Downside volatility-management of the industry momentum strategy

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Abstract

Many studies have shed light on the pervasive evidence supporting the benefits of managing the momentum strategy's risk: it is proven to generate substantial gains in performance and to considerably reduce the strategy's pronounced crash risk.

This study contributes to existing literature by investigating the effects of volatility-management in the context of the industry variation of the momentum strategy, instead of the traditional strategy using individual stocks. More specifically, it explores the effects of using a downside volatility-management scheme – computed using exclusively negative returns – and compares it to the traditional total volatility measure. Additionally, it analyses where the managed strategies' enhanced performance stems from by decomposing it into two components: volatility timing and return timing.

Managing the industry momentum strategy's risk is shown to provide benefits for investors, showcasing significant increases in performance, though not as pronounced as in individual stock momentum. However, downside volatility-management does not appear to outperform that using total volatility: it seems that, in the case of momentum, downside volatility alone may not adequately capture the full risk associated with the strategy. When decomposing the sources of the added performance of the managed momentum strategies, they exhibit positive return and volatility timing components, opposed to most factors and anomalies in the market. Volatility timing stands as the main driver of the resulting additional performance.

Keywords: Momentum: Industry Momentum; Volatility-management; Downside volatility; Alpha decomposition; Risk-managed strategies

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Resumo

Vários estudos têm contribuído para as provas generalizadas que apoiam os benefícios da gestão do risco nas estratégias de *momentum*: é comprovado que gera ganhos substanciais de desempenho e reduz consideravelmente o conhecido risco de *crashs* da estratégia.

Esta dissertação contribui para a literatura existente através da investigação dos efeitos de gestão de volatilidade da estratégia de *momentum* em portfolios de indústria, em vez da estratégia tradicional aplicada a ações individuais. Mais especificamente, este estudo explora os efeitos de gerir a estratégia pela volatilidade *downside* – calculada considerando apenas retornos negativos – e compara-os com os resultados da tradicional medida de volatilidade. Adicionalmente, analisa a origem do desempenho acrescido destes esquemas através da sua decomposição em duas componentes: previsão de volatilidade e previsão de retorno.

Gerir o risco das estratégias de *momentum* em portfolios de indústrias apresenta benefícios para investidores, registando aumentos significativos no desempenho, embora não tão pronunciadamente como na estratégia de *momentum* em ações. No entanto, o uso da volatilidade *downside* na gestão do risco da estratégia de *momentum* não parece superar os ganhos da gestão pela volatilidade total: no caso do *momentum*, a volatilidade *downside* parece não capturar adequadamente o risco total associado à estratégia. Ao decompor as fontes do aumento do desempenho destas estratégias de *momentum* geridas, elas apresentam componentes positivas de previsão de retorno (ao contrário da maioria dos fatores e anomalias no mercado) e de volatilidade. A componente de previsão da volatilidade é identificada como o principal *driver* do desempenho adicional.

Palavras-chave: *Momentum*; *Momentum* num contexto de indústria; Gestão de volatilidade; Volatilidade *downside*; Decomposição de alfas; Gestão do risco de estratégias

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1. Introduction

The momentum strategy, initially documented in Jegadeesh and Titman's (1993) seminal study, is today one of the most widespread market anomalies in asset allocation literature. Built by investing in high-performing stocks and shorting the low-performing ones in the recent past – buying winners and selling losers –, it has been proven to consistently deliver significant abnormal returns and outstanding risk-to-reward measures, even after accounting for common risk factors. Numerous studies have been conducted surrounding this strategy and its persistence across different asset classes, geographies and time periods is notorious. One of its variations is its industry portfolio form, referred to as industry momentum, first studied by Moskowitz and Grinblatt (1999). Instead of investing in single stocks according to their performance, this strategy consists in grouping all stocks within their respective industries and betting in the industries as a whole. Therefore, buying the stocks within the "winner" industry portfolios and selling those on the "loser" industries.

All the promising gains generated by the momentum strategy and its variations come at a great cost: they are subject to great crashes during market reversals. Grundy and Martin (2001) attribute this to momentum's time-varying beta: when markets conditions are favourable, the strategy invests in high-beta stocks and shorts low-beta ones. However, when market conditions revert, the previously created portfolios now generate great losses because they are betting in high-beta stocks, which are highly sensitive to these negative market movements.

In order to mitigate the impact of momentum's high volatility and drawdowns, Barroso and Santa-Clara (2015) suggest a volatility-management scheme that scales the momentum strategy by its realized volatility in the recent past. After doing so, the authors observe a significant reduction in the strategy's crash risk and considerable performance improvements. All the available research on this topic, like the ones of Daniel and Moskowitz (2016) or Moreira and Muir (2017), confirms one thing: volatility-management is highly effective when applied to momentum strategies.

However, most of the available research surrounding the volatility-management of momentum strategies is largely focused on its original individual stock momentum form.

Motivated by this gap in the available literature, the present study examines the performance of two volatility-scaling schemes on one of the momentum strategy's variations, industry momentum. It mainly bases itself on two specific studies: Grobys et al.'s (2018) research regarding volatility-scaling of the industry momentum strategy and it intends to add new insights by combining it with Wang and Yan's (2021) research covering downside volatility-management and the sources of the enhanced performances of managed strategies. The latter investigate the performance of the volatility-scaling scheme in known equity factors and market anomalies, but do not provide any evidence regarding momentum's industry variation.

Like Grobys et al. (2018), I construct the industry momentum strategy in the U.S. stock market, and apply Barroso and Santa-Clara's (2015) volatility-scaling approach. I then go one step further and apply Wang and Yan's (2021) methodology to test how controlling for downside volatility versus total volatility works in an industry momentum setting. While in the total volatility-scaling scheme all daily returns are taken into account in the computation of the strategy's realized volatility estimate, here only the negative returns are considered. I then follow the authors and evaluate the performance of the volatility-managed strategies using Moreira and Muir's (2017) spanning regressions, that essentially regress the managed strategies on the original unmanaged ones, as well as on each other. The managed momentum strategies generate significant positive alphas that can be explained by two effects: return timing (how past volatility predicts future returns) and volatility timing (how past volatility predicts future volatility). By decomposing the alpha into these two components, it is possible to assess where the enhanced performance of the total and downside volatility-managed industry momentum strategies truly stems from.

2. Literature Review

Every investor in the market is continuously searching for ways to improve their performance. Regardless of their individual goals and characteristics, investing approaches, or asset classes and securities chosen for their portfolios, investors ultimately strive to balance risk and reward: to get the highest returns they are capable of, while controlling for the risk they are exposed to. Yet, maintaining a consistent positive performance above the one of the general markets can pose a challenge among its participants. According to the Fama (1970) Efficient Market Hypothesis (EMH), markets are efficient and security prices uninterruptedly incorporate all available market and security-specific information. Depending on what is understood by available information, this hypothesis can take three different forms – weak, semi-strong or strong –, however, they all determine that it is theoretically impossible to predict future market values and consistently profit from trading strategies based on publicly available information and historical performance, that is, unless market participants incur in investments with higher associated risk premiums.

Nevertheless, it seems difficult to reconcile this hypothesis with the abundant evidence suggesting the existence of return-generating opportunities in the market that can be successfully exploited by investors: the market is filled with anomalies – unexpected stock behaviour inconsistencies that cannot be explained by conventional financial analysis. Even though many anomalies pose momentary opportunities that are instantly corrected in the market, there are some that seem to pervade, born from the identification of trends in price movements (technical analysis) or from security specific information (fundamental analysis).

Some examples of established market anomalies that are recognized to offer gains to investors, providing evidence of time-series properties in returns, range from DeBondt and Thaler's (1985) reversal effect – that finds past losers outperform past winners – or calendar effects like the rise of stock prices in the month of January – also known as the "January effect" – initially reported in academic literature by Wachtel (1942). Regarding fundamental variables, there are effects like Banz's (1981) small-firm effect – small-cap stocks tend to outperform those with large-caps over prolonged periods of time – or Basu's (1977) price-to-earnings effect that identifies the outperformance of stocks with low price-to-earnings ratios versus those with high ratios.

A specifically pervasive and widely discussed effect in asset allocation literature is the momentum anomaly. Initially identified by Levy (1967), and later documented by Jegadeesh and Titman (1993) in the US stock market, this strategy consists in investing in stocks that have performed well in the most recent past and shorting the worst performing ones in the same period – essentially, buying winners and selling losers. Though individual stock performance is extremely unpredictable, these winner portfolios seem to significantly outperform the loser ones. The strategy appears to consistently realize significant positive abnormal returns, as well as an outstanding risk-to-reward ratio, even when compared to the market itself and other well-known factors. In fact, it is found that factor models don't seem to be able to adequately capture its returns: not only does the "winners minus losers" strategy earn statistically and economically significant returns after controlling for the Fama and French (1993) three factors, but it also showcases a negative correlation with the market and value factors. Given this evidence, Carhart (1997) proposes in his study of mutual fund performance the inclusion of momentum as an additional risk factor to the Fama and French (1993) three-factor model.

