Y	0.0062	0.0152	0.4057	1989-12-19
AUS 10Y	0.0048	0.0149	0.3206	1987-09-21
CA 10Y	0.0195	0.0847	0.2298	1989-09-18
EURO 2Y	0.0050	0.0157	0.3200	1997-03-10
EURO 5Y	0.0198	0.0420	0.4713	1991-10-07
EURO 10Y	0.0353	0.0658	0.5359	1990-11-26
EURO 30Y	0.0396	0.1500	0.2637	1998-10-05
EuroDollar 1M	0.0033	0.0102	0.3276	1990-04-06
EuroDollar 3M	0.0022	0.0115	0.1909	1986-04-02
EUIBOR 3M	0.0025	0.0067	0.3734	1998-12-09
JP 5Y	0.0009	0.0228	0.0385	1996-02-19
JP 10Y	0.0181	0.0577	0.3138	1985-10-22
UK 1Y	0.0042	0.0171	0.2472	1988-02-29
UK 10Y	0.0120	0.1052	0.1143	1982-11-19
US 2Y	0.0034	0.0215	0.1573	1990-06-26
US 5Y	0.0084	0.0513	0.1635	1988-05-23
US 10Y	0.0230	0.0825	0.2795	1982-05-04
US 30Y	0.0296	0.1391	0.2124	1980-01-02
SWISS 10Y	0.0300	0.0632	0.4757	1992-06-17

This table introduces the summary statistics of our global asset classes. Panel A summaries the statistics of 27 constituents of the Standard and Poor's Goldman Sachs Commodity Indices. Panel B presents the statistics for 24 investable Morgan Stanley Capital International indices. Panel C reports the statistics of 19 sovereign bonds or short-term deposits futures. The prices of commodity and equity indices are obtained from Datastream, and those of fixed income are collected via Bloomberg. Columns two to four illustrate annualised average return (*Mean*), standard deviation (*SD*) and Sharpe ratio (*SR*). All results are based on daily returns over the entire sample period and converted to annual levels. the last column presents The start date of every instrument, and all return series end in July 2018.

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Appendix B. Excess volatility in foreign exchange market

Following Lustig et al. (2011) and Menkhoff et al. (2012*a*), our FX universe contains 48 currencies: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. Due to the introduction of Euro and data restrictions, the number of available currencies are dynamic over time horizon and ranges from 21 to 38, which is consistent with Menkhoff et al. (2012*a*).[32]

Different from other asset classes, excess returns here is composed of the spot price return and interest differentials. According to Menkhoff et al. (2012*a*) and Menkhoff et al. (2012*b*),[33] monthly percentage excess return on month $t+1$ of currency k is calculated as:

$$rx_{t+1}^{k} \equiv i_t^k - i_i - \frac{(s_{t+1}^k - s_t^k)}{s_t^k}, \tag{B.1}$$

where i_t^k is the foreign interest rate; i_t is the domestic interest rate, which is the short-term interest in U.S; s_t^k is the spot exchange rate at month end. We rationally assume that the forward discount rate is equivalent to the interest rate differentials as uncovered interest parity holds in this sample (Akram et al., 2008, Menkhoff et al., 2012*a*). Thus, the excess monthly percentage returns are approximate to:

$$rx_{t+1}^{k} \approx \frac{(f_t^k - s_t^k)}{s_t^k} - \frac{(s_{t+1}^k - s_t^k)}{s_t^k} = \frac{(f_t^k - s_{t+1}^k)}{s_t^k}, \tag{B.2}$$

where f_t^k is is the month end one-month forward in month t. The data of both spot and one-month forward exchange rates versus to U.S dollar are obtained from Barclays Bank International and WM/Reuters via Datastream.

[32]Thirteen currencies are omitted due to the introduction of Euro: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Portugal and Spain omit in 1999; Greece is omitted in 2000; Slovenia is omitted in 2006; Cyprus is omitted in 2007; Slovakia is omitted in 2008.

[33]Menkhoff et al. (2012*a*) and Menkhoff et al. (2012*b*) capture excess log returns of different currencies, but we measure percentage returns as documented by Koijen et al. (2018) to be consistent with the return calculations for the other asset classes.

