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On momentum crashes

A triple-screened momentum strategy

School of Accounting and Finance
Master's Thesis in Finance
Master's Degree Programme in Finance

Vaasa 2021

UNIVERSITY OF VAASA
School of Accounting and Finance
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Title of the Thesis: On momentum crashes: A triple-screened momentum strategy
Degree: Master of Science in Economics and Business Administration
Programme: Master's Degree Programme in Finance
Supervisor: Janne Äijö
Year: 2021 **Pages:** 83

ABSTRACT:
Momentum anomaly, an idea that past returns can predict near-future returns, remains one of the most persistent and puzzling features of the financial markets. Using a strategy that goes long in past winner stocks and short in past losers is widely confirmed to generate abnormal risk-adjusted returns across time, different markets and asset classes. Literature has documented that this effect exists both when implemented based on relative performance of stocks in a stock universe (cross-sectional momentum) as well as based on a stock's absolute performance alone (time series momentum), though the academics are more inconclusive of the latter. Despite the anomalous performance, momentum strategies may be subject to severe losses, called momentum crashes. These crashes occur as a result of outperforming past losers relative to winners, in periods when markets rebound after declining in bear markets.

Using a comprehensive set of individual stocks in the European stock markets over the period from January 1992 through December 2019, this thesis examines the profitability of the standalone cross-sectional momentum, time series momentum and a dual momentum strategy that combines elements from the two strategies. More importantly, inspired by recent literature, this study proposes a new triple-screened momentum strategy that augments the dual momentum strategy with a market screening step. Cross-comparisons are conducted in order to investigate whether such strategy outperforms its counterparts particularly from the standpoint of avoiding momentum crashes.

The findings show that the implemented triple-screened momentum strategy earns significant raw and abnormal risk-adjusted returns and higher Sharpe ratios relative to other momentum strategies and benchmark index. Along with higher mean returns, it appears that this performance is driven by the ability to diminish strings of negative returns associated with momentum crashes. These results are robust across subsamples. Furthermore, this thesis documents the following. First, consistent with prior research, dual momentum outperforms standalone cross-sectional momentum and time series momentum strategies measured by raw and risk-adjusted returns as well as Sharpe ratios. However, the findings indicate that the strategy may be even more prone to momentum crashes compared to the pure momentum strategies. Second, based on the regression tests, the results provide little evidence of abnormal time series momentum effects. In contrast, although the strategy is profitable, the results suggest that time series momentum is largely explained by the cross-sectional momentum premium. According to the results, time series momentum is also subject to momentum crashes. Third, and last, the findings generally corroborate the evidence on cross-sectional momentum. On average, the strategy generates significant raw and abnormal risk-adjusted returns, albeit earns lowest Sharpe ratios relative to its counterparts. In line with prior literature, it is further confirmed that cross-sectional momentum is subject to momentum crashes.

KEYWORDS: momentum, momentum crash, stock markets, market efficiency

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen yksikkö
Tekijä: Simo Ursin
Tutkielman nimi: On momentum crashes: A triple-screened momentum strategy
Tutkinto: Kauppatieteiden maisteri
Oppiaine: Rahoitus
Työn ohjaaja: Janne Äijö
Valmistumisvuosi: 2021 **Sivumäärä:** 83

TIIVISTELMÄ:
Momentum-anomalia, eli ajatus lähitulevaisuuden tuottojen ennustamisesta historiallisten tuottojen avulla, on rahoitusmarkkinoiden yksi merkittävimmistä ratkaisemattomista kysymyksistä. Strategia, joka ostaa historiallisia voittajaosakkeita ja myy lyhyeksi vastaavia häviäjäosakkeita on laajasti havaittu tuottavan riskikorjattua ylituottoa eri aikoina, markkinoilla ja omaisuusluokissa muodostettuna sekä osakkeen suhteellisten tuottojen perusteella tietyssä osakekorissa että myös absoluuttisten eli osakkeen omien historiallisten tuottojen perusteella – joskin tutkijat ovat jokseenkin erimielisiä jälkimmäisen toimivuudesta. Momentum-strategiat ovat kuitenkin alttiita suurille tappioille, niin kutsutuille momentum-romahduksille, jotka tapahtuvat tilanteissa, joissa markkinat elpyvät laskusuhdanteen jälkeen. Nämä romahdukset ovat seurausta häviäjäosakkeiden suuremmista tuotoista suhteessa voittajaosakkeisiin.

Tämä tutkielma tarkastelee momentum-strategioiden, mukaan lukien suhteellisen ja absoluuttisen momentumin sekä näiden kahden strategian yhdistävän kaksoismomentumin, kannattavuutta käyttäen laajaa otosta yksittäisistä osakkeista Euroopan osakemarkkinoilla vuosina 1992–2019. Tässä tutkielmassa ehdotetaan tuoreen kirjallisuuden innoittamana lisäksi uudenlaista kolmoisseulottua momentum-strategiaa, joka lisää uuden markkinaseulontavaiheen kaksoismomentumiin. Tutkielma selvittää suoriutuuko tällainen strategia paremmin suhteessa muihin momentum-strategioihin etenkin momentum-romahdusten näkökulmasta.

Tutkielman tulokset osoittavat muodostetun kolmoisseulotun momentum-strategian tuottavan tilastollisesti merkitseviä raaka- ja riskikorjattuja ylituottoja sekä korkeampia Sharpen lukuja verrattuna muihin momentum-strategioihin ja vertailuindeksiin. Suurempien keskimääräisten tuottojen ohella strategian suoriutumista näyttää ohjaavan myös kyky heikentää negatiivisten tuottojen ketjuja, jotka liittyvät erityisesti momentum-romahduksiin. Nämä tulokset ovat pitäviä myös tutkituissa osaotoksissa. Tämän lisäksi tutkielmassa havaitaan seuraavaa. Ensinnäkin tulokset yhtenevät aikaisemman kirjallisuuden kanssa kaksoismomentumin suoriutumisen osalta, sillä tulokset näyttävät kaksoismomentumin suoriutuvan suhteellista ja absoluuttista momentum-strategiaa paremmin sekä raaka- ja riskikorjattujen ylituottojen että Sharpen lukujen valossa. Toisaalta tulokset viittaavat myös siihen, että kaksoismomentum voi olla jopa suhteellisesti alttiimpi momentum-romahduksille. Toisekseen tulokset eivät tue ajatusta erillisestä absoluuttisen momentumin riskipreemiosta. Vaikka strategia onkin kannattava, toteutetut regressiotestit viittaavat suhteellisen momentumin riskipreemion laajalti selittävän absoluuttisen momentumin tuottoja. Tulosten mukaan strategia on myös altis momentum-romahduksille. Viimeiseksi tulokset vahvistavat yleisesti näyttöä suhteellisen momentumin olemassaolosta. Strategia tuottaa keskimääräisesti tilastollisesti merkitseviä raaka- ja riskikorjattuja ylituottoja, vaikkakin verrattain pienimpiä Sharpen lukuja. Tulokset tukevat niin ikään myös todisteita suhteellisen momentumin alttiudesta momentum-romahduksille.

AVAINSANAT: momentum, momentum-romahdus, osakemarkkinat, markkinatehokkuus

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1 Introduction

Market efficiency remains a popular topic amongst academics today, and the rationality of financial markets is constantly challenged. To date, at least over 450 different anomalies have been introduced, though all of them may not be able to prove their robustness (Hou, Xue & Zhang, 2020). Simultaneously, increasingly growing sources of information and ubiquitous electronic trading venues have enabled the race for generating higher and higher returns. Consequently, investors that seek to invent superior investing styles and methods may resort to these intriguing anomalies as a means of investing.

One well-known and persistent anomaly in the financial markets is the momentum anomaly first documented by Jegadeesh and Titman (1993), suggesting that stocks which have relatively beaten (lost to) other stocks in recent history also continue the same trend in the short-term future. The simple intuition is thus to buy stocks with relatively strong past performance, and to short-sell those with relatively poor performance. Since the publication of the anomaly, the concept has been broadly studied and observed across markets and asset classes as well as in different countries. However, while the indication of such cross-sectional momentum is that relative performance of an asset is a significant predictor of its short-term future performance, later Moskowitz, Ooi and Pedersen (2012) discover a different type of momentum, a so-called time series momentum, showing a positive relationship between an asset's past absolute performance and its short-term future performance. Their results demonstrate that time series momentum is robust across major futures markets and asset classes.

Recently, Lim, Wang and Yao (2018) extend the analysis of time series momentum to individual stocks in US and Europe. More importantly, they form a dual momentum strategy which combines cross-sectional and time series momentum by first decomposing stocks based on their signs of past returns (time series momentum component), followed by sorting based on their rank (cross-sectional momentum component). They discover that this strategy clearly outperforms standalone cross-sectional and time series momentum strategies.

One large concern with momentum strategies links to a phenomenon called momentum crash occuring when markets start to recover following a recession. These crashes are driven by a better performance of past loser stocks (short positions) compared to past winner stocks (long positions). Since momentum strategies hold long-short portfolios by default, they experience major losses as a result. (Daniel and Moskowitz, 2016.)

Because momentum crashes can be devastating and erase vast majority of the invested capital, Daniel and Moskowitz (2016), among others, have suggested risk-managed versions of momentum. A recent study by Singh, Walia, Jain and Garg (2020) also attempts to address this issue. In their study, they form a triple momentum strategy, expanding the dual momentum strategy of Lim et al. (2018) by checking the lagged 24-month and lagged 1-month market returns in order to determine what types of positions (i.e., a long-short, long-only or short-only) to engage in. They demonstrate that this triple momentum strategy does not only significantly outperform cross-sectional momentum, time series momentum and dual momentum strategies in Indian stock markets but may be able to reduce the overall downside risk.

1.1 Purpose of the study

On the basis of prior literature, this thesis examines the profitability of standalone cross-sectional momentum, time series momentum and dual momentum strategies in European stock markets from January 1992 to December 2019. More importantly, motivated by the idea of triple-screening in Singh et al. (2020) and the results of Daniel and Moskowitz (2016) on momentum crashes, this thesis proposes another type of triple-screened momentum that is simpler and distinct from the one in Singh et al. (2020). In contrast to their strategy which by definition selects the type of portfolio more generally regardless of the market state, this thesis harnesses a modified type of triple-screened momentum that, based on the insights from Daniel and Moskowitz (2016), is explicitly tied to preventing potential momentum crashes occurring in bear markets. By more directly using the results of Daniel and Moskowitz (2016), this thesis attempts to shed light on whether this alternative type of market indicator is particularly useful in bypassing momentum crashes. Furthermore, it is investigated whether such triple-screened momentum strategy outperforms its counterparts and benchmark index.

Daniel and Moskowitz (2016) show that momentum strategies are vulnerable to momentum crashes and exhibit option-like behavior during these periods. However, in contrast to cross-sectional momentum, existing research has not devoted much attention to studying if the more recently proposed time series momentum and dual momentum strategies are subject to optionality effects. To address this, this thesis tests whether time series momentum and dual momentum are subject to optionality effects, along with the proposed triple-screened momentum. The analysis is further extended to consider the drawdowns of the momentum strategies more in detail, adding value to understanding the downside risks associated with the portfolios.

Moreover, vast majority of the papers related to time series momentum have focused on examining the futures markets, while traditional stock markets that are in general more available for retail investors have been less pronounced in prior research. In general, the studies on momentum anomaly are also concentrating on the US markets, although understanding the phenomena in other settings is also important. By contrast, this thesis focuses on the stock markets in European region using a large set of individual stocks.

This thesis aims to expand existing literature in several ways. First, and foremost, this thesis offers a plausible alternative strategy for controlling the downside risk associated with momentum strategies especially from the perspective of momentum crashes by introducing a new type of triple-screened momentum strategy that builds on previous empirical work of Singh et al. (2020) and Daniel and Moskowitz (2016). Overall, such risk-managed versions of momentum have gained popularity in recent literature (e.g., see Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Moreira & Muir, 2017; Grobys & Kolari, 2020; Cederburg, O'Doherty, Wang & Yan, 2020). This thesis contributes to this stream of research by utilizing a kind of market indicator that is adapted from Daniel and Moskowitz (2016) and more straightforward to implement compared to existing volatility-scaling techniques. Second, this work enriches literature by giving explicit focus on jointly investigating the momentum crashes of different types of momentum strategies, inclusive of cross-sectional momentum, time series momentum, dual momentum and triple-screened momentum. More specifically, to the best of author's knowledge, the optionality effects associated with time series momentum, dual momentum and triple-screened momentum have not been studied before in this setting. Third, and last, this thesis uses a unique set of data by collecting all available individual stocks in 17 countries in the European region over the period that spans from January 1992 through December 2019. The used period constitutes the period when European stocks markets have mostly been active, starting from the first full year available based on the time required for constructing the momentum strategies beginning from the 1990s. Therefore, the results of this study also provide a relatively comprehensive view of the momentum anomaly in European stock markets.

1.2 Hypotheses

The question whether cross-sectional, time series, dual momentum and the triple-screened momentum strategies are existent in the European stock markets forms the basis of this study. In light of the assumption of market efficiency, one would expect that such strategies produce insignificant raw and abnormal risk-adjusted return under the null hypothesis. Furthermore, the following is expected in terms of the ordering of the profitability. First, consistent with Singh et al. (2020), although the triple screening process is different in this thesis, it is expected that triple-screened momentum strategy outperforms all other implemented momentum strategies. Second, based on the results of Lim et al. (2018), it is expected that dual momentum strategy exhibits superior performance to cross-sectional momentum and time series momentum. Third, following Moskowitz et al. (2012), time series momentum is expected to outperform cross-sectional momentum. In the same spirit, it is expected that time series momentum subsumes cross-sectional momentum. Finally, since momentum crashes are documented to be a prominent characteristic of momentum strategies, one can intuitively anticipate that the implemented momentum strategies in this thesis exhibit optionality effects as reported in Daniel and Moskowitz (2016). In conclusion, the previous hypotheses can be summarized as follows:

- $H_1(1)$: The implemented momentum strategies generate statistically significant raw and abnormal risk-adjusted returns
- $H_1(2)$: Triple-screened momentum outperforms dual momentum
- $H_1(3)$: Dual momentum outperforms cross-sectional momentum and time series momentum
- $H_1(4)$: Time series momentum outperforms cross-sectional momentum
- $H_1(5)$: Time series momentum subsumes cross-sectional momentum
- $H_1(6)$: The implemented momentum strategies are subject to optionality effects

1.3 Structure of the study

The remainder of this thesis takes the following form. Section II introduces the important underlying theoretical frameworks that form the basis for understanding the financial markets and momentum anomaly. First, the section reviews the influential, although highly controversial, efficient market hypothesis theory which is in stark contrast with the momentum anomaly examined in this thesis. Second, standard asset pricing models that are widely used in the endeavor of explaining portfolio excess returns, including momentum portfolios, are discussed. Following existing research, these risk-based factor models are subsequently employed in this study as well. Section III reviews prior research on momentum anomaly. The section starts by discussing the evidence on different types of momentum strategies and continues by presenting some of the potential underlying explanations that may contribute to the anomaly. Next, Section IV describes the data and methodology used in this research. Finally, Section V reports the empirical results and Section VI concludes the thesis.

2 Theoretical background

This section describes the underlying theoretical concepts which are important to acknowledge not only in order to understand the modern financial markets but also to understand the dynamics of the momentum strategies investigated in this thesis. The first subsection starts with a review regarding the framework of rationally and efficiently functioning financial markets, that is, *efficient market hypothesis*, which contradicts the momentum anomaly by asserting that historical market information cannot be exploited in the benefit of future because markets are expectedly saturated with price-relevant information. Under this assumption, it is therefore suggested that investors cannot earn abnormal gains by engaging in momentum strategies. In this sense, this thesis also aims to enrich the literature by further testing the market efficiency. The second subsection reviews the related standard asset pricing models as they are commonly employed in previous momentum literature in explaining the variations in the returns of different momentum portfolios. Following prior convention, these models are also subsequently utilized in this thesis.

2.1 Efficient market hypothesis

Efficient market hypothesis (EMH) is an investment theory that refers to the efficiency of capital markets, and to markets wherein resources are allocated efficiently (Fama, 1970). The centrality of the theory lies in a simple idea that ”*a market in which prices always fully reflect available information is called efficient*” (Fama, 1970). Introduced by an American Nobel Laureate and economist Eugene Fama originally in the 1960s but most notably in the 1970s, the efficient market hypothesis serves undeniably as an important background to which modern financial theories construct upon and to which financial phenomena such as momentum anomaly are benchmarked against. Also, as Fama (2014) describes, it may be considered the first pillar of asset pricing research, whereas asset pricing models discussed in the next subsection constitute the second pillar.

The basic idea is that if markets are efficient, investors cannot earn greater returns than market returns by exploiting public or private information since all information is already embedded in prices. Therefore, the expected abnormal return for the subsequent time period is zero. This can be expressed mathematically by

$$E\left(z_{i,t+1}\right) = 0 \tag{1}$$

and

$$z_{i,t+1} = r_{i,t+1} - E\left(r_{i,t+1}\right) \tag{2}$$

where $E\left(z_{i,t+1}\right)$ is the expected abnormal return for stock i at time $t+1$. The expected abnormal return is simply calculated as the difference between the realized and expected return for stock i at time $t+1$, that is, $r_{i,t+1}$ and $E\left(r_{i,t+1}\right)$. (Fama, 1970.)

The question whether capital markets are efficient is challenging and multidimensional. To start, it is necessary to first define the term *efficiency* which may be divided into two remarks. First, efficiency relates to a market condition in which all available information, both public and private, is completely incorporated into prices. Consequently, information asymmetries should be non-existent and investors should not be able to achieve any kind of advantage by possessing private information. Second, the process in which information is impounded into prices should be instantaneous in its nature. In other words, prices should instantly adjust as a result of new information. Assuming these conditions, capital markets should work seamlessly and allocate resources efficiently. (Fama, 1970.)