The momentum strategy continues to puzzle investors to this day, with its persistent presence not only in the U.S. stock market, but also across different markets, asset classes, geographies, and time periods. There is Menkhoff et al.'s (2012) evidence in currency markets, Erb and Harvey (2006) in commodities, Rouwenhorst (1998) in developed European equity markets and Rouwenhorst (1999) in emerging ones, along with many others, of which Moskowitz and Grinblatt's (1999) momentum evidence in industry portfolios.

In their paper, the authors sort stocks not according to their individual performance in the recent past but based on their industry's performance as a whole: they buy stocks from firms in well-performing industries and short those in under-performing ones. Assembling portfolios of companies in the same industry appears to be a natural grouping mechanism, since these firms have a tendency to be strongly correlated: they operate under similar corporate structures and regulations and are similarly vulnerable to market and economic fluctuations. Among their findings, Moskowitz and Grinblatt (1999) state that a considerable part of the individual stock momentum anomaly comes from its industry component, where it is found to be a prevalent momentum effect. This suggests that individual stock momentum strategies, or any strategy that groups stocks according to their performance, are not particularly diversified since the companies in each group frequently belong to the same industry and owe most of its performance to industry effects. On the other hand, Grundy and Martin (2001) consider it a big leap to claim that industry is the sole key driver of momentum profits. Through the analysis of "real industry" momentum strategies – regular industry momentum – and "random industry" momentum strategies – where all initial long (short) positions are substituted with a long (short) position in another company with the same formation period return as the ones on the real winner (loser) industry momentum – it is found that real strategies don't consistently beat the random ones, contradicting Moskowitz and Grinblatt's (1999) findings supporting the single crucial role of industry effects on momentum strategy returns.

Despite this discussion, the presence of industry effects is undeniable. Swinkels (2002) finds evidence for industry momentum in the European stock market, Su (2011) showcases significant profitability in the Chinese stock market, Ji and Giannikos (2010) provides global proof in different formation and holding periods, among others.

Though the momentum anomaly and its variants' noteworthy performance present great potential for investors to generate profit, this strategy is at times prone to extended periods of persistent negative returns. Its return distribution is shown to be negatively skewed: returns are susceptible to notable crashes throughout strong market reversals following subsequent market downturns and periods of high volatility. Grundy and Martin (2001) find that this occurs due to the strategy's time-varying systematic risk, in line with Kothari and Shanken's (1992) argument that strategies based on sorting stocks into portfolios according to past returns present time-varying exposure to systematic factors. Since momentum invests in stocks that have performed well in the recent past and sells those that haven't, during favourable market conditions, the strategy tends to have a positive market beta: it typically buys stocks with a positive beta and shorts those with a negative beta. Similarly, amid adverse market conditions, it is likely to place a negative bet on the market by going long on negative beta stocks and short on positive beta ones. The momentum strategy prospers when markets remain in the same state, the large losses primarily arise on the transitions: when markets rapidly change from one market state to the other, it can generate considerable unexpected losses to investors.

Grundy and Martin (2001) propose a hedging technique for the dynamic exposure to risk factors, however, Daniel and Moskowitz (2016) argue it is not implementable in real time, since the authors rely on ex-post information. Daniel and Moskowitz (2016) further investigate this issue and not only find remarkable correlation between the beta of the loser portfolio and the same-period market return, but also that losers' down-market betas are quite small, whereas up-market betas appear to be substantially high. Moreover, they find momentum seems to behave like a short call option on the market during its crashes after bear market states.

Many studies have been conducted as an attempt to gauge the momentum strategy's behaviour and prevent such pronounced crashes. For example, Blitz, Huij, and Martens (2011) propose an alternative form of the regular momentum strategy that, instead of sorting stocks according to their full returns, it does so based on the residual returns after controlling for several risk factors. Asness, Moskowitz and Pedersen (2013) suggest a strategy that exploits momentum and value's strong negative correlation, creating portfolios that combine both strategies over different markets, ultimately lowering the strategy's risk, when compared with regular momentum.

In turn, Barroso and Santa-Clara (2015) propose a volatility scaling scheme on the momentum strategy, focusing on managing momentum's specific risk (contrary to Daniel and Moskowitz's (2016) approach attending to systematic risk). These fit into the vast empirical research on volatility-managed strategies that derive from the combination between the prevalent evidence of positive autocorrelation in volatility and nearly predictable returns. Thus, combining both effects suggests that scaling strategies by their volatility would, in fact, generate predictable expected returns. Negative returns appear to be negatively related to the high volatility in the market, and these schemes essentially propose the investors reduce their investment in an underlying strategy in times of high volatility, and lever their positions when the opposite is observed, hence scaling the risk they are incurring in, in accordance with market conditions. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) report that, in comparison with the unmanaged momentum strategy, its scaled variations not only nearly eradicate crashes, as well as almost double its Sharpe ratio. Likewise, Barroso, Detzel and Maio (2021) demonstrate the same benefits for the volatility-managed betting-against-beta strategy, Eisdorfer and Misirli (2020) provide evidence for financial distress strategies, whilst Moreira and Muir (2017) confirm the significant performance improvement from scaling monthly returns by their recent past realized variance in nine equity factors, generating positive alphas when regressed on their plain counterparts – spanning regressions. Yet, using a wider range of equity strategies, though also observing significant positive alphas, Cederburg et al. (2020) find no indication that volatility-managed portfolios consistently outperform the plain ones risk-to-reward wise, further arguing the spanning regressions are not implementable in real time since they rely on ex-post information. Moreover, when applied out-of-sample, the managed strategies do not hold up to their in-sample performance and do not appear to outperform the unmanaged strategies. Despite the lack of systematic evidence across all equities, Cederburg et al. (2020) still report robust positive volatility-managed performance for momentum strategies, in line with the available literature.

Most volatility management schemes seem to solely concentrate on the use of total volatility as a measure of risk. Some literature on variations to using total volatility include Daniel and Moskowitz's (2016) use of a dynamic weighting scheme that incorporates forecasts of momentum returns and Wang and Yan's (2021) downside volatility-managed strategies. Instead of calculating the volatility of full returns, the latter concentrates on the volatility of the negative returns, which is a consistent choice since, when investors think of risk, they appear to have a tendency to associate it with losses instead of gains. This ensues Markowitz's (1959) recommendation on semi-variance over variance as a more fitting risk indicator and fits in with available literature that affirms downside risk contributes to insights about future risk and returns with likes of Barndorff-Nielsen et al. (2010) and Patton and Sheppard (2015). Wang and Yan (2021) test on a sample of equity factors and market anomalies and find the downside volatility-managed strategies significantly outperform the ones scaled by total volatility. Curiously, they observe this improved performance is, for the most part, attributable to the downside volatility's negative correlation with future returns, rather than with future volatility. Hanauer and Windmüller (2023) directly compare Barroso and Santa-Clara's (2015), Daniel and Moskowitz's (2016) and Wang and Yan's (2021) volatility management approaches applied to the momentum strategy and verify their enhanced performance and reduction of momentum crashes' effects across U.S. and international equities, though no strategy stands out as persistently superior.

Few studies can be found covering volatility management of the momentum's strategy industry variation. Du Plessis and Hallerbach (2016) are the first to explore risk-management schemes in time-series and cross-sectional U.S. industry momentum, followed by Grobys, et. al (2018) and Grobys and Kolari (2020). Grobys et al. (2018) apply Barroso and Santa-Clara's (2015) constant volatility-scaling approach on Moskowitz and Grinblatt's (1999) industry portfolio setting, finding robust gains across different momentum formation periods and realized volatility estimation windows. They also explore for Daniel and Moskowitz's (2016) optionality effect in the industry setting and do not find consistent evidence that plain or volatility-managed industry momentum strategies are subject to such effects.

This study further contributes to the available literature relating to the industry form of the momentum strategy in the U.S. stock market and the management of its risk. More specifically, it extends Wang and Yan's (2021) research to the industry momentum strategy, examining how both the total and downside volatility-scaling schemes behave and are driven in this context and how it compares to the results of the same schemes originally applied to individual stock momentum.

3. Data

To construct the industry momentum strategy, all the necessary U.S. industry data is retrieved from the Kenneth French's Data Library, where I download the 49 Industry Portfolios daily and monthly returns from the period ranging from July 1926 to January 2023. These portfolios include all NYSE, AMEX and NASDAQ stocks, which are then assigned to industry portfolios according to their Compustat or CRSP SIC code and updated every year. From the same source, and for the same time frame, I obtain the 10 Portfolios formed on Momentum monthly and daily data, to get regular stock momentum returns, as well as the monthly Fama and French three risk factors and the one-month U.S. treasury bill rate.

