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MERGING MOMENTUM

-THE EFFECTS OF COMBINED CRASH MITIGATING STRATEGIES

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Abstract

Momentum strategies offer tempting expected returns but suffer from occasional momentum crashes. Crash mitigating strategies, such as the Absolute momentum (Gulen and Petkova, 2018) and Extreme absolute strength momentum (Yang and Zhang, 2019), have proven effective in alleviating momentum crashes, while also offering better risk-adjusted returns compared to relative momentum strategies. We evaluate whether further improvement of absolute momentum strategies is feasible, by merging these strategies with the concept of Dynamic momentum developed by Dobrynskaya (2019). Our results suggest that absolute momentum strategies also benefit from dynamic momentum, reaping additional risk-adjusted returns, further improving these strategies, while also outperforming relative and absolute momentum strategies. Therefore, we suggest merging already existing absolute momentum strategies with the Dynamic momentum strategy is beneficial in terms of returns and the risk associated with those returns.

Keywords: momentum, momentum strategies, merging momentum, momentum crash, dynamic momentum, absolute strength momentum, extreme absolute strength momentum, risk-adjusted return, crash mitigating momentum

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1 Introduction

The success of momentum strategies, where investors buy past winners and short-sell past losers, has been studied thoroughly with prominent results in various financial markets (Jegadeesh and Titman, 1993; Fama and French, 2012) across time (Chabot et al., 2014) and different asset types (Asness et al., 2013). At first, it was considered a market anomaly as many academics frequently reported negative market betas when conducting momentum strategies with insignificant risk exposure to other risk factors (Fama and French, 2016). Even though momentum portfolios have produced significant abnormal returns along with higher Sharpe ratios, relative to the market portfolio, momentum strategies are exposed to occasional momentum crashes (Daniel and Moskowitz, 2016). This became evident in the recent financial crisis, as momentum returns suffer from leptokurtic and negative skewness characteristics (Daniel and Moskowitz, 2016; Daniel et al., 2017), implying many small gains but occasional large losses.

Between March and May of 2009, Daniel and Moskowitz (2016) report that the momentum portfolio's short positions rose by 163%, while long positions only gained 8%, as a consequence of rebounding markets following a severe market crash, implying heavy losses in the momentum portfolio. In order to mitigate momentum's crash risk, simple stop-loss strategies (Han et al., 2016) to more sophisticated dynamic momentum strategies have been suggested, where the latter includes forecasting instruments of future momentum crashes. However, as Dobrynskaya (2019) argues, most of these forecasting models with constant volatility scaling (Barasso and Santa-Clara, 2015) or dynamic volatility scaling (Daniel and Moskowitz 2016), depends on an additional in-or outflow of cash as well as sophisticated estimations, which may be restricted to some investors. Therefore, Dobrynskaya (2019) suggests an alternative dynamic momentum (DM) strategy in which investors change their winner-minus-loser (WML) positions momentarily when exposed to large market movements; when the market experience a loss larger than 1.5 standard deviations, the contrarian position loser-minus-winner (LMW) is taken in the relative momentum portfolio.

In contrast to the relative momentum strategy, Gulen and Petkova (2018) introduced the absolute strength (ABS) momentum strategy as a further development within the field. They argue that investors react more to actual price movements in a specific stock, rather than its performance relative to others. They reason, that in relative momentum, a stock can make it to the winning portfolio just by a decrease in overall market returns, without exhibiting any significant price changes. Therefore, Gulen and Petkova (2018) sort their portfolios based on absolute momentum, where the total historical distribution is considered, which improves performance of the momentum portfolio. Another momentum strategy, more recently proposed by Yang and Zhang (2019), also address the puzzle of momentum crashes, which they apply to absolute momentum. They suggest removing stocks with abnormal gains from the momentum portfolio, as these are considered to possess extreme absolute strength (EXT), and are more prone to crash and lose their momentum (Chabot et al.,2014b).

The aim of this study is to merge the DM (Dobrynskaya, 2019) to the ABS (Gulen and Petkova, 2018) and EXT (Yang and Zhang, 2019) strategies, to evaluate whether additional improvements are feasible. The reason for this is that each strategy aims to minimize crash risk, but in order to do so, they work in different ways. DM use momentum crashes to its advantage by holding the traditional WML portfolio in calm times, while switching to the reversed LMW portfolio when markets are in turmoil and momentum is likely to crash. The ABS and EXT strategies on the other hand, does not try to benefit from the crash, but to avoid it by forming more stable breakpoints for the winner and loser portfolios, using all available historical information. Further, the EXT strategy adds an additional filter to the portfolio formation, where stocks which exhibit extreme volatility are removed, as these are more prone to crash (Chabot et al.,2014b). However, instead of removing stocks that exhibit high volatility, which potentially could be turned into gains, we apply the DM strategy to the ABS strategy. Further, it is possible that the removal of high volatility stocks, which reduce downside volatility, could be combined with DM to reap smaller gains, which could boost risk-adjusted returns. Therefore, we argue that there are potential synergies to be made by applying DM to both the ABS and EXT strategies. We perform extensive tests to compare which combinations works best, if any, and if further improvements are attainable. The main contribution of our work is to evaluate whether synergies exist from merging different types of crash mitigating strategies, and to study its effect on portfolio performance.

We use monthly US stock data ranging from 1925 to 2019, whereas our analysis is based on data between 1965 and 2019, where our main findings are as follows. First, we find that the DM offers improvement of the relative WML portfolio, in terms of higher risk-adjusted returns and crash mitigating properties. We also find that EXT shows slightly more appealing crash mitigating properties relative to ABS, but with conflicting evidence regarding the value-weighted portfolio's performance, which is more penalized in our study. Secondly, when applying the DM strategy to either the ABS or EXT momentum strategies, portfolio returns and overall portfolio performances are boosted in each merged portfolio as previously argued, implying that synergies exist. Lastly, we extensively evaluate which merged portfolio performs best in relative terms, with respect to risk-adjusted returns and crash mitigating properties. We conclude that the equal-weighted EXT DM portfolio has the best overall performance with respect to its risk.

The remainder of our paper is constructed as follows. In section 2 we present previous studies conducted on momentum portfolios, in unison with papers that offer solutions to mitigate crash risk in momentum portfolios. In section 3 we present our data gathering procedure, and thoroughly describe the portfolio formation process for each strategy, along with our chosen methodology to analyse our data. In section 4 we present the results and analysis, which is extensively discussed. Finally, we conclude in section 5.

2 Literature review

The influential paper of Jegadeesh and Titman (1993) documented that stock returns show momentum behaviour. In their paper they conclude that stocks that have performed well in the past (winners) tend to continue to perform well the coming months, whereas stocks that have performed poorly (losers) tend to continue to perform poorly the coming months. In their paper from 1993, Jegadeesh and Titman tested if abnormal returns could be attained by using a trading strategy which take advantage of the momentum behaviour of stock returns. The momentum strategy utilizes this by buying past winners and selling past losers, creating a zero-cost portfolio. According to Jegadeesh and Titman (1993), significant abnormal returns were recorded between 1965-1989 by applying the momentum strategy. The relative momentum strategy used by Jegadeesh and Titman defines the winners as stocks that have outperformed the contemporary market returns, and the losers as the ones that have under-performed relative to market returns.

The presence of a momentum factor has been observed by several other studies. Fama and French (2012) studied the markets of North America, Europe, Japan and Asia Pacific and in their study, they find strong momentum returns in all these regions except for Japan. In addition, Asness et al. (2013), finds strong evidence in their paper for a return premium associated with momentum strategies, which is recorded globally across markets and asset classes. Barroso and Santa Clara (2015) also studied momentum and compared to market, value and size factors, they show that momentum yields the highest Sharpe ratio.

Although momentum have been shown to generate high average risk-adjusted returns, there are studies which shows significant drawbacks with momentum strategies. Daniel et al. (2017) discover that momentum strategies experience rare but large losses. They compare the features of a momentum portfolio to that of a written call option on the market portfolio. These characteristics get problematic during times of high market volatility and in states where markets are recovering. Studying almost 1.5 centuries of data, Chabot et al. (2014b) found several events that meant increased probability for momentum crashes. They concluded that momentum crashes tend to happen after momentum had experienced high returns, when momentum had outperformed the stock market or when interest rates had been relatively low. According to Daniel et al. (2017) the losses comes from the loser portfolio, since its resemblance of a written call option means that during a fall in the market it gains little, but when the market recovers and gains in value, it makes large losses. Daniel et al. (2017) finds that crashes tend to occur during times when market are stressed with high ex ante volatility and a fall in the overall market. Barosso and Santa-Clara (2015) also brings up the subject of momentum crashes and conclude that the negative skewness and kurtosis of momentum strategies makes it unappealing to some investors, since crashes can wipe out a large part of the gains generated, which could take years to recover from.

The risk of momentum crashes has given rise to several papers that propose modifications which aims to mitigate crash risk and enhance momentum returns and Sharpe ratios. Noticing that momentum betas was time-varying, Grundy and Martin (2001) suggested hedging the momentum crashes, which appeared to happen in tandem with market appreciations, were hedged by going long the market. The forward-looking betas used by Grundy and Martin (2001) was however criticized by Daniel and Moskowitz (2016), which showed that when real-time betas were used, it did not improve the momentum strategy, and argued that the strategy developed by Grundy and Martin (2001) was not feasible in practice.

To deal with momentum crashes, Daniel and Moskowitz (2016) suggested a dynamic momentum strategy, which is based on forecasts of mean and variance. They investigate whether momentum crashes can be predicted and find that: "crashes tend to occur in times of market stress, when the market has fallen and ex ante measures of volatility are high, coupled with an abrupt rise in contemporaneous market returns". Daniel and Moskowitz use the forecast ability of the momentum payoffs to construct an optimal dynamic portfolio that maximizes the unconditional Sharpe ratio by levering up or down the WML portfolio over time. The weights of the WML portfolio is scaled such that the unconditional volatility is proportional to the unconditional Sharpe ratio of the strategy. Next, estimation of the conditional moments is used to create the dynamic weights. Daniel and Moskowitz show that their optimal dynamic momentum strategy significantly outperforms the static momentum strategy, as Sharpe ratios more than doubles, along with a significant alpha relative to the market.

Barosso and Santa-Clara (2015) propose another way of handling momentum crashes. In their paper they find that the risk of momentum is predictable by estimating the realized variance of daily returns. This insight is used in their strategy by setting a constant volatility target, where the long-short portfolio is scaled by its previous six months realized volatility. This means that instead of keeping the same amount in the long and short portfolios over time, the portfolio is scaled in such a way that the volatility is kept constant over time. Using this strategy, Barosso and Santa Clara (2015) manage to improve the Sharpe ratio from 0.57 for the unmanaged momentum, to 0.97 for the risk-managed momentum. Their strategy also lowers kurtosis and reduce negative skewness of returns. Another strategy was introduced by Han et al. (2016), which suggest a stop-loss strategy to avoid momentum crashes; if the loss of an individual stock reaches 15% the position of that stock is closed.