A typical feature of theoretical models is that they tend to comprise certain stylized facts, as also in the case of efficient market hypothesis. First, it is assumed that transactions in the capital markets are costless. Put differently, trading assets such as stocks is free for investors. The second assumption relates to free access of information, that is, all market participants are presumed to be able to obtain all price-relevant information for free. This information is also distributed universally and immediately. Finally, market participants should share consistent beliefs on market prices, meaning that they agree on the implications of information for prices. However, to answer whether a market is de facto efficient, it is not strictly a requirement for all conditions to literally hold in practice. (Fama, 1970.)

Fama (1970) further divides market efficiency into three forms that include weak form, semi-strong form, and strong form. These three forms basically characterize the extent to which markets are efficient. More specifically, the valid interpretation is that if the strong form of market efficiency holds, then weak and semi-strong forms inherently also hold. On the contrary, the reverse interpretation does not hold. This relationship is illustrated in Figure 1.

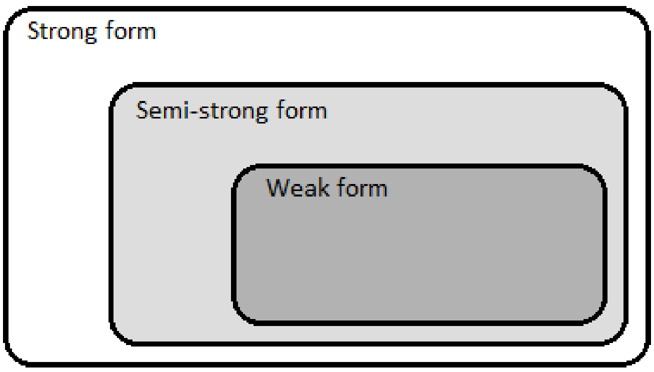

Figure 1. Forms of efficient markets.

In essence, the weak form signals that stock prices only incorporate in historical price information, and that the returns are not autocorrelated. If the weak form holds, this virtually invalidates taking advantage of technical analysis and technical trading strategies that exploit past prices and volume data. (Fama, 1970.) This rule is rather strict. For example, momentum strategies are types of technical trading strategies which exploit past trend in the favor of future returns. Therefore, the momentum strategies implemented in this study simultaneously provide a direct challenge and test against this form of market efficiency.

With regard to the semi-strong form, it suggests that stock prices incorporate in all public information, in addition to past information. For example, public information could contain information such as quarterly and annual financial statements as well as other announcements about relevant corporate events such as stock splits. Given the nature of the semi-strong form, the implication is that besides technical analysis, investors should not be able to exploit fundamental analysis in order to earn abnormal returns. Moreover, the semi-strong also asserts that once new information affecting an asset's fair value is announced, markets should react to this information immediately. Yet, it may be possible to benefit from any information that is private. (Fama, 1970.)

Finally, the strong form implies that stock prices contain all available information, including historical, public and private information. In accordance with this statement, generating abnormal returns is by definition considered impossible since all price-relevant information should already be incorporated in prices. In other words, regardless of the information possessed, investors are not able to earn returns superior to market returns. (Fama, 1970.) Though, Fama (1991) later notes that such assumption may not realistically hold in practice. Nevertheless, the strongest form may still be considered useful as a benchmark for market efficiency.

2.2 Asset pricing models

This subsection introduces the standard asset pricing models that are commonly used in literature. These models include capital asset pricing model (CAPM) described in Sharpe (1964), Lintner (1965) and Mossin (1966), three-factor model of Fama and French (1993), four-factor model of Carhart (1997) as well as five-factor and six-factor models of Fama and French (2015, 2018). Since the later risk factor models that comprise several risk factors are nested in nature, such as that Fama-French three-factor model is an expansion of CAPM, the discussion logically begins with CAPM and ends with Fama-French six-factor model.

2.2.1 Capital asset pricing model

Capital asset pricing model (CAPM) is arguably one of the most important theoretical themes in finance and a universal paradigm of asset pricing literature. Based on modern portfolio theory developed by Markowitz (1952), CAPM has later been derived independently by Sharpe (1964), Lintner (1965) and Mossin (1966). It is virtually a framework providing an impetus for understanding the risk-return relationships of assets, stocks in particular. Moreover, CAPM is important in valuation contexts such as in estimating cost of equity. Formally, CAPM formula can be denoted as follows:

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] \tag{3}$$

where $E(r_i)$ is the expected return on portfolio i, r_f is the risk-free rate of return, β_i is the beta coefficient of portfolio i and $E(r_m)$ is the expected return on market portfolio. The slope coefficient β_i essentially determines the sensitivity of portfolio i to the market factor (*MKT*) which is given by the market premium $E(r_m) - r_f$. A beta coefficient higher than one suggests that the portfolio is *aggressive* and riskier than the market portfolio. Conversely, if the beta coefficient is less than one, the portfolio is considered *defensive* and less risky than the market counterpart. Since the relationship is linear, aggressive (defensive) portfolios are expected to earn higher (lower) returns as a compensation for higher (lower) risk. Respectively, portfolios that are not exposed to the market factor (beta coefficient is zero) solely return the risk-free rate. (Sharpe, 1964; Lintner, 1965; Mossin, 1966.)

Equation 3 can also be slightly modified into another known form so that the return of portfolio i is described in excess of the risk-free rate r_f,

$$\underbrace{E(r_i) - r_f}_{r_i} = \beta_i \underbrace{\left[E(r_m) - r_f\right]}_{MKT} \tag{4}$$

where the r_i is the expected excess return of portfolio i. Accordingly, the excess return of the portfolio i equals the product of the beta coefficient and market premium. In the opposite, a risk-free portfolio does not include a market risk premium at all.

With respect to CAPM assumptions, there are several aspects to consider. First, the model assumes that there are no transaction costs and taxes, and that all assets are publicly traded. Second, consistent with efficient market hypothesis, investors share homogeneous expectations, are risk-averse mean-variance optimizers and cannot impact market prices with their transactions (i.e., perfect competition exists). Finally, investors are also able to invest in risk-free assets, borrow, lend at risk-free rate, and take short positions without constraints. (Sharpe, 1964; Lintner, 1965; Mossin, 1966.)

2.2.2 Fama-French three-factor model

Fama and French (1993) propose an extension of CAPM by adding two new risk factors to the model in the attempt of capturing the variation in portfolio excess returns more accurately. The first factor is a *size* factor (or *SMB, small minus big*), and the second factor is a *value* factor (or *HML, high minus low*). Consequently, the expected excess return of portfolio i takes the following form in the Fama-French three-factor model:

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML \tag{5}$$

where $E(r_i) - r_f$ is the expected excess return of portfolio i, MKT is the excess return of the market portfolio, SMB is the excess return of a long-short portfolio that takes long positions in small stocks and short positions in big stocks, and HML is the excess return of a long-short portfolio that takes long positions in stocks with high B/M ratio and short positions in stocks with low B/M ratio. The presented beta coefficients are factor loadings that determine the sensitivity of portfolio i to the corresponding risk factors ex post. (Fama & French, 1993.)

2.2.3 Carhart four-factor model

Motivated by Jegadeesh and Titman's (1993) insights into momentum anomaly, Carhart (1997) adds a *momentum* factor (or *WML*, *winner minus loser*) to the Fama-French three-factor model in order to examine mutual fund performance. More specifically, Carhart four-factor model can be expressed by the following:

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 WML \tag{6}$$

where $E(r_i) - r_f$ is the expected excess return of portfolio i, MKT is the excess return of the market portfolio, SMB is the excess return of a long-short portfolio that takes long positions in small stocks and short positions in big stocks, HML is the excess return of a long-short portfolio that takes long positions in stocks with high B/M ratio and short positions in stocks with low B/M ratio, and WML is the excess return of a momentum portfolio that takes long positions in past winner stocks and short positions in past loser stocks. Whether a stock is classified as a winner or loser depends on its historical cumulative returns that are computed for a given stock universe, and then used as a sort criterion to rank the stocks, as explained by Jegadeesh and Titman (1993). (Carhart, 1997.)

2.2.4 Fama-French five-factor model

Fama and French (2015) suggest that adding a *profitability* factor (or *RMW*, *robust minus weak*) and an *investment* factor (or *CMA*, *conservative minus aggressive*) to the popular Fama-French three-factor model provides higher explanatory power for explaining the variation in portfolio excess returns. This intuition stems particularly from an observation that these factors are related to another known type of stock pricing model, a dividend discount model (DDM), but is also especially motivated by the conclusions of Novy-Marx

(2013) and Titman, Wei and Xie (2004) (Fama & French, 2015). Namely, Novy-Marx (2013) finds a positive relationship between firm profitability and stock returns when measured by gross profits-to-assets, and respectively, Titman et al. (2004) show a negative relationship between capital investments and stock returns.

Consequently, *RMW* suggests that firms with higher operating profitability tend to generate higher returns than do firms with weak profitability, whereas the implication of *CMA* is that firms with more conservative investments, proxied by total asset growth, exhibit superior performance to those firms that invest more aggressively. Mathematically, the Fama-French five-factor model is given by the following:

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA \tag{7}$$

where $E(r_i) - r_f$ is the expected excess return of portfolio i, MKT is the excess return of the market portfolio, SMB is the excess return of a long-short portfolio that takes long positions in small stocks and short positions in big stocks, HML is the excess return of a long-short portfolio that takes long positions in stocks with high B/M ratio and short positions in stocks with low B/M ratio, RMW is the excess return of a long-short portfolio that takes long positions in stocks with robust profitability and short positions in stocks with weak profitability, and finally, CMA is the excess return of a long-short portfolio that takes long positions in stocks with conservative investments and short positions in stocks with aggressive investments. Again, the beta coefficients denote the sensitivities against the corresponding risk factors. (Fama & French, 2015.)

2.2.5 Fama-French six-factor model

Recently, Fama and French (2018) add the *momentum* factor (termed as *UMD*, *up minus down*) to the Fama-French five-factor model as a response of "popular demand", rather than strictly supporting its underlying motivation. The *UMD* factor is essentially synonymous to *WML* or *MOM* expressions. The Fama-French six-factor model is therefore denoted by the following:

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 UMD \tag{8}$$

where the model specification is identical to Fama-French five-factor model, except for UMD which is the excess return of a long-short portfolio that is long in stocks with relatively strongest historical performance and short in stocks with relatively weakest historical performance. (Fama & French, 2018.)

Different asset pricing models are further examined in the paper using a GRS test approach by Gibbons, Ross and Shanken (1989). In conclusion, there are two important observations. First, Fama-French six-factor model appears to outperform the preceding models from five-factor model to CAPM. Second, particularly a six-factor model that uses *small* stocks only (in terms of market capitalization), and a *cash profitability* factor (RMW_C) instead of operating proftability factor (RMW_O), is found to be the most effective in capturing portfolio excess returns, measured by the highest maximum squared Sharpe ratio, $Sh^2(f)$. The results are robust under full-sample, in-sample as well as out-of-sample simulations. (Fama & French, 2018.)

3 Literature review

This section discusses prior literature on the momentum anomaly. Given that extant research is roughly divided into examining either the profitability of momentum strategies and potential sources of the anomaly, these streams of research are distinguished in this context as well. The discussion starts with the main evidence on different types of momentum and ends with a discussion regarding the potential determinants of the momentum anomaly. Literature provides generally two kinds of explanations concerning the sources of momentum. These are either related to behavioral explanations or rational risk-based explanations.

3.1 Existence of momentum

Momentum anomaly, first documented in the seminal paper by Jegadeesh and Titman (1993), has proven to be a surprisingly pervasive feature of financial markets. In their study, Jegadeesh and Titman (1993) examine stock market trading strategies in the US from 1965 to 1989, relying on *relative strength* rules, and report strong results against market efficiency. Their basic underlying concept is that past stocks that have outperformed (underperformed) their peers in a given stock universe over a previous *formation period* have a tendency to continue winning (losing) during the following time horizon, or *holding period*. In other words, Jegadeesh and Titman (1993) show that relative performance in the past is a positive predictor of the future returns. As this type of momentum relies on relative performance, it is also referred to as cross-sectional momentum.

Jegadeesh and Titman (1993) first divide the stock universe into ten decile portfolios. Here, the top decile denotes the winner group, and the bottom decile the loser group. Accordingly, a momentum portfolio is constructed by going long in past winner stocks (top decile) and short in past loser stocks (bottom decile), and the resulting portfolio is then held for the next three to 12 months. Specifically, this portfolio is a combined zero-cost investment portfolio because equal number of positions are taken on both sides.

Overall, evidence of Jegadeesh and Titman (1993) shows that such portfolios generate abnormal risk-adjusted returns and that the effect is persists when tested against different sub-periods. They further argue that the anomaly is not driven by the exposure to systemic risk, but on the other hand can at least partially be a consequence of underreaction to firm-specific information. Finally, Jegadeesh and Titman (1993) document that holding momentum portfolios for longer than one year exhibit negative return reversals, which is also confirmed later in Jegadeesh and Titman (2001).

In addition to the existence of momentum in US equities (Jegadeesh & Titman 1993, 2001; Grundy & Martin, 2001; Wang & Wu, 2011), the anomaly has also been rather extensively observed in international markets (see, e.g., Rouwenhorst, 1998; Chan, Hameed & Tong, 2000; Griffin, Ji & Martin, 2003; Asness, Moskowitz & Pedersen, 2013), in different industries (Moskowitz & Grinblatt, 1999; Grobys & Kolari, 2020), across markets and asset classes such as stock indices (Chan et al., 2000; Bhojraj & Swaminathan, 2006), futures overall (Asness et al., 2013), commodities (Erb & Harvey, 2006; Miffre & Rallis, 2007; Gorton, Hayashi & Rouwenhorst, 2013), currencies (Menkhoff, Sarno, Schmeling & Schrimpf, 2012) and corporate bonds (Jostova, Nikolova, Philipov & Stahel, 2013; Li & Galvani, 2018).

What is more, momentum appears to exist on intraday timeframe. For example, Gao, Han, Li and Zhou (2018) find intraday momentum in S&P 500 ETF and other voluminously traded ETFs, showing a positive association between the first- and last-half hour returns within the same trading day. Moreover, their findings are robust under stressful market conditions. Consistent with these findings, Elaut, Frömmel and Lampaert (2018) provide evidence of intraday momentum in foreign exchange markets, whereas Zhang, Ma and Zhu (2019) discover the pattern in Chinese stock markets.

Even though there is comprehensive and strong evidence in support of momentum, some doubt is casted in other studies. For example, whether momentum is profitable after controlling for transaction costs is an interesting question. In this regard, some evidence is presented against the profitability. Lesmond, Schill and Zhou (2004) examine US stock markets using data from CRSP, and argue that stocks that drive the abnormal returns of momentum are subject to high transaction costs. They find that the associated abnormal gains essentially disappear when the transaction costs are accounted for. Korajczyk and Sadka (2005) partly echo this view. Using a sample of US stocks, they find that the profitability of an equal-weighted momentum strategy diminishes when transaction costs, measured by the price impact induced by the trading activity, are considered. If other weighting schemes are used, the result is contradictory and the profitability remains, however.

On the other hand, it has also been shown that momentum strategies can suffer from severe chains of negative returns in unorthodox market conditions. These periods are labeled as momentum crashes. Daniel and Moskowitz (2016) collect a comprehensive sample of US equities over the period from 1927 to 2013, and demonstrate that momentum portfolios are more vulnerable to large negative returns in volatile market conditions as well as during economic recessions such as the financial crisis in 2008. In particular, they show that when stock markets decline, and rebound afterwards, momentum portfolios crash. This results from short-selling past loser stocks which appear to earn more positive returns than the respective winner stocks in this setting, indicating reversal of the strategy in these periods. (Daniel & Moskowitz, 2016.)

However, Daniel and Moskowitz (2016) argue that it may be possible to at least partially predict such events in advance by using ex ante volatility measures and bear market indicators. Using a dynamically weighted momentum strategy that is conditional on the time-varying variance and mean of the momentum portfolio, Daniel and Moskowitz (2016) show that this risk-managed version earns nearly twice the alpha and Sharpe ratio of the unmanaged momentum strategy. Their results remain robust under out-of-sample simulations, split sample periods, different markets and asset classes.

The dynamically risk-managed momentum version of Daniel and Moskowitz (2016) is an alternative version of the version proposed in Barroso and Santa-Clara (2015) who analyze the impact of risk management on momentum returns as a result of predictable patterns of momentum risk. In contrast to using dynamic weighting, Barroso and Santa-Clara (2015) use a static weighting scheme that scales the momentum returns with a fixed 12% annualized volatility target. They find that these volatility-managed momentum portfolios yield significantly higher risk-adjusted abnormal returns than do the unmanaged counterparts. In addition, in their sample, the volatility-managed momentum strategy results in almost double as high Sharpe ratio and also essentially addresses momentum crashes. Overall, the results of Barroso and Santa-Clara (2015) as well as that of Daniel and Moskowitz (2016) imply that volatility management is beneficial in terms of accounting for the specific downside risk associated with momentum strategies. Recently, Cederburg et al. (2020) examine 103 different equity strategies using volatility-managed portfolios, and confirm that volatility-managed momentum is among the few equity strategies that survive their out-of-sample tests. This finding corroborates the view that managing for volatility enhances the performance of momentum.

Other types of momentum have also been suggested. A time series momentum introduced in the influential paper by Moskowitz et al. (2012) is arguably more powerful in relation to the standard cross-sectional momentum discussed before. Unlike cross-sectional momentum which relies on relative performance of assets in a stock universe, time series momentum bets on assets' absolute performance. Using a comprehensive sample data for all major futures contracts from January 1965 to December 2009, Moskowitz et al. (2012) show that the sign of an asset's own prior 12-month return indicates similar price-continuation trend for the subsequent month, and add that exploiting such strategy yields abnormal risk-adjusted returns. To employ this strategy, one is long assets with positive historical 12-month return and short assets with negative historical 12-month return.