The 10 Portfolios Formed on Momentum include the same set of stocks as the industry portfolios. They are built by ranking these stocks according to their returns from *t-12* until *t-2* (inclusive) and by subsequently distributing them into 10 groups in a value-weighted scheme, according to the NYSE decile breakpoints. The stock momentum strategy consists in going long in the highest decile portfolio and shorting the lowest one.

4. Methodology and Results

4.1. Industry Momentum

Following Novy-Marx's (2012) notation, I start by constructing three industry momentum strategies: the 12-2, the 6-2 and the 12-7. The *J-L* notation considers the interval from $t-J$ until $t-L$ (inclusive) as the formation period and the interval from t until $t+1$ as the holding period. That is, in the case of the 12-2 strategy, for example, the investor takes the available returns from *t-12* up until *t-2* (inclusive) as its formation period returns and holds the constructed portfolio from today until the next month, leaving a one-month interval between the formation and holding periods. The 12-2 is the classic momentum strategy usually analysed in most momentum studies, while the 6-2 and 12-7 check for momentum returns based on recent and intermediate past performance, respectively. Novy-Marx (2012) finds that not only most of momentum's gains in U.S. stocks are attributable to their intermediate horizon past performance, but that it also explains most of its recent horizon returns. In turn, Grobys et al. (2018) study these 3 momentum strategies and argue Novy-Marx's (2012) remarks are not observable in an industry momentum setting.

Taking the value-weighted 49 industry portfolios' monthly returns, I start by computing their excess returns and, at the beginning of every month, I calculate the formation period cumulative past excess returns for each strategy. The use of cumulative returns is in line with Grundy and Martin (2001), who describe the benefits of sorting according to cumulative as opposed to compounded returns. That is, using the 12-2 industry momentum strategy as an example, I rank stocks on $\sum_{\tau=t-12}^{t-2} r_{i\tau}$ instead of on $\prod_{\tau=t-12}^{t-2}(1 + r_{i\tau})$, where $r_{i\tau}$ represents the excess return of stock i in month τ.

Like Grobys et al. (2018), I sort the cumulative past returns into sextiles in an equal-weighting scheme, such that each group contains one sixth of the value-weighted industry portfolios, all equally combined within the group, in accordance with Moskowitz and Grinblatt (1999) who too construct equal-weighted groups of value-weighted industry portfolios.

The average monthly returns for each of the mentioned industry momentum strategies are presented in Table 1, below. Both the 12-2 and 12-7 generate statistically significant returns on a 1% level, while the 6-2 strategy fails to deliver significant returns. The highest return generating strategy is the 12-2, with a monthly payoff of 0.88% and a Newey and West (1987) t-statistic of 3.10, closely followed by the 12-7 strategy with 0.80% monthly returns and the same associated t-statistic of 2.74. The 6-2 momentum strategy based on short-term past performance underperforms the other strategies, in line with Novy-Marx (2012) findings that momentum based on intermediate past performance is more robust and persistent than momentum based on short-term past performance, however, against Grobys et al. (2018) who don't find any evidence of this phenomenon in their study.

Table 1: Momentum returns

This table reports the monthly average returns of the 12-2, 6-2 and 12-7 industry momentum strategies. The strategies were constructed by sorting cumulative past returns into six groups and the table presents each group's average monthly returns, as well as its average cumulative past returns. The sample of monthly returns used to build the strategies are from June 1926 to January 2023. In parenthesis are the associated Newey and West (1987) t-statistics, following Grobys et al. (2018), with a lag-order of three.

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**Winners - Losers**
Panel A: 12-2 Industry Momentum Strategy							
Monthly Returns	0.64	0.83	1.03	1.16	1.15	1.52	0.88***
Cumulative Past Returns	-13.94	-0.67	5.86	11.66	18.32	33.28	(3.10)
Panel B: 6-2 Industry Momentum Strategy							
Monthly Returns	0.82	1.01	0.99	1.06	1.14	1.29	0.47
Past Cumulative Returns	-10.60	-2.06	2.06	5.77	10.18	19.83	(1.17)
Panel C: 12-7 Strategy							
Monthly Returns	0.69	0.90	1.00	1.04	1.21	1.49	0.80***
Past Cumulative Returns	-11.27	-1.87	2.74	6.81	11.65	22.25	(2.74)

To test the statistical significance of each strategy's returns, like Grobys et al. (2018), I compute the Newey and West (1987) t-statistics. The traditional method of estimating standard errors assumes errors are independent and identically distributed, however Newey and West's (1987) approach takes into account potential autocorrelation and heteroskedasticity, an issue to look out for when working with time series data. Since the momentum strategy, as most financial time series data, presents pronounced heteroskedasticity, the latter provides a more robust adjustment to standard errors, ultimately making for a more accurate, though conservative, statistical test.

To provide a clearer picture and further assess the above computed industry momentum strategies' performance, I compare them with the regular stock momentum strategy and the Fama and French risk factors' performance in the last 95 years, from the period ranging between July 1927 to January 2023. Similar to Barroso and Santa-Clara's (2015) Table 1, Table 2 below reports the summary statistics for the mentioned strategies and risk factors.

Table 2: Summary statistics

This table compares the performance of the three mentioned industry momentum strategies – 12-2, 6-2 and 12-7 - with the regular stock momentum strategy, as well as the market (RMRF), size (SMB) and value (HML) Fama and French three risk factors. The reported values are calculated using monthly returns from the period ranging between July 1927 and January 2023. The reported values correspond to the sample's minimum and maximum one-month returns, the annualized average excess return and annualized standard deviation, the associated annualized Sharpe ratio, as well as the excess kurtosis and skewness, respectively.

Portfolio	Min	Max	Mean	Standard Deviation	Sharpe ratio	Excess kurtosis	Skewness
RMRF	-29.13	38.85	8.00	18.62	0.43	7.37	0.16
SMB	-17.23	36.56	2.40	11.03	0.22	18.57	1.83
HML	-13.95	35.61	4.22	12.38	0.34	18.39	2.11
Stock Momentum	-76.68	24.99	13.60	27.43	0.50	15.94	-2.24
Industry Momentum							
12-2 Strategy	-63.04	19.02	10.54	17.87	0.59	24.13	-2.15
6-2 Strategy	-63.22	20.77	5.68	17.12	0.33	28.77	-2.67
12-7 Strategy	-55.14	24.69	9.61	16.53	0.58	20.35	-1.63

The 12-2 and 12-7 industry momentum strategies yield lower average returns than the regular stock momentum, with annual returns of 10.54% and 9.61% versus 13.60%, respectively. They produce higher minimum returns but slightly lower maximum returns. However, given their significantly lower standard deviation, they offer a higher Sharpe ratio: the 12-2 strategy holds the highest Sharpe ratio of 0.59, closely followed by the 12-7 with a Sharpe ratio of 0.58.

When comparing the industry momentum strategies with the individual stock momentum, their pronounced excess kurtoses stand out: the industry momentum strategies present fatter tails - higher chance of getting more extreme returns. The fact that industry portfolios may exhibit a stronger correlation with macroeconomic variables, economic cycles and shocks, as well as industry-specific events, which have a similar impact on all companies operating within the same industry, is one possible explanation for this increase in excess kurtosis in an industry momentum setting. This can ultimately lead to an increase in the co-movement between individual stocks within the industries and the effects of shocks may be intensified, generating more extreme returns for industry portfolios.

As for skewness, though the 12-2 and 12-7 appear to somewhat ameliorate it, the industry momentum strategies continue to display one of momentum's main problems: its negative skewness.

4.2. Realized volatility of industry momentum

One of the momentum's strategy main characteristics is its time-varying risk. Grundy and Martin's (2001) research suggests that the risk of the momentum strategy fluctuates depending on market circumstances and stock characteristics over time: during optimistic market conditions in the formation period, winner stocks tend to possess high betas and loser stocks low betas, and vice versa during unfavourable market states. Therefore, the momentum strategy, as a whole, presents a positive beta after bull markets, while it exhibits a negative beta after opposite market conditions.

In their research, Engle (1982) and Bollerslev (1987) find excess kurtosis plays a significant role and may be one of the definers of time-varying risk in financial markets. Barroso and Santa-Clara (2015) see this as an opportunity to create a volatility-scaled approach to the momentum strategy, along with other studies conducted surrounding volatility management of trading strategies. While most studies focus on total volatility, Wang and Yan (2021) specifically concentrate on the management of downside volatility, following research indicating that downside risk is a more suitable measure of risk and that it can provide useful insight into future volatility and returns. In this study, I start by replicating Grobys et al.'s (2018) industry momentum total volatility-management approach and further investigate Wang and Yan's downside volatility management scheme in an industry momentum setting.

In the following sections of this study concerning the volatility-management of the industry momentum strategy, I mainly focus on the strategy built using the classic 12-2 scheme. This makes for a more direct assessment of the industry momentum strategy's performance when compared to individual stock momentum, formed under the same formation periods. Like mentioned in Section 3, I use the Kenneth French 10 Portfolios Formed on Momentum to compute the regular individual stock momentum returns, where they consider the time period ranging between *t-12* and *t-2* (inclusive) as the strategy's formation period.

