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

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Abstract

We investigate whether limits to arbitrage explain the abnormal returns of volatility-managed portfolios. To the contrary, these abnormal returns are negligible in long-only portfolios consisting of hard-to-arbitrage stocks. Moreover, utility gains from volatility management are at least twice as high for out-of-sample mean-variance-efficient portfolios constructed from easy-to-arbitrage stocks than from hard-to-arbitrage stocks. These results contrast with the common finding that anomalies are stronger where arbitrage is difficult. We also show the abnormal returns of volatility-managed portfolios are only significant in times of high liquidity and sentiment, consistent with models where unsophisticated traders under-react to informed order flow in such times.

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I. Introduction

Several recent studies find that volatility managing equity portfolios—taking more risk when volatility is low, and vice versa—produces significant alphas and large increases in investor utility (e.g., Fleming et al., 2001, 2003; Kirby and Ostdiek, 2012; Barroso and Santa-Clara, 2015; Moreira and Muir, 2017, 2018; Barroso and Maio, 2017*a*,*b*). This result obtains for the market portfolio as well as factors formed on book-to-market ratio, momentum, investment, profitability, and beta, among others. These volatility-management benefits occur because volatility is persistent from month to month but only weakly related to expected future returns. This stylized fact implies that the price of risk falls in times of high volatility, contrary to extant rational models of asset prices.[1] Violations of rational models are not surprising, however, if limits to arbitrage (LTA) prevent traders from correcting mispricing (e.g., Shleifer and Vishny, 1997). In this paper, we test the hypothesis that LTA cause the benefits of volatility management.

We proxy for LTA with idiosyncratic volatility (IV) and institutional ownership (IO). Idiosyncratic volatility limits arbitrage because it is a holding cost to traders attempting to exploit mispricing (e.g., Pontiff, 2006). IV also offers the benefit of data availability over the entire CRSP sample (1926–present). IO limits arbitrage, especially for overpriced stocks, because it is a crucial part of the supply of loanable shares in short-sales. (e.g., D'Avolio, 2002; Nagel, 2005). 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.[2] Our main strategy for testing our hypothesis is to sort stocks into low-, medium-, and high-LTA groups, and then compare the performance of volatility-managed portfolios across groups.

We contribute three main findings to the literature. They show the gains from volatility man-

[1] Moreira and Muir (2017) show that 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 et al., 2012), the time-varying rare disasters model (Wachter, 2013), and the intermediary asset-pricing model (He and Krishnamurthy, 2013).

[2] For example, 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), Larrain and Varas (2013), and Stambaugh and Yuan (2017) document that anomaly returns and other proxies for mispricing increase in the cross-section with idiosyncratic volatility. Similarly, D'Avolio (2002), Asquith et al. (2005), Nagel (2005), Duan et al. (2010), Hirshleifer et al. (2011), and Avramov et al. (2013) show that anomaly returns decrease in the cross-section with institutional ownership.

agement are greatest among the easiest-to-arbitrage stocks, contrary to our hypothesis and the common finding that anomaly returns are lowest in these segments. Moreover, our results show that the abnormal returns of volatility-managed portfolios are also only significant when market liquidity is high and arbitrage should be relatively easy.

We begin our analysis by examining volatility management of long IV- and IO-tercile portfolios. Long-only strategies are particularly interesting because they are easier and less costly to implement than short strategies. Moreover, the vast majority of investors only take long positions (e.g., Barber and Odean, 2008; Stambaugh et al., 2012). Our first main finding is as follows: Both the volatility-managed high-IV and low-IO (high-LTA) portfolios earn economically and statistically insignificant alpha. In contrast, the low- and medium-LTA volatility-managed portfolios earn significant alpha. The (mean-variance) utility gains for the volatility-managed low- and medium-LTA portfolios are also economically large, ranging from 46% to 175%. For comparison, Campbell and Thompson (2008) find that the utility gains of timing the aggregate stock market are about 30%.

Next, we expand our analysis to include long-short anomaly factors. We double-sort stocks into 3x5 value-weighted portfolios by first sorting into IV or IO terciles and then independently into quintiles based on size, book-to-market, momentum return, profitability, and investment. Within each IV or IO tercile, we form long-short factors as high-minus-low quintile returns. The availability of these factors benefits investors to the extent it increases the maximum attainable Sharpe ratio. Hence, we assess how volatility management improves performance of mean-variance efficient (MVE) portfolios constructed from the anomaly factors within each IV or IO tercile along with the corresponding tercile portfolio. Our second main finding, described further below, is that the gains from volatility managing MVE portfolios are highest in low- and medium-LTA stocks.

For each IV and IO tercile, volatility managing in-sample MVE portfolios produces statistically significant alpha. However, the associated utility gains are higher for the low-LTA portfolios than the high-LTA portfolios (by 12%–41%). As noted by Moreira and Muir (2017), the performance of in-sample MVE portfolios is much higher than what would be attainable in real-time, likely biasing downward the gains of volatility management. Hence, each month, we generate recursively estimated out-of-sample (OOS) MVE portfolios using the same factors as the in-sample analysis.

For each IV and IO tercile, we find that all three managed OOS-MVE portfolios earn significant alpha. However, the utility gains from volatility management are much higher for the low-IV OOS-MVE portfolios than the corresponding high-IV portfolios (65% vs 19%). Examining subsamples shows that the benefits of volatility managing OOS-MVE portfolios, as well as the difference in benefits between managing low- and high-IV portfolios, also increases over time. Over the 1986–2015 subsample, the volatility-managed low-IV OOS-MVE portfolio earns significant alpha of 4.39% and utility gains of 198%. In contrast, during the same period, volatility managing the high-IV OOS-MVE portfolio yields insignificant alpha and effectively no increase in utility. The gains from volatility managing OOS-MVE portfolios vary with IO in a consistent manner as with IV: volatility management yields larger utility gains in the high-IO OOS-MVE portfolio than the corresponding low-IO portfolio (233% vs 64%).

It is important to note that IV is highly correlated with transaction costs, which would increase the difference in benefits from volatility management between low- and high-IV portfolios.[3] Moreover, MVE portfolios also include anomaly factors whose performance relies on the success of short positions. In low-IO stocks, investors would find it very expensive, if not impossible, to execute the necessary short sales to obtain any documented benefits from volatility management. Thus, our results understate the difference in economic significance between volatility managing high-IO and low-IO portfolios. Overall, the economic benefits of volatility management are largely concentrated in low-LTA stocks.

Moreira and Muir (2017) argue that the most plausible explanation for the abnormal returns of volatility-managed portfolios is that investors are slow to trade relative to volatility. The evidence above reduces the likelihood of this explanation because LTA should slow trading, but do the opposite of explain these abnormal returns. However, it could be the case that slow trading is endogenously concentrated in low-LTA stocks. Perhaps the largest potential cause for this concentration is the practice of large institutional traders to trade slowly by breaking up trades to reduce price impact, especially in poor liquidity conditions. By definition, institutional trading is concentrated in stocks with relatively high IO (low-LTA). If this liquidity-motivated slow trading

[3]Novy-Marx and Velikov (2016) show that IV explains 55% of the cross-sectional variation in transaction costs.

causes the attenuated response of prices to volatility, we would expect the benefits of volatility management to be higher when liquidity is lower. Our third main finding is the opposite; the alphas of volatility-managed portfolios are only significant when liquidity is high.

This finding is not consistent with slow trading, but is consistent with the model of Baker and Stein (2004) in which unsophisticated traders under-react to informed order flow in times of high sentiment, thereby creating liquidity. This finding, which we verify also holds using the Baker and Wurgler (2006) sentiment index instead of liquidity, also compliments those of recent studies that anomaly returns are concentrated in times of high sentiment, although for differing reasons. For example, Antoniou et al. (2016) also argue that high sentiment increases the participation of unsophisticated traders and find evidence that these traders disproportionately overvalue high-beta stocks. Stambaugh et al. (2012) and Stambaugh and Yuan (2017) find that many anomaly returns are higher when sentiment is high. However, 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 et al. (2013) argues 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.

Our liquidity and sentiment results also contrast with the argument of Moreira and Muir (2017) that the alpha earned by volatility-managed portfolios is evidence against conventional investment wisdom that investors should either maintain their positions or increase risk-taking following large market crashes or during recessions, which coincide with low liquidity and sentiment.[4] While it is true that volatility-managed portfolios take less risk in these "bad times", our results show this is not when these portfolios outperform unmanaged strategies.

The remainder of this paper proceeds as follows. Section II describes our data. Section III presents our main results. Section IV evaluates explanations for the abnormal returns of volatility portfolios. Section V concludes.

[4] 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).

II. Data

We obtain daily and monthly data on individual common stocks from CRSP and annual accounting data from COMPUSTAT. We obtain monthly returns on the ten size-based portfolios as well as both daily and monthly returns on the Fama and French (1993, 2015) and Carhart (1997) factors (MKT, SMB, HML, MOM, CMA, and RMW) along with the risk-free rate (r_f) from the website of Kenneth French. The website of Jeffrey Wurgler provides us the sentiment index orthogonalized to economics conditions of Baker and Wurgler (2006). We obtain the Pástor and Stambaugh (2003) liquidity level from WRDS, and the TED spread (TED) from the St. Louis Federal Reserve.

We correct stock returns for delisting bias following Shumway (1997). We define momentum return ($r_{12,2}$), market capitalization (ME), book-to-market ratio (BM), operating profit (OP), and investment (INV) following Fama and French (2015, 2016). We measure idiosyncratic volatility for stock i in month t as the standard deviation $\sigma(\epsilon_{id})$ of the residuals from a CAPM regression estimated using daily data (17 days minimum) in month $t-1$:[5]

$$r_{id} - r_{fd} = a_{it} + \beta_{it} MKT_d + \epsilon_{id}, \ d \in t-1. \tag{1}$$

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, which uses IV, is 1926:7-2015:12. We also consider three 30-year subsamples: 1926:7–1955:12, 1956:1–1985:12, and 1986:1–2015:12. IO is only available for the most recent subsample. The factors CMA and RMW are only available for the period 1963:7–2015:12, while the other Fama-French factors are available over effectively the maximum sample (MOM is only available since 1927:1).

[5]Some studies define IV relative to a multi-factor model, such as the Fama-French 3-factor model (e.g., Ang et al., 2006). However, this practice potentially alters the interpretation of IV and thus studies that focus on the friction-aspect of IV often only use the market return as a factor (e.g., Novy-Marx and Velikov, 2016).

III. Main Results

A. Volatility-Managed Portfolio Construction

Our construction of volatility-managed portfolios and performance-evaluation methodology closely follow Moreira and Muir (2017). We construct volatility-managed portfolios by scaling excess returns by the inverse of variance.[6] Letting f_t denote a buy-and-hold excess return in month t, the the managed portfolio return (f_t^σ) is defined as:

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

where $\hat{\sigma}_{t-1}$ denotes the volatility of daily returns over month $t-1$ and the constant c is chosen to equate the unconditional volatilities of f_t and f_t^σ. The motivation for this strategy comes from 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 $\frac{1}{\gamma}\frac{E_t(f_{t+1})}{\sigma_t^2(f_{t+1})}$, where γ denotes relative risk aversion and $E_t(f_{t+1})$ ($\sigma_t^2(f_{t+1})$) denotes conditional expectation (variance) of f_{t+1}. Since expected returns are highly unpredictable at the monthly frequency and volatility is highly persistent, $\frac{c}{\hat{\sigma}_{t-1}^2}$ approximates the role of $\frac{E_t(f_{t+1})}{\sigma_t^2(f_{t+1})}$ in Eq. (2).