An alternative strategy to the relative momentum strategy was presented by Gulen and Petkova (2018). They propose a momentum strategy which is based on a pattern in stock return they call absolute strength momentum. They find that large individual stock price movements in one direction in the recent past tend to continue to move in the same direction in the near future. They define this pattern as absolute strength momentum. Their strategy is based on buying absolute strength winners and selling absolute strength losers. Where the relative momentum strategy determines what constitutes a winner or loser by the recent record of stock returns, the absolute strength momentum strategy uses the entire historical record of returns. By using a recursively updated distribution of cumulative returns as a benchmark, the absolute winners or losers are stocks whose recent cumulative returns are significant positive or negative. Thus, to be included in the buy or sell portfolio, a stock's recent return must fall in the tails of the historical distribution. Gulen and Petkova (2018) reasons that using the tails of the historical distribution helps to identify stocks with price movements significant enough to trigger continuation in returns. This feature differs from the relative strength momentum strategies. The relative strength strategies might not identify significant directional price movements according to Gulen and Petkova (2018). They also argue that in the relative strategy it is possible for a stock to get placed in the winner portfolio without any significant changes in its price, due to overall market movements. In their paper, Gulen and Petkova (2018) showed that their absolute strength momentum strategy generated large and significant returns, which outperformed the relative momentum presented by Jegadeesh and Titman (1993) among other strategies, and the profitability were consistent across asset classes, sample periods, holding periods and international markets.

Disadvantages with of some above-mentioned strategies was pointed out by Dobrynskaya (2019), where she also proposed a new strategy where these drawbacks were mitigated as well as the momentum crash risk. Dobrynskaya (2019) argues in her paper that her strategy does not need the extra in- or outflow of funds that some other strategies require. Furthermore, no extra estimations, which are not already needed in the standard momentum strategy, are required. Concisely expressed, the strategy Dobrynskaya (2019) suggests takes the form of the standard momentum strategy in calm times, but switches to a contrarian strategy when markets experience significant losses. Dobrynskaya (2019) shows that momentum crashes most likely happen within a three-month window, following a significant local market crash. She argues that the reason for this lagging behaviour has to do with the sorting of momentum portfolios by past performance. Further, since momentum crashes are predictable it is also possible to avoid them. Dobrynskaya (2019) designs a dynamic momentum strategy, which takes the same position as the traditional momentum strategy during normal times, but when markets experience a loss greater than 1.5 standard deviations, the position is switched to a contrarian position. The contrarian position is then held for three months, and if not another crash occurs, it switches back to the traditional WML portfolio. This dynamic momentum strategy yields higher average returns than the traditional momentum strategy, since it turns momentum crashes into gains (Dobrynskaya, 2019). Furthermore, she shows that the returns of the dynamic strategy are positively skewed, as opposed to the negative skewness of the traditional momentum strategy. In addition, the dynamic strategy has lower kurtosis and higher Sharpe ratio. Dobrynskaya (2019) also shows that the dynamic momentum return has positive market betas, but they are in general insignificant, and the strategy does not have any exposure to various risk factors.

A recent paper from Yang and Zhang (2019) proposes another modification to the momentum strategy which improves performance in the presence of momentum crashes. In their strategy, momentum crashes are mitigated by removing stocks with the most extreme returns, as these stocks carry considerable risk, which are highly probable to experience a reversal of returns during momentum crashes. The strategy used by Yang and Zhang (2019) therefore improves performance of the momentum portfolio, mainly by the reduction of portfolio risk. Yang and Zhang (2019) defines the most extreme stocks as those that exhibit extreme absolute strength. Absolute strength is defined as according to Gulen and Petkova (2018); a stock which has performed well/bad recently compared to the historical distribution of stock returns. Yang and Zhang (2019) finds that stocks with extreme absolute strength have a return that is not proportional to their high volatility, hence they do not contribute to the momentum portfolio in proportion to the risk they carry. In their paper, Yang and Zhang (2019) develops a crash mitigating strategy which removes the stocks that exhibits extreme absolute strength. They create breakpoints where a stock is removed if it gets ranked in the top or bottom percentiles of the historical distribution. They find that this enhances performance in traditional momentum strategies by reducing volatility and increasing average return, effectively increasing Sharpe ratios and Sortino ratios. Yang and Zhang (2019) shows that the extreme absolute strength strategy can mitigate the problem of momentum crashes, and they further comment that the increased performance comes mainly from avoiding momentum crashes. However, they also try the same method, using extreme relative strength, but this is not effective according to their study.

3 Data and Methodology

3.1 Data

In order to construct momentum portfolios we gather monthly returns, prices and number of shares outstanding from CRSP of all US common stocks (share codes 10 and 11) listed on NYSE, AMEX and Nasdaq (exchange codes 1, 2 and 3) ranging from December 1925 to December 2019. We use delisting returns whenever available on CRSP, as Eisdorfer (2008) shows that 40% of momentum profits are generated through delisting returns. Further, the same $1 price cut-off as suggested by Yang and Zhang (2019), is applied throughout our data set to avoid micro-structure effects. Monthly market and risk-free returns along with Fama-French and Momentum factors for the US market is gathered using Kenneth French's library, whereas Quality-Minus-Junk and Betting-Against-Beta factors are gathered from the AQR data library between January 1927 and December 2019. Further, we collect Pastor and Stambaugh's Traded Liquidity factor from Pastor's website which contain data from January 1968 to December 2019.

3.2 Methodology

As our study aims to merge different momentum strategies, we present three different approaches in this section. We try to harmonize their methods whenever possible, since all three strategies use similar, but not identical procedures in data sorting, data gathering, portfolio formation or holding periods. Naturally, each study use different time-horizons, therefore we will be using data ranging from 1925 to 2019, whereas our analysis will be based on the time period 1965 to 2019, as two portfolio strategies requires historical data in their portfolio forming. We will address this further in section 3.4. In order to construct portfolios sorted on momentum, we apply the following procedure, where we compute the 11-month cumulative return from t-12 to t-2, excluding the most recent month of stock returns[1]. The 11-month cumulative returns for each stock is computed using the following formula:

$$R_{[t-12,t-2],i} = (\prod_{\tau=2}^{12} (1 + R_{t-\tau,i})) - 1 \tag{1}$$

Each momentum strategy is sorted into decile momentum portfolios, where the two most extreme portfolios forms the long-short zero-cost momentum portfolio, which is held for one month[2]. This procedure is then repeated, implying a monthly re-balancing scheme. We create both equal-and value-weighted portfolios and impose the following restrictions

[1]Harmonized attempt, as all strategies deviate in periods and horizons

[2]Harmonized attempt, as all strategies deviate in holding periods

on portfolio forming for all our portfolios. For a stock to be included in the momentum portfolio at time t, it must have an observable return in month t to t-12, as well as an observable market-cap in t-1. We use the following formula to compute the average return of both the equal-and value-weighted portfolios:

$$R_{WML,t} = \sum_{i=1}^{N} w_{it} R_{it} \tag{2}$$

where the equal-weighted portfolio weights correspond to:

$$w_{it} = \frac{1}{N} \tag{3}$$

and the value-weighted portfolio weights:

$$w_{it} = \frac{mcap_{i,t-1}}{\sum_{i=1}^{N} mcap_{i,t-1}} \tag{4}$$

Further, both the equal-and value weighted portfolio weights must add up to one for the long positions, and negative one for the short positions.

3.3 Relative momentum

As previously described, the traditional relative momentum portfolio is constructed using an 11-month cumulative return window, in which a momentum score is recorded based on past returns. Momentum scores are then sorted from low to high on a relative stock basis, implying that stocks which possess a low momentum score in time t will represent a loser stock, whereas a winner stock possess a high momentum score in time t. Stocks are then split into decile portfolios conditional on their momentum score, where portfolio one represent the loser portfolio, whereas portfolio ten represent the winner portfolio. Together, portfolio one and ten forms the zero cost WML portfolio, in which one takes a long position in the winner portfolio and a short position in the loser portfolio such that $\mathbb{E}[R_{P10}] > \mathbb{E}[R_{P1}]$. The average return of the equal-and value-weighted WML portfolios are computed using equation (2).

3.4 Absolute momentum

As stated in the literature review, the absolute momentum strategy (ABS) exploit past returns to form portfolios like the traditional WML strategy. However, instead of forming portfolios strictly on a recent relative basis, portfolio forming is done on an absolute basis based on historical breakpoints. The WML strategy depends on relative 11-month cumulative returns to form a portfolio at time t, whereas the ABS strategy depends on all available historical 11-month cumulative returns to form a portfolio at time t. Therefore, all historical 11-month cumulative returns form the historical distribution of realized cumulative returns, whereas the most recent 11-month cumulative returns form the ranking distribution of realized cumulative returns.

First, we establish the historical distribution of all previous 11-month cumulative returns for each time period t, across all stocks, following the same procedure as Gulen and Petkova (2018). In order to do this, we use a non-overlapping 11-month window where all previous 11-month cumulative returns for all stocks up to time t are used. Following this procedure, we manage to avoid look-ahead bias, and as time transpires monthly breakpoint observations will increase by one for each passing year, rendering more stability in breakpoints as additional observations are added. Therefore, year 1965 serves as our baseline in our analysis. For example, in January 2019 we will have a total of 93 11-month returns (2019-1927) as it contains all previous 11-month cumulative January returns. Next, we create historical breakpoints based on the historical distribution in each time period t, which is continuously updated for each passing month, where the breakpoints are predetermined to the 10th and 90th percentiles of the historical distribution (Appendix A - Panel A: Figure 5). Further, the breakpoints serve as a cut-off point which determines whether a stock should be included in the portfolio formation at time t and which stock belongs in either the winner or loser portfolio. Lastly, the ranking distribution is set in relation to the historical distribution in each time period, where a stock is included in the short-leg (long-leg) if its ranking distribution is below (above) the historical distribution's breakpoints (Appendix A - Panel A: Figure 5). Together, portfolio one and ten forms the ABS WML portfolio, where portfolio 10 (1) indicates the winner (loser) portfolio. The following restriction describes the methodology:

$$\begin{cases} P_{10} & \text{Ranking distribution for stock i at time t} > \text{Historical distribution(90\%)} \\ P_1 & \text{Ranking distribution for stock i at time t} < \text{Historical distribution(10\%)} \end{cases} \tag{5}$$

Gulen and Petkova (2018) highlights a side effect of sorting stocks based on absolute rather than relative momentum scores, which is that portfolio sizes in the long-and short leg is more volatile over time (Appendix A - Panel B: Figure 6). In contrast, the relative momentum portfolios usually have the same amount of stocks in both legs across time after portfolio sorting. According to Gulen and Petkova (2018) this may be problematic from a diversification stand point, and in order to mitigate this we approach this in the same manner as Gulen and Petkova (2018); whenever the short-or long portfolio legs have less than 30 stocks in any time period, this portfolio leg is replaced by Treasury-bills.