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Table B.1 exhibits a summary statistic of our foreign exchange universe. *Indonesia* reports the highest annualised return at 48.93% per annum; *Ukraine* displays the poorest averaged return, at -37.87% per annual. Meanwhile, *Ukraine* shows the highest annualised standard deviation, at 27.45%; *Saudi Arabia* reports the lowest one, at 0.42%. Furthermore, *Egypt* illustrates the highest Sharpe ratio, at 1.8691; *Netherlands* shows the lowest value at -2.9886.

Following the portfolio construction method mentioned in Section 2.2, we conduct the XSMOM strategy in the FX market. We find that the excess volatility of the XSMOM strategy is 0.005, which is not statistically significant. We argue that the high reward-to-risk ratio in the FX market causes this pattern. The mean of absolute Sharpe ratio is greater that one in in this market, whereas this statistic is no more than 0.5 across other asses classes. This results in asset returns, as opposed to volatilities, over the formation period, dominating the momentum ranking for this asset class. Since GRJMOM aims to alleviate the excess volatility caused by the impact of high volatility instruments, a market without excess momentum volatility does not need such an adjustment. Hence, we exclude the FX market from our sample.

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Table B.1: Summary statistics of foreign exchange sample

Economics	*Mean*	*SD*	*SR*	*Start date*
Australia	0.0541	0.1392	0.3884	1985-01-31
Austria	-0.0587	0.1311	-0.4480	1985-01-31
Belgium	-0.0419	0.1285	-0.3256	1985-01-31
Brazil	0.1644	0.1833	0.8973	2004-03-30
Bulgaria	0.0128	0.1139	0.1119	2004-03-30
Canada	0.0126	0.0893	0.1415	1985-01-31
Croatia	0.0280	0.1180	0.2372	2004-03-30
Cyprus	-0.0626	0.0948	-0.6605	2004-03-30
Czech	0.0048	0.1422	0.0339	1997-01-01
Denmark	-0.0074	0.1203	-0.0619	1985-01-31
Egypt	0.3682	0.1970	1.8691	2004-03-30
EURO	0.0005	0.1158	0.0040	1999-01-01
Finland	0.0389	0.1059	0.3677	1997-01-01
France	-0.0255	0.1269	-0.2008	1985-01-31
Germany	-0.0619	0.1296	-0.4779	1985-01-31
Greece	0.2124	0.1258	1.6879	1997-01-01
Hongkong	-0.0035	0.0070	-0.5033	1985-01-31
Hungary	0.1019	0.1601	0.6365	1997-10-28
India	0.1092	0.0696	1.5677	1997-10-28
Indonesia	0.4893	0.2694	1.8161	1997-01-01
Ireland	-0.0018	0.0957	-0.0188	1993-11-01
Israel	-0.0118	0.0929	-0.1266	2004-03-30
Italy	0.0522	0.1266	0.4124	1985-01-31
Iceland	0.1281	0.1763	0.7270	2004-03-30
Japan	-0.0575	0.1264	-0.4547	1985-01-31
Kuwait	0.0090	0.0287	0.3139	1997-01-01
Malaysia	0.0951	0.1318	0.7220	1985-01-31
Mexcio	0.1587	0.1283	1.2367	1997-01-01
Netherlands	-0.3179	0.1064	-2.9886	1985-01-31
New Zealand	0.0496	0.1465	0.3388	1985-01-31
Norway	0.0316	0.1326	0.2380	1985-01-31
Philippines	0.1024	0.0978	1.0466	1997-01-01
Poland	0.0340	0.1631	0.2083	2002-02-12
Portugal	0.1039	0.1279	0.8125	1985-01-31
Russia	0.1757	0.1659	1.0594	2004-03-30
Saudi Arabia	0.0020	0.0042	0.4600	1997-01-01
Singapore	-0.0323	0.0640	-0.5040	1985-01-31
Slovak	-0.1299	0.1290	-1.0069	2002-02-12
Slovenia	-0.0295	0.1011	-0.2917	2004-03-30
South Africa	0.1909	0.1819	1.0493	1985-01-31
Korea	0.0068	0.1280	0.0533	2002-02-12
Spain	0.0554	0.1295	0.4283	1985-01-31
Sweden	0.0252	0.1297	0.1942	1985-01-31
Switzerland	-0.0537	0.1348	-0.3987	1985-01-31
Taiwan	-0.0036	0.0524	-0.0696	1997-01-01
Thailand	0.0504	0.1050	0.4805	1997-01-01
Ukraine	-0.3187	0.2745	-1.1610	2004-03-30
United Kingdom	0.0233	0.1169	0.1990	1985-01-31

Columns two to four illustrate annualised statistics: average return (*Mean*), standard deviation (*SD*) and Sharpe ratio (*SR*) captured by daily returns over entire sample period. The start dates of instruments are presented in the fifth column.

