Do Limits to Arbitrage Explain the Benefits of Volatility-Managed Portfolios?

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October 29, 2019

Abstract

We investigate whether transaction costs, arbitrage risk, and short-sale constraints explain the abnormal returns of volatility-managed equity portfolios. Even using five cost-mitigation strategies, after accounting for transaction costs, volatility management of common asset-pricing factors besides the market return generally produces zero abnormal returns and significantly reduces Sharpe ratios. In contrast, abnormal returns of the volatility-managed market portfolio are profitable after transaction costs and concentrated in the most easily arbitraged stocks, those with low arbitrage risk and short-sale constraints. Moreover, the managed-market strategy only provides superior performance when sentiment is high, consistent with prior theory that sentiment traders under-react to volatility.

JEL classification: G11, G12, G14
Keywords: Volatility-managed portfolios, limits to arbitrage, anomalies

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We investigate whether transaction costs, arbitrage risk, and short-sale constraints explain the abnormal returns of volatility-managed equity portfolios. Even using five cost-mitigation strategies, after accounting for transaction costs, volatility management of common asset-pricing factors besides the market return generally produces zero abnormal returns and significantly reduces Sharpe ratios. In contrast, abnormal returns of the volatility-managed market portfolio are profitable after transaction costs and concentrated in the most easily arbitraged stocks, those with low arbitrage risk and short-sale constraints. Moreover, the managed-market strategy only provides superior performance when sentiment is high, consistent with prior theory that sentiment traders under-react to volatility.

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I. Introduction

A pervasive stylized fact in equity markets is that volatility persists from one month to the next but only weakly correlates with future returns. This phenomenon implies that financial markets allow the price of risk to fall as risk rises, contrary to the predictions of rational asset-pricing models.[1] Said differently, investors seem to "underreact", or "trade slowly", relative to volatility shocks. Several recent studies find that trading strategies called volatility-managed portfolios ("VMPs"), which exploit this pattern in returns by dynamically varying portfolio leverage inversely with risk, produce significant abnormal returns and large increases in investor utility.[2] In particular, Moreira and Muir (2017) show this result obtains for the market portfolio along with common equity-pricing factors based on book-to-market ratio, momentum, investment, profitability, and beta.

Violations of rational models are not surprising, however, if limits to arbitrage ("LTA") prevent correction of mispricing. Arbitrageurs will only commit capital to a trade that produces abnormal returns to the extent it is possible and economically profitable (e.g., Jensen, 1978). Transaction costs, for example, can render anomalies in "paper" returns unprofitable (e.g., Novy-Marx and Velikov, 2016), short-sale constraints can allow "over-pricing" to persist by preventing trades that impound negative beliefs in prices (e.g., Miller, 1977), and arbitrage risk deters traders from taking arbitrarily large positions (e.g., Shleifer and Vishny, 1997; Pontiff, 2006). In this paper, we test the hypothesis that LTA prevent the elimination of the abnormal returns of volatility-managed portfolios, which require high degrees of turnover, leverage, and short selling, often in relatively expensive-to-trade individual stocks.

In the first part of this paper, we evaluate the performance of VMPs besides the managed market portfolio after transaction costs using the methodology of Novy-Marx and Velikov (2016), which infers marginal portfolio trading costs for a typical trader from the stock-level effective spread estimator of Hasbrouck (2009). An important benefit to this approach is that our spread

[1] Moreira and Muir (2017) show that the following rational models of asset prices predict a weakly positive risk-return tradefoff: The habits model (Campbell and Cochrane, 1999), the long-run-risk model (Bansal, Kiku, and Yaron, 2012), the time-varying rare disasters model (Wachter, 2013), and the intermediary asset-pricing model (He and Krishnamurthy, 2013).

[2] See, e.g., Fleming, Kirby, and Ostdiek, 2001, 2003; Marquering and Verbeek, 2004; Kirby and Ostdiek, 2012; Barroso and Santa-Clara, 2015; Moreira and Muir, 2017, 2018; Barroso and Maio, 2017; Cederburg, O'Doherty, Wang, and Yan, 2019; and Eisdorfer and Misirli, 2019.

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estimates are widely available for individual stocks over the entire CRSP sample period. We consider volatility-managed versions of the size, value, momentum, profitability, and investment factors of Fama and French (1993, 2015), Carhart (1997), and Hou, Xue, and Zhang (2015), along with the betting-against-beta factor of Frazzini and Pedersen (2014). Moreira and Muir (2017) document that these VMPs earn significant and economically large alphas. Unlike timing the market portfolio, traders can not implement strategies with these factors using relatively inexpensive-to-trade ETFs and derivatives; they must trade individual stocks. Moreover, these factors take relatively large positions in small-cap stocks that tend to be relatively expensive to trade. To make matters worse, time-varying leverage inherent to VMPs can significantly increase trading costs by increasing the maximum possible trade size and forcing trades when none would exist in corresponding unmanaged portfolios.

Our baseline specification of volatility management follows Moreira and Muir (2017) and scales monthly returns by the inverse of their prior month's realized variance. We find that this specification greatly increases monthly turnover by as much as 15 times relative to corresponding unmanaged factors, with transaction costs increasing by as much as 18% per year. As a result, after costs, none of the baseline VMPs earn positive alpha in the whole sample or any subsample we consider, and six out of eight managed factors have significantly lower Sharpe ratios than their unmanaged counterparts. We further find that five different cost-mitigation strategies designed to slow trading or screen out expensive-to-trade stocks generally fail to make VMPs profitable after costs, with one notable exception. The managed momentum strategy becomes profitable when scaling by realized volatility estimated over rolling prior-six-month windows, consistent with Barroso and Santa-Clara (2015), and when excluding small-cap stocks from the construction of the momentum factor. Overall, our transaction costs results provide a natural explanation for why slow trading relative to volatility shocks survives in markets to the degree necessary to generate the abnormal returns of volatility-managed long-short portfolios; it is simply unprofitable to trade "less slowly". Moreover, Arnott et al. (2017) and Patton and Weller (2019) show that many large institutional investors face higher "all-in" implementation costs of trading strategies than implied by our effective spread measures. For these investors, our trading cost estimates of VMPs are a sharp lower bound.

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In the second part of this paper, we examine whether LTA besides transaction costs can explain the abnormal returns of the volatility-managed market portfolio.[3] While traders can time the market with relatively low transaction costs, it is still possible that other LTA prevent arbitrageurs from eliminating mispricing of volatility shocks. To test this hypothesis, we evaluate whether two of the most widely used LTA, arbitrage risk and short-sale constraints, explain the abnormal returns of the volatility-managed market portfolio. Many studies show that anomaly returns increase in the cross-section with high levels of these quantities.[4] Following this literature, we partition the market portfolio into three value-weighted portfolios based on the LTA measures and then scale each of these portfolios by the leverage used in the managed-market strategy. Abnormal returns of these portfolios indicate the degree to which the managed-market strategy derives its performance from low-, medium-, or high-LTA stocks. We measure arbitrage risk with idiosyncratic volatility and short-sale constraints inversely by institutional ownership, which is the chief source of the supply loanable shares for short selling equities. In stark contrast with the LTA hypothesis, and the prior literature on anomalies, volatility management produces the largest abnormal returns for the portfolios consisting of stocks that are *easiest* to arbitrage, those with the lowest arbitrage risk and short-sale constraints. Thus, stock-level LTA do not explain the apparent under-reaction of prices to volatility shocks.

The existing literature overlooks a potential sentiment-based explanation of the managed-market portfolio's performance that is consistent with our LTA findings. Yu and Yuan (2011) argue theoretically, and show empirically, that while the predictive relationship between monthly realized volatility and future returns is insignificant *unconditionally*, it becomes significantly positive when sentiment is low and vice versa. Two assumptions about the behavior of sentiment traders generate this pattern: first, they under-react to volatility news when sentiment is high, and

[3]Moreira and Muir (2017) show this strategy is robust to realistic transaction costs even without using ETFs and derivatives. They do not, however, investigate the role of costs in explaining volatility-managed versions of non-market factors.

[4]For example, Pontiff (1996), Wurgler and Zhuravskaya (2002), Ali, Hwang, and Trombley (2003), Mashruwala et al. (2006), Zhang (2006), Scruggs (2007), McLean (2010), Li and Zhang (2010), Stambaugh, Yu, and Yuan (2015), Larrain and Varas (2013), and Stambaugh and Yuan (2017) document that anomaly returns increase in the cross-section with arbitrage risk measured by idiosyncratic return volatility. Similarly, D'Avolio (2002), Asquith et al. (2005), Nagel (2005), Duan et al. (2010), Hirshleifer, Teoh, and Yu (2011), and Avramov et al. (2013) show that anomaly returns decrease in the cross-section with short-sale constraints.

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second, they buy more aggressively than they sell short. In particular, these behaviors generate an "under-reaction" to volatility, which is necessary (though not sufficient) to explain the abnormal returns of the volatility-managed market portfolio, but only when sentiment is high. Consistent with Yu and Yuan (2011), following high realizations of the Baker and Wurgler (2006) sentiment index, volatility-management more than doubles the Sharpe ratio of the market portfolio. Conversely, when sentiment is low, volatility-management actually reduces the market Sharpe ratio by about half. Overall, these results are consistent with sentiment trading generating the abnormal returns of the volatility-managed market portfolio, which refines and substantiates the unconditional slow-trading hypothesis of Moreira and Muir (2017).

Our findings complement those of Cederburg et al. (2019), who find that estimating portfolio weights necessary to optimally benefit from the alphas of VMPs in real time is challenging. However, that same criticism applies more generally to the common practice of interpreting alphas as beneficial to investors. Similarly, Liu, Tang, and Zhou (2019) argue that estimating other parameters relevant for volatility management is difficult in real time. In these studies, estimation error deters volatility management. However, they can not rule out the possibility that investors have some way of estimating portfolio weights that take advantage of alphas, for example, using robust optimization methods (e.g., Kirby and Ostdiek, 2012) or naive 1/N weights (e.g., DeMiguel et al., 2009). Our results have stronger implications. The fact that for most factors and volatility management strategies, transaction costs eliminate the alpha produced by volatility management precludes the possibility of finding any weight on these managed factors that expands the mean-variance frontier.