3.5 Extreme absolute momentum

The third approach is based on the paper of Yang and Zhang (2019), where momentum portfolios are constructed similarly to that of Gulen and Petkova (2018). The historical distribution still serves as a breakpoint indicator for portfolio formation at time t, but rather than only using the cut-offs to include stocks, the extreme absolute momentum strategy (EXT) identifies which stocks to exclude and include. As mentioned in the literature review, stocks which have an abnormal high absolute momentum are considered to possess extreme absolute strength and are more likely to lose their momentum due to their volatile nature. We use the same ranking and historical distribution computation as before, but instead of only using the 10th and 90th percentiles, we also compute the 3rd and 97th percentiles for the historical distribution (Appendix B - Panel A: Figure 7). Initial portfolio formation is done according to equation (5), where the ranking distribution is set in relation to the historical distribution, but an additional filter is added where the top and bottom 3rd percentiles are removed from the EXT portfolio, as stocks below/above these breakpoints are considered to possess extreme absolute strength and are therefore removed from the long-short portfolio. After applying these conditions, portfolio one forms from the 3rd-10th percentiles, whereas the long portfolio includes stocks from the 90th-97th percentiles. Together, portfolio one and ten forms the EXT WML portfolio.

Due to the removal of additional stocks in the EXT relative to the ABS strategy, the EXT strategy will be even more volatile in portfolio sizes, as there are periods of great market movements when there are zero stocks in either one of the portfolio legs (Appendix B - Panel B: Figure 8). We apply the same condition to EXT as with our ABS portfolio, which is; whenever either portfolio leg have less than 30 stocks, these are replaced by Treasury-bills.

3.6 Application of Dynamic momemtum

Finally, we apply the concept of contrarian trading (Dynamic momentum) as introduced by Dobrynskaya (2019) to our WML, ABS and EXT strategies. Dynamic momentum (DM) is based on a reversal of the traditional long-short portfolio, where the WML portfolio is kept in normal times but is switched to a contrarian position (LMW) during significant market declines in market means which surpass 1.5 standard deviations. Switching to a contrarian position is therefore conditional on historical and present market means. Contrarian positions are held for three months conditional on that no further significant market crash occurs between month t to t+3. For instance, if period t suffers from a significant market decline, a contrarian position is taken in month t+1 and held until t+3. However, if month t+1 also experiences a significant market decline, the LMW position is held until t+4. We only use available information known to the investor at portfolio forming to avoid look-ahead bias. Therefore, our method deviates from that of Dobrynskaya (2019) as she uses the full sample of market returns to compute reversals. In order to determine the reversal, we compute a moving arithmetic average based on all historical US market returns for each time period t, accordingly:

$$\overline{R}_{MT} = \frac{\sum_{t=1}^{T} R_{Mt}}{N} \tag{6}$$

Along with a moving standard deviation:

$$\overline{\sigma}_T = \sqrt{\frac{\sum_{t=1}^{T} (R_{Mt} - \overline{R}_{MT})^2}{N-1}} \tag{7}$$

Followed by a moving Z-score:

$$\overline{Z}_T = \frac{R_{Mt} - \overline{R}_{MT}}{\overline{\sigma}_T} \tag{8}$$

We create an index, which serves as an indicator for when market returns decline more than 1.5 standard deviations below the historical mean. If the index triggers such an event, the WML portfolio is reversed into LMW accordingly:

$$\begin{cases} -1(WML_{T+1}), & \text{if } \overline{Z}_T < -1.5 \\ 1(WML_{T+1}), & \text{otherwise} \end{cases} \tag{9}$$

3.7 Portfolio performance measures

To evaluate portfolio performance, we use similar measures as the original authors of our strategies. Chosen key measurements are Sharpe-and Sortino Ratios along with various alpha computations.

3.7.1 Sharpe ratio

Sharpe ratio is defined and calculated as follows (Sharpe, 2007):

$$\text{Sharpe ratio} = \frac{R_P - R_F}{\sigma_P} \tag{10}$$

Where R_P and σ_P are portfolio return and volatility, while R_F denotes the risk-free. The ratio serves as a measurement to understand how the return of an investment is compared to its risk.

3.7.2 Sortino ratio

We use an extended version of the Sharpe ratio where we only consider the downside volatility of our portfolios. In order to compute the downside volatility, we use the risk-free as the minimum acceptable return, as Yang and Zhang (2019) use in their study but apply it to our sample period 1965-2019. During this period, the risk-free had an annual average return of 4.58%, which we deduct from all portfolios in each time period. Further, the negative values are kept, which are squared, added, and divided by the number of time periods accordingly:

$$\sigma_{P_D} = \begin{cases} \sqrt{\frac{\sum_{t=1}^{T}(R_{P,t}-\overline{R}_F)^2}{T}}, & \text{if } R_{P,t} - \overline{R}_F < 0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Instead of using portfolio volatility, we use portfolio downside-volatility to compute the Sortino ratio accordingly:

$$\text{Sortino ratio} = \frac{R_P - R_F}{\sigma_{P_D}} \tag{12}$$

Where R_P and σ_{P_D} are portfolio return and downside volatility, while R_F denotes the average risk-free return. We choose to add the Sortino ratio as an additional metric, as the Sharpe ratio penalizes both positive and negative deviations from average returns, whereas the Sortino ratio only penalizes deviations below a pre-specified target threshold. This may prove useful in identifying whether "good" or "bad" variation is removed from a portfolio as we remove stocks which possess extreme absolute strength.

3.8 Factor exposure

3.8.1 Market alpha

To determine each portfolio's market alpha and beta, we regress excess portfolio returns over the market risk premium, using the following time-series regression:

$$R_{it}^e = \alpha_i + \beta_{iMt} R_{Mt}^e \tag{13}$$

Market alpha serves as an indication of a portfolio's ability to gain abnormal returns relative to market returns, whereas market beta measures a portfolio's co-movement with market returns, i.e. market exposure.

3.8.2 Fama-French five factor model

We run the Fama-French five factor-model (2015) to determine each portfolio's alpha and its factor-exposure, using the following time-series regression:

$$R^e_{it} = \alpha_i + \beta_{iM} R^e_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iCMA} CMA_t + \beta_{iRMW} RMW_t + \epsilon_{it} \quad (14)$$

Alpha serves as an indicator of abnormal returns, whereas R^e_M is the market risk premium. The SMB-factor (small-minus-big) is made up of the difference in returns between small market capitalization firms and large market capitalization firms. The HML-factor (high-minus-low), considers the return premium associated with buying value stocks compared to buying growth stocks. Value stocks represent companies with high book-to-market ratio, while growth stocks represent companies with lower book-to-market ratios. The factor is the difference in returns between value and growth stocks. The CMA-factor is an investment-factor and is the difference in returns between companies which invests conservatively and companies that invests aggressively. The RMW-factor considers the difference in return between companies with high operating profitability and companies with low operating profitability. Since we form both equal-and value-weighted portfolios for each strategy, we run six different Fama-French five factor time-series regressions.

3.8.3 9-Factor model

In addition to the Fama-French five factors, we introduce four additional factors, which forms what we define as the 9-Factor-Model, where returns from each DM portfolio will be evaluated in terms of its risk exposure i.e. its co-movement with common factors from the literature. First, we add the momentum factor (Mom) which is constructed by Kenneth French as the intersection between size and prior returns. The factor is constructed as the difference between the average returns of the small cap winner plus the big cap winner, and the small cap loser plus the big cap loser. Secondly, the traded liquidity factor (PSLIQ) from Pastor and Stambaugh (2003) is also added, which is the difference in returns from stocks with high liquidity risk and stocks with low liquidity risk. The third factor to be added is Frazzini and Pedersen's (2014) BAB (betting-against-beta) factor. The factor is constructed by the difference in returns from low-beta-stocks and high-beta stocks. Finally, the QMJ (quality-minus junk) factor, developed by Asness et al. (2019) is added, which is the difference in returns between quality and junk firms, with the reasoning that quality firms outperform junk firms. What constitutes a quality firm is determined by giving a quality score to the stocks which is based on different criteria. Since we form both equal-and value-weighted portfolios for each strategy, we report six different 9-Factor time-series regressions.

4 Result and analysis

Table 1: Strategy descriptions and abbreviations

Abbreviation	Description	Portfolio sorting (percentiles)
WML	Relative momentum	Relative 10 and 90
ABS	Absolute momentum	Absolute 10 and 90
EXT	Extreme absolute momentum	Absolute 3-10 and 90-97
WML DM*	Relative dynamic momentum	Relative 10 and 90
ABS DM*	Absolute dynamic momentum	Absolute 10 and 90
EXT DM*	Extreme absolute dynamic momentum	Absolute 3-10 and 90-97

*Dynamic momentum (DM) refers to the reversal of WML to LMW during market turmoils.

As numerous studies have shown before us, investors may gain abnormal returns using the WML strategy, as it performs quite well over time. However, as mentioned in previous sections, WML portfolios are exposed to occasional crashes, where years of accumulated wealth may be wiped out. The behaviour of momentum crashes is demonstrated in Figure 1 where kinks represent a momentum crash, usually in unison with distressed markets, such as during the recent financial crisis. We present three crash mitigating strategies which have shown promising improvement of risk-adjusted momentum returns, along with our merged strategies, where we test whether further improvement is possible. This study does not consider transaction costs, which is a significant aspect of momentum portfolios and therefore a limitation in our study. However, since all our portfolios use a monthly rebalancing scheme on which we apply the dynamic momentum strategy, transaction costs should remain similar compared to relative momentum portfolio forming, as contrarian positions only are kept for 10% of total months.

4.1 Relative and Dynamic momentum

In this section we investigate whether WML DM outperforms WML portfolios as suggested by Dobrynskaya (2019). We present summary statistics for both the equal-and value-weighted portfolios, where WML corresponds to our benchmark relative momentum portfolios and WML DM corresponds to our dynamic momentum portfolios. In Figure 1 we present cumulative returns from a $1 investment in the value-weighted WML portfolio, along with the corresponding WML DM portfolio. The WML DM portfolio outperform the benchmark WML portfolio, where the aftermath of the dotcom bubble and the recent financial crisis serves as the main contributors to these additional returns.

The same story is true for the equal-weighted DM portfolio, which also outperforms WML in cumulative returns (Appendix C - Panel A: Figure 9).

