Zoom in on Momentum[1]

Junyong Kim[2]

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Abstract

Portfolios sorted by momentum show stronger return monotonicity than those formed using other anomalies. Compared with other strategies, the performance of such a momentum strategy improves monotonically with the number of portfolios. These improvements are significant beyond the influences of the usual pricing factors. Momentum factors based on more portfolios span those based on fewer portfolios, whereas the opposite effects do not hold. The evidence reported in this study suggests that a momentum factor formed on more than 10 portfolios sharpens the factor and its stylized facts.

JEL classification: G11; G12

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[2] University of North Carolina at Pembroke. junyong.kim@uncp.edu. https://junyongkim.github.io/.
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1. Introduction

Empirical asset pricing papers conventionally use 10 characteristic-sorted portfolios (Cochrane, 2011).[4] But some researchers argue that 10 one-way (or similarly, 5×5 two-way) sorted portfolios do not sufficiently represent stock market returns, because these portfolios poorly abstract the factor structure (Lewellen, Nagel, and Shanken, 2010; Ang, Liu, and Schwartz, 2020; Cattaneo *et al.*, 2020; Bryzgalova, Pelger, and Zhu, 2023).[5] Forming more portfolios might pay off if a certain financial variable monotonically increases or decreases the expected return. For example, the investment literature shows that returns monotonically increase with the prior one-year returns (Johnson, 2002; Patton and Timmermann, 2010). If monotonicity repeats within each portfolio, then forming more portfolios can sharpen the strategy, because winners in the top portfolio will outperform losers in the same top portfolio. If this is the case, the next question we can ask is: is this choice of 10 enough to understand an anomaly?

To answer this question, I reexamine momentum strategies and determine that the profitability of WML_n (*i.e.*, the winner-minus-loser factor based on n momentum portfolios) monotonically improves as n increases from 10 to 100.[6] Figure 1 depicts this idea and outlines the core motivation for this research, by displaying the cumulative monthly returns to top and bottom quantiles calculated with 10, 25, 50, and 100 portfolios sorted by momentum. Winner (loser) returns monotonically increase (decrease) with the number of

[4] The pioneering work includes Blume (1971), Fama and MacBeth (1973), Ross (1978). Momentum literature similarly has adopted this convention, starting with early work by Jegadeesh (1990) and Jegadeesh and Titman (1993).
[5] For example, the monthly stock file of the Center for Research in Security Prices (CRSP) has 496 returns in January 1926 and 7533 returns in December 2019.
[6] Although WML_n's average return also increases as n increases from 100 to 200, its Sharpe ratio insignificantly decreases.

the quantiles. The evidence suggests that zooming in on momentum portfolios (*i.e.*, increasing the number of quantiles) may sharpen momentum strategies. When n is greater than m, WML_n spans WML_m, but not vice versa (Barillas and Shanken, 2017). These findings imply that the former can better proxy momentum than the latter.

Figure 1 Accordingly, this study contributes to asset pricing literature by empirically examining, for the first time, how the number of anomaly portfolios affects the performance of the anomaly. Prior literature indicates the importance of the number of basis assets for tests of pricing models (Ang, Liu, and Schwarz, 2020), changes in the optimal number of anomaly portfolios over time (Cattaneo *et al.*, 2020; Bryzgalova, Pelger, and Zhu, 2023), and various degrees of return monotonicity associated with anomaly portfolios (Patton and Timmermann, 2010).[7] In addition to this literature, I find that the performance of the momentum factor depends on the number of the momentum portfolios and that neither major factors nor the conventional momentum factor span the improved momentum factor. The finding that the more- and fewer-portfolio momentum factors carry distinct information is important not only for academics, as such a tendency is rare among the other factors in this study, but also for practitioners, as momentum is a major element in style investing (Asness, Moskowitz, and Pedersen, 2013). In addition, the finding that the more-portfolio momentum factor outperforms its fewer-portfolio counterpart is also in line with studies interested in the practical feasibility of academic factors (Israel *et al.,* 2021; Kaufmann,

[7] By contrast, relatively fewer studies address the potential performance of factors based on more quantiles relative to those based on fewer quantiles. Some studies explore more than 10 portfolios for robustness checks, but they do not link the number of portfolios to the performance of anomalies. For example, Grauer and Janmaat (2004) use 100 portfolios formed on the basis of size; Sadka (2006) use 25 portfolios formed on the basis of momentum and standardized unexpected earnings; Liu and Zhang (2008) use 30 portfolios formed on the basis of size, book-to-market, and momentum; and Pazaj (2018) simulates 100 portfolios formed on the basis of momentum.

Messow, and Wisser, 2022).

The improvements are consistent across all subperiods and robust to major factor models (Fama and French, 1993; Stambaugh and Yuan, 2017; Fama and French 2018; Daniel, Hirshleifer, and Sun, 2020; Hou *et al.*, 2021). The results are also robust to factor momentum (Leippold and Yang, 2021; Ehsani and Linnainmaa, 2022; Grobys, Kolari, and Rutanen, 2022; Arnott, Kalesnik, and Linnainmaa, 2023), both recent and intermediate horizon past performance (Novy-Marx, 2012; Gong, Liu, and Liu, 2015; Goyal and Wahal, 2015), residual momentum (Blitz, Huij, and Martens, 2011; Chang *et al.*, 2018), alpha momentum (Hühn and Scholz, 2018; Zaremba, Umutlu, and Karathanasopoulos, 2019), two-way momentum (Chan, Jegadeesh, and Lakonishok, 1996; Hong, Lim, and Stein, 2000; Jegadeesh and Titman, 2001; Chordia and Shivakumar, 2006; Novy-Marx, 2015), industry momentum (Moskowitz and Grinblatt, 1999), portfolio momentum (Lewellen, 2002), macromomentum (Bhojaj and Swaminathan, 2006), and European momentum (Rouwenhorst, 1998; Asness, Moskowitz, and Pedersen, 2013).[8] Using more quantile portfolio not only improves the momentum's short-term return but also enhances its long-term reversal (Jegadeesh and Titman, 2001; McLean, 2010). Furthermore, volatility-managed WML_n ($vWML_n$) becomes much stronger, consistent with the prior literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017; Cederburg *et al.*, 2020). As my findings show, $vWML_n$'s significant improvements over WML_n survive both the factor and the spanning regressions; they also hold for both recent and intermediate horizon past performance. Finally, the investment factor, similar to the momentum factor, improves with the number of portfolios,

[8] Momentum factors seldom improve with the number of portfolios in Japan or the Asia Pacific excluding Japan. As Chui, Titman, and Wei (2010) show, momentum effects in Asian markets are weaker than those in other markets.

whereas the size, value, and operating profitability factors do not. The momentum and investment portfolios exhibit stronger return monotonicity than size, book-to-market, and operating profitability portfolios. This combined evidence suggests that the optimal number of quantiles to form a factor varies by the anomaly.

2. Data

2.1. Basis Assets

The 10, 25, 50, and 100 momentum portfolios are based on the Center for Research in Security Prices (CRSP) data.[9] The data span the period from January 1927 to December 2019. Following prior literature, the portfolios of NYSE, NYSE MKT, NASDAQ, and Arca stocks use the NYSE-only breakpoints. Momentum portfolios in month t are then formed on the basis of prior returns from t−12 to t−2. This study also includes the (t−12,t−7) and the (t−6,t−2) momentum portfolios, in acknowledgement of the ongoing debate about the term structure of momentum strategies' profitability (Novy-Marx, 2012; Goyal and Wahal, 2015). Furthermore, it addresses residual momentum and alpha momentum portfolios, because these forms of momentum arguably outperform a simple momentum (Blitz, Huij, and Martens, 2011; Chang *et al.*, 2018; Hühn and Scholz, 2018; Zaremba, Umutlu, and Karathanasopoulos, 2019). Following prior literature, a Fama–French (1993) three-factor model with a 36-month trailing window is used for the (t−12,t−2) residual momentum portfolios, whereas the capital asset pricing model (CAPM) with an 11-month trailing window is used for the (t−12,t−2) alpha momentum portfolios. For these assessments, the data are from July 1929 to December 2019. In addition, I form the 5×5 and 5×10 value-weighted portfolios according to size and momentum (192701–), book-to-market and

[9] The 10 momentum portfolios from Professor Kenneth R. French are also used for robustness checks.

momentum (192701–), operating profitability and momentum (195107–), and investment and momentum (195207–). Then I obtain WML_5 and WML_{10} for each size, book-to-market, operating profitability, and investment quintile. Missing WMLs take 0 values.

Figure 2 Figure 2 relates the number of momentum portfolios to the feasible investment opportunity set. The figure indicates minimum-variance frontiers and capital allocation lines from 10 to 100 momentum portfolios. The momentum portfolios' maximum Sharpe ratios increase from 0.91 to 1.56 over this span. Furthermore, the results show a 26.7% certainty equivalent return difference[10] and a 192.9% percentage utility gain.[11] The non-tabulated 5×5 size and book-to-market portfolios' maximum Sharpe ratio is 1.04. Next, the alphas from the spanning regressions of the maximum-Sharpe ratio portfolios that are based on the momentum portfolios onto the maximum-Sharpe ratio portfolio that is based on the size and book-to-market portfolios significantly increase from 12.7% to 38.1%.[12] That is, increasing the number of the portfolios helps expand the investment opportunity set, and the opportunity sets from the 10 momentum and the 5×5 size and book-to-market portfolios do not span those from the 25, 50, and 100 momentum portfolios.

Figure 3 Figure 3 shows the average monthly returns, standard deviations, Sharpe ratios, CAPM alphas, and market betas of the 10 to 100 momentum portfolios.[13] The most loser and the

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[10] $\Delta\mathrm{CER} = \frac{\mathrm{SR}_{\mathrm{new}}^2 - \mathrm{SR}_{\mathrm{old}}^2}{2\gamma}$, where γ=3 (Campbell and Thompson, 2008; Cederburg *et al.*, 2020).

[11] $\Delta\mathrm{U} = \frac{\mathrm{SR}_{\mathrm{new}}^2 - \mathrm{SR}_{\mathrm{old}}^2}{\mathrm{SR}_{\mathrm{old}}^2}$ (Moreira and Muir, 2017; Barroso and Detzel, 2021).

[12] Gibbons–Ross–Shanken (GRS) (1989) statistics depend on the number of portfolios and thus are inapplicable, but the non-tabulated GRS statistics of the most winner and the most loser portfolios from the 10/25/50/100 portfolios on the Fama–French (1993) three factors are 37.59/43.03/40.20/33.14.

[13] As Figure A1 in the appendix shows, the results of the equal-weighted portfolios are similar.

most winner portfolios are on the left and right, respectively.[14] As Figure 3 shows, both the average return and the alpha increase with the percentile in each panel, and they exhibit polarization as the number of the portfolios increases. As n increases from 10 to 100, the loser leg's average return monotonically decreases from 4.1% to −7.3%, and the winner leg's average return monotonically increases from 18.1% to 26.1%.

Figure 4 Then Figure 4, Panel A, presents the cumulative, non-compounding,[15] monthly WML returns from the 10 to 100 momentum portfolios. The cumulative return to $\mathrm{WML}_{\mathrm{n}}$ monotonically improves with n. In December 2019, WML_{100}'s cumulative return is approximately 138.9% higher than WML_{10}'s.

I also form 5 and 10 value-weighted momentum portfolios based on 30 industry portfolios (Moskowitz and Grinblatt, 1999; 192701–), the 5×5 size and book-to-market portfolios (Lewellen, 2002; 192707–), and the 5×5 operating profitability and investment portfolios (196407–). Next, I form 3 and 7 value-weighted macromomentum portfolios using 21 international equity indices (Bhojraj and Swaminathan, 2006; 198701–). For 5 and 10 value-weighted momentum portfolios, I also use the 5×5 size and book-to-market portfolios (199107–) in Europe, Japan, and Asia Pacific excluding Japan. Finally, the 4 and 8 value-weighted momentum portfolios are based on 2×4×4 size, operating profitability, and investment portfolios (199107–) in Europe, Japan, and Asia Pacific excluding Japan. The equity indices come from AQR Capital Management's website,[16] and the other data are from Professor Kenneth R. French's website.

[14] For example, the annualized average return, standard deviation, alpha, and beta of the 10 portfolios' winner (loser) leg are 4.1%, 34.1%, −11.6%, and 1.6 (18.1%, 22.3%, 6.7%, and 1.0), respectively.
[15] Long-short returns are accumulated without compounding (Pedersen, 2019).
[16] https://www.aqr.com/Insights/Datasets (Frazzini and Pedersen, 2014).

2.2. Pricing Factors

The Fama–French three (1993) and six (2018) factors are from Professor Kenneth R. French's website. The three- and six-factor data run from July 1926 and July 1963, respectively, to December 2019. The three factors are the market (Mkt-RF), size (SMB), and book-to-market (HML); the six factors add operating profitability (RMW), investment (CMA), and momentum[17] (UMD) factors.[18] For the Hou–Mo–Xue–Zhang (2020) five factors (196701–201912), I rely on Professors Kewei Hou, Chen Xue, and Lu Zhang's website. They include market (R_MKT), size (R_ME), investment (R_IA), return on equity (R_ROE), and expected growth (R_EG) factors. The Stambaugh–Yuan (2017) four factors (196301–201612) come from Professor Robert F. Stambaugh's website,[19] namely market (MKTRF), size (SMB), management (MGMT), and performance (PERF). For the Daniel–Hirshleifer–Sun (2020) three factors (197207–201812), the source is Professor Kent Daniel's website,[20] and they encompass post-earnings announcement drift (PEAD) and financing (FIN), as well as the market factor.