B. Empirical Methodology

We regress the excess returns of volatility-managed portfolios on their unmanaged counterparts:

$$f_t^\sigma = \alpha + \beta \cdot f_t + \epsilon_t. \tag{3}$$

A positive alpha indicates that access to f_t^σ increases the maximum possible Sharpe ratio relative to that of a buy-and-hold position in f_t. When f_t is a systematic factor, such as the market portfolio, that summarizes common variation for many assets, a positive alpha implies that volatility management improves the mean-variance frontier.

[6] Barroso and Santa-Clara (2015) and Barroso and Maio (2017*a*) scale by the inverse of volatility instead of variance. Empirically, both variance-scaling and volatility-scaling yield similar results and we use variance scaling to maintain direct comparability with Moreira and Muir (2017).

The ultimate benefit of volatility management to an investor is increased utility from a higher maximum Sharpe ratio for their whole portfolio. Thus, alpha only matters to the extent that it expands the mean-variance frontier. Intuitively, this expansion depends on the alpha relative to the residual risk investors must bear to capture it. The maximum Sharpe ratio (SR_{New}) attainable from access to f_t and f_t^{σ} is given by:

$$SR_{New} = \sqrt{\left(\frac{\alpha}{\sigma(\epsilon_t)}\right)^2 + SR_{Old}^2}, \tag{4}$$

where SR_{Old} is the Sharpe ratio of f_t (e.g., Bodie et al., 2014). Hence, we use the appraisal ratio $\left(\frac{\alpha}{\sigma(\epsilon_t)}\right)$ as one measure of volatility-management benefits to compare across assets.

A disadvantage of the appraisal ratio is that its effect on Sharpe ratios is nonlinear. The same appraisal ratio has a greater impact on a lesser SR_{Old} than vice versa. Thus, to further facilitate comparison across assets, we measure the percentage increase in mean-variance utility, which—for any level of risk aversion—is equal to:

$$\text{Utility gain} = \frac{SR_{New}^2 - SR_{Old}^2}{SR_{Old}^2}. \tag{5}$$

Campbell and Thompson (2008) find that timing expected returns on the stock market increases mean-variance utility by approximately 35%, providing a useful benchmark utility gain.

C. Long-Equity Portfolios

We begin our analysis by comparing the performance of volatility-managed long-only portfolios constructed from stocks with different levels of IV or IO. Long portfolios are the basic building block of more complicated strategies and most interesting to the outstanding majority of investors who only take long positions. Moreover, the performance of long-only strategies does not require potentially costly or difficult short positions.

Each month, we sort every stock in CRSP into value-weighted IV or IO terciles, denoted, respectively, IV_1, IV_2, and IV_3, or IO_1, IO_2, and IO_3. Table 1 presents average excess returns and estimates of CAPM regressions for the unmanaged IV- and IO-tercile portfolios. Panel A shows that consistent with prior evidence, over 1926–2015, average excess returns decrease with IV, and are even insignificant for IV_3 (e.g., Ang et al., 2006). Similarly, Panel B shows that IV_1 earns a significant positive CAPM alpha of 1.23% per year, while this figure decreases to -7.56% per year for IV_3. Panel C shows analogous findings as Panel A, but for the IO terciles. Although insignificantly, IO_1 actually under-performs the risk-free rate over 1986–2015. Average returns increase with IO with a significant spread of about 10.0% per year between IO_1 and IO_3. Panel D shows a parallel pattern in CAPM alphas, which significantly increase by 9.4% from -9.4% per year for IO_1 to an insignificant 0.0% per year for IO_3. The abysmally poor returns and negative alpha's of low-IO stocks are consistent with limits to short selling.

Figure 1 plots the cumulative log value of $1 invested at the beginning of the sample in each of the volatility-managed IV and IO portfolios relative to their unmanaged counterparts. Panel A shows that IV_1^σ and IV_2^σ steadily outperform the remaining portfolios over the 90-year window 1926–2015 and each accumulate to about 10.7 log dollars ($44,356). The unmanaged IV_1 and IV_2 accumulate to about 8.8 log dollars ($6,634 $\approx$ 15% of $44,356). In contrast, IV_3^σ and IV_3 have much lower cumulative returns of about 1.9 log dollars ($7). The findings are similar in Panel B for IO portfolios. The volatility-managed IO_2^σ and IO_3^σ greatly outperform the remaining portfolios and avoid the Sharpe decreases of their unmanaged counterparts. The IO_1^σ avoids a couple of the crashes experienced by IO_1, but still earns very low returns.

Panels A through C of Table 2 present performance results—based on Eq. (3)—of the volatility-managed IV portfolios as well as a long-short portfolio ($IV_1 - IV_3$). Panel A shows that over 1926–2015 each of the IV_i^σ has a beta with respect to IV_i of about 0.6. The low- and medium-LTA IV_1^σ and IV_2^σ earn statistically significant alpha and economically large appraisal ratios and utility gains (46% for both factors). In contrast, the high-LTA IV_3^σ earns effectively no alpha with respect to IV_3. The volatility-managed long-short $(IV_1 - IV_3)^\sigma$ also earns significant and economically large alpha with respect to $IV_1 - IV_3$. It is important to note that observing volatility-timing benefits for a long-short factor does not imply that volatility timing improves performance for the long leg more than the short leg. The volatility of a factor is a function of the volatilities of the long and short legs as well as the covariances between them.

We find similar patterns over subsamples for IV_1^σ as Moreira and Muir (2017) find for the market factor. Alphas of IV_1^σ are the largest in the early and late samples (1926–1955 and 1986–2015) and insignificant in the middle sample (1956–1985). The low gains from volatility management derive from low variation in volatility over 1956–1985. IV_2^σ only earns significant alpha in the early sample and IV_3^σ does not earn significant alpha in any sample. The $(IV_1 - IV_3)^\sigma$ earns significant alpha in every sample. Furthermore, the alphas remain unchanged controlling for additional factors (MKT, SMB, and HML) in addition to the unmanaged portfolios. Thus, the benefits of volatility timing seem to robustly decline with IV.

Panel D presents results analogous to those of Panel A, but for IO portfolios. The main result is the same between both Panels. The (high-LTA) IO_1^σ exhibits no benefit from volatility management. In contrast, IO_2^σ and IO_3^σ earn significant alphas and have economically significant appraisal ratios that result in large utility gains of 68%–175%. The volatility-managed $(IO_3 - IO_1)^\sigma$ also earns statistically significant alpha and Panel E shows that alphas are effectively unchanged when including the Fama-French factors.

Overall, the evidence from Table 2 shows that the benefits from volatility managing long-equity portfolios concentrate in low- and medium-LTA stocks and are insignificant for high-LTA stocks. Thus, these results reject our main hypothesis and leave the anomalous returns of volatility-managed portfolios unexplained by frictions or rational models.

With a similar motivation as our long-only portfolio tests, Moreira and Muir (2017) investigate whether market-wide limits-to-arbitrage explain the apparent profitability of volatility-timing the market factor. They show the managed-market strategy does not require short selling, can be executed with derivatives, and is profitable after transaction costs. Their time-series analysis shows that several arbitrage frictions do not eliminate the profitability of the managed-market strategy. However, this analysis does not address whether arbitrage frictions impact the underlying equity prices to make the strategy profitable in the first place. In contrast, our cross-sectional analysis directly investigates whether LTA affects stock prices in a way that renders volatility-management profitable—specifically by preventing prices from adjusting to maintain the risk-return trade off predicted by frictionless rational models. This distinction is also important because unlike the well-documented cross-sectional positive correlation between LTA and anomaly returns, these returns can be higher when market-wide limits to arbitrage are lower. For example, Avramov et al. (2016) shows that the momentum strategy is more profitable when market liquidity is higher (LTA are lower), consistent with a positive correlation between liquidity and the proportion of irrational traders in the market.

Figures 2 and 3 illustrate why the Table 2 results work. In these figures, for each IV or IO tercile, respectively, we sort months into quintiles based on that month's volatility of IV_i or IO_i. We then plot the volatility, average return, and average return divided by average variance (risk-return trade-off) within those quintiles. Figure 2 presents results for IV-sorted portfolios. Panels A, B, and C show that volatility is persistent from month-to-month for each IV_i. However, Panels D and E show that on average, the returns of IV_1 and IV_2 are at most weakly related to volatility. This necessarily implies a negative relation between risk and subsequent return, which is seen in Panels G and H, and produces the benefits of volatility timing. In contrast, Panel F shows a clear positive risk-return tradeoff for IV_3, which prevents superior performance of IV_3^{σ}. The IV_3 result is interesting because it is more consistent with rational and frictionless theories than the negative risk-return relation for IV_1 and IV_2, in spite of the high arbitrage frictions in IV_3.

The takeaways from Figure 3 parallel those of Figure 2, though are noisier because of the smaller sample size. Each IO_i exhibits persistence in volatility in Panels A through C. However, Panels D through I show the risk-return trade-off is flatter for IO_1 than IO_2 and IO_3. The risk-return relation is negative, if anything, for IO_2 and IO_3.

D. Long-short portfolios

Next we examine the performance of volatility-managed long-short factors constructed within each IV and IO tercile. Independently of IV and IO, we sort stocks each month into quintiles based on each characteristic (ME, BM, MOM, INV, and OP) associated with the Fama and French (1993, 2015) and Carhart (1997) factors (MKT, SMB, HML, MOM, RMW, and CMA). Within each IV or IO quintile, we construct high-minus-low or low-minus-high long-short portfolios (denoted, for example, by BM_{5-1} or ME_{1-5}) that are signed to be positive on average. For each characteristic X, we also construct low-minus-high-IV (high-minus-low-IO) difference portfolios, denoted $IV_{1-3}(X_{5-1})$ or $IV_{1-3}(X_{1-5})$ ($IO_{1-3}(X_{5-1})$ or $IO_{1-3}(X_{1-5})$). Table 3 presents CAPM alphas of the 3x5 and long-short portfolios constructed for each characteristic.

Panels A through C show that in the 1926–2015 sample, the spread in abnormal returns associated with ME, BM, and MOM increases with IV. This increase is large and significant for BM and MOM. Moreover, examining the subsample results shows that the spread in these three anomalies' abnormal returns increases over time and are all significant in the most recent sample. Panels D and E show that over the 1963–2015 sample, the abnormal returns associated with the INV and OP anomalies typically increase with IV, although the significance of the increase is only marginally significant. Overall, anomalies appear to grow stronger with IV, consistent with its role as a limit to arbitrage. Panels F through J show a similar pattern for IO as for IV. Anomaly returns, especially the short legs, increase going from IO_3 to IO_1. This increase is significant for BM, MOM, and OP. These results are consistent with the limits-to-arbitrage property of IO.[7]

Table 4 presents alphas and utility gains from Eq. (3) for each long-short anomaly factor in Table 3. Results using IV include those for the different subsamples. Overall, the main takeaway is that no consistent pattern exists between the IV or IO rank and the performance of the managed factors, contrary to our main hypothesis.

E. Mean-Variance Efficient Portfolios

Next, we apply the volatility-timing strategy to mean-variance-efficient (MVE) portfolios, which are constructed to have the maximum possible Sharpe ratios attainable from a set of factors. The alpha and utility gains of managed MVE portfolios approximate the potential gains of volatility management for investors who have access to many assets.