Formally, Moskowitz et al. (2012) describe the time series momentum portfolio return by the following:

$$r_{t,t+1}^{TSMOM} = \frac{1}{N_t}\sum_{i=1}^{N_t} \mathrm{sign}(r_{t-12,t}^{i})\frac{40\%}{\sigma_t^i} r_{t,t+1}^{i} \tag{9}$$

where $r_{t,t+1}^{TSMOM}$ is the portfolio return in t, N_t is the total number of securities available in t, $r_{t-12,t}^{i}$ is the previous 12-month return for instrument i, σ_t^i is the ex ante volatility of instrument i, and $r_{t,t+1}^{i}$ is the return for instrument i. Here, $\frac{40\%}{\sigma_t^i}$ is a scaling factor forcing each instrument to have ex ante annualized volatility of 40%. This means that the positions are leveraged if the estimate of the ex ante volatility is less than 40% and vice versa. (Moskowitz et al., 2012).

Similar conclusions are drawn by, for example, Baltas and Kosowski (2013) who find consistent evidence regarding the profitability of time series momentum by examining futures markets and trend-following funds. He and Li (2015) demonstrate that time series momentum strategy can be particularly profitable over shorter time horizons, in contrast to longer time horizons during which time series momentum reverses. They argue that the profitability is particularly determined based on time horizons and market state as well as to some extent explained by market under- and overreaction and autocorrelated returns. Koijen, Moskowitz, Pedersen and Vrugt (2018), in turn, adopt time series momentum as a risk factor in studying currency markets and carry trades.

Georgopoulou and Wang (2017) use monthly price data for a number of equity and commodity indices in both developed and emerging markets over a time period that spans from 1969 through 2015. There are several important findings. First, they find that time series momentum strategy earns abnormal risk-adjusted returns after testing against different formation and holding periods as well but the profitability begins to deteriorate if the holding period exceeds 12 months. Second, they show that even though there are differences in time series momentum between developed and emerging countries, the difference is virtually insignifcant if currency fluctuations are accounted for. Third, they show results in support of Cujean and Hasler (2017), that time series momentum tends to more likely generate positive returns in recessions such as the global financial crisis, as opposed to overall market returns and cross-sectional momentum which are found to display weaker performance during such periods.

Goyal and Jegadeesh (2018) mimick the effect of time series momentum on individual US stocks using a similar strategy and portfolio weighting as in Moskowitz et al. (2012), and document superior returns to cross-sectional momentum. However, they argue that this deviation in returns stems from different portfolio weighting schemes that are used between time series momentum and cross-sectional momentum. First, in contrast to cross-sectional momentum, the number of long and short positions time series momentum takes is conditional on market state. Second, they posit that the returns of time series momentum are also driven by leverage. Once these differences are adjusted, cross-sectional momentum outperforms time series momentum. Goyal and Jegadeesh (2018) further conclude that time series momentum is more likely explained by mean returns rather than predictable return patterns. Moreover, they find no evidence of TSMOM subsuming CSMOM.

A concurrent paper by Lim et al. (2018) addresses the described weighting issue by replicating dollar-neutral weighting for the time series momentum portfolio in order to achieve better comparability between time series momentum and cross-sectional momentum. Using individual stocks and different weighting schemes, Lim et al. (2018) show that the risk-adjusted performance of time series momentum improves if the portfolios are dollar-neutral (i.e., the dollar value of long and short positions is equal). Contradictory to Goyal and Jegadeesh (2018), running regressions using Carhart four-factor model yields significant alphas for dollar-neutral portfolios, whereas the alphas are insignificant for non-neutral portfolios. In this sense, the evidence on time series momentum is mixed.

Pitkäjärvi, Suominen and Vaittinen (2020) introduce a cross-asset time series momentum strategy which overperforms the original time series momentum. This strategy rests on an idea that historical bond market returns are correlated with the future stock market returns and vice versa. Specifically, Pitkäjärvi et al. (2020) argue that past bond returns positively predict subsequent returns on equities, whereas past equity market returns are a negative predictor of future bond market returns. They conclude that time series momentum and cross-asset momentum may be partly explained by underreaction due to slowly moving capital in these markets, and that they may also encompass broader information about future economic activities.

Huang, Li, Wang and Zhou (2020) are more conservative regarding whether it is the predictability of past returns driving the returns of time series momentum, challenging the findings of Moskowitz et al. (2012) who argue that time series momentum performance stems from return predictability. More specifically, Huang et al. (2020) imply that although time series momentum is profitable, the performance is less likely associated with explanatory power of past returns, but in contrast may link to variation in historical sample means at least when it comes to futures markets. This result is supported by comparing time series momentum with a conventional 12-month formation period against a time series history (TSH) strategy which is long in assets with past positive historical means and short in the opposite case. In general, these two strategies seem to produce relatively similar results. However, the findings of Huang et al. (2020) do not preclude the possibility of return predictability using other time horizons and using other assets such as individual stocks. Moreover, whether time series momentum is more profitable than cross-sectional momentum is not examined in this setting.

The paper by Lim et al. (2018) further introduces a dual momentum strategy that combines both the cross-sectional and time series momentum strategies. In essence, this strategy double-sorts stocks, first based on the signs of past returns and then based on ranking. Formulating a strategy that is long in the highest quintile within the winner stocks and short in the lowest quintile within the loser stocks leads to interesting results. First, it is demonstrated that measured by raw returns and regardless of weighting scheme, the strategy approximately doubles the gains in proportion to time series momentum strategy. In similar fashion, the Sharpe ratio is almost twice relative to the Sharpe ratio of time series momentum. Second, based on the difference tests and monthly returns, DMOM is statistically distinct from TSMOM (CSMOM) with a mean difference of 0.92% (0.82%) when examined in US stock markets over the time period from January 1927 to September 2017. Overall, their results for dual momentum remain robust across markets and sub-periods.

Recently, Singh et al. (2020) study Indian stock markets and suggest a triple momentum strategy in order to decrease the impact of momentum crashes. This strategy is an extension of the dual momentum strategy of Lim et al. (2018), adding a market screener to the strategy. Using lagged 24-month market returns and lagged 1-month market returns, Singh et al. (2020) determine whether to establish a long-short portfolio, a long-only winners portfolio, or a short-only losers portfolio. They find the following. First, using a 12-month formation period combined with a 1-month holding period, the triple momentum significantly outperforms the dual momentum strategy as well as standalone cross-sectional momentum and time series momentum strategies. For example, in their sample, triple momentum earns 2.86% monthly returns on average and a Sharpe ratio of 1.07, whereas dual momentum earns an average monthly return of 2.28% and a Sharpe ratio of 0.60. Second, triple momentum produces statistically significant CAPM and Fama-French three-factor alphas that are higher than its counterparts. The results are robust when using sub-periods and alternative configurations. However, although Singh et al. (2020) find that downside risk of TRIMOM overall decreases in terms of smaller maximum drawdowns and VaR measures, it is unclear whether the strategy is subject to optionality effects as this is not tested.

3.2 Sources of momentum

Attempting to explain possible determinants of the momentum anomaly has been a longstanding debate and remains a central question in academic literature. In general, the related literature is split into two. On the one hand, one strand of literature has focused on providing explanations through behavioral biases and information processing. On the other hand, alternative explanations have emphasized more rational determinants that account for risk-based factors.

According to Chan, Jegadeesh and Lakonishok (1996), momentum premium is at least to some extent, but not entirely, linked to initial underreaction to earnings announcements as a large proportion of momentum returns is generated around these releases. Overall, their evidence largely supports the idea that adjustment to new information occurs gradually. Furthermore, slowly changing analyst forecasts may also contribute to lagged responses of the markets. In contrast, the findings are not supportive of the explanatory power of firm size and book-to-market effects in explaining momentum returns. (Chan et al., 1996.)

Hong and Stein (1999) propose a theoretical framework in which investors initially underreact to new information in the short-term but overreact in the long-term. Motivated by this, Hong, Lim and Stein (2000) further present evidence in support of the sluggish information diffusion especially when it comes to negative news. They also argue that profitability of momentum is negatively associated with firm size and analyst coverage, suggesting that momentum performs better among the smallest stocks and stocks with lower analyst coverage. Recently, Luo, Subrahmanyam and Titman (2021) present analogous views. First, they agree with the role of analyst coverage in explaining momentum profits. In particular, they argue that momentum effect is weakened if sell-side analysts release new information faster to slowly-reacting investors. Second, they link momentum profits to overconfident investors that are skeptical about external signals as they trust their own abilities more. Under certain model assumptions, this behavior causes a chain of events leading into underreaction (causing momentum profits) and overreaction (causing subsequent momentum reversals).

With respect to underreaction, a number of underlying behavioral errors are believed to explain it, in addition to the possible contributing role of slow information diffusion in underreaction as suggested by Chan et al. (1996), Hong and Stein (1999) and Hong et al. (2000). For instance, Barberis, Shleifer and Vishny (1998) document that underreaction can partially be explained by conservatism as investors update their beliefs slowly upon the arrival of new information and neglect its relevance in relation to their entrenched beliefs. What is more, disposition effect which is characterized by investors who are reluctant to exit losing investments but inclined to prematurely exit profitable investments, is observed to explain underreaction (Shefrin & Statman, 1985; Frazzini, 2006; Birru, 2015). Eyster, Rabin and Vayanos (2019) demonstrate that circumstances where investors are dismissive of the information content that is already contained in prices, can result in underreaction.

Delayed overreaction is also believed to impact the profitability of momentum, given that momentum has a propensity to generate positive returns especially over the 1-month horizon up to a 3-year time horizon, but reverse in the long-run (Jegadeesh & Titman, 1993; Barberis et al., 1998; Cooper, Gutierrez & Hameed, 2004), as opposed to contrarian strategies that are shown to do well over 3-year to 5-year time horizons (De Bondt & Thaler, 1985). Barberis et al. (1998) suggest that representativeness heuristic – a tendency of investors to believe that history of a firm repeats itself, although it is not a guarantee – may drive overreaction. Daniel, Hirshleifer and Subrahmanyam (1998) find that overconfidence and self-attribution bias may cause overreaction, implying that such behavior may induce short-term momentum and long-term reversals. In this context, overconfidence refers to tendency of investors to exaggerate their own abilities and precision of their estimates, whereas self-attribution denotes the tendency to claim success based on own abilities but failures based on external factors (Daniel et al., 1998). Consistent with the overconfidence hypothesis, Chuang and Lee (2006) show that overconfident investors underreact (overreact) to public (private) information. Finally, some other explanations for overreaction also include positive feedback trading discussed in De Long, Shleifer, Summers and Waldmann (1990), and investor sentiment (Baker & Wurgler, 2006, 2007).

As said, however, alternative reasonable sources may exist. Moskowitz and Grinblatt (1999) suggest that industry-effects are a major factor contributing to equity momentum returns. On the other hand, Nijman, Swinkels and Verbeek (2004) mix this view. They study whether equity momentum profits are impacted by country- and industry-effects in Europe, and they conclude that this is largely not the case. Rather, they imply that equity momentum links to individual stock effects. Chordia and Shivakumar (2002), in turn, present evidence that supports the explanatory power of a set of lagged macroeconomic factors, related to business cycle, in describing the payoffs of momentum strategies. Though, Cooper et al. (2004) observe that a lagged market return may be a better predictor of momentum payoffs. They conjecture that market state is an important driver of momentum.

Lewellen (2002) examines momentum in stock returns with industry, size and value factors, and shows that momentum is neither related to firm-specific or industry-specific returns. Rather, it seems that momentum stems from autocorrelation structure of stock returns, “excessively covarying prices”, which at least partially challenges the view of behavioral theories. In line with more rational reasoning, Grundy and Martin (2001) demonstrate that time-varying systematic risk has a substantial effect on momentum returns. When they control for this risk, momentum gains increase. Barroso and Santa-Clara (2015) favor the idea of time-varying risk, however, they focus on momentum-specific risk and show that momentum strategies are subject to large negative skewness and (excess) kurtosis. They relate the results particularly to that of Daniel and Moskowitz

(2016) regarding momentum crashes. In both papers, ex ante scaling for the risk yields superior performance to portfolios not managed for risk.

Ruenzi and Weigert (2018) examine the US stock markets between 1963 and 2012, and argue that systematic crash risk drives momentum profitability. To explain this, they create a CRASH variable by forming a self-financing portfolio which goes long (short) in stocks with high (low) crash susceptibility, where the crash susceptibility is proxied by a "lower-tail dependence" (LTD) indicator introduced in Chabi-Yo, Ruenzi and Weigert (2018). When Ruenzi and Weigert (2018) next regress UMD factor on Fama-French five-factor model in conjunction with the CRASH variable, they discover positive and statistically significant loadings on the CRASH factor and statistically insignificant alphas. The implication is that momentum strategies may be compensated by this exposure.

Finally, literature has documented that market liquidity is an important risk factor affecting stock returns (e.g., see Liang & Wei, 2012). Research shows that this effect extends to momentum profits. Using a sample of individual stocks in the US stock markets over a time period that spans from January 1966 through December 1999, Pástor and Stambaugh (2003) find that when they augment Fama-French three-factor model with an aggregate liquidity risk factor measured by a "cross-sectional average of individual-stock liquidity measures", momentum alphas decrease roughly by 50% and the loadings on the factor are statistically significant, and positive. Asness et al. (2013) find similar effects using a global sample. Respectively, Avramov, Cheng and Hameed (2016) show that momentum returns tend to be large and positive when markets are more liquid. Luo et al. (2021) describe that investors' overconfidence and skepticism about the quality or accuracy of external signals may be partly an explanation of this phenomenon.

4 Data and methodology

This section describes the data and methodology utilized in this thesis more in detail. The discussion begins by explaining the main characteristics of the sample data after which the portfolio construction procedure, regression tests and eventual performance evaluation are explained.

4.1 Data

The empirical analysis of this thesis concentrates on the stock markets in European region. In order to create a good representativeness of the region, 17 countries are used as a proxy for European stock markets. These countries encompass Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom. This basket of countries follows, among others, the same definition as STOXX Europe 600 which is a known benchmark market index for European stock markets and can virtually be considered European equivalent to S&P 500 index.

Primary sample data is obtained from Datastream for a sample period that spans from January 1992 through December 2019. The data comprises monthly adjusted closing prices for all publicly traded stocks in the aforementioned 17 countries. To examine risk-adjusted implications, monthly returns for European Fama-French risk factors are additionally collected from Kenneth French’s data library. From the same source, this thesis uses the US one-month T-bill rate as the risk-free rate. Finally, monthly data is extracted for European benchmark market index, STOXX Europe 600, to allow analysis of the implemented momentum strategies against the market. The source of the index data is Datastream.

In similar fashion to Moskowitz et al. (2012) and literature in general, all potentially illiquid or price-stagnant stocks are omitted from the sample, making the momentum strategies to be more applicable in practice. At each month, this issue is addressed by discarding all stocks that belong to below than 70^{th} percentile of the market capitalization of the stock universe. Put differently, this means that only top 30% largest stocks are included in the sample. The final dataset contains 2963 individual stocks, however the number of total stocks available at a given period inherently varies on a monthly basis. Lastly, to avoid survivorship bias, the dataset does not exclude stocks that may have gone bankrupt during the sample period. As a consequence, if a stock goes bankrupt during the holding period, the holding period return is -100% multiplied with the corresponding weight.

4.2 Methodology

Four types of momentum strategies are implemented in this thesis: cross-sectional momentum, time series momentum, dual momentum and triple momentum (from now on abbreviated as CSMOM, TSMOM, DMOM and TRIMOM, respectively). In general, the methodology follows existing literature. CSMOM portfolios are mainly constructed as in Jegadeesh and Titman (1993, 2001), TSMOM portfolios as in Moskowitz et al. (2012), and DMOM portfolios as in Lim et al. (2018). As for TRIMOM which is an enhanced version of DMOM introduced by Lim et al. (2018), the original inspriration of an additional screening stems from Singh et al. (2020). However the same implementation style is not followed here. Rather, TRIMOM implemented in this thesis is more strongly based on the market indicator and empirical evidence on momentum crashes presented in Daniel and Moskowitz (2016). All implementation procedures are described in detail in the following subsection.

To test for the risk-adjusted implications of the momentum strategies, standard asset pricing models are used, including CAPM (Sharpe, 1964; Lintner, 1965), Carhart's (1997) four-factor model and Fama-French three-factor, five-factor and six-factor models (Fama & French, 1993, 2015, 2018). As for examining the exposures to momentum crashes, optionality regressions are run according to Daniel and Moskowitz (2016). For the same reason, both worst monthly returns as well as worst drawdowns are also analyzed. To confirm robustness of the results, the analysis ends by examining two subsamples.

4.2.1 Portfolio formation

Broadly, construction of CSMOM, TSMOM, DMOM and TRIMOM portfolios are close to but different from each other. CSMOM considers how stocks have performed against a certain stock universe in the past; TSMOM looks at stock's own past performance. DMOM involves a two-step sorting process, first sorting based on TSMOM criterion, then on CSMOM. TRIMOM adds another trading rule to DMOM by checking the overall market trend before applying TSMOM and CSMOM sorts. Depending on market state, TRIMOM is not always a winner minus loser (from now on labeled as WML) portfolio, in contrast to CSMOM, TSMOM and DMOM.

Following literature, the CSMOM, TSMOM and DMOM portfolios are formed as follows. First, CSMOM goes long in the winner group and short in the loser group. Two breakpoints, 30th and 70th percentiles, are considered to create the categories in which the stocks are allocated. Measured by past cumulative returns over a certain lookback period, and ranking the performance in descending order, a stock is considered a winner (loser) if it belongs to the best (worst) 30% past performers. Second, TSMOM is long in all winners and short in all loser stocks. In contrast to CSMOM, TSMOM assigns a stock in the winner (loser) group if its past performance has been positive (negative) over a certain lookback period. Third, DMOM goes long in the strongest winner group and short in the worst loser group. In this case, the strongest winner group denotes the best-performing 20% winners within the winner stocks (fifth quintile). In contrast, the worst loser group is the weakest-performing 20% losers within the loser stocks (first quintile). Summarization of the described CSMOM, TSMOM and DMOM strategies is shown in Figure 2.

