Volatility and mutual fund manager skill

Bradford D. Jordan
bjordan@uky.edu

Timothy B. Riley*
tim.riley@uky.edu

Gatton College of Business and Economics
University of Kentucky
Lexington, KY 40506

First draft: August 12, 2013
This draft: May 1, 2014

* Contact author. We thank Yakov Amihud, Malcolm Baker, Alice Bonaimé, Martijn Cremers, Eric Falkenstein, Jon Fulkerson, Ruslan Goyenko, Russell Jame, Lasse Pedersen, Jay Ritter, and seminar participants at the University of Kentucky, University of Florida, Oklahoma State University, and the Securities and Exchange Commission for helpful comments and suggestions. The usual disclaimer applies.

Volatility and mutual fund manager skill

Abstract

Low volatility mutual funds outperform high volatility funds to a remarkable degree, and, in a standard four-factor framework, past volatility is a reliable, persistent, and powerful predictor of future abnormal returns. Analyses patterned after Kosowski, Timmerman, Wermers, and White (2006) and Fama and French (2010) indicate that low volatility fund managers have significant skill. However, the addition of a factor contrasting returns on diversified portfolios of low and high volatility stocks eliminates differences in risk-adjusted performance. We conclude that either our volatility measure is associated with a pervasive, systematic pricing factor, or else the volatility effect is a market inefficiency of extraordinary size. Either way, failure to account for the volatility effect can lead to substantial mismeasurement of fund manager skill.

Volatility and mutual fund manager skill

Past return volatility is a powerful determinant of future mutual fund performance. A dollar invested in a portfolio of mutual funds with low past return volatility at the beginning of 2000 is worth about $2.00 at the end of 2011. A portfolio of mutual funds with high past return volatility invested over the same time period has an ending value of only $0.73, while a zero-fee fund tracking the CRSP value-weighted index would be worth $1.19.

In the Fama-French (1993) framework, a portfolio of low volatility funds has a four-factor alpha about 5.4% per year greater than that of a portfolio of high volatility funds. This difference in performance is robust to changes in evaluation models and in the sample of funds. Low volatility mutual funds do tend to be larger and older with lower expenses and turnover, but these differences do not explain their outperformance.

Consistent with at least some other studies, fund size, age, expense ratio, and turnover are all statistically significant predictors of future abnormal returns. A one standard deviation move in any of these leads to a change in next year's Fama-French alpha on the order of .20% – .40%. In contrast, a one standard deviation decrease in fund volatility in the prior year predicts an increase in alpha of about 2.5% in the following year, so the impact is as much as ten times greater. We also show that total fund return volatility is driving the effect, not idiosyncratic volatility.

We explore whether the outperformance of low volatility funds is a reflection of manager skill. Using tests patterned after Kosowski, Timmerman, Wermers, and White (2006) and Fama and French (2010), we find that low volatility fund managers appear to have significant skill. However, we find that a similar performance gap exists between low and high volatility funds among funds that deviate from their benchmark and funds that do not (if the difference in performance is skill, it should not exist among funds that are "closet indexers").

We further test whether the difference in performance can be attributed to efficient asset allocation. Using fund holdings, we show that low volatility funds have low volatility returns primarily because they invest in low volatility stocks, not because of manager skill with respect to portfolio construction. We also show that the gap between fund return volatility and fund holdings volatility has little influence on the performance of low and high return volatility funds. We then construct simulated mutual funds that mechanically invest in the same proportions of low or high volatility stocks as actual low and high volatility mutual funds. We find return patterns in our simulated funds similar to those observed among real funds, suggesting that something other than manager skill is at work.

To complete our evaluation of the skill question, we add a new pricing factor, LVH (low volatility versus high volatility) and repeat our analyses. The LVH factor is equal to the return on a portfolio of low volatility stocks less the return on a portfolio of high volatility stocks. The difference in alpha between low and high volatility mutual funds drops and becomes statistically indistinguishable from zero. With LVH included, we find no evidence of skill among low volatility fund managers and no evidence of a difference in skill between low and high volatility fund managers.

Overall, our results strongly support the notion that low volatility funds benefit from a pervasive volatility effect. There are two implications. First, the volatility effect is either associated with a substantial systematic pricing factor or else represents a market inefficiency of great size. Second, failure to account for the volatility effect can lead to large errors in the assessment of fund manager skill.

I. Volatility and Returns

Haugen and Heins (1972, 1975) first showed that stocks with low volatility past returns subsequently outperformed those with high volatility, a result that has come to be known as the "vol anomaly." We do not attempt to explain the cause of the vol anomaly here, but instead explore it using mutual funds to answer two important questions.[1] First, can investors actually obtain the large vol anomaly returns found in previous studies? And second, how does the vol anomaly affect the measurement of mutual fund manager skill?

The vol anomaly is large, persistent, and ubiquitous in security returns. Amihud (2002) and Ang, Hodrick, Xing, and Zhang (2006, 2009) show past volatility is a strong cross-sectional predictor of future stock returns. Baker, Bradley, and Wurgler (2011) show that one dollar invested in portfolio of low volatility stocks in 1968 is worth $59.55 in 2008. The matching high volatility portfolio is worth only $0.58. Baker and Haugen (2012) find the vol anomaly in all twenty-one developed countries they study, and Blitz and Vliet (2007) demonstrate that a global portfolio of large cap, low volatility stocks outperforms the matching high volatility portfolio by about 12% per year. Frazzini and Pedersen (2013) find the vol anomaly in stocks, bonds, and other asset classes across many different countries.

However, all those results are based on simulated portfolios, and it is unclear if actual portfolios can realize such large returns. Fu (2009) finds the vol anomaly is only strong among very small stocks. Garcia-Feijoo, Li, and Sullivan (2012) show that trading on the vol anomaly requires frequent rebalancing among stocks with low liquidity. Han and Lesmond (2011) claim that after adjusting for microstructure effects, such as bid-ask bounce, the vol anomaly disappears. Baker, Bradley, and Wurgler (2011) argue that leverage constraints make investing in the vol anomaly difficult for institutional investors.

[1] See Hou and Loh (2012) for a thorough review and analysis of potential explanations for the vol anomaly.

Unlike the hypothetical investments of previous studies, we examine the impact of the vol anomaly on actual mutual fund returns. Our approach avoids arguments over whether returns to the vol anomaly can be realized. In our sample of funds, either they were or they were not.

We further examine the vol anomaly in the context of mutual fund manager skill. The conventional wisdom is well-known: the average active mutual fund underperforms compared to passive investments. Sharpe (1966) and Jensen (1968) first showed that the average mutual fund underperformed while Sharpe (1991) uses the "the arithmetic of active management" to demonstrate that the average dollar invested in mutual funds must have a negative alpha because investing is (1) a zero sum game and (2) funds have expenses. Carhart (1997) attributes any persistence in equity mutual fund performance to the momentum effect, not manager skill.[2]

Recent studies have not questioned the conventional wisdom, but instead have shifted the focus from determining if the *average* manager has skill to whether *any* manager has skill. Kosowski, Timmerman, Wermers, and White (2006) study the distribution of fund alphas and find that many funds generate consistent, positive alphas not attributable to luck alone. They find that skilled funds add about $1.2 billion per year in wealth to the mutual fund industry, but funds that appear to lack skill also lose about $1.5 billion per year. Barras, Scaillet, and Wermers (2010) control for the "false discovery" of skill by adjusting for funds with significant, positive estimated alphas but true alphas of zero.[3] They show that about 76% of funds do have stock picking ability, but nearly all extract the rents from this ability through fees.

If some mutual fund managers do have skill, then being able to identify them is a valuable exercise. Cremers and Petajisto (2009) show that funds that deviate the furthest from

[2] Many papers had documented persistence in returns prior to Carhart (1997). For instance: Brown and Goetzmann (1995), Elton, Gruber, and Blake (1996), Goetzmann and Ibbotson (1994), Grinblatt and Titman (1992), and Hendricks, Patel, and Zeckhauser (1993).
[3] The authors use the "False Discovery Rate" (FDR) approach developed by Storey (2002) for this estimation.

their benchmark tend to have better performance than "closet index" funds, i.e., funds that claim to be active but hold a portfolio similar to their benchmark. In similar work, Amihud and Goyenko (2013) find that fund performance can be predicted by fund selectivity, which they measure by the r^2 from regressing fund returns on a multifactor benchmark model. Funds with low r^2 (high selectivity) outperform funds with high r^2 (low selectivity).