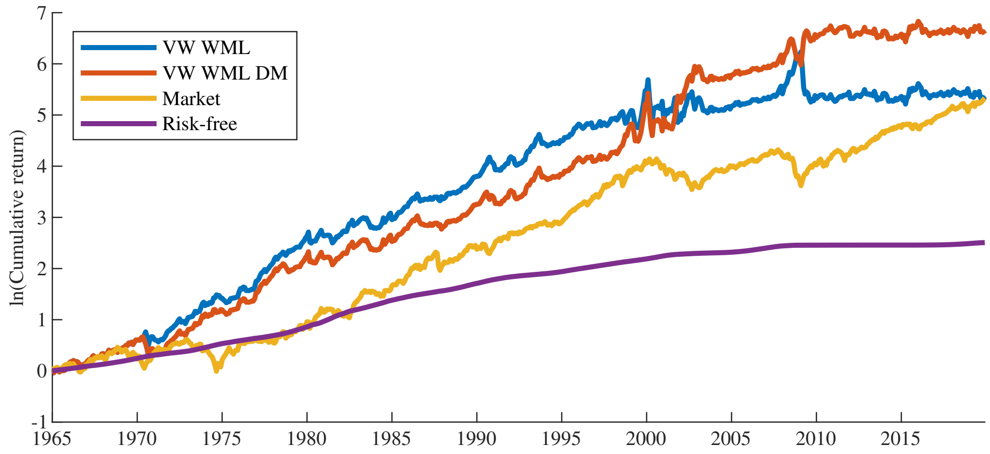

Figure 1: WML portfolio, market and risk-free returns

Table 2 report summary statistics for traditional WML and WML DM portfolios. By implementing the DM strategy, both the equal-and value-weighted portfolios increase in average annual returns, whereas annual volatilities are similar but slightly lower, relative to their corresponding WML portfolios. Therefore, Sharpe ratios appreciate by 35% (31%) for the equal (value-weighted) DM portfolios, where the increase is mainly driven by higher returns as volatilities remain similar. Further, Sortino ratios are also higher with the DM portfolios, where the increase is even more dramatic as the equal(value)-weighted DM appreciate by 75% (48%). This means that both DM portfolios exhibit considerably lower downside volatilities relative to the WML portfolios, implying lower risk. Another valuable characteristic is the shift from negative to positive skewness in the distribution of returns, which means that both DM portfolios are less exposed to crash-risk. This becomes more evident when we observe the portfolio return series more closely, as the equal-weighted WML portfolio's minimum monthly return (-35.06%), is reduced to half the amount in the WML DM portfolio (-16.50%). The decrease is not as dramatic between the value-weighted WML (-33.45%) and WML DM (-29.38%) portfolios, however the story remains the same; significant losses are turned into significant gains. Further, Fama-French five factor alphas are highly significant and positive in all portfolios. However, alphas increase for both the equal-and value-weighted DM portfolios relative to their corresponding WML portfolios. 9-F alphas are insignificant in both WML portfolios, whereas the WML DM portfolio alphas are highly significant and large, even though we control for additional factors.

Table 2: Relative and Dynamic momentum 1965-2019

	Equal-weighted		Value-weighted		Market
	WML	WML DM	WML	WML DM	
Average return	12.91	15.68	11.96	14.18	10.91
	[6.02]	[7.29]	[4.08]	[4.80]	[5.14]
Standard deviation	15.46	15.24	21.00	20.88	15.32
Skewness	-1.85	1.02	-0.82	0.33	-0.51
Sharpe ratio	0.54	0.73	0.35	0.46	0.41
Sortino ratio	0.95	1.66	0.64	0.95	0.78
Market beta	-0.28	-0.00	-0.28	0.09	1
	[5.13]	[-0.08]	[-3.49]	[1.11]	
Market alpha	10.14	11.14	9.14	9.05	
	[5.15]	[5.30]	[3.24]	[3.09]	
FF5 alpha	9.23	12.77	8.91	12.91	
	[4.14]	[5.53]	[2.80]	[4.31]	
9-F alpha	1.33	11.82	-0.43	10.89	
	[0.80]	[3.07]	[-0.21]	[2.36]	
Min monthly return	-35.06	-16.50	-33.45	-29.38	-22.64
% of contrarian months		10%		10%	

Newey-west standard errors are reported in brackets

Average returns, standard deviations and performance measures are annualized in %

Our results are in line with Dobrynskaya (2019), which reports similar findings, such as higher returns, Sharpe and Sortino ratios in unison with positive skewness and significant Fama-French five factor alphas for both WML DM portfolios. Therefore, DM still works in our extended data set which covers additional years.

4.2 Absolute strength and Dynamic momentum

In this section we investigate whether there is room for improvement in Gulen and Petkova's (2018) ABS strategy by applying the DM concept. We present summary statistics for both the equal-and value-weighted portfolios, where ABS correspond to our benchmark absolute momentum, whereas ABS DM corresponds to our absolute dynamic momentum portfolios. In Figure 2 we present cumulative returns from a $1 investment in the value-weighted ABS portfolio, along with the corresponding ABS DM portfolio. The ABS DM portfolio outperform the benchmark ABS portfolio, where the increase becomes more prominent after the recent financial crisis. The equal-weighted ABS and ABS DM cumulative returns are displayed in Appendix C - Panel B: Figure 10.

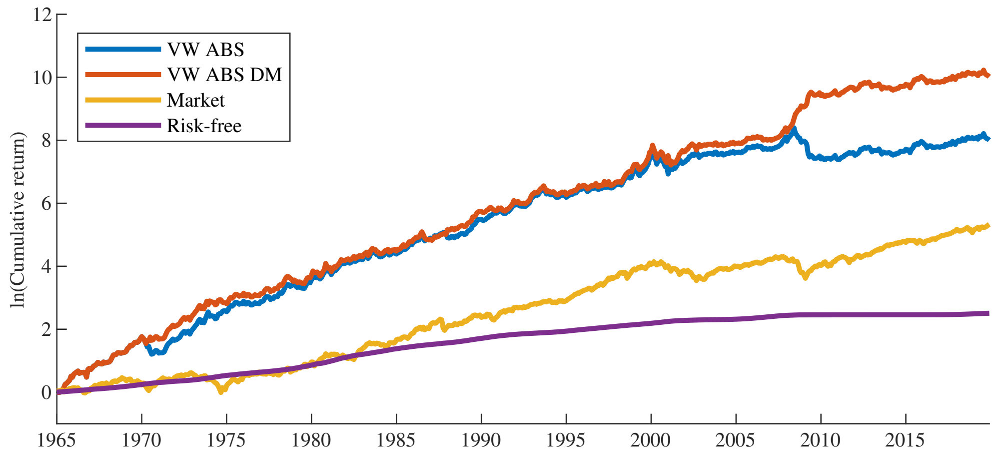

Figure 2: ABS portfolio, market and risk-free returns

Table 3 report summary statistics for the ABS and ABS DM portfolios. Once again, by applying the DM strategy, we observe an increase in average returns in the equal-weighted (11%) and the value-weighted portfolio (22%) in unison with a slight decrease in volatilities for both DM portfolios. Consequently, Sharpe ratios appreciate by 16% and 32% for the equal-and value-weighted portfolios respectively, which is almost entirely due to higher average returns. Sortino ratios for the equal-and value-weighted portfolios display a similar but more dramatic increase of 29% and 48% for each portfolio respectively, implying that downside volatilities are lower in both DM portfolios. The distribution of returns is once again being transformed from negative to positive skewness, implying lower crash-risk. Since the ABS strategy already have crash mitigating components in its portfolio formation, the effect is not as sizeable as between the relative WML and WML DM portfolios in Table 2. However, minimum monthly returns are once again reduced from -29.66% (-26.33%) to -17.58% (-16.45%) for the equal(value)-weighted portfolios, implying that significant losses are turned into gains. Fama-French five factor alphas are positive and highly significant across all portfolios; however, the ABS DM alphas are higher. Further, 9-Factor alphas are also positive and highly significant across all portfolios, but both ABS DM alphas are larger. Even though the 9-Factor model controls for the momentum factor along with additional factors, alphas manage to remain large and significant.

Table 3: Absolute strength and Dynamic momentum 1965-2019

	Equal-weighted		Value-weighted		Market
	ABS	ABS DM	ABS	ABS DM	
Average return	16.64	18.40	16.69	20.30	10.91
	[7.41]	[8.28]	[6.04]	[7.50]	[5.14]
Standard deviation	17.13	16.98	20.25	19.98	15.32
Skewness	-0.67	0.32	-0.25	0.30	-0.51
Sharpe ratio	0.70	0.81	0.60	0.79	0.41
Sortino ratio	1.40	1.81	1.20	1.78	0.78
Market beta	-0.06	0.03	-0.11	0.03	1
	[-1.06]	[0.44]	[-1.62]	[0.51]	
Market alpha	12.47	13.66	12.83	15.52	
	[5.84]	[6.30]	[4.66]	[5.65]	
FF5 alpha	13.91	17.00	15.34	20.07	
	[5.32]	[7.32]	[5.01]	[7.26]	
9-F alpha	5.03	14.59	6.01	17.15	
	[2.88]	[4.02]	[2.66]	[4.37]	
Min monthly return	-29.66	-17.58	-26.33	-16.45	-22.64
% of contrarian months		10%		10%	

Newey-west standard errors are reported in brackets

Average returns, standard deviations and performance measures are annualized in %

4.2.1 WML vs ABS

Comparing our benchmark WML and ABS portfolios from Table 2 and 3 respectively, our results are similar to that of Gulen and Petkova (2018), which report higher returns, lower volatilities and better performance measures. Therefore, it seems as if the ABS strategy indeed offers improvements to the traditional WML portfolio. However, by also applying the contrarian trading strategy on top of the ABS strategy, it is possible to attain even higher returns with lower risk, as volatilities decrease in unison with positive portfolio skewness, which mitigates crash-risk even further.

4.3 Extreme absolute strength and Dynamic momentum

This section presents the result of applying the DM strategy to the EXT strategy developed by Yang and Zhang (2019). Since EXT is an attempt to improve the ABS strategy of Gulen and Petkova (2018), applying the DM strategy proposed by Dobrynskaya (2019) to EXT will effectively mean running two momentum crash-mitigation strategies on ABS. As ABS alleviate effects from momentum crashes compared to the relative momentum strategy, three modifications are in fact applied to the relative momentum strategy. In Figure 3 we depict cumulative returns from a $1 investment in the value-weighted EXT, along with the corresponding EXT DM portfolio. We observe a similar pattern as before, where EXT DM outperform the EXT portfolio in cumulative returns, where additional returns are attained after 2008. The equal-weighted EXT and EXT DM cumulative returns are displayed in Appendix C - Panel C: Figure 11.