In addition, I also form, following prior literature, three different types of factor momentum strategies: the Leippold–Yang (2021) 12-month (LY_{12}) factor momentum and the Arnott–Kalesnik–Linnainmaa (2023) one- (AKL_1) and six-month (AKL_6) factor momentum. These factor momentum strategies are based on 210 US equity factors from Pro-

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[17] The UMD is based on two-way 2×3 portfolios formed on the basis of size and momentum; WML is based on one-way portfolios formed using momentum.

[18] The six factors from Professor Kenneth R. French's website, unlike adjusted factors (Fama and French, 2018) such as the cash profitability factor, refer to the original five factors (Fama and French, 2015) and the momentum factor based on the 2×3 size-momentum portfolios.

[19] http://finance.wharton.upenn.edu/~stambaug/.

[20] http://kentdaniel.net/data.php.

fessor Markus Leippold's website.[21] Specifically, LY is time-series factor momentum similar to Moskowitz, Ooi, and Pedersen (2012) and uses all the factors, whereas AKL is cross-sectional factor momentum similar to Moskowitz and Grinblatt (1999) and longs (shorts) the top (bottom) 15% of the factors.

2.3. Volatility Management

I also form volatility-managed momentum as well as its non-managed counterpart and test whether this volatility management affects the outperformance of the more-portfolio momentum in this study over the fewer-portfolio momentum in other studies, because momentum literature shows that the volatility management influences the performance of the non-managed momentum (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Cederburg *et al.*, 2020). Intuitively, such volatility targeting scales the WML position's exposure up (down) in month t if the position's daily return in t−1 is calm (volatile), such that it stabilizes the volatility of the volatility (Harvey *et al.*, 2018). Specifically, I form the Moreira–Muir (2017) vWML return as follows:

$$\mathrm{vWML}_t = \frac{c}{\hat{\sigma}_{t-1}^2}\mathrm{WML}_t,$$

where vWML_t is the volatility-managed winner-minus-loser return in t, c is a parameter that equalizes the unconditional variance estimates of vWML and WML,[22] and ${\hat{\sigma}_{t-1}}^2$ is the simple WML position's conditional variance from month t−1. In detail,

$$\hat{\sigma}_t^2 = \sum_{d\in t}(\mathrm{WML}_d - \overline{\mathrm{WML}_t})^2, \qquad c = \sqrt{\frac{\widehat{\mathrm{Var}}[\mathrm{WML}_t]}{\widehat{\mathrm{Var}}[\mathrm{WML}_t/\hat{\sigma}_{t-1}^2]}},$$

[21] https://osf.io/6sxc8.

[22] This ex-post scaling strategy is impossible in real time (Cederburg *et al.*, 2020), but similar strategies (*e.g.*, Harvey *et al.*, 2018), which use an ex-ante volatility target, are possible. Also, the volatility-managed Sharpe ratios are independent of the parameter choice (Moreira and Muir, 2017).

hence the conditional variance in month t is the corrected sum of squares from the daily WML returns in t.[23] The data are based on CRSP and span February 1927 to December 2019.

Similarly, Figure 4, Panel B, shows cumulative, non-compounding, monthly vWML returns from the 10 to 100 momentum portfolios. According to this figure, the vWML_n's cumulative monthly return, like the WML_n's, monotonically improves with n. In December 2019, vWML_{100}'s cumulative return was approximately 100.2% higher than vWML_{10}'s. Consistent with prior literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017; Cederburg *et al.*, 2020), the vWML_n positions outperform the corresponding simple WML_n positions. In December 2019, vWML_{10}'s cumulative return was approximately 88.4% higher than WML_{10}'s.

Table 1 Table 1 provides summary statistics. The first, second, and third panels use the full 93-year sample, the post-1963 subsample, and the last 10-year subsample, respectively. First, both WML_n and vWML_n monotonically improve with n. The WML_ns' average returns and standard deviations increase in all samples. The Sharpe ratios and quantiles also increase or decrease, though non-monotonically. The results show a 1.5% to 3.7% certainty equivalent return difference and a 9.6% to 72.3% percentage utility gain. Second, vWML_n monotonically enhances WML_n, also consistent with prior literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017; Cederburg *et al.*, 2020). The average return, Sharpe ratio, and skewness value of every vWML_n outperform those of its simple counterpart. These results show a 10.2% to 12.9% certainty equivalent return difference and a 132.3% to 255.4% percentage utility gain. In summary, the more-portfolio momentum factors

[23] The conditional variance of factor momentum, unlike that of stock momentum, is proxied by the previous year's realized variance, as the 210 factors above are monthly data.

exhibit more enhanced features than their fewer-portfolio counterparts and outperform them, both before and after volatility management. The subsequent tests address whether the usual pricing factors might explain this outperformance.

3. Results

3.1. Factor Models

Do the enhanced momentum factors result from conventional pricing factors? Table 2 contains the results of time-series regressions based on CAPM, Fama–French three-factor (1993; FF3) and six-factor (2018; FF6) models, the Hou–Mo–Xue–Zhang (2020; HMXZ) five-factor model, the Stambaugh–Yuan (2017; SY) four-factor model, and the Daniel–Hirshleifer–Sun (2020; DHS) three-factor model.

Table 2 First, WML_{10}, the usual decile momentum factor, cannot be explained by CAPM and FF3[24] but can be explained by FF6, HMXZ, SY, and DHS. The important factors are UMD in FF6, R_EG in HMXZ, PERF in SY, and PEAD in DHS. The alphas become 16.26% (*t*=5.11) without UMD, 5.79% (1.86) without R_EG,[25] 17.25% (4.97) without PERF, and 15.39% (4.03) without PEAD. Second, Table 2 indicates that WML_n significantly improves with n. Accordingly, the WML_{100} alpha is 17.1% for FF6, 11.6% for HMXZ, 15.7% for SY, and 10.8% for DHS.[26,27] The R^2 values also show monotonic decreases for FF6 (84.8%→42.2%), HMXZ (29.9%→18.2%),

[24] The non-tabulated CAPM and FF3 α estimates for WML_{10} based on the subsample from July 1963 to December 2019 are 16.85% (*t*=5.31) and 19.56% (6.24), respectively.
[25] Without both R_ROE and R_EG, the alpha becomes 17.72% (*t*=5.13).
[26] The non-tabulated generalized method of moments Lagrange multiplier statistics that test whether the alphas are the same provide values of 28.44 (*p*<0.01) for FF6, 11.98 (<0.01) for HMXZ, 44.60 (<0.01) for SY, and 9.87 (0.02) for DHS, using Newey–West (1987) standard errors with 12 lags. The results remain robust with varying numbers of lags.
[27] In addition, I reexamine factor regressions in this table, zooming in on not only momentum but also others, *i.e.,* regressing WML_n on SMB_n, HML_n, *etc.* Table A4 in the appendix, consistent with other results, shows that other zoomed factors cannot span the zoomed momentum, whose alpha increases from 17% (*t*=5.47) to 38% (5.69) as n increases from 10 to 100. I appreciate helpful comments by the anonymous reviewer.

SY (51.6%→29.3%), and DHS (23.9%→12.3%). Third, according to Table 2, WML_n significantly improves with volatility management. Every $vWML_n$ shows a higher alpha and a lower R^2 value than its simple counterpart. All the volatility-managed alphas are statistically and economically significant after the inclusion of all the pricing factors; with the sole exception of the alpha of $vWML_{50}$, they also monotonically improve with n.[28]

In addition to these conventional factors, some recent studies such as Gupta and Kelly (2019), Leippold and Yang (2021), Ehsani and Linnainmaa (2022), Grobys, Kolari, and Rutanen (2022), and Arnott, Kalesnik, and Linnainmaa (2023) argue the role of so-called factor momentum, *i.e.,* momentum effects amid factors, in explaining conventional momentum in the cross-section of stock returns.[29] Does the factor momentum drive and hence span the stock momentum? To answer this question, I also regress WML_n on three different factor momentum strategies: the Leippold–Yang (2021) 12-month (LY_{12}) factor momentum and the Arnott–Kalesnik–Linnainmaa (2023) one- (AKL_1) and six-month (AKL_6) factor momentum. Both Table A5 and Figure A2 in the appendix indicate that the interplay between the factor momentum and the stock momentum cannot fully explain the increasing alpha of the zoomed momentum regardless of volatility management.

The combined results reveal that the outperformance of the more-portfolio momentum factors before and after volatility management is statistically and economically significant, beyond the effects of the usual pricing factors. With further tests, I seek to determine if the fewer-portfolio momentum factors span their more-portfolio counterparts.

3.2. Spanning Tests

[28] For example, the alphas are 25.32% to 53.81% after FF6, 20.60% to 44.32% after HMXZ, 25.54% to 54.98% after SY, and 16.42% to 44.54% after DHS.

[29] I appreciate helpful comments by the anonymous reviewer.

Table 3 contains the spanning regression results of the more-portfolio momentum factors across their fewer-portfolio counterparts. Panel A regresses the simple more-portfolio factors on their fewer-portfolio counterparts, Panel B regresses the volatility-managed more-portfolio factors on their fewer-portfolio counterparts, and Panel C regresses the volatility-managed more-portfolio factors on the simple fewer-portfolio factors (*e.g.*, WML_{25} is regressed on WML_{10}, and WML_{50} is regressed on WML_{10} and WML_{25}).

Table 3 First, Panel A indicates that the simple fewer-portfolio momentum factors do not span their more-portfolio counterparts. All regressions of WML_n on WML_m for n>m show statistically and economically significant alphas. The alphas (R^2 values) monotonically increase (decrease) with n. Specifically, WML_{25} has a lower spanning alpha on WML_{10} (6.28%) than WML_{50} (11.71%), and WML_{50} has a lower one than WML_{100} (15.67%) in turn. The marginal alphas monotonically decrease with n. In this case, WML_{25} has a significant spanning alpha on WML_{10} (6.28%), WML_{50} does so on WML_{25} (4.28%), and WML_{100} has one on WML_{50} (2.89%). Second, consistent with Panel A, Panel B shows that the volatility-managed fewer-portfolio momentum factors do not span their more-portfolio counterparts. All regressions show statistically and economically significant alphas. The alphas (R^2 values) monotonically increase (decrease) with n. However, the marginal alphas in Panel B, unlike those in Panel A, do not monotonically decrease with n. Specifically, vWML_{25}'s alpha on vWML_{10} is 11.72%, vWML_{50}'s alpha on vWML_{25} is 5.73%, and vWML_{100}'s alpha on vWML_{50} is 13.18%. Third, in further consistent results, Panel C reveals that the simple fewer-portfolio momentum factors do not span the volatility-managed more-portfolio momentum factors. All regressions of vWML_n on WML_m for n≥m show statistically and economically significant alphas, ranging from 19.55% to 43.61%. The alphas (R^2 values) monotonically increase (decrease) with n. The marginal alphas, similar to those in Panel B, do not monotonically decrease with n.

These results establish that the more-portfolio momentum factors outperform their fewer-portfolio counterparts due to the spanning alphas rather than the spanning betas. The non-tabulated spanning regression results of WML_n ($vWML_n$) on WML_m ($vWML_m$) for n<m also show that the more-portfolio momentum factors span their fewer-portfolio counterparts.

3.3. Momentum Crashes

A problem of momentum strategies is their crashes, the negative skewness of momentum returns (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). However, the foregoing regressions do not indicate whether momentum crashes differentially affect more-portfolio momentum factors versus their fewer-portfolio counterparts. With the tests in this section, I investigate whether the more-portfolio factors are more subject to crashes.

Figure A4 in the appendix presents the cumulative, non-compounding, monthly returns to WML_{10}, WML_{100}, and $vWML_{100}$. This figure also features bear-down and bear-up shades to highlight the momentum crashes.[30] As would be expect, it indicates two visible momentum crashes in 1932 and 2009. In detail, WML_{10} underperforms WML_{100} in 1932, but the opposite is true in 2009. These crashes affect $vWML_{100}$ less than either WML_{10} or WML_{100} in 1932 and 2009. Therefore, WML_ns have different exposures to the momentum crashes, and $vWML_n$s are less exposed to the crashes than WML_ns.

The time-varying beta can partly explain momentum crashes (Grundy and Martin, 2001;

[30] The bear-market indicator equals 1 if the trailing two-year cumulative market return is negative, and the up-market indicator equals 1 if the contemporaneous excess return is positive (Daniel and Moskowitz, 2016).

Daniel and Moskowitz, 2016). Figure A5 in the appendix presents the trailing 60-month market betas of WML_{10}, WML_{100}, and $vWML_{100}$ from December 1931 to December 2019. Figure A5, like Figure A4, provides bear-down and bear-up shades to highlight how the betas behave around the crashes. The betas vary and tend to become negative around bear markets. Again, the evidence depicted in this figure confirms that the betas behave differently around the momentum crashes. For example, WML_{100}'s beta becomes the most negative around 2009, followed by the beta for WML_{10} and then for $vWML_{100}$. That is, the different momentum crashes relate to different time-varying betas.

Table 4 Table 4 contains the results of the Daniel–Moskowitz (2016) market timing regressions, which relate a momentum factor to a market factor, a bear-market indicator, and an up-market indicator, as follows:

$$\mathrm{WML_t} = \alpha + \left[\beta_0 + \mathrm{I^B_{t-1}}\left(\beta_B + \mathrm{I^U_t}\beta_{BU}\right)\right]\mathrm{MKTRF_t} + \varepsilon_t,$$

where $\mathrm{I^B}$ is the bear-market indicator, and $\mathrm{I^U}$ is the up-market indicator. Momentum crashes, which tend to occur when a bear market rebounds, are related to the sum of all the betas. Consistent with the previous tables, Table 4 shows that both the simple and the volatility-managed alpha monotonically increase with n.