To date, studies of fund manager skill have not accounted for the potential impact of the vol anomaly. This omission raises the possibility that there may be significant biases in determining both (1) the proportion of skilled funds and (2) the specific funds that have skill, particularly if fund managers have significant variation in volatility across their holdings and investment styles.

II. Data and Methods

We use the CRSP Survivor-Bias-Free U.S. Mutual Fund database to build our sample of actively managed U.S. equity funds. We drop funds that (1) CRSP identifies as index funds, ETFs, or variable annuities, (2) have a Lipper asset code of TX or MB, or (3) have terms in their name not associated with unleveraged, active management or equity investment.[4] We also require that a fund has at least 80% of its assets invested in equity during the previous year and a Lipper class code consistent with equity investing.[5,6] We restrict our sample to funds that are at

[4] We drop funds with any permutation of the following terms in their fund name: bear, bull, bond, cash, convertible, cycle, ETF, fixed, government, index, ishare, leverage, lifestyle, maturity, money, mortgage, municipal, powershare, principal protection, profund, proshare, rate, real estate, realty, tax, term, treasury, variable, 2005, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 529, 1.5x, 2x, 3x, -1.5x, -2x, and -3x.

[5] CRSP is missing equity percentages from 1998 through 2002 for most funds, so we check this constraint using asset allocations from 1997 to determine the sample in 1999 through 2003.

[6] We use funds with the following Lipper class codes associated with market cap and value/growth tilt: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If we expand the list of eligible codes to include funds that use other strategies, e.g., LSE – Long/Short Equity, our results are unchanged.

least a year old and have at least \$20 million in assets to control for the incubation bias of Evans (2010).

We combine multiple share classes of a single fund using the CRSP class group variable (crsp_cl_grp). The assets of the combined fund are the sum of the assets held across all share classes. We weight all other fund attributes (including return) by the assets held in each class.

We use the CRSP daily return file to calculate measures of past performance and volatility for each fund each calendar year.[7] This file begins in September 1998, so we first measure performance and volatility in 1999. We estimate the Fama-French-Carhart (1993, 1997) four-factor model for each fund that records a return every day during each calendar year. We use the standard deviation of the residuals from that regression as our idiosyncratic standard deviation of returns.

III. Results

3a. The performance of low and high volatility mutual funds

We first capture the difference in performance between low and high volatility mutual funds by sorting funds into portfolios based on past return volatility. At the beginning of each year, we sort funds into deciles based on the standard deviation of their daily fund returns during the prior calendar year. The low (high) volatility portfolio holds the 10% of mutual funds in the sample with the lowest (highest) standard deviation in the prior calendar year. Each portfolio is equal weighted and has the same number of funds at the start of the year. A fund remains in the same portfolio for the entire year.

[7] We explore the choice between daily and monthly return volatility in Appendix B. We find daily return volatility is more persistent through time and creates a stronger performing portfolio of low volatility mutual funds.

Figure 1 shows the value of one dollar invested in five such volatility portfolios starting in January 2000 and ending December 2011.[8] There is a clear pattern of decreasing returns as volatility rises. The low volatility portfolio is worth about $2.00 at the end of 2011. The high volatility portfolio is worth only $0.73. The pattern holds within the middle groups as well, e.g., funds in the third lowest volatility group beat those in the fifth and seventh, and those in the fifth lowest group beat those in the seventh.

[Figure 1 about here]

Table 1, Panel A, shows the average return and performance evaluation measures for the Figure 1 portfolios. The arithmetic (geometric) average return for the low volatility portfolio was 6.0% (8.4%) greater per year than that of the high volatility portfolio. This large difference occurs despite the fact that the low volatility portfolio has an annualized return standard deviation of 14.2%, compared to 25.8% for the high volatility portfolio. The Sharpe and Treynor ratios of the high volatility portfolio are both slightly negative while the low volatility portfolio has the highest ratios among all ten portfolios. Overall, the low volatility portfolio has the best performance regardless of the method of evaluation.

[Table 1 about here]

Table 1, Panel B, shows the correlation between the monthly returns of the volatility portfolios. The returns of all the portfolios are strongly related, but the correlation grows somewhat weaker as the difference in volatility increases. The low and high volatility portfolios have a return correlation of .83.

[8] We change our portfolio construction requirements in Appendix A to expand our time period to January 1992 through December 2011. We find the low volatility portfolio has Sharpe and Treynor ratios about 50% higher than those for the high volatility portfolio over that twenty year period, although the difference in average return is more modest.

While the difference in average return between the low and high volatility funds is large, it is possible that well-known market anomalies could explain the result. Table 2 shows the Fama-French four-factor alpha and factor exposures for the low and high volatility portfolios. The low volatility portfolio has an alpha of .16% per month (1.9% per year), which exceeds the alpha of the high volatility portfolio by about .45% per month (5.4% per year). Low volatility funds tend to hold larger, low beta, value stocks, and the high volatility funds tend to hold smaller, high beta, growth stocks, but these differences do not explain the difference in their performance. If the portfolios are formed in January, but only evaluated in January through June or July through December, the results are similar. Because this lag between volatility measurement and portfolio formation does not affect the results, it does not appear necessary to update measurements of volatility often to maintain the difference in performance.

[Table 2 about here]

We further test the persistence of fund volatility as predictor of future fund performance in Figure 2. In Table 2, we used fund volatilities measured in the prior calendar year (*t-1*) to form portfolios in the subsequent calendar year (*t*). Here we construct the portfolios in an identical fashion, except we also form the portfolios in calendar years *t+1* through *t+4*. We measure the monthly Fama-French four-factor alphas for the low and high volatility portfolios in those years and report results for the fifth decile portfolio for comparison. This method mimics Figure 2 from Carhart (1997), which shows that past returns predict only short-term future performance.

[Figure 2 about here]

Regardless of the delay between volatility measurement and portfolio formation, Figure 2 shows that there is a large difference in performance between the low and high volatility portfolios. The difference in performance is largest when we delay a full year (.64% per month), and delaying four years still leaves a gap of .20% per month (p-value = .10). In each measurement period, the low volatility portfolio has the best performance, the 5th decile portfolio the second best, and the high volatility portfolio the worst. In contrast to the momentum effect, the effect of fund volatility on future fund performance is highly persistent.

The result that low volatility funds generally outperform high volatility funds is also robust to the choice of evaluation model. Table 3, Panel A, tests the difference in alpha between the low and high volatility portfolios using alternative evaluation models. We again start with the Fama-French four-factor model, but then add the liquidity factors of Pastor and Stambaugh (2003) and Sadka (2006).[9] We then substitute the Cremers, Petajisto, and Zitzewitz (2012) seven-factor (CPZ7) model for the Fama-French model and repeat the tests.[10] In addition, we present results for the original equal weighted portfolios and for the same portfolios weighted by fund assets to test if small funds alone are driving the result.

[Table 3 about here]

As shown in Panel A of Table 3, the difference in performance between the low and high volatility portfolios is large regardless of the model.[11] For the equal weighted portfolios evaluated with the CPZ7 model and all the liquidity factors, there is a difference in alpha of about .19% per month (p-value .169). The asset weighted portfolios with the same model and factors have a difference in alpha of about .25% per month (p-value .063). These results indicate that allowing for the effect of liquidity and modifying the factor model does lower alpha, but still leaves a large gap in performance between high and low volatility funds. Since the effect is as

[9] We thank Ronnie Sadka for making his liquidity factors available at https://www2.bc.edu/~sadka/.
[10] We thank the authors for making their pricing factors available at http://www.petajisto.net/data.html.
[11] Our base result here varies slightly from Table 2 because 2011 is excluded. Neither the CPZ7 nor the Sadka factors are available for that year.

strong for the asset weighted portfolios as it is for the equal weighted portfolios, it does not appear that small funds are driving the results.