Firstly, like Barroso and Santa-Clara (2015), and following Grobys et al.'s (2018) approach, I start by computing the strategy's realized variance estimator for each month:

$$RV_t = \sum_{i=0}^{D_t} r_{it}^2 \tag{1}$$

RV_t represents the realized variance in month *t*, D_t the exact number of trading days in month *t* and r_{it}^2 the squared daily returns of the momentum strategy over said trading days of month *t*. The number of trading days over the sample period and its plot can be found in Appendix 1 – Figure 1A, in the appendices section.

As for the downside realized variance, I follow Wang and Yan's (2021) methodology, which is similar to the previous approach but, instead of considering all the returns in a month, it exclusively ponders each month's negative daily returns. That is:

$$\mathrm{RV}_t^{down} = \sum_{i=0}^{D_t} r_i^2 * I_{[r_i<0]} \tag{2}$$

where RV_t^{down} is the realized downside variance in month *t*, D_t the number of trading days in month *t* and $I_{[r_i<0]}$ is a dummy variable that takes the value of one if the return of the strategy in day *i* is negative, and the value of zero, otherwise.

To convert the realized variance into realized volatility, I first scale each month's realized variance and realized downside variance by that month's number of trading days and multiply it by 21, in order to get a standardized volatility measure for all months:

$$\sigma_{total,t} = \sqrt{\mathrm{RV}_t^*} \quad \text{, where} \quad \mathrm{RV}_t^* = 21 * \frac{RV_t}{D_t} \tag{3}$$

$$\sigma_{down,t} = \sqrt{RV_t^{down^*}} \quad \text{, where} \quad RV_t^{down^*} = 21 * \frac{RV_t^{down}}{D_t} \tag{4}$$

As opposed to Barroso and Santa-Clara (2015) that use a six-month window to calculate the strategy's realized variance, I solely use last month's daily returns in my computations. I follow Grobys et al.'s (2018) findings that the performance of the risk-managed industry momentum strategies increases as the timeframe for estimating the realized variance contracts. In their study, the authors try out three different volatility estimation windows – one, three and six months – and observe consistent evidence that using the one-month time frame generate higher gains than the three and six-month windows.

Figure 1 below plots both the total and downside monthly realized volatilities for the 12-2 industry momentum and individual stock momentum strategies, over the sample period ranging from January 1930 to January 2023.

Figure 1: Realized volatility of momentum

Figure 1A: Monthly total realized volatility of the individual stock momentum strategy
Figure 1B: Monthly total realized volatility of the 12-2 industry momentum strategy
Figure 1C: Monthly downside realized volatility of the individual stock momentum strategy
Figure 1D: Monthly downside realized volatility of the 12-2 industry momentum strategy

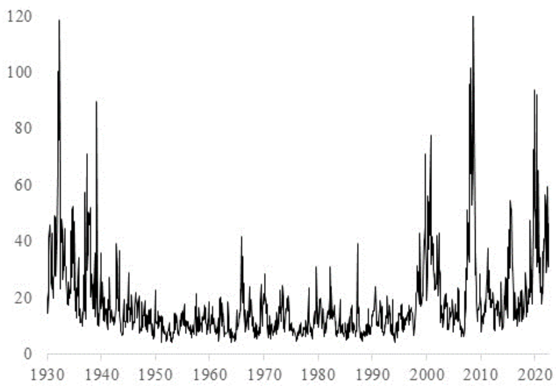

Figure 1A

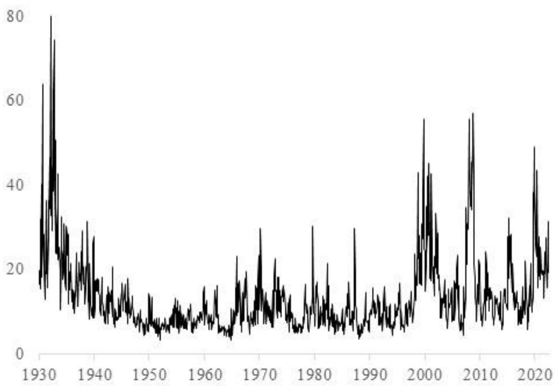

Figure 1B

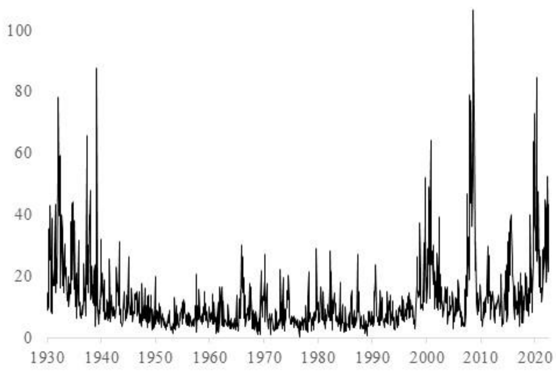

Figure 1C

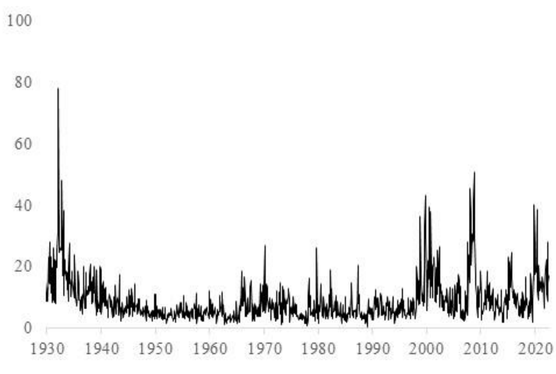

Figure 1D

It is clear from the figures above that both industry momentum's total and downside realized volatilities are considerably lower than the ones produced by individual stock momentum strategy.
On industry momentum, we are investing according to the industries' performance as a whole, rather than betting on particular individual stock movements. The industry momentum strategy is far less vulnerable to firm-specific news and events, instead, it is more affected by macroeconomic factors and industry trends, which are less volatile and more predictable overall. Thus, it would make sense that it ultimately results in a more stable performance since, as can be seen by the found realized volatilities, it requires more sustained movements within the industries as a whole rather than singular variations in individual stocks.
The average total and downside realized volatilities for the 12-2 industry momentum strategy are, in percentage terms, 13.42 and 9.01, respectively, while for the individual stock momentum they are 18.17 and 12.44. It seems that the industry momentum realized volatilities and those of the individual stock momentum showcase similar patterns, peaking around similar time periods. Curiously, the individual stock momentum realized volatilities are at their highest during the 2007-2009 crisis, while the industry momentum's most dramatic realized volatility peaks happen at the beginning of the sample, during the Great Depression period.

4.3. Risk-managed industry momentum

Just like proposed by Barroso and Santa-Clara (2015), I use the computed realized volatilities as an estimate of momentum risk. I then scale the exposures to the strategies in order to have a constant risk level over time. For every month *t*, I take last month's realized volatility as my volatility forecast, that is:

$$\hat{\sigma}_{total,t} = \sigma_{total,t-1} \tag{5}$$

$$\hat{\sigma}_{down,t} = \sigma_{down,t-1} \tag{6}$$

Since the industry momentum strategy is a zero-cost strategy, I can scale it without restrictions and use the forecasted volatility to scale the returns as:

$$r_t^* = \frac{\sigma_{target}}{\hat{\sigma}_t} r_t \ , \tag{7}$$

where r_t is the unscaled industry momentum return in month *t*, r_t^* is its risk-managed counterpart in the same month, σ_{target} is a constant corresponding to the target level of volatility and $\hat{\sigma}_t$ the forecasted volatility in that same month (either total volatility or downside volatility, according to the chosen risk-management strategy).

This dynamic scaling scheme can be looked at as a leverage measure: when realized volatility is lower than the target volatility, we leverage our investment on the strategy, while when it is higher, we decrease our investment. Figure 2 plots the unconstrained weights for the total and downside risk-managed individual stock and industry momentum strategies, computed using the corresponding realized volatilities in the previous month.

Like Wang and Yan (2021), the target volatility is selected so that the full-sample volatility is the same for both the scaled and unscaled strategies, which makes for an easier comparison between methods. This can raise some issues since σ_{target} is not observable by investors in real time, but the choice of the target ultimately has no considerable effect on the overall strategies' performance and conclusions. Furthermore, given the following analysis using spanning regressions and alpha decomposition, it is important that the same ex-post level of volatility is maintained to ensure comparability between the different managed strategies.