Our sentiment results also relate to other studies that many anomaly returns are relatively high in times of high sentiment for similar reasons. For example, Antoniou, Doukas, and Subrahmanyam (2013) argue that momentum returns are concentrated in high-sentiment times because irrational investors are "overconfident" in their high valuations when sentiment is high and under-react to negative news. Stambaugh et al. (2012) and Stambaugh and Yuan (2017) find that returns on eleven anomalies are relatively high when sentiment is high. They attribute the finding to overvaluation of anomaly short legs caused by high sentiment being harder to correct than undervaluation of long legs caused by low sentiment. Antoniou, Doukas, and Subrahmanyam (2016) argue that high

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sentiment increases the participation of unsophisticated traders and find evidence that these traders disproportionately overvalue high-beta stocks.

The rest of this paper is organized as follows. Section II describes our data and methodology. Section III presents results for factors besides the market portfolio. Section IV presents results for the market portfolio. Section V concludes.

II. Data and methods

A. Volatility-managed portfolio construction

Following Moreira and Muir (2017), our baseline formulation of VMPs is defined as follows. Letting f_t denote a buy-and-hold ("unmanaged") excess return in month t, the volatility-managed version of f_t, denoted f_t^{σ}, is defined as:

$$f_t^{\sigma} = \frac{c}{RV_{t-1}^2} \cdot f_t, \tag{1}$$

where RV_{t-1}^2 is the realized sample variance of daily returns on f_t in month $t-1$, and the constant c is chosen to equate the unconditional volatility of f_t and that of f_t^{σ}. The motivation for Eq. (1) comes from the optimal portfolio choice of a mean-variance investor. If f_t is the market return, or uncorrelated with other factors, then the optimal weight in f_{t+1} is proportional to $\frac{E_t(f_{t+1})}{\sigma_t^2(f_{t+1})}$, where $E_t(f_{t+1})$ and $\sigma_t^2(f_{t+1})$ denote the conditional mean and variance, respectively, of f_{t+1}. Since expected returns are highly unpredictable at the monthly frequency while volatility is highly persistent, $\frac{c}{RV_{t-1}^2}$ approximates $\frac{E_t(f_{t+1})}{\sigma_t^2(f_{t+1})}$ in Eq. (1). While scaling by RV is theoretically sound, it is not necessarily the most cost-effective option, so we also consider several cost-mitigation strategies below that include alternative leverage factors to $\frac{c}{RV_{t-1}^2}$.

B. Data

Daily and monthly before-costs returns on the equity factors come directly from the website of Kenneth French (for the market return, MKT, and the Fama and French, 1993; Carhart, 1997, and Fama and French, 2015 factors: SMB, HML, MOM, CMA, and RMW), Chen Xue (for the

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Hou et al., 2015 factors: ROE, and IA), and the AQR website (for the Frazzini and Pedersen, 2014 betting-against-beta factor, BAB).[5] Daily and monthly data on individual common stocks from CRSP and annual accounting data from COMPUSTAT. Following Yu and Yuan (2011), we obtain the annual-frequency Baker and Wurgler (2006) index orthogonalized to economic conditions, BW, from the website of Jeffrey Wurgler. Institutional ownership, IO, is the percentage of shares owned by institutional owners and comes from Thomson Financial 13(f) Institutional Holdings at the quarterly frequency.

Following Moreira and Muir (2017), our maximum sample period is July 1926 to December 2015 and we also consider the three 30-year subsamples: July 1926 to December 1955, January 1956 to December 1985, and January 1986 to December 2015. The factors CMA and RMW are only available for the period July 1963 to December 2015, while the other Fama-French factors are available over effectively the maximum sample (MOM is available since January 1927). The sentiment index BW is available since 1965.

C. Replicated factors and transaction costs

We follow Novy-Marx and Velikov (2016) to compute strategy trading costs in two steps. First, we estimate effective one-way stock-level proportional transaction costs for a typical trader ("spreads" or "bid-ask spreads") following Hasbrouck (2009).[6] Second, we use these stock-level spread estimates to compute portfolio-level costs (See Appendix A for relevant formulas). Like most leading measures of spreads, the Hasbrouck measure is based on the classic microstructure model of Roll (1984), which assumes the efficient value of a stock follows a random walk, and the observed trade prices deviate from this value by the effective spread. The key advantage of the Hasbrouck measure is that it uses daily CRSP data instead of high-frequency TAQ data, and therefore has very wide

[5] See, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` and `https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly`, respectively

[6] Hasbrouck provides SAS code to estimate effective spreads at http://people.stern.nyu.edu/jhasbrou/. We also fill in missing observations following Novy-Marx and Velikov (2016) by assigning to each stock-month i, t missing an estimate of effective spread that of the stock j, t with the closest match in terms of market capitalization and idiosyncratic volatility, or only the former if the latter is unavailable. Idiosyncratic volatility is defined to be the standard deviation of residuals from a CAPM regression over the three months of daily data ending in month t.

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coverage over the entire CRSP sample.[7] The primary limitation of the Hasbrouck spread measure is that it does not consider the price impact of very large trades. Hence, it should be interpreted as the marginal transaction cost for the typical trader. It is appropriate to assume the use of market orders because the equity factors are constructed under the assumption that trades happen immediately. For example, the construction of HML assumes execution of the strategy each year at exactly the closing price and instant at the end of June. Our approach is also used by a growing literature, including Detzel and Strauss (2018), Detzel, Schaberl, and Strauss (2019), DeMiguel, Martín-Utrera, Nogales, and Uppal (2019), and Chen and Velikov (2019).[8]

Figure 1 depicts annual time series of value-weighted Hasbrouck spreads for four portfolios formed on the basis of NYSE July market-capitalization-quartile breakpoints. This figure demonstrates two key empirical facts for understanding the asset-pricing implications of transaction costs. First, small-cap stocks, which receive substantial weight in the factors used in this paper, have relatively high costs, especially during the depression era. Second, transaction costs decline later in the sample.[9] Considering both patterns, it is important to examine subsample performance when accounting for transaction costs.

FIGURE 1 ABOUT HERE

Table I presents summary statistics of the (unmanaged) asset pricing factors. Over the entire sample, before costs, the factors have statistically significant average returns of 2.53% (SMB) to 8.25% (MOM) per year. However, transaction costs, which range from 0.62% for SMB, which trades only once per year, to 8.52% for MOM, which trades monthly, bring down the economically large before-costs Sharpe ratios by up to 0.52 per year. After costs, MOM even has negative average net returns, which is consistent with Lesmond, Schill, and Zhou (2004) and Patton and Weller (2019), who also find that momentum is unprofitable after accounting for costs. Comparing the subsample results shows that transaction costs have the largest reductions in profitability in

[7]In spite of being based on daily data, Hasbrouck shows this is a highly accurate measure of transaction costs as it has a 96.5% correlation with effective spreads based directly on Trade and Quote (TAQ) data.

[8]Strictly speaking, DeMiguel et al. (2019) follow Brandt, Santa-Clara, and Valkanov (2009) and use a parametric proportional spread measure based on market value, but the parameters were originally calibrated against the spread measure of Hasbrouck (2009) so their spreads are close to our values.

[9]See Detzel and Strauss (2018) for more details on these patterns.

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the first 30 years of the subsample. Average net returns and Sharpe ratios are generally positive and relatively large in the subsequent subsamples.

Table I about here

III. Results: Non-market factors

A. Baseline results without transaction costs

Panel A of Table II, which presents performance statistics of the managed factors ignoring transaction costs, replicates and extends the main managed equity-factor results of Moreira and Muir (2017) (their Table I). We run regressions of excess returns on the managed factors on those of their unmanaged counterparts:

$$f_t^{\sigma} = \alpha + \beta f_t + \epsilon_t. \tag{2}$$

A nonzero alpha measures abnormal returns and indicates that the maximum Sharpe ratio attainable from access to the buy-and-hold and volatility-managed versions of the factor, $SR(f, f^{\sigma})$, is higher than that of the buy-and-hold position in f alone, $SR(f)$. Following Campbell and Thompson (2008), we gauge economic significance of alphas by reporting the gains in certainty-equivalent returns (ΔCER) experienced by a mean-variance investor with risk aversion of three who achieves the increased Sharpe ratio from $SR(f)$ to $SR(f, f^{\sigma})$.[10]

Table II about here

Panel B presents alphas and significance tests for the difference in Sharpe ratios $SR(f^{\sigma})-SR(f)$ for the three 30-year subsamples (1926 to 1955, 1956 to 1985, and 1986 to 2015). The results generally show reliably positive alpha point estimates for the seven portfolios with significantly

[10]This quantity is given by:

$$\Delta CER = \left(E(r^*_{f,f^{\sigma}}) - \frac{\gamma}{2}\sigma^2(r^*_{f,f^{\sigma}})\right) - \left(E(f) - \frac{\gamma}{2}\sigma^2(f)\right), \tag{3}$$

where $r^*_{f,f^{\sigma}}$ is the return on the ex-post MVE portfolio in the span of f and f^{σ}, and γ is risk aversion. In the absence of transaction costs, the following relationship also holds: $\Delta CER = (2\gamma)^{-1}(SR^2(f, f^{\sigma}) - SR^2(f))$. In the case of mean-variance utility, ΔCER can also be interpreted as (i) the increase in utility achieved by investing in r^* instead of the buy-and-hold f, or (ii) the maximum fee a mean-variance investor would pay to invest in r^* as instead of f.

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positive alpha in Panel A. The number of significant Sharpe ratio improvements from $SR(f)$ to $SR(f^{\sigma})$ increases from none in the early subsample to three in the most recent subsample. Taken as a whole, the results in Panel B indicate the alphas from of Panel A are not driven only by a single subsample.

B. Main specification with transaction costs

Figure 2 depicts the average turnover and transaction costs associated with the baseline strategies in Table II besides the managed-market strategy. Volatility management dramatically increases turnover and transaction costs. Panel A shows that for factors with annual rebalancing (SMB, HML, CMA, and RMW), managed factor turnover ranges from six (CMA) to fifteen (SMB) times that of the unmanaged factor. This is because management forces large monthly trades when none would otherwise exist, rendering a relatively large increase in costs compared to factors with higher frequency rebalancing (see, e.g., Barroso and Santa-Clara, 2015). For factors that rebalance monthly (MOM, ROE, IA, and BAB), volatility management increases turnover by two (ROE) to seven (BAB) times. Panel B shows that transaction costs for the VMPs are commensurate with the turnover and range from seven (RMW) to eighteen (MOM and BAB) percent per year for the strategies with significant alphas in Table II.