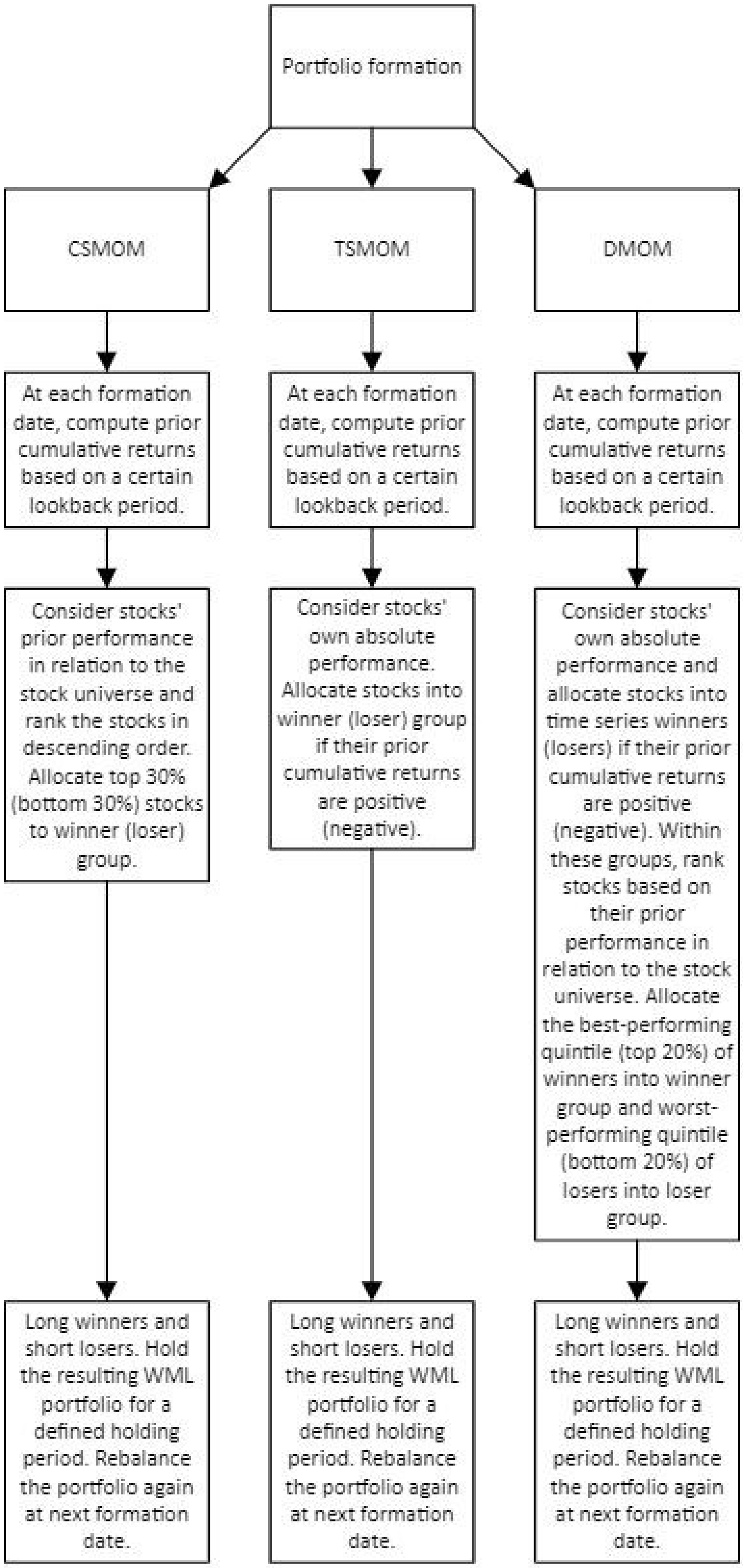

Figure 2. Implementing CSMOM, TSMOM and DMOM strategies.

TRIMOM adds one more layer to DMOM, evaluating the prevailing market trend before determining what kind of position(s) to take (Singh et al., 2020). Their market screening is motivated by Daniel and Moskowitz (2016) and based on lagged 24-month and 1-month market returns, representing the macro-level trend and latest market development, respectively. In this sense, this thesis is also inspired by the idea of Singh et al. (2020) when it comes to using a market screening process. However, TRIMOM in this thesis is different and attempts to specifically capture situations when markets are more likely to rebound after market declines, exploiting two major results presented in Daniel and Moskowitz (2016).

First, optionality regressions of Daniel and Moskowitz (2016) present a statistically significant and negative $\hat{\beta}_{B,U}$ coefficient, implying a negative exposure of momentum portfolios to market recovery following a decline in bear markets. The $\hat{\beta}_{B,U}$ coefficient is estimated from a variable $I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^{e}_{m,t}$, where $I_{B,t-1}$ is an ex ante bear market indicator that gets a value of 1 if the lagged 24-month market return is negative and 0 otherwise, $I_{U,t}$ is a contemporaneous up-market indicator that gets value of 1 if the market excess return is positive at month t and 0 otherwise, and $\tilde{R}^{e}_{m,t}$ is market excess return (Daniel & Moskowitz, 2016). As a result of the observed negative relationship between $I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^{e}_{m,t}$ and momentum, one can hypothetically ask if the $I_{B,t-1} \cdot I_{U,t}$ part can be used as an ex ante indicator. However, making the indicator usable in real-time requires a minor tweak by transforming the contemporaneous $I_{U,t}$ into a lagged variable, $I_{U,t-1}$. At each formation date, the resulting dummy variable $I_{B,t-1} \cdot I_{U,t-1}$ gets a value of 1 if the lagged 24-month market return is simultaneously negative while the lagged 1-month market return is positive.

Second, Daniel and Moskowitz (2016) show that the expected returns for losers are substantially higher than the expected returns for winners in bad times, leading to momentum crashes as a result of holding WML portfolios. Therefore, a strategy that goes long in past losers is a more preferable selection during such periods. As a result, this thesis proposes a new type of strategy that combines these two insights. Finally,

Figure 3 and Figure 4 display the algorithm used Singh et al. (2020) and the version that is used in this thesis, respectively.

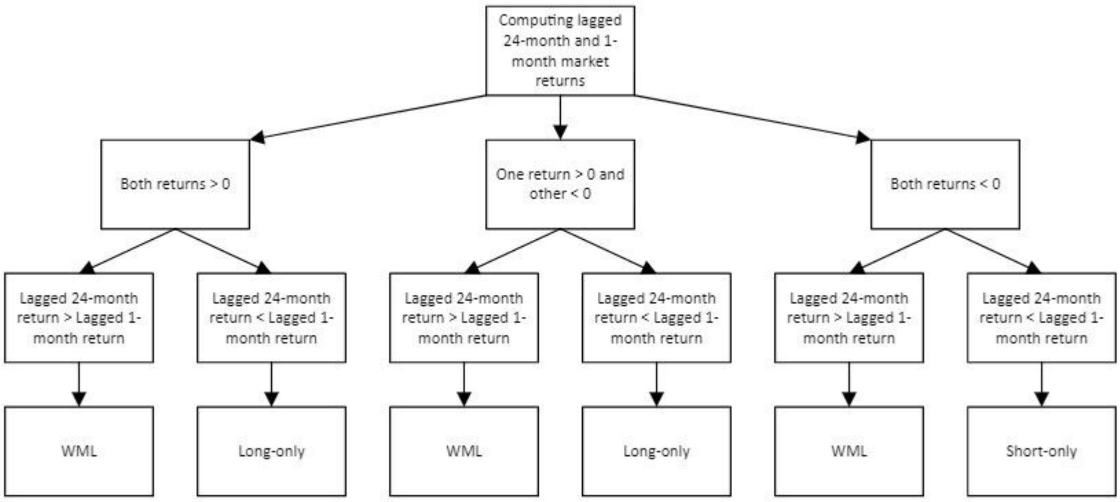

Figure 3. TRIMOM market screening process in Singh et al. (2020).

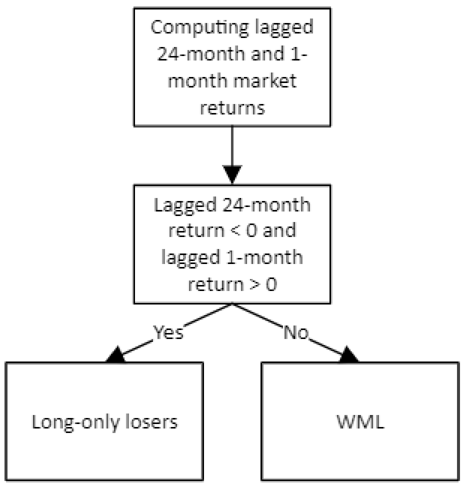

Figure 4. Proposed TRIMOM market screening process.

In both cases, the strategies are implementable in real-time, given that the market screening is based on lagged market returns. However, when comparing the proposed TRIMOM strategy to the one in Singh et al. (2020), two important differences are noted. First, Singh et al. (2020) compare the lagged 24-month market return with the lagged 1-

month market return. This means that in addition to the signs of the lagged market returns, the condition takes into account the magnitude of the lagged market returns. If the goal is only to minimize the impact of momentum crashes, accounting for the magnitude may introduce unwanted noise outside the crash periods, which in turn may harm the overall performance of the strategy. In contrast, the trading rule proposed in this thesis only checks the signs of the lagged returns which is more directly related to the market indicator used to capture momentum crashes in Daniel and Moskowitz (2016). That is, the proposed condition jointly checks if both the lagged 24-month market return is negative and the lagged 1-month market return is positive. Second, the trading rule of Singh et al. (2020) more generally determines whether to establish a long-only *winners* portfolio, a short-only *losers* portfolio or a WML portfolio. In turn, the used TRIMOM strategy only establishes either a long-only losers portfolio or a WML portfolio based on whether the condition is true or false. When the condition is true, TRIMOM goes long-only in past losers, since according to Daniel and Moskowitz (2016), their expected returns are higher than those of winners on average in such environment. Otherwise, TRIMOM is equal to the WML of DMOM strategy.

In terms of formation and holding periods, Jegadeesh and Titman (1993, 2001) find that CSMOM produces strong returns at least for formation and holding periods ranging between three to 12 months. The same formation and holding periods also apply to TSMOM, however the convention is to use past 12 months as the formation period and one month as the holding period (Moskowitz et al., 2012). Because DMOM is derived from TSMOM and CSMOM, and TRIMOM is based on DMOM, the same underlying formation and holding periods are used.

In general, recent literature has devoted more attention to examining 12–1 momentum combinations (e.g., see Goyal & Jegadeesh, 2018; Lim et al., 2018; Huang et al., 2020). A general principle has also been to skip the most recent month between the formation and holding period in order to account for possible bid-ask spread bias and short-term reversals that are explained in Jegadeesh (1990). For consistency with prior literature and considering the way how TRIMOM is formulated, the 12–1 combination as well as the 1-month skipping period is also used in this thesis. All returns are equal-weighted in this thesis, as the bucket of stocks contains relatively large stocks (i.e., largest 30% of the universe). Therefore, it is expected that the sample is not subject to instrumental size bias.

Accounting for the skipping period, momentum combinations can be generalized with J–L–K, where J denotes the formation period, L denotes the skipping period and K denotes the holding period, respectively. All periods are expressed in months. Using a 12–1–1 combination means that a 12-month formation period is used with a 1-month skip between J and K and the portfolio is held for a month. In this case, past cumulative returns are computed over $t-12$ to $t-2$ since the most recent month, $t-1$, between J and K is skipped.

4.2.2 Performance evaluation

Standard asset pricing models, including CAPM (Sharpe, 1964), Fama-French three-factor model (Fama & French, 1993), Fama-French five-factor model (Fama & French, 2015) and Fama-French six-factor model (Fama & French, 2018) are employed to examine exposures of the formed CSMOM, TSMOM, DMOM and TRIMOM portfolios to common risk factors. TSMOM is additionally regressed on Carhart 4-factor model (Carhart, 1997) which includes the UMD risk factor. This is necessary in order to measure the relationship between CSMOM and TSMOM and to examine the extent to which CSMOM is able to explain the variations in TSMOM returns. Results in this regard are mixed. According to, for instance Moskowitz et al. (2012) and Lim et al. (2018), CSMOM and TSMOM are related but distinct phenomena, however Goyal and Jegadeesh (2018) document the opposite. In sum, the following regression models are run:

$$r_{i,t}^{*} = \alpha_i + \beta_i MKT_t + \varepsilon_{i,t} \tag{10}$$

$$r_{i,t}^{*} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{11}$$

$$r_{i,t}^{*} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t} \quad (12)$$

and additionally,

$$r_{i,t}^{*} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + m_i UMD_t + \varepsilon_{i,t} \quad (13)$$

$$\begin{aligned} r_{i,t}^{*} = {} & \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \\ & + m_i UMD_t + \varepsilon_{i,t} \end{aligned} \quad (14)$$

where $r_{i,t}^{*}$ is the excess return on portfolio i at t, α_i is the constant (alpha), MKT_t is the market risk factor, SMB_t is the size factor measured by the difference between small and big stocks, HML_t is the value factor measured by the difference between high and low B/M stocks, RMW_t is the profitability factor measured by the difference between robust and weak profitability stocks, CMA_t is the investment factor measured by the difference between the stocks of firms with conservative and aggressive investments, UMD_t is the momentum factor measured by the difference between stocks with relatively high and poor past cumulative returns, and finally, $\varepsilon_{i,t}$ is the error term. The models from (10) to (14) are the CAPM, Fama-French three-factor model, Fama-French five-factor model, Carhart four-factor model and Fama-French six-factor model, respectively.

Following Daniel and Moskowitz (2016), an optionality regression model is specified to further consider the market timing implications, as follows:

$$\begin{aligned} R_{i,t}^{*} = {} & \alpha_0 + \alpha_B \cdot I_{B,t-1} + \beta_0 \cdot \tilde{R}_{m,t}^{e} + \beta_B \cdot I_{B,t-1} \cdot \tilde{R}_{m,t}^{e} \\ & + \beta_{B,U} \cdot I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}_{m,t}^{e} + \varepsilon_{i,t} \end{aligned} \quad (15)$$

where $R_{i,t}^{*}$ is the excess return of portfolio i at t, α_0 is the constant, $I_{B,t-1}$ is an ex ante bear market indicator that equals 1 if the lagged 24-month market return is negative (and 0 otherwise), $\tilde{R}_{m,t}^{e}$ is the market excess return (Fama-French market factor), $I_{U,t}$ is an up-market indicator that gets a value of 1 if the contemporaneous market excess return is positive (and 0 otherwise), and $\varepsilon_{i,t}$ is the error term.

While the regression tests attempt to capture the extent to which standard risk factors and Daniel and Moskowitz (2016) market indicators are able to explain the variations in the returns of the formed strategies, it is also important to measure how the strategies compare to each other as well as to a passive long investment in the market. Therefore, cumulative returns on each strategy, along with market index, are plotted over time. Descriptive statistics are also reported to uncover the key differences between the portfolios. Subsequently, the analysis examines how the strategies compare in terms of worst monthly payoffs and drawdowns.

Drawdowns in this thesis are defined as per convention, denoting a change that is calculated from peak-to-trough, until a new peak is reached. Examining drawdowns is essential because monthly returns alone only reveal the performance at a given time, whereas comparing drawdowns is more important considering the overall performance of a strategy across time. For instance, if one (another) strategy experiences a loss of 10% (15%) at month t, it does not provide information whether the first (second) strategy has experienced a streak of large losses prior to month t or if this particular loss is one-off. By fact, streaks of negative returns naturally affect the subsequent recovery more in comparison to one-off events.

In general, a drawdown is an ex post measure that is formulated as follows:

$$\mathrm{dd}_t = \frac{\mathrm{peak}_t - \mathrm{trough}_t}{\mathrm{peak}_t} \tag{16}$$

where the peak_t is the highest prevailing cumulative equity return value at a given period t and trough is the lowest prevailing cumulative equity return value at a given period t. More formally, excluding the first observation ($t = 0$) and using a \$1 initial investment, peak_t can be programmatically determined by the following:

$$\text{peak}_t = \begin{cases} c_t, & \text{if } c_t > c_{t-1} \text{ and } c_t > c_{t+1} \text{ and } c_t > \text{peak}_{t-1} \\ \text{peak}_{t-1}, & \text{otherwise} \end{cases} \tag{17}$$

where c_t is the cumulative equity return using at a given period t and $t = \{1, 2, 3, \dots\}$. When the condition is true, peak_t equals c_t, and otherwise the previous peak value, peak_{t-1}. For the period $t = 0$, peak is unconditional, equaling the first cumulative equity return value.

Finally, similarly using a $1 initial investment, a trough can be computed as follows:

$$\text{trough}_t = \begin{cases} c_t, & \text{if } c_t < c_{t-1} \text{ and } c_t \leq c_{t+1} \\ \text{trough}_{t-1}, & \text{otherwise} \end{cases} \tag{18}$$

where c_t is the cumulative equity return at a given period t and $t = \{1, 2, 3, \dots\}$. In similar fashion to peaks, when the condition is true, trough_t equals c_t, and otherwise the previous trough value, trough_{t-1}. Moreover, for the period $t = 0$, calculating the trough is unconditional, equaling the first cumulative equity return value.

5 Results

In this section, the empirical findings regarding the previously described data and methodology are presented. The section starts with a full sample analysis which first reports the cumulative performance along with the main descriptive statistics for the implemented strategies. Furthermore, the strategies are risk-adjusted by estimating the exposures to standard risk factors. Downside risk is assessed based on the exposures to the market indicators introduced in Daniel and Moskowitz (2016) as well as by comparing the worst monthly payoffs and drawdowns associated with the strategies. Subsequently, this section reports the subsample results to confirm robustness of the results. Following prior convention in literature, the empirical part of this study focuses on 12–1–1 momentum strategies. To compare the performance to overall European stock market performance, this study uses STOXX Europe 600 (from now on labeled as market) as a benchmark market index.

5.1 Full sample performance

Figure 5 plots the cumulative returns on the implemented 12–1–1 momentum portfolios along with market index over the sample period that spans from January 1992 through December 2019. Based on the plot, a number of interesting observations can be made. First, in market turmoil and particularly during the 2008 financial crisis, TRIMOM has at least partly been able to dodge the momentum crash while the other momentum strategies and market have collapsed. As expected, however, TRIMOM exhibits quite similar return pattern compared to DMOM in a more normal market environment.

