Volatility-Adjusted Momentum*,†

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Abstract

Motivated by standard portfolio theory, this paper incorporates ex-ante volatility estimates in the construction of winner-minus-loser stock momentum portfolio. I find that over the 1927-2015 period this leads to an increase in the Sharpe ratio from 0.34 to 1.14 and strongly reduced crash risk. This result is driven, in part, by the under weighting of high-volatility loser stocks, which tend to perform well, and cannot be attributed to small caps. In an out-of-sample test on USD-denominated corporate bonds, similar improvements are found.

Keywords: momentum, cross-section, volatility, stocks, corporate bonds

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1 Introduction

Cross-sectional momentum premia have been thoroughly documented in the academic literature for many asset classes over the past two decades, first for US equities by Jegadeesh and Titman (1993), and subsequently in other asset classes such as international equities (Rouwenhorst, 1998), commodities (Miffre and Rallis, 2007), currencies (Okunev and White, 2003; Menkhoff et al., 2012), high-yield corporate bonds (Jostova et al., 2013), sovereign bonds (Asness, Moskowitz, and Pedersen, 2013) and real estate (Derwall et al., 2009; Beracha and Skiba, 2011). Ever since the first study in 1993, the de-facto standard methodology is to construct a non-levered long-short quantile portfolio based on past returns. This "winner-minus-loser" (*WML*) momentum portfolio is long assets with the highest past returns, and finances these long positions with short positions in assets with the lowest past returns.

There are a number of details in the exact construction of the momentum portfolio that vary across studies, such as the percentage of assets in the long and short leg (e.g., decile, quintile or tertile portfolios), the horizon over which past returns are measured (the formation period length), whether to skip the most recent week/month or not to account for bid-ask bounces (Jegadeesh and Titman, 1993), the rebalancing frequency and the weighting scheme within the portfolio (equal or market value weighted). Despite these differences, sorting assets based on past returns seems to be taken as a given.

The main contribution of this paper, motivated by portfolio theory going back to Markowitz (1952), is to make assets with different volatilities comparable to each other, such that there is a "level playing field". I achieve this by incorporating ex-ante volatility estimates in both the sorting stage and the weighting scheme when constructing the momentum portfolio. The resulting *volatility-adjusted momentum* portfolio differs in three ways from the standard momentum portfolio, namely (1) assets should not be sorted into quantile portfolios based on their past returns, but rather on their past returns-to-volatility ratio, (2) the weight of an asset within the quantile portfolio should be inverse proportional to its volatility and (3) each quantile portfolio should target a constant volatility through time.

The empirical contribution of this paper is to compare volatility-adjusted momentum, and each of the individual steps from standard momentum to volatility-adjusted momentum, to standard momentum on CRSP U.S. stock data from January 1927 to December 2015. I find that the Sharpe ratio increases from 0.34 for standard momentum to 1.14 for volatility-adjusted momentum, the alpha more than doubles and that volatility-adjusted momentum has much less crash risk as evidenced by the reduction in skewness (from -3.91 to -1.02). This improvement is visible in both large caps and small caps.

The stronger performance is primarily driven by two effects. First, volatility-adjusted momentum avoids selling the highest volatility losers. Although high volatility stocks do not tend to have higher returns than low volatility stocks in general (Haugen and Heins, 1972), this is not the case amongst the losers, where the high volatility stocks do not continue their decline, but rather have an alpha close to zero. Avoiding the short-selling of high volatility losers raises the Sharpe ratio from 0.34 to 0.85.

Second, volatility-adjusted momentum (de-)levers the winner and loser portfolios when past 12-1 month daily return volatility of the stocks selected has been low (high), targeting a constant volatility instead. As future Sharpe ratios of the winner and loser portfolios are almost uncorrelated to their ex-ante volatility estimates, de-levering high volatility months and levering low volatility months boosts the Sharpe ratio. In particular, the winner portfolio is improved as a negative relation exists between ex-ante volatility and the realized 1-month Sharpe ratio. For the loser portfolio, the relation is flat, leading to a smaller increase in Sharpe ratio. Also, the constant volatility targeting reduces the natural imbalance in volatilities between winners and losers: losers tend to be more risky, as also documented by Haesen, Houweling, and Van Zundert (2017). The reduced volatility imbalance increases the winner-minus-loser Sharpe ratio by 0.12. In total, the Sharpe ratio rises from 0.85 to 1.14 due to the constant volatility targeting.

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), instead of levering the individual winner and loser portfolios, lever the standard *WML* portfolio as a whole. In particular, Barroso and Santa-Clara (2015) target a constant volatility of *WML* by scaling with the volatility of the past 6 month of daily returns of the same portfolio. Adding this *WML*-specific leverage on top of the volatility-adjusted momentum portfolio increases the Sharpe ratio even further, to 1.31. Stand-alone, this timing element leads to a Sharpe ratio of only 0.74, well below the ratio of 1.14 for volatility-adjusted momentum.

As an out-of-sample test, I employ volatility-adjusted momentum on USD-denominated corporate bond data spanning the 1994-2015 period. Especially the application on investment-grade bonds, i.e., higher credit quality bonds, is of interest as it is one of the few asset classes for which no momentum effect has been found so far (Khang and King, 2004; Gebhardt, Hvidkjaer, and Swaminathan, 2005). In line with those earlier findings, no momentum effect is visible using traditional return-based sorts. I find the *WML* alpha to be only 1.80% per annum and statistically insignificant, and the Sharpe ratio with a value of 0.04 is close to zero as well. However, as the dispersion in volatility is very large within this dataset, the volatility-adjusted momentum portfolio generates a significant positive alpha of 3.26% per annum with a Sharpe ratio of 1.04.

This paper relates to several streams in the literature. First, it is closely connected to recent studies on understanding and improving stock momentum. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find that timing the momentum factor for US stocks, using indicators like the past 6-month realized return volatility of the winner-minus-loser momentum portfolio itself, substantially improves the performance. In particular, the crashes associated with standard momentum are largely mitigated. I deviate from their work by not scaling the *WML* portfolio, but go one level deeper by first making the individual assets comparable in terms of ex-ante risk. This is an important difference as it also affects the selection of assets in the long and short portfolios, whereas scaling after the construction of the long and short portfolio completely ignores biases in the selection of individual assets, leading to suboptimal portfolios to start with. The Sharpe ratio of Barroso and Santa-Clara (2015) risk-managed momentum (0.74) is lower than the Sharpe ratio of volatility-adjusted momentum (1.14).

Second, it relates to the concurrent work of Ledoit, Wolf, and Zhao (2016) who test a large number of anomalies on U.S. stock data. Similar to this paper, they argue that the standard portfolio sort ignores the covariances of the asset returns. The key challenge with the mean-variance portfolio of Markowitz (1952) is exactly to estimate the covariance matrix of asset returns. Ledoit, Wolf, and Zhao (2016) solve this by using the *DCC-NL* estimator of Engle, Ledoit, and Wolf (2017). In contrast, the adjustment proposed in this paper assumes a uniform correlation structure and explicitly creates quantile portfolios rather than a single optimized portfolio. This simplifies the portfolio construction drastically and provides a clear interpretation of the differences versus the standard quantile portfolio sort.

Third, it relates to earlier work on momentum in corporate bond markets. Gebhardt, Hvidkjaer, and Swaminathan (2005) and Khang and King (2004) find evidence for reversals in the investment grade market. Jostova et al. (2013) and Houweling and Van Zundert (2017) do not find momentum in investment grade bonds, but do find momentum in high yield bonds. Barth, Hühn, and Scholz (2017) document similar findings for euro-denominated bonds. A concurrent paper by Lin, Wu, and Zhou (2016) identifies momentum effects in the US corporate bond market, but with a different methodology. First, Lin, Wu, and Zhou (2016) empirically determine the optimal combination of moving averages of bond yields over eight horizons, ranging from 1 month to 60 months, to form a signal. In contrast, in this paper a single horizon is used as is standard in the momentum literature. Second, this paper purposely uses excess returns over duration matched Treasuries, i.e. the credit component of returns, not total returns as used by

Lin, Wu, and Zhou (2016). The reason is that, especially for investment grade bonds, a sizable part of the return is driven by the interest rate component. Any momentum effects documented could thus entirely be due to momentum in Treasuries, not by momentum in the firm-related credit return. By zooming in on the credit return, I ensure that the results are driven by the firm-related credit component.

The remainder of this paper is structured as follows: Section 2 discusses the theoretical framework in which volatility-adjusted momentum is optimal. Section 3 contains the main empirical analyses. Section 4 describes the results of the out-of-sample check on corporate bonds. Section 5 concludes.

2 Methodology

In this section I explain and motivate the volatility adjustments to the standard momentum portfolio. First, I explain the adjustment to the standard top 10% winner minus bottom 10% loser momentum portfolio. Then, I use a reduced-form model to motivate the inclusion of volatility in the momentum portfolio construction process. This model is not meant as an explanation to momentum, rather, it shows why the incorporation of volatility in the construction process is optimal from the point of view of a rational momentum trader. Finally, I break down the adjustment from standard momentum to volatility-adjusted momentum in three steps. The empirical section shows results for each of the steps as to better understand the source of the improvement versus standard momentum.