Figure 2: Scaled momentum weights

Figure 2A: Total volatility individual stock momentum weights
Figure 2B: Total volatility 12-2 industry momentum weights
Figure 2C: Downside volatility individual stock momentum weights
Figure 2D: Downside volatility 12-2 industry momentum weights

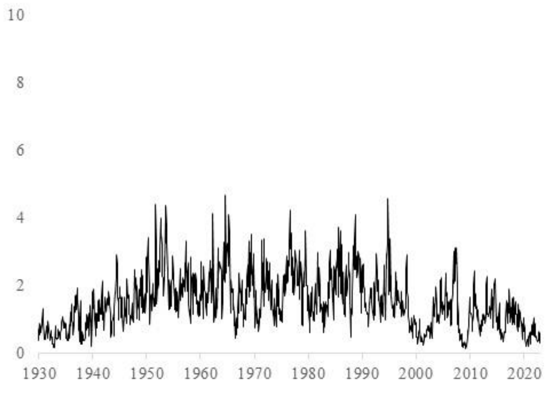

Figure 2A

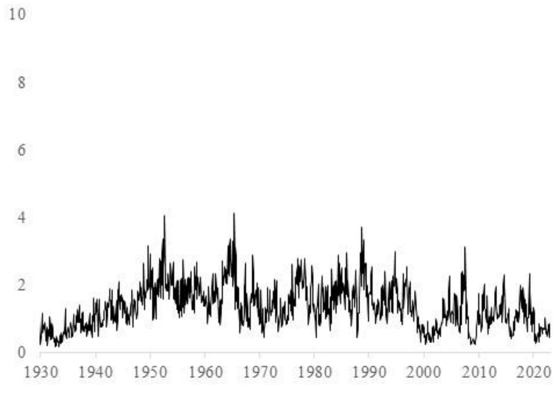

Figure 2B

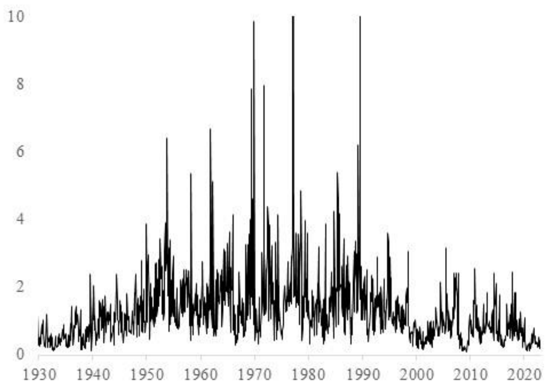

Figure 2C

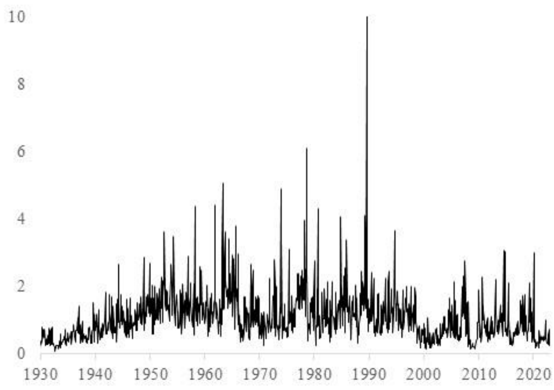

Figure 2D

The average weight for the total volatility-managed industry momentum strategy is of 1.34, with a minimum weight of 0.17 and maximum leverage of about 4.14. In turn, the obtained weights for the downside volatility-managed strategy suggest much more extreme positions in the industry momentum strategy, with positions ranging between 0.08 up to 10.13, raising questions about the strategies applicability once considering practical limitations, such as trading costs or leverage constraints.

Assuming the same volatility target for both the industry and individual stock momentum strategies, it would be expected that the industry momentum strategies' weights would be much more extreme given their lower realized volatilities. Since the target volatilities are chosen such that the volatility-managed strategies' ex-post volatilities and the one of the corresponding plain strategy are the same, and given that the plain industry momentum and individual stock momentum strategies possess different volatilities (17.87% and 27.37%, respectively), comparing these weights does not provide any conclusions. However, one thing can be noted: the weight patterns of the analogous volatility-managed schemes on industry momentum and the individual stock momentum strategies are relatively similar.

These radical weights of up to 10.13 are not realistic to actual investors in the stock market due to issues like liquidity constraints or even regulatory restrictions. Therefore, to compute what a more realistic strategy to investors would look like, like Moreira and Muir (2017) and Barroso and Detzel (2021), I apply a weight constraint to the computed volatility-managed strategies that caps the strategy's leverage at 1.50, also known as the standard margin constraint.

Table 3 below showcases the summary statistics of the total and downside volatility-scaled industry momentum strategies, alongside the analogous individual stock momentum managed strategies and their unscaled counterparts, all in the analysed period of August 1927 to January 2023. I include the results for both the unconstrained and leverage constrained volatility-managed strategies.

Table 3: Scaled industry momentum summary statistics

This table reports the descriptive statistics of the 12-2 total volatility-managed industry momentum (T-vol.), the 12-2 downside volatility-managed industry momentum (D-vol.), along with its original unscaled version. I also include the total and downside volatility-scaled individual stock momentum, as well as its unmanaged version, as mean of comparison. Panel A shows the unconstrained results and Panel B the results accounting for a 1.50 leverage constraint. The considered sample period is from August 1927 to January 2023. The reported mean, standard deviation and Sharpe ratio are annualized.

	Min	Max	Mean	Standard Deviation	Sharpe ratio	Excess kurtosis	Skewness
Panel A: Unconstrained							
Industry Momentum							
T-vol. managed	-28.85	21.72	14.55	17.87	0.81	1.38	-0.17
D-vol. managed	-29.77	66.24	12.68	17.87	0.71	30.07	2.46
Unmanaged	-63.04	19.02	10.54	17.87	0.59	24.13	-2.15
Stock Momentum							
T-vol. managed	-42.44	33.71	25.64	27.43	0.93	1.92	-0.33
D-vol. managed	-39.81	92.33	23.00	27.43	0.84	18.47	1.43
Unmanaged	-76.68	24.99	13.51	27.43	0.49	15.95	-2.24
Panel B: Including 1.50 leverage constraint							
Industry Momentum							
T-vol. managed	-29.69	20.31	13.90	17.87	0.78	1.79	-0.27
D-vol. managed	-22.72	24.41	13.69	17.87	0.77	1.44	-0.08
Stock Momentum							
T-vol. managed	-56.36	30.21	20.88	27.43	0.76	3.78	-0.78
D-vol. managed	-67.89	30.21	20.04	27.43	0.73	6.80	-1.06

In line with the vast existing literature on volatility-management, scaling the momentum strategy by its past volatility, whether in its individual stock momentum setting or industry portfolio variation, creates value for investors. As shown by the table above, for the same level of volatility, all the risk managed strategies present higher average returns than their unmanaged counterparts. This ultimately generates more attractive risk-to-reward trade-offs for investors, as demonstrated by their higher Sharpe ratios. Managing momentum's risk also produces, overall, higher minimum returns, as well as higher maximum returns. It dramatically decreases the registered excess kurtosis, nearly eliminating momentum's tail risk associated with extreme returns (except for downside volatility-managed unconstrained strategies) and assists its negative skewness problem by lowering it (in absolute values) or even turning it into positive skewness.

Downside volatility-managed strategies do not appear to outperform those scaled by total volatility. Wang and Yan (2021) provide empirical evidence supporting the significant outperformance of portfolios scaled by downside volatility, in relation to total volatility, across various equity factors and market anomalies, however, the momentum factor is not one of them. I also find no evidence this happens in both the industry and individual stock momentum: though all the managed strategies, whether constrained or unconstrained, produce higher risk-to-reward ratios than the unmanaged strategies, the ones that scale momentum by recent past downside volatility do not outperform those scaled by total volatility. Recent research conducted by Hanauer and Windmüller (2023), examining the effects of different volatility-scaling methods in a momentum setting, register similar results: in their analysis of volatility-managed stock momentum strategies, in U.S. and non-U.S. samples, the authors do not indicate any evidence that downside volatility-scaled momentum yields a superior risk-adjusted performance than total volatility-scaled momentum. It seems that downside volatility alone may not adequately capture the full risk associated with the momentum strategy - total volatility may represent a more complete measure of risk, since it includes both upside and downside risk, and, as a result, provide a better performance when used in volatility management schemes. Additionally, it is also possible to see that the individual stock momentum strategies seem to benefit more, performance wise, from volatility management schemes than industry momentum ones: they showcase higher relative increases in their Sharpe ratios from the unmanaged to the managed strategies.

Examining the unconstrained versions of the volatility-scaled strategies, in Panel A, it is clear that the individual stock momentum reaps the biggest rewards from volatility management. It produces the highest Sharpe ratios – 0.93 and 0.84 – as well as the highest relative increases from the original risk-to-reward measure – around 90% and 70% for total and downside volatility-management, respectively. The total volatility-managed strategies produce better Sharpe ratios and better excess kurtosis estimates, dramatically lower than those of the plain strategies. Those scaled by downside volatility, however, though they produce higher excess kurtosis than the original strategies, register a considerable increase in skewness, completely fixing momentum's issue with the left tail of its return distribution.