We further test for robustness by excluding certain types of funds in Table 3, Panel B. We test the difference in alpha using the Fama-French four-factor model, but we now exclude certain groups from the sample before sorting the funds into the portfolios. In particular, we exclude funds with less than $300 million in assets and funds with a small cap or growth orientation.[12] The asset limit further tests if small funds drive the result, and the orientation exclusions test if our results are driven by those risky fund types alone. If a particular group is included (excluded) in the sample, the table marks the category row Yes (No).

Excluding any of the groups lowers alpha by about .1% to .2% per month. Excluding all the groups simultaneously decreases the difference in equal weighted alpha from .45% per month to .28% per month (*p*-value .008). Taken as a whole, the results in Table 3 suggest that fund size, style, and the evaluation model together explain some, but not all, of the difference in performance between low and high volatility funds.

To further explore whether the difference in performance is related to heterogeneity in fund characteristics, Table 4 shows the characteristics of funds when they first enter the low and high volatility portfolios. Most surprising is that funds sorted into the high volatility portfolio have an average return about 2.8% per year greater than those in the low volatility portfolio; however, the median return for funds entering the low volatility portfolio (not reported in the table) is about 1.7% per year greater. Low volatility funds have an average four-factor alpha of .07% per year, compared to -1.14% per year for the high volatility funds. So, on average, the

---

[12] Small cap funds are identified by Lipper classes SCGE, SCVE, and SCCE. Growth funds are identified by Lipper classes LCGE, MLGE, MCGE, and SCGE.

sorting process does place funds with higher past risk-adjusted returns into the low volatility portfolio.

[Table 4 about here]

Low volatility funds have different levels of systematic and unsystematic risk compared to high volatility funds. Low volatility funds have about half the daily standard deviation of returns of high volatility funds (.98% vs. 1.82%), and Panel B shows that low volatility funds have lower market risk, less small cap exposure, less growth exposure, and less momentum exposure than high volatility funds. The difference in total volatility of returns is driven in part by these different exposures, but high volatility funds also have about twice the daily idiosyncratic volatility as low volatility funds (.51% vs. .28%).

The average (median) size for the low volatility funds is \$3.0 billion (\$360 million) compared to \$901 million (\$240 million) for the high volatility funds. The average low volatility fund is about 4 years older than the average high volatility fund, charges .18% less in expenses per year, and has a turnover of 56.6% (vs. 116.6% for high volatility funds). The low expense and turnover of the low volatility funds are indicators of future better performance (e.g., Carhart, 1997), but large fund size has been found to lower returns (e.g., Chen, Hong, Huang, and Kubik, 2004).

We test whether past volatility or other firm characteristics predict future performance using the following panel model:

$$\mathrm{Alpha}_{i,t+1} = \mathrm{Alpha}_{i,t} + \mathrm{SD}_{i,t} + \mathrm{Idio}_{i,t} + \mathrm{Fund\ Controls}_{i,t} + \mathrm{Obj\ FE} + \mathrm{Time\ FE} + \epsilon_{i,t} \quad (1)$$

where $\mathrm{Alpha}_{i,t+1}$ is the annualized percentage alpha for fund *i* in calendar year *t+1* calculated from the Fama-French four-factor model using daily returns. $\mathrm{Alpha}_{i,t}$ is the same alpha in the prior year. $\mathrm{SD}_{i,t}$ and $\mathrm{Idio}_{i,t}$ are the standard deviation and idiosyncratic standard deviation of the daily returns in year t. $\text{Fund Controls}_{i,t}$ include the natural log of assets, natural log of age, expense ratio, and turnover all as of December of year t. We also include all four Fama-French four-factor exposures measured using daily returns during year t. Lipper class fixed effects are included in addition to year fixed effects.[13] We cluster the standard errors on year and calculate them using a bootstrap procedure. All continuous variables are winsorized at the .5% and 99.5% levels.[14] All continuous right-hand-side variables are z-scored (demeaned and divided by their standard deviation), so that the coefficients can be interpreted as the change in next year's alpha from a one standard deviation change in the variable.[15]

We present results from estimating eq. (1) in Table 5. The standard deviation of past returns is the strongest predictor (economically) of future fund performance. A one standard deviation increase in the standard deviation of past returns decreases next year's alpha by about 2.5%, a very large decline. Idiosyncratic volatility is not predictive of future alpha, and past alpha is a weak predictor. Small size, old age, and low turnover and expense ratios have a statistically significant positive effect on alpha, but the impacts of a one standard deviation move are relatively small (.2% to .4% per year). The Fama-French factor exposures have no statistically significant effect when the standard deviation of past returns is included in the model. Overall, the results in Table 5 show that future abnormal performance does have a degree of predictability to it, with historic total volatility playing a particularly important role.

[Table 5 about here]

3b. Do low volatility mutual fund managers have skill?

Our results thus far have shown that fund managers with low volatility past returns outperform managers with high volatility past returns and that past volatility is a strong predictor

[13] We do not explore fund fixed effects because expense ratios are typically time invariant.
[14] The unwinsorized results lead to the same conclusions.
[15] This normalization does not affect the statistical significance of the coefficients.

of future performance. This finding raises the obvious question of whether the performance differential is due to skill. To explore this possibility, we compare the actual distributions of both low and high volatility fund alphas to a theoretical distribution where all alpha is due to luck. To create the zero-skill distribution, we follow the bootstrap procedures in Kosowski, Timmerman, Wermers, and White (KTWW) (2006) and Fama and French (2010). There are some differences in the two approaches, but our conclusions are similar regardless of method. Both methods focus on the *t*-statistic associated with alpha, rather than alpha itself, and that is what we do as well in this section.

For brevity, we present only the Fama and French results here (results using KTWW's approach are available in Appendix C). We closely follow Fama and French, so we refer readers to that paper for full methodological details. But in brief, the Fama and French method (1) estimates zero-skill returns by calculating the four-factor alpha for each fund and subtracting it from the fund returns, (2) randomly samples (with replacement) from the calendar months in the sample, and (3) estimates four-factor alphas for each fund using the zero-alpha returns and the sample of months. Repeating steps (2) and (3) thousands of times provides the results used to form the zero-skill alpha distribution.

In our tests, we consider a mutual fund low (high) volatility in every month after the standard deviation of its daily returns first falls into the lowest (highest) 10% among funds in the prior calendar year. Only fund months between January 2000 and December 2011 and after a fund is labeled low or high volatility are used in the analysis. Because we are interested in manager skill, we focus on gross returns, where gross returns are created by adding back 1/12 of the annual expense ratio each month.

In Figure 3, we present (1) a plot of the cumulative distribution of the alpha *t*-statistics for the low volatility mutual funds, (2) a plot of the cumulative distribution of the alpha *t*-statistics for the high volatility mutual funds, and (3) a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. If the cumulative distribution of *t*-statistics for the low or high volatility portfolio is lower than the no-skill distribution at a point on the figure, then better performance than would be expected by luck alone is occurring. As shown in Figure 3, the cumulative distribution for the low-volatility funds always lies on or below the no-skill distribution, so there is evidence of considerable skill among the low-volatility funds. In contrast, there is a clear lack of skill among the high volatility funds.

[Figure 3 about here]

To further explore the role of skill, we turn to the Active Share measure of Cremers and Petajisto (2009) and the r^2 measure of Amihud and Goyenko (2013). Using either measure, these studies show better performance for managers who deviate more from their benchmarks (or the overall market). Active Share for a fund is equal to the sum of the absolute deviations between fund holdings and benchmark holdings.[16] A higher Active Share implies a more selective manager. r^2 for a fund is the r^2 value calculated after regressing the past twenty-four monthly returns against the Fama-French four-factor model. A lower r^2 implies a more selective manager.