2.1 Adjusting for volatility

The volatility adjustment aims to make assets with different levels of volatility comparable by scaling their returns $R_{i,t}$ with an ex-ante volatility estimate $\widehat{\sigma_{i,t}}$, where the subscript i (t) denotes the asset (time). This adjustment is common in studies involving multiple asset classes, such as Moskowitz, Ooi, and Pedersen (2012) who study time series momentum over numerous asset classes.

Denote the money weight as $w_{i,t}$, the past k-period return per unit of ex-ante volatility as $R^*_{i,t-k:t} \quad \left(= \frac{R_{i,t-k:t}}{\widehat{\sigma_{i,t}}}\right)$, and the weight in units of volatility as $w^*_{i,t} \quad (= w_{i,t} \times \widehat{\sigma_{i,t}})$.

The concept of volatility-adjusted momentum, as introduced in this paper, works a follows. I construct the top (bottom) decile momentum portfolio as an equal $w^*_{i,t}$ weighted portfolio of the 10% assets with the highest (lowest) $R^*_{i,t-k:t}$, with the total weight of the top (bottom) portfolio $\sum_i w^*_{i,t}$ constant through time. I.e., after scaling the returns of the assets with their ex-ante volatility and adjusting positions correspondingly, the methodology of volatility-adjusted momentum is exactly the same as the standard momentum portfolio sorts.

2.2 A single optimal portfolio

I now present a simple model to motivate the concept for volatility-adjusted momentum. In this model an agent has information on past price innovations to construct an optimal portfolio at time t. The agent has a constant relative risk aversion utility with risk aversion parameter γ and can invest in N risky assets which have normally distributed returns with mean μ_t and a variance-covariance matrix Σ_t. For simplicity, the problem is assumed to be single-period. I assume a riskless asset exists, and without loss of generality set it's return to zero. Under these assumptions, the optimal portfolio is the mean-variance portfolio, with weights given by (Markowitz, 1952):

$$w_t = \frac{1}{\gamma} {\Sigma_t}^{-1} \mu_t \tag{1}$$

The disadvantage of this solution is that the full variance-covariance matrix Σ_t has to be estimated, and that the optimal weights w_t are very sensitive to the estimated covariance terms. Therefore, I make the assumption that the pairwise correlations are uniform, which has been shown to produce better out-of-sample forecasts than many more sophisticated methods (Elton and Gruber, 1973). This simplifies Equation 1. Setting the correlation to a specific value $\rho \in (0,1)$[1], the *relative* weight[2] of asset i in the portfolio at time t, $z_{i,t}$, is given by (Elton, Gruber, and Padberg, 1976, Equation 12):

$$z_{i,t} = \frac{1}{1-\rho}\frac{1}{\sigma_{i,t}}\left[\frac{\mu_{i,t}}{\sigma_{i,t}} - \frac{\rho}{1-\rho+N\rho}\sum_{j=1}^{N}\frac{\mu_{i,t}}{\sigma_{i,t}}\right] \tag{2}$$

where $\sigma_{i,t}$ is the volatility of asset i at time t. Note that this is a relative weight, not an absolute weight. The absolute weight depends on the exact level of risk aversion of the investor.

2.3 Translation of single optimal portfolio to quantile portfolios

In the momentum literature, the usage of non-levered long-only quantile portfolios is standard. For comparability, I convert the single optimal portfolio into quantile portfolios. Although this reduces the optimality of the portfolio, it provides a clear interpretation of the differences between the standard and the volatility-adjusted momentum quantile portfolios. The differences can be broken down in three steps, and for better understanding of the differences I test each step separately in the empirical section.

Step 1 selecting assets To translate the portfolio in Equation 2, I use the insight that if a limited number of assets may be selected for the optimal portfolio, those assets included should be the ones with the highest Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$ (Elton, Gruber, and Padberg, 1976, p. 1354). Thus, these assets do not have to be the ones with the highest weight in the single optimal portfolio! For instance, an asset with a just above-average Sharpe ratio and very low volatility will receive a high weight, but would not be selected

[1] Correlations could also be negative, but in the context of individual stocks they are positive in general. For example, Pollet and Wilson (2010) show that the average pairwise correlation between the 500 largest exchange-traded stocks in the U.S. is approximately 0.3.

[2] I.e., $w_{i,t} = \frac{z_{i,t}}{\sum_j z_{j,t}}$. Later the absolute weight will be derived.

in the top portfolio as the Sharpe ratio does not belong to the highest values. Intuitively, given that leverage is possible in the Markowitz (1952) framework, the optimal risky-asset portfolio will be the one that produces the highest Sharpe ratio. As all assets are equal in terms of diversification benefits due to the assumption of uniform correlations, the assets with the highest Sharpe ratio are most attractive to include. Leverage can be used to attain the desired risk given the risk aversion of the investor.

The assets in the top decile portfolio are therefore the 10% assets with the highest Sharpe ratios. The next decile portfolio, which cannot select assets already included in the top decile portfolio by construction, should thus include the next 10% assets sorted by Sharpe ratio. This process is repeated until the bottom decile contains the 10% assets with the lowest Sharpe ratio. The sorting of assets into quantile portfolios is thus straightforward: sort on the Sharpe ratio, rather than on raw returns.

Step 2 weighting assets within the (non-levered) portfolio The next question is how large the weight of an asset within its decile portfolio should be. Due to the sorting of the assets by their Sharpe ratio into decile portfolios, the k assets included in a specific decile portfolio will have approximately the same Sharpe ratio $\overline{SR^q}$. Under the simplifying assumption that all assets included in the quantile portfolio have exactly the same Sharpe ratio[3], the weight of each asset in a quantile portfolio is given by (Appendix A provides the details for the derivation)

$$w_{i,t} = \frac{1}{\sigma_{i,t}} \frac{1}{\gamma} \left(\frac{1}{1 - \rho + k\rho} \right) \overline{SR^q} \tag{3}$$

In this step, I aim to construct portfolios that are not levered, since this is what

[3] Between the quantile portfolios, the Sharpe ratios will differ, as that is the goal of constructing anomaly portfolios. As the focus is on optimizing each individual quantile portfolio and show the difference in risk and return characteristics across the quantile portfolios, the same Sharpe ratio for each portfolio is implicitly assumed in step 3. As for the standard momentum methodology, which also creates \$1 decile portfolios from D1 to D10, I make each decile portfolio the same. A momentum trader would invest more in D1 than in D2, and short-sell less in D9 than in D10.

standard momentum does. Thus the portfolio money weights $w_{i,t}$ have to add up to 1, implying

$$w_{i,t} = \frac{\sigma_{i,t}^{-1}}{\sum_{j=1}^{k_t} \sigma_{j,t}^{-1}} \tag{4}$$

as γ, ρ, k and $\overline{SR^q}$ cancel out. Thus within the quantile portfolio, assets should be weighted with the reciprocal of their volatility.

Step 3 levering portfolios After steps 1 and 2, there are 10 non-levered decile portfolios by sorting assets on their Sharpe ratio and within each portfolio weighting the assets by the inverse of their volatility. However, Equation 3 shows that the total portfolio weight, i.e. leverage, varies through time as the investors risk-aversion γ, the correlation parameter ρ, the number of assets k, the risk premium $\overline{SR^q}$ and the asset specific volatilities $\sigma_{i,t}$ can vary through time. Under the assumption that γ, ρ and $\overline{SR^q}$ are constant through time (i.e., the momentum trader does not update correlation nor risk premium estimates), Appendix A shows that $w_{i,t}$ can be approximated by

$$w_{i,t} = c\sigma_{i,t}^{-1} k_t^{-1} \tag{5}$$

where the parameter c is a scaling parameter. This parameter depends on the assumed risk aversion γ, the correlation parameter ρ and the assumed risk premium $\overline{SR^q}$. In the empirical section I set c to 0.60. As I explicitly construct WML portfolios with equal full sample volatility to allow a meaningful comparison of mean returns and alphas between portfolios, the exact value is not important.

To conclude, the leverage of the portfolio is inverse proportional to the volatilities $\sigma_{i,t}$. If the volatilities double (halve), the weights $w_{i,t}$ halve (double). Due to this levering, the quantile portfolio volatility is (approximately) constant through time. See Appendix A for the details. The parameter k_t is included to control for the number of assets. Otherwise, if the number of assets included in the portfolio would double, the leverage would also double, as the total weight invested, w^q, is the sum over all individual positions: $w^q = \sum_{j=1}^{k} w_{j,t}$.

2.4 Momentum trader inputs

In the concept of volatility-adjusted momentum, the momentum trader uses past returns to forecast future volatilities and Sharpe ratios. For the volatilities, the momentum trader estimates the volatility of asset i at time t, $\sigma_{i,t}$, by the past 12-1 month daily return volatility $S_{i,t-12:t-2}$. For the Sharpe ratio, the trader assumes that the returns over the past 12 months, skipping the most recent month, continue into the future:

$$\widehat{SR_{i,t}} = \frac{R_{i,t-12:t-2}}{S_{i,t-12:t-2}} \tag{6}$$

where $R_{i,t-12:t-2}$ is the realized return of asset i over the past 12-1 months. The decile volatility-adjusted momentum portfolios are thus constructed by sorting on $\frac{R_{i,t-12:t-2}}{S_{i,t-12:t-2}}$, and weighting with $S^{-1}_{i,t-12:t-2}$.