Though these results are promising and represent great potential for the strategies' improvement in both industry and individual stock context, they are unrealistic for investors trading in the market given their extreme leverage needs.

Looking at Panel B, it seems that, when controlling for the maximum leverage investors take on, the volatility-managed industry momentum strategies actually exhibit a better performance than those of the individual stock momentum. The total volatility-managed industry momentum strategy registered the best performance in the analysed period, with average annual gains of 3.36 percentage points versus its plain counterpart, and an associated Sharpe ratio of 0.78, closely followed by its downside volatility-managed version with a Sharpe ratio of 0.77. Though the total volatility-managed industry momentum strategy produces the highest Sharpe ratio of 0.78, a 31.8% increase when compared with the Sharpe ratio of the unmanaged strategy, the total volatility-managed individual stock momentum registered the highest Sharpe ratio improvement, with an increase of around 54.5%. Despite the fact that managed industry momentum strategies display a superior performance, the analogous individual stock momentum ones are shown to benefit more substantially from the studied volatility-management schemes once again, generating more pronounced improvements in mean returns and associated Sharpe ratios.

Further analysing the constrained industry momentum strategies, the gains of managing for downside volatility instead of total volatility show up in the higher-order statistical moments. Its excess kurtosis is lower than the total volatility-managed strategy's excess kurtosis by about 20%, while its negative skewness is nearly eliminated and only represents about 29% of the skewness of the strategy scaled by total risk. This differs from what is observed on the scaled individual stock momentum, where the total volatility-managed strategy exhibits both a better risk-adjusted performance and more favourable estimates for high-order moments.

Overall, without any leverage constraints, volatility-management of industry momentum does not outperform the analogous schemes applied on individual stock momentum. However, in more realistic conditions, controlling for a 1.50 maximum leverage, both its total and downside volatility-scaled strategies not only seem to generate higher Sharpe ratios than the individual stock momentum strategy, but also better higher-order moments estimates.

4.4. Spanning regressions

To further assess the performance of the momentum strategies deriving from volatility management schemes, like Wang and Yan (2020), I start by following Moreira and Muir's (2017) approach of using spanning regressions on volatility-scaled portfolios. These time-series regressions consist in regressing the volatility-managed strategies' returns on the contemporary unmanaged strategy's returns:

$$r_t^{managed} = \alpha + \beta * r_t + \epsilon_t, \tag{8}$$

where $r_t^{managed}$ corresponds to the risk-managed industry momentum returns (either using total - $r_t^{total^*}$ - or downside - $r_t^{down^*}$ - volatility) and r_t the plain industry momentum returns. Given the superior performance of the analysed volatility-managed strategies, one can expect that these regressions generate a positive alpha when compared to their unmanaged counterparts: a positive alpha suggests volatility management raises the Sharpe ratio of the original strategy.

The results of the spanning regressions for both the total and downside volatility-managed momentum strategies are shown in table 4 below. Similar to Wang and Yan (2020), I also control for the Fama and French (1993) 3 factors, which offers a clearer picture of the strategies' true performance. Additionally, to provide a more robust statistical test, I display the estimates' associated t-statistics based on White (1980) standards errors. I include the regressions for both the constrained and unconstrained versions of the volatility-managed strategies.

Table 4: Spanning regressions on unmanaged strategies

This table reports the results from the time-series regressions of the total and downside volatility managed momentum strategies on the unmanaged ones, represented by equation (8). Panel A reports the results for the unconstrained strategies and Panel B those with a 1.50 leverage constraint. Panels A1 and B1 report the results for the total volatility-managed strategies and Panels A2 and B2 the ones for the downside volatility-managed. The Fama and French (1993) three factors are also included as additional controls in the regressions. The strategies' return sample considers the period ranging from August 1927 to January 2023. The reported alphas are annualized and in percentage terms. T-statistics based on White (1980) standard errors are represented in parentheses.

	Industry Momentum		**Stock Momentum**	
	Univariate	Controlling for FF3	Univariate	Controlling for FF3
Panel A: Unconstrained				
Panel A1: Results from $r_t^{total^*} = \alpha + \beta * r_t + \epsilon_t$,				
Alpha, α	5.68	4.56	14.81	11.53
	(4.07)	(4.15)	(7.10)	(6.31)
Beta, β	0.84	0.87	0.80	0.88
	(12.23)	(15.50)	(13.54)	(19.80)
R^2	0.71	0.72	0.64	0.67
Panel A2: Results from $r_t^{down^*} = \alpha + \beta * r_t + \epsilon_t$,				
Alpha, α	5.40	4.38	14.00	11.33
	(3.44)	(3.42)	(5.95)	(5.25)
Beta, β	0.69	0.71	0.67	0.73
	(9.01)	(11.03)	(11.13)	(16.29)
R^2	0.48	0.49	0.44	0.46
Panel B: Including 1.5 leverage constraint				
Panel B1: Results from $r_t^{total^*} = \alpha + \beta * r_t + \epsilon_t$,				
Alpha, α	4.42	3.41	8.81	6.09
	(3.53)	(3.57)	(4.84)	(4.04)
Beta, β	0.90	0.92	0.89	0.96

	(13.54)	(16.98)	(14.92)	(21.82)
R^2	0.81	0.82	0.80	0.82
Panel B2: Results from $r_t^{down^*} = \alpha + \beta * r_t + \epsilon_t$,				
Alpha, α	4.40	3.33	8.21	5.48
	(3.10)	(3.20)	(4.07)	(3.56)
Beta, β	0.88	0.91	0.88	0.94
	(11.26)	(14.20)	(12.86)	(20.11)
R^2	0.78	0.79	0.77	0.78

All volatility management schemes generate significant and positive alphas relative to their plain counterparts. The alphas for the unconstrained versions in Panel A are higher, while the betas relative to the plain strategy and R-squared estimates are lower than the corresponding ones in Panel B. These results make sense since we are looking at the volatility-management schemes' true performance, and not a capped version that may distort its more extreme outcomes that truly characterize the volatility-managing schemes.

For both the constrained and unconstrained forms, the total volatility-managed strategies generate a higher alpha with a higher associated t-statistic than the downside volatility-managed ones. Subsequent analysis controlling for the Fama and French (1993) three risk factors in addition to the unmanaged strategy, which help isolate the specific differences in performance between the analyzed strategies, deliver the same conclusions. The previous observation regarding the fact that volatility-management provides a larger upsurge in performance for the individual stock momentum strategy is now visible in the higher t-statistics compared with those of industry momentum.

Now comparing the alphas of total versus downside volatility-scaling, the relative difference between the alphas is higher for the stock momentum strategy: while the constrained downside industry momentum alpha is only 0.43% lower (0.45% in the capped version) than that of the total volatility-managed strategy, the stock momentum downside alpha is 6.73% lower (6.81%% in the capped version). This suggests that though the downside volatility-managed strategies do not outperform the ones scaled by total volatility, they appear to work relatively better in the industry momentum context than for the individual stock momentum.

To explore in greater depth the relationship between total and downside volatility-scaled strategies, I apply Wang and Yan's (2021) alternative spanning regressions that regress the volatility-managed strategies on one another – equations (9) and (10) – and additionally on the unmanaged counterpart – equations (11) and (12).

$$r_t^{total^*} = \alpha + \beta * r_t^{down^*} + \epsilon_t, \tag{9}$$

$$r_t^{down^*} = \alpha + \beta * r_t^{total^*} + \epsilon_t, \tag{10}$$

$$r_t^{total^*} = \alpha + \beta_1 * r_t^{down^*} + \beta_2 * r_t + \epsilon_t, \tag{11}$$

$$r_t^{down^*} = \alpha + \beta_1 * r_t^{total^*} + \beta_2 * r_t + \epsilon_t, \tag{12}$$

I report the results for the equations stated above, applied to the unconstrained volatility-managed strategies, in Table 5.

The regression results for the constrained strategies are presented in Table 1 of the Appendix. Capping the weights of the volatility-managed strategies takes away from more extreme outcomes that significantly differentiate the strategies between each other, making the strategies highly correlated: when regressing the constrained strategies on one another, unrealistic R-squared estimates of above 0.97 and mostly insignificant alpha estimates are observed, which hinder the ability to draw any meaningful conclusions about the relationship between the strategies.

Table 5: Spanning regressions on unconstrained managed strategies

This table reports the results from the time-series regressions of the total and downside volatility managed momentum strategies on each other and on the plain strategy, as represented by equations (9) through (12). Panel A reports the results for the total volatility-managed strategies regressed on the downside volatility-managed strategies and Panel B the opposite. Panels C and D present the results for the two previous regressions, but also accounting for their unmanaged counterpart, represented by equations (11) and (12). The Fama and French (1993) three factors are also included as additional controls in the regressions. The strategies' return sample considers the period ranging from August 1927 to January 2023. The reported alphas are annualized in percentage terms. T-statistics based on White (1980) standard errors are represented in parentheses.