We first sort funds into quintiles based on their Active Share or r^2 each month. We use the most recent value for Active Share available unless that value is more than three months old. A fund whose most recent value of Active Share is more than three months old is ineligible for inclusion in the portfolios that month. For the r^2 measure, we require a fund to have at least the past twelve months of returns available to be eligible for inclusion in the portfolios that month.

[16] We thank the authors for making Active Share data available at http://www.petajisto.net/data.html.

We then sort funds within Active Share or r^2 quintiles into quintiles based on the standard deviation of fund daily returns in the prior calendar. The time period is reduced to January 2001 through August 2009 for this double sort because only during that period are both the r^2 and Active Share measures available.

If manager skill is driving the result, we expect to find no difference in performance between high and low volatility funds among funds with low selectivity (these funds are "closet indexers"). However, Table 6 shows that the difference in performance between low and high volatility funds exists regardless of the level of selectivity. For the Active Share results in Panel A, the overall difference in performance between the low and high volatility funds is about .36% per month. Among the least selective funds, this difference is about .21% per month, and among the most selective funds, this difference is about .54% per month. For the r^2 results in Panel B, the overall difference in performance between the low and high volatility funds is about .38% per month. Among the least selective funds, this difference is about .33% per month, and among the most selective funds, this difference is about .41% per month. A large gap between the low and high volatility funds exists regardless of selectivity. So while stock selectivity may affect fund performance, that ability does not appear to explain the difference in performance driven by volatility.

[Table 6 about here]

We also note that the difference in performance driven by volatility is much larger than the selectivity differences. The difference in performance between high and low selectivity funds varies between .09% and .14% per month. In contrast, we find a .36% to .38% per month difference in performance between all low and high volatility funds in Table 6. Further, high

Active Share funds with high volatility are actually the worst performers with an alpha of -.44% per month.

While stock selectivity cannot explain the difference in performance, a more subtle manager skill may drive the result. A fund with low volatility returns does not necessarily hold low volatility stocks. As it stands, it is unclear if the performance of the low volatility portfolio is a result of (1) purchasing a large number of low volatility stocks or (2) selecting an efficient asset allocation (a form of skill).

We test these two possibilities by matching stock volatilities to fund holdings. We first measure the standard deviation of monthly returns each calendar year for all stocks that pass our screens. We then sort stocks into deciles each calendar year based on that standard deviation. We only use U.S. equities of the types commonly held by mutual funds.[17] In particular, we use only ordinary shares (CRSP share codes 10 and 11) that trade on the NYSE, NASDAQ, or AMEX (CRSP exchange codes 1, 2, and 3). We consider a stock a penny stock and omit it from the sample until its price exceeds $5 at the end of a month. From that point forward, it remains in the sample regardless of future price movement. We only use stocks with a market capitalization greater than the 10% NYSE breakpoint to remove microcaps. We replace any missing returns or prices with delisting returns and prices when possible.

We match those stock volatility results to the CRSP mutual fund holdings database for all fund holdings snapshots available from 2003 to 2011.[18] The stock volatility results from the previous year are matched to fund holdings in the current year, e.g., holdings in March 2004 are matched to calendar year 2003 stock volatility results. We then calculate multiple measures of stock holdings volatility for our sample of active U.S. equity mutual funds.

[17] Results are qualitatively the same if we drop all the listed constraints.

[18] The database starts in 2002, but that year has only 1,188 fund holdings snapshots across all funds in the CRSP database. There are 9,580 snapshots in 2003 and 10,221 snapshots in 2004.

In Table 7, Panel A, we present statistics on the stock holdings volatility of low and high return volatility funds. Funds are assigned to the low and high return volatility deciles based on their daily return volatility in the year of the holdings.[19] We calculate all measures at the snapshot level and then average across snapshots. The average dollar invested in a low return volatility mutual fund is invested in a stock with an annualized standard deviation of returns of 25.3%, compared to 41.2% for a high return volatility mutual fund. About 28.1% of stocks held by low return volatility funds fall into the lowest stock volatility decile, but only 1.3% fall into the highest stock volatility decile. High volatility funds have about 6.1% of their stocks in the low stock volatility decile and 11.1% in the high stock volatility decile. Our evidence here is consistent with low return volatility mutual funds buying low volatility stocks, but it is still possible the best performers within each return volatility decile achieve their performance through efficient asset allocation.

[Table 7 about here]

To further test if efficient asset allocation is driving performance we use double sorts similar to those in Table 6. We first sort funds into quintiles based on the standard deviation of their daily returns in the prior calendar year. We then sort funds within those quintiles into quintiles by a fund's dollar weighted standard deviation of stock returns.[20] We use the most recent holdings snapshot available for each fund in the prior calendar year. Our time period for measuring alphas is reduced to January 2004 through December 2011 to accommodate the sample period for fund holdings.

We present results from this double sort in Panel B of Table 7. If efficient asset allocation is driving performance, we might expect the best performing low return volatility funds to be

[19] Results are qualitatively the same if the return volatility from the prior year is used.
[20] If we perform this secondary sort using average standard deviation or average rank instead, the results are similar.

those with the highest stock volatility. Instead we find alphas of about negative -.01% to -.04% per month for low return volatility funds regardless of stock volatility. Among the high volatility funds, those with the lowest stock volatility have an alpha of -.18% per month. The other high volatility portfolios have alphas ranging between -.10% and -.32% per month, so it does not appear that low return volatility funds do well or that high return volatility funds do poorly because of asset allocation.

If manager skill does not explain the differential performance between low and high volatility funds, the remaining candidate is exposure to an important systematic pricing factor (or market inefficiency) related to low and high volatility stocks. As a first test of this possibility, we create simulated mutual fund portfolios that mechanically invest like actual low or high volatility funds using the same time period as our mutual fund sample, January 2000 through December 2011.[21] Each year a simulated low (high) volatility fund chooses 100 stocks based on the decile percentages for the actual low (high) volatility funds in Table 7. For example, 28 of the stocks chosen for a simulated low volatility fund each year are from the low stock volatility decile and 1 is from the high stock volatility decile. The decile percentages used are constant but stocks selected each year from each decile are random. The same stocks remain in the portfolio for a full calendar year unless they fail a screen or leave the sample. Then, at the beginning of the next year, 100 new stocks are chosen.

We repeat this procedure to create 1000 simulated fund holdings histories for both the low and high volatility groups. Using those holdings histories, we construct portfolios that are either equal, value, or randomly weighted. Value weighted portfolios use market capitalization to generate weights. Randomly weighted portfolios use the same market capitalization weights but

---

[21] We test the simulated mutual funds from January 1980 through December 2009 in Appendix D. We find qualitatively similar results in the full sample, but note that the differential performance between the low and high volatility portfolios does vary over time.

randomly assign them to stocks. For each of the resulting portfolios, we measure the same performance characteristics as in Table 1 and then average across groups. If the fund holdings volatility can explain the difference in performance between low and high return volatility funds, we would expect the performance of our simulated funds to be similar to the actual funds in Table 1.

Table 8 shows the performance of our simulated low and high volatility funds. The simulated low volatility funds outperform the simulated high volatility funds regardless of weighting and method of evaluation, but we focus on the value weighted results in Panel B. The arithmetic (geometric) average return on the simulated low volatility funds is 1.4% (2.4%) greater per year than the return on the simulated high volatility funds. That difference occurs despite the simulated low volatility funds having an annualized standard deviation of returns of 15.7%, compared to 21.0% for the simulated high volatility funds. The simulated low volatility funds have Sharpe and Treynor ratios almost four times those of the simulated high volatility funds. While these differences in performance are smaller than among the real funds, our simulated funds have no systematic leanings common to the actual funds, e.g., small cap/large cap, except to the extent that (1) low and high volatility stocks naturally lean towards the same exposures as our actual funds and (2) equal (value) weighting favors small (large) cap exposure.