3 Empirical results

3.1 Data

For the stock data, I select all common equity (share codes 10 and 11) listed on the New York Stock Exchange, the American Stock Exchange and the Nasdaq Stock Market (exchange codes 1, 2 and 3) in the Center of Research in Security Prices (CRSP) database from the daily files. The resulting dataset contains stock returns at a daily frequency over the period January 1926 to December 2015. All stocks are made long-short assets by subtracting the risk-free rate, which I proxy with the 1-month T-bill rate from the CRSP Treasury index files. As this is a monthly available rate, it is converted to a daily rate at the beginning of each month, and assumed to be constant throughout the month.

Momentum decile portfolios are constructed by ranking each month all stocks on their past 12-month returns, excluding the most recent month in line with previous studies on stock momentum to avoid the bid-ask bounce (Jegadeesh and Titman, 1993). Both the returns, as well as the volatilities for the volatility-adjusted momentum portfolios are based on these 11 calendar months of returns. The stocks with the 10% highest returns (or return-to-volatility) are incorporated in the first decile portfolio (D1), the next 10% in D2, etcetera, until the lowest 10% which are included in D10. The momentum portfolios are rebalanced every month-end. In between rebalancing moments the weights are updated with the daily stock returns. The constituents of the decile portfolios remain constant throughout the remainder of the month, except for delistings. If delisting returns are provided in the CRSP dataset, I include these in the return calculation. The proceeds from the divestment of the delisted stocks are reinvested proportionally in the remaining constituents of the momentum portfolios.

3.2 Momentum versus volatility-adjusted momentum

As the benchmark for volatility-adjusted momentum, I compute equal weighted standard momentum decile portfolios, as equal weighting is a natural benchmark in the context of portfolio choice. In Section 3.5, I discuss the robustness of the results to value-weighting, which is also commonly used in stock momentum studies. Moreover, the portfolios are recalculated on a large cap universe. The conclusions are unchanged. Due to the 12-month look back window, the portfolio returns start from the 2nd of January 1927.

Table 1 reports the results of the standard momentum portfolios (panel A), the volatility-adjusted momentum portfolios (panel D) as well as the in-between steps (panels B and C). In line with existing literature, the standard momentum deciles in Panel A show a near-monotonic declining pattern in mean return, Sharpe ratio, and alpha when moving the winners (D1) to the losers (D10). The winner portfolio excess return of 18.59% is much higher than the loser's portfolio returns of 8.64%. The long-short momentum portfolio WML, which is long D1 and short D10, achieves a return of 9.95% per annum, with a volatility of 29.40%, resulting in a Sharpe ratio of 0.34.

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find Sharpe ratios of 0.53 and 0.60 respectively for the standard momentum *WML* portfolio. The difference with those studies is caused by the usage of equal weights instead of market cap weights. If I apply value weighting, I find a Sharpe ratio of 0.61 over the 1927:01-2013:03 period studied in Daniel and Moskowitz (2016), close to their estimate of 0.60. Section 3.5 discusses the impact of value weighting and the interaction with inverse volatility weighting. In particular, the improvement of volatility-adjusted momentum over standard momentum is not driven by small caps.

The final two rows of panel A report the Fama and French (1993) 3-factor alpha. This alpha is computed by estimating a full-sample OLS regression on the *RMRF*, *SMB* and *HML* factors.[4] The alphas are monotonously declining across the momentum deciles. The *WML* 3-factor alpha amounts to 16.67% per annum, which is higher than the raw return due to negative loadings on *RMRF* (-0.25), *SMB* (-0.48) and *HML* (-0.75) while all three factors have a positive premium over this sample.

Panel B reports step 1, sorting stocks based on return to 12-1 month ex-ante volatility rather than on raw returns. Compared to standard momentum, the return of the loser portfolio (D10) is substantially lower, from 8.64% to 3.31%, while the return for the winner portfolio stays approximately the same. This increases the return of *WML* by 48%. Moreover, the volatility of *WML* declines from 29.40% to 18.78%, which is mainly driven by the decline in volatility of the loser portfolio from 41.03% to 28.09% per annum. The correlation between the winner and loser portfolio increases only slightly, from 0.70 to 0.75. In summary, step 1 improves the *WML* portfolio by lowering the loser portfolio return and volatility.

Panel C reports step 2, where stocks are not only sorted on return-to-volatility, but

[4]These have been obtained from the website of Kenneth French (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`)

also weighted with the inverse of their ex-ante 12-1 month volatility following Equation 4. The improvement over step 1 is relatively small, with the *WML* Sharpe ratio increasing from 0.79 to 0.85. Adjusting the within-portfolio weighting scheme thus has very limited impact.[5]

The volatility-adjusted momentum results are shown in panel D. The Sharpe ratio increases from 0.85 for step 2 to 1.14. The returns and alphas in panel D are not directly comparable with those in the previous panels, as leverage is used. Therefore, the final column WML^C reports the results of *WML* scaled to an annualized volatility of 30% using the full sample *WML* portfolio volatility for each of the steps. The raw returns (alphas) more than triple (double) when considering volatility-adjusted momentum (panel D) instead of standard momentum (panel A).

What is even more surprising is that the negative skewness, dubbed "crash risk" by Daniel and Moskowitz (2016), largely disappears. While standard momentum has a skewness of -3.91, this reduces to just -1.02 for volatility-adjusted momentum. This negative skewness is pronounced during and just after crisis periods. Figure 1 shows the cumulative log returns through time. The standard momentum portfolio ("MOM") experiences substantial crashes in 1929, 1939, 2000 and 2009. It is exactly during these periods that volatility-adjusted momentum ("VA-MOM") outperforms. The high *WML* alpha of 17% per annum could be explained by an aversion of investors to the crash risk. However, volatility-adjusted momentum has relatively small crash risk, but obtains an alpha of over 39% per annum. This suggests crash risk is an unlikely explanation of the momentum premium, in line with the conclusions of both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

Table 2 shows the details of the Fama and French (1993) regression for the standard (panel A) and volatility-adjusted (panel B) momentum portfolios. I use the 30% volatility scaled versions to make the alphas comparable between the two portfolios.

[5]If the standard momentum portfolio is adjusted by only adjusting the weighting scheme (step 2), but not the sorting (step 1), the Sharpe ratio increases from 0.34 to 0.43, which is also a small improvement.

Volatility-adjusted momentum, due to the per-stock volatility target, is constructed to be close to market-neutral and this is confirmed by the zero coefficient on *RMRF*, while standard momentum has a significant negative exposure in line with previous literature (Barroso and Santa-Clara, 2015). Specification 2 in both panels shows that volatility-adjusted momentum can fully explain the alpha of standard momentum, but not the other way around. Still, volatility-adjusted momentum can only explain up to 63% of the total variant in standard momentum, which shows that the two also behave differently through time.

In specification 3, a levered *LOWVOL* factor is included. This factor is constructed like volatility-adjusted momentum, but instead of sorting stocks based on their past return-to-volatility ratio, stocks are sorted based on their volatility, selecting low volatility stocks in the top and high volatility stocks in the bottom. The reason for considering this factor is that volatility-adjusted momentum will overweight low volatility stocks in the winner portfolio (but also, as it is a short position, underweight low volatility stocks in the loser portfolio). It might be that part of the alpha is driven by the low volatility anomaly (Haugen and Heins, 1972). Table 2 shows that indeed part of the alpha disappears after including *LOWVOL*, as the alpha drops from 39.1% to 33.4% for volatility-adjusted momentum. Interestingly, also for standard momentum (panel A), the alpha declines, by more than 7%-point. Thus the low volatility exposure of volatility-adjusted momentum seems to be a feature of momentum in general, and not the construction procedure in particular. Haesen, Houweling, and Van Zundert (2017) provide evidence for this low volatility bias. Most importantly, low volatility cannot explain the high alpha of volatility-adjusted momentum.

3.3 The source of the improvement

The results from the previous section indicate that volatility-adjusted momentum has a substantial higher Sharpe ratio than standard momentum, mainly due to (1) the inclusion of different assets in the winner and loser portfolios, i.e. step 1, and (2) targeting a constant volatility for the winner and loser portfolios in step 3. These two steps present two dimensions of volatility: the first step improves the profitability of individual positions by relating momentum and volatility in the cross-section, and the second step (de)levers the winner and loser portfolios through time.[6] To better understand the source of the improvement, I analyze the relation between momentum and volatility both in the cross-section and through time.