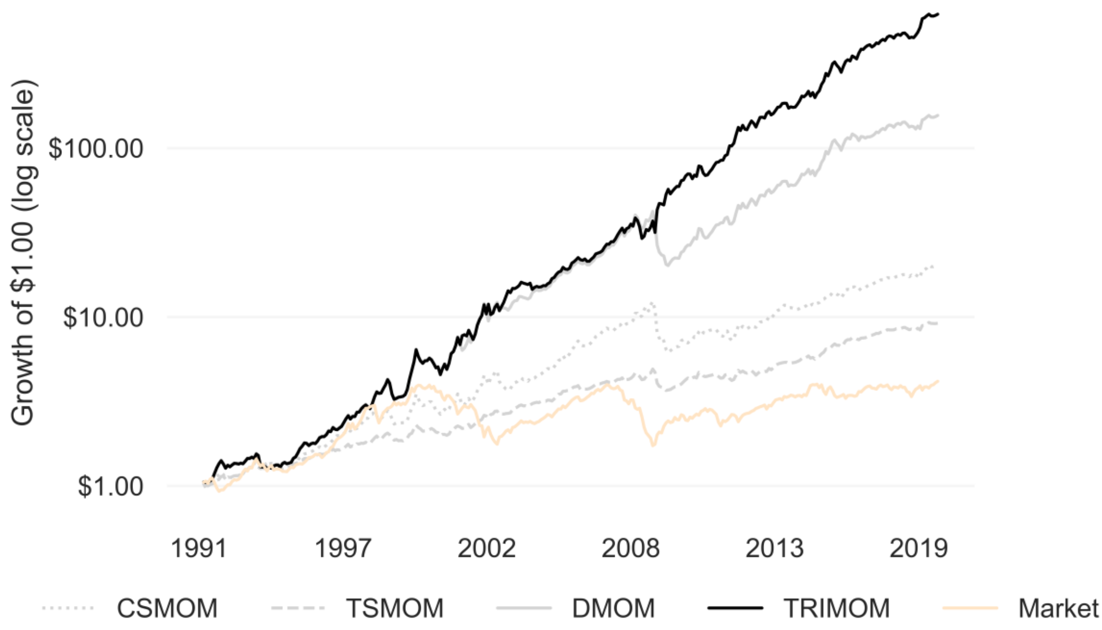

Figure 5. Cumulative returns of 12–1–1 momentum strategies.

Second, all of the momentum strategies have produced significantly higher cumulative returns compared to the market, except for CSMOM and TSMOM before the beginning of 2000s. The plot shows that especially TRIMOM and DMOM have achieved robust cumulative returns, with TRIMOM being clearly the best-in-class over other strategies and market. An initial one dollar investment in TRIMOM is approximately worth $619.81 at the end of the sample period, a four times higher end balance compared to DMOM ($155.94). In turn, a one dollar investment in CSMOM is worth around $20.28 at the end of the sample period, which is 2.2 and 4.9 times more than an investment in TSMOM and market ($9.18 and $4.16), respectively. The most striking difference emerges between TRIMOM and market, TRIMOM displaying around 149 times higher cumulative returns to the market.

As noted, although TSMOM is profitable in the sample period, it performs worse than CSMOM at least when it comes to raw returns. This result supports the findings of Goyal and Jegadeesh (2018) and challenges the results presented in Moskowitz et al. (2012) and Lim et al. (2018). Goyal and Jegadeesh (2018) show that when TSMOM portfolios are volatility-managed, leverage associated with the implemented portfolios mainly drives the performance. Once both TSMOM and CSMOM use equal-weighted returns, TSMOM generates substantially lower returns compared to CSMOM. However, further investigation is needed before drawing conclusions.

Table 1. Descriptive statistics for 12–1–1 momentum strategies.

Measure	CSMOM	TSMOM	DMOM	TRIMOM	Market
Min (%)	-27.20	-13.64	-26.21	-14.64	-14.14
Max (%)	13.40	7.97	17.77	36.16	13.47
Mean (%)	0.98	0.69	1.65	2.08	0.52
(*t*-statistic)	(4.56)	(5.48)	(5.78)	(6.91)	(2.21)
Standard deviation (%)	3.93	2.30	5.23	5.51	4.30
Annualized mean return (%)	12.41	8.58	21.73	28.01	6.41
Annualized standard deviation (%)	13.63	7.97	18.13	19.09	14.89
Sharpe ratio	0.72	0.75	1.04	1.31	0.26
Skewness	-1.31	-0.75	-0.55	0.52	-0.57
Kurtosis	8.29	4.41	2.76	4.61	0.87
Beta	-0.13	-0.08	-0.33	-0.01	
Correlation	-0.14	-0.15	-0.27	-0.01	
Average no. stocks	748	1246	250	234	
Win rate (%)	66.67	68.45	65.48	66.67	59.52

This table reports the main characteristics of 12–1–1 momentum portfolios. All reported measures are based on the equal-weighted monthly returns. Kurtosis is the unbiased excess kurtosis, beta is estimated by regressing each momentum portfolio on the benchmark market index, correlation is the correlation between a given momentum portfolio and benchmark market index and average number of stocks is the monthly average total stocks held in each momentum portfolio over the sample period. Win rates, positions with positive payoffs divided by total positions taken, are also reported for each portfolio. The used benchmark market index is STOXX Europe 600. The sample period is from January 1992 to December 2019.

To understand the implemented strategies more in detail, Table 1 summarizes the properties of the 12–1–1 strategies. In all cases, the average monthly returns are statistically significant and positive at the 1% level, and the ordering is consistent with Figure 5. TRIMOM and DMOM have generated significantly greater returns (2.08% and 1.65%, respectively) compared to standalone CSMOM and TSMOM strategies (0.98% and 0.69%, respectively). The performance is not deteriorated measured by Sharpe ratios, although standard deviations increase for DMOM and TRIMOM. By fact, DMOM earns around 40% higher Sharpe ratio (1.04) than CSMOM (0.72) and TSMOM (0.75), while TRIMOM earns around 26% higher Sharpe ratio (1.31) than DMOM. On average, all strategies display better performance than a passive long investment in the market.

Other main results from Table 1 can be summarized as follows. First, the skewness and kurtosis indicate a positive up-risk and a fat-tailed distribution for TRIMOM, while for other 12–1–1 strategies the signal is in the opposite direction, indicating heavier downside risk. Also, TRIMOM has also relatively moderate worst return but substantially higher maximum return compared to other strategies. The fact that outliers of TRIMOM are more likely positive is a desired property and more unusual for momentum portfolios. As Barroso and Santa-Clara (2015) show, momentum strategies are typically manifested by negative skewness and fat tails, entailing large negative outliers. Second, CSMOM, TSMOM and DMOM strategies seem to at least partly move in the opposite direction of the market movements. This can be observed as negative relationships between the strategies and market since the betas and correlations are slightly negative. As for TRIMOM, the virtually zero-valued beta and correlation rather suggest that the strategy is uncorrelated with the market over the sample period.

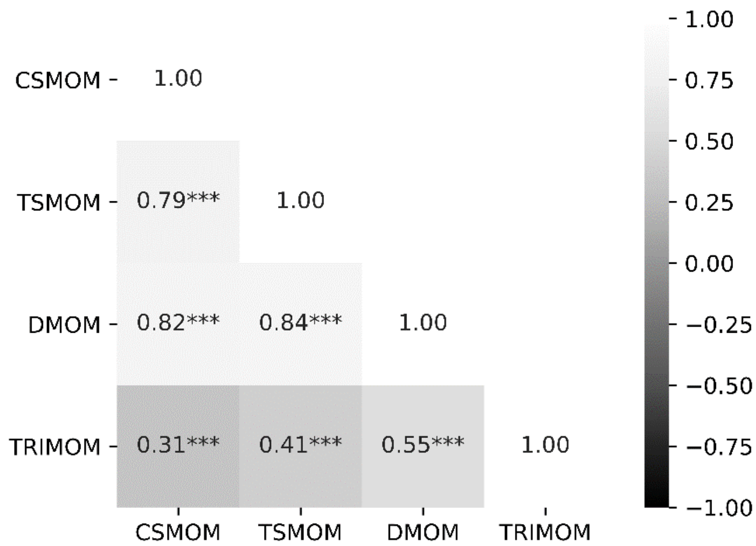

Figure 6. Correlation matrix.

Figure 6 further shows how the 12–1–1 strategies are related to each other. Based on it, it can be seen that all of the strategies are positively correlated with each other at the 1% level. The smallest correlation (0.31) is observed between CSMOM and TRIMOM, and highest correlation (0.84) between TSMOM and DMOM. TRIMOM is most closely related to DMOM which is no surprising since it is basically the same strategy but includes an additional screening step. However, although all reported correlations are significantly positive, TRIMOM is somewhat less linked to other strategies as the correlations between TRIMOM and other strategies range between 0.31 and 0.55, whereas the cross-correlations between CSMOM, TSMOM and DMOM are all close to 0.80.

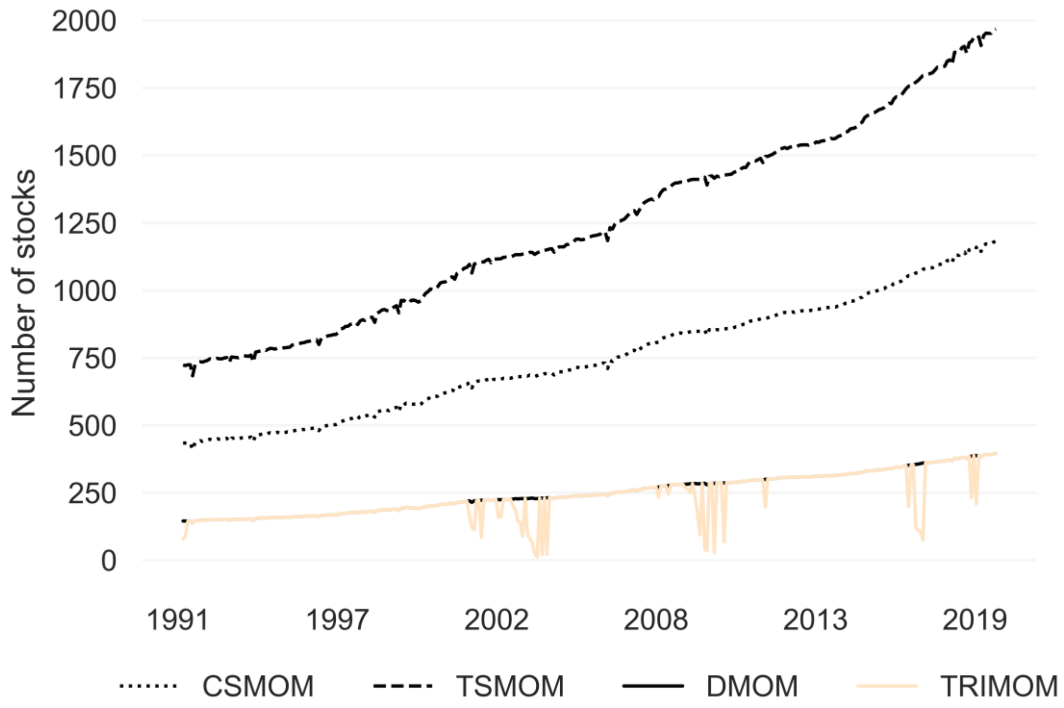

Figure 7. Number of stocks involved in implementing 12–1–1 momentum strategies.

Finally, Figure 7 depicts how the 12–1–1 strategies differ in terms of the total number of stocks involved in formulating each portfolio over time. Overall, the plot shows that the number of stocks has gradually increased as markets have grown. Moreover, the plot shows that a tighter screening process reduces the number of stocks used. TSMOM, which involves the least stringent screening, includes the largest number of stocks. In the opposite, DMOM and TRIMOM comprise the smallest number of stocks due to more stringent screening. By nature, the number of stocks held in DMOM and TRIMOM is relatively same on average. However, when TRIMOM is only long in losers, this results in smaller number of total stocks involved in such periods.

5.1.1 Risk-adjusted implications

To estimate the exposures of the 12–1–1 strategies to standard risk factors, the portfolios are regressed on common asset pricing models. These results are presented in Table 2.

Table 2. Regressing 12–1–1 momentum strategies on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel A: CSMOM								
Coefficient	0.86***	-0.16**						0.03
(*t*-statistic)	(4.21)	(-2.14)						
Coefficient	0.95***	-0.11	0.10	-0.36***				0.08
(*t*-statistic)	(4.80)	(-1.60)	(0.91)	(-2.89)				
Coefficient	0.60***	-0.04	0.12	-0.20	0.67***	0.14		0.12
(*t*-statistic)	(2.82)	(-0.73)	(1.18)	(-0.79)	(3.40)	(0.50)		
Panel B: TSMOM								
Coefficient	0.54***	-0.09**						0.03
(*t*-statistic)	(4.25)	(-2.20)						
Coefficient	0.60***	-0.06	0.03	-0.27***				0.10
(*t*-statistic)	(5.09)	(-1.57)	(0.53)	(-4.59)				
Coefficient	0.45***	-0.02	0.05	-0.22*	0.30***	0.09		0.13
(*t*-statistic)	(3.49)	(-0.66)	(0.74)	(-1.77)	(3.04)	(0.63)		
Coefficient	0.09	0.04	-0.01	-0.10***			0.46***	0.60
(*t*-statistic)	(1.00)	(1.55)	(-0.13)	(-3.03)			(19.20)	
Coefficient	0.11	0.04	-0.01	-0.10*	-0.05	-0.02	0.46***	0.60
(*t*-statistic)	(1.15)	(1.39)	(-0.19)	(-1.90)	(-0.72)	(-0.25)	(18.22)	

(*Continued on next page*)

Table 2. (*Continued*)

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel C: DMOM								
Coefficient	1.62***	-0.32***						0.08
(*t*-statistic)	(5.91)	(-3.99)						
Coefficient	1.76***	-0.24***	0.16	-0.61***				0.16
(*t*-statistic)	(6.81)	(-3.10)	(1.10)	(-3.94)				
Coefficient	1.28***	-0.15**	0.19	-0.36	0.96***	0.16		0.21
(*t*-statistic)	(4.61)	(-2.12)	(1.38)	(-1.43)	(4.18)	(0.52)		
Panel D: TRIMOM								
Coefficient	1.90***	-0.05						0.00
(*t*-statistic)	(6.34)	(-0.48)						
Coefficient	1.97***	0.02	0.36**	-0.44**				0.05
(*t*-statistic)	(7.01)	(0.21)	(2.15)	(-2.35)				
Coefficient	1.82***	-0.01	0.35**	-0.11	0.41	-0.39		0.06
(*t*-statistic)	(5.65)	(-0.16)	(2.24)	(-0.32)	(1.29)	(-1.03)		

This table reports the estimated coefficients from regressing the excess returns of 12–1–1 momentum portfolios on standard risk factors. Models in Panel A, C and D include CAPM, Fama-French three-factor model and Fama-French five-factor model, where MKT is the Fama-French market factor, SMB (small minus big) is the size factor, HML (high minus low) is the value factor, RMW (robust minus weak) is the profitability factor, CMA (conservative minus aggressive) is the investment factor. Models in Panel B additionally include Carhart four-factor and Fama-French six factor models, where the configuration is same as aforementioned, except for UMD (up minus down) which is the momentum factor representing CSMOM. All returns are monthly and equal-weighted. Estimated alphas are reported in percent (i.e., multiplied by 100). Reported in the parentheses are the *t*-statistics which are adjusted for heteroskedasticity using White's (1980) heteroskedasticity-robust standard errors. Statistical significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively. The sample period is from January 1992 to December 2019.

Table 2 documents increasing alphas when one switches from CSMOM to DMOM and from DMOM to TRIMOM. All alphas are positive and statistically significant at 1% level, irrespective of the regression model. Using CAPM, CSMOM, DMOM and TRIMOM report monthly alphas of 0.86%, 1.62% and 1.90%, respectively. Using Fama-French five-factor model, the monthly alphas of CSMOM and DMOM remain large but decrease slightly, to 0.60% and 1.28%. As for TRIMOM, the monthly alpha is virtually unchanged, decreasing from 1.90% to 1.82%. Consistent with prior research, these results in conjunction with the weak explanatory power of the models, reported by adjusted R^2, imply that standard risk factors are unable to adequately capture the variations in the CSMOM, DMOM and TRIMOM returns.

TSMOM alphas are also significant and positive based on the exposures to CAPM, Fama-French three-factor and five-factor models. However, the TSMOM alphas become insignificant when TSMOM is regressed on Carhart four-factor and Fama-French six-factor models. The adjusted R^2 simultaneously experiences a notable increase. The insignificant alphas, highly significant and positive UMD factors as well as large adjusted R^2 jointly indicate that TSMOM may be subsumed by CSMOM, weakening the evidence on TSMOM and supporting the findings of Goyal and Jegadeesh (2018) and Huang et al. (2020).

The 12–1–1 strategies are generally unassociated with the market factor, as the loadings are more often statistically insignificant than significant, except for CSMOM and TSMOM which have significant and negative loadings on the factor when using CAPM, and DMOM which reports significant negative exposures to the market factor in all cases. As expected based on the preliminary results, TRIMOM has insignificant loadings on the market factor in all cases.

Based on the results, loadings on the size factors are typically insignificant, and the loadings on the value factor significant and negative, respectively. Concerning the value factor, the negative relationship generally indicates that the returns on the 12–1–1 strategies may be more attributed to the behavior of growth portfolios than value portfolios. However, the fact that the size factor is positive and statistically significant for TRIMOM is a little surprising in a sense that the sample contains top 30% largest stocks of the stock universe. This result may be explained by Chen and Bassett (2014) who demonstrate that a positive loading on SMB is possible even if the sample mostly consists of large-cap stocks.

When it comes to the profitability factor, the loadings are significant and positive for all but TRIMOM, for which the loading is insignificant. As for CSMOM, TSMOM and DMOM, this result suggests that the portfolios tend to be more related to firms with robust profitability on average. Finally, in all cases, the investment factors are insignificant, suggesting that investment portfolios are not able to explain the returns of the 12–1–1 strategies.