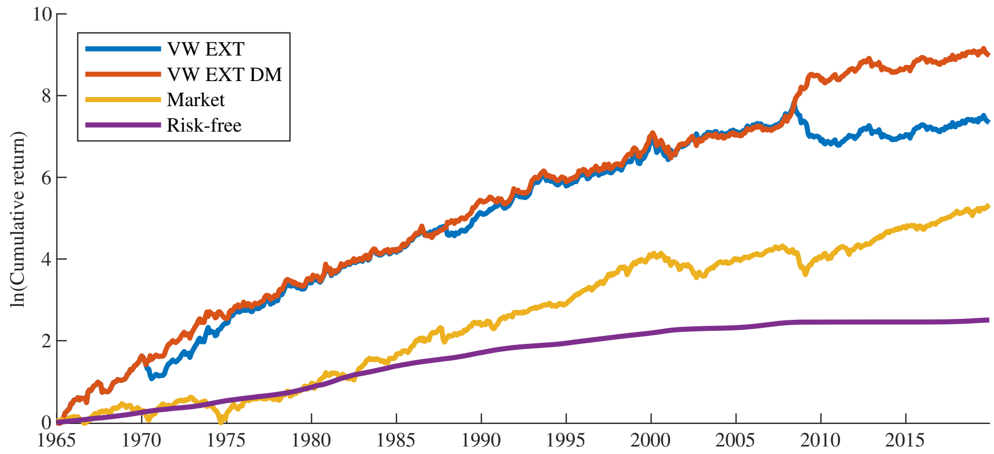

Figure 3: EXT portfolio, market and risk-free returns

Summary statistics for both the equal-and value-weighted portfolios are presented in Table 4, where EXT corresponds to our benchmark extreme absolute strength portfolios, whereas EXT DM corresponds to the dynamic extreme absolute strength momentum portfolios. Applying the DM strategy to EXT improves average returns for both the equal (3%) and value-weighted (19%) portfolios, while standard deviations remain similar. Naturally, this results in higher Sharpe ratios, where the equal(value)-weighted appreciate by 5% (31%) respectively. Further, Sortino ratios for the equal-and value-weighted EXT DM portfolios increase by 7% and 40% respectively, implying that both DM portfolios exhibit lower downside volatilities. The equal-weighted EXT DM portfolio's skewness is reduced but it remains negative, whereas the value-weighted EXT DM portfolio's skewness is positive. Neither EXT nor EXT DM portfolios suffers from large negative skewness in this setting, which means that all portfolios have beneficial skewness characteristics. Further, we observe no change in minimum monthly returns between EXT and EXT DM in the equal-weighted portfolios, while the value-weighted DM portfolio's minimum monthly return is reduced to -18.15% from -19.20%, turning significant losses into gains. Fama-French five factor alphas are positive and highly significant across all portfolios. The equal-weighted portfolios have similar alphas, whereas the value-weighted EXT DM portfolio's alpha appreciates. Further, the 9-factor model also have positive and significant alphas across all portfolios, however, they increase in both EXT DM portfolios. Even though this model considers additional factors, alphas remain large and significant. Thus, by applying the DM strategy to EXT, it is possible to attain even higher performance measures, further improving the strategy.

Table 4: Extreme absolute strength and Dynamic momentum 1965-2019

	Equal-weighted		Value-weighted		Market
	EXT	EXT DM	EXT	EXT DM	
Average return	15.79	16.32	15.27	18.22	10.91
	[8.90]	[9.26]	[5.75]	[6.99]	[5.14]
Standard deviation	13.36	13.31	19.30	19.09	15.32
Skewness	-0.30	-0.25	-0.08	0.19	-0.51
Sharpe ratio	0.84	0.88	0.55	0.72	0.41
Sortino ratio	1.77	1.90	1.12	1.57	0.78
Market beta	-0.03	-0.01	-0.11	0.01	1
	[-0.64]	[-0.32]	[-1.74]	[0.11]	
Market alpha	11.40	11.83	11.40	13.61	
	[6.51]	[6.71]	[4.29]	[5.15]	
FF5 alpha	13.16	13.88	13.18	16.69	
	[6.66]	[7.47]	[4.66]	[6.22]	
9-F alpha	8.19	11.37	5.83	13.79	
	[5.17]	[5.14]	[2.44]	[4.04]	
Min monthly return	-16.52	-16.52	-19.20	-18.15	-22.64
% of contrarian months		10%		10%	

Newey-west standard errors are reported in brackets

Average returns, standard deviations and performance measures are annualized in %

4.3.1 ABS vs EXT

Comparing our benchmark ABS and EXT portfolios from Table 3 and 4 respectively, we observe that both average returns and volatilities decrease when removing stocks which possess extreme absolute strength from the absolute momentum portfolio. These attributes are also reported by Yang and Zhang (2019). However, only the equal-weighted EXT portfolio benefits from these attributes in terms of Sharpe-and Sortino ratios, as these metrics increase from 0.7 to 0.84 and 1.40 to 1.77, respectively. The value-weighted

EXT portfolio is penalized from these attributes, as both Sharpe-and Sortino ratios decrease from 0.60 to 0.55 and 1.20 to 1.12, respectively. This contradict Yang and Zhang's (2019) results, as their value-weighted EXT portfolio does indeed decrease average return and volatility, but not at the expense of lower Sharpe-and Sortino ratios. An explanation for this could be that as we harmonize data gathering throughout our portfolios, we replicate each strategy using slightly different data sampling compared to the authors. However, both the equal-and value-weighted EXT portfolios exhibit less negative skewness relative to the benchmark ABS portfolios. This aspect, in unison with reduced minimum monthly returns is more desirable from a crash mitigating perspective, which is supported and addressed by Yang and Zhang (2019).

4.3.2 ABS DM vs EXT

Considering that EXT is an attempt to improve ABS, we compare the ABS DM with the benchmark EXT portfolios from Table 3 and 4 respectively. This is to determine whether DM is a more desirable crash mitigating strategy than EXT. The discrepancy between average returns is now even greater, as contrarian trading boost returns, while keeping similar volatilities, whereas the EXT strategy decrease both returns and volatilities. In terms of the equal-weighted portfolios, EXT has a higher Sharpe ratio (0.84) relative to ABS DM (0.81), which indicates a better risk-reward profile. However, the Sortino ratio of EXT is lower (1.77) relative to ABS DM (1.81), which means that the trade-off between downside volatility and average return does not benefit the EXT strategy. Even though both Sharpe-and Sortino ratios are similar, they deviate with respect to skewness, where ABS DM is positive (0.32) and EXT is negative (-0.30), which means that ABS DM has more appealing crash mitigating properties. Both portfolios have similar minimum monthly returns, where EXT is slightly lower (-16.52%) relative to ABS DM (-17.58%). Fama-French and 9-factor alphas are highly significant in both portfolios, but EXT's alphas are 4% and 6.4% lower in annual terms, respectively.

In terms of the value-weighted portfolios, EXT has a Sharpe-and Sortino ratio of 0.55 and 1.12, respectively, whereas ratios for the ABS DM is 0.79 and 1.78, respectively. Therefore, both Sharpe-and Sortino ratios are in favour of the ABS DM portfolio, implying that the trade-off between return and volatility is not beneficial for the EXT strategy in relative terms. Further, ABS DM exhibit positive skewness (0.30), whereas EXT is negative (-0.08), implying similar crash mitigating traits. Minimum monthly returns are in favour of ABS DM (-16.45%) compared to EXT's (-19.20%), which means that EXT experience larger losses. Fama-French and 9-factor alphas are both highly significant and positive, but ABS DM has 7% and 11.32% higher annual alphas, respectively. Therefore, in terms of crash mitigating properties, the value-weighted ABS DM portfolio offers quite beneficial characteristics compared to the already improved EXT portfolio, whereas the equal-weighted portfolio has similar characteristics.

4.4 Dynamic momentum

In this section we evaluate all DM portfolios on a relative basis to determine which performs best. As described in previous sections, applying DM to either strategy boost returns and decrease volatilities and downside volatilities, which inflates both Sharpe-and Sortino ratios. Also, DM renders more favourable skewness characteristics in almost all portfolios. Therefore, applying DM does enhance WML as well as the crash mitigating ABS and EXT strategies. Figure 4 depicts cumulative returns for a $1 investment in either value-weighted DM portfolio, where ABS DM outperform both WML DM and EXT DM. The equal-weighted DM portfolios cumulative return is portrayed in Appendix C - Panel D: Figure 12. Table 5 display summary statistics for all DM portfolios from previous sections, where WML, ABS and EXT all refer to their corresponding DM equal-and value-weighted portfolios.

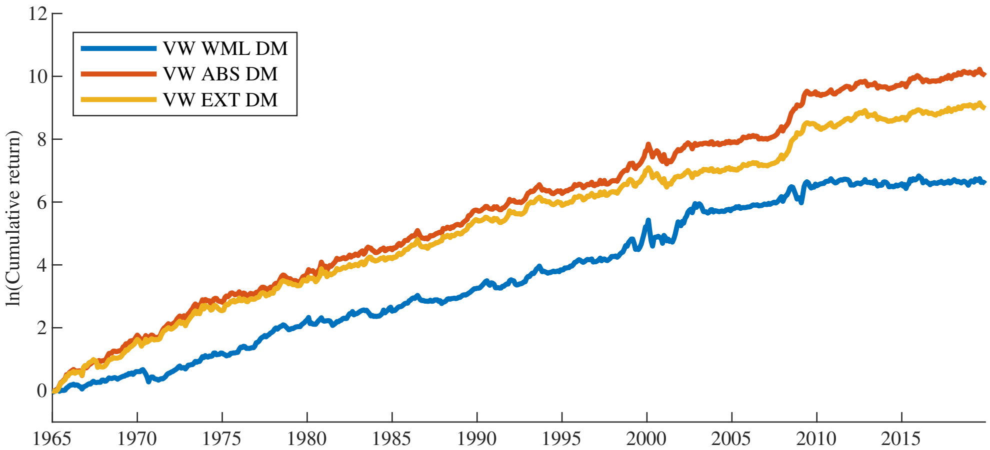

Figure 4: Dynamic momentum portfolio returns

4.4.1 Equal-weighted DM portfolios

The relative worst equal-weighted portfolio in terms of returns and performance measures is the WML DM portfolio, which falls short in almost every metric. However, skewness and minimum monthly return are both favourable, as skewness is positive and quite high (1.02), along with a minimum monthly return of -16.50%. The ABS DM portfolio performs best in terms of returns, but it possesses a higher standard deviation, which penalizes both Sharpe-and Sortino ratios. However, relative to WML DM, both Sharpe-and Sortino ratios are 11% and 9% higher, respectively. Skewness is positive, but not

Table 5: Dynamic momentum portfolios 1965-2019

	Equal-weighted			Value-weighted		
	WML	ABS	EXT	WML	ABS	EXT
Average return	15.68	18.40	16.32	14.18	20.30	18.22
	[7.29]	[8.28]	[9.26]	[4.80]	[7.50]	[5.14]
Standard deviation	15.24	16.98	13.31	20.88	19.98	19.09
Skewness	1.02	0.32	-0.25	0.33	0.30	0.19
Sharpe ratio	0.73	0.81	0.88	0.46	0.79	0.72
Sortino ratio	1.66	1.81	1.90	0.95	1.78	1.57
FF5 alpha	12.77	17.00	13.88	12.91	20.07	16.69
	[5.53]	[7.32]	[7.47]	[4.31]	[7.26]	[6.22]
9-F alpha	11.82	14.59	11.37	10.89	17.15	13.79
	[3.07]	[4.02]	[5.14]	[2.36]	[4.37]	[4.04]
Min monthly return	-16.50	-17.58	-16.52	-29.38	-16.45	-18.15
Cumulative return $	2,867	10,685	4,615	722	22,399	7,913

Newey-west standard errors are reported in brackets

Average returns, standard deviations and performance measures are annualized in %

as high as in the WML DM portfolio and with less favourable minimum monthly return (-17.58%). The EXT DM portfolio performs better than WML DM but worse than ABS DM in terms of returns, however, it exhibits a lower relative standard deviation, which spills over to Sharpe-and Sortino ratios, which are 9% and 5% higher than the ABS DM portfolio, and 21% and 14% higher than the WML DM portfolio, respectively. However, skewness remains negative, which from a crash mitigating perspective is not as favourable, whereas minimum monthly return is favourable from a relative perspective. In terms of average and cumulative returns, the ABS portfolio outperforms both WML DM and EXT DM quite dramatically, where a $1 investment in 1965 would accumulate to $10,685 at the end of 2019. In terms of both risk and returns, the EXT DM portfolio outperforms both WML DM and ABS DM, which is an effect of lower volatility and downside volatility.