To determine the impact of the cross-sectional adjustment, I employ a 5x5 doublesort.[7] First, five momentum portfolios are created based on past 12-1 month stock returns. Then, within each momentum portfolio, stocks are sorted into five 12-1 month daily return volatility portfolios, resulting in 25 portfolios in total. Table 3 shows the raw returns (panel A) as well as the 3-factor alphas (panel B). Within the momentum portfolios, high volatility has a higher return but lower alpha than low volatility in general, reflecting the empirical finding that the relation between risk and return is too flat (Haugen and Heins, 1972). Within each volatility portfolio, high momentum portfolios have higher returns and alphas than low momentum portfolios (i.e., the momentum effect). However, there is an exception for the high volatility loser portfolio: it has above average return, even higher than the high volatility winner portfolio, and by far the highest alpha across the losers. It thus seems that of the losers, for the ones with the highest volatility the downward trend does not continue but remains (risk-adjusted) flat, suggesting that the negative news has been priced in already. Volatility-adjusted momentum avoids short selling these stocks as it uses return-to-volatility rather than raw returns to construct quantile portfolios.

For the time series component, step 3, we note that both top and bottom portfolio Sharpe ratios improve with 0.19 and 0.06 respectively due to scaling the portfolios

[6] Step 2 shows that weighting assets based on the reciprocal of their volatility within the portfolio, but not through time, is just a minor improvement.

[7] A 10x10 sort is not feasible in the earlier part of the sample, as there is an insufficient number of stocks to select from.

through time versus step 2. The scaling adds value as the relation between the ex-ante volatility and the realized Sharpe ratio is negative. For the top (bottom) portfolio, an OLS regression of the realized annualized 1-month Sharpe ratio on the ex-ante volatility results in a coefficient of -0.076 (-0.0137) on the ex-ante volatility. Hence, the Sharpe ratios of both the loser, but especially the winner portfolio, improve, as more (less) weight is given to high (low) Sharpe ratio months.[8]

Figure 2 shows the leverage ratios of the winner and loser portfolios, where 1 means that the portfolio is fully invested in stocks, a value greater than 1 that part of the long stock position is financed by borrowing at the risk-free rate and a value below 1 that part of the portfolio is not invested in stocks but in the riskfree asset instead. The average level is above 1 due to the choice of 60% per stock volatility. This is merely a scaling constant. However, the average leverage of the winners is also higher than of the losers by 20%, as stocks with improving momentum tend to have lower volatility than losers. This effect has been documented before by Haesen, Houweling, and Van Zundert (2017), and by reducing this imbalance in portfolio volatilities the *WML* Sharpe ratio rises from 0.85 to 0.97 already.[9] The remainder of the improvement, from 0.97 to 1.14, is driven by the increase in the winner portfolio Sharpe ratio versus the loser portfolio Sharpe ratio.

3.4 How does volatility-adjusted momentum compare to *WML* timing?

Barroso and Santa-Clara (2015), taking the standard *WML* portfolio as given, show that this portfolio can be timed, as the volatility is relatively predictable while returns are unrelated to the volatility. Although this is similar to step 3 of this study, it is not the

[8]Even if the relation is positive, the smoothing of the volatility through time can potentially outweigh the loss in average monthly return per unit of risk.

[9]Simple algebra shows that the Sharpe ratio of the *WML* portfolio can be written as $SR_{WML} = \frac{\delta SR_W - SR_L}{\sqrt{1+\delta^2-2\delta\rho_{W,L}}}$, where SR_W and SR_L are the Sharpe ratios of the winner and loser portfolio respectively, $\delta = \frac{\sigma_W}{\sigma_L}$ is the ratio of the volatilities, and $\rho_{W,L}$ the correlation between the winner and loser portfolios. Plugging in all values of step 2, but with the ratio of volatilities (δ) of step 3, gives a Sharpe ratio of 0.97

same as on the one hand their method does not separately consider winners and losers, but on the other hand there might also be information in the volatility of the *WML* portfolio itself that is not captured in the bottom-up stock volatility adjustment used in this study.

To verify which effect is stronger, I replicate the Barroso and Santa-Clara (2015) methodology. That is, given a *WML* portfolio, I scale the returns over month t with the annualized volatility estimated on the daily returns over the past 6 calendar months:

$$S_{t-6:t-1} = \sqrt{\frac{250}{K}\sum_{j=1}^{K} {r_j}^2} \tag{7}$$

where r_j is the return on day j in the window and K the total number of days in the six-month window.

Table 4 reports the results for the standard momentum portfolio (columns 1 and 2), as well as for volatility-adjusted momentum (columns 3 and 4). All portfolios are scaled to a full-sample volatility of 30% for comparability of raw returns and alphas. I find that the Barroso and Santa-Clara (2015) method more than doubles the standard momentum portfolio Sharpe ratio, from 0.34 to 0.74. The Fama and French (1993) 3-factor alpha also increases by 9.9%-point to 26.9%, which is a relative increase of just over 50%. Still, this is lower than the Sharpe ratio (alpha) of volatility-adjusted momentum (1.14; 39.1%).

However, this does not mean that there is no value in the timing element. In the final column of Table 4, the Barroso and Santa-Clara (2015) methodology is applied on top of the volatility-adjusted momentum portfolio. The Sharpe ratio increases from 1.14 to 1.31, and the alpha from 39.1% to 42.5%.

To conclude, bottom-up adjusting for volatility in the construction of the momentum portfolio is superior to ex-post timing of the momentum portfolio as a whole, but it does not subsume this method.

3.5 Volatility and market cap

As noted in Section 3.2, many studies use value weighting rather than equal weighting to control for liquidity concerns. In this study, I deliberately use equal weighting as from a portfolio optimization perspective equal weighting is a logical base case. To ensure the results are not driven by the small caps in the dataset, I make a direct comparison between equal weighted momentum, value weighted momentum, and volatility-adjusted momentum on three size universes: all caps, large caps and small caps.

Table 5 reports the results on the winner-minus-loser portfolios. For the all cap universe, I indeed find that value weighted momentum has a much higher Sharpe ratio of 0.62, compared to 0.34 for equal weighted momentum. This difference in Sharpe ratios is driven by higher returns for the value weighted portfolios.

Zooming in on the large cap and small cap universe results, the main cause of the relative under performance of the equal weighted versus the market weighted portfolio is with the small caps, where the Sharpe ratio is a mere 0.24 (although the alpha is still highly significant). Within the large caps, the performance of the equal-weighted portfolio is actually slightly better than for the value weighted portfolio. Both the equal and value weighted portfolios Sharpe ratios and alphas are, however, low compared to volatility-adjusted momentum. Within the large caps (small caps), the Sharpe ratio increases from 0.53 (0.71) for the value weighted portfolio to 1.06 (1.17) for volatility-adjusted momentum. Thus the finding that volatility-adjusted momentum substantially improves over both equal or value weighted momentum is robust to the exclusion of the small cap stocks.

In addition to the analysis in Table 5, I also repeat the base case analysis in Table 1 in Table 6, excluding the 20% smallest stocks in the data sample. The improvement in Sharpe ratio, although less strong than in the base case results, is still high as it increases from 0.74 to 1.25.

3.6 Is volatility-adjusted momentum idiosyncratic momentum?

Several studies (Grundy and Martin, 2001; Gutierrez and Pirinsky, 2007; Blitz, Huij, and Martens, 2011) in the literature document improved momentum portfolio performances when the portfolios are constructed on "idiosyncratic" or "residual" stock returns rather on the full return. The idiosyncratic return is the return that remains after taking out systematic returns, where typically the *RMRF*, *SMB* and *HML* factors of Fama and French (1993) are used as systematic factors.

I follow Blitz, Huij, and Martens (2011) by using the past 3-year monthly returns from the monthly CRSP files to estimate the following regression

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{RMRF} RMRF_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \epsilon_{i,t} \tag{8}$$

where $\epsilon_{i,t}$ is the residual return. As for standard momentum, the past 12 month residuals, skipping the most recent month, are taken. To control for noise in the estimation, the resulting cumulative residual return is divided by the standard deviation of the 36 residuals.

As a three year window is required, the idiosyncratic momentum portfolio is formed from January 1929 onwards. I find that for the 30% *WML* the alpha amounts to 31.8% per annum, while for volatility-adjusted momentum it is 38.1%.

4 Corporate bond results

Momentum effects have been documented in many different asset classes. However, investment grade corporate bonds seem to be a notable exception to this empirical finding. Previous studies have either found no momentum premium (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova et al., 2013; Houweling and Van Zundert, 2017), or even a reversal effect (Khang and King, 2004). On the other hand, within high yield bonds momentum premia exist (Jostova et al., 2013; Houweling and Van Zundert, 2017). Therefore corporate bonds provide a suitable out-of-sample test for volatility-adjusted momentum.

4.1 Data

For the corporate bond dataset, I use all constituents in the Barclays U.S. Corporate Investment Grade and Barclays US High Yield indices. The data is on a monthly frequency and spans the period January 1994 to December 2015, containing 1,350,229 bond-month observations. The indices consist of US dollar denominated corporate bonds with a time-to-maturity of at least one year and a minimum notional of 150 million, preventing the most illiquid bonds to enter the index.