Portfolio	**Industry Momentum**		**Stock Momentum**	
	Equation	Controlling for FF3	Equation	Controlling for FF3
Panel A: Results from $r_t^{total^*} = \alpha + \beta * r_t^{down^*} + \epsilon_t,$				
Alpha, α	3.46	3.89	5.13	6.56
	(3.10)	(3.54)	(3.25)	(3.85)
Beta, β	0.88	0.87	0.89	0.87
	(9.60)	(9.56)	(11.24)	(10.82)
R^2	0.77	0.77	0.80	0.80
Panel B: Results from $r_t^{down^*} = \alpha + \beta * r_t^{total^*} + \epsilon_t,$				
Alpha, α	-0.06	-0.21	0.13	-0.17

	(-0.08)	(-0.32)	(0.13)	(-0.17)
Beta, β	0.88	0.88	0.89	0.90
	(21.63)	(21.45)	(31.37)	(32.46)
R^2	0.77	0.77	0.80	0.80
Panel C: Results from $r_t^{total^*} = \alpha + \beta_1 * r_t^{down^*} + \beta_2 * r_t + \epsilon_t$,				
Alpha, α	2.65	2.14	5.80	4.43
	(3.43)	(3.16)	(4.61)	(4.05)
Beta 1, β_1	0.56	0.55	0.64	0.63
	(6.04)	(6.06)	(7.08)	(6.98)
Beta 2, β_2	0.45	0.47	0.37	0.42
	(6.58)	(7.18)	(5.87)	(6.29)
R^2	0.87	0.88	0.87	0.88
Panel D: Results from $r_t^{down^*} = \alpha + \beta_1 * r_t^{total^*} + \beta_2 * r_t + \epsilon_t$,				
Alpha, α	-0.33	-0.22	-0.83	-0.31
	(-0.50)	(-0.35)	(-0.84)	(-0.31)
Beta 1, β_1	1.01	1.01	1.00	1.01
	(14.79)	(14.23)	(20.20)	(18.93)
Beta 2, β_2	-0.16	-0.16	-0.14	-0.16
	(-4.05)	(-3.77)	(-4.33)	(-3.74)
R^2	0.77	0.77	0.80	0.80

Given the total volatility-managed strategies' superior performance, as expected, all the alphas generated by equations (9) and (11) are positive and significant, even after controlling for the Fama and French (1993) three factors. The ones generated by equations (10) and (12), however, are mostly negative and insignificant, with the exception of the positive one produced by the stock momentum strategy on Panel B, in line with the results obtained by Wang and Yan (2021), who too obtain a positive and insignificant alpha estimate for the same regression in their downside volatility-managed momentum.

These results show a clear advantage for overall total volatility-managed strategies. Strategies scaled by total volatility cannot be fully explained by those managed using downside volatility, supporting once again the notion that total volatility poses for a more complete measure of momentum's risk. On the other hand, the results for the downside volatility-managed strategies' regressions indicate that they are in fact spanned by those managed by total volatility and therefore do not offer investors any further advantages over the strategies scaled by total volatility.

Though not statistically reliable, the results obtained using the constrained strategies, in the Appendices section Appendix 2 – Table 1A, offer similar conclusions regarding the insignificant alpha estimates for the downside volatility-managed strategies' regressions and positive significant alphas for the total volatility-scaled stock momentum. The total volatility-managed industry momentum strategy, however, only presents both significant positive alphas after controlling for the Fama and French (1993) risk factors.

4.5. Alpha decomposition

According to Wang and Yan (2021), a positive alpha generated by the spanning regressions of volatility-managed strategies on their unmanaged counterpart can arise due to 3 possibilities: volatility timing, return timing, or a combination of both.

For the use of a volatility-management scheme on a strategy to be consistent with an increase in performance, it is expected that past volatility is positively related to future volatility (volatility timing) and that it is either uncorrelated or negatively related to future returns (return timing). Volatility timing is likely to be confirmed, due to the widespread phenomenon in finance studies commonly referred to as volatility clustering. However, for return timing, the relationship between volatility and returns seems to be unclear in the existing literature.

Following Wang and Yan's (2021) methodology, I use the authors' spanning regression alpha decomposition method, shown in equation (13), to evaluate the separate roles of return and volatility timing on the managed strategies.

$$\hat{\alpha} = \left(1 + \frac{E^2(r_t)}{var(r_t)}\right) * cov(w_t\ ,\ r_t) - \frac{E(r_t)}{var(r_t)} * cov(w_t\ , r_t^2)\ , \tag{13}$$

w_t are the weights used on the volatility-managed strategy for month *t* and r_t are the returns of the corresponding unmanaged momentum strategy. $E(r_t)$ and $var(r_t)$ are the expected return and variance of the unmanaged strategy.

The return timing component is $RT = \left(1 + \frac{E^2(r_t)}{var(r_t)}\right) * cov(w_t\ ,\ r_t)$, while the volatility timing component corresponds to $VT = -\frac{E(r_t)}{var(r_t)} * cov(w_t\ , r_t^2)$. Return timing is determined by the covariance between the weights used on the volatility-managed strategies and its returns, while volatility timing is subject to the covariance between the weights and the returns' variance.

Table 6 reports the alpha decomposition in return and volatility timing for both the industry and the individual stock momentum strategies. Panel A presents the alpha decompositions for the unconstrained total and downside volatility-managed strategies, while Panel B showcases those for the constrained strategies.

Table 6: Alpha decomposition

This table reports the Table 4 alpha's decomposition into return and volatility timing for both the total and downside volatility-managed strategies, following the methodology described in equation (13). Panel A presents the return and volatility timing components of the alphas generated by the unconstrained managed strategies, while Panel B does so for the constrained ones. The alphas are annualized and stated in percentage terms.

	Industry Momentum	**Stock Momentum**
Panel A: Unconstrained		
Panel A1: Total volatility-managed strategy		
Return Timing	0.41	5.43
Volatility Timing	5.27	9.38
Total	5.68	14.81
Panel A2: Downside volatility-managed strategy		
Return Timing	1.36	5.66
Volatility Timing	4.04	8.34
Total	5.40	14.00
Panel B: Including 1.5 leverage constraint		
Panel B1: Total volatility-managed strategy		
Return Timing	0.76	3.21
Volatility Timing	3.66	5.60
Total	4.42	8.81
Panel B2: Downside volatility-managed strategy		
Return Timing	0.63	2.66
Volatility Timing	3.77	5.55
Total	4.40	8.21

As seen in the table above, the positive spanning regression alphas resulting from the volatility-management of momentum strategies arise from both positive return and volatility timing. In Wang and Yan's (2021) research, while most of the studied factors and anomalies present negative return timing, the authors find that the momentum factor is one of the few that exhibits a positive return timing component for both the total and downside volatility-managed versions, which explains why momentum works so well when subject to volatility management.

The overall attained spanning regressions' positive alphas arising from the volatility-management of the momentum strategies mainly come from its volatility timing component. This effect of volatility timing seems to be even more prevalent on the industry momentum strategies, where it accounts for more than 75% of the total spanning regression alphas, while on the individual stock momentum context it stands for around 65% of the total alpha.

Interestingly, though the total and downside volatility-managed strategies are strongly correlated, their ability to predict returns is quite distinct. Examining Panel A, in the scaled strategies' unconstrained pure form, controlling for downside instead of total volatility results in an increase in the spanning regression alpha's return timing component. For the industry momentum strategy, it increases from a 7% return timing component in the total volatility-scaling scheme to 25% in the downside volatility. As for stock momentum, it goes from 37% to 40%. This is in line with Wang and Yan's (2021) findings that managing a strategy by its downside rather than its total risk is mainly reflected in the return timing component. While this increase in return timing results in a superior performance for most of the factors and anomalies studied by the authors, it is not the case for their momentum factor, which exhibits a worse performance when scaled by downside volatility.

When controlling for the volatility-managed strategies' leverage, the opposite is observed: controlling for downside volatility actually decreases the spanning regression alpha's return timing component, from 17% to 14% on industry momentum and 37% to 32% on stock momentum. It seems that capping the strategies' weights restricts the downside volatility-management's enhancement of the return timing component.

5. Limitations

Like any research, this study presents limitations that should be taken into consideration when examining its specific findings.

One of the main limitations observed throughout this study is the presence of leverage constraints to real participants in the market. Whether related to liquidity or regulatory constraints, it poses as a barrier for investors, making them unable to extract the volatility-managed strategies' full potential. For real life implementation, a leverage constraint mechanism needs to be put into action, however, the choice of leverage capping limit or method may considerably alter the observed outcomes. For example, in this study, it was found that, for a 1.50 leverage constraint, the industry momentum strategies actually outperform the stock momentum ones and the downside volatility-managed industry momentum strategy positively benefited from this leverage constraint. However, selecting a slightly different weight cap might alter these results and generate different findings and conclusions.