4.4.2 Value-weighted DM portfolios

The dynamic value-weighted portfolios exhibit similar patterns as the equal-weighted portfolios in terms of risk and returns. WML DM is yet again the worst performing portfolio in relative terms, as average return is lower and standard deviation is higher, penalizing both Sharpe-and Sortino ratios. Once again, the ABS DM portfolio has a higher average return but a lower standard deviation than WML DM. Therefore, the ABS DM portfolio has 72% and 87% higher Sharpe-and Sortino ratios, respectively. Average return of the EXT DM portfolio is higher than WML DM but lower than ABS DM, with a standard deviation below both WML DM and ABS DM. Higher return and lower standard deviation yields higher Sharpe-and Sortino ratios relative to WML DM. However, relative to ABS DM, the reduction in standard deviation does not offset the relative lower returns. Therefore, ABS DM has 10% and 14% higher Sharpe-and Sortino ratios, respectively. Skewness is positive and on par for all value-weighted portfolios, which is an appealing crash mitigating property. However, WML DM's minimum monthly return (-29.38%) is almost twice as high relative to ABS DM's (-16-45%) and EXT DM's (-18.15%). In terms of average and cumulative returns, the ABS DM portfolio outperforms both WML DM and EXT DM quite dramatically, where a $1 investment in 1965 would accumulate to $22,399 at the end of 2019. In terms of both risk and returns, the ABS DM portfolio outperforms both WML DM and EXT DM, in unison with appealing crash mitigating properties.

4.4.3 Value-weighted winner and loser portfolios

When the market rebounds after a crash, WML usually makes large losses from the short leg, since price recoveries also happen among stocks in the loser portfolio. Being short these stocks may therefore incur a loss to such an extent that it offsets the gain in the winner portfolio. As presented in Figure 1, the value-weighted DM portfolio manage to generate additional returns compared to the value-weighted WML portfolio during the dotcom bubble and the recent financial crisis. The additional gains accumulated in the aftermath of the dotcom bubble is mainly attained by the rebounding loser leg, whereas the additional gains generated from the recent financial crisis is attained through both the long and short legs (Appendix D - Panel A: Figure 13). Regarding the crash mitigating portfolios ABS and EXT, Figure 2 and 3 portraits additional returns during the recent financial crisis when applying the DM strategy. Most of these gains are attributed to the long leg in contrast to the relative momentum portfolio, where both the long and short leg contributes to these additional returns (Appendix D - Panel B and C: Figure 14 and 15). This is most likely due to ABS's and EXT's built in crash mitigating properties, which reduce crash-risk in the short leg. Therefore, by applying DM, both portfolios manage to reap additional returns from the crashing long portfolio

4.5 Does dynamic momentum improve crash mitigating portfolios?

Given that we know what happened during previous crashes, we acknowledge that DM could, to some extent, suffer from look-ahead-bias as this model is generated to fit known large crashes from historical information. This said, DM works well overall when applied to the traditional momentum portfolio, but it is also effective in improving crash mitigating momentum strategies. Both the ABS and EXT benchmark portfolios exhibit negative skewness in their original setting. However, by implementing DM on these strategies, skewness is reduced even further, while minimum monthly returns also are reduced, turning significant losses into gains during a market crash. Even though the equal-weighted EXT DM still has a negative skewness, it is improved when DM is applied, and for all the other momentum portfolios, skewness changes from negative to positive.

As mentioned above, the equal-weighted EXT DM portfolio still has negative skewness. However, this strategy has both the highest Sharpe-and Sortino ratios, which indicates that it delivers best returns in relation to its risk. Further, it has the lowest standard deviation among all the strategies. This, in combination with that the equal-weighted EXT has the second lowest standard deviation, might imply that EXT overall is a rather effective way of mitigating crash risk and an improvement of ABS. The equal-weighted EXT also places itself as the strategy with the second highest Sharpe ratio, and performs well in other metrics. The implementation of DM therefore results in a strategy which both succeeds in lowering risk compared to previous strategies, while also improving returns because of the contrarian position taken by the DM strategy. A concern with combining EXT with DM is that EXT, by removing the most extreme percentiles of stocks, might make DM less effective. Potential gains could be lost, since the contrarian position used in DM uses the reversal stocks during a crash as an advantage. However, even though we observe lost average returns when comparing ABS to EXT, this loss is offset by a decrease in volatility instead, implying that Sharpe-and Sortino ratios benefits from this trade-off. Another explanation is that the EXT stocks, which are removed, do not produce high returns for the contrarian positions due to their risky nature. This would be in line with the reasoning of Yang and Zhang (2019) for not including them in the first place, namely that the risk is disproportionate compared to the return they generate.

When considering average return across strategies, the ABS DM performs best, as the value-weighted ABS DM has the highest average-and cumulative returns in our data set.

These high returns point toward that there are additional gains to be had from stocks which are excluded from the EXT DM strategy. In ABS the improved performance comes from the refined way of finding movements in stocks which trigger investor behaviour and momentum returns. ABS offers better response to momentum crashes than WML, but the reversal is still there and has significant effects on performance. ABS is an effort of improving WML by trying to explain momentum better, but it does not fully explain crashes. This might be why DM works so well together with ABS, since, as long as ABS is working, DM profits from ABS's advantages. When a crash occurs and ABS would have made a loss, DM is applied and use the crash as an advantage, turning losses into gains. The DM strategy does not try to fight the crash, but to anticipate and profit from it.

The positive effects of applying DM is true for both ABS and EXT. ABS explains momentum better, EXT makes ABS less risky by excluding stocks, and DM does not try to do either but to benefit from crashes. These strategies work well together since they mitigate crash risk in different ways. However, even if they all improve performance, DM is the strategy that has the most positive effect when merged with other strategies. Also, when controlling for the momentum factor in the 9-factor regressions, alphas are still positive and significant, which strengthens the argument of positive effects attributed to the DM strategy.

4.6 Factor exposure

We evaluate whether DM portfolio returns are exposed to various risk factors, which according to literature explains equity returns. To determine the exposure each DM portfolio has towards various risk factors, we run several alternate time-series regressions. Table 6, 7 and 8 corresponds to regressions related to the dynamic WML, ABS and EXT portfolios, where each row corresponds to a different regression. Regression (1) is the Fama-French five factor model, whereas regression (2) corresponds to what we call the 9-factor-model, which consist of various factors introduced in section 3.8.3.

The results show positive and significant alphas throughout all regressions for all DM portfolios. The result also indicates that DM indeed produces excess return in combination with other crash mitigation strategies. Dobrynskaya (2019) presents highly significant alphas for all regressions with similar specifications for both the equal-and value-weighted WML DM, which is in line with the result of this study. Considering exposure to other risk factors, this study diverges slightly from the results of Dobrynskaya (2019). In her paper, Dobrynskaya (2019) reports that all risk factors, apart from QMJ which is negative, are insignificant and close to zero. We find significance among other factors, although only a few. The risk factors which most frequently show significance are Mom and BAB factors. The BAB factor is significant in all but the WML DM portfolios and has a negative exposure to the DM portfolios. The other notable factor to frequently show significance is the Mom factor which is positive and significant in all 9-factor regressions. This is not surprising, since the mom factor is constructed to consider momentum returns. With that said, adjusted R^2 for most regressions are low, the highest being the 9-factor regression of the value-weighted ABS DM, which shows an adjusted R^2 value of 0.21. However, differences in the results of this study and Dobrynskaya (2019), could stem from a different method in calculating Z-scores for which the reversal is dependent on, along with a different time-horizon. Most importantly, it seems as if neither DM portfolio have high factor sensitivity towards other return factors. Also, even though we account for both the momentum and additional factors in the 9-factor, relative to the Fama-French five factor model, alphas remain highly significant and large. This implies, that all DM portfolios manage to gain abnormal returns, even in the presence of a momentum factor.

Table 6: Factor exposure - WML DM

Equal-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	12.77**	-0.07	0.03	-0.11	-0.22	-0.07					0.01
(2)	11.82**	-0.03	0.04	0.01	-0.21	-0.11	0.15**	0.12	0.04	-0.11	0.03
Value-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	12.91**	-0.09	0.19	-0.35	-0.51**	-0.13					0.08
(2)	10.89*	-0.02	0.17	-0.11	-0.46	-0.16	0.44*	0.13	-0.07	-0.21	0.16

Newey-west t-statistics; * $p < 0.05$, ** $p < 0.01$. Alpha's are annualized in %. R^2 is adjusted

(1):Fama-French-5-Factor-model

(2):9-factor-model

Table 7: Factor exposure - ABS DM

Equal-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	17.00**	-0.09	0.01	-0.32*	-0.25	-0.21					0.06
(2)	14.59**	0.01	0.01	-0.08	-0.25	-0.15	0.35*	0.15*	0.08	-0.29**	0.17
Value-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	20.07**	-0.14	0.04	-0.28	-0.33	-0.47*					0.07
(2)	17.15**	-0.03	0.01	0.03	-0.18	-0.39	0.54**	0.14	-0.13	-0.38**	0.21

Newey-west t-statistics; * $p < 0.05$, ** $p < 0.01$. Alpha's are annualized in %. R^2 is adjusted

(1):Fama-French-5-Factor-model

(2):9-factor-model

Table 8: Factor exposure - EXT DM

Equal-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	13.88**	-0.08	-0.04	-0.24*	-0.09	-0.13					0.04
(2)	11.37**	0.01	-0.06	-0.04	-0.14	-0.10	0.34**	0.08	0.05	-0.17*	0.18
Value-weighted	α	R_m^e	SMB	HML	RMW	CMA	Mom	PSLIQ	QMJ	BAB	R^2
(1)	16.69**	-0.10	-0.03	-0.18	-0.10	-0.41					0.04
(2)	13.79**	0.00	-0.05	0.07	-0.00	-0.32	0.47**	0.13	-0.07	-0.32**	0.15

Newey-west t-statistics; * $p < 0.05$, ** $p < 0.01$. Alpha's are annualized in %. R^2 is adjusted

(1):Fama-French-5-Factor-model

(2):9-factor-model

5 Conclusions

Our study evaluates and merges three different momentum strategies; DM, ABS and EXT, which are suggested by Dobrynskaya (2019), Gulen and Petkova (2018) and Yang and Zhang (2019), respectively, to deal with momentum crashes. The first strategy is based on the concept of contrarian trading, in which one keeps the traditional WML portfolio in calm times but switch to the reversed LMW portfolio when markets are in turmoil. The second strategy forms portfolios based on absolute rather than relative strength, meaning that monthly portfolio formations are not only based on the most recent ranking distribution of returns, but rather where the recent ranking distribution is in relation to the historical distribution of cumulative returns. The third strategy is based on the second strategy with an additional filter, where stocks which possesses extreme absolute strength are removed from the ABS portfolio. Our results verify conclusions made by previous authors; each strategy mitigates momentum crashes to some extent, while generating higher returns compared to the relative WML portfolio. Moreover, each strategy shows more appealing portfolio characteristics, such as higher Sharpe-and Sortino ratios, while also shifting the distribution of returns from negative towards zero or even positive skewness.