5.1.2 Downside risk

Momentum strategies have widely suffered from serious crashes during market declines such as recessions, as comprehensively studied in Daniel and Moskowitz (2016). Following these findings, it is important to examine the extent to which the implemented 12–1–1 momentum strategies are prone to momentum crashes.

Table 3. Optionality regressions for 12–1–1 momentum strategies.

Coefficient	Variable	CSMOM	TSMOM	DMOM	TRIMOM
$\hat{\alpha}_0$	1	0.83***	0.50***	1.61***	1.59***
		(3.66)	(3.43)	(5.07)	(4.33)
$\hat{\alpha}_B$	$I_{B,t-1}$	0.55	1.00***	1.34	0.09
		(0.93)	(2.65)	(1.62)	(0.10)
$\hat{\beta}_0$	$\tilde{R}^e_{m,t}$	0.17***	0.01	-0.06	0.00
		(3.08)	(0.20)	(-0.78)	(-0.01)
$\hat{\beta}_B$	$I_{B,t-1} \cdot \tilde{R}^e_{m,t}$	-0.42***	0.02	-0.15	-0.23
		(-3.80)	(0.23)	(-0.98)	(-1.30)
$\hat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^e_{m,t}$	-0.64***	-0.49***	-0.89***	0.39
		(-3.61)	(-4.39)	(-3.63)	(1.37)
Adj. R^2		0.24	0.11	0.17	0.00

This table reports the estimated coefficients from regressing the excess returns of 12–1–1 momentum portfolios on market indicators in accordance with Daniel and Moskowitz (2016). Along with the intercept (alpha), the independent variables include $I_{B,t-1}$ which is a bear market indicator that gets a value of 1 if the lagged 24-month market return is negative (and 0 otherwise), $\tilde{R}^e_{m,t}$ which is the market excess return and $I_{U,t}$ which is an up-market indicator that gets a value of 1 if the contemporaneous market return is positive (and 0 otherwise). All returns are monthly and equal-weighted. Estimated $\hat{\alpha}_0$ and $\hat{\alpha}_B$ are reported in percent (i.e., multiplied by 100). Reported in the parentheses are the corresponding *t*-statistics. Statistical significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively. The sample period is from January 1992 to December 2019.

Table 3 reports the optionality effects associated with the 12–1–1 momentum strategies. Based on the results, the following can be observed. First, the results indicate that TRIMOM does not exhibit option-like behavior. Rather, the $\hat{\beta}_{B,U}$ of TRIMOM is statistically insignificant and the coefficient is more tilted towards a positive than a negative value. On average, the presented evidence therefore supports the idea of using a market screening in bypassing momentum crashes. Second, for CSMOM, TSMOM and DMOM, the $\hat{\beta}_{B,U}$ coefficients are negative and statistically significant at 1% level, indicating that the strategies exhibit optionality effects, and consistent with Daniel and Moskowitz (2016), basically mimick the behavior of a short call option during market rebounds following market declines in bear markets.

An interesting finding is that although DMOM outperforms CSMOM and TSMOM by raw and risk-adjusted returns, it may be more vulnerable to momentum crashes compared to CSMOM and TSMOM. In fact, DMOM is economically the most strongly impacted by crash periods as the $\hat{\beta}_{B,U}$ coefficient is the most negative, -0.89, in comparison to -0.64 and -0.49 reported for CSMOM and TSMOM, respectively. Because DMOM goes long in the strongest winners short in the worst loser group, this result may at least partially be explained by asymmetric optionality effects as shown in Daniel and Moskowitz (2016). They demonstrate that the optionality effects appear stronger for the most extreme portfolio return deciles, meaning that in bear markets, the more extreme the decile is for past losers (winners), the larger (smaller) the up-market beta and more sensitive to momentum crashes the portfolio is. For example, Daniel and Moskowitz (2016) report a $\hat{\beta}_{B,U}$ of -0.815 for the CSMOM WML portfolio when using the most extreme portfolio return deciles (i.e., 1st and 10th deciles). Respectively, when they use 2nd and 9th deciles for otherwise the same portfolio, the $\hat{\beta}_{B,U}$ is -0.532 which indicates relatively less negative exposure to momentum crashes.

To further shed light on the extent to which the 12–1–1 strategies compare to each other during times when the worst monthly returns are generated, Table 4 reports the top 15 worst monthly returns for the 12–1–1 portfolios. Panels A, B, C, D are sorted by CSMOM, TSMOM, DMOM and TRIMOM, respectively. Furthermore, market performance for the past 24 months as well as the contemporaneous monthly returns are also reported.

Table 4. Worst monthly returns of 12–1–1 momentum strategies.

Rank	Month	CSMOM	TSMOM	DMOM	TRIMOM	MKT-24	MKT
Panel A: Sorted on CSMOM							
1	2009-04	-27.20	-13.64	-26.21	36.16	-48.25	13.47
2	2003-04	-13.48	-4.42	-8.51	-8.51	-43.02	10.47
3	2009-08	-10.81	-3.60	-10.80	15.27	-37.22	4.93
4	2009-03	-10.78	-4.37	-14.46	-14.46	-52.85	2.05
5	2012-01	-9.13	-5.57	-8.77	12.67	3.02	4.04
6	2001-11	-8.75	-2.13	-8.32	13.02	-15.54	4.16
7	2002-11	-8.03	-2.83	-10.68	14.30	-38.76	4.44
8	1999-04	-7.10	-3.02	-6.73	-6.73	58.56	5.12
9	2000-11	-6.98	-2.93	-5.41	-5.41	33.91	-6.39
10	1999-03	-6.83	-4.34	-14.06	-14.06	54.33	2.48
11	2009-05	-6.70	-4.30	-9.05	9.03	-47.52	3.99
12	1998-08	-6.18	2.89	7.13	7.13	71.48	-13.44
13	2000-03	-6.14	-3.33	-8.90	-8.90	36.88	2.10
14	2001-10	-6.10	-1.31	-9.33	-9.33	-12.56	4.18
15	2008-12	-5.93	4.73	-1.57	-1.57	-45.69	-3.83
Panel B: Sorted on TSMOM							
1	2009-04	-27.20	-13.64	-26.21	36.16	-48.25	13.47
2	2012-01	-9.13	-5.57	-8.77	12.67	3.02	4.04
3	2006-05	-5.46	-5.27	-2.90	-2.90	34.34	-5.23
4	2008-01	-2.86	-4.77	-6.05	-6.05	0.35	-11.65
5	2008-09	2.14	-4.48	-6.51	-14.64	-25.01	-11.15
6	2003-04	-13.48	-4.42	-8.51	-8.51	-43.02	10.47
7	2009-03	-10.78	-4.37	-14.46	-14.46	-52.85	2.05
8	1999-03	-6.83	-4.34	-14.06	-14.06	54.33	2.48
9	2009-05	-6.70	-4.30	-9.05	9.03	-47.52	3.99
10	2002-03	-4.98	-4.27	-6.03	-6.03	-23.11	4.56
11	2001-01	-4.62	-4.16	-9.94	-9.94	25.67	0.71
12	1998-09	-5.03	-3.63	-1.96	-1.96	49.85	-9.10
13	1992-11	-5.20	-3.62	-5.67	-5.67	9.47	3.86
14	2011-01	-4.47	-3.62	-8.42	-8.42	46.44	1.54
15	1997-08	-2.42	-3.61	-4.46	-4.46	62.52	-6.72

(*Continued on next page*)

Table 4. (*Continued*)

Rank	Month	CSMOM	TSMOM	DMOM	TRIMOM	MKT-24	MKT
Panel C: Sorted on DMOM							
1	2009-04	-27.20	-13.64	-26.21	36.16	-48.25	13.47
2	2009-03	-10.78	-4.37	-14.46	-14.46	-52.85	2.05
3	1999-03	-6.83	-4.34	-14.06	-14.06	54.33	2.48
4	1994-03	-3.50	-1.96	-14.04	-14.04	26.52	-4.50
5	2002-10	-3.84	-0.97	-11.78	-11.78	-45.10	9.38
6	2009-08	-10.81	-3.60	-10.80	15.27	-37.22	4.93
7	2002-11	-8.03	-2.83	-10.68	14.30	-38.76	4.44
8	2001-01	-4.62	-4.16	-9.94	-9.94	25.67	0.71
9	2001-10	-6.10	-1.31	-9.33	-9.33	-12.56	4.18
10	2009-05	-6.70	-4.30	-9.05	9.03	-47.52	3.99
11	2000-03	-6.14	-3.33	-8.90	-8.90	36.88	2.10
12	2012-01	-9.13	-5.57	-8.77	12.67	3.02	4.04
13	2003-04	-13.48	-4.42	-8.51	-8.51	-43.02	10.47
14	2011-01	-4.47	-3.62	-8.42	-8.42	46.44	1.54
15	2001-11	-8.75	-2.13	-8.32	13.02	-15.54	4.16
Panel D: Sorted on TRIMOM							
1	2008-09	2.14	-4.48	-6.51	-14.64	-25.01	-11.15
2	2009-03	-10.78	-4.37	-14.46	-14.46	-52.85	2.05
3	1999-03	-6.83	-4.34	-14.06	-14.06	54.33	2.48
4	1994-03	-3.50	-1.96	-14.04	-14.04	26.52	-4.50
5	2002-12	9.16	5.07	11.95	-13.27	-43.93	-9.33
6	2002-10	-3.84	-0.97	-11.78	-11.78	-45.10	9.38
7	2001-01	-4.62	-4.16	-9.94	-9.94	25.67	0.71
8	2001-10	-6.10	-1.31	-9.33	-9.33	-12.56	4.18
9	2000-03	-6.14	-3.33	-8.90	-8.90	36.88	2.10
10	2003-04	-13.48	-4.42	-8.51	-8.51	-43.02	10.47
11	2011-01	-4.47	-3.62	-8.42	-8.42	46.44	1.54
12	2004-07	-0.91	1.96	6.55	-8.24	3.85	-1.85
13	2008-08	-5.35	-2.33	-8.11	-8.11	-13.91	1.56
14	2001-04	-3.08	-1.18	-6.91	-6.91	9.50	6.32
15	1999-04	-7.10	-3.02	-6.73	-6.73	58.56	5.12

This table reports the worst returns on 12–1–1 momentum portfolios. Panels A, B, C and D are sorted on CSMOM, TSMOM, DMOM and TRIMOM, respectively, and in ascending order (smallest to highest). For all panels, past 24-month and contemporaneous market returns are also included as in Daniel and Moskowitz (2016). All returns are monthly and equal-weighted. The sample period is from January 1992 to December 2019.

The results in Table 4 indicate that the 12–1–1 strategies are relatively related to each other when it comes to periods during which the worst negative returns are generated. Most notably, CSMOM coincides with DMOM for 73% (11 of 15) of the reported periods. The matching periods are less notable in case of TSMOM and TRIMOM, with which CSMOM coincides 40% of the periods. Moreover, the periods with the most negative returns for TSMOM match with DMOM for 53% of the observations. For DMOM and TRIMOM, the coincidence is 60% of the observations, respectively. This is unsurprising because TRIMOM is equal to DMOM for all the periods that coincide, meaning that TRIMOM holds the WML portfolio of DMOM during these periods. In this spirit, the results also demonstrate that TRIMOM is not able to avoid all of the most negative returns which are also equivalent to DMOM, and this may simply be due to the one-month lagged response to market events. For instance, TRIMOM is able to avoid the largest negative return occurring in April 2009 but not the second largest negative return occurring in March 2009.

The results are also consistent with the optionality regressions in Table 3. CSMOM and DMOM, which displayed the most negative $\hat{\beta}_{B,U}$ coefficients, also have the highest share of periods that are linked to market upswings occurring after market declines (i.e., periods when the contemporaneous market return is positive and past two-year market return is negative) as roughly 53% (60%) of the most negative returns occur during these periods. In comparison, the corresponding shares are only 33% for both TSMOM and TRIMOM. Further limiting the attention to the top five most negative returns of CSMOM (DMOM), it can be seen that 80% (60%) of the returns are related to momentum crashes. However, only 20% (1 of 5) of the periods are linked to momentum crashes in case of TSMOM and TRIMOM. These findings imply that TRIMOM is an attractive strategy especially when the goal is to mitigate the impact of momentum crashes. From this perspective, TSMOM is also preferable to CSMOM and DMOM, however less so than TRIMOM, since TSMOM is still significantly negatively exposed to momentum crashes as the estimated $\hat{\beta}_{B,U}$ in Table 3 shows.

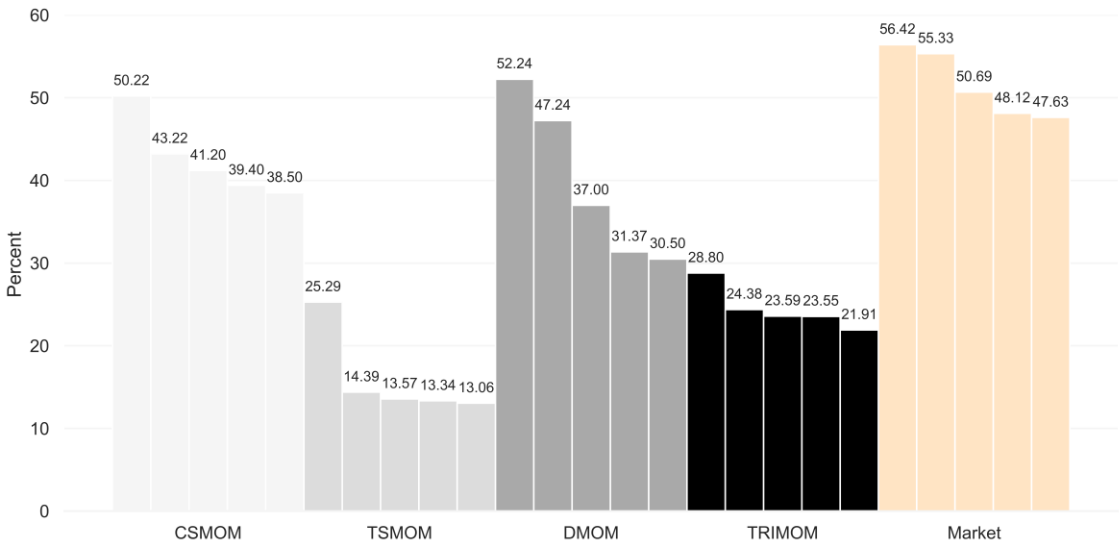

Figure 8. Top five largest drawdowns for 12–1–1 momentum strategies.

It is essential to examine how severely the 12–1–1 strategies are impacted by chains of losses, considering individual monthly returns merely characterize performance at a certain period. As a consequence of this, Figure 8 displays the top five largest drawdowns for each strategy from January 1992 to December 2019. Moreover, to improve the quality of the comparisons, Table 5 also shows timing of the corresponding drawdowns.

Table 5. Timing of the top five largest drawdowns.

Rank	CSMOM	TSMOM	DMOM	TRIMOM	Market
1	2009-09	2009-08	2009-09	2001-01	2009-02
2	2010-06	2012-02	2010-02	2008-09	2003-03
3	2012-02	2001-01	2010-07	2001-04	2002-09
4	2009-05	2010-07	2010-10	1999-04	2009-06
5	2010-10	2001-04	2011-02	2000-11	2003-09

This table reports the timing of the top five largest drawdowns experienced by 12–1–1 momentum portfolios. Drawdown is an ex post measure defined as the peak-to-trough change until a new peak is achieved. The results are in descending order (i.e., first rank denotes the period at which the largest drawdown is reported). The sample period is from January 1992 to December 2019.

According to Figure 8 and Table 5, the largest drawdowns of TSMOM and TRIMOM are remarkably lower in proportion to CSMOM, DMOM and market, signaling that the drawdowns associated with TSMOM and TRIMOM are significantly less severe on average. For example, the largest drawdowns of TSMOM and TRIMOM are 25.29% and 28.80%, while the magnitude roughly doubles for others, amounting 50.22%, 52.24% and 56.42% for CSMOM, DMOM and market, respectively. However, none of the 12–1–1 strategies have generated larger drawdowns compared to the market.

The largest drawdown of CSMOM, TSMOM and DMOM appear to occur during the aftermath of the financial crisis, pointed at August and September 2009. In terms of CSMOM and DMOM, the largest five drawdowns are all dated between years 2009 and 2012. As for TSMOM, three of five largest drawdowns take place during this period, while the rest seem to occur as a result of dotcom bubble in the beginning of 2000s. Overall, TRIMOM seems not to be as strongly impacted by the financial crisis. The results show that the only listed drawdown period associated with the financial crisis occurs notably earlier (September 2008) than that of CSMOM, TSMOM and DMOM, while rest of the periods generally date back in the beginning of 2000s.

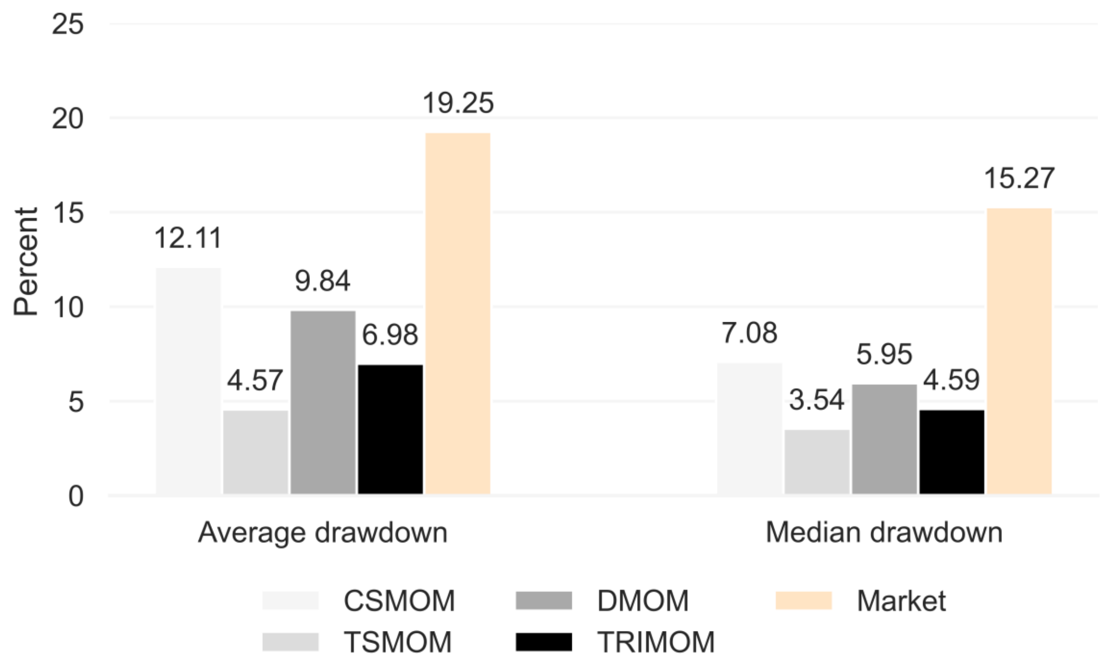

Figure 9. Average and median drawdowns.