Another limitation stems from the fact that this study solely focuses on the volatility-management of the industry momentum strategies in the U.S. stock market context, which does not guarantee that the same results and conclusions are extended to other markets and geographies under different dynamics and macroeconomic conditions.

When analysing momentum strategies, one thing to keep in mind are trading costs. These can significantly erode the strategies' performances given the high levels of trading activity necessary to continuously rebalance the portfolios according to new performance information. In fact, Moskowitz and Grinblatt (1999) suggest that, in the case of industry momentum, this can stand as a problem: stocks in the winner and loser industries may be more volatile than the ones on the industries in-between, possibly causing a temporary increase in trading costs for the stocks included in the momentum strategy. For example, Grobys et al. (2018) control their three total risk-managed strategies for trading costs and find that, after accounting for such costs, only two of them benefit from volatility-scaling. Going even further than trading costs, another issue to look out for regarding the momentum strategy is the price impact of very large trades: executing large orders can have an impact on market dynamics and consequently generate considerable stock price fluctuations. Barroso and Detzel (2021) provide evidence on the robustness of returns of volatility-managed momentum strategies after considering trading costs, however, the authors find their performance is constrained in its capacity due to price impacts.

6. Further research

This study leaves space for further research to shed additional insights on the present results. One possible route would be to also study the effects of controlling for upside instead of downside volatility. As seen by the results of this study supported by existing literature, it seems the downside volatility-scaling scheme does not provide any enhanced performance to the momentum strategy and is in fact spanned by the total volatility-scaled strategy. It would be interesting to see how controlling for upside volatility compares with the total and downside schemes and the effects it produces on both individual stock and industry momentum.

Another path could be further exploring other levels of leverage constraints on the industry momentum volatility-managed strategies and assess how downside volatility would respond. More interestingly, one could also explore other ways of constraining the strategies instead of simply imposing a fixed cap throughout the full studied sample, for example, by extending Wang and Yan's (2021) further analysis on their study of volatility-managed factors and market anomalies.

In line with the above mentioned limitations, another possible further research area could be testing whether the enhanced performance of the studied downside volatility-managed industry momentum strategy persists under the presence of trading costs and price impacts. Particularly, by incorporating these matters on the leverage constrained versions, one can get an even better assessment of the strategy's feasibility for real-life investors in the stock market.

7. Conclusion

The momentum strategy, along with its many variations, is one of the most extensively covered strategies in modern finance literature given its wide pervasiveness and the great potential it presents to investors in the market.

Along with available literature, I find the industry momentum strategy, built by betting in industries as whole instead of individual stocks, offers investors better risk-to-reward estimates in the analysed sample, for the strategies built using the 12-2 and 12-7 formation periods. However, though these strategies are far less volatile than the individual stock momentum, they showcase higher tail risk.

This appears to be a problem within momentum strategies possibly explained by its time-varying risk, which makes them extremely problematic in periods of transition between market states. Mitigating a strategy's risk using volatility-management schemes is known to be extremely effective when applied to momentum strategies: it generates substantial gains in performance and nearly eliminates crash risk, as reported by Barroso and Santa-Clara (2015).

This study aims to analyse the performance of two volatility-management schemes on an industry momentum setting: total volatility-scaling, as proposed by Barroso and Santa-Clara (2015), and a variation of this approach using solely negative returns, downside volatility, recently studied by Wang and Yan (2021).

Firstly, as expected, managing industry momentum's risk creates value for investors: it generates higher payoffs than its plain counterpart. However, industry momentum doesn't seem to benefit as abundantly from volatility-management as the individual stock momentum strategy, that is, the relative gains in performance associated with the analogously managed stock momentum strategies are higher, as well as the actual performance estimates. Interestingly, managed industry momentum actually outperforms individual stock momentum when controlling for a leverage constraint of 1.50. Therefore, for real investors in the market, industry momentum actually poses for a better choice as far as implementation goes.

Secondly, in line with Wang and Yan's (2021) findings for individual stock momentum, I do not find any evidence that downside volatility is better at predicting risk than total volatility in an industry momentum context. It appears that downside volatility does not gauge all the risk associated with momentum, making total volatility pose as a more complete risk measure.

Both total and downside volatility-managed strategies produce significant positive alphas when regressed against their plain counterparts, presenting positive return and volatility timing components. Volatility timing stands as the main driver of the managed industry momentum's superior performance. Managing for downside volatility increases the return timing component (for the unconstrained strategies), however, this does not appear to benefit the momentum strategies as it does with other factors studied by Wang and Yan (2021).

Additional analysis regressing downside on total volatility-scaled strategies produce insignificant alpha estimates. This means that the industry (and individual stock) momentum strategies controlled for downside volatility do not present any additional benefits to investors over those offered by total volatility and that these strategies are indeed spanned by those scaled by total volatility.

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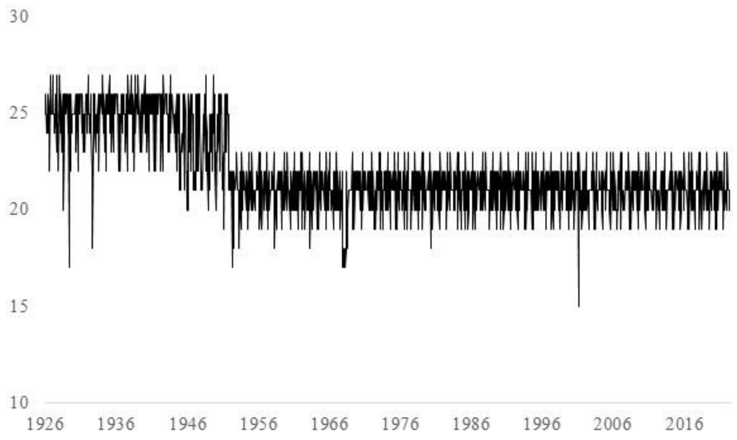
9. Appendices

Appendix 1 – Figure 1A: Number of trading days in each month

Number of trading days per month from the sample ranging between July 1926 to January 2023.



Appendix 2 – Table 1A: Spanning regressions on constrained managed strategies

This table reports the results from the time-series regressions of the total and downside volatility managed momentum strategies on each other and on the plain strategy, as represented by equations (9) through (12). Panel A reports the results for the total volatility-managed strategies regressed on the downside volatility-managed strategies and Panel B the opposite. Panels C and D present the results for the two previous regressions, but also accounting for their unmanaged counterpart, represented by equations (11) and (12). The Fama and French (1993) three factors are also included as additional controls in the regressions. The strategies' return sample considers the period ranging from August 1927 to January 2023. The reported alphas are annualized in percentage terms. T-statistics based on White (1980) standard errors are represented in parentheses.

Portfolio	**Industry Momentum**		**Stock Momentum**	
	Equation	Controlling for FF3	Equation	Controlling for FF3
Panel A: Results from $r_t^{total^*} = \alpha + \beta * r_t^{down^*} + \epsilon_t$,				
Alpha, α	0.40	0.53	1.07	1.40
	(1.23)	(1.82)	(1.71)	(2.42)
Beta, β	0.99	0.98	0.99	0.98
	(76.76)	(80.99)	(64.60)	(70.55)
R^2	0.97	0.97	0.98	0.98
Panel B: Results from $r_t^{down^*} = \alpha + \beta * r_t^{total^*} + \epsilon_t$,				
Alpha, α	-0.01	-0.10	-0.60	-0.74
	(-0.03)	(-0.33)	(-0.95)	(-1.33)
Beta, β	0.99	0.99	0.99	0.99
	(89.93)	(98.98)	(70.51)	(84.42)
R^2	0.97	0.97	0.98	0.98
Panel C: Results from $r_t^{total^*} = \alpha + \beta_1 * r_t^{down^*} + \beta_2 * r_t + \epsilon_t$,				

Alpha, α	0.61	0.54		1.56	1.31
	(2.25)	(2.00)		(2.70)	(2.42)
Beta 1, β_1	0.87	0.86		0.88	0.87
	(41.34)	(41.85)		(37.24)	(32.42)
Beta 2, β_2	0.14	0.14		0.12	0.14
	(7.48)	(7.95)		(6.78)	(5.38)
R^2	0.98	0.98		0.98	0.98
Panel D: Results from $r_t^{down^*} = \alpha + \beta_1 * r_t^{total^*} + \beta_2 * r_t + \epsilon_t$,					
Alpha, α	-0.06	-0.11		-0.80	-0.77
	(-0.21)	(-0.38)		(-1.29)	(-1.36)
Beta 1, β_1	1.01	1.01		1.02	1.03
	(35.07)	(37.03)		(40.77)	(37.29)
Beta 2, β_2	-0.03	-0.02		-0.04	-0.04
	(-0.70)	(-0.65)		(-1.52)	(-1.47)
R^2	0.97	0.97		0.98	0.98