First, the bull beta β_0 is insignificant and neither increases nor decreases with n. The Lagrange multiplier statistics that test whether the bull betas are the same equal 3.42 (p=0.33) for WML_ns and 2.44 (0.49) for $vWML_n$s. Second, the bear beta difference β_B monotonically decreases with n without volatility management. The more-portfolio momentum factors thus outperform their fewer-portfolio counterparts partly because the former load more negatively on the market factor than the latter in the bear market, in which the market factor's expected return is negative.[31] Third, before volatility management, the beta sum, $\beta_0 + \beta_B + \beta_{BU}$, neither increases nor decreases with n because unlike β_B, the bear-up beta difference β_{BU} monotonically increased with n. The sums are −1.40, −1.60, −1.44, and −1.27 for WML_{10}, WML_{25}, WML_{50}, and WML_{100}, respectively. The Lagrange multiplier statistic, which tests whether the sums are the same, equals 5.85 (p=0.12). Therefore, despite the decrease of β_B, the more-portfolio momentum factors are just as exposed to the crashes as their fewer-portfolio counterparts due to β_{BU} increasing. The former behaves less like written call options than the latter though (Daniel and Moskowitz, 2016; Daniel, Jagannathan, and Kim, 2019). Fourth, $vWML_n$s are less exposed to the crashes than WML_ns. Specifically, the beta sums are −0.28, −0.43, −0.54, and −0.46 for $vWML_{10}$, $vWML_{25}$, $vWML_{50}$, and $vWML_{100}$, respectively. Therefore, the volatility-managed momentum factors behave less like written call options than their simple counterparts (Daniel and Moskowitz, 2016; Daniel, Jagannathan, and Kim, 2019). The post-1963 subsample, unlike the full sample, indicates that WML_ns are significantly more exposed to momentum crashes than WML_ms for n>m. Consistent with the prior results, though, the subsample implies that $vWML_n$s are less exposed to the crashes than WML_ns.

In summary, more-portfolio momentum factors are exposed to crashes, to a similar extent or even more than their fewer-portfolio counterparts. The volatility-managed momentum factors are less exposed to the crashes than their simple counterparts.

4. Robustness Checks

4.1. Term Structure

Momentum literature often investigates 11-month cumulative returns, in line with

[31] The market factor's average return is 6.52% (−5.90%) in the bull (bear) market (192807-201912).

pioneering papers by Jegadeesh and Titman (1993). Novy-Marx (2012) and Trigilia and Wang (2019) instead highlight intermediate horizon past performance, and Gong, Liu, and Liu (2015) and Goyal and Wahal (2015) consider recent past performance. The tests in this section therefore address whether the term structure of momentum affects more-portfolio momentum factors.

Figure A6 in the appendix presents the cumulative, non-compounding, monthly returns to the simple/volatility-managed recent/intermediate horizon past performance WMLs from the 10/25/50/100 momentum portfolios. First, consistent with Figures 4 and 5, Figure A6 shows that the cumulative WML return increases with n before and after volatility management. The cumulative returns to $\mathrm{WML}_{\mathrm{n}}^{6,2}$ and $\mathrm{vWML}_{\mathrm{n}}^{6,2}$ improve more monotonically than those to $\mathrm{WML}_{\mathrm{n}}^{12,7}$ and $\mathrm{vWML}_{\mathrm{n}}^{12,7}$. In December 2019, the cumulative returns to $\mathrm{WML}_{100}^{6,2}$, $\mathrm{vWML}_{100}^{6,2}$, $\mathrm{WML}_{100}^{12,7}$, and $\mathrm{vWML}_{100}^{12,7}$ were approximately 172.7%, 102.8%, 110.1%, and 56.3% higher than those to $\mathrm{WML}_{10}^{6,2}$, $\mathrm{vWML}_{10}^{6,2}$, $\mathrm{WML}_{10}^{12,7}$, and $\mathrm{vWML}_{10}^{12,7}$, respectively. Second, Panels A and C, consistent with both Novy-Marx (2012) and Trigilia and Wang (2019), show that the momentum factors based on intermediate horizon past performance outperform those based on recent past performance before volatility management. The outperformance monotonically decreases with n. In December 2019, cumulative returns to $\mathrm{WML}_{10}^{12,7}$, $\mathrm{WML}_{25}^{12,7}$, $\mathrm{WML}_{50}^{12,7}$, and $\mathrm{WML}_{100}^{12,7}$ were approximately 48.0%, 33.8%, 15.3%, and 14.0% higher than those to $\mathrm{WML}_{10}^{6,2}$, $\mathrm{WML}_{25}^{6,2}$, $\mathrm{WML}_{50}^{6,2}$, and $\mathrm{WML}_{100}^{6,2}$, respectively. Third, in Panels B and D, unlike in Panels A and C, the momentum factors based on recent past performance outperform those based on intermediate horizon past performance after volatility management. The outperformance increases with n, though nonmonotonically. In December

2019, the cumulative returns to $\text{vWML}_{10}^{2,6}$, $\text{vWML}_{25}^{2,6}$, $\text{vWML}_{50}^{2,6}$, and $\text{vWML}_{100}^{2,6}$ were approximately 13.9%, 2.82%, 20.2%, and 47.8% higher than those to $\text{vWML}_{10}^{12,7}$, $\text{vWML}_{25}^{12,7}$, $\text{vWML}_{50}^{12,7}$, and $\text{vWML}_{100}^{12,7}$, respectively.

In summary, more-portfolio momentum factors based on both recent and intermediate horizon past performance outperform their fewer-portfolio counterparts. The intermediate horizon factors outperform their recent counterparts before volatility management, and this outperformance decreases with n, but they underperform after volatility management, and in this case, the outperformance increases with n.

Table 5 Table 5 contains the results of time-series regressions based on the Hou–Mo–Xue–Zhang (2020) five-factor model and the Daniel–Hirshleifer–Sun (2020) three-factor model.[32] First, consistent with Novy-Marx (2012), these results indicate that $\text{WML}_{10}^{6,2}$ can be explained by either HMXZ or DHS, but $\text{WML}_{10}^{12,7}$ cannot. Both HMXZ and DHS show negative (−0.95% and −3.31%, respectively) and insignificant $\text{WML}_{10}^{6,2}$ alphas but positive (5.50% and 7.47%, respectively) and significant (at the 5% level) $\text{WML}_{10}^{12,7}$ alphas. Second, for both the recent and the intermediate horizon past performance momentum factor, the HMXZ and the DHS alphas increase with n both before and after volatility management, respectively. Consistent with the results in Figure A6, these findings indicate that intermediate horizon alphas outperform their recent counterparts before volatility management but underperform them after volatility management.

The spanning regressions in the appendix also indicate that both the recent and the

[32] Table 5 only reports the results for HMXZ and DHS, because Table 2 shows that they outperform the other models. The appendix also provides the summary statistics, the spanning regression results, and the market timing regression results, in parallel with Tables 1, 3, and 4, respectively.

intermediate horizon WML_{10} do not span the corresponding WML_{25}s, WML_{50}s, and WML_{100}s, either before or after volatility management.[33] Likewise, the market timing regressions in the appendix imply that the beta sum, $\beta_0 + \beta_B + \beta_{BU}$, neither increases nor decreases (cf. $WML_{100}^{6,2}$) with n before and after volatility management.[34] That is, both the recent and the intermediate horizon more-portfolio momentum factors are exposed to the momentum crashes to a similar extent but more than the fewer-portfolio counterparts, such that they experience less exposure to crashes through volatility management. The outperformance of the more-portfolio momentum factors thus is robust to the term structure of momentum. Consistent with Novy-Marx (2012), the intermediate horizon momentum portfolios show stronger return monotonicity than recent momentum portfolios.

4.2. Residual Momentum

Momentum strategies based on residual returns outperform those based on simple returns partly because the former show less time-varying factor exposure (Grundy and Martin, 2001; Martens and van Oord, 2014) than the latter (Blitz, Huij, and Martens, 2011; Chang *et al.*, 2018). The tests in this section check whether the more-portfolio residual momentum factors, similar to more-portfolio simple momentum factors, outperform their fewer-portfolio counterparts.

Figure A7 in the appendix, in parallel with Figure 4, shows cumulative, non-compounding,

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[33] The non-tabulated alphas of $WML_{25}^{6,2}$, $WML_{50}^{6,2}$, and $WML_{100}^{6,2}$ on $WML_{10}^{6,2}$ are 6.25% (t=3.91), 9.92% (3.85), and 12.25% (3.24) before volatility management, respectively, and 9.55% (4.09), 17.05% (5.15), and 24.81% (5.44) after volatility management. The non-tabulated alphas of $WML_{25}^{12,7}$, $WML_{50}^{12,7}$, and $WML_{100}^{12,7}$ on $WML_{10}^{12,7}$ are 7.30% (5.32), 8.69% (4.27), and 12.04% (3.45) before volatility management, respectively, and 11.49% (5.57), 14.33% (5.11), and 12.24% (3.13) after volatility management.

[34] The Lagrange multiplier statistics that test whether the sums are the same for $WML_n^{6,2}$, $vWML_n^{6,2}$, $WML_n^{12,7}$, and $vWML_n^{12,7}$ are 11.10 (p=0.01), 2.86 (0.41), 5.56 (0.14), and 5.33 (0.15), respectively.

monthly WML returns from the 10 to 100 residual momentum portfolios.[35] It affirms that the cumulative residual momentum return improves with n. In December 2019, WML_{100}'s cumulative return was approximately 38.8% higher than WML_{10}'s.

According to Figure A7, cumulative momentum returns based on residual returns underperform those based on simple returns.[36] In December 2019, the former (latter), accumulate 777% (1300%), 877% (2076%), 987% (2658%), and 1079% (3105%) for WML_{10}, WML_{25}, WML_{50}, and WML_{100}, respectively, as I depict in Figure A7, Panel A (Figure 4, Panel A). However, according to Table A9, the former sometimes produce higher Sharpe ratios than the latter; for example, WML_{10}'s Sharpe ratio based on residual (simple) returns is 0.68 (0.52). Consistent with Blitz, Huij, and Martens (2011), $\mathrm{WML}_{10}^{\mathrm{residual}}$ spans $\mathrm{WML}_{10}^{\mathrm{simple}}$ (α=4.99%, *t*=4.51) but not vice versa (3.54%, 1.47). Table A9 also shows that $\mathrm{WML}^{\mathrm{residual}}$'s average return, like $\mathrm{WML}^{\mathrm{simple}}$'s, increases with n before and after volatility management, but the former's Sharpe ratio, unlike the latter's, decreases with n before and after volatility management. Notably, $\mathrm{WML}_{25}^{\mathrm{residual}}$, $\mathrm{WML}_{50}^{\mathrm{residual}}$, and $\mathrm{WML}_{100}^{\mathrm{residual}}$ span $\mathrm{WML}_{25}^{\mathrm{simple}}$, $\mathrm{WML}_{50}^{\mathrm{simple}}$, and $\mathrm{WML}_{100}^{\mathrm{simple}}$, respectively, and vice versa.

Table A10 in the appendix contains the HMXZ (Panel A) and DHS (B) factor regression results of the residual momentum factors.[37] Panels A and B parallel Table 2 in using factors based on full (t−12, t−2) past performance. Panels C and D match Table 5, by using factors based on recent (t−6, t−2) and intermediate horizon (t−12, t−7) past performance. First,

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[35] Table A9 and Figure A7 present the portfolio statistics, the cumulative volatility-managed residual momentum returns, and the trailing 60-month betas.
[36] Following Hou, Xue, and Zhang (2020), but in contrast with Blitz, Huij, and Martens (2011), I use value-weighted residual momentum portfolios.
[37] The appendix also provides the summary statistics, the spanning regression results, and the market timing regression results, matching Tables 1, 3, and 4, respectively.

consistent with Tables 2 and 4, this table indicates that for both the full and the intermediate horizon past performance momentum factors, the HMXZ and the DHS alphas increase with n, both before and after volatility management, but for the recent past performance momentum factor, these alphas increase with n only after volatility management. Consistent with Novy-Marx (2012), intermediate horizon, rather than recent past performance, appears to drive the residual momentum factor and its simple counterpart.

Second, again consistent with Novy-Marx (2012), this table shows that $\mathrm{WML}_{10}^{\mathrm{residual},6,2}$ can be explained by either HMXZ or DHS, but $\mathrm{WML}_{10}^{\mathrm{residual},12,7}$ cannot. The $\mathrm{WML}^{6,2}$'s HMXZ/DHS alphas are negative (−3.37%/−4.20%) and significant (5%/1%), whereas the $\mathrm{WML}^{12,7}$'s alphas are positive (5.33%/6.47%) and significant (0.1%). The evidence also confirms the use of intermediate horizon rather than recent past performance.

The spanning regressions in Table A11 suggest that $\mathrm{WML}_{\mathrm{n}}^{\mathrm{residual},12,2}$ and $\mathrm{WML}_{\mathrm{n}}^{\mathrm{residual},6,2}$ improve with n only after volatility management, but $\mathrm{WML}_{\mathrm{n}}^{\mathrm{residual},12,7}$ improves both before and after volatility management. The market timing regressions in Table A12 further show that the beta sum, with the exception of WML_{100}, neither increases nor decreases with n but decreases due to volatility management.

In summary, the outperformance of the more-portfolio momentum factors is robust to the residual momentum. Consistent with Blitz, Huij, and Martens (2011), I find that residual momentum factors, except for recent past performance, exhibit more significant alphas than their simple counterparts. The results also reveal more significant alphas of the simple momentum factors than their residual counterparts.