[Table 8 about here]

These results, along with the stock selectivity results, strongly suggest that low volatility fund managers are benefiting from a pervasive, mechanical effect. To explore this explanation, we introduce a new pricing factor, LVH (low volatility versus high volatility), into the Fama-French four-factor model. We create the factor using the same sample and volatility measurement as used in our simulated portfolios. Each month, the LVH factor is equal to the return to a value weighted portfolio of all stocks that pass our screens that are in the lowest decile of standard deviation of monthly returns during the previous calendar year less the return on a value weighted portfolio of all stocks that pass our screens in the highest decile.

Panel A of Table 9 shows the basic characteristics of the LVH factor and compares it to the four Fama-French factors and the Pastor and Stambaugh (2003) liquidity factor. The LVH factor has a mean (median) monthly return of 1.16% (.16%). This return is large compared to the four Fama-French factors, but it is also two to three times as volatile. Panel B shows that LVH is correlated with multiple factors. It has a correlation of -.71 with the market risk factor (Mktrf), -.66 with the market capitalization factor (SMB), and .52 with the value factor (HML). Given that low volatility stocks are typically low beta, large market capitalization, and high book-to-market compared to high volatility stocks, these relationships are as expected.

[Table 9 about here]

In Table 10, we reproduce our Table 2 results using LVH as an additional factor. Alpha for the low volatility portfolio falls from .16% per month to .03% with the addition of LVH. Alpha for the high volatility portfolio increases from -.30% per month to -.05%. Neither alpha is statistically significant. The difference in alpha between the two portfolios falls from .45% to an insignificant .07% per month.

The addition of LVH also causes a substantial convergence of risk factor loadings for the low and high volatility portfolios. Beta for the low volatility portfolio increases from .79 to .92 while beta for the high volatility portfolio decreases from 1.24 to .99. The absolute difference in value (HML) exposure between the low and high volatility portfolios decreases from .54 to .20, and the absolute difference in small cap (SMB) exposure decreases from .46 to .06. These results suggest that mutual fund performance differences commonly attributed to market cap and value/growth exposure may actually be more related to differences in LVH exposure.

[Table 10 about here]

Figure 4 recreates Figure 3 but includes the LVH factor as a pricing factor along with the other Fama-French factors. Again focusing on gross returns, we now see that both low and high volatility fund managers construct portfolios that perform about as well as would be expected if they had no skill. The low volatility, high volatility, and no-skill distributions closely overlap over the full length of the distributions.

[Figure 4 about here]

IV. Conclusions

A mutual fund's past return volatility is a powerful determinant of future performance. In the context of the Fama-French four-factor model, a portfolio of low volatility funds has an alpha 5.4% per year greater than a portfolio of high volatility funds. After controlling for heterogeneity in fund characteristics, we show that a one standard deviation decrease in fund volatility in the prior year predicts an increase in the annual Fama-French alpha of a fund of about 2.5% in the following year.

We explore the reason for this performance difference and conclude that it is not due to fund manager skill. Instead, we show that stock volatility has a pervasive impact on portfolio returns. Among other things, we simulate low and high volatility mutual funds that invest by randomly selecting stocks based on their return volatility in the same proportions as actual low and high volatility funds. We find return patterns in our simulated funds similar to those of actual low and high volatility mutual funds. For instance, the average simulated low volatility fund has Sharpe and Treynor ratios two to four times those of the average simulated high volatility fund.

To account for the impact of volatility, we create a new pricing factor, LVH (low volatility versus high volatility), and we find it eliminates the difference in alpha between real low and high volatility mutual funds. Further, we perform bootstrapped alpha tests that show no evidence of (1) skill among low volatility funds or (2) difference in skill between low and high volatility funds after including the LVH factor in the pricing model. Overall, our results suggest that accounting for the volatility effect is an essential part of properly specifying tests of manager skill because a large systematic bias favoring low volatility funds exists in common evaluation models. In addition, we are left with the conclusion that either the volatility effect is an important systematic pricing factor or a market inefficiency of great size.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Yakov, and Ruslan Goyenko. 2013. Mutual fund's r^2 as predictor of performance. *Review of Financial Studies* 26, 667-694.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 1-23.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler. 2011. Benchmarks as limits to Arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal* 67, 40-54.

Baker, Nardin L., and Robert A. Haugen. 2012. Low risk stocks outperform within all observable markets of the world. Working paper.

Barras, Laurent, Olivier Scaillet, and Russ Wermers. 2010. False discoveries in mutual fund performance: Measuring luck in estimated alphas. *Journal of Finance* 65, 179-216.

Blitz, David, and Pim Van Vliet. 2007. The volatility effect: Lower risk without lower return. *Journal of Portfolio Management*, 102-113.

Carhart, Mark M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* 94, 1276-1302.

Cremers, K.J. Martijn, and Antti Petajisto. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22, 3329-3365.

Cremers, K.J. Martijn, Antti Petajisto, and Eric Zitzewitz. 2012. Should benchmark indices have alpha? Revisiting performance evaluation. *Critical Finance Review*, forthcoming.

Evans, Richard B. 2010. Mutual fund incubation. *Journal of Finance* 64, 1581-1611.

Fama, Eugene F., and Kenneth R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French. 2010. Luck versus skill in the cross-section of mutual fund returns. *Journal of Finance* 65, 1915-1947.

Frazzini, Andrea, and Lasse H. Pederson. 2013. Betting against beta. *Journal of Financial Economics*, forthcoming.

Fu, Fangjian. 2009. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics* 91, 24-37.

Garcia-Feijoo, Luis, Xi Li, and Rodney Sullivan. 2012. The limits to arbitrage revisited: the low-risk anomaly, *Financial Analysts Journal*, forthcoming.

Han, Yufeng and David Lesmond. 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. *Review of Financial Studies* 24, 1590-1629.

Haugen, Robert A., and A. James Heins. 1972. On the evidence supporting the existence of risk premiums in the capital market. Working paper.

Haugen, Robert A., and A. James Heins. 1975. Risk and the rate of return on financial assets: Some old wine in new bottles. *Journal of Financial and Quantitative Analysis* 10, 775-784.

Hirshleifer, David. 1988. Residual risk, trading costs, and commodity futures risk premia. *Review of Financial Studies* 1, 173-193.

Hou, Kewei, and Roger K. Loh. 2012. Have we solved the idiosyncratic volatility puzzle?. Working paper.

Jensen, Michael C. 1968. The performance of mutual funds in the period 1945-1964. *Journal of Finance* 23, 389-416.

Kosowski, Robert, Allan Timmerman, Russ Wermers, and Hal White. 2006. Can mutual fund "stars" really pick stocks? New evidence from a bootstrap analysis. *Journal of Finance* 61, 2551-2596.

Pastor, Lubos, and Robert F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Petajisto, Antti. 2013. Active share and mutual fund performance. Working paper.

Sadka, Ronnie. 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics* 80, 309-349.

Sharpe, William F. 1966. Mutual fund performance. *Journal of Business* 39, 119-138.

Sharpe, William F. 1991. The arithmetic of active management. *Financial Analysts' Journal* 47, 7-9.

Storey, John D. 2002. A direct approach to false discovery rates. *Journal of the Royal Statistical Society* 64, 479-498.

Figure 1: The return on one dollar invested in mutual funds sorted on past return volatility

This figure shows the changing value of $1 invested in January 2000 through December 2011 in five equal weighted portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of daily returns in the prior calendar year. For clarity, we present only the 1st (low volatility), 3rd, 5th, 7th, and 10th (high volatility) deciles.