The dataset contains a number of characteristics per observation. The *total return* is the return of the bond from the previous month-end to the current month-end, and assumes coupons are reinvested. In case of a default, the last available return of the bond is based on the last traded price, hence reflecting the market perception of the recovery rate. There is thus no survivorship bias. The *excess return* is the total return over the duration-matched Treasury return. I use duration-matched excess returns throughout this section to properly clean for interest rate risk differences. The momentum results are thus only driven by the firm-related credit part, not by momentum across the Treasury curve. This is an important difference from most earlier studies, which tend to focus on the total return. The usage of total returns has the disadvantage that any momentum effect found could be driven by momentum in Treasuries alone, not necessarily in the firm-specific component of corporate bond returns. The excess returns can be obtained in practice by hedging the interest rate exposure with interest rate swaps or bond futures. The duration used to match the corporate bond with the correct Treasury includes adjustments for embedded options and is provided by Barclays. The *credit rating* is the middle credit rating of the three rating agencies Standard and Poor's, Moody's and

Fitch. If only two ratings are known, the lowest rating is assumed.

To control for systematic risks, I use the five Fama and French (1993) risk factors and the Carhart (1997) momentum factor. The equity market factor (*RMRF*), the equity size factor (*SMB*), the equity value factor (*HML*) and equity momentum factor (*MOM*) are from the website of Kenneth French. For the bond factors, I use the return-based term and default factors. Specifically, for the bond term factor (*TERM*), I use the return of the Barclays U.S. Treasury 7-10 year index over the 1-month T-bill return (from the website of Kenneth French). For the default risk factor (*DEF*), I use the excess return over duration-matched Treasuries of the Barclays U.S. Corporate Investment Grade index. This definition, in contrast to the Fama and French (1993) Ibbotson based factor, properly cleans for interest rate risk (Hallerbach and Houweling, 2013).

4.2 Empirical results

Volatility-adjusted momentum, which improves standard momentum by sorting on return relative to risk rather than return alone, is especially effective if the volatility differences between securities are large. As a proxy for the cross-sectional dispersion, I compute each month the ratio between the 90th and 10th percentile of the past 12-1 month return volatility per bond/stock, and subsequently take the average of the ratios over time. For the stock sample, the average ratio amounts to 3.1, which is small relative to the ratio of 14.2 for the corporate bonds data. The reason for this large dispersion is that bonds cannot only differ in terms of their credit rating (lower rated bonds tend to be more volatile), but also in their time-to-maturity. As a result, some bonds have a duration of 20, while others have a duration of just 1. Thus a parallel upward spread curve shift will mean the long bond suffers a 20 times larger loss than the short bond. Due to the large dispersion, it is expected that volatility-adjusted momentum can provide even larger improvements for corporate bond momentum.

To compute the momentum signal, a 7-minus-1 month window is used, following previous studies on corporate bond momentum (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova et al., 2013). Table 7 reports the full sample, i.e. investment grade and high yield together, decile portfolio results for standard momentum (panel A) and volatility-adjusted momentum (panel B). As with stock momentum, the more volatile assets tend to be among the winner and loser portfolios, as indicated by the higher volatility of those portfolios. Intuitively, high volatility assets are more likely to show extreme returns, and thus to be selected in the extreme portfolios. Although the mean return of the winners is larger than that of the losers by 0.38% per annum, the *WML* column shows clearly that it has a very insignificant t-statistic of 0.12. Also after correcting for the five Fama and French (1993) bond risk factors, the alpha is not significantly positive (t-statistic of 0.81). However, for volatility-adjusted momentum there is a significant positive premium of 3.18% per annum (t-statistic of 4.58), and this remains after controlling for the bond risk factors. Thus while the standard momentum methodology does not pick up a premium, volatility-adjusted momentum does.

Table 8 shows the results for the winner-minus-loser portfolio for various credit qualities. Panel A makes a distinction between investment grade and high yield. Both raw returns and alphas show significant positive premia for volatility-adjusted momentum, while standard momentum has only a significantly positive alpha in high yield.

Panel B provides a more granular breakdown by credit quality. As the number of observations becomes smaller within a particular bucket, this analysis uses momentum quintiles rather than deciles. Except for AAA/AA rated bonds, which account for just 8.4% of the total dataset, volatility-adjusted momentum has significant positive returns. Risk-adjusted, the premium in A-rated bonds is not significant though. Interestingly, standard momentum, which has been found by previous studies to have a positive premium in high yield (Jostova et al., 2013), only shows a statistically significant premium for bonds rated CCC and lower. These bonds constitute just 20.2% of high yield, and 5.8% of the total dataset.

In conclusion, based on the standard methodology, momentum seems to be largely absent in corporate bond markets. This is, however, due to the large volatility dispersion. Volatility-adjusted momentum reveals significant momentum premia in both high yield as well as investment grade.

5 Conclusions

Sorting assets based on past returns into unlevered quantile portfolios is a natural way to test for cross-sectional momentum. Therefore, this method has become the de-facto standard method to test for the existence of momentum in many asset classes since the first momentum study of Jegadeesh and Titman (1993). However, standard portfolio theory suggests to scale assets, i.e. the past returns to sort on as well as the position size, with their ex-ante expected volatility to construct quantile momentum portfolios. I call this volatility-adjusted momentum.

For US stock data, 1927 to 2015, the annualized alpha increases from 17% for standard momentum to 39% for volatility-adjusted momentum, and this result is robust when the universe is restricted to large caps only. A detailed analysis shows that the benefit mainly comes from two sources.

First, it comes from not selecting high volatility stocks among the losers. Such stocks, which have experienced very negative and also very volatile returns over the past year, tend to have average returns going forward, in contrast to lower volatility losers which tend to keep under performing. Second, as the winner and loser portfolios differ in volatility, i.e. losers tend to have higher volatility than winners going forward, the constant volatility targeting through time of the quantile portfolios reduces the imbalance in volatility between winners and losers, benefiting the winner-minus-loser portfolio

As an out-of-sample check, the analysis is repeated for USD-denominated corporate bonds over the 1994-2015 period. Due to the high cross-sectional dispersion in volatility of the individual bonds, the standard momentum methodology does not even reveal momentum premia except for the 6% lowest-rated bonds. This has led previous studies to conclude momentum is largely absent from corporate bond markets. However, volatility-adjusted momentum has economically and statistically significant alphas for both high and low rated bonds, revealing a momentum premium previously masked by the large dispersion in volatility in the cross-section.

A Derivation optimal portfolio

This appendix provides more details on the derivation of the optimal portfolio weights. The optimal portfolio is a simplification of the mean-variance optimal portfolio, given by (Markowitz, 1952):

$$w_t = \frac{1}{\gamma} {\Sigma_t}^{-1} \mu_t \tag{9}$$

where t denotes the time, μ_t is the vector of mean returns and Σ_t the variance-covariance matrix.

Elton, Gruber, and Padberg (1976) show that the optimal *relative* portfolio weights $z_{i,t}$ under the assumption of uniform correlations (ρ)[10] and no short-sales is (Elton, Gruber, and Padberg, 1976, p. 1354):

$$z_{i,t} = \frac{1}{1-\rho} \frac{1}{\sigma_{i,t}} \left[\frac{\mu_{i,t}}{\sigma_{i,t}} - \frac{\rho}{1-\rho+k\rho} \sum_{j=1}^{k} \frac{\mu_{j,t}}{\sigma_{j,t}} \right] \tag{10}$$

for all non-zero weight assets, where k is the number of included assets in the portfolio and $\mu_{i,t}$ and $\sigma_{i,t}$ the mean and volatility of the return of asset i, respectively.

This formula provides a straightforward decision rule to determine whether a particular asset should be included (Elton, Gruber, and Padberg, 1976): asset i should be included as long as $z_{i,t}$ is positive. Clearly, $z_{i,t} > 0$ is only satisfied if the term in square

[10] I assume $\rho \in (0, 1)$.

brackets is positive. The last term in the square brackets is, given any k, a constant if a particular asset with Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$ is included, any asset with a higher ratio should also be included in the portfolio. Thus, determining which assets should be included is based on the Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$: order all assets from high to low, and continue adding until $z_{i,t}$ turns negative. To translate this to quantile portfolios: assets are sorted on $\frac{\mu_{i,t}}{\sigma_{i,t}}$, and the top 10% is put in the first decile portfolio, the next 10% in the second decile, etcetera, until the final 10% is put in the bottom decile.

The ordering on Sharpe ratio is an intuitive result, as the goal is to optimize the portfolio's Sharpe ratio. Leverage is used to attain the risk level that fits the investor's risk aversion γ. As all assets are, in terms of diversification, equal, i.e. the assumption of uniform correlations, the most attractive asset is the one with the highest Sharpe ratio.

Equation 10 is the solution for the relative weight $z_{i,t}$, not for the absolute weight $w_{i,t}$. To compute the absolute weight, I use the *separation theorem* of Tobin (1958). That is, the relative weights in the risky asset portfolio are independent of the allocation of the total portfolio to the (optimal) risky asset portfolio and the riskfree asset. The optimal portfolio can thus always be written as a linear combination of the riskfree asset and the (unscaled) optimal risky asset portfolio.