4.3. Grid Search

The preceding results indicate that portfolios formed on the basis of momentum achieve significant return monotonicity at n=10. However, the summary statistics show that, with n, monotonicity weakens while profitability strengthens. The spanning regression results also signal that the marginal improvement decreases. Formally, $\Delta \mathrm{E}[\mathrm{WML_n}]/\Delta \mathrm{n} > 0$ but $\Delta^2 \mathrm{E}[\mathrm{WML_n}]/\Delta \mathrm{n}^2 < 0$ at n=10. Tests with a grid search approach serve to determine whether n=10 significantly differs from argmax $\mathrm{E}[\mathrm{WML_n}]$ for n∈{5,10,⋯,200}.

Figure 5 Figure 5 shows the average returns and Fama–French (2018) six-factor alphas[38] of the simple and the volatility-managed value-weighted $\mathrm{WML_n}$s for n∈{5,10,⋯,200}.[39] It presents both the estimates and their two standard error bands. First, $\mathrm{WML_n}$'s average return and alpha improve with n until around 75 but not thereafter. The average returns (alphas) for n=5, 100, and 200 are 10%, 34%, and 38% (1%, 17%, and 22%), respectively. The non-tabulated spanning alphas on $\mathrm{WML_{10}}$ are −2%, 10%, and 12%, respectively. These results thus continue to show that the momentum factor significantly improves with n around 10. Second, Figure 5 shows that $\mathrm{vWML_n}$'s average return and alpha improve with n more than $\mathrm{WML_n}$'s. The average returns (alphas) for n=5, 100, and 200 are 19%, 56%, and 70% (14%, 45%, and 58%), respectively. The non-tabulated spanning alphas on $\mathrm{vWML_{10}}$ are 1%, 23%, and 35%, respectively. Thus, the more-portfolio momentum factors improve through volatility management more so than their fewer-portfolio counterparts do.

4.3.1. Term structure

[38] The Fama–French (2018) six factors, unlike other factors, start in July 1963. The appendix also provides the Hou–Mo–Xue–Zhang (2020) five-factor alphas, which start in January 1967, and Daniel–Hirshleifer–Sun (2020) three-factor alphas, which start in July 1972.

[39] The data span from July 1963 to December 2019 for each of the 200 portfolios to ensure there are enough firms. The 10 portfolios formed on momentum from Professor Kenneth R. French's website indicate a total number of firms in portfolios of 1089 in July 1963, 1856 in August 1963, and 3314 in December 2019. The portfolio with the most losers (winners) contains 6 (5) in July 1963, 39 (16) in August 1963, and 80 (87) in December 2019. This number jumps in August 1963 because CRSP first stated including AMEX firms in July 1962 (Linnainmaa and Roberts, 2018).

Figure A8 in the appendix provides the average returns and Fama–French (2018) six-factor alphas of the simple and the volatility-managed WML_ns, for the recent and intermediate horizon past performance, at $n \in \{5,10,\cdots,200\}$. Both $WML^{6,2}$ and $WML^{12,7}$ improve with n until around 100 and 50, respectively. But $vWML^{6,2}$ and $vWML^{12,7}$ improve with n more than $WML^{6,2}$ and $WML^{12,7}$, whereas $vWML^{6,2}$ monotonically improves with n more than $vWML^{12,7}$ does. As these results show, both the recent and the intermediate horizon more-portfolio momentum factors outperform their fewer-portfolio counterparts, before and after volatility management. Furthermore, $WML^{11,3}$ and $vWML^{11,3}$, which adjust estimation biases (Gong, Liu, and Liu, 2015), improve with n.

Consistent with prior literature (Novy-Marx, 2012; Goyal and Wahal, 2015), this study shows that momentum factors based on recent and intermediate horizon past performance are distinct. Momentum literature relates the intermediate horizon momentum factor to earnings momentum (Chordia and Shivakumar, 2006; Novy-Marx, 2015), and volatility management literature shows that momentum-related strategies improve with volatility management more than others (Moreira and Muir, 2017; Cederburg *et al.*, 2020). The current results add that the intermediate horizon simple momentum factor improves with n more than its recent counterpart, because its basis portfolios achieve stronger return monotonicity. Furthermore, the recent volatility-managed momentum factor improves with n more than its intermediate horizon counterpart, because recent momentum is less related to earnings momentum.

4.3.2. Residual momentum

Figure A9 in the appendix lists the average returns and Fama–French (2018) six-factor alphas of the simple and volatility-managed WML_ns, based on residual returns (Blitz, Huij, and Martens, 2011) for n∈{5,10,⋯,200}. Consistent with the preceding results the residual momentum factor monotonically improves with n more than its simple counterpart before volatility management. However, the results are inconsistent with the monotonicity test results, in that the base portfolio for the residual momentum factor exhibits weaker return monotonicity than that for the simple momentum factor.[40] A possible explanation is that more-portfolio improvement might relate to both the portfolios' cross-sectional monotonicity and the factor's time-series variability; from n=5 to 200, the residual momentum factor's standard deviations increase from 10% to 26%, while the simple momentum factor's increase from 19% to 63%. Figure A9 also shows that $\mathrm{vWML}_{\mathrm{n}}^{\mathrm{residual}}$ improves with n but less monotonically than $\mathrm{WML}_{\mathrm{n}}^{\mathrm{residual}}$ does.

Then Figure A10 in the appendix provides the average returns and Fama–French (2018) six-factor alphas of $\mathrm{WML}_{\mathrm{n}}$s and $\mathrm{vWML}_{\mathrm{n}}$s based on alphas (Hühn and Scholz, 2018; Zaremba, Umutlu, and Karathanasopoulos, 2019) for n∈{5,10,…,200}. The alpha momentum also improves with n around 10, before and after volatility management.

4.3.3. Other factor models

Figure A11 in the appendix provide the results obtained from Hou–Mo–Xue–Zhang (2020) five-factor alphas and Daniel–Hirshleifer–Sun (2020) three-factor alphas of $\mathrm{WML}_{\mathrm{n}}$s and $\mathrm{vWML}_{\mathrm{n}}$s, across full, recent, and intermediate horizon past performance, for n∈{5,10,⋯,200}. Consistent with Figure 4, Figure A11 shows that $\mathrm{WML}_{\mathrm{n}}$'s HMXZ and DHS full past performance alphas improve with n until around 75, and $\mathrm{vWML}_{\mathrm{n}}$'s HMXZ and DHS alphas improve with n more than $\mathrm{WML}_{\mathrm{n}}$'s. Before volatility management, the HMXZ alpha is −1.4%

[40] Table A2 in the appendix shows that the MR statistics of 11-month residual momentum, with a 1-month holding period, and prior 11-month returns, with a 1-month holding period, are −1.17% (*p*=0.278) and −0.20% (0.002), respectively.

(t=−0.40) for n=5 but 13.6% (1.99) for n=85, and the DHS alpha is −0.9% (−0.25) for n=5 but 14.0% (1.84) for n=75. After volatility management, as n increases from 5 to 200, the HMXZ alpha increases from 18% (5.49) to 73% (6.93), and the DHS alpha increases from 17% (5.27) to 78% (7.20).

Therefore, before volatility management, both HMXZ and DHS explain the improvement of the full and the recent momentum factors, respectively, but not that of the intermediate horizon momentum factor for n≤100. After volatility management, neither HMXZ nor DHS explains the improvements. Regardless of the term structure, it thus appears that the momentum factor improves with n; that is, $\left.\frac{\Delta \mathrm{E}[\mathrm{WML_n}]}{\Delta \mathrm{n}}\right|_{\mathrm{n}=10} > 0$.

4.3.4. Zoom in on others

Figure 6 Do other anomaly strategies also improve with the number of portfolios? As mentioned previously, researchers argue that the 10 and 5×5 portfolios might pixelate the cross-section. Using a grid search approach in this section, I investigate whether the long-short performance of the size, book-to-market, operating profitability, and investment portfolios also improves with n.[41] Figure 6 contains the average returns and Fama–French (2018) six-factor alphas[42] of the size, book-to-market, operating profitability, and investment strategies as functions of n∈{5,10,⋯,200}. On the left, this figure shows that only the average return of CMA improves with n (3.5%→15.7%), whereas those of SMB, HML, and RMW do not. The panels on the right offer similar results, namely, that only the alpha of CMA improves with n

[41] In addition, Figures A13 and A14 in the appendix inspect 49 anomalies in Kozak (2020) and 128 anomalies in Chen and Zimmermann (2022), respectively. These additional results also indicate that (1) the more-portfolio momentum significantly and robustly improves its fewer-portfolio counterpart, and (2) other more-portfolio anomalies infrequently present these improvements of the more-portfolio momentum.

[42] Figure A12 in the appendix shows the HMXZ and DHS alphas.

(−0.6%→9.6%) and becomes significant for n≥50, but those of SMB, HML, and RMW do not; in some cases, they even weaken with n.

These results are consistent with the monotonicity test results, such that the basis portfolios of the investment factor indicate stronger return monotonicity than those of the size, book-to-market, and operating profitability factors.[43] Likewise, the investment factor improves with n less than the momentum factor, because the portfolios for the investment factor display weaker monotonicity than those for the momentum factor. The combined evidence thus suggests that the profitability of the momentum factor strengthens with n (the number of momentum portfolios) around 10, regardless of the term structure of momentum and the residual momentum. It also persists regardless of usual pricing factors, whereas the profitability of the size, book-to-market, operating profitability, and investment factors do not strengthen, weaken, or improve less with n than the momentum factor. They do not survive conventional pricing factors either.

4.4. Two-Way Portfolios

Do more-portfolio momentum factors persist in two-way portfolios with other anomalies? Other factors might affect momentum factors' profitability (Chan, Jegadeesh, and Lakonishok, 1996; Hong, Lim, and Stein, 2000; Jegadeesh and Titman, 2001; Novy-Marx, 2015).[44]

[43] Table A2 in the appendix provides the MR statistics of investment-to-assets (asset growth), market equity, book-to-market equity, and operating profits-to-book equity, which are −0.72% (*p*=0.062), −0.63% (0.196), −0.83% (0.120), and −1.35 (0.401), respectively.

[44] Chan, Jegadeesh, and Lakonishok (1996) indicate that two-way portfolios formed on the basis of earnings and price momentum exhibit stronger momentum than one-way portfolios formed on price momentum. Fundamental and price momentum also appear relevant (Novy-Marx, 2015; Daniel, Hirshleifer, and Sun, 2020). Hong, Lim, and Stein (2000) assert that momentum strategies with smaller stocks outperform those with larger stocks because investors underreact more, due to slower information diffusion (Hong and Stein, 1999). In contrast, Jegadeesh and Titman (2001) propose that the momentum factors are profitable for both small and large stocks. In analyzing global stocks, Hou, Karolyi, and Kho (2011) determine that two-way portfolios formed on momentum and dividend yield exhibit weaker momentum than one-way portfolios formed on the basis of momentum.

Therefore, the goal of this section is to test whether the more-portfolio momentum factors from two-way portfolios outperform their fewer-portfolio counterparts. Figure A15 in the appendix provides the average returns of the 5×5 size and momentum, book-to-market and momentum, operating profitability and momentum, and investment and momentum portfolios. Each panel contains five size, book-to-market, operating profitability, and investment partitions, and each partition comprises five momentum columns, moving from loser portfolios on the left to winners on the right. Furthermore, each panel indicates the MR statistic and its *p*-value, which represent the test of whether momentum portfolios in every partition are jointly monotonic. The results affirm that momentum portfolios' strong return monotonicity persists in two-way portfolios, even in the presence of other anomalies. The *p*-values of the size and momentum, the book-to-market and momentum, and the operating profitability and momentum portfolios all reject the null hypothesis of a flat or weakly decreasing pattern at the 0.5% level, though the *p*-value of the investment and momentum portfolios does not.[45] In all the partitions, the WMLs are profitable. Small-cap stocks (11.5%) attain higher momentum profits than large-cap stocks (7.5%), consistent with prior literature (Hong, Lim, and Stein, 2000; Jegadeesh and Titman, 2001). The momentum profits are highest in the fifth investment quintile (15.7%) and lowest in the second (5.81%). Across 20 momentum profits, the average value is 9.6%.

Table A13 in the appendix contains the spanning regression results of the more-portfolio momentum factors formed by the 5×10 portfolios, as well as their fewer-portfolio counterparts formed with the 5×5 portfolios. Providing evidence related to size, book-to-

[45] The second and third momentum portfolios in the second and third investment quintiles show nonmonotonic patterns, yet the winner and loser portfolios in the quintiles indicate monotonic patterns.

market, operating profitability, and investment, respectively, Panels A–D regress the simple more-portfolio factors on their fewer-portfolio counterparts. Then Panels E–H regress the volatility-managed factors on their simple counterparts.

Consistent with Table 3, Panels A–D of Table A13 show that the fewer-portfolio momentum factors do not span their more-portfolio counterparts before or after volatility management. Among the 20 regressions of WML_{10} on WML_{5} (vWML_{10} on vWML_{5}), I find significant alphas before (after) volatility management, with the exceptions of the fifth size, the third operating profitability, and the first, fourth, and fifth investment quintiles (fourth size and fifth investment quintile). Improvements before volatility management are highest in the third investment quintile (21.0%) and lowest in the first (0.14%), whereas those after volatility management are highest in the third investment quintile (17.0%) and lowest in the fifth (2.6%). Before volatility management, the non-tabulated alphas of the five quintiles' average more-portfolio factors on their fewer-portfolio counterparts for size, book-to-market, operating profitability, and investment are 1.9%, 4.1%, 2.9%, and 5.3%, respectively. These results are consistent with the 4.3% alpha of WML_{50} on WML_{25} in Table 3, Panel A.