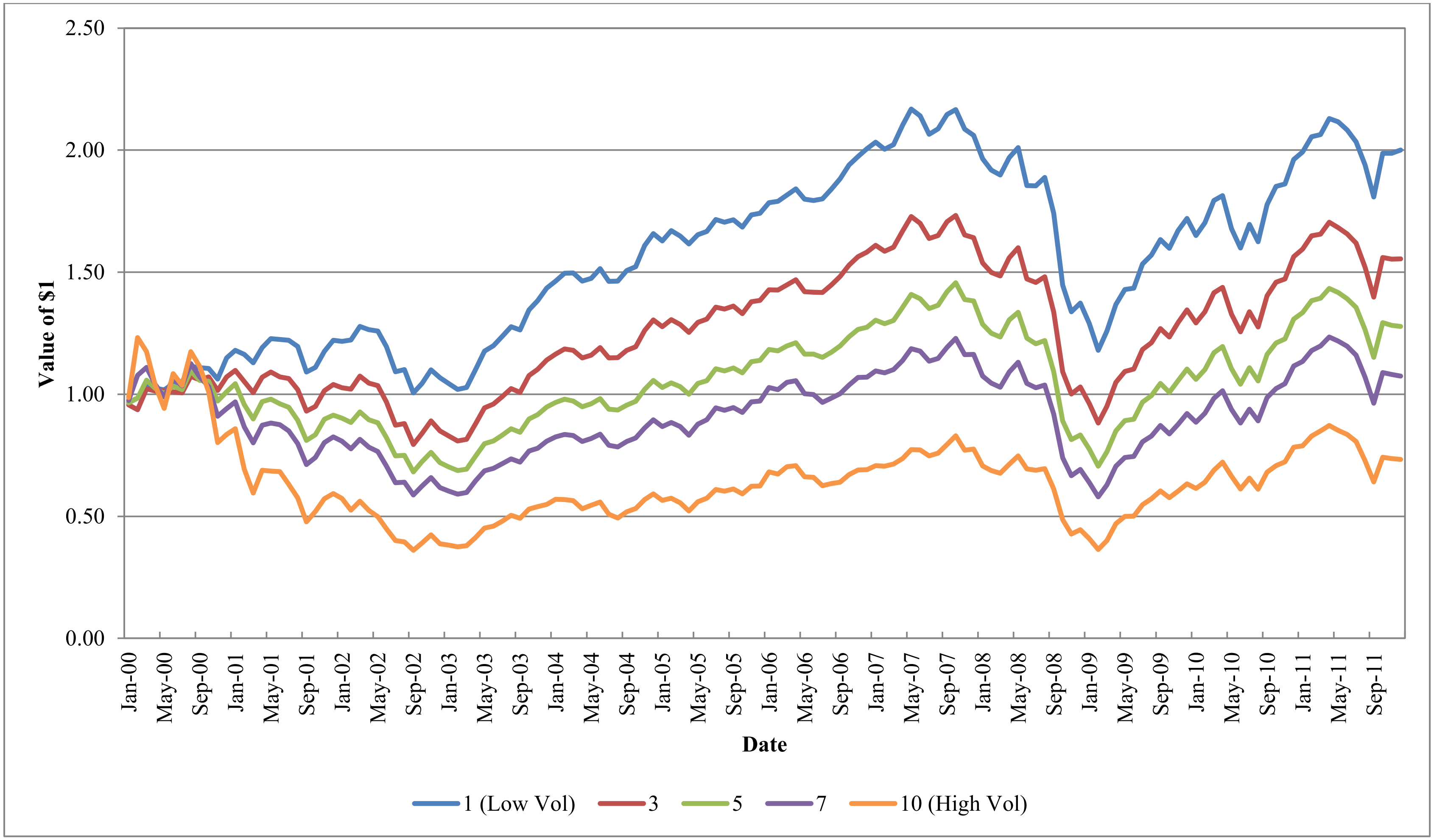


Figure 2: How long does volatility persist as a predictor of future fund performance?
This figure shows the monthly percentage alpha from a Fama-French four-factor regression on the monthly returns on portfolios of low and high volatility mutual funds. The low (high) volatility portfolio is an equal weighted portfolio of active U.S. equity funds with the lowest (highest) 10% of standard deviation of daily returns in previous calendar years. We also present results for the fifth volatility decile. We measure volatility in calendar year *t-1* and use that measure to form portfolios in calendar years *t* through *t+4*.

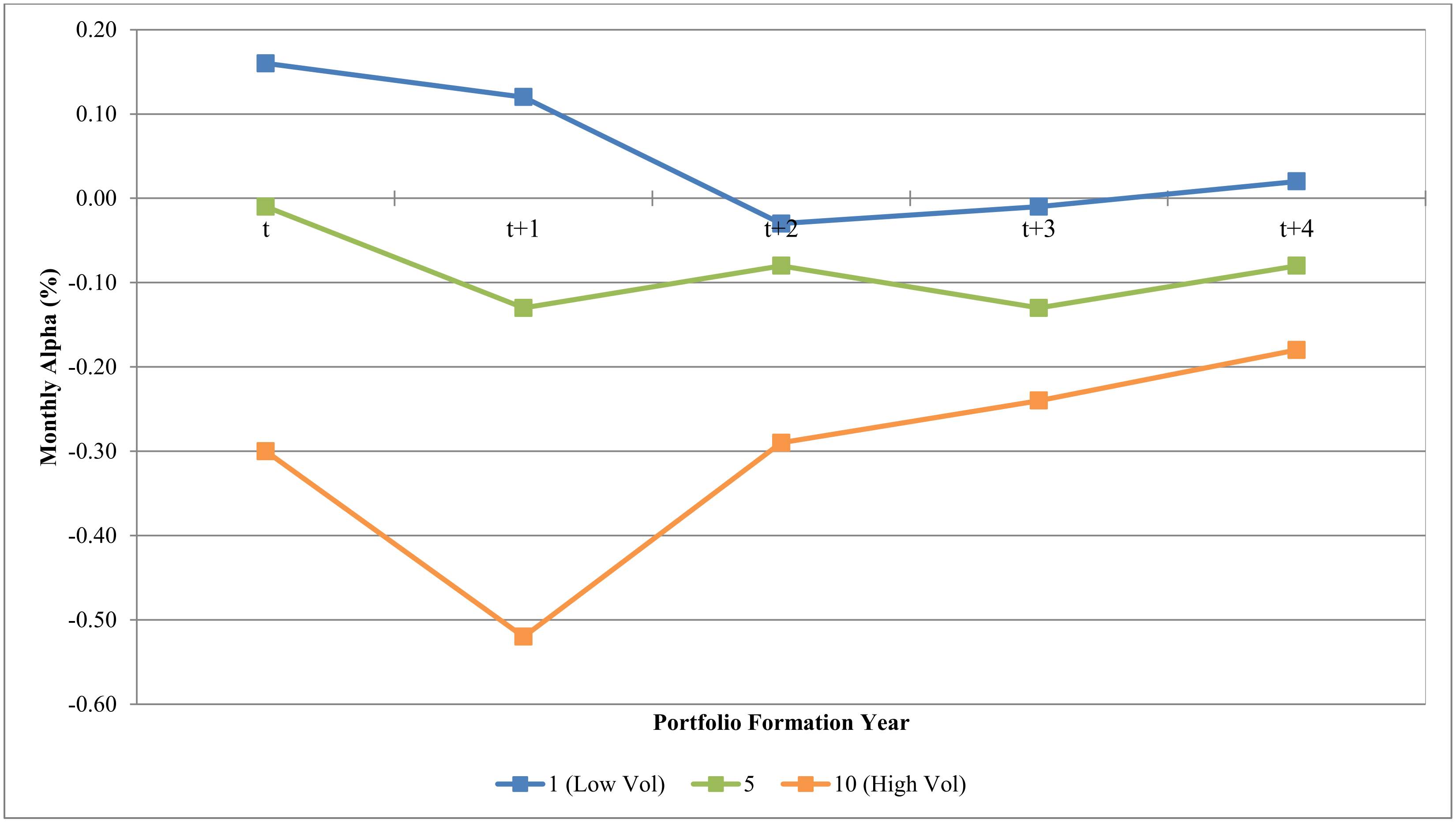


Figure 3: How does the distribution of mutual fund alpha differ with respect to fund volatility?
This figure shows (1) a plot of the cumulative distribution of the alpha *t*-statistics for the low volatility mutual funds, (2) a plot of the cumulative distribution of the alpha *t*-statistics for the high volatility mutual funds, and (3) a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. A mutual fund is considered low (high) volatility in every month after the standard deviation of its daily returns first falls into the lowest (highest) 10% among funds in the prior calendar year. Only fund months between January 2000 and December 2011 and after a fund is labeled low or high volatility are used. We follow the Fama-French (2010) bootstrap procedure with one thousand simulations to calculate alpha for the low and high volatility funds under the restriction of no manager skill. We use the Fama-French four-factor model to calculate fund alphas using gross returns. We define a fund's gross return for a month as the net return plus one twelfth the annual expense ratio.