Summarization presented in Figure 9 confirms that average drawdowns of TSMOM and TRIMOM have been significantly less harmful relative to CSMOM, DMOM and the market over the sample period. An average drawdown is 4.57% and 6.98% for TSMOM and TRIMOM, respectively, while the corresponding averages are 12.11%, 9.84% and 19.25% for CSMOM, DMOM and the market. Examining median drawdowns essentially shows the same pattern, with TSMOM and TRIMOM displaying 3.54% and 4.59% median drawdowns, in comparison to much larger, 7.08%, 5.95% and 15.27% median drawdowns experienced by CSMOM, DMOM and the market, respectively.

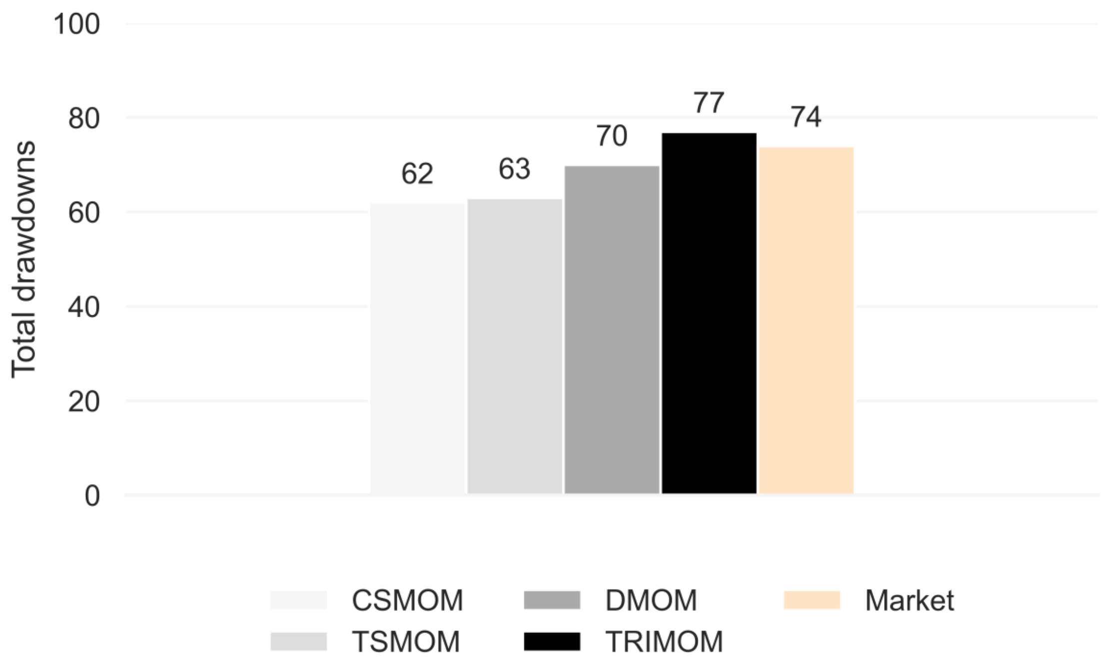

Figure 10. Total drawdowns.

Finally, Figure 10 presents the total number of drawdowns reported over the sample period. Interestingly, TRIMOM records the highest number of drawdowns (77), compared to all other strategies and the market. However, it is to be noted that regardless of the number of total drawdowns, the performance of TRIMOM is not materially affected which is likely due to the fact that the drawdowns are significantly smaller in size. In contrast, CSMOM records the smallest number of drawdowns, totaling 62. Yet, CSMOM simultaneously experiences the second most severe drawdowns as shown in Figure 9. Respectively, although TSMOM reports nearly the same number of total drawdowns (63), it is not as strongly impacted by them based on the average and median figures. DMOM, in turn, records the third highest number of drawdowns, totaling 70, while also experiencing the third largest average and median drawdowns as well as the most negative $\hat{\beta}_{B,U}$ coefficient. On balance, these remarks highlight the importance of considering both the magnitude and number of drawdowns in evaluating downside risk.

5.2 Subsample performance

As the previously presented full sample results may be sample-specific, this section examines the robustness of the results. To overcome this issue, the sample period is split into two equal length periods. The first period spans from January 1992 through December 2005. The second period is from January 2006 to December 2019.

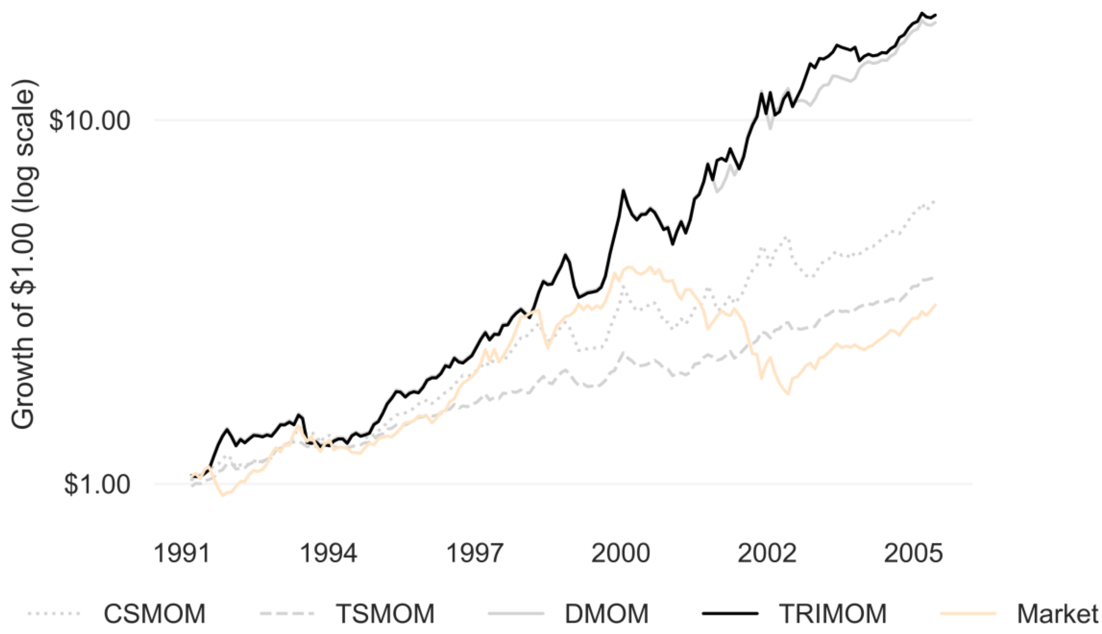

Figure 11. Subsample cumulative returns from January 1992 to December 2005.

Figure 11 and Figure 12 plot the cumulative returns on the 12–1–1 momentum strategies during the two subsample periods. In sum, the results remain same as in the full sample. During the first period, the performance of TRIMOM and DMOM is alike as the lines are largely overlapping. This is expected because notable momentum crashes are not present in the first period. Consequently, for most of the time, TRIMOM holds the WML portfolio that is equivalent to that of DMOM.

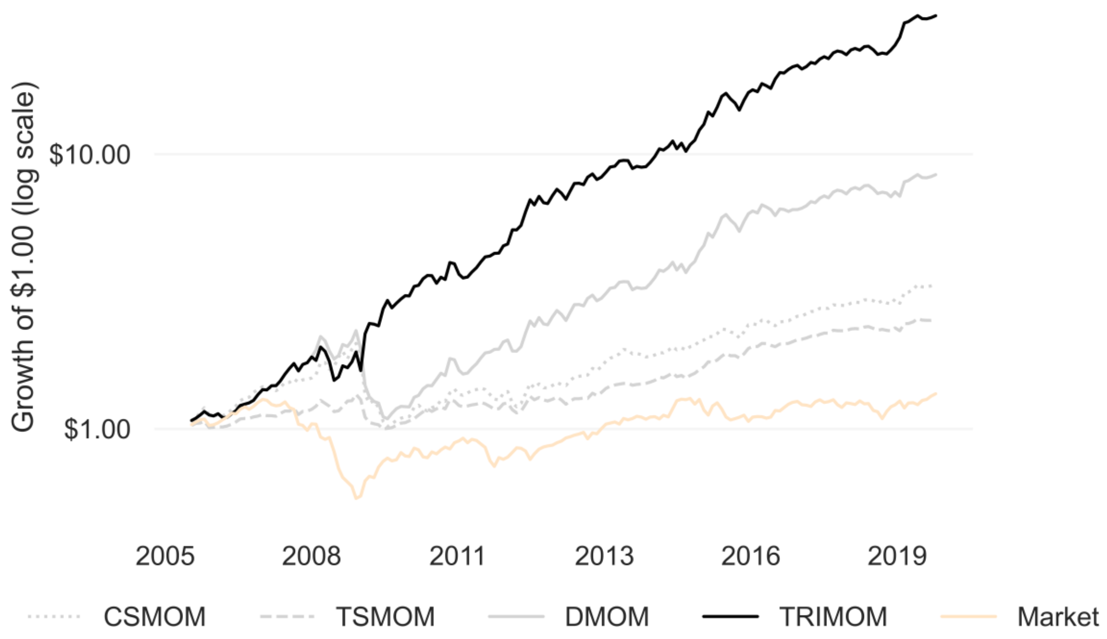

Figure 12. Subsample cumulative returns from January 2006 to December 2019.

The second subsample period better illustrates the benefit of TRIMOM. While the other 12–1–1 strategies hold WML portfolios and subsequently experience significant losses due to short positions in past losers, TRIMOM goes long in the past losers and earns large positive returns which is observed at the bottom of 2008 financial crisis. The gap between cumulative returns on TRIMOM and other strategies persists large across time. However, because of the one-month lagged response to the market events, TRIMOM does also generate negative returns during a part of the financial crisis.

Table 6. Descriptive statistics for 12–1–1 momentum strategies across subsamples.

Measure	CSMOM	TSMOM	DMOM	TRIMOM	Market
Panel A: 01/1992-12/2005					
Min (%)	-13.48	-4.42	-14.06	-14.06	-14.14
Max (%)	13.40	6.54	17.77	17.77	10.92
Mean (%)	1.15	0.80	1.89	1.93	0.78
(*t*-statistic)	(3.88)	(4.99)	(4.62)	(4.54)	2.23
Standard deviation (%)	3.83	2.07	5.29	5.50	4.52
Annualized mean return (%)	14.70	10.03	25.22	25.80	9.76
Annualized standard deviation (%)	13.27	7.18	18.34	19.05	15.65
Sharpe ratio	0.80	0.85	1.13	1.12	0.37
Skewness	-0.32	-0.15	-0.14	-0.13	-0.64
Kurtosis	1.71	0.36	1.16	0.99	0.62
Beta	-0.02	-0.02	-0.28	-0.10	
Correlation	-0.02	-0.05	-0.24	-0.08	
Average no. stocks	565	940	189	175	
Win rate (%)	69.05	70.24	66.67	65.48	61.90
Panel B: 01/2006-12/2019					
Min (%)	-27.20	-13.64	-26.21	-14.64	-13.27
Max (%)	10.29	7.97	15.25	36.16	13.47
Mean (%)	0.81	0.58	1.41	2.23	0.26
(*t*-statistic)	(2.60)	(2.98)	(3.54)	(5.22)	(0.82)
Standard deviation (%)	4.03	2.50	5.16	5.52	4.05
Annualized mean return (%)	10.16	7.15	18.34	30.26	3.14
Annualized standard deviation (%)	13.96	8.67	17.88	19.11	14.03
Sharpe ratio	0.64	0.68	0.95	1.51	0.14
Skewness	-2.16	-1.03	-1.00	1.17	-0.54
Kurtosis	13.61	5.91	4.51	8.23	1.33
Beta	-0.28	-0.15	-0.40	0.11	
Correlation	-0.28	-0.25	-0.32	0.08	
Average no. stocks	932	1552	311	293	
Win rate (%)	64.29	66.67	64.29	67.86	57.14

This table reports the main characteristics of 12–1–1 momentum portfolios for the subsamples. All reported measures are based on the equal-weighted monthly returns. Kurtosis is the unbiased excess kurtosis, beta is estimated by regressing each momentum portfolio on the benchmark market index, correlation is the correlation between a given momentum portfolio and benchmark market index and average number of stocks is the average total stocks held in each momentum portfolio over the subsample period. Win rates, positions with positive payoffs divided by total positions taken, are also reported for each portfolio. The used benchmark market index is STOXX Europe 600. The subsample periods in Panel A and B span from January 1992 through December 2005 and from January 2006 through December 2019, respectively.

Panels A and B in Table 6 report the descriptive statistics of the 12–1–1 strategies using subsamples from January 1992 to December 2005 and from January 2006 to December 2019, strengthening the earlier evidence. Overall, the main results remain unchanged. All 12–1–1 strategies outperform the benchmark index measured by raw returns and Sharpe ratios. The monthly average returns are positive and statistically significant at 1% level for all portfolios in both periods. Over the second period, however, the average returns experience a drop in all cases, except for TRIMOM for which the average returns increase from 1.93% to 2.23% per month.

Consistent with prior results, the Sharpe ratios increase in order by switching from CSMOM to TSMOM, from TSMOM to DMOM, and also from DMOM to TRIMOM with the exception of the first period during which DMOM and TRIMOM are essentially equal, as discovered. In the second period, the Sharpe ratio of TRIMOM (1.51) does not only outperform its counterparts but also increases substantially relative to the first period. In contrast, the other momentum portfolios earn lower Sharpe ratios in the second period compared to the first period. This result suggests that TRIMOM is not only able to alleviate the impact of momentum crashes but may take advantage of such on risk-adjusted basis.

The negative skewness and positive excess kurtosis indicate a slight downside risk and fat-tailed distributions for all 12–1–1 strategies in the first period, including TRIMOM as expected, though the skewness values are higher (more positive) than that of market (-0.64) and range between -0.13 and -0.32 which may be considered fairly close to a normal distribution. According to the moderate betas and correlations, DMOM and TRIMOM (CSMOM and TSMOM) strategies are somewhat negatively related (unrelated) to overall market movements in the first period.

In the second period, it can be observed that the skewness values stay negative for all but TRIMOM which by contrast reports a positive skewness value of 1.17. Consistent with the full sample results, this implies right-tail risk for TRIMOM and left-tail risk for the other implemented momentum strategies. Also, the increasing excess kurtosis values relative to the first period indicate proportionally heavier tails for all portfolios. All betas and correlations remain negative, except for TRIMOM for which the signs reverse. The slightly positive beta and correlation of TRIMOM signal that the strategy is positively linked to market movements but this dependence is not very strong.

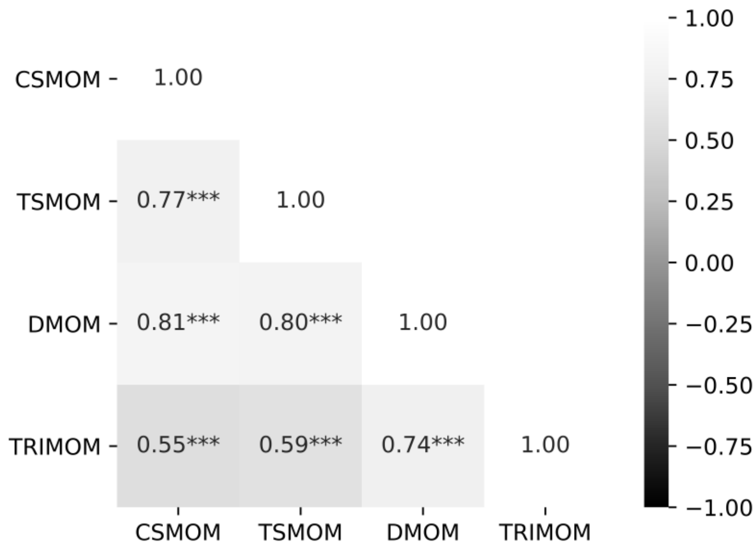

Figure 13. Subsample correlation matrix from January 1992 to December 2005.

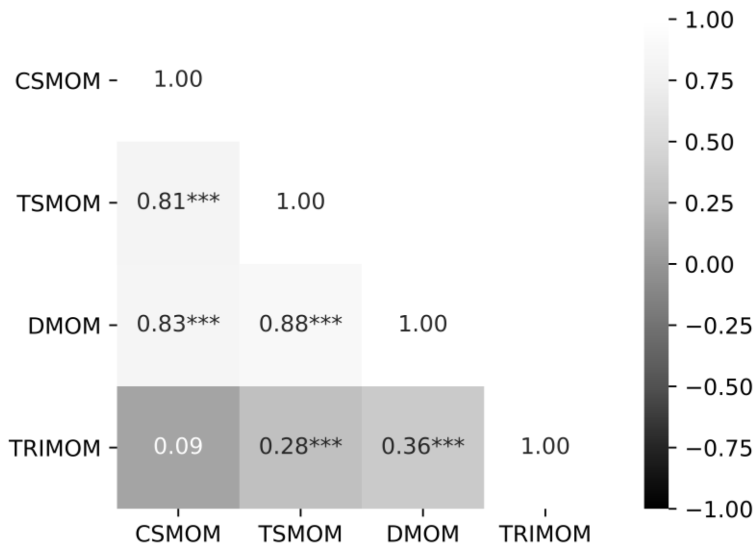

Figure 14. Subsample correlation matrix from January 2006 to December 2019.