As suggested by prior literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017; Cederburg *et al.*, 2020), Panels E–H also reveal that the simple momentum factors do not span their volatility-managed counterparts. The improvements for vWML_{5} are highest in the first size quintile (28.7%) and lowest in the second investment quintile (7.7%); those for vWML_{10} are highest in the first size quintile (22.0%) and lowest in the fourth investment quintile (5.44%). Therefore, the outperformance of volatility-managed momentum portfolios is due primarily to smaller-size, lower-book-to-market, lower-operating profitability, or higher-investment stocks. Overall, the 5×5 momentum portfolios exhibit robust return monotonicity, and the 5×10 more-portfolio momentum factors consistently outperform their fewer-portfolio counterparts, before and after volatility management. The alphas of the two-way 5×10 on the 5×5 factors are consistent with those of WML_{50} on WML_{25}.

4.5. Postholding Period

The more-portfolio momentum factors also might produce other results consistent with prior literature. For example, postformation momentum returns tend to be positive in the first year but negative in the second through fifth years (Jegadeesh and Titman, 2001; Nagel, 2001; McLean, 2010; Ali, Daniel, and Hirshleifer, 2017). Perhaps the more-portfolio momentum factors strengthen such postholding, as well as holding period, returns. Figure A16 in the appendix contains the cumulative momentum returns over 120 months after formation. Panel A presents the WML_{100}'s cumulative return and its two standard error bands; Panel B provides the cumulative returns of WML_{10}, WML_{25}, WML_{50}, and WML_{100}; and Panels C and D list these same cumulative returns for recent and intermediate horizon past performance, respectively. Both WML_{n}'s short-term return and its long-term reversal increase with n. The cumulative return of WML_{100}, according to the full set of (t−12, t−2) past performance, is 15.21% after 9 months, −18.30% after 60 months, and −47.72% after 120 months. The same returns for WML_{10} reach 6.65% after 9 months, −3.34% after 60 months, and −16.76% after 120 months. As Figure A16 shows, both the short-term return and the long-term reversal of the (t−6, t−2) recent and the (t−12, t−7) intermediate horizon past performance momentum factors grow stronger with n.

To support a comparison with Ali, Daniel, and Hirshleifer (2017), Figure A17 also presents cumulative WML_{n} returns over 120 months after formation by past momentum performance (PMP) quintiles, where the PMP in month t is WML_{10}'s average return from t−24 to t−1. Panels A–D reflect the cumulative WML_{10}, WML_{25}, WML_{50}, and WML_{100} returns, respectively, after the lowest-, second-, third-, fourth-, and highest-quintile months.[46]

The results align with Ali, Daniel, and Hirshleifer's (2017) findings, in that WML_{10} in Panel A reverses only after the highest-quintile PMP months. The 12-month cumulative returns are 9.49%, −2.94%, 8.91%, −17.98%, and −80.90% after the lowest- to highest-quintile months. Then in Panels B, C, and D, WML_{25}, WML_{50}, and WML_{100} reverse even after the lowest-quintile months. The 120-month cumulative WML_{100} returns are −80.83%, −92.72%, −48.38%, −5.96%, and −12.99% after the lowest- to highest-quintile months.[47] Some non-tabulated results are also consistent with such recent and intermediate horizon past performance. Notably, WML_{100}, after the highest-quintile months, rebounds between t+60 and t+84. Thus, the more-portfolio momentum factors sharpen not only the short-term returns but also the long-term reversals. The more-portfolio momentum factors reverse even after the low-quintile PMP months, and their fewer-portfolio counterparts do so only after high-quintile months.

4.6. Industry Momentum

This section tests whether more-portfolio outperformance is robust to industry momentum (Moskowitz and Grinblatt, 1999), portfolio momentum (Lewellen, 2002), macromomentum (Bhojraj and Swaminathan, 2006), and alpha momentum (Hühn and Scholz, 2018; Zaremba, Umutlu, and Karathanasopoulos, 2019). In prior studies, both well-diversified portfolios and individual stocks exhibit momentum; my goal is to determine if more-portfolio momentum

[46] Figure A18 in the appendix depicts these cumulative returns and their two standard error bands.
[47] The cumulative WML_{100} returns after 60 months are −9.89% (lowest quintile), −37.80%, −23.36%, −22.03%, and −40.66% (highest quintile).

factors from portfolios rather than stocks also outperform their fewer-portfolio counterparts.

Table A14 in the appendix, maps to Tables 1 and 2; it contains the summary statistics and time-series regression results of 5 and 10 value-weighted momentum portfolios, from 30 industry portfolios. Similar to Moskowitz and Grinblatt (1999), these momentum portfolios sort the industry portfolios according to their past six-month returns; then, each quintile or decile portfolio invests in six or three industries, respectively.

The results, consistent with those presented thus far, indicate that the more-portfolio industry momentum factor significantly outperforms its fewer-portfolio counterpart. The average return, CAPM alpha, and Fama–French (1993) three-factor alpha of WML_5 from the 30 industry portfolios are 4.48%, 6.00%, and 6.38%, respectively, with a 0.28 Sharpe ratio. The parallel values for WML_{10} are 6.62%, 8.16%, and 8.75%, with a 0.33 Sharpe ratio. The difference between WML_{10} and WML_5 signals a 2.14% (t=6.40) average return, a 2.15% (1.83) CAPM alpha, and a 2.37% (2.02) FF3 alpha.

In addition, Tables A15 and A16 in the appendix affirm that the results are also consistent for the 5×5 size and book-to-market portfolios, the 5×5 operating profitability and investment portfolios, and the 21 international equity indices,[48] as well as the 30 industry portfolios. With the 5×5 size and book-to-market portfolios, WML_5's average return, CAPM alpha, and FF3 alpha are 5.91%, 6.46%, and 6.34%, respectively, and then WML_{10}'s are

[48] AQR Capital Management's website provides 24 international equity indices (Frazzini and Pedersen, 2014), referring to all 23 MSCI developed markets and Greece. The first months are (1) July 1926 for the United States; (2) January 1984 for Canada; (3) November 1985 for Australia; (4) January 1986 for Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Hong Kong, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Singapore, and Sweden; (5) August 1986 for Portugal; (6) September 1988 for Greece; and (7) December 1994 for Israel. The 21 equity indices include (1)–(4) and exclude (5)–(7).

7.65%, 8.83%, and 9.00%, respectively. Their differences are 1.74% (t=5.36), 2.37% (2.10), and 2.66% (2.41), respectively. With the 5×5 operating profitability and investment portfolios, WML_5's average return, CAPM alpha, and Fama–French six-factor (2018) alpha are 4.70%, 5.32%, and −0.66%; WML_{10}'s are 5.83%, 6.54%, and 0.83%; and their differences are 1.13% (t=5.20), 1.22% (1.58), and 1.49% (1.91), respectively. For the 21 international equity indices, I find WML_3 average returns, CAPM alphas, and FF3 alphas of 4.47%, 4.76%, and 4.07%; WML_7 value of 10.73%, 11.44%, and 12.16%; and differences of 6.26% (t=1.63), 6.68% (1.73), and 8.08% (2.08), respectively. Also consistent with Chui, Titman, and Wei's (2010) finding that the momentum effects in Asian markets are weaker than those in other markets, Table A17 in the appendix shows that the 5×5 size and book-to-market and the 2×4×4 size, operating profitability, and investment portfolios exhibit consistent results in Europe but inconsistent outcomes in Japan and the Asia-Pacific excluding Japan. With the 5×5 portfolios, the FF3 alpha of the difference between WML_{10} and WML_5 is 1.82% (t=1.63) in Europe, 1.61% (1.17) in Japan, and −0.74% (−0.49) in the Asia-Pacific excluding Japan. With the 2×4×4 portfolios, the alpha is 1.85% (1.59) in Europe, −1.03% (−0.80) in Japan, and 2.11% (1.16) in the Asia-Pacific excluding Japan.

In summary, more-portfolio momentum factors from portfolios (indices), similar to those from stocks, outperform their fewer-portfolio counterparts, and this outperformance is robust to the choice of portfolios. It also survives the impact of conventional pricing factors. The momentum factors appear to improve with the number of portfolios, but only in markets with strong momentum effects.

5. Conclusion

The number of portfolios to construct the momentum factor affects momentum performance.

The returns of 10 portfolios formed on momentum are more monotonic than those of 10 portfolios formed on other anomalies. The momentum strategy also indicates higher returns than other anomaly strategies. Across the one-way 10 or two-way 5×5 portfolios, more-portfolio momentum sharpens the cross-section of returns and outperforms its fewer-portfolio counterpart.

This outperformance is not subsample-specific and persists in the presence of other pricing factors. Increasing the number of portfolios also improves volatility-managed momentum, recent past performance momentum, intermediate horizon past performance momentum, residual momentum, two-way momentum, industry momentum, portfolio momentum, and macromomentum. More-portfolio momentum is subject to momentum crashes, just as its fewer-portfolio counterpart may be—or even more so in some cases. The increased number of portfolios enhances both long-term reversals and short-term returns.

Unlike the momentum factor, the size, value, and operating profitability factors seldom improve with the number of portfolios. As a notable exception, the investment factor improves with the number of portfolios, just as the momentum factor does. Thus, the monotonicity of portfolio returns appears to affect more-portfolio improvements, in that the investment portfolios show stronger return monotonicity than the size, book-to-market, and operating profitability portfolios. Such evidence suggests that the recommended number of portfolios will vary by the anomaly being considered. More generally, I conjecture that an anomaly with more monotonic portfolio returns also has more significant long-short enhancements as the number of portfolios increases and hence, for future research, hypothesize that there is a correlation between the anomaly portfolios' return monotonicity and their long-short improvements.

Understanding such more-portfolio improvements can encourage stronger, more effective strategies. For example, according to the evidence presented in the current study, increasing the number of portfolios from about 10 to about 100 will strengthen momentum. Increasing numbers continue to strengthen volatility-managed momentum. These results are consistent with arguments and concerns that conventional 10 or 5×5 portfolios cannot represent markets very well. Considering and accounting for more-portfolio momentum also enhances existing stylized facts. Both the short-term return and the long-term reversal become finer at greater values, such that the increasing number of portfolios allow researchers to rule out alternative explanations for momentum (Subrahmanyam, 2018).

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Table 1. Summary statistics.

The table shows summary statistics for WML_n, the simple WML strategy based on n value-weighted momentum portfolios, in the left four columns, and $vWML_n$, the volatility-managed WML strategy (Moreira and Muir, 2017), in the right four columns. Panels A, B, and C show summary statistics based on the full sample from January 1927, the modern subsample from July 1963, and the last 10-year subsample from January 2010, respectively. Average returns, standard deviations, and Sharpe ratios are annualized.

	Simple winner-minus-loser				Volatility-managed winner-minus-loser			
	WML_{10}	WML_{25}	WML_{50}	WML_{100}	$vWML_{10}$	$vWML_{25}$	$vWML_{50}$	$vWML_{100}$
	Panel A. Full sample 192701-201912							
Mean	13.97	22.32	28.58	33.38	26.35	38.12	43.58	52.77
St dev	26.92	35.06	41.95	51.52	26.93	35.07	41.96	51.51
Sharpe	0.52	0.64	0.68	0.65	0.98	1.09	1.04	1.02
Skew	-2.31	-2.58	-1.98	-2.16	1.72	2.02	0.85	2.57
Kurt	17.40	24.75	17.61	18.16	14.63	11.69	9.54	22.65
Min	-77.02	-114.05	-108.87	-129.12	-36.80	-31.69	-73.19	-66.57
Q1	-1.79	-2.12	-2.29	-2.56	-0.97	-1.19	-1.61	-2.01
Med	1.48	2.34	2.73	3.44	1.11	1.44	1.83	1.90
Q3	5.06	6.48	8.33	9.64	4.69	6.51	7.40	8.77
Max	26.16	59.02	77.48	91.81	82.27	80.10	88.93	178.43
	Panel B. Subsample 196307-201912							
Mean	15.07	25.36	31.91	34.43	32.10	50.09	56.33	67.26
St dev	24.03	30.96	37.69	49.23	29.85	39.91	47.88	58.73
Sharpe	0.63	0.82	0.85	0.70	1.08	1.25	1.18	1.15
Skew	-1.36	-0.92	-1.03	-2.65	2.02	2.07	0.61	2.46
Kurt	7.59	8.01	10.72	22.74	14.02	9.91	7.86	20.40
Min	-45.58	-49.24	-67.12	-129.12	-28.37	-31.33	-73.19	-66.57
Q1	-1.49	-1.80	-1.78	-2.18	-0.95	-1.10	-1.58	-2.04
Med	1.66	2.53	2.96	3.90	1.40	2.08	2.73	3.42
Q3	4.99	6.75	8.27	9.16	5.15	7.47	9.13	10.65
Max	26.16	59.02	77.48	91.81	82.27	80.10	88.93	178.43
	Panel C. Subsample 201001-201912							
Mean	7.95	22.12	30.28	44.23	5.47	18.78	25.08	43.30
St dev	20.65	33.77	41.37	50.28	13.49	20.67	26.73	38.84
Sharpe	0.38	0.66	0.73	0.88	0.41	0.91	0.94	1.11
Skew	-0.11	1.28	1.74	1.30	0.22	2.10	2.09	1.89
Kurt	1.46	10.09	12.59	11.44	3.03	8.61	9.71	6.76
Min	-19.77	-31.41	-31.14	-43.67	-11.30	-10.11	-17.08	-20.58
Q1	-3.21	-3.54	-3.30	-2.68	-1.02	-1.50	-2.09	-1.65
Med	0.48	1.96	2.03	3.94	0.21	0.71	1.11	2.37
Q3	4.33	6.66	8.64	10.63	2.16	3.99	4.74	6.82
Max	20.38	59.02	77.48	91.81	15.50	33.28	47.13	56.91

Table 2. Factor regressions.