[7]Numerous studies find that the size effect in returns is insignificant post-1980 (see, e.g., van Dijk (2011) for a recent survey). However, the evidence in Panels A and F show that the size effect is significant in low-LTA stocks, which complements the findings of Asness et al. (2017) that the size effect is robust controlling for measures of firm quality.

E.1. In-Sample MVE Portfolios

Following Moreira and Muir (2017), for each IV_i (IO_i), we estimate the unconditional in-sample (ex-post) MVE portfolio, denoted MVE_{IV_i} (MVE_{IO_i}), constructed from one of two sets of factors. The first set of factors, denoted FF3+MOM, consists of the excess return on IV_i (IO_i) as well as the long-short ME_{1-5}, BM_{5-1}, and MOM_{5-1} factors constructed within IV_i (IO_i) from Table 3. The second set of factors, denoted FF5+MOM, adds the corresponding OP_{5-1} and INV_{1-5}.

Panel A of Table 5 reports CAPM alphas for the unmanaged MVE_{IV_i}. Both the FF3+MOM and FF5+MOM MVE_i^{IV} alphas increase significantly and monotonically from IV_1 to IV_3. This result follows from the higher returns to anomalies in high-LTA stocks. Panel B reports performance statistics for the managed $MVE^{\sigma}_{IV_i}$. Using the FF3+MOM factors, the $MVE^{\sigma}_{IV_i}$ each earn significant alpha with respect to MVE_{IV_i} over 1926–2015. The highest utility gain of 55% belongs to the low-LTA $MVE^{\sigma}_{IV_1}$, although the $MVE^{\sigma}_{IV_3}$ still has an economically large gain of 43%. Over 1963–2015, all three FF5+MOM $MVE^{\sigma}_{IV_i}$ also earn statistically significant alpha. However, the economic significance of these alphas is higher for the low-IV portfolio (utility gain of 26%) than the high-IV portfolio (utility gain of 9%).

Panel C presents CAPM alphas of the unmanaged FF3+MOM and FF5+MOM MVE_{IO_i}. Similar to Panel A, The CAPM alphas of the MVE_{IO_i} increase significantly and monotonically going from low-LTA to high-LTA. This pattern reflects the greater returns to anomalies, especially the short legs, when LTA are high as indicated by low IO. Panel D shows the $MVE^{\sigma}_{IO_i}$ typically earn statistically significant alpha with respect to the unmanaged MVE_{IO_i}. However, the economic significance is two to three times higher for low-LTA $MVE^{\sigma}_{IO_3}$ than the $MVE^{\sigma}_{IO_1}$. For the FF3+MOM and FF5+MOM $MVE^{\sigma}_{IO_i}$, respectively, the utility gains of MVE^{σ}_{IO3} are 59% and 63% compared to 18% and 31% for the $MVE^{\sigma}_{IO_1}$.

Even if investors knew the in-sample MVE weights ex ante, they would have difficulty and bear large expenses to execute the strategies with high-LTA stocks. For example, the success of the MVE depends critically on executing the short positions associated with each anomaly. In the low-IO tercile, investors would likely find it prohibitively costly, if not impossible, to execute these short positions. Moreover, Novy-Marx and Velikov (2016) find that IV explains the cross-sectional variation in stock-level transaction costs with an R^2 of 55%. Thus, the performance of the high-IV portfolios above is also overstated relative to what investors could realize. Conversely, the relatively high economic gains of volatility timing MVE_{IO_3} and MVE_{IV_1} are much more likely to be realizable because they have lower transaction costs as well as easier and less-costly short-selling. Thus, after frictions are considered, the economic gains to volatility managing in-sample MVE portfolios are greatest in low-LTA stocks.

E.2. Out-of-Sample MVE Portfolios

In-sample MVE portfolios overstate the maximum Sharpe ratios investors could obtain because their weights depend on future information. As a result, Moreira and Muir (2017) argue that gains from volatility managing in-sample MVE portfolios likely understate the true potential benefits of volatility timing. Hence, we estimate the benefits of volatility timing out-of-sample MVE portfolios.

Let F_{it}^{IV} (F_{it}^{IO}) denote the FF3+MOM factors for each IV- (IO-)tercile portfolio IV_i (IO_i). For each month $t > 120$, we construct out-of-sample MVE portfolios, $MVE_{IVi,t} = b'_{t-1}F_{it}^{IV}$ ($MVE_{IO_i} = b'_{t-1}F_{it}^{IO}$) by estimating b_{t-1} such that:

$$b_{t-1} = \arg\max_{b} \; SR(b)_{i,t-1}, \tag{6}$$

where $SR(b)_{i,t-1}$ is the Sharpe ratio of the portfolio $b'F_{i\tau}^{IV}$ ($b'F_{i\tau}^{IO}$) over the window $\tau = 1, ..., t-1$. DeMiguel et al. (2009) show that out-of-sample estimates of tangency portfolios do not reliably outperform simple "1/N" strategies that equal weight each asset in optimizations such as Eq. (6). Hence, we also apply our analysis to 1/N strategies constructed from the same factors as the MVE portfolios. We denote the latter $(1/N)_{IV_i}$ or $(1/N)_{IO_i}$.

Table 6 presents CAPM alphas of the unmanaged out-of-sample MVE portfolios and performance results of the volatility-managed counterparts. To take advantage of the maximum possible sample and thoroughly analyze subsamples while avoiding a profusion of panels, we only present results using the FF3+MOM factors.[8] Each Panel corresponds to a choice of out-of-sample window. The estimation of the MVE portfolios begins with data 120 months (10 years) before the start of

[8] The results using the FF5+MOM factors, which are qualitatively similar, are available upon request.

the window. For example, Panel A presents results over 1936:2–2015:12. The first observation (1936:2) of the MVE portfolios in Panel A is based on portfolio weights estimated over the prior 120 months (1927:2–1936:1). The second observation is based on the prior 121 months, and so on.

Panel A presents CAPM alphas of the un-managed MVE_{IV_i} portfolios over 1926–2015. Like their in-sample counterparts in Table 5, the CAPM alphas of these portfolios increase significantly with LTA, going from low-to-high IV.

Panel B presents Sharpe ratios of the unmanaged MVE_{IV_i} and performance results of the volatility-managed $MVE^{\sigma}_{IV_i}$ over 1937–2015. The Sharpe ratios of the unmanaged portfolios are economically large, ranging from 0.91 to 1.22. For comparison, the market Sharpe ratio was 0.49 over the same time period. The Sharpe ratios of the $(1/N)$ portfolios are only slightly smaller, ranging from 0.78 to 1.13. These high Sharpe ratios validate the use of the MVE and $(1/N)$ portfolios as reasonable approximations to the mean-variance frontier in their respective groups of stocks. The alphas of the $MVE^{\sigma}_{IV_i}$ during this sample are all significant, however the utility gains for $MVE^{\sigma}_{IV_1}$ are more than three times as high as those of $MVE^{\sigma}_{IV_3}$ (65% vs 19%). The $(1/N)^{\sigma}_{IV_3}$ earns an insignificant alpha and has a lower Sharpe ratio than the unmanaged $(1/N)_{IV_3}$. In contrast, the $(1/N)^{\sigma}_{IV_1}$ earns a significant alpha and increases utility by 49%.

Panel C shows that over the 1937:2–1955:12 subsample, none of the MVE_{IV_i} or $(1/N)_{IO_i}$ earn significant alpha, perhaps because of the relatively short sample window. Panel D shows that in contrast to the results in the rest of the paper, two of the MVE_{IV_i} portfolios—but none of the $(1/N)_{IV_i}$ portfolios—earn significant alpha during the 1956–1985 sample that tends to exhibit weak gains of volatility management. However, the corresponding economic significance of these alphas is small (utility gains range from 0% to 12%).

Panel D shows that over the recent subsample 1986–2015, the gains to volatility managing the MVE portfolios are generally more significant than those of the earlier samples. The $MVE^{\sigma}_{IV_3}$ and $(1/N)_{IV_3}$ do not earn significant alpha or generate meaningful utility gains. Volatility management even dramatically lowers the Sharpe ratios of $MVE^{\sigma}_{IV_3}$ and $(1/N)_{IV_3}$, from 1.13 to 0.84 and 1.04 to 0.54, respectively. In contrast, the $MVE^{\sigma}_{IV_1}$ and $MVE^{\sigma}_{IV_2}$ earn significant alphas and generate utility gains of 198% and 44%, respectively. The economic benefits of volatility management are also large for $(1/N)_{IV_1}$ and $(1/N)_{IV_2}$ during this time period with dramatic increases in Sharpe ratios and large utility gains of 200% and 27%, respectively.

Panel F presents CAPM alphas of unmanaged MVE_{IO_i} and $(1/N)_{IO_i}$. Like the MVE_{IV_i} alphas in Panel A, the alphas of MVE_{IO_i} increase significantly going from low-to-high LTA. However, the corresponding increase in alphas is insignificant for the $(1/N)_{IO_i}$ portfolios.

Panel G presents performance results for the $MVE^{\sigma}_{IO_i}$ and $(1/N)^{\sigma}_{IO_i}$ over 1996:2-2015:12. Both sets of portfolios earn significant alpha. However, the economic significance of the volatility-management benefits increases dramatically going from low to high LTA. The utility gain of $MVE^{\sigma}_{IO_3}$ is 233% relative to the gain of 64% earned by $MVE^{\sigma}_{IO_1}$. Similarly, the utility gain of $(1/N)^{\sigma}_{IO_3}$ (45%) is more than twice the utility gain of $(1/N)^{\sigma}_{IO_1}$ (27%). The utility gain of MVE_{IO_1} may seem economically significant, however, it is again important to note that investing in MVE_{IO_1} requires implementing the short legs of the constituent anomaly factors. This would almost certainly be prohibitively expensive or even impossible given the low IO.

Overall, the results in Table 6 show that the ability of volatility management to improve the investment opportunity set is concentrated in stocks with the lowest LTA.

IV. Potential Explanations

The evidence above renders the profitability of volatility management very puzzling because the phenomenon is contrary to the predictions of frictionless rational models and limits to arbitrage do the opposite of explaining the contrast. In this section, we provide new evidence on potential explanations for this anomaly.

A. Slow Trading

Any explanation for the profitability of volatility managed portfolios must explain why prices do not covary strongly enough with volatility to maintain a Sharpe ratio that is either constant or increasing with volatility. Moreira and Muir (2017) argue that slow trading is the most likely explanation for this phenomenon. The results above reduce the likelihood of this "slow trading hypothesis" because LTA—including IV and IO—should contribute to slow trading, although they actually weaken the volatility-management effect. However, IV and IO are not the only cause of slow trading. Large traders such as institutions intentionally trade slowly by breaking up large trades to minimize price impact, especially in the presence of low liquidity (e.g., Chan and Lakonishok, 1995; Keim and Madhavan, 1995; Hameed et al., 2017). This practice could explain our results if institutional traders are most likely to invest in stocks with low- and medium-LTA. In fact, this possibility is a tautology with IO. Hence, we investigate whether the liquidity-motivated intentional slow-trading of institutions and other large traders explains the abnormal returns on volatility-managed portfolios.