Figure 2 about here

Table III presents net-of-costs performance statistics for the strategies in Table II and Figure 2. After costs, the regression-based α from Eq. (2) does not represent realizable abnormal returns. Hence, Table III uses the generalized alpha of Novy-Marx and Velikov (2016), which has similar units and interpretation as the standard notion of alpha after considering costs (see Appendix B for details). The first four rows of Panel A show that over 1927 to 2015, the costs shown in Figure 2 are so great that they render the average net returns negative for all managed factors in Table II. No managed factor achieves a non-zero generalized alpha and for six of the eight factors, volatility management significantly lowers ($p < 0.01$) the Sharpe ratio relative to the buy-and-hold strategy. Panels B, C, and D report effectively the same result over all three subsamples. Overall, Table III

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shows that transaction costs eliminate the profits associated with the VMPs of Moreira and Muir (2017).

Table III about here

C. Cost-mitigation strategies

The main strategy of Moreira and Muir (2017) for volatility management, which scales by monthly realized variance, was not designed to economize on costs. Hence, we next evaluate whether cost-mitigation techniques render VMPs profitable after costs.

Cost-mitigation strategies reduce liquidity demand by using one of two kinds of techniques: (i) slowing down trading or (ii) avoiding stocks that are expensive to trade. As seen in Figure 2, slowing down trading in the unmanaged factor tends to worsen the relative after-cost performance of VMPs.[11] Instead, slowing down the time-series variation in the factor leverage has more potential to reduce costs. We use five cost-mitigation techniques that either slow down leveraging and deleveraging with volatility or filter out expensive-to-trade stocks. The first three techniques, which fall into the former category, are proposed by Moreira and Muir (2017) for the market factor and include: scaling by prior-month standard deviation instead of variance, using expected rather than realized variance, and capping leverage at 1.5.

The fourth technique follows Barroso and Santa-Clara (2015) and scales by realized standard deviation estimated using daily data over the prior rolling six-month period instead of prior-month variance. This approach does not necessarily aim at an optimal allocation from the perspective of a mean-variance investor. Rather, it is a simple risk-management approach that aims to keep the volatility of the managed factor constant in face of time-varying volatility of the underlying unmanaged factor while also maintaining relatively smooth weights by using a longer window to calculate realized volatility.

Finally, we also construct factors excluding small-cap stocks, which are expensive to trade.

[11] DeMiguel et al. (2019) show that forming portfolios with multiple characteristics can mitigate transaction costs because trades implied by one characteristic can offset trades implied by another characteristic. This would reduce trading in unmanaged portfolios, but would not reduce costs associated with the time-varying leverage of VMPs. In fact, by reducing costs of the unmanaged portfolio, combining characteristics should make the relative performance of the volatility-managed version worse for similar reasons as discussed for managed SMB and HML.

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In doing so, this technique reduces the number of portfolio breakpoints in the construction of the Fama and French (1993, 2015), Carhart (1997), and Hou et al. (2015) factors. SMB, HML, MOM, RMW, CMA, ROE, and IA are constructed using 2x3 or 2x3x3 sorts where stocks are first sorted into two portfolios based on market capitalization (relative to the NYSE median). When excluding small-caps, we simply drop the small-cap portfolios from factor construction. For example, we compute the "excluding small-caps" return on HML as the return on the large-cap portfolio of high-book-to-market stocks minus that of the large-cap low-book-to-market stocks. The "excluding small-caps" BAB factor is made by simply excluding stocks each month whose market cap is below the NYSE median and then following the remaining portfolio construction steps in Frazzini and Pedersen (2014). Novy-Marx and Velikov (2016) show that filtering out expensive-to-trade stocks often improves net-of-costs performance of many anomalies, which is not a tautology given the potential for reducing before-costs performance.

Figure 3 depicts before-costs alphas and Sharpe ratio gains from volatility management of the baseline and cost-mitigated strategies. Like Table II, the alphas of each factor besides SMB^{σ} and CMA^{σ} are generally significant. Similarly, the same three factors (MOM, ROE, and BAB) generally have significant Sharpe ratio gains using each of the mitigation strategies except excluding small-cap stocks, which only yields significant Sharpe ratio gains when applied to MOM.

Figure 3 about here

Figure 4 depicts average transaction costs of the baseline and cost-mitigated factors over the whole sample, and the thirty-year subsamples. Scaling by one-month volatility or one-month expected variance instead of one-month realized variance does relatively little to mitigate costs. However, limiting leverage to 150%, scaling by realized volatility over a six-month trailing window, and excluding small-cap stocks each succeed at mitigating costs by 2% to 14%, on average. Combined, Figures 3 and 4 show that the cost-mitigation strategies largely maintain the before-costs performance of VMPs, while substantially reducing transaction costs.

Figure 4 about here

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Table IV presents net-of-costs performance statistics for VMPs that use cost-mitigation techniques. Panels A, B, and C, which present results using the three cost-mitigation techniques proposed by Moreira and Muir (2017), show that, after costs, none of the eight managed factors earn significant alpha over any subsample and about six of the managed factors consistently have significantly lower Sharpe ratios than their unmanaged counterparts. Consistent with Barroso and Santa-Clara (2015), but in contrast to the results in Panels A through C, scaling by six-month standard deviation yields a significant alpha and Sharpe ratio improvement from volatility managing MOM. The robustness of this result after transaction costs for momentum, using 6 months realized volatility, is noteworthy as the study originally proposing the strategy does not feature any estimate of transaction costs using stock-level information as we do. This technique also yields a significant alpha and Sharpe ratio increase for ROE, although the effect is concentrated in the most recent subsample. Moreover, the ROE^{σ} alpha is small (1.9% per year), which could easily be rendered insignificant by short-selling fees that are unaccounted for in our analysis. In fact, Drechsler and Drechsler (2017) show that short-selling expenses are relatively high for momentum and profitability factors. The remaining six factors do not benefit from scaling by six-month standard deviation.

Table IV about here

Panel E of Table IV shows that dropping small-cap stocks causes MOM^{σ} to earn a significant alpha, and higher Sharpe ratio than MOM. However, for the remaining seven factors, excluding small-cap stocks yields no performance improvement, or a significant performance reduction. Overall, even after cost-mitigation, volatility management generally yields no performance improvements net-of-costs, and more often than not, even significantly reduces Sharpe ratios. Out of the 39 combinations of factors and cost-mitigation strategies in Table IV, only three yield full-sample alphas that are significantly positive at the 5% level. Only for momentum do any volatility management strategies reliably yield economically sizable performance improvements.

That the volatility-managed momentum strategy can be profitable is consistent with prior findings that momentum uniquely experiences large predictable crashes, the sources of which remain

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a mystery, even in models that offer a structural explanation for momentum (e.g., Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Goncalves et al., 2019).

D. Discussion

Transaction costs are only one implementation friction that prevents investors from realizing the documented benefits of volatility management. Another is short-selling fees. Unfortunately, short-sale fee data are unavailable over the vast majority of the sample period. However, we know ex ante that, if anything, they would further deteriorate the performance of VMPs, which take more extreme short positions and have higher turnover on the factors' short legs than the unmanaged factors. More generally, many institutional investors have higher "all-in" costs of implementing trading strategies than those implied by effective spreads alone (e.g., Arnott, Kalesnik, and Wu, 2017; Patton and Weller, 2019), and for these traders our estimates of trading costs are a sharp lower bound. A small number of highly sophisticated traders may have relatively low trading costs (e.g., Frazzini, Israel, and Moskowitz, 2018). As Novy-Marx and Velikov (2016) note, "Large institutional investment managers devote entire departments to the sole purpose of reducing the costs of executing trades." A hypothetical investor able to trade for a very low marginal cost would indeed harvest the alphas of volatility management documented in previous studies.[12] However, this fact does not mean they necessarily earn economic profits. Such investors need to incur relatively large fixed costs—such as years of training, sophisticated equipment, and expensive data—to lower their marginal trading cost. Moreover, relatively low trading-cost estimates in the literature, such as those earned by the anonymous institution of Frazzini et al. (2018), are based on stock-selection strategies, and should not be extrapolated to timing strategies like volatility-managed portfolios. For example, traders can *wait* to trade based on cross-sectional signals like book-to-market ratio more aggressively when liquidity is relatively high. By construction, however, they can not necessarily take advantage of time-variation in liquidity when the timing of their trades is dictated by volatility.

The abnormal returns of VMPs are a puzzle in the asset pricing literature. Moreira and Muir

[12] Although he still has to deal with the estimation issues pointed out by Cederburg et al. (2019). Further, see Patton and Weller (2019) for a discussion of limitations of the low cost estimates reported by Frazzini et al. (2018).

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(2017) note they are "easy to implement in real time" and after considering several explanations—such as business-cycle risk, leverage constraints, and transaction costs—conclude the most likely explanation is that investors are just slow to trade when reacting to volatility. Our results suggest a different explanation. While the benefits of volatility management are robust to transaction costs for the market factor, as Moreira and Muir (2017) show, the results in Section III show they are not so for most other factors. Hence the dismissal of transaction costs as an explanation is premature. They seem, in fact, a serious obstacle in the pricing of volatility shocks. The typical investor is not necessarily oblivious about the information contained in volatility. He simply cannot profit from its mispricing in an economically meaningful manner.

IV. Results: Market factor

The results above show that transaction costs can largely explain why *non-market* VMPs generate alpha—it is simply not profitable to arbitrage away. In contrast, Moreira and Muir (2017) show that transaction costs can not explain the performance of the volatility-managed *market* factor. However, it is still possible that other important LTA prevent arbitrageurs from more aggressively trading relative to volatility shocks, leading to the apparent"under-reaction" of prices to volatility. We investigate this possibility in this section.

A. Arbitrage risk and short-sale constraints

We consider two of the most widely known stock-level LTA besides transaction costs, namely arbitrage risk and short-selling constraints. Rational traders optimally weight a given "arbitrage" position based on that position's expected abnormal returns relative to its risk. For example, if two stocks each had the same expected positive alpha, a rational arbitrageur would optimally allocate less capital in the stock with higher arbitrage risk. As is standard in the literature, we proxy for arbitrage risk using idiosyncratic volatility, IV (see, e.g., Pontiff, 2006).[13] Following Novy-Marx and Velikov (2016), we estimate IV each month using CAPM regressions based on rolling

[13]In the case of mean-variance preferences, the optimal weight of a long-short factor is exactly proportional to the ratio of alpha to idiosyncratic variance. See, e.g., Treynor and Black (1973).

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three-month windows of daily data. Unlike many measures of LTA, IV offers the benefit of data availability over the entire CRSP sample (1926 to present).