The optimal weight of the quantile portfolio in the total portfolio of the riskfree asset and the risky-asset portfolio w^q is again the mean-variance optimal portfolio (dropping subscripts t for notational convenience):

$$w^q = \frac{1}{\gamma} \frac{\mu^q}{\sigma^{q2}} \tag{11}$$

where μ^q and σ^q are the (unscaled) risky asset quantile portfolio mean return and volatility respectively, with weight per asset given by z_i. If w^q is known, then it is straightforward to derive the absolute weight, as $w_i^q = w^q z_i$.

All that remains is to solve for w^q. For analytical tractability, and as a reasonable approximation, I assume that for a quantile portfolio q the following holds:

$$\frac{\mu_i}{\sigma_i} = \overline{SR^q} \quad \forall i \in q \tag{12}$$

Thus, the Sharpe ratios are assumed to be equal in the cross-section. This a reasonable assumption, as the quantile portfolios are created by sorting on the Sharpe ratio, and thus by definition the Sharpe ratios will be close to each other.

Given this assumption, the relative weight becomes

$$\begin{aligned} z_i &= \frac{1}{1-\rho}\frac{1}{\sigma_i}\left[\frac{\mu_i}{\sigma_i} - \frac{\rho}{1-\rho+k\rho}\sum_{j=1}^{k}\frac{\mu_j}{\sigma_j}\right] \\ &= \frac{1}{1-\rho}\frac{1}{\sigma_i}\left[\overline{SR^q} - \frac{\rho}{1-\rho+k\rho}k\overline{SR^q}\right] \\ &= \frac{1}{\sigma_i}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q} \end{aligned} \tag{13}$$

The portfolio mean return is then

$$\begin{aligned} \mu^q &= \sum_{i=1}^{k} z_i \mu_i \\ &= \sum_{i=1}^{k}\frac{\mu_i}{\sigma_i}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q} \\ &= \left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2 \end{aligned} \tag{14}$$

and the variance is equal to

$$
\begin{aligned}
\sigma^{q2} &= \sum_{i=1}^{k}\sum_{j=1}^{k} z_i z_j \sigma_i \sigma_j \rho_{i,j} \\
&= \sum_{i=1}^{k}\sum_{j=1}^{k} \frac{1}{\sigma_i}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q}\frac{1}{\sigma_j}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q}\sigma_i\sigma_j\rho_{i,j} \\
&= \left(\frac{1}{1-\rho+k\rho}\right)^2 \overline{SR^q}^2 \sum_{i=1}^{k}\sum_{j=1}^{k}\rho_{i,j} \\
&= \left(\frac{1}{1-\rho+k\rho}\right)^2 \overline{SR^q}^2 \left(k+k(k-1)\rho\right) \\
&= \left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2
\end{aligned}
\tag{15}
$$

where $\rho_{i,j}$ is equal to ρ if $i \neq j$, and 1 otherwise. The optimal weight in the risky asset portfolio is then given by

$$
\begin{aligned}
w^q &= \frac{1}{\gamma}\frac{\left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2}{\left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2} \\
&= \frac{1}{\gamma}
\end{aligned}
\tag{16}
$$

This implies that the absolute weight of an asset is given by

$$
w_i = \frac{1}{\sigma_i}\frac{1}{\gamma}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q} \tag{17}
$$

Instead of estimating the parameters γ and ρ and forecasting $\overline{SR^q}$, I assume that each of these are equal through time.[11,12] Approximating the term $\frac{1}{1-\rho+k\rho}$ by $\frac{1}{\rho k}$[13], an

[11] This is more restrictive than necessary. As long as the combination in which they appear in the equation is constant, the individual parts are allowed to be dynamic.

[12] Empirically, I find that the Sharpe ratio of the winner and loser portfolios is negatively related to the ex-ante volatility estimate, but only mildly.

[13] This is a slight overestimation. Given $\rho = 0.3$ and $k = 50$, the overestimation is 4.7%. If $k = 100$, the estimation error is 2.3%. The larger k, the smaller the error is.

intuitive formula for the proportional weight appears:

$$w_{i,t} \propto \sigma_{i,t}^{-1} k_t^{-1} \tag{18}$$

where the subscript t has been added back to emphasize that both volatilities and the number of assets can change through time. Thus, under the assumption of a constant premium per unit of risk (Sharpe ratio), constant pairwise correlations, constant risk aversion and the number of assets not too small, the weight per asset is inverse proportional to (1) the number of assets k in the quantile portfolio and (2) its own volatility σ_i. Thus if from one period to the next all volatilities double, all money weights w_i will halve, resembling a constant volatility strategy. Indeed, simple algebra shows that the portfolio volatility, under the solution in Equation 17, is given by $\frac{1}{\gamma}\overline{SR^q}\sqrt{\frac{k}{1-\rho+k\rho}}$, which is constant given the assumptions.

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Tables and figures

Table 1: Performance statistics of momentum portfolios

Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (panel A) or past 12-1 month return-to-volatility ratios (panels B, C & D), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are equal weighted (panels A & B) or inverse volatility weighted (panels C & D). The portfolios are either non-levered (panels A, B & C) or target a constant volatility per stock of 60% per annum (panel D). The column WML reports the results of the long D1 - short D10 portfolio. The final column WML^C is the same portfolio as WML, but scaled to a volatility level of 30% per annum using the full-sample volatility. For each portfolio the mean return (mean), volatility (vol), Sharpe ratio (SR), skewness (skew) and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	WML	WML^C
Panel A: Momentum												
mean	18.59	15.85	14.43	12.99	12.24	10.43	11.03	8.58	8.64	8.64	9.95	10.15
vol	26.34	22.83	22.18	22.68	22.98	24.21	26.74	28.13	32.70	41.03	29.40	30.00
SR	0.71	0.69	0.65	0.57	0.53	0.43	0.41	0.31	0.26	0.21	0.34	0.34
skew	0.14	0.13	0.98	1.22	1.35	1.81	2.45	1.88	2.85	2.73	-3.91	-3.91
alpha	8.93***	6.42***	4.78***	2.74***	1.70***	-0.78	-1.32*	-4.08***	-5.75***	-7.74***	16.67***	17.01***
	(7.88)	(9.00)	(8.58)	(5.31)	(3.40)	(-1.48)	(-1.84)	(-4.67)	(-4.58)	(-3.98)	(6.91)	(6.91)
Panel B: Momentum sorted on return-to-volatility (Step 1)												
mean	18.08	15.64	14.68	13.61	12.49	12.18	11.86	11.62	7.92	3.31	14.77	23.60
vol	23.75	24.58	23.69	25.05	26.19	26.68	29.37	30.78	29.64	28.09	18.78	30.00
SR	0.76	0.64	0.62	0.54	0.48	0.46	0.40	0.38	0.27	0.12	0.79	0.79
skew	1.36	3.71	1.76	1.76	1.74	1.58	2.28	2.22	1.37	0.99	-0.64	-0.64
alpha	8.92***	5.07***	4.06***	2.24***	0.50	0.22	-1.31	-1.90**	-4.52***	-8.40***	17.32***	27.67***
	(9.71)	(6.68)	(7.06)	(3.98)	(0.79)	(0.29)	(-1.48)	(-2.05)	(-4.15)	(-7.23)	(9.88)	(9.88)
Panel C: Momentum sorted on return-to-volatility and inverse volatility weighted (Step 2)												
mean	16.64	14.67	13.45	12.38	11.41	10.16	9.88	9.30	6.93	2.83	13.81	25.62
vol	19.66	21.06	20.62	21.67	22.46	22.84	24.85	25.96	25.64	24.70	16.17	30.00
SR	0.85	0.70	0.65	0.57	0.51	0.44	0.40	0.36	0.27	0.11	0.85	0.85
skew	-0.02	3.06	1.79	1.54	1.47	1.22	1.70	1.63	1.06	0.73	-1.17	-1.17
alpha	9.25***	5.61***	4.20***	2.47***	1.02**	-0.21	-1.47**	-2.38***	-4.10***	-7.63***	16.88***	31.33***
	(11.06)	(8.44)	(7.86)	(4.95)	(1.96)	(-0.35)	(-2.16)	(-3.29)	(-4.45)	(-7.12)	(10.80)	(10.80)
Panel D: Volatility-adjusted momentum (Step 3)												
mean	34.40	29.70	25.93	22.89	20.08	16.88	15.39	13.36	10.61	6.20	28.20	34.18
vol	33.17	31.75	30.81	30.61	30.10	29.71	30.96	31.79	32.61	36.54	24.75	30.00
SR	1.04	0.94	0.84	0.75	0.67	0.57	0.50	0.42	0.33	0.17	1.14	1.14
skew	-0.66	-0.55	-0.46	-0.29	-0.23	-0.15	0.21	0.27	0.31	0.40	-1.02	-1.02
alpha	23.99***	18.79***	14.86***	11.33***	8.29***	5.23***	2.86*	0.30	-2.45	-8.24***	32.23***	39.07***
	(10.66)	(9.16)	(7.55)	(6.28)	(5.18)	(3.36)	(1.83)	(0.20)	(-1.44)	(-4.22)	(12.88)	(12.88)