Under this explanation, we should expect to see higher abnormal returns to volatility-managed portfolios in the presence of lower liquidity, all else equal.[9] Hence, following Stambaugh et al. (2015), Panels A and B of Table 7 present estimates from regressions of the form:

$$rx_t^\sigma = \alpha_H d_{H,t} + \alpha_L d_{L,t} + \beta rx_t + \epsilon_t, \tag{7}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables that indicate when liquidity is "high" or "low", respectively. The rx^σ are the managed long-only portfolios IV_i^σ or IO_i^σ, however untabulated tests show that each of the results in Table 7 are effectively the same for $mktrf^\sigma$ as for IV_1^σ. Eq. (7) is similar to our "main" regression given by Eq. (3), however the alpha can now vary across the two liquidity states. Panel A presents results using the Pástor and Stambaugh (2003) liquidity measure (*Liquidity*), which measures the state of liquidity in the equity market.[10] Panel B uses the three-month return on the CRSP value-weighted index ($r_{m,t-3,t-1}$) as a proxy for liquidity. Hameed et al. (2010) shows that a negative value of $r_{m,t-3,t-1}$ indicates a deterioration of the supply of liquidity. The $r_{m,t-3,t-1}$ also offers the rare benefit among liquidity measures of being available over our entire sample. We define *Liqudity* to be "high" when it is at least the 50^{th} percentile for our sample, and "low" otherwise. Following Hameed et al. (2010), we define $r_{m,t-3,t-1}$ to be "high" if it is positive or zero, and "low" otherwise. For each liquidity measure and choice of IV or IO, we intersect the samples for which the liquidity measure is available with those where volatility-

[9] The "all else equal" is important; institutions may be forced to trade quickly in adverse liquidity conditions.

[10] Li et al. (2018) find that *Liquidity* continues to measure liquidity in the post-study period of Pástor and Stambaugh (2003).

management is profitable. For example, (*Liquidity*) is available since 1965, however there was no benefit to managing volatility from 1956–1985 (because of limited time variation in volatility) and therefore nothing to explain. Thus, for tests with *Liquidity*, we use the 1986–2015 subsample from our main tests. The other resulting sample periods are enumerated in Table 7.

Panel A shows that contrary to the institutional slow-trading explanation, the alphas of the volatility-managed low- and medium-LTA portfolios (IV_1^σ, IV_2^σ, IO_2^σ, IO_3^σ) are actually higher in the high-liquidity states than the low-liquidity states. Moreover, this difference is both economically large (7.45%–9.29%) and statistically significant for three of these four portfolios. Similarly, Panel B shows that the alphas of the volatility-managed low- and medium-LTA portfolios are only significantly positive on average following a positive three-month market return—when liquidity is relatively high—although the difference is only significant for IV_1^σ. Taken together, the results from Panels A and B provide strong evidence against the institutional slow-trading explanation.

While institutional traders are economically significant, slow trading could be driven by retail investors instead. Many retail investors—e.g. retirement savers—have passive strategies and might not react to volatility news at all. While this behavior would contribute to slow trading, it does not explain why these investors are the marginal investor setting prices, nor does it explain why slow trading only appears to affect prices in times of high liquidity. Moroever, among the scant data available on large retail investors, Hoopes et al. (2016) show that high-income households—who are likely to be relatively competent investors—sold more quickly alongside volatility increases during the 2008 market crash than other traders. Thus, the evidence does not support slow trading per se. Hence, we consider alternative reasons why investors would under-react to volatility.

B. Sentiment

To the best of our knowledge, market sentiment is the only well-documented force that can induce widespread mispricing regardless of asset-level limits to arbitrage per se.[11] For example, the models of Daniel et al. (2001) and Kozak et al. (2017) show that sentiment can induce commonality in mispricing such that returns conform to an (arbitrage-free) factor structure even if prices are

[11]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).

irrational. In this setting, mispricing persists, even in the absence of trading frictions like IV or low IO, because trading against the mispricing requires bearing exposure to factor risk. Thus, we investigate the possibility that sentiment explains our results.

Baker and Stein (2004) and Baker and Wurgler (2006) argue that liquidity is a proxy for sentiment because the relative difficulty of short selling compared to purchasing will lead to the relatively high presence of sentiment traders—who under-react to informed order flow—when sentiment is high.[12] Assuming informed traders do not trade "too slowly" relative to volatility shocks, the under-reaction by sentiment traders, which resembles slow trading, is consistent with the attenuated response of prices to these shocks.[13] This attenuated response of prices to volatility shocks in high-liquidity and high-sentiment times is consistent with the results from Panels A and B of Table 7, which show the profitability of volatility managing low-and medium-LTA stocks is concentrated in high-liquidity times. Before accepting this explanation of our results, we first verify this finding using a direct measure of sentiment instead of liquidity. Using the Baker and Wurgler (2006) sentiment index that is orthogonalized to economic conditions, Panel C of Table 7 presents estimates of a regression of the form Eq. (7) where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating "high" or "low" sentiment. Consistent with the liquidity-as-sentiment interpretation of Panels A and B, we find that the alphas on our low- and medium-LTA volatility-managed portfolios are only significant in months following high sentiment.

Overall, the results from Table 7 are consistent with models in which unsophisticated traders under-react to informed order flow in times of high sentiment. These results complement those of prior studies that anomaly returns are highest in times of high sentiment. However, the theory motivating these studies is typically somewhat different. For example, Stambaugh et al. (2012) argues that short-sale constraints render over-valuation induced by high sentiment harder to arbitrage away than undervaluation induced by low sentiment. Consistent with the theory of Daniel et al. (1998), Antoniou et al. (2013) argues that momentum returns are higher in times of high

[12]Grinblatt and Keloharju (2009) document empirically that unsophisticated traders participate more heavily in the stock market when valuations are high.

[13]For example, in times of high sentiment, unsophisticated buyers might "buy-the-dip" without acting on price-relevant information. Thaler and Johnson (1990) also document a potential behavioral cause for "under-reaction" to volatility shocks in good economic states when liquidity is high: individuals' risk aversion can decrease following positive returns.

sentiment because sentiment traders likely exhibit over-confidence and self-attribution resulting in an under-reaction to negative news in high-sentiment times.[14] Finally, Antoniou et al. (2016) argue that the betting-against-beta anomaly is higher in times of high sentiment because unsophisticated investors will be more active in such times (similar to the liquidity-as-sentiment theory) and these traders invest heavily in high-beta stocks. These results suggest that, when sentiment is high, investors demand a relatively low premium for the marginal contribution to the volatility of the market portfolio (beta). This implication parallels our finding that investors seem to demand a relatively low premium in the time series for market-wide volatility when sentiment is high.[15]

V. Conclusion

Prior studies find that volatility managing portfolios—scaling up when risk is low and down when risk is high—produces significant alphas and utility gains. This phenomenon contradicts conventional investment advice and is not explained by rational asset pricing models, which would not be surprising if the phenomenon could instead be explained by arbitrage frictions that are known to increase the returns on many anomalies. To the contrary, the results in this paper show that the economic gains from volatility management are actually concentrated in stocks with the lowest limits to arbitrage. Moreover, these gains increase when liquidity is higher and arbitrage should be easier. These results are not consistent with typical motivations for slow trading explaining the profitability of volatility-managed portfolios, however they are consistent with models in which unsophisticated traders under-react to informed order flow when sentiment is high.

Our results also show that consistent with conventional investment wisdom—but contrary to the conclusion of other studies on volatility-managed-portfolio—investors do not benefit from reducing their positions following market crashes.

[14] Avramov et al. (2016) finds that momentum returns are higher when liquidity is higher and concludes with a similar explanation as Antoniou et al. (2013).

[15] One question raised by the evidence in Table 7 is why the effects of sentiment effect are concentrated in low- and medium-LTA stocks. The simplest explanation, which we do not test, is that unsophisticated sentiment-driven traders prefer easy-to-trade stocks. This answer is consistent with the spirit of the liquidity-as-sentiment theory where high sentiment attracts these traders more than low sentiment because it is easier to buy than to sell. Similarly, 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).

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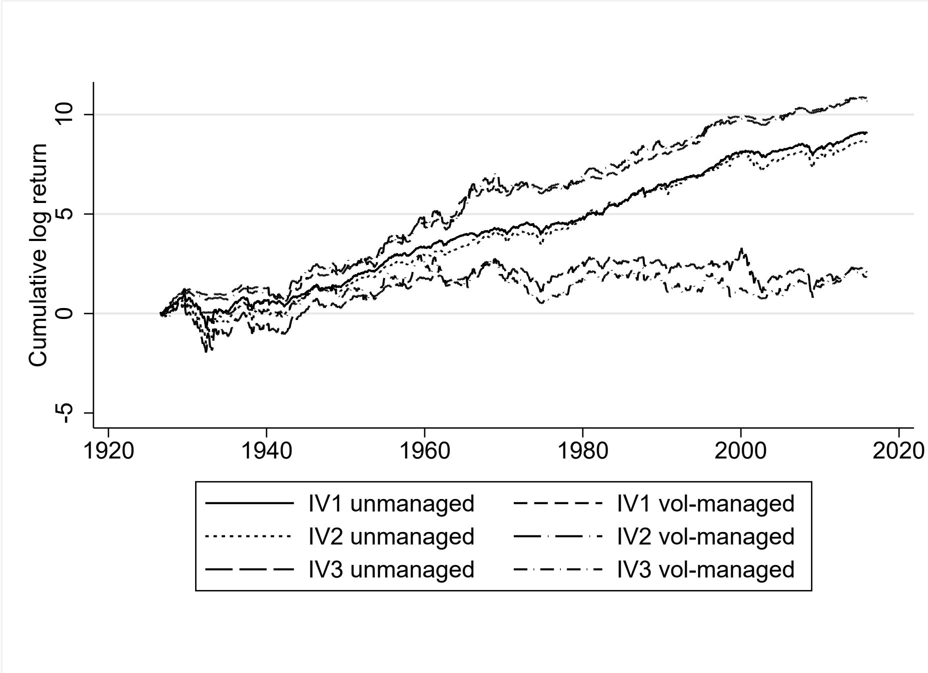
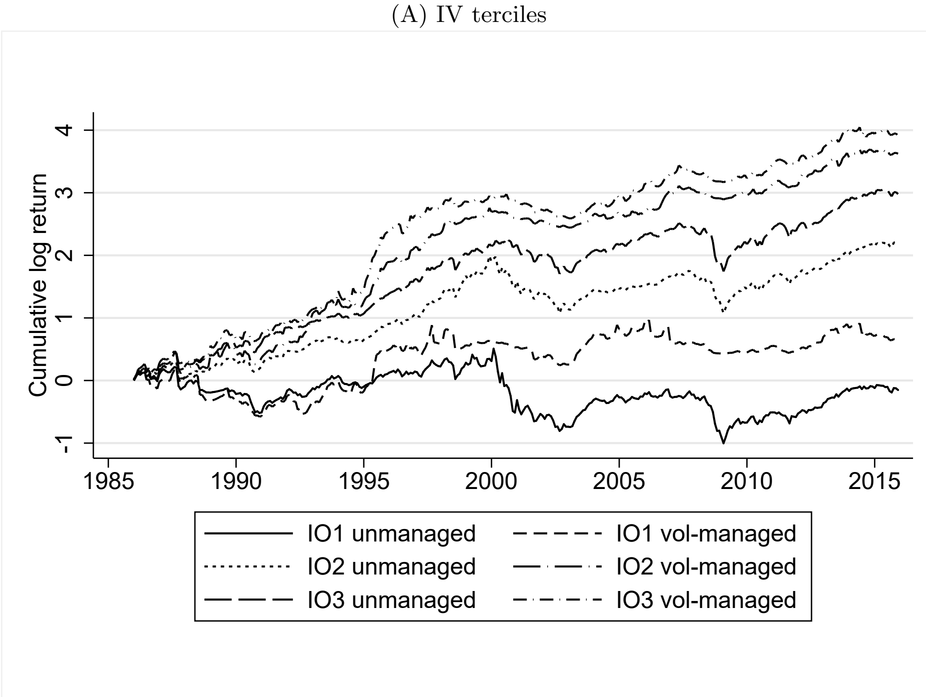


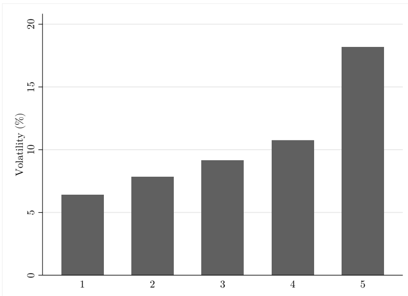
(A) IV terciles



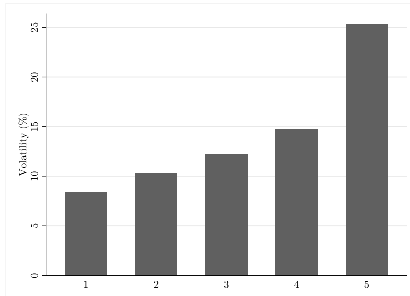
(B) IO terciles

Figure 1: Cumulative log returns on unmanged and volatility-manged institutional ownership- and idiosyncratic volatility-tercile portfolios.