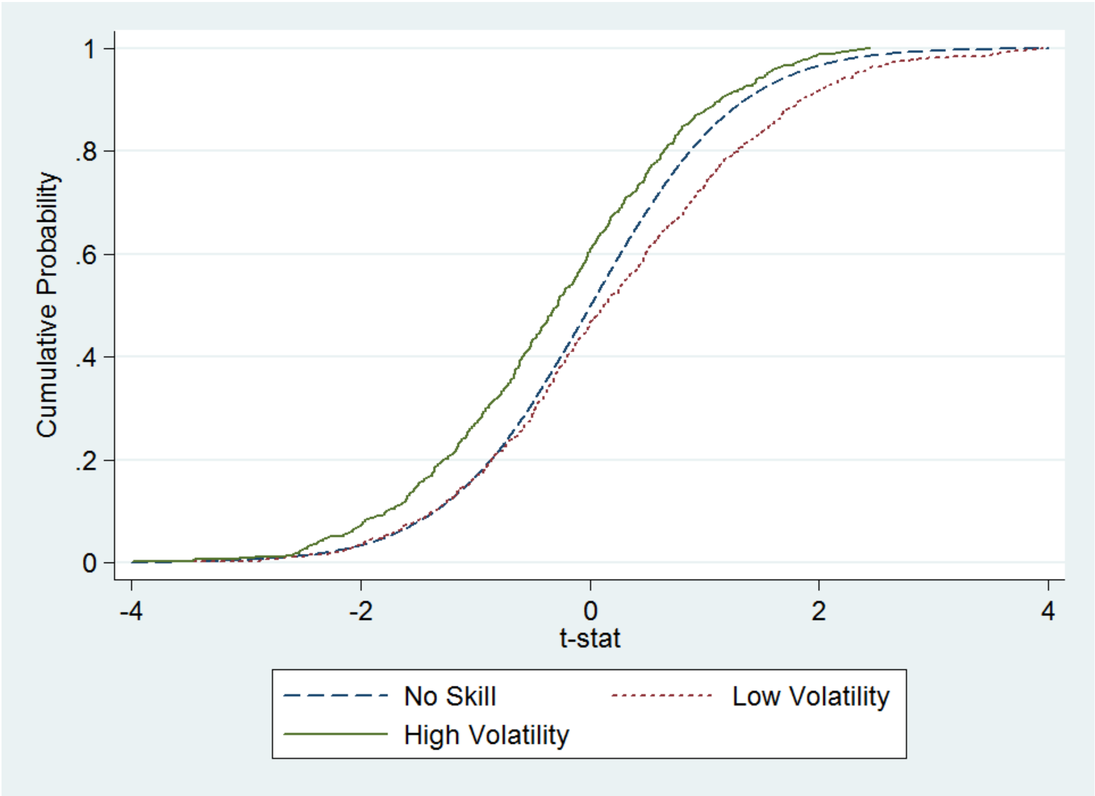


Figure 4: How is the distribution of mutual fund alpha affected by accounting for the vol anomaly?
This figure shows (1) a plot of the cumulative distribution of the alpha *t*-statistics for the low volatility mutual funds, (2) a plot of the cumulative distribution of the alpha *t*-statistics for the high volatility mutual funds, and (3) a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. A mutual fund is considered low (high) volatility in every month after the standard deviation of its daily returns first falls into the lowest (highest) 10% among funds in the prior calendar year. Only fund months between January 2000 and December 2011 and after a fund is labeled low or high volatility are used. We follow the Fama-French (2010) bootstrap procedure with one thousand simulations to calculate alpha for the low and high volatility funds under the restriction of no manager skill. We use the Fama-French four-factor model along with the LVH factor to calculate fund alphas using gross returns. The LVH factor is equal to the return to a value weighted portfolio of all stocks that pass our screens that are in the lowest decile of standard deviation of monthly returns during the previous calendar year less the return to a value weighted portfolio of all stocks that pass our screens in the highest decile. We define a fund's gross return for a month as the net return plus one twelfth the annual expense ratio.

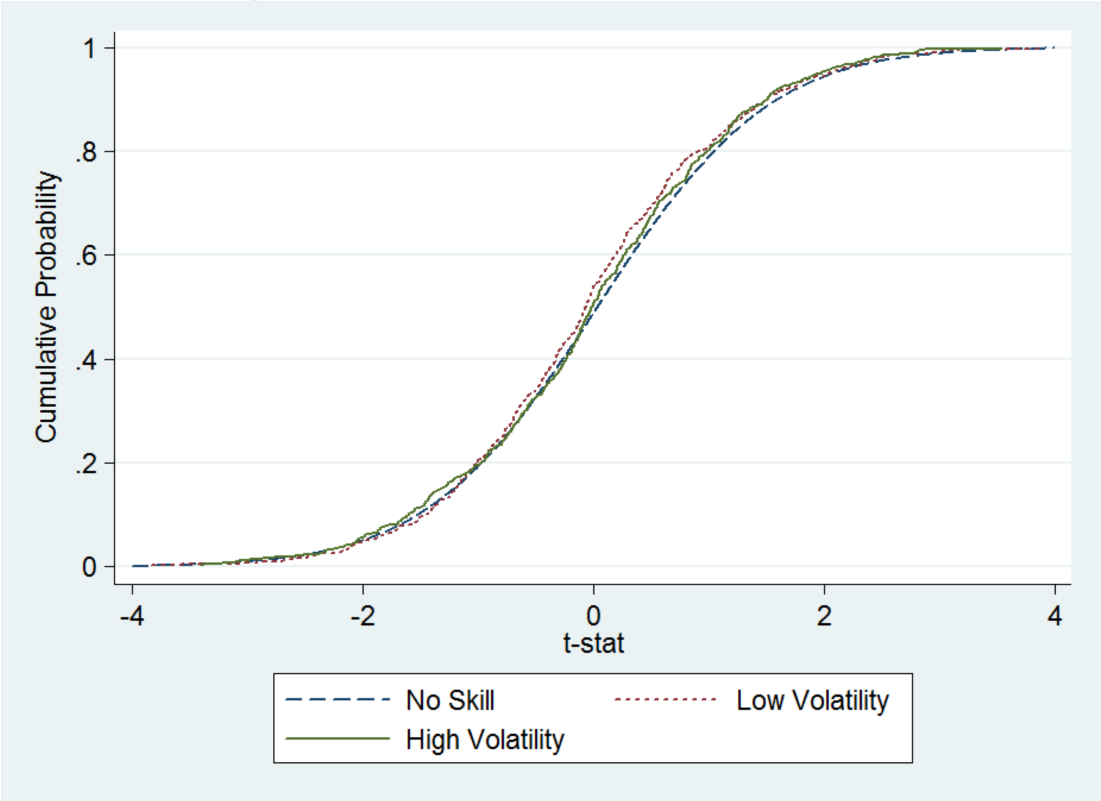


Table 1: The returns on portfolios of mutual funds sorted on past return volatility

This table shows the return on five equal weighted portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of daily returns in the prior calendar year. To save space, we present only the 1st (low volatility), 3rd, 5th, 7th, and 10th (high volatility) deciles. Panel A shows the performance of each portfolio from January 2000 through December 2011. Average Return is the mean monthly return for the portfolio multiplied by twelve. Geometric Return is the annualized monthly compound return. Standard Deviation is the annualized standard deviation of monthly portfolio returns. Sharpe (Treynor) Ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized portfolio standard deviation (CAPM beta). Panel B shows the correlation of monthly returns across the portfolios.