In the presence of short-sale constraints, it is well known that differences of opinion can lead to over-valuation (e.g., Miller, 1977; D'Avolio, 2002; Nagel, 2005). In our context, short-sale constraints could deter traders from lowering prices when volatility increases. Following Nagel (2005), we proxy for short-sale constraints using institutional ownership, IO (defined in Section II). Low values of IO indicate limits to arbitrage of overpricing because institutions are a crucial part of the supply of loanable shares in short-sales. (e.g., D'Avolio, 2002; Nagel, 2005).

If the alpha earned by the volatility-managed market factor is an artifact of mispricing that persists because of LTA, the alpha should be greatest among stocks where these limits are highest.[14] Consistent with the LTA interpretation of IV and IO, many studies show that anomaly returns increase in the cross-section with IV and decrease with IO. Our main strategy for testing our hypothesis is to sort stocks into low-, medium-, and high-LTA groups, and then compare the performance of VMPs across groups.

Each month, we sort every stock in CRSP into value-weighted terciles based on IV or IO.[15] We then form managed versions of these portfolios using the same leverage as MKT$^{\sigma}$. That is, letting

$$L_{t-1}^{MKT} = \left(\frac{c}{RV_{t-1}^2(MKT)} \right), \tag{4}$$

where $RV_{t-1}^2(MKT)$ is the realized variance of MKT using daily returns over month $t-1$, we define

$$rx_{it}^{\sigma} = L_{t-1}^{MKT} \cdot rx_{it}, \tag{5}$$

where rx_{it} denotes the month-t excess return on IO or IV portfolio $i = 1$ (low-IV or IO), 2, or 3 (high).

[14]This premise is used by Pontiff (1996), Wurgler and Zhuravskaya (2002), Ali et al. (2003), Mashruwala et al. (2006), Zhang (2006), Scruggs (2007), McLean (2010), Li and Zhang (2010), Stambaugh et al. (2015), and Larrain and Varas (2013) for idiosyncratic volatility as a proxy for arbitrage risk; and D'Avolio (2002), Asquith et al. (2005), Nagel (2005), Duan et al. (2010), Hirshleifer et al. (2011), and Avramov et al. (2013) using institutional ownership as a proxy for short-sale constraints.

[15]Following Novy-Marx and Velikov (2016), IV is defined to be the standard deviation from the residuals in a CAPM regression over the prior three-months of daily returns.

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In Table II, we show that MKT^{σ} earns significant alpha in the regression

$$MKT_t^{\sigma} = \alpha + \beta \cdot MKT_t + \epsilon_t. \tag{6}$$

The IV and IO tercile portfolios are essentially partitions of the stocks in MKT. Hence, by applying the common L_{t-1}^{MKT} to each IO and IV portfolio and using MKT_t on the right-hand-side, we can effectively observe which portfolios are responsible for contributing the greatest portion of the MKT^{σ} alpha in Eq. (6).[16]

Table V presents the results from the regressions defined by Eq. (5). Overall, for both IV and IO, the alpha have the opposite pattern as that predicted by the limits-to-arbitrage explanation. The VMPs with low IV and high IO have greatest alpha, and the most economically significant as well in terms of Sharpe ratio and certainty equivalent returns improvements. The alpha point estimates are even negative for the high-IV and low-IO portfolios. Overall, the evidence from Table V shows that the benefits from volatility managing the market seem to come from low- and medium-LTA stocks and are insignificant for high-LTA stocks.

Table V about here

B. Sentiment

The evidence above renders the profitability of the volatility-managed market portfolio very puzzling because the phenomenon is contrary to the predictions of rational models and idiosyncratic stock-level LTA do the opposite of explain the contrast. However, the literature on VMPs overlooks the role of sentiment in the mean-variance tradeoff. Yu and Yuan (2011) show theoretically that the presence of irrational traders who buy when sentiment is high, but do not short when it is low, will dampen the mean-variance tradeoff, but only when sentiment is high.[17] Consistent with this theory, they show empirically that volatility positively forecasts the market return when sentiment is low,

[16] Inferences remain the same, however, if we replace MKT_t with the unmanaged IV_i or L_{t-1}^{MKT} with leverage based on the IV portfolio's own volatility.

[17] Grinblatt and Keloharju (2009) document empirically that unsophisticated traders participate more heavily in the stock market when valuations are high. This behavior is also reminiscent of unsophisticated traders "buying-the-dip" without acting on price-relevant information, potentially dampening the effects of informed selling.

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and vice versa, resulting in the familiar insignificant predictive relationship over the whole sample. The alpha of the volatility-managed market portfolio is an artifact of the fact that, unconditionally, volatility is persistent from one month to the next, but uncorrelated to future returns. Thus, the sentiment theory of the mean-variance relationship can plausibly explain the benefits of volatility timing the market.[18] More generally, to the best of our knowledge, market sentiment is the only well-documented force that can induce widespread mispricing regardless of asset-specific LTA.[19] The sentiment theory is also ex-ante consistent with the evidence in Table V under the assumption that sentiment traders tend to trade stocks that are easy to trade (low-IV and high-IO stocks), which seems reasonable given that they tend to not expend the incremental effort to sell short. It is simply easier to find and buy liquid (low-LTA) S&P 500 stocks with high IO than obscure illiquid small-cap stocks with low IO (high-LTA) (e.g., Barber and Odean, 2008).

The performance of MKT^{σ} depends critically on the risk-return tradeoff deteriorating when volatility increases. Hence, to evaluate whether sentiment can explain this performance, we examine whether this deterioration is concentrated in high-sentiment times. Following Yu and Yuan (2011), we classify each month as having "high" or "low" sentiment if the Baker and Wurgler (2006) index, BW, is above or below, respectively, its sample median at the end of the prior year. We separately classify each month as having "high" or "low" volatility if the prior-month realized variance, $RV_{t-1}^2(MKT)$, is above or below its sample median. Figure 5 depicts the Sharpe ratio of MKT over the four subsamples that result from the intersection of the high/low-sentiment and high/low-volatility classifications. We use both the whole sample that BW is available, 1966 to 2015, and the most recent subsample for which the MKT^{σ} alpha is significant, 1986 to 2015.[20] Consistent with the sentiment theory of the benefits of MKT^{σ}, the Figure clearly shows that the

[18]But this is not guaranteed. The positive mean-variance tradeoff when sentiment is low could still be weak enough to allow for volatility management to improve performance.

[19]See, e.g. Hirshleifer and Shumway (2003), Kamstra et al. (2003), Baker and Wurgler (2006), Kaplanski and Levy (2010), Stambaugh et al. (2012), Huang et al. (2015), Stambaugh et al. (2015), and Stambaugh and Yuan (2017). For example, the models of Daniel et al. (2001) and Kozak et al. (2018) show that sentiment can induce commonality in mispricing such that returns conform to an (arbitrage-free) factor structure even if prices are irrational. In this setting, mispricing persists, even in the absence of *idiosyncratic* trading frictions like idiosyncratic volatility or short-sale constraints, because trading against the mispricing requires bearing exposure to factor risk.

[20]As documented in Moreira and Muir (2017) and Table II, because of the low variation in volatility over this time, the MKT^{σ} alpha is insignificant in the 1956 to 1985 sample. Untabulated results show this alpha is insignificant over 1966 to 2015 as well.

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market Sharpe ratio falls with volatility, but only when sentiment is high. Conversely, the opposite pattern holds when sentiment is low.

Figure 5 about here

Table VI investigates the performance of MKT_t^{σ} during high and low sentiment months. Consistent with the sentiment theory, volatility management increases the Sharpe ratio when sentiment is high, and reduces the Sharpe ratio when sentiment is low, and this pattern is robust to using any of the cost-mitigated versions of volatility-management. Moreover, the contrast between high- and low-sentiment period is economically large; over the 1986 to 2015 sample, the baseline volatility management strategy yields gains in certainty equivalent returns and alphas that are 13.5% and 7.7% higher, respectively, when sentiment is high than when it is low. Over the 1966 to 2015 sample, volatility management doubles the Sharpe ratio when sentiment is high, and roughly halves it when sentiment is low.

Table VI about here

Overall, the results from Figure 5 and Table VI are consistent with the Yu and Yuan (2011) model in which unsophisticated traders under-react to volatility shocks in times of high sentiment. This evidence refines and substantiates the unconditional slow trading hypothesis of Moreira and Muir (2017). Our results also impact the interpretation of the investment advice implied by the performance of VMPs. Moreira and Muir (2017) argue that the performance of VMPs is evidence against conventional investment wisdom that investors should either maintain their positions or increase risk-taking following large market crashes.[21] Our evidence partially vindicates this conventional wisdom. There is, after all, an extra reward for enduring volatile times in the stock market when sentiment is low. It is only when the conditions are ripe to draw unsophisticated noise traders, high sentiment periods, that a suspension of conventional wisdom becomes advisable.

[21]See, e.g. John Cochrane ("Is now time to buy stocks?" 2008, Wall Street Journal) and Warren Buffet ("Buy America. I am," 2008, The New York Times)

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V. Conclusion

Prior studies find that volatility-managed portfolios that increase leverage when risk is low produce significant abnormal returns and Sharpe ratio improvements. This phenomenon contradicts conventional investment advice and is not explained by rational asset pricing models. Hence, it would not be surprising if the phenomenon persisted only because of arbitrage frictions. Indeed, with one notable exception, we show that volatility-managed non-market factors are generally not profitable after accounting for transaction costs. In contrast, transaction costs do not explain the performance of the volatility-managed market factor, which is actually strongest in the subset of stocks that are easiest to arbitrage. However, we find that the managed market factor's performance is concentrated in high-sentiment times, consistent with prior theory that assumes sentiment traders buy more aggressively than they sell short, dampening the effects of volatility shocks when sentiment is high. When sentiment is low, investors are better off not volatility timing the market.

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Appendix

A. Portfolio transaction costs

For the long leg of an unmanaged factor, f, we compute turnover (TO) and transaction costs (TC) as (e.g., Kirby and Ostdiek, 2012):

$$TO_{long,t} = \frac{1}{2}\sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-1}|, \text{ and} \tag{7}$$

$$TC_{long,t} = (1 + f_{long,t})\sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-1}| \cdot c_{i,t}, \tag{8}$$

where $c_{i,t}$ (r_{it}) is the one-way Hasbrouck (2009) transaction cost (return) of stock i at time t, $N_t =$ number of stocks at time t, $w_{i,t}$ is the weight of stock i in the leg at time t after rebalancing, $\tilde{w}_{i,t-1} = \frac{w_{i,t-1}(1+r_{it})}{\sum_{j=1}^{N_t} w_{j,t-1}(1+r_{jt})}$ is the weight of stock i in the leg at time t before rebalancing, and $f_{long,t}$ denotes the return on the long leg of f. The transaction costs for the corresponding short leg ($TC_{Short,t}$) are defined similarly. The net-of-costs return on f (f_t^{net}) are:

$$f_t^{net} = f_t^{gross} - TC_{Long,t} - TC_{Short,t}, \tag{9}$$

where f_t^{gross} denotes the return ignoring costs. We estimate the w_{it} of the portfolios by replicating the factors following the respective studies (Specifically, Frazzini and Pedersen, 2014; Fama and French, 2015; Hou et al., 2015). In doing so, we obtain necessary accounting data from COMPUSTAT.