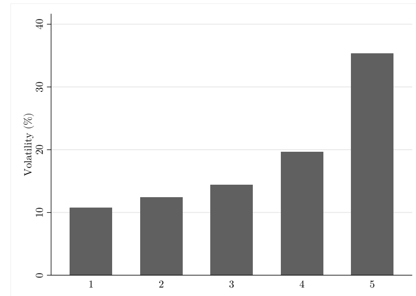
Panel A (B) plots the cumulative returns to a buy-and-hold strategy versus a volatility-managed strategy for each idiosyncratic volatility (IV)-tercile (institutional ownership (IO)-tercile) portfolio from 1926 to 2015 (1986 to 2015). The y-axis is on a log scale and the volatility-managed strategies have the same unconditional monthly standard deviation as their unmanaged counterparts.



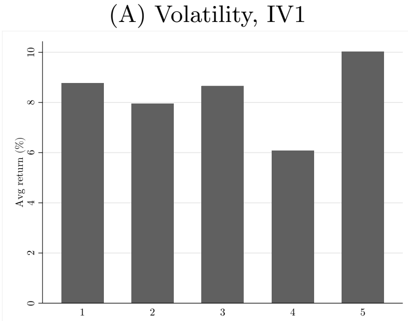
(A) Volatility, IV1



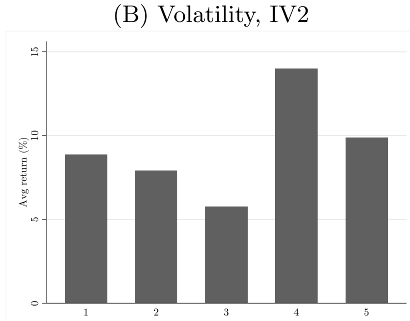
(B) Volatility, IV2



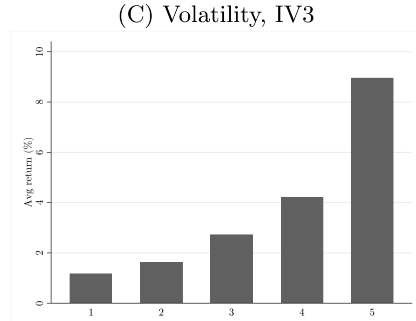
(C) Volatility, IV3



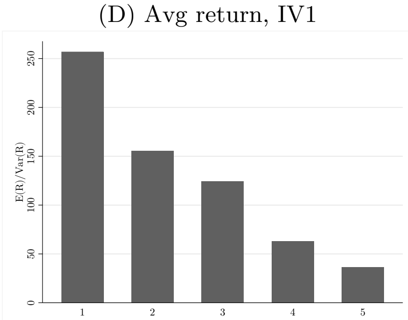
(D) Avg return, IV1



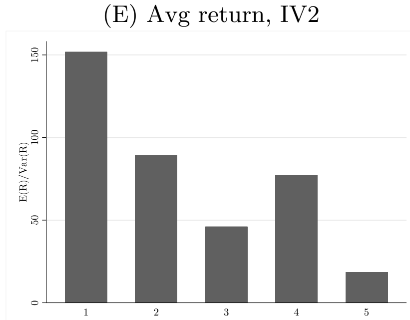
(E) Avg return, IV2



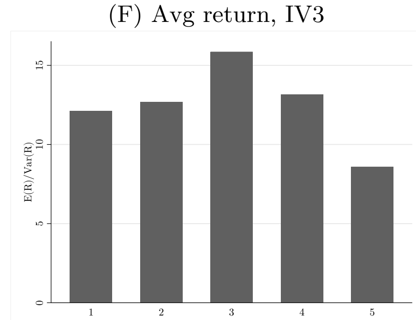
(F) Avg return, IV3



(G) $E(r)/\sigma^2(r)$, IV1



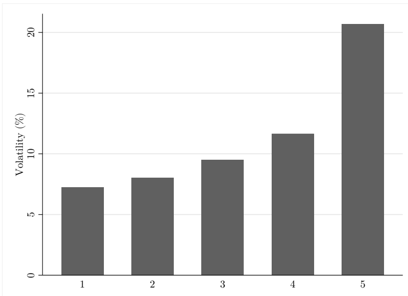
(H) $E(r)/\sigma^2(r)$, IV2



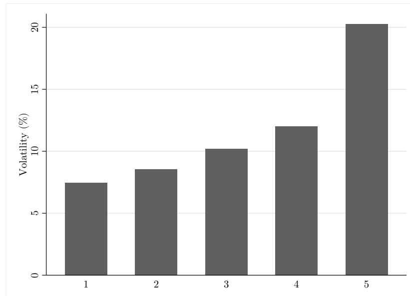
(I) $E(r)/\sigma^2(r)$, IV3

Figure 2: Sorts on previous month's volatility quintile by idiosyncratic-volatility.

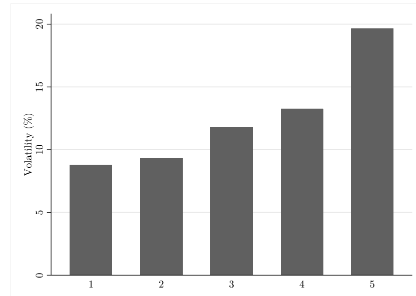
For each IV-tercile portfolio, we use the monthly time series of realized volatility to sort the following months returns into five buckets. The lowest, "1" looks at the properties of returns over the month following the lowest 20% of realized volatility months. We show the average return over the next month, the standard deviation over the next month, and the average return divided by variance for each tercile.



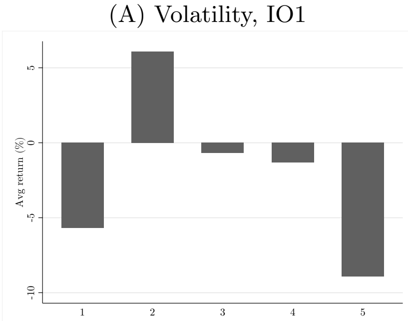
(A) Volatility, IO1



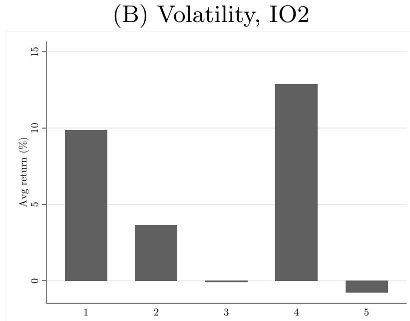
(B) Volatility, IO2



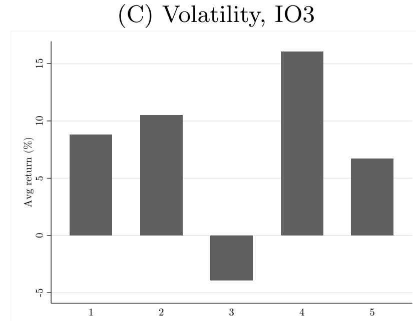
(C) Volatility, IO3



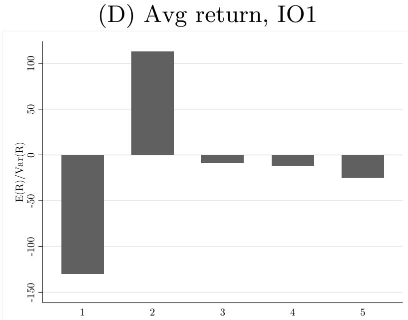
(D) Avg return, IO1



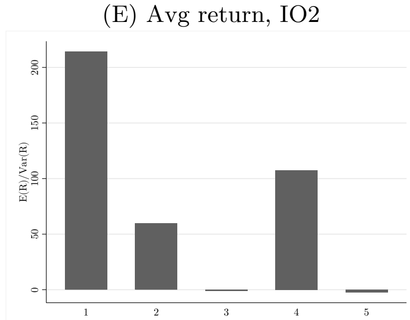
(E) Avg return, IO2



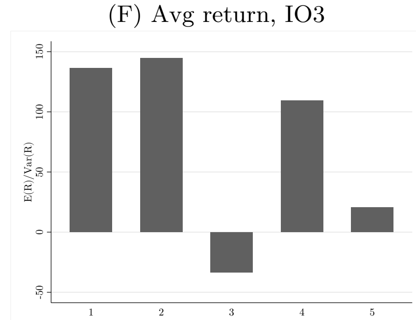
(F) Avg return, IO3



(G) $E(r)/\sigma^2(r)$, IO1



(H) $E(r)/\sigma^2(r)$, IO2



(I) $E(r)/\sigma^2(r)$, IO3

Figure 3: Sorts on previous month's volatility quintile by institutional ownership.

For each IO-tercile portfolio, we use the monthly time series of realized volatility to sort the following months returns into five buckets. The lowest, "1" looks at the properties of returns over the month following the lowest 20% of realized volatility months. We show the average return over the next month, the standard deviation over the next month, and the average return divided by variance for each tercile.

Table 1: Average returns and CAPM alphas of unmanaged idiosyncratic volatility (*IV*)- and institutional ownership (*IO*)-tercile portfolios

Panels A and B, respectively, present average excess returns and CAPM alphas for each of the idiosyncratic volatility (*IV*) portfolios IV_1, IV_2, IV_3 or the low-minus-high factor $IV_1 - IV_3$. Panels C and D present the same statistics for each of the institutional ownership (*IO*) portfolios (IO_1, IO_2, IO_3), or the high-minus-low-*IO* factor ($IO_3 - IO_1$). t-statistics are below point estimates in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes adjusted R^2 in all tables. In Panels A and B the sample period is 1926:8-2015:12 (N=1073). In Panels C and D the sample is 1986:1-2015:12 (N=360).