To identify how the subsample periods affect the cross-correlations of the 12–1–1 strategies, Figure 13 and Figure 14 illustrate the dependences across the two sub-periods. According to the estimates, the correlations are positive and mainly statistically significant at 1% level for both periods. TRIMOM is positively but comparably less correlated with CSMOM and TSMOM (reporting correlations of 0.55 and 0.59, respectively), than with DMOM (0.74) in the first period. The cross-correlations between CSMOM, TSMOM and DMOM are high, ranging between 0.77 and 0.81 in the first period, and even higher in the second period, ranging between 0.81 and 0.88. On the other hand, TRIMOM becomes less correlated with other portfolios in the second period. Most notably, the correlation between CSMOM and TRIMOM becomes statistically insignificant, indicating that the correlation is statistically not different from zero.

Table 7. Subsample regressions from January 1992 to December 2005.

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel A: CSMOM								
Coefficient	0.86***	-0.03						0.00
(*t*-statistic)	(2.84)	(-0.28)						
Coefficient	0.99***	-0.02	0.15	-0.18				0.01
(*t*-statistic)	(2.82)	(-0.19)	(1.05)	(-1.02)				
Coefficient	0.37	0.05	0.18	0.33	1.03***	-0.40*		0.16
(*t*-statistic)	(1.12)	(0.56)	(1.27)	(1.57)	(4.69)	(-1.88)		
Panel B: TSMOM								
Coefficient	0.51***	-0.03						0.00
(*t*-statistic)	(3.06)	(-0.57)						
Coefficient	0.62***	-0.03	0.04	-0.14*				0.02
(*t*-statistic)	(3.54)	(-0.72)	(0.50)	(-1.79)				
Coefficient	0.38**	0.00	0.05	0.04	0.41***	-0.13		0.09
(*t*-statistic)	(2.13)	(0.05)	(0.65)	(0.34)	(3.86)	(-0.98)		
Coefficient	0.12	0.04	-0.03	-0.04			0.38***	0.53
(*t*-statistic)	(0.84)	(1.10)	(-0.49)	(-0.87)			(14.37)	
Coefficient	0.12	0.03	-0.03	-0.02	-0.01	-0.04	0.38***	0.53
(*t*-statistic)	(0.86)	(0.97)	(-0.47)	(-0.30)	(-0.16)	(-0.46)	(12.64)	

(*Continued on next page*)

Table 7. (*Continued*)

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel C: DMOM								
Coefficient	1.74***	-0.26**						0.04
(*t*-statistic)	(4.26)	(-2.27)						
Coefficient	2.03***	-0.27**	0.16	-0.39*				0.07
(*t*-statistic)	(4.50)	(-2.47)	(0.82)	(-1.70)				
Coefficient	1.30***	-0.14	0.19	0.07	1.25***	-0.20		0.18
(*t*-statistic)	(3.04)	(-1.40)	(1.05)	(0.26)	(4.67)	(-0.68)		
Panel D: TRIMOM								
Coefficient	1.70***	-0.12						0.00
(*t*-statistic)	(3.89)	(-0.97)						
Coefficient	2.05***	-0.14	0.11	-0.45**				0.04
(*t*-statistic)	(4.43)	(-1.19)	(0.53)	(-2.00)				
Coefficient	1.80***	-0.12	0.13	-0.22	0.42	-0.21		0.04
(*t*-statistic)	(3.56)	(-1.00)	(0.61)	(-0.73)	(1.06)	(-0.60)		

This table reports the estimated coefficients from regressing the excess returns of 12–1–1 momentum portfolios on standard risk factors over the subsample period from January 1992 to December 2005. Models in Panel A, C and D include CAPM, Fama-French three-factor model and Fama-French five-factor model, where MKT is the Fama-French market factor, SMB (small minus big) is the size factor, HML (high minus low) is the value factor, RMW (robust minus weak) is the profitability factor, CMA (conservative minus aggressive) is the investment factor. Models in Panel B additionally include Carhart four-factor and Fama-French six factor models, where the configuration is same as aforementioned, except for UMD (up minus down) which is the momentum factor representing CSMOM. All returns are monthly and equal-weighted. Estimated alphas are reported in percent (i.e., multiplied by 100). Reported in the parentheses are the *t*-statistics which are adjusted for heteroskedasticity using White's (1980) heteroskedasticity-robust standard errors. Statistical significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.

The estimated regressions in Table 7 present the exposures of the 12–1–1 portfolios to common risk factors in the first subsample period spanning January 1992 through December 2005. Starting with CSMOM, the strategy produces 0.99% and 0.86% monthly alphas which are statistically significant at 1% level using CAPM and Fama-French three-factor models. However, the significance drops using Fama-French five-factor model. The significantly positive RMW coefficient and negative CMA coefficient suggest that CSMOM tends to be invested in firms with robust operating profitability and firms with aggressive investments in the first period. With regard to TSMOM, the alphas are initially significant using CAPM as well as Fama-French three-factor and five-factor models but become insignificant when the models are augmented with the momentum factor. These results are supportive with the full sample findings and imply that TSMOM may largely be driven by CSMOM premium.

Both DMOM and TRIMOM display large positive alphas that are significant at 1% level, with DMOM reporting monthly alphas ranging between 1.30% and 2.03% and TRIMOM 1.70% and 2.05%, respectively. Overall, the results are robust regardless of the specified model and the explanatory power of the risk factors is generally weak, contributing to the previous findings.

Table 8. Subsample regressions from January 2006 to December 2019.

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel A: CSMOM								
Coefficient	0.83***	-0.23**						0.09
(*t*-statistic)	(2.95)	(-2.48)						
Coefficient	0.68**	-0.10	0.09	-0.61***				0.17
(*t*-statistic)	(2.38)	(-1.39)	(0.59)	(-3.06)				
Coefficient	0.52*	0.02	0.24*	-0.94**	-0.03	0.92*		0.22
(*t*-statistic)	(1.79)	(0.30)	(1.82)	(-2.04)	(-0.06)	(1.95)		
Panel B: TSMOM								
Coefficient	0.54***	-0.12**						0.06
(*t*-statistic)	(2.87)	(-2.14)						
Coefficient	0.42**	-0.02	0.05	-0.49***				0.20
(*t*-statistic)	(2.37)	(-0.42)	(0.49)	(-4.49)				
Coefficient	0.39**	0.03	0.10	-0.65***	-0.07	0.35		0.22
(*t*-statistic)	(2.09)	(0.57)	(1.20)	(-2.87)	(-0.33)	(1.46)		
Coefficient	-0.02	0.08*	0.07	-0.14**			0.56***	0.70
(*t*-statistic)	(-0.12)	(1.94)	(1.10)	(-2.11)			(17.25)	
Coefficient	0.02	0.06	0.04	-0.09	-0.04	-0.19	0.58***	0.70
(*t*-statistic)	(0.14)	(1.38)	(0.65)	(-0.70)	(-0.29)	(-1.11)	(16.11)	

(*Continued on next page*)

Table 8. (*Continued*)

	α	MKT	SMB	HML	RMW	CMA	UMD	Adj. R^2
Panel C: DMOM								
Coefficient	1.49***	-0.35***						0.12
(*t*-statistic)	(4.02)	(-3.25)						
Coefficient	1.21***	-0.11	0.14	-1.13***				0.30
(*t*-statistic)	(3.58)	(-1.21)	(0.77)	(-5.44)				
Coefficient	1.17***	-0.04	0.22	-1.40***	-0.15	0.53		0.30
(*t*-statistic)	(3.30)	(-0.43)	(1.22)	(-3.13)	(-0.36)	(1.15)		
Panel D: TRIMOM								
Coefficient	2.13***	0.00						-0.01
(*t*-statistic)	(5.11)	(0.01)						
Coefficient	1.92***	0.12	0.67***	-0.57*				0.07
(*t*-statistic)	(4.55)	(1.17)	(2.71)	(-1.76)				
Coefficient	1.99***	0.04	0.57**	-0.29	0.11	-0.64		0.08
(*t*-statistic)	(4.64)	(0.38)	(2.47)	(-0.40)	(0.20)	(-0.83)		

This table reports the estimated coefficients from regressing the excess returns of 12–1–1 momentum portfolios on standard risk factors over the subsample period from January 2006 to December 2019. Models in Panel A, C and D include CAPM, Fama-French three-factor model and Fama-French five-factor model, where MKT is the Fama-French market factor, SMB (small minus big) is the size factor, HML (high minus low) is the value factor, RMW (robust minus weak) is the profitability factor, CMA (conservative minus aggressive) is the investment factor. Models in Panel B additionally include Carhart four-factor and Fama-French six factor models, where the configuration is same as aforementioned, except for UMD (up minus down) which is the momentum factor representing CSMOM. All returns are monthly and equal-weighted. Estimated alphas are reported in percent (i.e., multiplied by 100). Reported in the parentheses are the *t*-statistics which are adjusted for heteroskedasticity using White's (1980) heteroskedasticity-robust standard errors. Statistical significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.

The regression results for the second subsample period are presented in Table 8. In conclusion, the results are consistent with the results for the first subsample period as well as with the full sample. The joint evidence suggests that CSMOM, DMOM and TRIMOM are generally weakly related to standard risk factors, albeit the implications for CSMOM are slightly more ambiguous. Furthermore, the results do not support the idea of TSMOM being a distinguishable phenomenon from CSMOM. Instead, the results further suggest that TSMOM may be subsumed by CSMOM.

Table 9. Subsample optionality regressions.

Coefficient	Variable	CSMOM	TSMOM	DMOM	TRIMOM
Panel A: 01/1992–12/2005					
$\hat{\alpha}_0$	1	0.55**	0.41**	1.33***	1.12**
		(1.98)	(2.23)	(3.04)	(2.31)
$\hat{\alpha}_B$	$I_{B,t-1}$	0.13	0.39	0.77	1.20
		(0.17)	(0.76)	(0.62)	(0.87)
$\hat{\beta}_0$	$\tilde{R}^e_{m,t}$	0.46***	0.12**	0.20*	0.24*
		(6.02)	(2.44)	(1.69)	(1.77)
$\hat{\beta}_B$	$I_{B,t-1} \cdot \tilde{R}^e_{m,t}$	-1.00***	-0.24**	-0.89***	-0.75***
		(-6.08)	(-2.22)	(-3.50)	(-2.66)
$\hat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^e_{m,t}$	-0.33	-0.24	-0.37	-0.05
		(-1.25)	(-1.40)	(-0.89)	(-0.10)
Adj. R^2		0.37	0.10	0.19	0.08
Panel B: 01/2006–12/2019					
$\hat{\alpha}_0$	1	1.06***	0.56**	1.84***	2.04***
		(3.09)	(2.53)	(4.14)	(3.87)
$\hat{\alpha}_B$	$I_{B,t-1}$	0.76	1.44***	1.52	-0.86
		(0.90)	(2.65)	(1.40)	(-0.67)
$\hat{\beta}_0$	$\tilde{R}^e_{m,t}$	-0.04	-0.08	-0.26**	-0.18
		(-0.54)	(-1.55)	(-2.58)	(-1.51)
$\hat{\beta}_B$	$I_{B,t-1} \cdot \tilde{R}^e_{m,t}$	-0.06	0.18*	0.28	0.08
		(-0.39)	(1.91)	(1.49)	(0.36)
$\hat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^e_{m,t}$	-0.79***	-0.64***	-1.13***	0.65*
		(-3.46)	(-4.29)	(-3.80)	(1.85)
Adj. R^2		0.22	0.15	0.20	0.03

This table reports the estimated subsample coefficients from regressing the excess returns of 12–1–1 momentum portfolios on market indicators in accordance with Daniel and Moskowitz (2016). Along with the intercept (alpha), the independent variables include $I_{B,t-1}$ which is a bear market indicator that gets a value of 1 if the lagged 24-month market return is negative (and 0 otherwise), $\tilde{R}^e_{m,t}$ which is the market excess return and $I_{U,t}$ which is an up-market indicator that gets a value of 1 if the contemporaneous market return is positive (and 0 otherwise). All returns are monthly and equal-weighted. Estimated $\hat{\alpha}_0$ and $\hat{\alpha}_B$ are reported in percent (i.e., multiplied by 100). Reported in the parentheses are the corresponding *t*-statistics. Statistical significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively. The subsample periods in Panel A and B span from January 1992 through December 2005 and from January 2006 through December 2019, respectively.

Finally, Table 9 reports the results for optionality regressions across the subsamples. As expected based on the previous subsample results, none of the 12–1–1 appear to be subject to optionality effects in the first period since notable momentum crashes are not present. However, by contrast, CSMOM, TSMOM and DMOM show clear optionality effects in bear markets during the second period, and essentially replicate the behavior of a short call option. Based on the results, TRIMOM does also exhibit signs of optionality during the second period, however in the opposite direction as the $\hat{\beta}_{B,U}$ coefficient is significantly positive (though, only at 10% level). In other words, the interpretation is inverse, suggesting that TRIMOM may be positively influenced when market rebounds following declines in bear markets. Consequently, TRIMOM may not only be able to mitigate the adverse effects of momentum crashes on average but also benefit from the stressful environment in which other momentum strategies collapse.

5.3 Limitations and suggestions for future research

Given the limited scope of this thesis, several potential avenues of research arise. First, the introduced triple-screened momentum strategy is not exclusive to the proposed design. On the one hand, the possibilities are extensive in the search of other alternative triple-screened momentum strategies by using the described market screening process. These can include but do not restrict to combining other asset classes, or combining these market screening signals with volatility-scaling that may be useful for momentum strategies (e.g., see Cederburg et al., 2020). On the other hand, it may also be possible that the used market indicator that relies on the lagged 24-month and 1-month market returns is sub-optimal. Therefore, examining how different input periods and calculation methods – such as moving averages with different smoothing variations that are common in technical trading – influence the profitability can be fruitful.

Second, future research is encouraged to study the potential underlying explanations that may drive TRIMOM performance. Third, studying the effect of other formation and holding periods on the profitability as well as analyzing robustness of the results in different markets with varying sample sizes, sample horizons and weighting schemes can offer insightful information. What is more, although this thesis concentrates on relatively large stocks by selecting only the top 30% largest stocks of the stock universe, certain caution may be warranted because the overall sample is rather extensive and encompasses 17 countries. As a result, it cannot be completely ruled out whether the relatively smallest stocks out of the used top 30% largest stocks contribute to the observed results to some extent. To preclude this possibility, investigating if the results remain intact using only the largest stock decile is recommended. Lastly, the analysis could extend to consider transaction costs that may affect and attenuate profitability of momentum strategies (e.g., see Lesmond et al., 2004; Korajczyk & Sadka, 2005).

6 Conclusions

Prior literature finds significant abnormal profits associated with momentum strategies, however these strategies are also subject to streaks of large negative returns, termed as momentum crashes, occurring in bearish market states when markets start to recover from declines. Motivated by recent research and using a large number of individual stocks in the European stock markets from January 1992 to December 2019, this thesis proposes and examines whether a new risk-managed version of momentum, labeled as triple-screened momentum (TRIMOM), is able to detect and bypass the impact of momentum crashes while outperforming its counterparts, including standalone cross-sectional momentum (CSMOM), time series momentum (TSMOM) and dual momentum (DMOM) strategies.

The empirical results show that TRIMOM produces both significant raw and abnormal risk-adjusted returns with an attractive Sharpe ratio of 1.31 in the full sample, outperforming all other examined momentum portfolios and market index. Interestingly, the employed optionality regressions demonstrate that this strategy is not prone to optionality effects. Rather, the subsample optionality regressions for the sub-period containing the global financial crisis period coupled with an even increasing Sharpe ratio of 1.51 suggest that TRIMOM may instead be positively influenced by the described situations in which momentum strategies tend to crash, albeit this relation is only statistically significant at 10% level. Furthermore, the performed drawdown analysis and positive skewness also provide evidence in favor of a lower downside risk. Overall, these findings imply that the formed TRIMOM strategy is not only profitable but also beneficial in dampening momentum crashes without sacrificing risk-adjusted performance. Therefore, TRIMOM strategy may be a desirable alternative stock strategy for investors.

Consistent with previous literature, this thesis finds that CSMOM, TSMOM and DMOM strategies are profitable, producing significant raw returns and higher Sharpe ratios compared to market index. Moreover, on balance, these strategies generally yield statistically significant alphas when controlled for standard risk factors. DMOM is found to outperform pure CSMOM and TSMOM strategies, in support of Lim et al. (2018), generating notable raw and risk-adjusted returns and a high full sample Sharpe ratio of 1.04 in comparison to Sharpe ratios of 0.72 and 0.75 earned by CSMOM and TSMOM, respectively. However, the results suggest that TSMOM overall does not outperform CSMOM nor explain it. Also, measured by cumulative returns, CSMOM is more profitable than TSMOM, although the Sharpe ratios are approximately equal. In line with Goyal and Jegadeesh (2018), the findings show that the TSMOM alphas become insignificant upon exposure to the momentum risk factor (i.e., UMD factor representing CSMOM). The findings demonstrate that variations in CSMOM excess returns are able to explain the variations in TSMOM excess returns to a large extent, weakening the evidence on TSMOM risk premium suggested by Moskowitz et al. (2012).

In the opposite of TRIMOM, this thesis finds exposures of CSMOM, TSMOM and DMOM to momentum crashes that are statistically significant at 1% level. From economical point of view, the results indicate that DMOM may be more sensitive to these periods than other momentum strategies. Because DMOM is based on relatively more extreme ranks of past performance of stocks, one possible explanation can relate to asymmetric optionality effects reported in Daniel and Moskowitz (2016), suggesting that in bear markets, stocks belonging to the most extreme historical return deciles are associated higher tail risks compared to the deciles inbetween.

In order to draw a more detailed picture of the documented results, future research could shed light at least on the following. First, investigating the possible underlying sources of the observed performance of TRIMOM is an intriguing topic for future research. Second, a more thorough analysis that examines whether the used market screening process is optimal would provide new insights. Third, examining TRIMOM using other configurations such as sample sizes, weighting schemes and formation and holding periods would be a valuable extension in order to better understand the strategy and further confirming the robustness of the findings presented in this thesis.

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