The most notable result is the effect of merging DM to the other strategies. Besides verifying the positive effects of DM on WML, as proposed by Dobrynskaya (2019), this study also shows that crash mitigating strategies benefit from having DM implemented. This is true for all strategies tested in this study. Furthermore, the result indicates that it is possible to merge several crash mitigation strategies simultaneously to increase performance, implying that synergies exist. We conclude that this is mainly possible because of the different approaches taken by each strategy in their attempt to mitigate crash risk. This is especially true when applying DM, since ABS and EXT tries to avoid crashes, while DM turn crashes into gains. Since neither ABS nor EXT manages to completely get rid of crash risk, DM works as a complement, which becomes very apparent after the recent financial crisis. Further, all DM portfolios exhibit large and significant alphas even when we are controlling for the momentum factor in the 9-factor model. This indicates that even though we control for additional factors, alpha is not eliminated in neither regression.

In terms of relative performance between the DM portfolios, we find that the equal-weighted EXT DM portfolio yields highest Sharpe-and Sortino ratios, implying that this portfolio offers the best risk-adjusted returns. The negative skewness is heavily reduced, in unison with reduced minimum monthly returns. For all the other portfolios, skewness is positive after DM has been applied, which is a desirable characteristic from a crash mitigating perspective. Both the equal-and value-weighted ABS DM portfolios have the highest average returns, and yield the highest cumulative returns over the sample period, implying that some gains are lost in the EXT DM compared to the ABS DM portfolios due to the exclusion of stocks. This said, these removed stocks are riskier, as both Sharpe and Sortino ratios are penalized compared to the equal-weighted EXT DM portfolio's. However, if we only compare value-weighted portfolios, the ABS DM offers the best risk-adjusted returns.

We only test DM on two momentum strategies, but it would be interesting for future research to apply the concept of contrarian trading to various other strategies as well. By finding more strategies which can be combined, further knowledge about how momentum works could be obtained. Also, the research could be extended to other strategies in other regions, as DM works in several markets, according to Dobrynskaya (2019).

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A

Panel A: Historical 10th and 90th percentile breakpoints for the absolute strength portfolio, ranging from 1965-2019. If a stock's ranking distribution is above (below) the 90th (10th) breakpoint, it is indicated as a winner (loser).

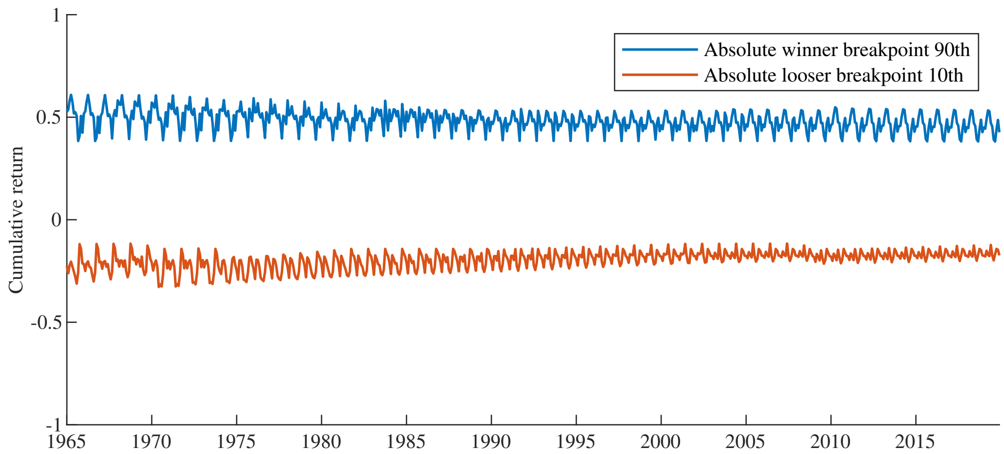

Figure 5: Historical ABS breakpoints

Panel B: Historical long and short portfolio sizes for the absolute strength strategy, ranging from 1965-2019.

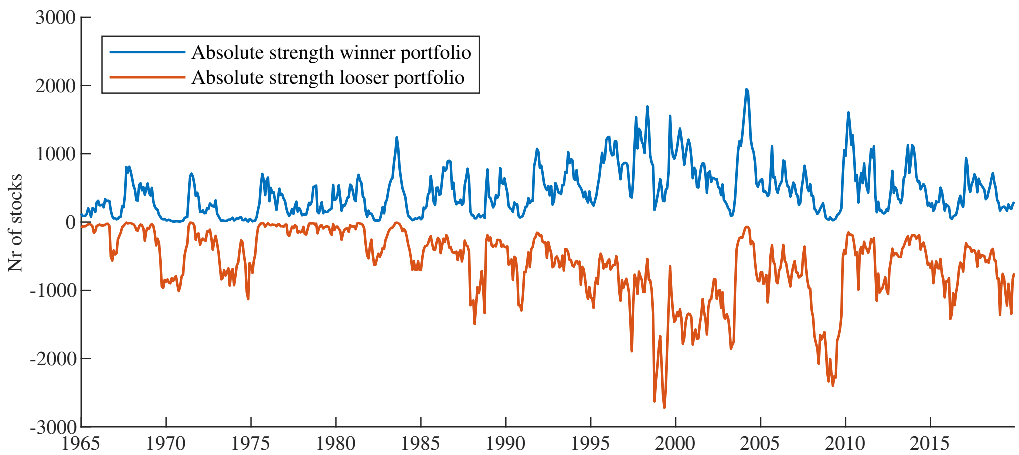

Figure 6: Historical ABS portfolio sizes

B

Panel A: Historical 3rd and 97th percentile breakpoints for the extreme absolute strength portfolio, ranging from 1965-2019. If a stock's ranking distribution is above (below) the 97th (3rd) breakpoint, it is excluded from the extreme absolute strength portfolio.

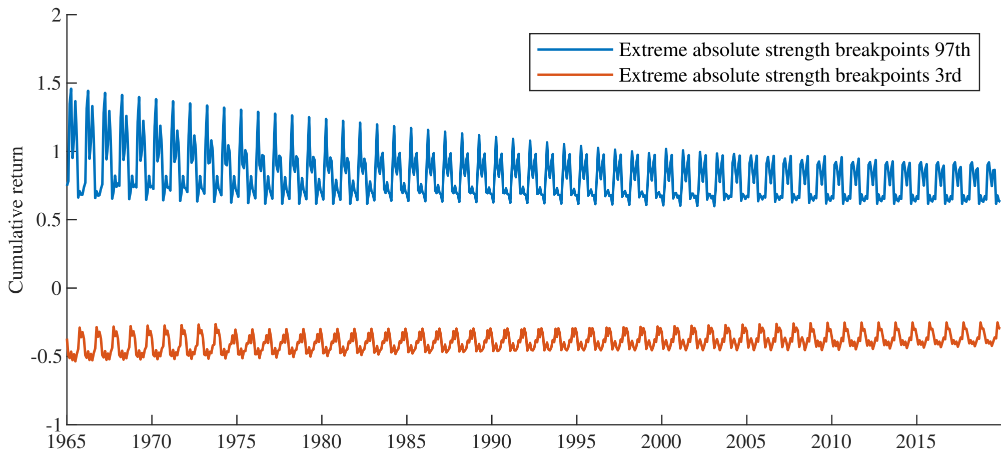

Figure 7: Historical EXT breakpoints

Panel B: Historical long and short portfolio sizes for the extreme absolute strength strategy, ranging from 1965-2019.

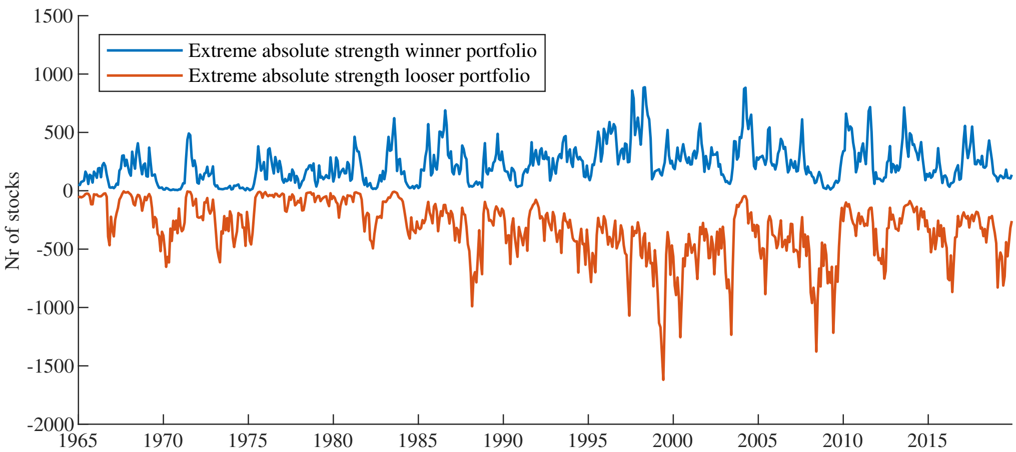

Figure 8: Historical EXT portfolio sizes

C

Panel A: Figure 9 display cumulative returns from a $1 investment in the equal-or value-weighted momentum portfolios, along with the corresponding dynamic momentum portfolios between 1965-2019

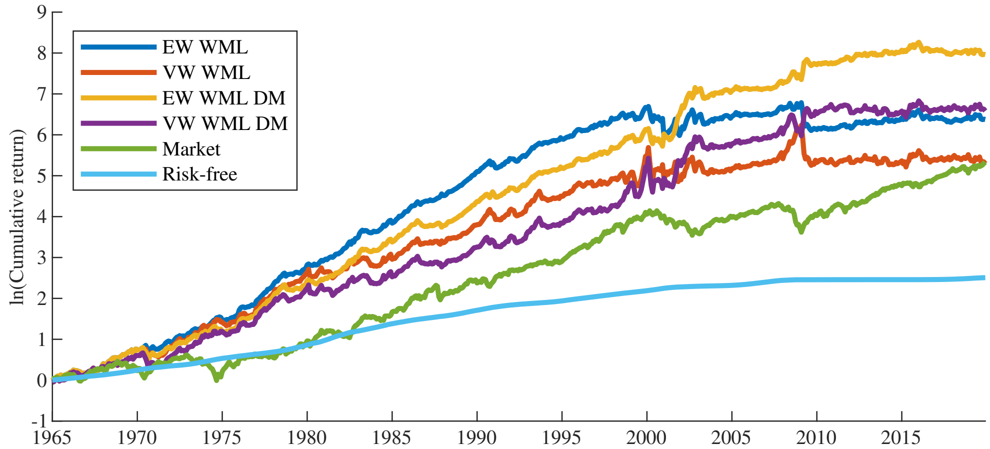

Figure 9: WML Portfolio, market and risk-free returns

Panel B: Figure 10 display cumulative returns from a $1 investment in the equal-or value-weighted absolute momentum portfolios, along with the corresponding dynamic absolute momentum portfolios between 1965-2019