This table shows time-series regression results of the form $y_t=\alpha+\boldsymbol{\beta}'\mathbf{x}_t+\varepsilon_t$, where y is either the simple or the volatility-managed WML return based on 10, 25, 50, or 100 momentum portfolios, and $\mathbf{x}$ is the market factor (Panel A), Fama–French three (1993) (Panel B) or six (2018) (Panel C) factors, Hou–Mo–Xue–Zhang (2020) five factors (Panel D), Stambaugh–Yuan (2017) four factors (Panel E), or Daniel–Hirshleifer–Sun (2020) three-factors (Panel F). Each panel shows the covered months. The *t*-statistics are in parentheses, and alphas are annualized.

	Simple winner-minus-loser				Volatility-managed winner-minus-loser			
	WML_{10}	WML_{25}	WML_{50}	WML_{100}	$vWML_{10}$	$vWML_{25}$	$vWML_{50}$	$vWML_{100}$
	Panel A. CAPM (192701-201912)							
α	18.21	27.21	33.18	37.20	26.94	39.20	44.53	53.05
	(6.95)	(7.85)	(7.82)	(7.01)	(9.58)	(10.71)	(10.16)	(9.85)
Mkt_RF	-0.53	-0.61	-0.58	-0.48	-0.07	-0.13	-0.12	-0.04
	(-13.09)	(-11.43)	(-8.78)	(-5.83)	(-1.69)	(-2.37)	(-1.77)	(-0.42)
R^2	13.34	10.49	6.47	2.96	0.26	0.50	0.28	0.02
	Panel B. Fama–French (1993) three-factor model (192701-201912)							
α	20.65	30.20	36.42	41.03	27.88	40.28	45.86	54.73
	(8.42)	(9.21)	(8.96)	(8.04)	(9.98)	(11.09)	(10.55)	(10.23)
Mkt_RF	-0.38	-0.42	-0.36	-0.19	0.01	-0.02	0.02	0.13
	(-9.30)	(-7.68)	(-5.30)	(-2.19)	(0.29)	(-0.38)	(0.27)	(1.41)
SMB	-0.20	-0.30	-0.37	-0.69	-0.27	-0.39	-0.49	-0.52
	(-2.92)	(-3.32)	(-3.36)	(-4.93)	(-3.53)	(-3.93)	(-4.15)	(-3.57)
HML	-0.74	-0.89	-0.95	-1.05	-0.23	-0.24	-0.29	-0.40
	(-12.45)	(-11.16)	(-9.62)	(-8.45)	(-3.37)	(-2.72)	(-2.76)	(-3.06)
R^2	24.71	20.49	14.72	11.00	2.47	2.62	2.57	2.08
	Panel C. Fama–French (2018) six-factor model (196307-201912)							
α	3.38	11.85	16.77	17.05	25.32	41.95	45.20	53.81
	(2.54)	(4.72)	(4.69)	(3.20)	(6.84)	(8.32)	(7.53)	(7.13)
Mkt_RF	-0.55	-0.57	-0.21	1.43	0.82	0.74	1.85	4.45
	(-1.66)	(-0.92)	(-0.24)	(1.08)	(0.89)	(0.59)	(1.24)	(2.38)
SMB	-0.04	-0.07	-0.10	-0.34	-0.26	-0.43	-0.55	-0.68
	(-0.99)	(-1.04)	(-1.03)	(-2.22)	(-2.50)	(-2.96)	(-3.19)	(-3.14)
HML	-0.03	0.00	0.12	-0.25	0.31	0.41	0.44	0.38
	(-0.56)	(-0.03)	(0.86)	(-1.18)	(2.05)	(1.99)	(1.82)	(1.23)
RMW	0.12	0.19	0.27	0.48	-0.02	-0.03	0.10	0.23
	(2.18)	(1.93)	(1.86)	(2.23)	(-0.14)	(-0.17)	(0.39)	(0.75)
CMA	0.05	0.01	-0.19	0.16	-0.56	-0.67	-0.68	-0.66
	(0.65)	(0.07)	(-0.90)	(0.51)	(-2.54)	(-2.25)	(-1.92)	(-1.48)
UMD	1.51	1.73	1.92	2.12	1.01	1.26	1.54	1.67
	(57.32)	(34.91)	(27.22)	(20.20)	(13.82)	(12.62)	(13.01)	(11.24)
R^2	84.81	67.49	55.48	42.17	23.89	21.07	22.28	18.19

Table 2. *Continued.* Factor regressions.

	Simple winner-minus-loser				Volatility-managed winner-minus-loser			
	WML_{10}	WML_{25}	WML_{50}	WML_{100}	$vWML_{10}$	$vWML_{25}$	$vWML_{50}$	$vWML_{100}$
	Panel D. Hou–Mo–Xue–Zhang (2020) five-factor model (196701-201912)							
α	-0.79	6.22	10.31	11.59	20.60	35.00	35.50	44.32
	(-0.24)	(1.40)	(1.88)	(1.56)	(4.38)	(5.52)	(4.70)	(4.74)
R_MKT	-0.10	-0.09	-0.07	0.03	0.10	0.13	0.23	0.44
	(-1.56)	(-1.08)	(-0.70)	(0.19)	(1.17)	(1.09)	(1.62)	(2.51)
R_ME	0.38	0.43	0.46	0.29	0.03	-0.03	-0.04	-0.08
	(4.48)	(3.78)	(3.32)	(1.54)	(0.28)	(-0.18)	(-0.19)	(-0.34)
R_IA	-0.24	-0.21	-0.29	-0.31	-0.16	-0.17	-0.03	0.03
	(-1.72)	(-1.13)	(-1.23)	(-0.99)	(-0.80)	(-0.62)	(-0.10)	(0.08)
R_ROE	1.21	1.45	1.79	2.25	0.67	0.78	1.24	1.46
	(10.72)	(9.68)	(9.66)	(8.97)	(4.22)	(3.65)	(4.85)	(4.61)
R_EG	0.83	0.96	0.93	0.82	0.74	1.07	1.11	1.18
	(5.00)	(4.31)	(3.38)	(2.21)	(3.13)	(3.39)	(2.95)	(2.52)
R^2	29.91	25.12	22.65	18.22	8.06	7.80	9.37	8.01
	Panel E. Stambaugh–Yuan (2017) four-factor model (196301-201612)							
α	1.25	9.49	15.78	15.66	25.54	41.91	46.08	54.98
	(0.49)	(2.82)	(3.61)	(2.55)	(5.91)	(7.27)	(6.76)	(6.52)
MKTRF	0.09	0.09	0.13	0.26	0.19	0.22	0.32	0.55
	(1.62)	(1.25)	(1.42)	(2.00)	(2.04)	(1.83)	(2.24)	(3.12)
SMB	0.14	0.07	0.01	-0.23	-0.10	-0.31	-0.43	-0.58
	(1.23)	(0.95)	(1.07)	(1.52)	(1.55)	(1.39)	(1.70)	(2.36)
MGMT	0.28	0.26	0.25	0.25	0.17	0.23	0.24	0.30
	(1.06)	(0.81)	(0.93)	(1.31)	(1.33)	(1.20)	(1.46)	(2.03)
PERF	1.35	1.57	1.74	2.05	0.80	1.03	1.34	1.45
	(1.64)	(1.26)	(1.43)	(2.02)	(2.06)	(1.85)	(2.26)	(3.14)
R^2	51.57	45.24	37.27	29.27	11.04	10.87	12.96	10.43
	Panel F. Daniel–Hirshleifer–Sun (2020) three-factor model (197207-201812)							
α	0.38	8.08	11.06	10.82	16.42	33.48	33.31	44.54
	(0.11)	(1.69)	(1.87)	(1.34)	(3.86)	(5.72)	(4.52)	(5.11)
Mkt_RF	-0.12	-0.12	-0.08	-0.02	0.16	0.15	0.21	0.41
	(25.82)	(22.62)	(21.21)	(17.60)	(12.98)	(10.03)	(12.33)	(10.22)
PEAD	1.79	2.09	2.43	2.76	1.07	1.14	1.76	1.72
	(12.35)	(10.82)	(10.15)	(8.42)	(6.21)	(4.80)	(5.90)	(4.89)
FIN	0.18	0.24	0.32	0.39	0.29	0.32	0.43	0.50
	(2.17)	(2.24)	(2.42)	(2.12)	(2.99)	(2.41)	(2.59)	(2.52)
R^2	23.87	19.37	17.18	12.25	7.38	4.62	6.57	4.95

Table 3. Spanning regressions.

This table shows time-series regression results of the form $y_t=\alpha+\boldsymbol{\beta}'\mathbf{x}_t+\varepsilon_t$, where y is either the simple (Panel A) or the volatility-managed (Panel B) WML return based on 25, 50, or 100 momentum portfolios, and $\mathbf{x}$ is the corresponding (or cross-referencing in Panel C) WML return based on 10, 25, 50, or 100 momentum portfolios. The data span January 1927 (WML) or February 1927 (vWML) to December 2019. The *t*-statistics are in parentheses, and alphas are annualized.

	Panel A. Simple winner-minus-loser					
	WML_{25}	WML_{50}	WML_{50}	WML_{100}	WML_{100}	WML_{100}
α	6.28	11.71	4.28	15.67	7.56	2.89
	(3.62)	(4.21)	(6.37)	(3.87)	(4.67)	(5.81)
WML_{10}	1.15	1.21		1.27		
	(62.41)	(40.92)		(29.51)		
WML_{25}			1.09		1.16	
			(73.13)		(46.67)	
WML_{50}						1.07
						(69.54)
R^2	77.76	60.05	82.76	43.87	61.95	75.46
	Panel B. Volatility-managed winner-minus-loser					
	$vWML_{25}$	$vWML_{50}$	$vWML_{50}$	$vWML_{100}$	$vWML_{100}$	$vWML_{100}$
α	11.72	16.93	5.73	24.35	16.57	13.18
	(4.85)	(4.92)	(6.65)	(3.69)	(3.96)	(4.51)
$vWML_{10}$	1.00	1.01		1.08		
	(40.18)	(28.44)		(22.77)		
$vWML_{25}$			0.99		0.95	
			(49.59)		(28.26)	
$vWML_{50}$						0.91
						(36.72)
R^2	59.20	42.09	68.84	31.78	41.78	54.78

	Panel C. Volatility-managed winner-minus-loser by simple winner-minus-loser									
	$vWML_{10}$	$vWML_{25}$	$vWML_{25}$	$vWML_{50}$	$vWML_{50}$	$vWML_{50}$	$vWML_{100}$	$vWML_{100}$	$vWML_{100}$	$vWML_{100}$
α	19.55	30.12	26.55	34.60	30.50	28.06	43.61	39.68	37.37	35.73
	(4.75)	(5.13)	(5.36)	(4.22)	(4.39)	(4.55)	(3.34)	(3.40)	(3.46)	(3.63)
WML_{10}	0.49	0.57		0.64			0.66			
	(38.28)	(28.85)		(25.35)			(20.02)			
WML_{25}			0.52		0.59			0.59		
			(38.77)		(30.38)			(23.53)		
WML_{50}						0.54			0.54	
						(36.13)			(27.50)	
WML_{100}										0.51
										(35.32)
R^2	23.77	19.42	27.00	17.05	24.07	29.61	11.78	16.00	19.35	26.37

Table 4. Market timing regressions.

This table shows Daniel and Moskowitz's (2016) market timing regression results obtained from the following form:

$$y_t = \alpha + [\beta_0 + I_{t-1}^{B}(\beta_B + I_t^{U}\beta_{BU})]R_{Mt}^{e} + \varepsilon_t,$$

where y is either the simple WML (left four columns) or the vWML (right four columns) return based on 10, 25, 50, or 100 momentum portfolios, I^B is a bear-market indicator that equals 1 if the trailing two-year cumulative market return is negative and 0 otherwise, I^U is an up-market indicator that equals 1 if the contemporaneous excess market return is positive and 0 otherwise, and $R_M{}^e$ is the excess market return. The table also shows the beta sum, $\beta_0 + \beta_B + \beta_{BU}$, and the *t*-statistic. The data span July 1928 to December 2019. The *t*-statistics are in parentheses, and alphas are annualized.

	Simple winner-minus-loser				Volatility-managed winner-minus-loser			
	WML_{10}	WML_{25}	WML_{50}	WML_{100}	$vWML_{10}$	$vWML_{25}$	$vWML_{50}$	$vWML_{100}$
α	19.49	28.93	33.75	37.06	28.83	41.98	48.22	57.62
	(7.80)	(8.54)	(7.82)	(6.77)	(9.65)	(10.82)	(10.39)	(10.08)
Mkt_RF	-0.02	-0.03	-0.03	0.07	-0.02	-0.03	0.02	0.09
	(-0.42)	(-0.47)	(-0.35)	(0.62)	(-0.32)	(-0.37)	(0.27)	(0.75)
Bear	-0.71	-0.80	-0.84	-0.94	0.07	0.04	0.06	0.15
	(-6.97)	(-5.77)	(-4.75)	(-4.18)	(0.57)	(0.23)	(0.31)	(0.63)
BearUp	-0.67	-0.77	-0.57	-0.40	-0.33	-0.44	-0.63	-0.70
	(-5.79)	(-4.92)	(-2.87)	(-1.60)	(-2.37)	(-2.47)	(-2.94)	(-2.66)
Sum	-1.40	-1.60	-1.44	-1.27	-0.28	-0.43	-0.54	-0.46
	(-9.46)	(-8.04)	(-4.69)	(-2.62)	(-3.88)	(-4.04)	(-4.81)	(-4.34)
R^2	30.67	23.87	14.17	7.85	0.98	1.43	1.58	0.92

Table 5. Term structure of momentum: factor regressions.