Following Barroso and Santa-Clara (2015), the turnover and transaction costs for the long leg of a managed portfolio are given by:

$$TO_{Long,t} = \frac{1}{2}\sum_{i=1}^{N_t} |L_t(f)w_{i,t} - L_{t-1}(f)\tilde{w}_{i,t-1}|, \text{ and} \tag{10}$$

$$TC_{Long,t} = \sum_{i=1}^{N_t} |L_t(f)w_{i,t} - L_{t-1}(f)\tilde{w}_{i,t-1}| \cdot c_{i,t}, \tag{11}$$

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and the transaction costs of the short-leg are defined similarly. $w_{i,t}$ refer to the weights of the unmanaged portfolio immediately after rebalancing and $\tilde{w}_{i,t-1}$ refer to the corresponding weights immediately before.

Eq. (11) shows what turns out to be a key disadvantage of VMPs. By definition, they constantly change L_t based on volatility, which creates an additional source of turnover and transaction costs. Suppose, for illustration, the unmanaged weights (w_{it}) did not change over time at all; variation in L_t would still cause turnover.

B. Generalized Alphas

We measure performance of our trading strategies net of transaction costs using the generalized α_{net} of Novy-Marx and Velikov (2016), which, in our setting, is defined as follows. Let $MVE_{\{f,f^\sigma\}}$ denote the net-of-costs excess return on the MVE portfolio consisting of f and f^σ, and $w_{f^\sigma,MVE_{\{f,f^\sigma\}}}$ denote the weight f^σ has in $MVE_{\{f,f^\sigma\}}$. The net-of-costs alpha (α_{net}) is defined to be the intercept in the following regression:

$$w^{-1}_{f^\sigma,MVE_{\{f,f^\sigma\}}} MVE_{\{f,f^\sigma\}} = \alpha_{net} + \beta f_t + \epsilon_t, \tag{12}$$

where f_t is measured net-of-costs, and we set $\alpha_{net} = 0$ if $w_{f^\sigma,MVE_{\{f,f^\sigma\}}} = 0$. In the presence of transaction costs, the alpha in a typical factor regression does not measure abnormal returns because it is not attainable by any strategy. This necessitates the definition of α_{net} that uses the MVE portfolio of the left- and right-hand-side factors as the dependent variable. However, like the standard regression-based alphas, the α_{net} measures how access to the left-hand-side excess return expands the ex-post investment opportunity set beyond the set of right-hand-side factors. The term $w^{-1}_{f^\sigma,MVE_{\{f,f^\sigma\}}} MVE_{\{f,f^\sigma\}}$ is the excess return on the $MVE_{\{f,f^\sigma\}}$ leveraged to hold \$1 in f^σ. With this scaling, α_{net} reduces to the standard regression-based alpha in the absence of transaction costs and the two alphas have comparable units.

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Figure 1: Transaction costs by NYSE size quartile: 1926 to 2015

This figure depicts the annual time-series of the value-weighted Hasbrouck (2009) stock-level effective one-way spread across four size portfolios of CRSP common stocks. Size in each year is defined to be the market capitalization at the end of July, and the portfolios are formed with quartile breakpoints for NYSE stocks.

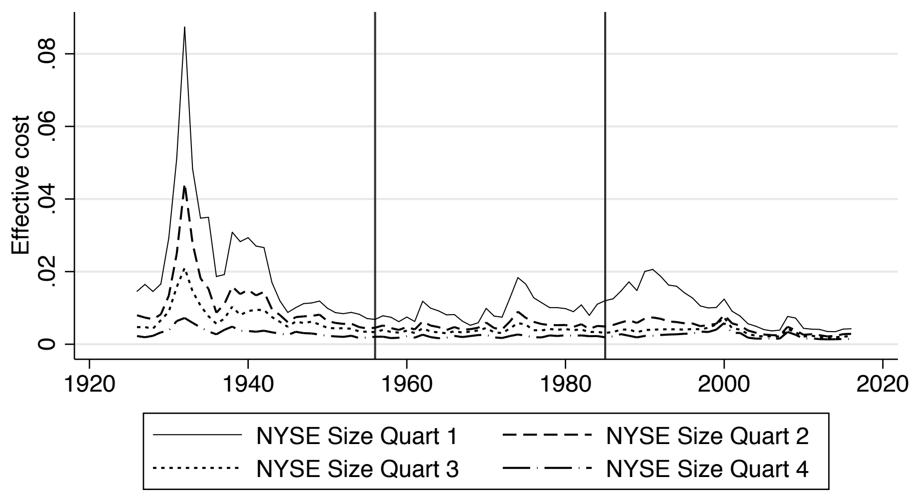

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Table I: Performance statistics of unmanaged factors

For each equity factor, this table presents average annualized monthly before-costs returns and Sharpe ratios, $E(f_{gross})$ and $SR(f_{gross})$, respectively, monthly turnover, TO, annualized transaction costs, TC, and annualized after-costs returns and Sharpe ratios, $E(f_{net})$ and $SR(f_{net})$, respectively. Panel A presents whole-sample statistics, and Panels B through D present subsample statistics. The data are monthly and the sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB.

	SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
Panel A: Whole sample								
$E(f_{gross})$	2.53	4.58	8.25	2.91	3.61	6.75	4.92	8.04
$t(f_{gross})$	2.15	3.58	4.73	2.72	3.74	5.38	5.29	6.71
TO	3.92	5.26	55.03	4.98	9.65	35.74	23.46	8.87
TC	0.62	0.86	8.52	0.59	1.04	3.95	2.55	2.94
$E(f_{net})$	1.91	3.74	-0.33	2.32	2.57	2.74	2.34	5.11
$t(f_{net})$	1.62	2.90	-0.18	2.16	2.61	2.04	2.37	4.20
$SR(f_{gross})$	0.23	0.38	0.50	0.37	0.52	0.77	0.77	0.73
$SR(f_{net})$	0.17	0.31	-0.02	0.30	0.36	0.31	0.36	0.46
N	1073	1073	1068	629	629	528	528	1020
Panel B: 1926 to 1955								
$E(f_{gross})$	2.97	5.82	7.10					4.00
$t(f_{gross})$	1.26	1.92	1.87					1.68
TO	4.32	5.59	59.26					6.98
TC	0.99	1.38	13.96					2.74
$E(f_{net})$	1.98	4.44	-7.10					1.26
$t(f_{net})$	0.83	1.46	-1.75					0.52
$SR(f_{gross})$	0.24	0.36	0.35					0.34
$SR(f_{net})$	0.16	0.28	-0.33					0.11
N	353	353	348					300
Panel C: 1956 to 1985								
$E(f_{gross})$	3.93	5.51	10.44	1.23	3.87	7.44	6.53	10.77
$t(f_{gross})$	2.28	3.52	4.96	1.05	2.68	4.07	4.68	7.56
TO	3.74	5.06	52.96	4.71	9.70	39.04	24.78	9.00
TC	0.42	0.57	5.83	0.58	1.04	4.63	2.89	1.98
$E(f_{net})$	3.50	4.93	4.61	0.65	2.83	2.93	4.14	8.79
$t(f_{net})$	2.03	3.14	2.19	0.55	1.94	1.34	2.71	6.13
$SR(f_{gross})$	0.42	0.64	0.90	0.22	0.57	0.92	1.11	1.38
$SR(f_{net})$	0.37	0.57	0.40	0.11	0.42	0.36	0.72	1.12
N	360	360	360	269	269	168	168	360
Panel D: 1986 to 2015								
$E(f_{gross})$	0.72	2.50	7.14	4.17	3.41	6.29	3.90	8.70
$t(f_{gross})$	0.36	1.35	2.42	2.52	2.64	3.73	3.16	3.69
TO	3.72	5.15	52.94	5.18	9.60	34.20	22.84	10.32
TC	0.47	0.64	5.88	0.60	1.04	3.64	2.40	4.06
$E(f_{net})$	0.25	1.86	1.26	3.57	2.37	2.66	1.50	4.64
$t(f_{net})$	0.13	0.99	0.43	2.15	1.79	1.57	1.19	1.94
$SR(f_{gross})$	0.07	0.25	0.44	0.46	0.48	0.68	0.58	0.67
$SR(f_{net})$	0.02	0.18	0.08	0.39	0.33	0.29	0.22	0.35
N	360	360	360	360	360	360	360	360

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Table II: Performance of Volatility-Managed Factors Without Transaction Costs

We run time-series regressions of each volatility-managed factor on the unmanaged factor: $f_t^\sigma = \alpha + \beta f_t + \epsilon_t$. The managed factor scales by the unmanaged factor's inverse realized variance in the preceding month: $f_t^\sigma = (c/RV_{t-1}^2)f_t$. Along with regression statistics, we also report Sharpe ratios for the unmanaged and managed factors, $SR(f)$ and $SR(f^\sigma)$, respectively, the maximum Sharpe ratio attainable combining f and f^σ, $SR(f, f^\sigma)$, and the improvement in certainty equivalent return, ΔCER, realized by a mean-variance investor with risk aversion of three who earns the Sharpe ratio $SR(f, f^\sigma)$ instead of $SR(f)$ (in % per year). The data are monthly and the sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB. t-statistics are in parentheses and adjust for heteroskedasticity. $z(SR(f^\sigma))$ denotes the z statistic from the Jobson and Korkie (1981) test of the null that $SR(f^\sigma) - SR(f) = 0$. All alphas, Sharpe ratios, and appraisal ratios are annualized.