Panel A: Average returns of IV portfolios				
	IV_1	IV_2	IV_3	$IV_1 - IV_3$
$\overline{r^e}$	8.32***	9.32***	3.65	4.68**
	(4.55)	(3.52)	(1.12)	(2.25)
Panel B: CAPM alphas of IV portfolios				
	IV_1	IV_2	IV_3	$IV_1 - IV_3$
β	0.92***	1.30***	1.45***	-0.53***
	(148.98)	(56.25)	(33.12)	(-11.09)
α	1.23***	-0.75	-7.55***	8.78***
	(4.30)	(-1.23)	(-4.85)	(4.91)
R^2	0.98	0.94	0.77	0.25
Panel C: Average returns of IO portfolios				
	IO_1	IO_2	IO_3	$IO_3 - IO_1$
$\overline{r^e}$	-2.01	5.30*	7.96***	9.98***
	(-0.58)	(1.80)	(2.67)	(4.21)
Panel D: CAPM alphas of IO portfolios				
	IO_1	IO_2	IO_3	$IO_3 - IO_1$
β	0.96***	0.98***	1.04***	0.08
	(22.65)	(42.10)	(74.55)	(1.60)
α	-9.35***	-2.15**	0.04	9.39***
	(-4.24)	(-2.12)	(0.07)	(3.89)
R^2	0.61	0.89	0.97	0.01

Table 2: Performance of volatility-managed IV and IO portfolios

Panel A presents regressions of the form: $rx_t^\sigma = \alpha + \beta \cdot rx_t + \epsilon_t$, where rx_t denotes the unmanaged excess return on IV_1, IV_2, IV_3 or $IV_1 - IV_3$, and rx_t^σ denotes the volatility-managed version of rx_t. Beneath each regression is the Sharpe ratio of the unmanaged and managed factors, the appraisal ratio $\left(\frac{\alpha}{\sigma(\epsilon)}\right)$ of the managed factor, and the utility gain from access to rx_t^σ. The sample period in panel A is 1926:9-2015:12 (N=1072), and Panel B presents α from the same regression as Panel A, but over 30-year subsamples (1926:9-1955:12, 1956:2-1985:12, and 1986:2-2015:12). Panel C presents alphas from the same regression as Panel A, but also including the Fama-French three-factors (MKT, SMB, HML). Panels D and E present, respectively, analogous statistics as Panels A and C, but for *IO* portfolios instead of *IV* portfolios over 1986:2-2015:12 (N=359).

Panel A: Univariate regressions of volatility-managed *IV* portfolios 1926-2015				
	(1)	(2)	(3)	(4)
	IV_1^σ	IV_2^σ	IV_3^σ	$(IV_1 - IV_3)^\sigma$
IV_1	0.63***			
	(10.97)			
IV_2		0.58***		
		(9.68)		
IV_3			0.59***	
			(11.79)	
$IV_1 - IV_3$				0.56***
				(11.03)
α(%)	4.37***	5.16**	-0.17	6.98***
	(3.03)	(2.45)	(-0.06)	(4.03)
N	1072	1072	1072	1072
R^2	0.40	0.33	0.35	0.31
Original Sharpe	0.48	0.37	0.12	0.24
Vol-managed Sharpe	0.55	0.42	0.06	0.49
Appraisal ratio	0.33	0.25	0.00	0.43
Utility gain	0.46	0.46	0.00	3.26
Panel B: Alphas of volatility-managed *IV* portfolios over subsamples				
1926-1955	8.53***	9.27**	4.16	8.29***
	(2.97)	(2.49)	(1.07)	(3.02)
1956-1985	0.79	1.73	-2.00	5.43**
	(0.32)	(0.43)	(-0.42)	(2.01)
1986-2015	3.34**	2.33	-1.23	6.15**
	(2.21)	(1.05)	(-0.30)	(2.18)
Panel C: Alphas also controlling for Fama-French three factors				
α(%)	4.32***	4.79**	-1.01	8.23***
	(2.91)	(2.26)	(-0.37)	(4.81)

Panel D: Univariate regressions of volatility-managed IO portfolios 1986-2015				
	(1)	(2)	(3)	(4)
	IO_1^σ	IO_2^σ	IO_3^σ	$(IO_3 - IO_1)^\sigma$
IO_1	0.62***			
	(8.20)			
IO_2		0.70***		
		(12.01)		
IO_3			0.72***	
			(12.87)	
$IO_3 - IO_1$				0.49***
				(3.61)
$\alpha(\%)$	0.70	4.99**	4.53**	4.78***
	(0.26)	(2.32)	(2.14)	(3.17)
N	360	360	360	360
R^2	0.38	0.49	0.52	0.24
Original Sharpe	-0.11	0.33	0.49	0.77
Vol-managed Sharpe	-0.03	0.54	0.63	0.75
Appraisal ratio	0.05	0.44	0.40	0.42
Utility gain	0.00	1.75	0.68	0.30
Panel E: Alphas also controlling for Fama-French three factors				
$\alpha(\%)$	-0.77	3.99*	4.59**	3.80***
	(-0.27)	(1.84)	(2.14)	(2.87)

Table 3: CAPM alphas of unmanaged portfolios sorted on *IV* or *IO* as well as size, book-to-market, momentum, operating profits, or investment

Each month, we independently sort stocks into *IV* or *IO* terciles (IV_i or IO_i, respectively) and characteristic quintiles. The quintile characteristics are market cap (ME), book-to-market (BM), momentum return (MOM), operating profit (OP), or investment (INV). For each IV_i or IO_i, we also construct high-minus-low or low-minus-high long-short portfolios (denoted, for example, by BM_{5-1} or ME_{1-5}) that are signed to be positive on average. For each characteristic X, we also construct a low-minus-high-IV_i return $IV_{1-3}(X_{5-1})$ equal to the return on the long-short portfolio for characteristics X in IV_1 minus the return on the long-short portfolio in IV_3. We construct a high-minus-low-*IO* portfolio $IO_{3-1}(X_{5-1})$ similarly. Each panel presents CAPM alphas of each portfolio over the full sample as well as CAPM alphas of the $IV_{1-3}(X_{5-1})$ and $IO_{3-1}(X_{5-1})$ over the subsamples defined in Table 2. t-statistics are below point estimates in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: 3x5 sorts on *IV* and *ME*								
	1926:8-2015:12						subsamples	
	ME_1	ME_2	ME_3	ME_4	ME_5	ME_{1-5}		$IV_{1-3}(ME_{1-5})$
IV_1	8.49***	7.17***	5.97***	4.12***	1.05***	7.44***	1926-	-0.76
	(3.73)	(5.96)	(6.23)	(5.40)	(3.51)	(3.16)	1955	(-0.11)
IV_2	9.36***	5.94***	3.15***	1.27	-2.17***	11.53***	1956-	-3.36
	(4.59)	(3.96)	(2.71)	(1.32)	(-3.25)	(5.67)	1985	(-1.28)
IV_3	3.63	-6.72***	-7.68***	-7.16***	-8.04***	11.67***	1986-	-9.82**
	(1.34)	(-3.26)	(-4.31)	(-4.10)	(-3.61)	(3.80)	2015	(-2.39)
IV_{1-3}						-4.23		
						(-1.46)		

Panel B: 3x5 sorts on *IV* and *BM*								
	1926:8-2015:12						subsamples	
	BM_1	BM_2	BM_3	BM_4	BM_5	BM_{5-1}		$IV_{1-3}(BM_{5-1})$
IV_1	0.80	0.87	1.22	1.63	1.83	1.04	1926-	-7.62
	(1.23)	(1.53)	(1.62)	(1.59)	(1.15)	(0.55)	1955	(-1.22)
IV_2	-2.47**	-1.07	0.62	2.48**	2.95*	5.42***	1956-	-7.08**
	(-2.55)	(-1.27)	(0.64)	(2.13)	(1.94)	(2.95)	1985	(-2.57)
IV_3	-10.23***	-8.02***	-4.71***	-5.20***	0.94	11.17***	1986-	-16.15***
	(-4.78)	(-4.92)	(-2.84)	(-2.78)	(0.42)	(4.28)	2015	(-3.92)
IV_{1-3}						-10.14***		
						(-3.83)		

Panel C: 3x5 sorts on *IV* and *MOM*								
	1927:1-2015:12						subsamples	
	MOM_1	MOM_2	MOM_3	MOM_4	MOM_5	MOM_{5-1}		$IV_{1-3}(MOM_{5-1})$
IV_1	-5.77***	-1.90*	0.00	3.36***	6.30***	12.07***	1927-	5.43
	(-2.99)	(-1.69)	(0.01)	(5.13)	(6.61)	(4.76)	1955	(1.06)
IV_2	-9.62***	-5.51***	-1.97**	1.00	6.39***	16.01***	1956-	-5.73**
	(-5.59)	(-4.94)	(-2.24)	(1.12)	(5.30)	(6.69)	1985	(-1.97)
IV_3	-16.32***	-10.23***	-4.13**	-2.08	1.06	17.38***	1986-	-15.10***
	(-7.52)	(-6.28)	(-2.23)	(-1.07)	(0.52)	(6.44)	2015	(-3.06)
IV_{1-3}						-5.30**		
						(-2.07)		

Table 3: (continued)

Panel D: 3x5 sorts on *IV* and *OP*								
	1963:7-2015:12						subsamples	
	OP_1	OP_2	OP_3	OP_4	OP_5	OP_{5-1}		$IV_{1-3}(OP_{5-1})$
IV_1	0.57	-0.79	1.43*	0.49	1.81***	1.24	1963-	1.60
	(0.31)	(-0.81)	(1.81)	(0.70)	(2.59)	(0.58)	1985	(0.43)
IV_2	-2.36	-1.33	0.25	-0.98	1.36	3.73*	1986-	-9.89**
	(-1.12)	(-0.95)	(0.20)	(-0.90)	(1.21)	(1.70)	2015	(-2.15)
IV_3	-11.84***	-10.91***	-7.42***	-5.03**	-5.76***	6.08**		
	(-4.03)	(-4.43)	(-3.50)	(-2.05)	(-2.83)	(2.11)		
IV_{1-3}						-4.84		
						(-1.57)		

Panel E: 3x5 sorts on *IV* and *INV*								
	1963:7-2015:12						subsamples	
	INV_1	INV_2	INV_3	INV_4	INV_5	INV_{1-5}		$IV_{1-3}(INV_{1-5})$
IV_1	2.40**	2.87***	1.59**	0.59	1.06	1.34	1963-	-5.74**
	(2.05)	(3.62)	(2.42)	(0.87)	(1.24)	(0.92)	1985	(-1.98)
IV_2	2.20	1.65	1.97*	0.28	-2.14*	4.34**	1986-	-3.16
	(1.37)	(1.47)	(1.96)	(0.28)	(-1.71)	(2.57)	2015	(-0.92)
IV_3	-8.00***	0.13	-4.68**	-5.63**	-13.74***	5.74***		
	(-2.97)	(0.06)	(-2.02)	(-2.57)	(-6.01)	(2.90)		
IV_{1-3}						-4.40*		
						(-1.89)		

Panel F: 3x5 sorts on *IO* and *ME*, 1986:1-2015:12						
	ME_1	ME_2	ME_3	ME_4	ME_5	ME_{1-5}
IO_1	4.42	-4.05	-5.84**	-4.32*	-3.85	8.27**
	(1.19)	(-1.49)	(-2.21)	(-1.79)	(-1.37)	(2.01)
IO_2	6.86*	1.71	-0.00	-1.64	-0.58	7.44*
	(1.66)	(0.62)	(-0.00)	(-0.88)	(-0.54)	(1.70)
IO_3	9.76	-3.05	0.68	0.72	0.55	9.21
	(1.33)	(-0.94)	(0.29)	(0.41)	(1.12)	(1.25)
IO_{3-1}						0.94
						(0.15)