This table shows the regression results of simple/volatility-managed recent/intermediate horizon past performance WML returns (Novy-Marx, 2012; Goyal and Wahal, 2015; Moreira and Muir, 2017) based 10/25/50/100 momentum portfolios on Hou–Mo–Xue–Zhang (2020) five (Panel A)/Daniel–Hirshleifer–Sun (2020) three factors (Panel B). Each panel shows the covered months. Alphas are annualized.

			Simple winner-minus-loser				Volatility-managed winner-minus-loser			
			WML_{10}	WML_{25}	WML_{50}	WML_{100}	$vWML_{10}$	$vWML_{25}$	$vWML_{50}$	$vWML_{100}$
Panel A. Hou–Mo–Xue–Zhang (2020) five-factor model (196701-201912)	(6,2) winner-minus-loser	α	-0.95	4.58	9.57	12.99	16.88	26.40	39.22	42.24
			(-0.29)	(1.12)	(1.93)	(2.01)	(4.03)	(5.14)	(6.06)	(5.01)
		R_MKT	-0.17	-0.14	-0.16	-0.10	0.02	0.01	0.01	0.23
			(-2.84)	(-1.86)	(-1.71)	(-0.83)	(0.19)	(0.11)	(0.08)	(1.47)
		R_ME	0.33	0.41	0.30	0.15	-0.10	-0.11	-0.28	-0.33
			(4.02)	(3.98)	(2.35)	(0.89)	(-0.94)	(-0.87)	(-1.69)	(-1.52)
		R_IA	-0.07	-0.03	-0.01	-0.31	-0.10	0.04	-0.06	-0.04
			(-0.54)	(-0.19)	(-0.04)	(-1.14)	(-0.54)	(0.16)	(-0.20)	(-0.10)
		R_ROE	0.86	1.04	1.16	1.46	0.36	0.55	0.51	0.36
			(7.81)	(7.54)	(6.92)	(6.69)	(2.54)	(3.14)	(2.35)	(1.26)
		R_EG	0.57	0.79	0.79	0.75	0.68	0.70	0.72	1.49
			(3.49)	(3.85)	(3.19)	(2.32)	(3.25)	(2.73)	(2.22)	(3.53)
		R^2	20.21	19.22	16.38	13.27	6.64	6.91	5.25	5.17
	(12,7) winner-minus-loser	α	5.50	9.70	15.33	13.80	16.06	24.82	28.54	30.13
			(1.97)	(2.82)	(3.92)	(2.87)	(3.99)	(4.75)	(4.66)	(3.71)
		R_MKT	0.06	0.06	0.07	0.13	0.11	0.23	0.35	0.38
			(1.24)	(0.95)	(1.00)	(1.45)	(1.52)	(2.36)	(3.09)	(2.51)
		R_ME	0.19	0.19	0.09	0.06	0.23	0.15	-0.10	0.08
			(2.65)	(2.14)	(0.94)	(0.51)	(2.19)	(1.09)	(-0.61)	(0.38)
		R_IA	-0.40	-0.43	-0.57	-0.28	-0.24	-0.33	-0.34	-0.31
			(-3.39)	(-2.98)	(-3.48)	(-1.39)	(-1.44)	(-1.51)	(-1.31)	(-0.91)
		R_ROE	0.74	1.05	0.99	1.34	0.56	0.84	0.69	1.09
			(7.79)	(9.03)	(7.44)	(8.24)	(4.13)	(4.76)	(3.31)	(3.95)
		R_EG	0.49	0.54	0.63	0.51	0.72	0.89	1.20	0.99
			(3.54)	(3.17)	(3.24)	(2.12)	(3.59)	(3.42)	(3.93)	(2.43)
		R^2	17.53	20.22	16.81	16.08	8.04	9.33	8.35	6.21
Panel B. Daniel–Hirshleifer–Sun (2020) three-factor model (197207-201812)	(6,2) winner-minus-loser	α	-3.31	4.05	6.88	5.36	11.91	22.25	32.52	36.97
			(-1.02)	(0.97)	(1.37)	(0.81)	(2.90)	(4.40)	(5.06)	(4.46)
		Mkt_RF	-0.15	-0.14	-0.18	-0.09	0.05	0.04	0.05	0.23
			(26.32)	(23.32)	(23.26)	(21.43)	(13.56)	(13.18)	(11.85)	(11.60)
		PEAD	1.66	1.89	2.26	2.74	1.08	1.29	1.47	1.86
			(12.59)	(11.16)	(11.13)	(10.25)	(6.49)	(6.31)	(5.67)	(5.55)
		FIN	0.16	0.24	0.26	0.28	0.27	0.29	0.34	0.48
			(2.22)	(2.52)	(2.28)	(1.88)	(2.88)	(2.56)	(2.36)	(2.54)
		R^2	25.36	21.00	20.84	17.11	8.17	7.67	6.31	5.92
	(12,7) winner-minus-loser	α	7.47	10.22	16.15	13.25	18.32	25.77	31.68	31.59
			(2.46)	(2.69)	(3.81)	(2.53)	(4.66)	(4.95)	(5.34)	(3.79)
		Mkt_RF	0.04	0.05	0.03	0.10	0.15	0.27	0.36	0.39
			(16.19)	(16.65)	(15.51)	(13.98)	(9.84)	(9.66)	(10.13)	(6.73)
		PEAD	0.95	1.22	1.27	1.42	0.75	0.97	1.16	1.09
			(7.75)	(7.97)	(7.42)	(6.69)	(4.71)	(4.62)	(4.84)	(3.22)
		FIN	0.01	0.13	0.07	0.21	0.16	0.27	0.34	0.34
			(0.11)	(1.51)	(0.74)	(1.77)	(1.80)	(2.28)	(2.51)	(1.80)
		R^2	9.84	10.47	9.12	7.71	4.22	4.55	5.23	2.58

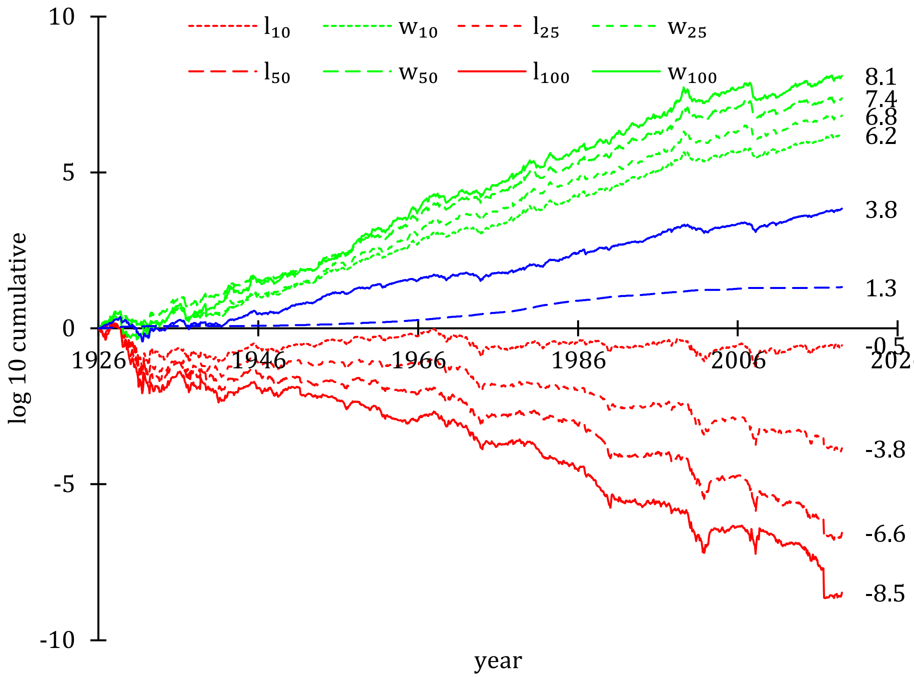

Figure 1. Winner and loser portfolios.

The figure shows log 10-scaled cumulative monthly returns to winner and loser portfolios from value-weighted momentum portfolios. Green and red lines are the winner and the loser portfolios, respectively. Dotted (most inside), hyphened, dashed, and solid (most outside) lines are from the 10, 25, 50, and 100 momentum portfolios, respectively. Because the y-axis is log 10-scaled, the winner portfolios' 8.1, 7.4, 6.8, and 6.2 correspond to about 126.3M, 24.2M, 6.7M, and 1.6M dollars, respectively, and the loser portfolios' −0.5, −3.8, −6.6, and −8.5 correspond to about 0.287, 0.000142, 0.000000277, and 0.000000003348 dollars, respectively. Blue lines are the market (solid, 6.8K dollars) and the risk-free position (dashed, 20.9 dollars), respectively. The data are based on CRSP and span December 1926 to December 2019.

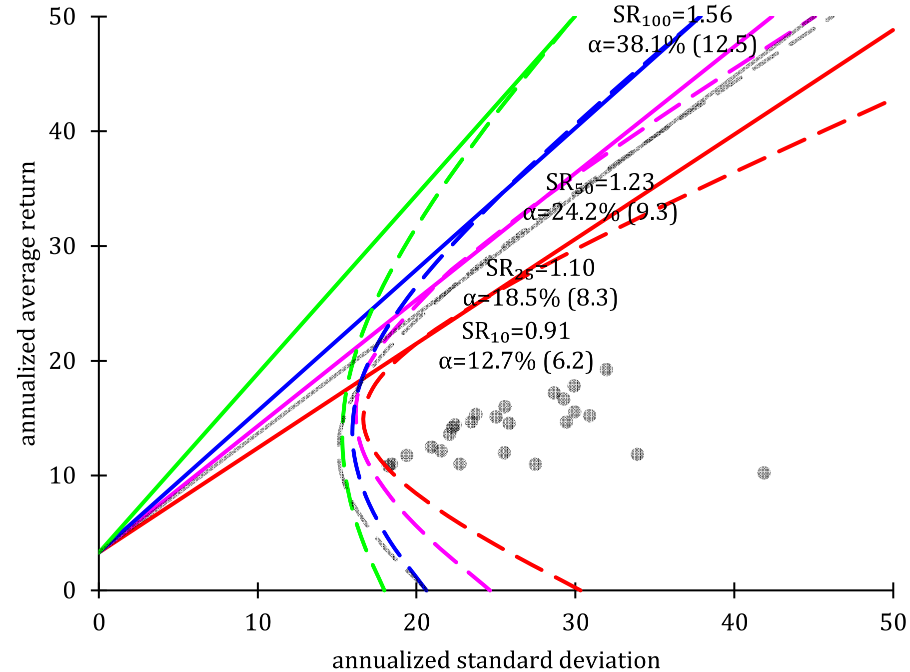

Figure 2. Minimum-variance frontiers and capital allocation lines.

The figure shows minimum-variance frontiers (dashed) and capital allocation lines (solid) spanned from value-weighted momentum portfolios. Red, magenta, blue, and green lines are from 10, 25, 50, and 100 momentum portfolios, respectively. The y-intercept is the risk-free rate. The figure also shows maximum ex-post Sharpe ratios and their spanning regression alphas on the maximum ex-post Sharpe ratio of 5×5 size and book-to-market portfolios. Average returns, standard deviations, Sharpe ratios, and spanning alphas are annualized, and the *t*-statistics are in parentheses. Transparent black circles, dashed lines, and solid lines are the size and book-to-market portfolios, the spanned minimum-variance frontier, and the corresponding capital allocation line, respectively. The data span January 1927 to December 2019.