Panel A: Full sample									
	MKT	SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
α	4.81	-0.46	1.74	12.53	2.68	0.36	5.03	1.41	6.83
	(3.05)	(-0.50)	(1.64)	(8.06)	(3.06)	(0.50)	(5.15)	(2.06)	(6.85)
β	0.61	0.61	0.57	0.47	0.58	0.68	0.65	0.70	0.58
	(25.17)	(25.23)	(22.71)	(17.36)	(17.97)	(22.94)	(20.62)	(23.51)	(22.95)
N	1073	1073	1073	1068	629	629	587	587	1020
R^2	0.37	0.37	0.32	0.22	0.34	0.46	0.42	0.49	0.34
$SR(f)$	0.41	0.23	0.38	0.50	0.37	0.52	0.77	0.77	0.73
$SR(f, f^\sigma)$	0.53	0.23	0.42	1.00	0.56	0.52	1.07	0.83	1.05
ΔCER	1.76	0.00	0.55	12.46	2.88	0.06	9.44	1.73	9.62
$SR(f^\sigma)$	0.51	0.09	0.37	1.00	0.56	0.39	1.07	0.77	1.04
$z(SR(f^\sigma))$	1.02	-1.45	-0.15	4.46	1.44	-1.12	2.47	0.00	3.09
Panel B: Subsample alphas and z-statistics for test of $SR(f) = SR(f^\sigma)$									
	1926 to 1955								
α	8.40	0.06	0.82	8.33					1.62
	(2.72)	(0.03)	(0.57)	(3.06)					(1.07)
$z(SR(f^\sigma))$	1.28	-0.59	-0.43	1.51					0.17
	1956 to 1985								
α	2.11	-2.55	0.66	11.32	2.95	0.09	3.74	0.70	4.71
	(0.74)	(-1.43)	(0.37)	(4.35)	(2.62)	(0.07)	(2.45)	(0.62)	(2.85)
$z(SR(f^\sigma))$	0.01	-2.13	-0.81	2.03	2.20	-0.91	0.96	-1.06	0.03
	1986 to 2015								
α	3.77	-0.76	0.71	12.95	2.69	0.46	5.35	1.50	8.89
	(2.32)	(-1.23)	(0.43)	(5.51)	(2.77)	(0.54)	(4.46)	(1.77)	(5.18)
$z(SR(f^\sigma))$	1.10	-1.27	-0.22	3.45	1.19	-0.63	2.30	0.35	2.82

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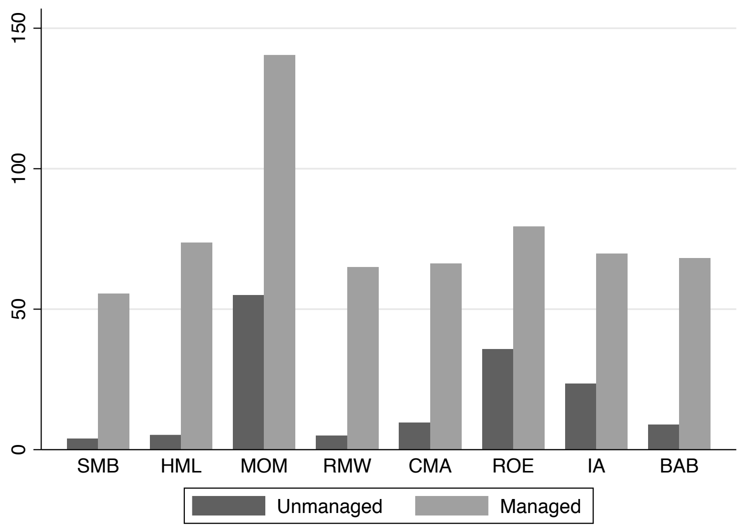
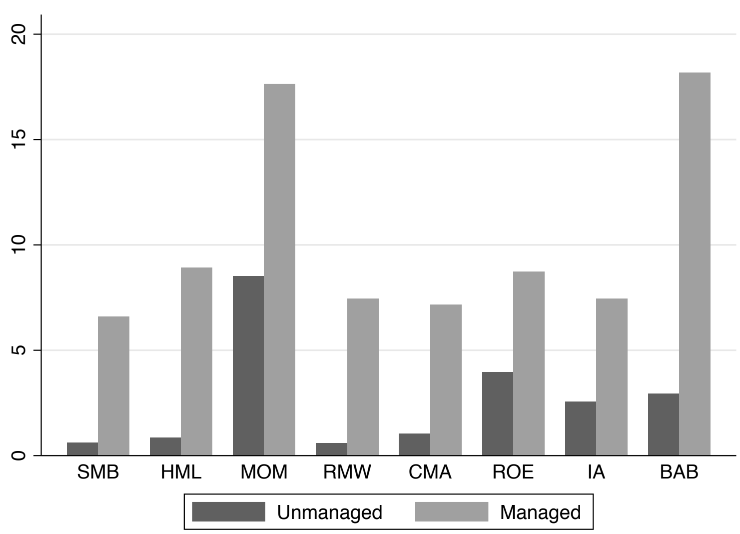
Figure 2: Turnover and transaction costs of unmanaged and volatility-managed factors

Panels A and B, respectively, present the average turnover (% per month) and transaction costs (% per year) for the non-market equity factors used in Table II. The sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB.



Panel (A): Turnover



Panel (B): Transaction Costs

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Table III: Net-of-Costs Performance of Volatility-Managed Factors

This Table presents performance statistics for the managed and unmanaged factors defined in Table II. $E(f_{net})$ is annualized average excess return net of transaction costs, α_{net} denotes the generalized net-of-costs alpha defined in Eq. (12), $t(\alpha_{net})$ denotes the heteroskedasticity-robust t-statistic of the α_{net}, and $z(SR(f^{\sigma}))$ denotes the z statistic from the Jobson and Korkie (1981) test of the null that $SR(f^{\sigma}_{net}) - SR(f_{net}) = 0$. The sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB. Panel A presents whole-sample results and Panels B through D uses subsamples.

Panel A: Whole sample factor performance and transaction cost statistics								
	SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
$E(f^{\sigma}_{net})$	-5.56	-4.48	-1.33	-3.13	-4.43	0.85	-2.25	-6.67
α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$t(\alpha_{net})$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$z(SR(f^{\sigma}_{net}))$	-6.76	-6.84	-0.59	-5.61	-8.54	-0.40	-4.06	-7.92
Panel B: 1926 to 1955								
$E(f^{\sigma}_{net})$	-7.32	-5.48	-7.78					-6.83
α_{net}	0.00	0.00	0.00					0.00
$t(\alpha_{net})$	0.00	0.00	0.00					0.00
$z(SR(f^{\sigma}_{net}))$	-4.60	-4.83	-0.74					-4.29
Panel C: 1956 to 1985								
$E(f^{\sigma}_{net})$	-5.90	-2.54	2.88	-4.58	-4.88	0.31	-1.29	-1.20
α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$t(\alpha_{net})$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$z(SR(f^{\sigma}_{net}))$	-5.67	-5.98	-1.66	-4.69	-6.00	-0.67	-3.25	-7.05
Panel D: 1986 to 2015								
$E(f^{\sigma}_{net})$	-3.48	-5.44	0.69	-2.05	-4.08	1.10	-2.70	-12.00
α_{net}	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00
$t(\alpha_{net})$	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00
$z(SR(f^{\sigma}_{net}))$	-5.16	-3.78	-0.01	-4.12	-6.53	-0.07	-3.12	-5.24

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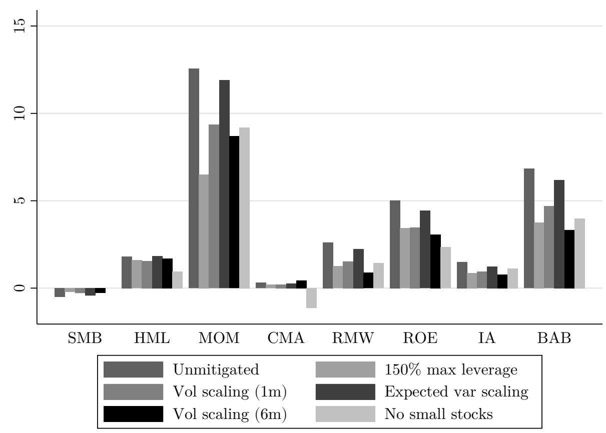
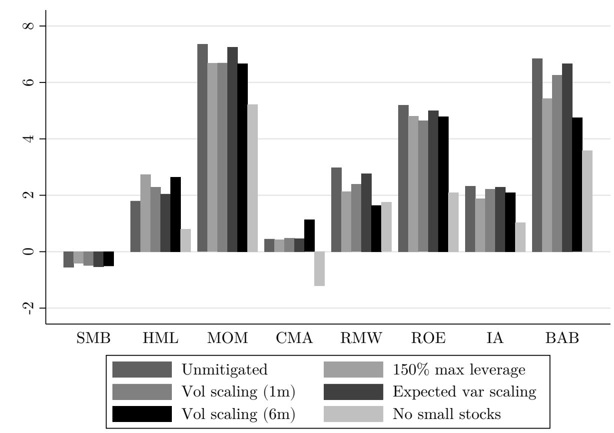
Figure 3: Before costs performance of cost-mitigated volatility-managed factors

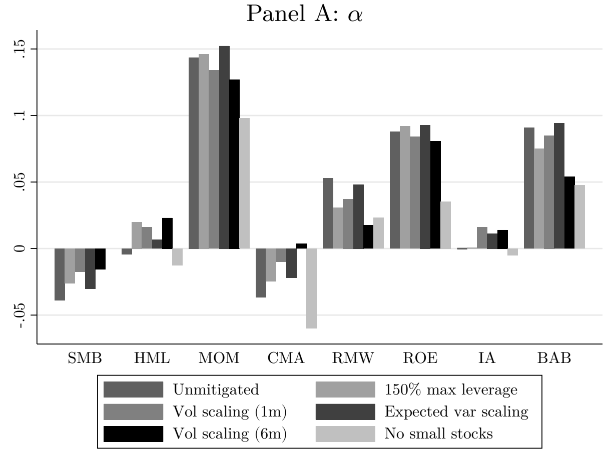
Panels A and B present, respectively, alphas and heteroskedasticity-robust t-statistics from regressions of the managed factors on the unmanaged factors: $f_t^\sigma = \alpha + \beta \cdot f_t + \epsilon_t$, where f_t^σ uses the baseline scaling, "Unmitigated", from Table II, or one of five cost-mitigation techniques. The first technique limits leverage to 150%. The next three scale by one of the following variables instead of prior-month realized variance: prior-month standard deviation of daily returns, expected variance, or rolling standard deviation estimated using daily data over the prior six months. For expected variance, we run an AR(1) for log variance to form our forecast. The fifth cost-mitigation technique excludes small-cap stocks from the construction of the asset-pricing factors. Panels C and D present, respectively, differences in Sharpe ratios between the managed and unmanaged factors, $SR(f^\sigma) - SR(f)$, and Jobson and Korkie (1981) z statistics, $z(SR(f^\sigma))$, of the null that $SR(f^\sigma) - SR(f) = 0$. The sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB.