Panel G: 3x5 sorts on *IO* and *BM*, 1986:1-2015:12						
	BM_1	BM_2	BM_3	BM_4	BM_5	BM_{5-1}
IO_1	-11.52***	-1.69	1.10	5.14**	4.92**	16.44***
	(-3.35)	(-0.58)	(0.52)	(2.22)	(2.15)	(4.56)
IO_2	-2.16	-0.36	0.82	2.17	1.93	4.09
	(-1.35)	(-0.27)	(0.58)	(1.18)	(1.02)	(1.41)
IO_3	-0.31	1.13	1.88	-0.10	2.56	2.87
	(-0.28)	(1.22)	(1.45)	(-0.07)	(1.33)	(1.19)
IO_{3-1}						-13.57***
						(-3.79)

Table 3: (continued)

Panel H: 3x5 sorts on *IO* and *MOM*, 1986:1-2015:12						
	MOM_1	MOM_2	MOM_3	MOM_4	MOM_5	MOM_{5-1}
IO_1	-18.99***	-1.62	-1.11	6.75***	1.98	20.98***
	(-4.27)	(-0.65)	(-0.63)	(3.28)	(0.62)	(4.22)
IO_2	-12.75***	-3.51	0.59	0.63	2.82	15.56***
	(-3.37)	(-1.51)	(0.42)	(0.43)	(1.36)	(3.14)
IO_3	-10.48***	-1.46	-0.96	2.19**	2.77	13.25***
	(-2.86)	(-0.73)	(-0.78)	(2.24)	(1.47)	(2.73)
IO_{3-1}						-7.72**
						(-1.97)
Panel I: 3x5 sorts on *IO* and *OP*, 1986:1-2015:12						
	OP_1	OP_2	OP_3	OP_4	OP_5	OP_{5-1}
IO_1	-15.05***	-4.49	2.27	1.15	2.10	17.15***
	(-3.33)	(-1.54)	(1.26)	(0.57)	(0.93)	(3.84)
IO_2	-10.40***	-5.17***	0.61	0.54	1.60	12.00***
	(-2.99)	(-2.89)	(0.40)	(0.35)	(1.38)	(3.14)
IO_3	-5.03	-3.91***	-0.88	0.95	1.75*	6.78*
	(-1.53)	(-2.80)	(-0.91)	(1.15)	(1.96)	(1.82)
IO_{3-1}						-10.37**
						(-2.50)
Panel J: 3x5 sorts on *IO* and *INV*, 1986:1-2015:12						
	INV_1	INV_2	INV_3	INV_4	INV_5	INV_{1-5}
IO_1	-4.68	3.29	1.28	0.67	-10.46***	5.78*
	(-1.26)	(1.59)	(0.72)	(0.37)	(-3.76)	(1.81)
IO_2	-0.05	1.89	1.46	0.67	-0.51	0.46
	(-0.02)	(1.36)	(1.01)	(0.47)	(-0.28)	(0.18)
IO_3	0.14	2.81***	2.48***	0.32	-3.35***	3.50*
	(0.11)	(2.79)	(2.64)	(0.40)	(-2.82)	(1.92)
IO_{3-1}						-2.28
						(-0.66)

Table 4: Performance of volatility-managed *IV*/characteristic and *IO*/ characteristic portfolios

This table presents the intercept from regressions of the form: $rx_t^{\sigma} = \alpha + \beta \cdot rx_t + \epsilon_t$, where rx_t denotes the unmanaged excess return on one of the long-short *IV*/characteristic or *IO*/characteristic portfolios defined in Table 3, and rx_t^{σ} denotes the volatility-managed version of rx_t. Beneath each intercept is a t-statistic in parentheses followed by the utility gain from access to rx_t^{σ}. Each panel corresponds to a choice of *IV* or *IO* along with a choice of ME, BM, MOM, OP, or INV. The sample periods are specified in the Panel headings. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ME_{1-5}^{σ}					
		1926-2015	1926-1955	1956-1985	1986-2015
IV_1	α (%)	3.31*	-4.19	0.86	6.19***
		(1.67)	(-1.18)	(0.25)	(2.97)
	Utility gain	0.23	0.00	0.00	27.72
IV_2	α (%)	3.76**	2.73	4.20	0.98
		(2.43)	(0.86)	(1.57)	(0.90)
	Utility gain	0.15	0.05	0.10	0.24
IV_3	α (%)	2.96	7.50	-1.66	-3.76
		(1.16)	(1.60)	(-0.40)	(-1.16)
	Utility gain	0.06	0.39	0.00	0.00

Panel B: BM_{5-1}^{σ}					
		1926-2015	1926-1955	1956-1985	1986-2015
IV_1	α (%)	1.00	4.63*	-0.51	-1.94
		(0.65)	(1.81)	(-0.27)	(-0.78)
	Utility gain	0.16	2.32	0.00	0.00
IV_2	α (%)	0.71	-1.54	1.45	-0.17
		(0.55)	(-0.79)	(0.73)	(-0.07)
	Utility gain	0.02	0.00	0.05	0.00
IV_3	α (%)	6.23***	6.10*	3.38	3.32
		(2.98)	(1.72)	(1.50)	(0.87)
	Utility gain	0.36	0.44	0.13	0.10

Panel C: MOM_{5-1}^{σ}					
		1927-2015	1926-1955	1956-1985	1986-2015
IV_1	α (%)	11.53***	11.46***	6.88**	10.25***
		(4.79)	(2.69)	(2.01)	(3.16)
	Utility gain	2.32	1.32	0.30	24.35
IV_2	α (%)	15.79***	15.32***	11.65***	10.65***
		(6.63)	(4.20)	(3.80)	(3.86)
	Utility gain	2.29	6.10	0.40	2.06
IV_3	α (%)	14.83***	5.96	10.45***	13.85***
		(5.65)	(1.59)	(2.78)	(3.45)
	Utility gain	1.45	2.15	0.30	0.86

Panel F: ME_{1-5}^{σ}		
		1986-2015
IO_1	α (%)	-2.51
		(-0.62)
	Utility gain	0.00
IO_2	α (%)	-3.71
		(-1.23)
	Utility gain	0.00
IO_3	α (%)	-3.93
		(-0.86)
	Utility gain	0.00

Panel G: BM_{5-1}^{σ}		
		1986-2015
IO_1	α (%)	0.44
		(0.15)
	Utility gain	0.00
IO_2	α (%)	0.26
		(0.11)
	Utility gain	0.04
IO_3	α (%)	-1.54
		(-0.96)
	Utility gain	0.00

Panel H: MOM_{5-1}^{σ}		
		1986-2015
IO_1	α (%)	12.63***
		(3.26)
	Utility gain	1.04
IO_2	α (%)	15.43***
		(4.00)
	Utility gain	2.98
IO_3	α (%)	16.05***
		(4.32)
	Utility gain	4.63

Panel D: OP^{σ}_{5-1}				
		1963-2015	1963-1985	1986-2015
IV_1	α (%)	2.20	3.65	0.55
		(1.47)	(1.62)	(0.32)
	Utility gain	67.97	8.56	5.84
IV_2	α (%)	1.07	0.82	2.32
		(0.72)	(0.38)	(1.49)
	Utility gain	0.39	6.36	1.03
IV_3	α (%)	2.11	1.37	4.09
		(1.02)	(0.59)	(1.51)
	Utility gain	0.41	45.41	0.65
Panel E: INV^{σ}_{1-5}				
		1963-2015	1963-1985	1986-2015
IV_1	α (%)	0.18	1.37	-0.69
		(0.19)	(1.09)	(-0.48)
	Utility gain	0.16	21.39	0.00
IV_2	α (%)	-0.70	0.28	-1.79
		(-0.65)	(0.23)	(-1.12)
	Utility gain	0.00	0.01	0.00
IV_3	α (%)	-0.75	-0.12	-1.64
		(-0.66)	(-0.11)	(-0.93)
	Utility gain	0.00	0.00	0.00

Panel I: OP^{σ}_{5-1}		
		1986-2015
IO_1	α (%)	4.77
		(1.46)
	Utility gain	0.36
IO_2	α (%)	5.58**
		(2.12)
	Utility gain	1.88
IO_3	α (%)	4.20*
		(1.65)
	Utility gain	5.13
Panel J: INV^{σ}_{1-5}		
		1986-2015
IO_1	α (%)	-3.55*
		(-1.82)
	Utility gain	0.00
IO_2	α (%)	-0.85
		(-0.47)
	Utility gain	0.00
IO_3	α (%)	-1.34
		(-0.94)
	Utility gain	0.00

Table 5: In-sample performance of unmanaged and volatility-managed mean-variance efficient (MVE) portfolios

Within each IV (IO) tercile IV_i (IO_i), we construct the ex-post tangency portfolio, denoted MVE_{IV_i} $\left(MVE_{IO_i}\right)$, from of one of two sets of factors. The first set of factors, denoted FF3+MOM, includes the excess return on IV_i (IO_i) along with the ME_{1-5}, BM_{5-1}, and MOM_{5-1} factors defined in Table 4 for IV_i (IO_i). The second set of factors, denoted FF5+MOM, includes the FF3+MOM factors as well as the OP_{5-1} and INV_{1-5} for IV_i (IO_i). We also define $MVE^{IV}_{1-3} = MVE_{IV_1} - MVE_{IV_3}$ and $MVE^{IO}_{3-1} = MVE_{IO_3} - MVE_{IO_1}$. Panel A (C) presents CAPM alphas of the unmanaged MVE_{IV_i} (MVE_{IO_i}). Panel B (D) presents performance results from regressions of volatility-managed MVE portfolios, denoted $MVE^{\sigma}_{IV_i}$ ($MVE^{\sigma}_{IO_i}$), on their un-managed counterparts. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAPM alphas of unmanaged MVE portfolios by IV tercile

	FF3+MOM (1927:1-2015:12)				FF5+MOM (1963:7-2015:12)			
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	MVE^{IV}_{1-3}	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	MVE^{IV}_{1-3}
α (%)	5.83***	9.63***	12.43***	-6.59***	4.05***	7.71***	10.85***	-6.80***
	(7.10)	(10.39)	(9.14)	(-5.14)	(5.75)	(8.54)	(10.24)	(-7.10)

Panel B: Performance of managed MVE portfolio by IV tercile (full-sample)

	FF3+MOM (1927:2-2015:12)			FF5+MOM (1963:8-2015:12)		
	$MVE^{\sigma}_{IV_1}$	$MVE^{\sigma}_{IV_2}$	$MVE^{\sigma}_{IV_3}$	$MVE^{\sigma}_{IV_1}$	$MVE^{\sigma}_{IV_2}$	$MVE^{\sigma}_{IV_3}$
α (%)	5.03***	4.73***	7.16***	1.92***	2.75***	2.40***
	(5.81)	(5.81)	(5.68)	(3.12)	(4.51)	(2.75)
Original Sharpe	0.82	1.14	1.02	0.89	1.27	1.46
Vol-managed Sharpe	0.98	1.20	1.13	0.95	1.32	1.34
Appraisal ratio	0.61	0.63	0.67	0.45	0.59	0.45
Utility gain	0.55	0.31	0.43	0.26	0.21	0.09