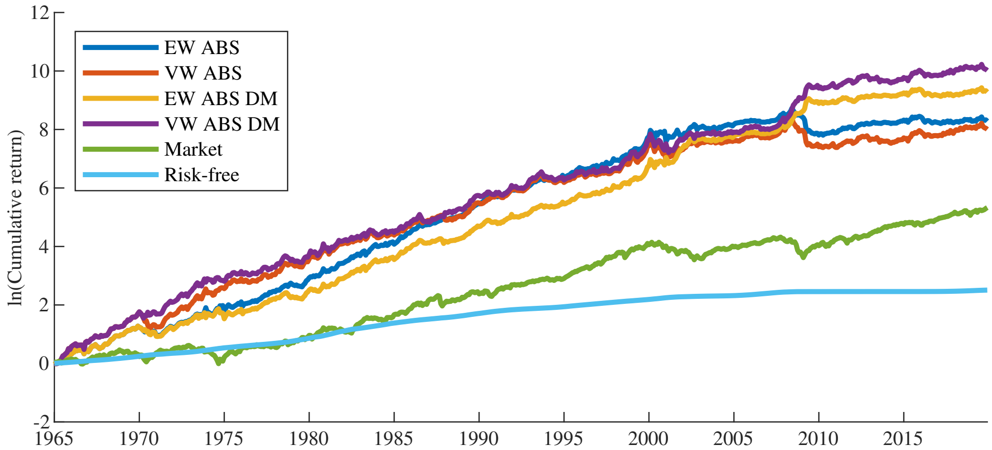

Figure 10: ABS portfolio, market and risk-free returns

Panel C: Figure 11 display cumulative returns from a $1 investment in the equal-or value-weighted extreme absolute momentum portfolios, along with the corresponding dynamic extreme absolute momentum portfolios between 1965-2019

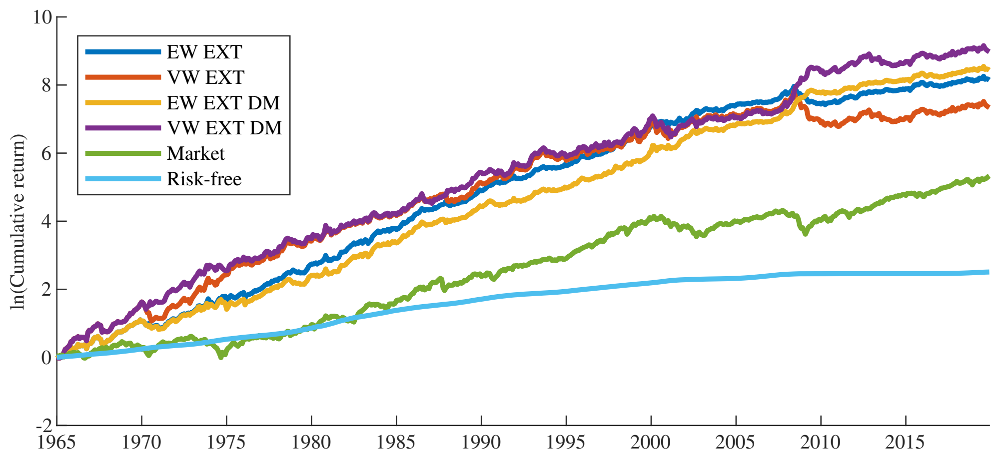

Figure 11: EXT portfolio, market and risk-free returns

Panel D: Figure 12 display cumulative returns from a $1 investment in the equal-or value-weighted dynamic momentum portfolios between 1965-2019.

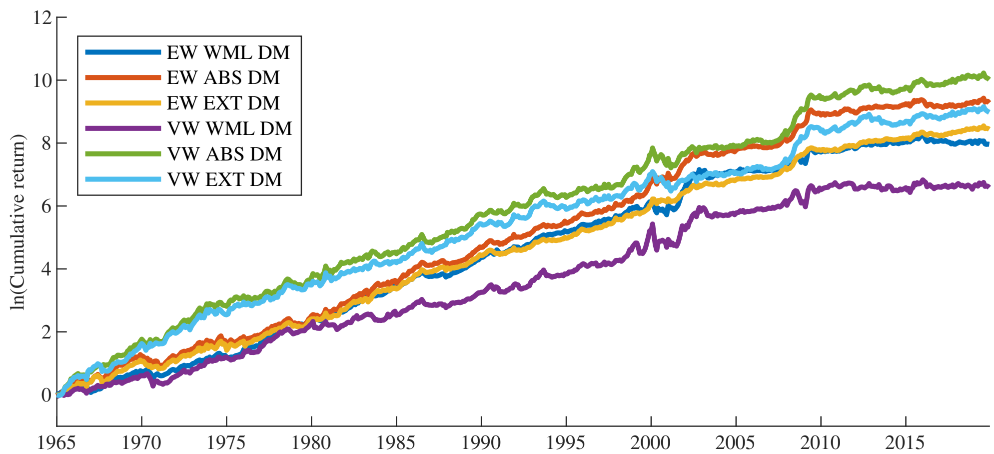

Figure 12: DM portfolio, market and risk-free returns

D

Panel A: Figure 13 display cumulative returns from a $1 investment in the value-weighted short and long leg separately for the momentum strategy, along with the corresponding dynamic momentum strategy between 1965-2019. The asterisks (*) indicate months when the reversal (LMW) positions are held. Each short portfolio leg is multiplied by negative one to reflect the positive returns of the short positions.

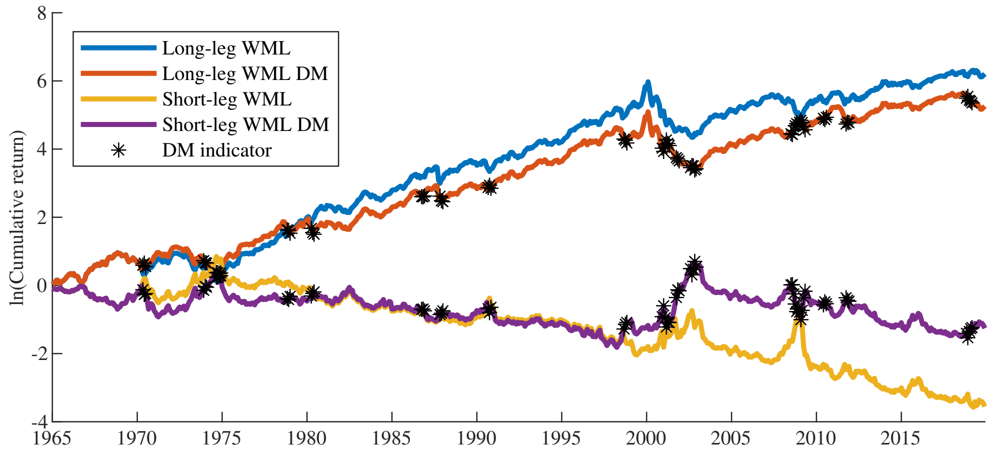

Figure 13: Long and short portfolio legs for WML and WML DM

Panel B: Figure 14 display cumulative returns from a $1 investment in the value-weighted short and long leg separately for the absolute momentum strategy, along with the corresponding absolute dynamic momentum strategy between 1965-2019. The asterisks (*) indicate months when the reversal (LMW) positions are held. Each short portfolio leg is multiplied by negative one to reflect the positive returns of the short positions.

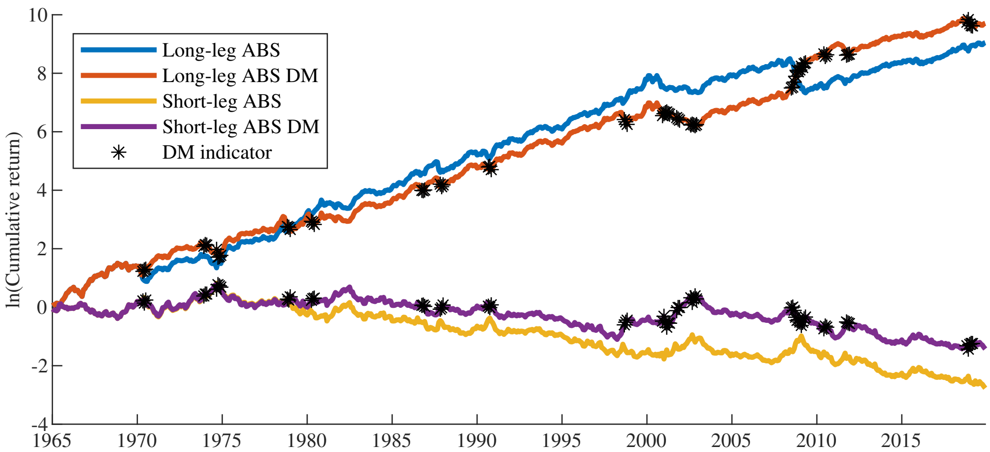

Figure 14: Long and short portfolio legs for ABS and ABS DM

Panel C: Figure 15 display cumulative returns from a $1 investment in the value-weighted short and long leg separately for the extreme absolute momentum strategy, along with the corresponding extreme absolute dynamic momentum strategy between 1965-2019. The asterisks (*) indicate months when the reversal (LMW) positions are held. Each short portfolio leg is multiplied by negative one to reflect the positive returns of the short positions.

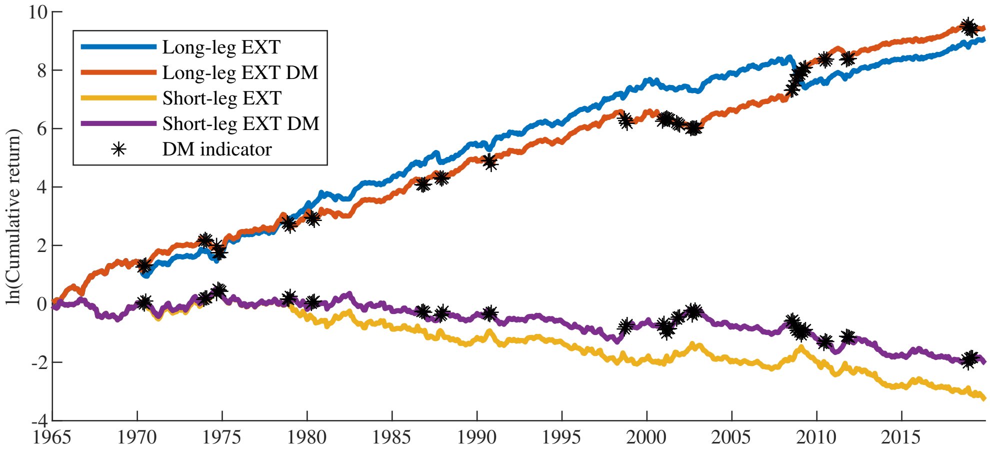

Figure 15: Long and short portfolio legs for EXT and EXT DM