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Appendix C. GRJMOM and momentum crashes (global asset classes)

Table C.1 reports the monthly performance of GRJMOM over the crash periods in commodity, equity index, and fixed income markets. For most parts, we find that our innovation successfully mitigates momentum crashes. In the commodity market, the largest downward of XSMOM -32.9% in March 1998, is reduced to -9.9% after GRJMOM ranking. In nine of these ten worst months, GRJMOM reduces the losses of XSMOM, or even creates profits in two cases, i.e., May 2009 and March 2002. In comparison with the SRMOM strategy, our innovation also performs better in each of these months. Similar patterns are also observable in the equity index and fixed income markets. Thus, we conclude that GRJMOM successfully alleviates the momentum crashes in each asset class, which is consistent with our previous findings for UK stocks shown in Table 9.

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Table C.1: Performance of GRJMOM and momentum crashes (global asset classes)

Order	Date	Strategy			Difference	
		XSMOM	SRMOM	GRJMOM	GRJ-XS	GRJ-SR
Panel A: commodity						
1	1999-03	-0.329	-0.099	-0.099	0.230	0.000
2	1985-07	-0.168	-0.106	-0.106	0.062	0.000
3	2010-07	-0.148	-0.140	-0.131	0.017	0.010
4	2015-02	-0.146	-0.177	-0.167	-0.021	0.010
5	2003-03	-0.143	-0.124	-0.074	0.069	0.050
6	2008-07	-0.141	-0.147	-0.132	0.009	0.015
7	2009-05	-0.140	0.004	0.131	0.272	0.128
8	2012-09	-0.133	-0.130	-0.071	0.062	0.059
9	2002-03	-0.128	-0.022	0.009	0.137	0.031
10	1990-02	-0.128	-0.102	-0.037	0.091	0.065
Panel B: equity index						
1	1975-01	-0.316	-0.208	-0.208	0.108	0.000
2	1987-10	-0.233	-0.233	-0.213	0.021	0.021
3	1998-09	-0.177	-0.112	-0.101	0.076	0.011
4	1973-04	-0.166	-0.103	-0.103	0.063	0.000
5	1998-10	-0.161	-0.065	-0.042	0.118	0.023
6	1999-04	-0.146	-0.033	-0.002	0.144	0.030
7	1986-10	-0.144	-0.141	-0.133	0.011	0.008
8	1998-02	-0.140	-0.140	-0.099	0.041	0.041
9	1974-05	-0.136	-0.130	-0.130	0.006	0.000
10	1986-05	-0.129	-0.106	-0.071	0.058	0.035
Panel C: fixed income						
1	2003-09	-0.064	-0.020	-0.022	0.042	-0.001
2	2003-07	-0.047	0.007	0.054	0.101	0.047
3	2009-01	-0.042	0.017	0.033	0.075	0.016
4	2015-06	-0.039	-0.026	0.000	0.039	0.025
5	2014-01	-0.037	-0.031	0.018	0.055	0.049
6	2010-12	-0.035	-0.022	-0.008	0.028	0.014
7	2016-10	-0.034	-0.017	0.006	0.040	0.023
8	1996-02	-0.033	-0.012	-0.012	0.021	0.000
9	1994-02	-0.033	-0.022	-0.022	0.011	0.000
10	2011-07	-0.031	-0.023	0.000	0.031	0.023

This table reports the ten worst single month returns of the XSMOM strategy in commodity, equity index, and fixed income markets. Order one means the poorest one. GRJ-XS (GRJ-SR) is the difference between GRJMOM returns and XSMOM (SRMOM) returns, which is calculated by using the returns of GRMOM and subtracting those of XSMOM (SRMOM).

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