Table 2: Factor regressions momentum portfolios
Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (panel A) or past 12-1 month return-to-volatility ratio (panel B), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are equal weighted (panels A) or a volatility of 60% per stock is targeted (panel B). Both momentum portfolios are scaled to 30% volatility per annum to make the alphas comparable. The monthly returns of the portfolios are regressed on several factors. Factors included are the three Fama and French (1993) factors *RMRF*, *SMB* and *HML*, a levered low vol factor *LOWVOL* and the momentum portfolios themselves (*MOM* & *VA-MOM*). The alphas are annualized. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	alpha	RMRF	SMB	HML	VA-MOM	MOM	LOWVOL	Adj R2
Panel A: Momentum (MOM)								
(1)	17.01***	-0.26***	-0.49***	-0.77***				0.21
	(6.91)	(-2.92)	(-2.78)	(-3.38)				
(2)	-10.16***	-0.26***	-0.23***	-0.18	0.70***			0.63
	(-3.27)	(-4.79)	(-2.58)	(-1.08)	(11.86)			
(3)	9.63***	-0.64***	-0.24	-0.74***			0.35***	0.29
	(2.73)	(-4.56)	(-1.56)	(-3.63)			(4.23)	
Panel B: Volatility-adjusted momentum (VA-MOM)								
(1)	39.07***	0.00	-0.38**	-0.84***				0.15
	(12.88)	(0.02)	(-2.08)	(-5.85)				
(2)	26.23***	0.20***	-0.01	-0.26***		0.75***		0.59
	(11.27)	(3.23)	(-0.06)	(-2.68)		(13.35)		
(3)	33.43***	-0.29**	-0.18	-0.82***			0.27***	0.19
	(10.03)	(-2.48)	(-1.05)	(-5.97)			(4.11)	

Table 3: Doublesort momentum and volatility
Each month-end, all stocks are first sorted into 5 groups based on their past 12-1 month returns, and then within each group the stocks are sorted into 5 groups based on past 12-1 month daily return volatility, yielding a total of 25 portfolios. For each of the 25 portfolios the raw returns (panel A) and Fama and French (1993) 3-factor alphas (panel B) are reported. Returns and alphas are annualized. The sample runs from January 2, 1927 to December 31, 2015.

		volatility groups				
		Q1 (high)	Q2	Q3	Q4	Q5 (low)
Panel A: Raw returns						
	Q1 (high)	17.09	19.01	17.29	16.97	15.72
	Q2	16.50	14.39	13.53	13.20	10.98
momentum groups	Q3	14.27	12.00	11.34	9.80	9.35
	Q4	13.97	10.34	8.71	8.86	7.31
	Q5 (low)	18.30	7.82	6.02	5.00	6.26
Panel B: Alphas						
	Q1 (high)	3.77	7.62	8.07	9.17	9.60
	Q2	2.35	2.75	3.89	4.98	4.75
momentum groups	Q3	-0.70	-0.37	0.72	0.43	2.19
	Q4	-2.38	-3.83	-3.69	-2.34	-1.25
	Q5 (low)	-0.39	-8.80	-9.52	-9.36	-5.57

Table 4: Timing the winner-minus-loser portfolio

Portfolios are computed as described in Section 3.4. Every portfolio is scaled to a volatility level of 30% per annum using the full-sample volatility. For each portfolio the mean return (mean), volatility (vol), Sharpe ratio (SR), skewness (skew) and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) *t*-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

Volatility-adjusted	no	no	yes	yes
Timing	no	yes	no	yes
mean	10.15	22.34	34.18	39.21
vol	30.00	30.00	30.00	30.00
SR	0.34	0.74	1.14	1.31
skew	-3.91	-1.38	-1.02	-0.46
alpha	17.01***	26.88***	39.07***	42.52***
	(6.91)	(9.60)	(12.88)	(12.46)

Table 5: Performance statistics of size x momentum portfolios

Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (MOM-VW & MOM-EW) or past 12-1 month return-to-volatility ratio (VA-MOM), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are market cap weighted (MOM-VW), equal weighted (MOM-EW) or inverse volatility weighted (VA-MOM). The portfolios are either non-levered (MOM-VW & MOM-EW) or target a constant volatility per stock such that the MOM portfolio has 30% volatility (VA-MOM). This procedure is applied on the full universe ("all caps"), the 50% largest stocks by market capitalization at the moment of sorting ("large caps") and the 50% smallest stocks ("small caps"). For each portfolio the mean return, volatility, Sharpe ratio, skewness and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) *t*-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	all caps			large caps			small caps		
	MOM-VW	*MOM-EW*	*VA-MOM*	*MOM-VW*	*MOM-EW*	*VA-MOM*	*MOM-VW*	*MOM-EW*	*VA-MOM*
mean	18.41	9.95	34.18	14.08	15.84	31.93	20.89	7.49	35.12
vol	29.93	29.40	30.00	26.77	25.27	30.00	29.31	31.58	30.00
SR	0.62	0.34	1.14	0.53	0.63	1.06	0.71	0.24	1.17
skew	-1.98	-3.91	-1.02	-2.42	-2.95	-0.73	-3.08	-3.95	-1.12
alpha	25.50***	16.67***	39.07***	19.88***	21.72***	37.03***	27.17***	13.23***	41.08***
	(9.64)	(6.91)	(12.88)	(8.13)	(9.32)	(11.96)	(10.48)	(5.21)	(14.13)

Table 6: Performance statistics of momentum portfolios without micro caps

This table is like Table 1, but excludes each rebalancing the 20% smallest stocks by market capitalization.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	WML	WML^C
Panel A: Momentum												
mean	17.73	14.77	13.07	12.01	11.07	9.38	8.81	7.29	5.74	-1.39	19.11	22.24
vol	25.90	22.11	21.28	21.18	21.72	22.51	24.00	25.98	29.23	36.19	25.78	30.00
SR	0.68	0.67	0.61	0.57	0.51	0.42	0.37	0.28	0.20	-0.04	0.74	0.74
skew	-0.16	-0.18	0.29	0.57	0.79	1.24	1.55	1.62	1.99	2.19	-3.41	-3.41
alpha	8.72***	6.02***	4.04***	2.69***	1.29**	-0.92*	-2.17***	-4.42***	-7.25***	-16.48***	25.19***	29.32***
	(7.31)	(8.31)	(7.18)	(5.38)	(2.51)	(-1.66)	(-3.55)	(-5.72)	(-7.17)	(-10.25)	(10.78)	(10.78)
Panel B: Momentum sorted on return-to-volatility (Step 1)												
mean	18.03	14.35	13.51	11.90	11.33	9.62	8.53	6.96	4.69	-0.46	18.49	31.41
vol	22.89	22.08	22.30	23.29	24.29	24.84	26.04	27.32	27.45	26.63	17.66	30.00
SR	0.79	0.65	0.61	0.51	0.47	0.39	0.33	0.25	0.17	-0.02	1.05	1.05
skew	0.21	0.80	0.83	1.00	1.25	1.35	1.38	1.49	0.96	0.69	-0.57	-0.57
alpha	9.54***	5.06***	3.79***	1.49***	0.24	-1.68***	-3.31***	-5.17***	-6.90***	-11.61***	21.15***	35.91***
	(9.94)	(7.67)	(6.68)	(2.71)	(0.47)	(-2.73)	(-5.26)	(-6.53)	(-7.16)	(-9.99)	(11.72)	(11.72)
Panel C: Momentum sorted on return-to-volatility and inverse volatility weighted (Step 2)												
mean	16.79	13.91	12.91	11.48	10.81	9.49	8.47	6.96	5.61	0.80	16.00	30.08
vol	19.52	19.41	19.69	20.58	21.44	22.06	23.15	23.96	24.55	23.99	15.95	30.00
SR	0.86	0.72	0.66	0.56	0.50	0.43	0.37	0.29	0.23	0.03	1.00	1.00
skew	-0.40	0.71	0.81	0.95	1.10	1.28	1.25	1.03	0.84	0.52	-0.70	-0.70
alpha	9.71***	5.79***	4.31***	2.26***	1.01*	-0.60	-2.09***	-3.75***	-4.92***	-9.33***	19.05***	35.82***
	(11.04)	(9.26)	(7.64)	(4.30)	(1.90)	(-1.06)	(-3.49)	(-5.22)	(-5.71)	(-8.73)	(11.78)	(11.78)
Panel D: Volatility-adjusted momentum (Step 3)												
mean	35.27	30.31	27.27	23.89	21.02	18.02	15.33	12.68	10.40	3.63	31.64	37.64
vol	34.15	33.36	32.62	32.44	32.36	31.97	32.76	33.54	34.83	37.94	25.21	30.00
SR	1.03	0.91	0.84	0.74	0.65	0.56	0.47	0.38	0.30	0.10	1.25	1.25
skew	-0.68	-0.55	-0.49	-0.33	-0.30	-0.17	-0.02	0.07	0.21	0.30	-0.88	-0.88
alpha	24.59***	19.00***	15.59***	11.78***	8.45***	5.33***	2.13	-0.91	-3.53**	-11.35***	35.94***	42.77***
	(10.81)	(9.08)	(7.88)	(6.57)	(4.94)	(3.32)	(1.37)	(-0.56)	(-2.04)	(-5.71)	(13.76)	(13.76)