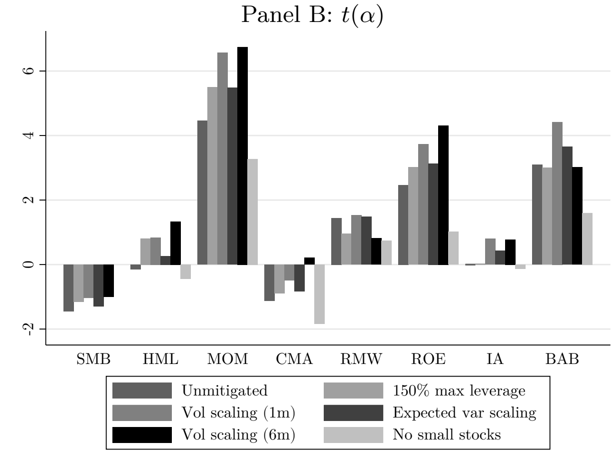
Panel A: α



Panel B: $t(\alpha)$



Panel C: $SR(f^\sigma) - SR(f)$



Panel D: $z(SR(f^\sigma))$

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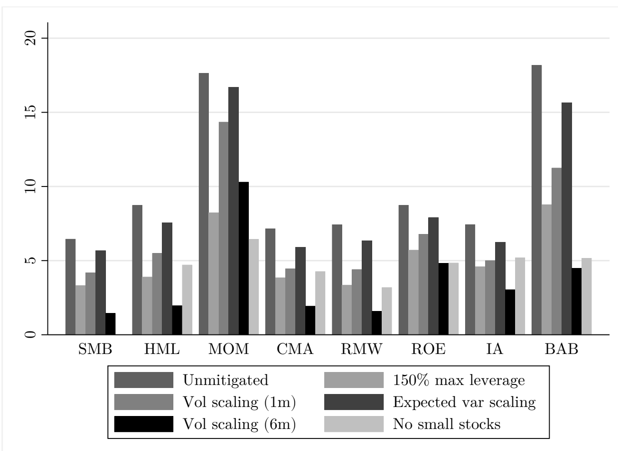
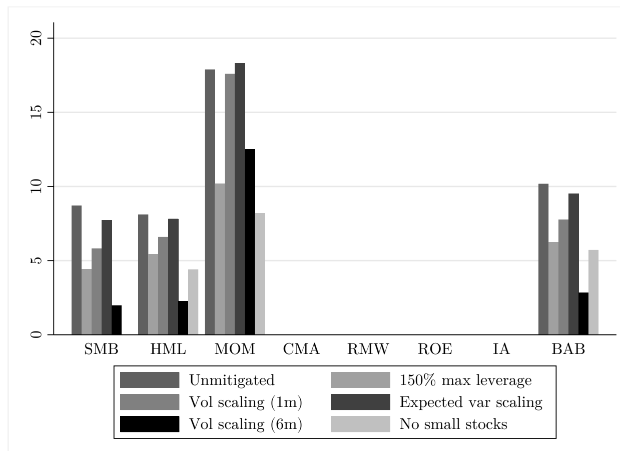
Figure 4: Average transaction costs of cost-mitigated volatility-managed factors

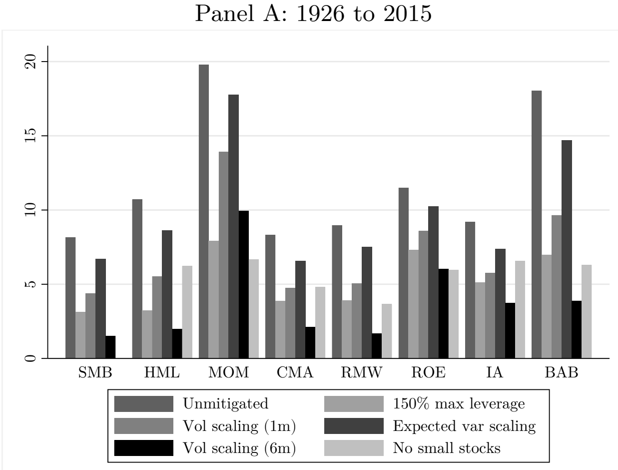
This Figure presents transaction costs (% per year) for the managed factors defined in Figure 3, which use the baseline strategy, "Unmitigated", from Table II, or one of five cost-mitigation techniques. The sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB. Panel A presents whole-sample results and Panels B through D uses subsamples.



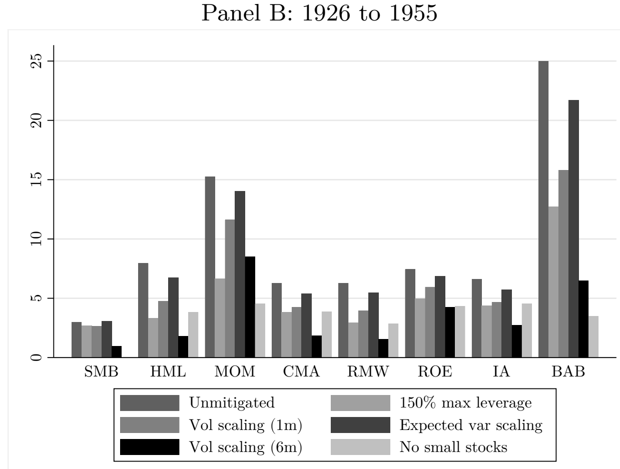
Panel A: 1926 to 2015



Panel B: 1926 to 1955



Panel C: 1956 to 1985



Panel D: 1986 to 2015

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Table IV: Net-of-Costs Performance of Volatility-Managed Factors Using Cost-Mitigation

This Table presents whole- and sub-sample performance statistics for managed factors using the cost-mitigation techniques defined in Figure 3. α_{net} denotes the generalized net-of-costs α. $t(\alpha_{net})$ denotes the heteroskedasticity-robust t-statistic for the α_{net}. $SR(\cdot)$ denotes the annualized Sharpe ratio and $z(SR(f^{\sigma}))$ denotes the z statistic from the Jobson and Korkie (1981) test of the null that $SR(f^{\sigma}) - SR(f) = 0$. The sample period is 1926 to 2015 for MKT, SMB, HML; 1927 to 2015 for MOM; 1963 to 2015 for RMW and CMA; 1967 to 2015 for ROE and IA; and 1931 to 2015 for BAB.

Panel A: 150% maximum leverage constraint									
		SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
1926 to 2015	α_{net}	0.00	0.00	1.27	0.00	0.00	0.17	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	1.26	0.00	0.00	0.24	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-5.72	-3.97	1.65	-3.79	-6.66	-0.52	-4.27	-6.23
1926 to 1955	α_{net}	0.00	0.00	0.00					0.00
	$t(\alpha_{net})$	0.00	0.00	0.00					0.00
	$z(SR(f^{\sigma}_{net}))$	-3.62	-3.73	-0.45					-3.94
1956 to 1985	α_{net}	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-4.83	-3.08	0.33	-4.53	-4.75	-1.92	-4.35	-5.92
1985 to 2015	α_{net}	0.00	0.00	2.14	0.00	0.00	0.90	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	1.67	0.00	0.00	1.09	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-5.14	-2.35	1.35	-2.28	-5.09	0.38	-3.03	-4.13
Panel B: Factors scaled by volatility instead of variance									
1926 to 2015	α_{net}	0.00	0.00	1.42	0.00	0.00	0.31	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.82	0.00	0.00	0.42	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-6.39	-5.11	1.51	-4.31	-7.35	-0.12	-3.98	-6.35
1926 to 1955	α_{net}	0.00	0.00	0.00					0.00
	$t(\alpha_{net})$	0.00	0.00	0.00					0.00
	$z(SR(f^{\sigma}_{net}))$	-4.19	-3.97	-0.39					-3.98
1956 to 1985	α_{net}	0.00	0.00	0.59	0.00	0.00	0.00	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-5.87	-5.02	-0.09	-4.74	-5.54	-1.43	-3.89	-6.32
1985 to 2015	α_{net}	0.00	0.00	2.47	0.00	0.00	0.86	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	1.46	0.00	0.00	1.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-4.80	-3.12	1.28	-2.79	-5.50	0.53	-3.09	-4.36

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Table IV: Continued

		SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
Panel C: Factors scaled by expected variance									
1926 to 2015	α_{net}	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-6.76	-6.15	0.27	-5.09	-8.02	-0.94	-5.02	-7.98
1926 to 1955	α_{net}	0.00	0.00	0.00					0.00
	$t(\alpha_{net})$	0.00	0.00	0.00					0.00
	$z(SR(f^{\sigma}_{net}))$	-4.48	-4.50	-0.69					-4.30
1956 to 1985	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-5.82	-5.57	-0.99	-4.68	-5.82	-1.67	-4.44	-7.43
1985 to 2015	α_{net}	0.00	0.00	1.47	0.00	0.00	0.44	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	0.73	0.00	0.00	0.41	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-5.07	-3.54	0.49	-3.56	-6.08	-0.22	-3.78	-5.23
Panel D: Factors scaled by six-month volatility									
1926 to 2015	α_{net}	0.00	0.39	5.01	0.00	0.00	1.92	0.09	1.23
	$t(\alpha_{net})$	0.00	0.61	2.88	0.00	0.00	3.20	0.22	1.77
	$z(SR(f^{\sigma}_{net}))$	-2.45	-0.27	5.09	-0.94	-1.93	2.86	-0.31	0.63
1926 to 1955	α_{net}	0.00	0.77	0.00					0.00
	$t(\alpha_{net})$	0.00	0.75	0.00					0.00
	$z(SR(f^{\sigma}_{net}))$	-1.64	0.29	2.05					-0.88
1956 to 1985	α_{net}	0.00	0.00	3.80	0.00	0.00	0.87	0.00	0.00
	$t(\alpha_{net})$	0.00	0.00	3.38	0.00	0.00	1.30	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	-2.92	-2.16	3.05	-0.78	-1.59	1.16	-1.09	-2.31
1985 to 2015	α_{net}	0.00	0.00	4.89	0.18	0.00	2.31	0.00	1.43
	$t(\alpha_{net})$	0.00	0.00	2.93	0.26	0.00	3.17	0.00	1.16
	$z(SR(f^{\sigma}_{net}))$	-2.43	-1.04	2.72	-0.35	-1.50	2.81	-0.43	0.57
Panel E: No small caps									
1926 to 2015	α_{net}		0.00	4.04	0.00	0.00	0.00	0.00	0.35
	$t(\alpha_{net})$		0.00	3.25	0.00	0.00	0.00	0.00	0.43
	$z(SR(f^{\sigma}_{net}))$		-2.66	2.82	-2.29	-4.40	-0.39	-2.05	-0.43
1926 to 1955	α_{net}		0.00	3.42					0.00
	$t(\alpha_{net})$		0.00	1.68					0.00
	$z(SR(f^{\sigma}_{net}))$		-1.76	1.43					-1.34
1956 to 1985	α_{net}		0.00	1.98	0.00	0.00	0.00	0.00	0.00
	$t(\alpha_{net})$		0.00	1.42	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$		-3.50	0.92	-0.71	-4.39	-0.58	-2.88	-1.75
1985 to 2015	α_{net}		0.00	3.80	0.00	0.00	0.03	0.00	1.39
	$t(\alpha_{net})$		0.00	2.08	0.00	0.00	0.04	0.00	1.02
	$z(SR(f^{\sigma}_{net}))$		-1.95	1.85	-2.07	-3.15	-0.12	-1.92	0.40