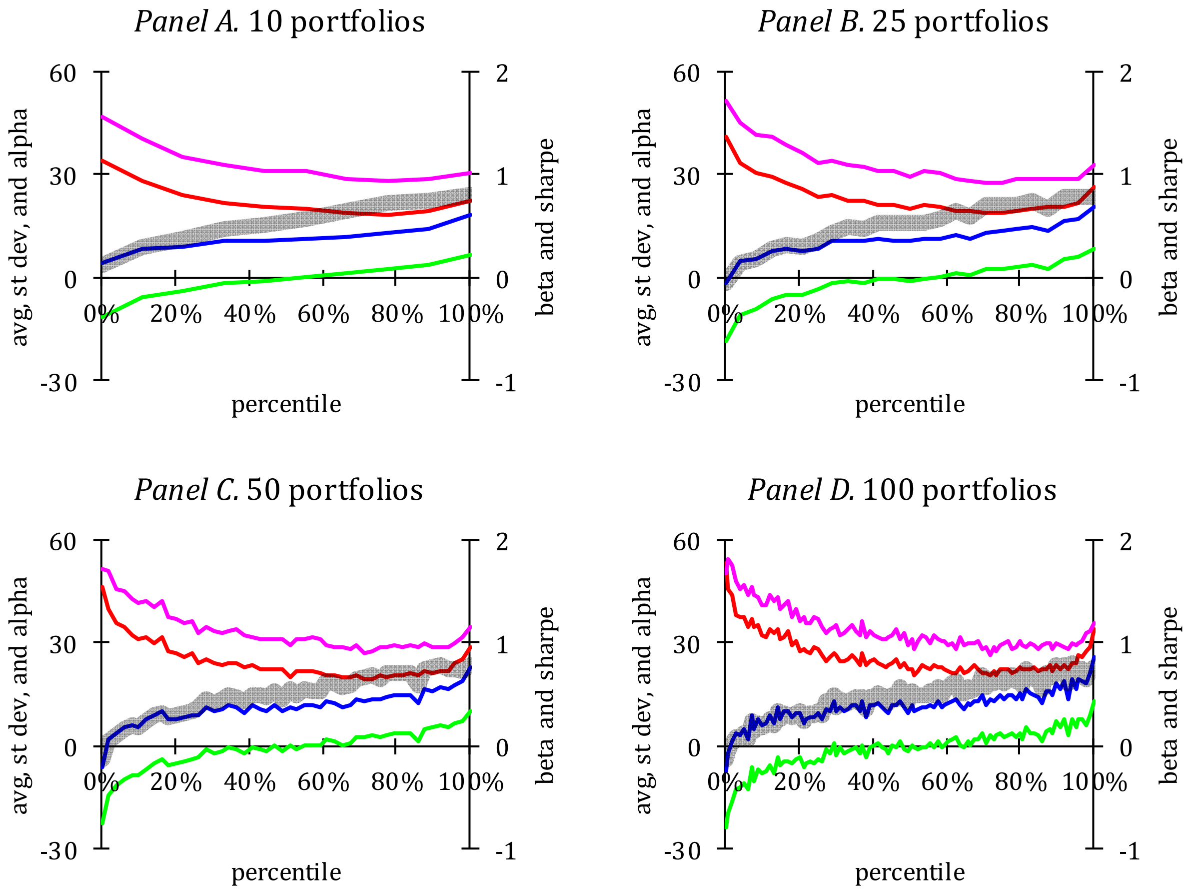

Figure 3. Average returns, standard deviations, Sharpe ratios, alphas, and betas of momentum portfolios. The figure shows the annualized monthly average returns, standard deviations, Sharpe ratios, CAPM alphas, and market betas of 10, 25, 50, and 100 momentum portfolios. The x-axis shows the percentile—the most loser and the most winner portfolio are at 0% and 100%, respectively. Blue, red, green, and magenta lines are the average returns, standard deviations, alphas, and betas of the momentum portfolios, respectively. Black shades are the Sharpe ratios. The data are based on CRSP and span December 1926 to December 2019.

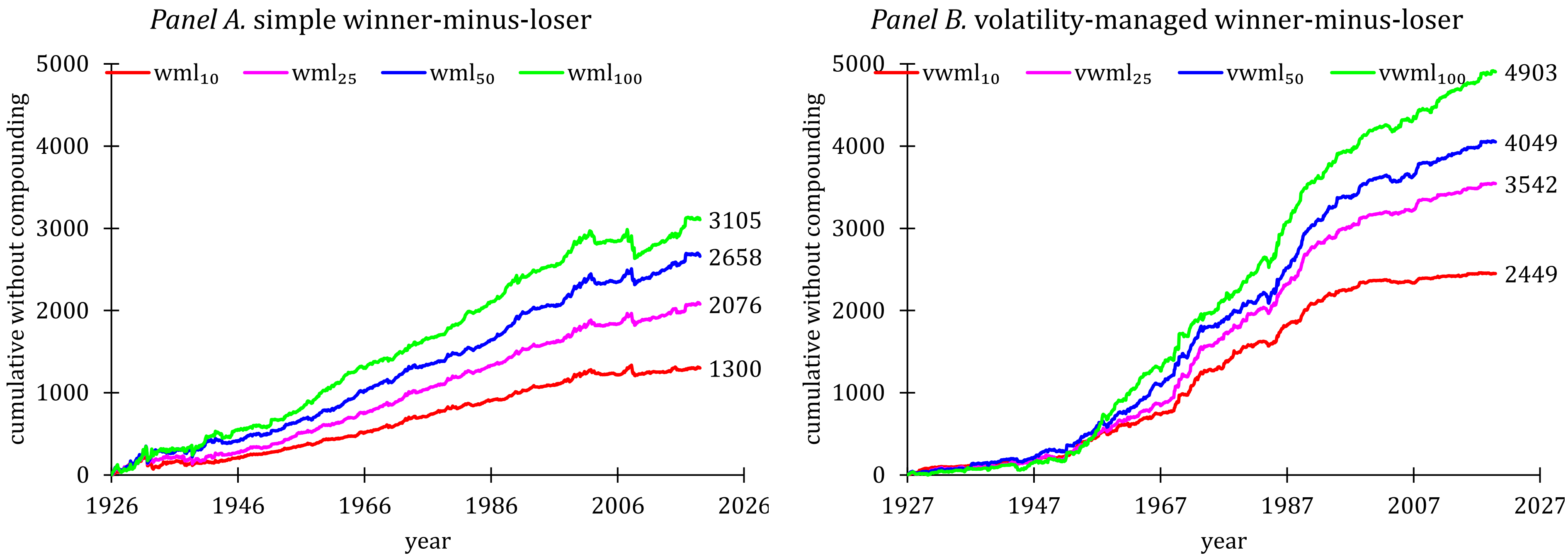

Figure 4. Cumulative simple winner-minus-loser returns.

The figure shows cumulative, non-compounding, returns to simple (Panel A) and volatility-managed (Panel B) winner-minus-loser positions, respectively, from value-weighted momentum portfolios. Red, magenta, blue, and green lines are the winner-minus-loser positions from 10, 25, 50, and 100 value-weighted momentum portfolios, respectively. The data are based on CRSP and span December 1926 to December 2019.

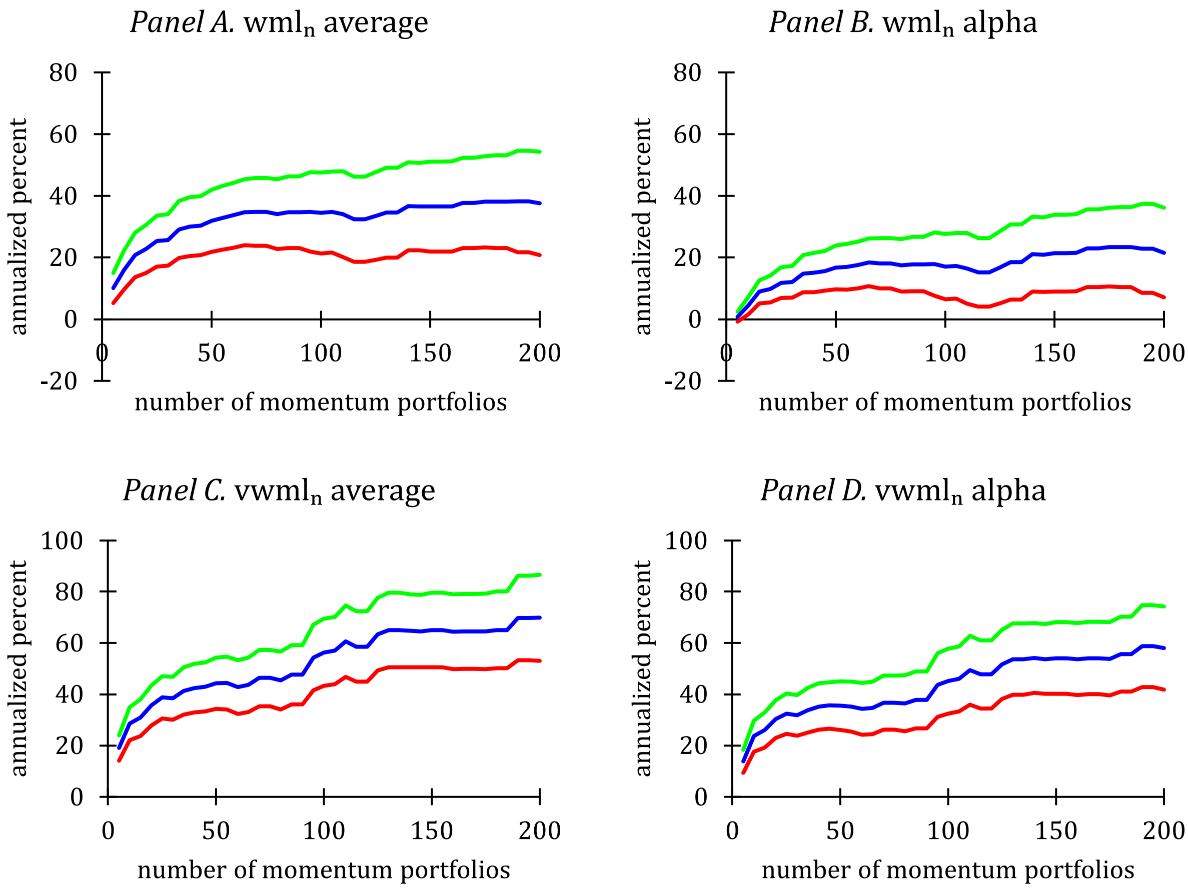

Figure 5. Number of momentum portfolios and winner-minus-loser performance.

The figure shows the average return (Panel A) and alpha (Fama and French, 2018) (Panel B) of the simple winner-minus-loser position and the average return (Panel C) and alpha (Panel D) of the volatility-managed winner-minus-loser position (Moreira and Muir, 2017) as functions of $n \in \{5, 10, \cdots, 200\}$, the number of momentum portfolios—for example, WML_5 and WML_{200} are on the left and the right. Blue, green, and red are the statistics and their two standard error bands. Average returns and alphas are annualized. The data are based on CRSP and span July 1963 to December 2019.

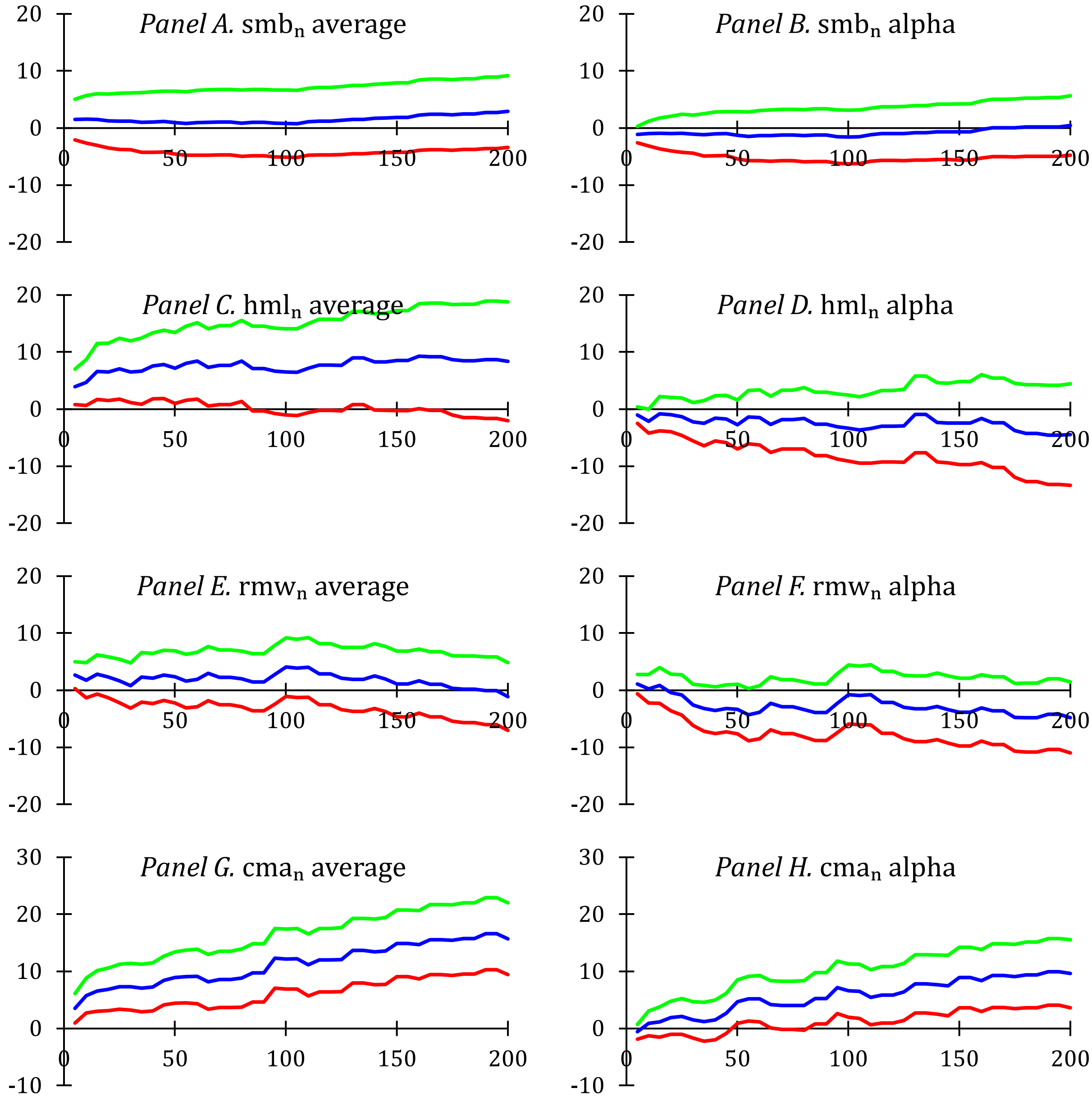

Figure 6. Number of portfolios and long-short performance.

The figure shows the average returns (left) and Fama–French six-factor (2018) alphas (right) of the long-short positions formed on size (first; small-minus-big), book-to-market (second; high-minus-low), operating profitability (third; robust-minus-weak), and investment (fourth; conservative-minus-aggressive), respectively, as functions of $n \in \{5,10,\cdots,200\}$, the number of portfolios. Blue, green, and red are the statistics and their two standard error bands. The data span July 1963 to December 2019. In addition, Figures A13 and A14 in the appendix show extensive results for Kozak's (2020) 49 anomalies and Chen and Zimmermann's (2022) 128 anomalies, respectively.