Table 7: Momentum portfolios corporate bonds
Each month t, bonds are ranked into equal-weighted decile portfolios D1 (highest returns/winners) to D10 (lowest returns/losers) based on their excess return over duration matched Treasuries over the months $t-6$ to $t-1$. In Panel B, all bonds are first scaled with $\frac{1.7\%}{\widehat{\sigma_{i,t-12:t-1}}}$, where $\widehat{\sigma_{i,t-12:t-1}}$ is the monthly standard deviation of the excess returns over the past 12 months, skipping the most recent month. Positions are held for 6 months. The return of a portfolio is the average of the portfolios formed at $t-6$ up to $t-1$. The table reports per portfolio and the difference between D1 and D10 (*WML*) average excess returns over duration matched Treasuries (mean), the volatility (vol), annualized Sharpe ratio (SR) and the alpha over the five Fama and French (1993) bond risk-factors. The mean return, volatility and alpha are annualized and in percentages. In brackets the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. The sample period is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	*WML*
Panel A: Momentum decile portfolios											
mean	2.48	1.40	1.18	1.04	1.11	1.07	1.13	1.18	1.24	2.10	0.38
	(1.18)	(1.05)	(1.01)	(0.94)	(0.96)	(0.82)	(0.76)	(0.68)	(0.53)	(0.47)	(0.12)
vol	7.54	5.06	4.33	4.02	4.11	4.56	5.10	5.92	7.82	14.37	10.49
SR	0.33	0.28	0.27	0.26	0.27	0.23	0.22	0.20	0.16	0.15	0.04
alpha	1.80*	0.90	0.70*	0.63*	0.73**	0.75*	0.79	0.87	0.58	0.00	1.80
	(1.83)	(1.56)	(1.70)	(1.75)	(2.03)	(1.70)	(1.52)	(1.32)	(0.67)	(0.00)	(0.81)
Panel B: Volatility-adjusted momentum decile portfolios											
mean	2.68*	1.60	1.25	1.07	0.95	0.73	0.43	0.30	-0.13	-0.50	3.18***
	(1.91)	(1.25)	(0.98)	(0.84)	(0.74)	(0.56)	(0.31)	(0.21)	(-0.09)	(-0.30)	(4.58)
vol	5.35	5.02	5.10	5.12	5.15	5.20	5.35	5.40	5.77	6.23	3.06
SR	0.50	0.32	0.24	0.21	0.18	0.14	0.08	0.05	-0.02	-0.08	1.04
alpha	2.02*	1.00	0.69	0.49	0.39	0.20	-0.17	-0.31	-0.80	-1.24	3.26***
	(1.94)	(1.16)	(0.82)	(0.61)	(0.48)	(0.25)	(-0.21)	(-0.40)	(-0.90)	(-1.31)	(4.82)

Table 8: Momentum portfolios corporate bonds by credit quality
Decile (Panel A)/quintile (Panel B) top-bottom momentum portfolios are within the respective credit quality group (investment grade/high yield in Panel A; AAA-AA/A/BBB/BB/B/CCC-C in panel B) constructed following Table 7. The table reports the average absolute number of observations per month, the percentage this constitutes of the total universe, the return and the alpha of the momentum portfolios, where *MOM* indicates the standard momentum portfolio and *VA-MOM* the volatility-adjusted momentum portfolio. The alpha is computed versus the five Fama and French (1993) bond risk-factors. The return and alpha are annualized and in percentages. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. The sample period is from January 1994 to December 2015.

credit rating	observations		mean return		5-factor alpha	
	absolute	percentage	*MOM*	*VA-MOM*	*MOM*	*VA-MOM*
Panel A: Momentum decile portfolios (D1-D10)						
investment grade	3185	71.3	-1.08	2.47***	-1.27	2.40***
			(-0.66)	(3.19)	(-0.98)	(3.06)
high yield	1284	28.7	2.56	4.02***	6.29**	4.52***
			(0.60)	(4.03)	(2.05)	(4.44)
Panel B: Momentum quintile portfolios (Q1-Q5)						
AAA/AA	377	8.4	-0.33	0.46	-0.20	0.74
			(-0.41)	(0.62)	(-0.26)	(0.99)
A	1410	31.6	-0.85	1.26**	-1.20	0.92
			(-0.74)	(2.11)	(-1.16)	(1.38)
BBB	1398	31.3	-0.64	2.75***	-0.74	2.77***
			(-0.41)	(3.66)	(-0.64)	(3.59)
BB	467	10.4	-0.99	1.78***	-0.54	1.82***
			(-0.44)	(2.79)	(-0.34)	(3.01)
B	559	12.5	2.09	2.71***	3.93	2.95***
			(0.62)	(3.91)	(1.36)	(4.57)
CCC-C	258	5.8	7.17	4.36***	10.44***	4.85***
			(1.64)	(4.98)	(2.99)	(5.98)

Figure 1: Cumulative log return of momentum portfolios

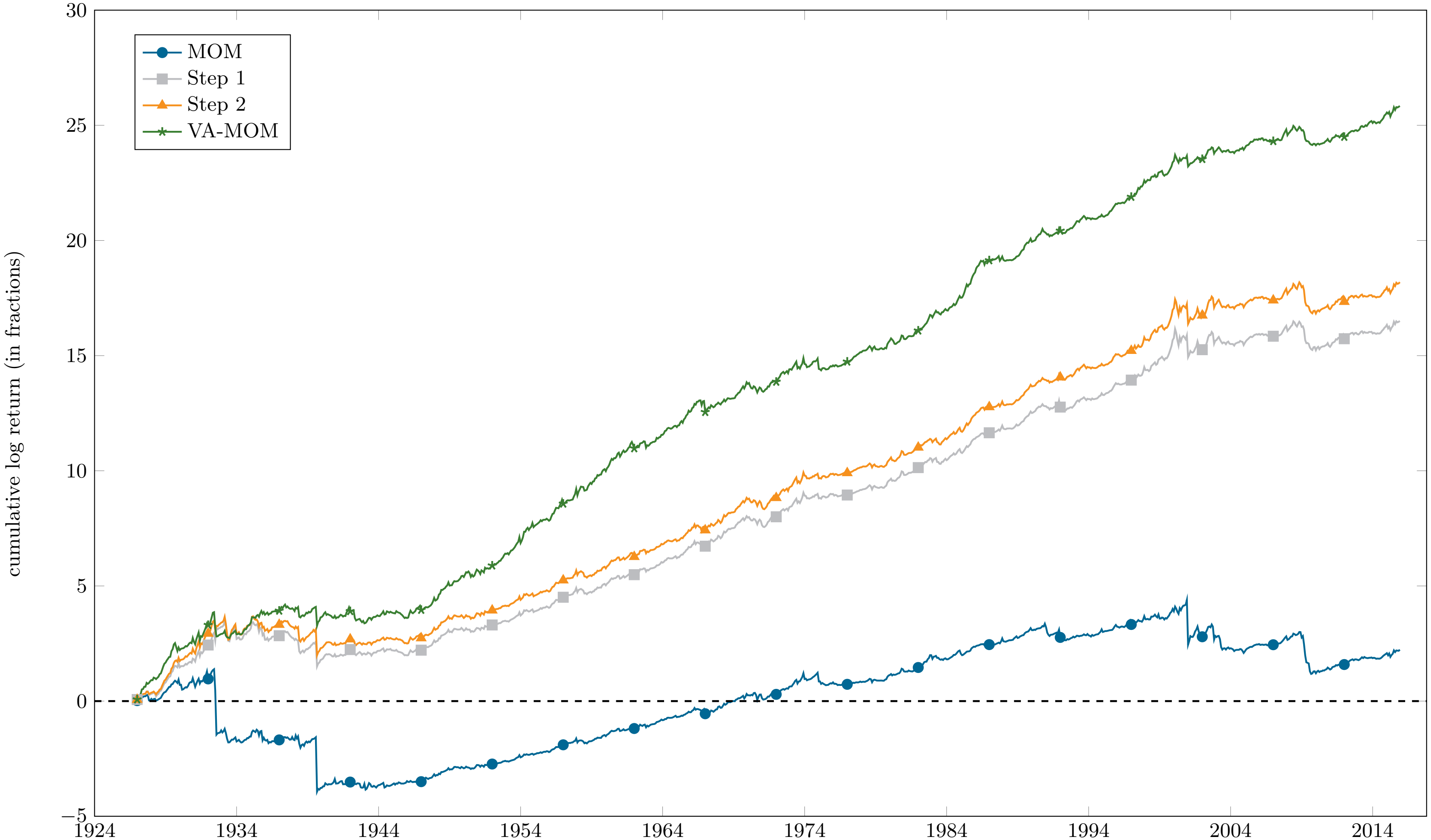

Figure 2: Leverage D1 & D10 volatility-adjusted momentum portfolios

This figure shows the leverage used in the winners (D1) and losers (D10) of volatility-adjusted momentum.