Panel C: CAPM alphas of MVE portfolios by IO tercile

	FF3+MOM (1986:1-2015:12)				FF5+MOM (1986:1-2015:12)			
	MVE_{IO_1}	MVE_{IO_2}	MVE_{IO_3}	MVE^{IO}_{3-1}	MVE_{IO_1}	MVE_{IO_2}	MVE_{IO_3}	MVE^{IO}_{3-1}
α (%)	10.94***	6.32***	5.02***	-5.92***	8.69***	6.48***	4.98***	-3.70***
	(5.97)	(4.01)	(3.61)	(-3.68)	(6.59)	(5.55)	(4.21)	(-3.10)

Panel D: MVE portfolios by IO tercile (1986:2-2015:12, N=359)

	FF3+MOM			FF5+MOM		
	$MVE^{\sigma}_{IO_1}$	$MVE^{\sigma}_{IO_2}$	$MVE^{\sigma}_{IO_3}$	$MVE^{\sigma}_{IO_1}$	$MVE^{\sigma}_{IO_2}$	$MVE^{\sigma}_{IO_3}$
α (%)	3.41***	3.43***	3.70***	3.75***	1.23	3.55***
	(2.93)	(3.36)	(3.55)	(3.66)	(1.49)	(4.21)
Original Sharpe	1.09	0.89	0.85	1.28	1.17	0.95
Vol-managed Sharpe	1.05	1.04	1.06	1.33	1.06	1.21
Appraisal ratio	0.46	0.58	0.65	0.71	0.29	0.76
Utility gain	0.18	0.43	0.59	0.31	0.06	0.63

Table 6: Out-of-sample performance of unmanaged and volatility-managed MVE portfolios

Each month, for each IV (IO) tercile IV_i (IO_i), we construct recursively estimated out-of-sample (OOS) MVE portfolios, denoted MVE_{IV_i} $\left(MVE_{IO_i}\right)$, consisting of the same FF3+MOM factors for IV_i (IO_i) as specified in Table 5. To do so, we first estimate (ex-post) tangency portfolio weights for the four factors over the 120 months prior to the beginning of the OOS window defined in the Panel heading, and then apply these weights to the factors in the first OOS month. For returns in the second OOS month, we estimate tangency portfolio weights over the prior 121 months, and so on, through the end of the OOS window. We also construct "1/N" portfolios that equally weight the four factors. Panel A (F) presents CAPM alphas of the unmanaged MVE portfolios by IV_i (IO_i). Panels B, C, D, and G present performance results from regressions of volatility-managed MVE or 1/N portfolios, denoted by a superscript σ, on their un-managed counterparts over samples specified by the Panel heading. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAPM alphas of unmanaged MVE portfolios by IV tercile (1937:1-2015:12, N=948)								
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	MVE_{1-3}^{IV}	$(1/N)_{IV_1}$	$(1/N)_{IV_2}$	$(1/N)_{IV_3}$	$(1/N)_{1-3}^{IV}$
α (%)	5.14***	9.44***	13.91***	-8.76***	4.80***	7.87***	8.76***	-3.96***
	(5.11)	(9.50)	(10.55)	(-6.71)	(5.82)	(9.11)	(8.16)	(-4.06)

Panel B: Performance of volatility-managed MVE portfolios by IV tercile (1937:2-2015:12, N=947)						
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	$(1/N)_{IV_1}$	$(1/N)_{IV_2}$	$(1/N)_{IV_3}$
α (%)	4.02***	3.97***	4.79***	3.78***	2.64***	1.32
	(4.11)	(5.68)	(3.95)	(4.43)	(3.47)	(1.07)
Original Sharpe	0.72	1.14	1.15	0.78	1.13	1.02
Vol-managed Sharpe	0.91	1.22	1.10	0.93	1.05	0.78
Appraisal ratio	0.58	0.61	0.51	0.54	0.38	0.13
Utility gain	0.65	0.28	0.19	0.49	0.11	0.02

Panel C: Performance of volatility-managed MVE portfolios by IV tercile (1937:2-1955:12, N=227)						
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	$(1/N)_{IV_1}$	$(1/N)_{IV_2}$	$(1/N)_{IV_3}$
α (%)	2.60	2.76*	3.27	1.48	2.67	3.10
	(1.59)	(1.80)	(1.35)	(0.91)	(1.37)	(1.01)
Original Sharpe	0.71	1.08	0.89	0.76	0.99	0.88
Vol-managed Sharpe	0.76	0.95	0.74	0.67	0.83	0.66
Appraisal ratio	0.38	0.36	0.35	0.21	0.28	0.25
Utility gain	0.29	0.11	0.15	0.08	0.08	0.08

Panel D: Performance of volatility-managed MVE portfolios by IV tercile (1956:2-1985:12, N=359)						
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	$(1/N)_{IV_1}$	$(1/N)_{IV_2}$	$(1/N)_{IV_3}$
α (%)	0.34	3.14**	3.71***	-0.03	1.05	0.86
	(0.38)	(2.54)	(2.88)	(-0.03)	(0.99)	(0.84)
Original Sharpe	1.20	1.45	1.53	1.24	1.38	1.13
Vol-managed Sharpe	1.01	1.44	1.48	0.98	1.19	1.01
Appraisal ratio	0.08	0.50	0.49	0.00	0.20	0.15
Utility gain	0.00	0.12	0.10	0.00	0.02	0.02

Table 6: (continued)

Panel E: Performance of volatility-managed MVE portfolios by *IV* tercile (1986:2-2015:12, N=359)						
	MVE_{IV_1}	MVE_{IV_2}	MVE_{IV_3}	$(1/N)_{IV_1}$	$(1/N)_{IV_2}$	$(1/N)_{IV_3}$
α (%)	4.39***	3.73***	2.69	3.41***	3.11***	-1.56
	(4.56)	(3.29)	(1.15)	(3.07)	(2.85)	(-0.95)
Original Sharpe	0.60	0.92	1.13	0.42	0.99	1.04
Vol-managed Sharpe	1.03	1.06	0.84	0.72	1.04	0.54
Appraisal ratio	0.85	0.61	0.24	0.60	0.52	0.00
Utility gain	1.98	0.44	0.05	2.00	0.27	0.00

Panel F: CAPM alphas of unmanaged MVE portfolios by *IO* tercile (1996:2-2015:12, N=239)								
	MVE_{IO_1}	MVE_{IO_2}	MVE_{IO_3}	MVE^{IO}_{1-3}	$(1/N)_{IO_1}$	$(1/N)_{IO_2}$	$(1/N)_{IO_3}$	$(1/N)^{IO}_{1-3}$
α (%)	12.36***	6.96***	3.49*	-8.86***	8.72***	5.82***	5.28**	-3.44
	(4.02)	(2.64)	(1.86)	(-3.39)	(4.33)	(3.05)	(2.14)	(-1.34)

Panel G: Performance of MVE portfolios by *IO* tercile (1996:2-2015:12, N=239)						
	MVE_{IO_1}	MVE_{IO_2}	MVE_{IO_3}	$(1/N)_{IO_1}$	$(1/N)_{IO_2}$	$(1/N)_{IO_3}$
α (%)	7.33**	5.60***	6.08***	3.84***	2.38*	3.37**
	(2.50)	(2.73)	(4.01)	(2.74)	(1.70)	(2.35)
Original Sharpe	0.77	0.64	0.58	1.06	0.83	0.67
Vol-managed Sharpe	0.93	0.87	1.02	1.03	0.76	0.71
Appraisal ratio	0.61	0.60	0.88	0.55	0.37	0.45
Utility gain	0.64	0.90	2.33	0.27	0.20	0.45

Table 7: Performance of volatility-managed IV and IO portfolios controlling lagged liquidity and sentiment.

Each column presents regressions of the form: $rx_t^\sigma = \alpha_H d_{H,t} + \alpha_L d_{L,t} + \beta \cdot rx_t + \epsilon_t$, where rx_t denotes the unmanaged excess return on IV_1, IV_2, IV_3, IO_1, IO_2, or IO_3 and rx_t^σ denotes the volatility-managed version of rx_t. The d_H and d_L denote, respectively, dummy variables that indicate whether the one-month lag of the variable defined in the column heading is "high" or "low". We define the Pástor and Stambaugh (2003) liquidity level (*Liquidity*) and Baker and Wurgler (2006) sentiment index (*Sentiment*) to be "high" if they are greater than their respective 50^{th} percentiles during the sample period, and "low" otherwise. We define the prior 3-month stock-market return ($r_{m,t-3,t-1}$) to be "high" if it is positive, and "low" otherwise. $Diff$ denotes the difference ($\alpha_H - \alpha_L$) and $p(Diff)$ denotes the p-value from the robust Wald-test of the null $\alpha_H - \alpha_L = 0$. Unless otherwise stated, the sample is 1986:2-2015:12 (N=359). t-statistics are below point estimates in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *Liquidity*						
	IV_1^σ	IV_2^σ	IV_3^σ	IO_1^σ	IO_2^σ	IO_3^σ
$\alpha_H(\%)$	7.14***	3.56	3.54	-1.12	9.52***	9.25***
	(3.20)	(1.16)	(0.65)	(-0.28)	(3.21)	(2.99)
$\alpha_L(\%)$	-0.31	1.13	-6.02	2.53	0.54	-0.04
	(-0.16)	(0.36)	(-1.01)	(0.68)	(0.18)	(-0.02)
$Diff$	7.45***	2.43	9.56	-3.65	8.98**	9.29**
$p(Diff)$	0.01	0.57	0.23	0.51	0.03	0.02
R^2	0.55	0.53	0.38	0.38	0.51	0.54

Panel B: $r_{m,t-3,t-1}$						
	1926:9-2015:12 (N=1072)			1986:2-2015:12 (N=359)		
	IV_1^σ	IV_2^σ	IV_3^σ	IO_1^σ	IO_2^σ	IO_3^σ
$\alpha_H(\%)$	6.27***	7.37***	0.89	1.64	5.98**	5.62**
	(3.33)	(2.66)	(0.26)	(0.47)	(2.26)	(2.25)
$\alpha_L(\%)$	0.44	0.60	-2.35	-1.53	2.65	2.01
	(0.20)	(0.18)	(-0.64)	(-0.38)	(0.76)	(0.53)
$Diff$	5.84**	6.76	3.24	3.17	3.34	3.61
$p(Diff)$	0.04	0.12	0.53	0.56	0.44	0.42
R^2	0.41	0.34	0.35	0.38	0.50	0.54

Table 7: (continued)

Panel C: *Sentiment*, 1986:2-2015:10 (N=357)						
	IV_1^σ	IV_2^σ	IV_3^σ	IO_1^σ	IO_2^σ	IO_3^σ
$\alpha_H(\%)$	4.49**	5.60*	0.29	1.15	9.12***	6.92**
	(2.07)	(1.86)	(0.04)	(0.26)	(2.96)	(2.25)
$\alpha_L(\%)$	2.25	-0.85	-2.65	0.29	0.89	2.27
	(1.05)	(-0.26)	(-0.54)	(0.09)	(0.30)	(0.77)
$Diff$	2.24	6.45	2.93	0.86	8.23**	4.65
$p(Diff)$	0.46	0.15	0.72	0.88	0.05	0.28
R^2	0.55	0.54	0.38	0.38	0.51	0.54