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Table V: Performance of volatility-managed IV and IO portfolios

Each month, we sort stocks into value-weighted tercile portfolios based on idiosyncratic volatility, IV, or institutional ownership, IO. Portfolio 1 (3) denotes Low (High) IV or IO. We estimate regressions of the form: $rx_t^{\sigma} = \alpha + \beta \cdot MKT_t + \epsilon_t$, where rx_t denotes the unmanaged excess return on one of the IV or IO portfolios, and rx_t^{σ} denotes the volatility-managed version of rx_t. This Table presents statistics from these regressions along with the Sharpe ratio of rx_t, the maximum Sharpe ratio attainable from rx_t and rx_t^{σ}, $SR(rx_t, rx_t^{\sigma})$, and the improvement in certainty equivalent return (ΔCER) realized by a mean-variance investor with risk aversion of three who earns the Sharpe ratio $SR(rx_t, rx_t^{\sigma})$ as opposed to $SR(rx_t)$ (in % per year). The sample in panel A, which presents results for IV sorted portfolios is 1926 to 2015. Panel A also presents subsample α's. Panel B presents results for IO-sorted portfolios from over the 1986 to 2015 sample.

	Panel A: IV, 1926 to 2015			Panel B: IO, 1986 to 2015		
	(1)	(2)	(3)	(1)	(2)	(3)
	IV1	IV2	IV3	IO1	IO2	IO3
MKT	0.56***	0.72***	0.84***	0.55***	0.65***	0.71***
	(11.19)	(11.47)	(10.92)	(12.24)	(13.23)	(13.48)
Alpha (%)	5.77***	5.38***	-1.46	-0.33	2.41	5.46***
	(3.84)	(2.74)	(-0.54)	(-0.13)	(1.13)	(2.63)
N	1072	1072	1072	360	360	360
R^2	0.35	0.34	0.27	0.29	0.43	0.48
$SR(f)$	0.49	0.38	0.13	0.27	0.42	0.52
$SR(f, f^{\sigma})$	0.63	0.47	0.13	0.27	0.47	0.71
ΔCER	2.67	1.38	0.00	0.00	0.74	3.82
	Subsample alphas					
1926-1955	9.55***	7.65**	6.40			
	(3.30)	(2.04)	(1.21)			
1956-1985	3.06	5.16	-4.67			
	(1.10)	(1.37)	(-0.92)			
1986-2015	4.60***	3.14	-6.19**			
	(2.81)	(1.59)	(-2.07)			

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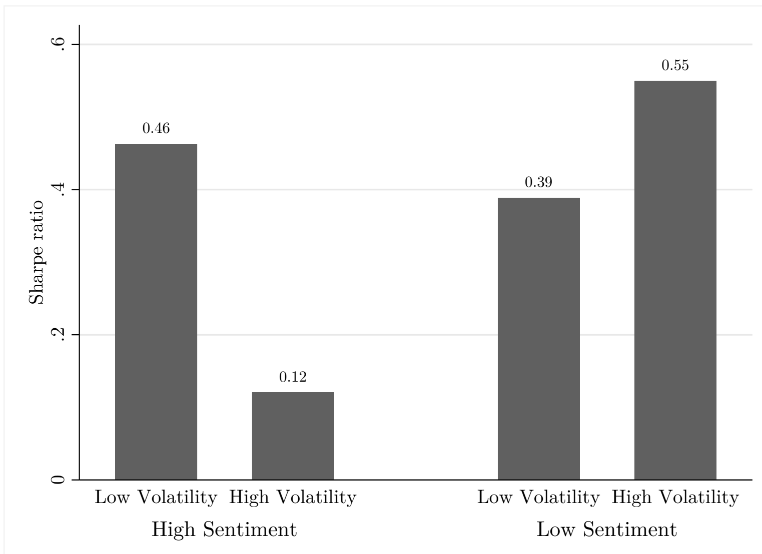
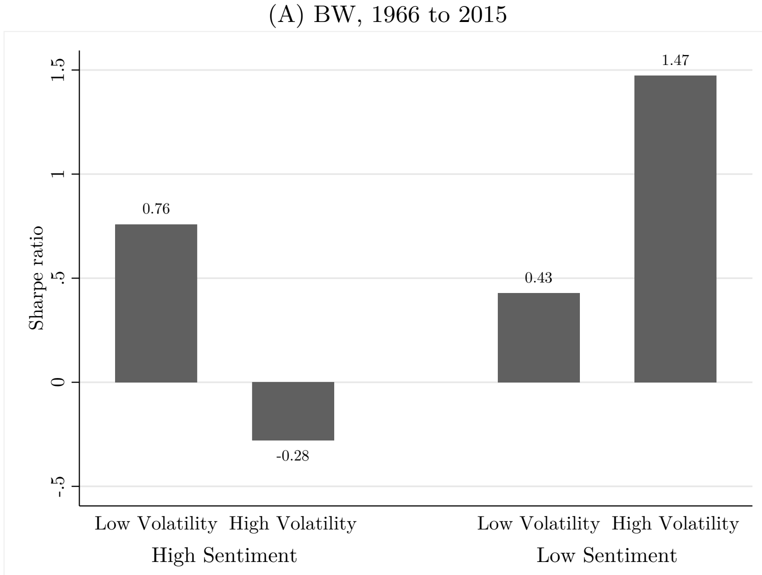
Figure 5: Market Sharpe ratio by sentiment and volatility regime

We classify each month in our sample period as "high" or "low" volatility if the realized variance over the prior month is, respectively, above or below its sample-median value. We classify each year in our sample period as "high" or "low" sentiment if the prior-year value of BW was above or below its sample median, where BW denotes the Baker and Wurgler (2006) sentiment index orthogonalized to economic conditions. This table presents the annualized Sharpe ratio of MKT over the four sub-sample periods defined by intersection of the classifications into high or low sentiment and volatility. Panel A presents results over the whole sample period for which BW is available, 1966 to 2015, and Panel B presents results over the 1986 to 2015 subsample during which MKT$^{\sigma}$ earns significant alpha.



(A) BW, 1966 to 2015



(B) BW, 1986 to 2015

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Table VI: Sharpe ratios of managed and unmanaged market factor by sentiment regime

We classify each month in our sample period as "high" or "low" sentiment based on the whether the prior-year Baker and Wurgler (2006) sentiment index orthogonalized to economic conditions is above or below its median value, respectively. For high- and low-sentiment periods, this table presents the annualized Sharpe ratio of MKT and MKT$^\sigma$, the z statistic from the Jobson and Korkie (1981) test of the null that $SR(f^\sigma) - SR(f) = 0$, the improvement in certainty equivalent return realized by a mean-variance investor with risk aversion of three who holds MKT^σ as opposed to MKT (in % per year), and the α from regressions of the form: $MKT^\sigma = \alpha + \beta \cdot MKT_t + \epsilon_t$. t-statistics are robust to heteroskedasticity, and the z reported for the difference in the Sharpe ratio gain, $SR(f^\sigma) - SR(f)$, between high- and low-sentiment periods is based on a heteroskedasticity-robust GMM estimation. Panel A presents results for the baseline construction of MKT^σ over the 1986 to 2015 period during which MKT^σ earns significant alpha, and Panel B expands the sample to 1966 to 2015. Panels C through E present similar results as Panel A, but using versions of MKT^σ that employ the cost-mitigation techniques described in Figure 3.

	$SR(f^\sigma)$	$SR(f)$	$z(SR(f^\sigma))$	ΔCER	α	$t(\alpha)$
Panel A: Baseline Variance Scaling, 1986 to 2015						
Low Sentiment	0.74	1.01	-1.38	-5.10	-0.03	-0.02
High Sentiment	0.60	0.08	2.49	8.39	7.65	2.87
High-Low	-0.14	-0.93	3.00	13.48	7.69	2.39
Panel B: Baseline Variance Scaling, 1966 to 2015						
Low Sentiment	0.31	0.61	-1.99	-4.60	-1.94	-0.91
High Sentiment	0.32	0.13	1.37	3.25	3.48	1.70
High-Low	0.01	-0.49	2.40	7.85	5.42	1.84
Panel C: Max Leverage 150%, 1986 to 2015						
Low Sentiment	0.81	-	-1.13	-4.91	0.22	0.14
High Sentiment	0.48	-	2.31	6.42	4.64	2.56
High-Low	-0.33	-	2.49	11.33	4.42	1.83
Panel D: Expected Var Scaling, 1986 to 2015						
Low Sentiment	0.86	-	-0.92	-2.91	0.31	0.17
High Sentiment	0.49	-	2.52	6.90	6.48	2.76
High-Low	-0.38	-	2.57	9.82	6.17	2.09
Panel D: Volatility Scaling (1m), 1986 to 2015						
Low Sentiment	0.95	-	-0.46	-1.19	0.55	0.35
High Sentiment	0.38	-	2.46	5.11	4.95	2.60
High-Low	-0.58	-	2.11	6.30	4.41	1.79
Panel E: Volatility Scaling (6m), 1986 to 2015						
Low Sentiment	0.90	-	-0.99	-1.78	-0.33	-0.22
High Sentiment	0.31	-	2.48	3.96	3.97	2.56
High-Low	-0.59	-	2.33	5.75	4.30	2.00

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