Panel A: Portfolio Returns

	Low	3	5	7	High	L - H
Average Return	6.8%	5.0%	3.5%	2.4%	0.8%	6.0%
Geometric Return	5.9%	3.7%	2.1%	0.6%	-2.5%	8.4%
Standard Deviation	14.2%	16.0%	16.9%	18.8%	25.8%	-11.6%
Sharpe Ratio	0.32	0.17	0.07	0.01	-0.06	0.38
Treynor Ratio	0.06	0.03	0.01	0.00	-0.01	0.07

Panel B: Portfolio Return Correlations

	Low	3	5	7	High
Low	1				
3	0.98	1			
5	0.97	0.98	1		
7	0.93	0.93	0.98	1	
High	0.83	0.81	0.89	0.96	1

Table 2: Do low volatility mutual funds outperform high volatility mutual funds?
This table shows the Fama-French four-factor regression results for monthly returns on portfolios of low and high volatility mutual funds from January 2000 through December 2011. The low (high) volatility portfolio is an equal weighted portfolio of active U.S. equity funds with the lowest (highest) 10% of standard deviation of daily returns in the prior calendar year. We divide the sample into equal time periods and test the portfolios only in the first six months of the year in Models (4) through (6) and only in the last six months in Models (7) through (9). *p*-values from robust standard errors are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

	Full Sample			January - June			July - December		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low	High	L - H	Low	High	L - H	Low	High	L - H
Beta	0.79***	1.24***	-0.45***	0.73***	1.31***	-0.58***	0.82***	1.21***	-0.39***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SMB	0.08***	0.54***	-0.46***	0.05	0.53***	-0.48***	0.17***	0.55***	-0.38***
	[0.000]	[0.000]	[0.000]	[0.118]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
HML	0.25***	-0.28***	0.54***	0.23***	-0.32***	0.55***	0.26***	-0.24***	0.50***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]
UMD	0.02	0.04	-0.02	0.01	0.03	-0.03	0.04	0.07	-0.03
	[0.356]	[0.479]	[0.758]	[0.700]	[0.652]	[0.756]	[0.233]	[0.190]	[0.690]
Alpha	0.16%**	-0.30%**	0.45%***	0.15%	-0.28%	0.43%*	0.18%*	-0.32%**	0.51%**
	[0.044]	[0.020]	[0.008]	[0.151]	[0.106]	[0.073]	[0.074]	[0.041]	[0.019]
Observations	144	144	144	72	72	72	72	72	72
Adjusted r^2	0.94	0.95	0.79	0.94	0.95	0.82	0.96	0.96	0.76

Table 3: How robust is the difference in alpha between low and high volatility mutual funds?
This table shows the difference in monthly percentage alpha between portfolios of low and high volatility mutual funds. The low (high) volatility portfolio is a portfolio of active U.S. equity funds with the lowest (highest) 10% of standard deviation of daily returns in the prior calendar year. Portfolios are weighted using either equal or total net asset (TNA) weighting. The difference in alpha is measured from January 2000 through December 2010 for Panel A and from January 2000 through December 2011 for Panel B. Panel A shows results using both the Fama-French four-factor model (FF4) and the Cremers, Petajisto, and Zitzewitz (2012) seven-factor (CPZ7) model. We also include the Pastor and Stambaugh (2003) and Sadka (2006) liquidity factor in some specifications. Yes (No) indicates that the factor was (was not) included in the regression. Panel B shows results using the Fama-French four-factor model with certain groups of mutual funds excluded. In different specifications we drop small funds (assets less than $300 million at the beginning of the year), funds that primarily invest in small stocks (Lipper classes SCGE, SCVE, and SCCE), and funds that primarily invest in growth stocks (Lipper classes LCGE, MLGE, MCGE, and SCGE). Yes (No) indicates that the group was (was not) included in the sort. *p*-values from robust standard errors are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

Panel A: Different Models

Factor Model	FF4	FF4	FF4	FF4	CPZ7	CPZ7	CPZ7	CPZ7
PS Liquidity	No	Yes	No	Yes	No	Yes	No	Yes
Sadka Liquidity	No	No	Yes	Yes	No	No	Yes	Yes
Equal Weight	0.42%**	0.22%	0.41%**	0.23%	0.30%*	0.18%	0.30%**	0.19%
	[0.024]	[0.212]	[0.029]	[0.212]	[0.050]	[0.175]	[0.047]	[0.169]
TNA Weight	0.41%**	0.26%	0.41%**	0.27%	0.33%**	0.24%*	0.33%**	0.25%*
	[0.019]	[0.127]	[0.020]	[0.121]	[0.019]	[0.068]	[0.018]	[0.063]

Panel B: Including Groups

Small Funds	Yes	Yes	No	No	Yes	No	Yes	No
Small Stocks	Yes	No	Yes	No	Yes	Yes	No	No
Growth Stocks	Yes	No	No	Yes	No	Yes	Yes	No
Equal Weight	0.45%***	0.26*%*	0.38%***	0.33%*	0.38%***	0.46%***	0.34%*	0.28%***
	[0.008]	[0.015]	[0.001]	[0.078]	[0.001]	[0.009]	[0.067]	[0.008]
TNA Weight	0.46%***	0.29%**	0.32%**	0.39%**	0.32%**	0.49%***	0.43%**	0.26%**
	[0.004]	[0.013]	[0.012]	[0.024]	[0.011]	[0.003]	[0.014]	[0.025]

Table 4: The characteristics of low and high volatility mutual funds

This table shows average characteristics for funds in the year prior to entering into either the low or high volatility portfolio. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of daily returns in the prior calendar year. We also present results for the full sample of funds. Panel A shows average fund level information, and Panel B provides average fund level Fama-French four-factor exposures. Annual Return is the net fund return over the past year. Daily St. Dev. is the standard deviation of daily returns over the past year. Daily Idio. St. Dev. is the standard deviation of the daily Fama-French four-factor residuals over the past year. Assets are the net assets of the fund in millions of dollars. Age is the number of months since the fund started its first share class. Expense is the annual expense ratio of the fund. Turnover is the annual turnover ratio of the fund. Beta, SMB, HML, and UMD are the Fama-French four-factor exposures of the fund over the past calendar year estimated from daily returns. Annualized Alpha is the annualized (250 days) Fama-French four-factor alpha over the past calendar year. A *p*-value from a test of difference in means is provided for each characteristic.

Panel A: Fund Level Characteristics

	Low	High	Difference	*p*-value	Full Sample
Annual Return	7.41%	10.23%	-2.82%	0.011	7.73%
Daily St. Dev.	0.98%	1.82%	-0.85%	<.001	1.33%
Daily Idio. St. Dev.	0.28%	0.51%	-0.23%	<.001	0.33%
Assets (Millions)	2970	901	2068	<.001	1627
Age (Months)	198	149	49	<.001	179
Expense	1.19%	1.37%	-0.18%	<.001	1.23%
Turnover	60.4%	118.9%	-58.5%	<.001	86.8%
Observations	1485	1474			14792

Panel B: Fund Level Fama-French Exposures

	Low	High	Difference	*p*-value	Full Sample
Beta	0.87	1.13	-0.26	<.001	1.01
SMB	0.07	0.63	-0.56	<.001	0.22
HML	0.13	-0.11	0.24	<.001	0.01
UMD	-0.03	0.09	-0.12	<.001	0.03
Annualized Alpha	0.07%	-1.14%	1.21%	.002	-0.61%
Observations	1485	1474			14792

Table 5: Does fund volatility predict future performance?

This table presents results from the following panel model:

$$\text{Alpha}_{i,t+1} = \text{Alpha}_{i,t} + \text{SD}_{i,t} + \text{Idio}_{i,t} + \text{Fund Controls}_{i,t} + \text{Obj FE} + \text{Time FE} + \epsilon_{i,t}$$

The dependent variable is the annualized percentage alpha for fund *i* in calendar year *t+1* calculated from the Fama-French four-factor model using daily returns. Daily St. Dev. is the standard deviation of daily returns during calendar year *t*. Daily Idio. St. Dev. is the idiosyncratic standard deviation of daily returns during calendar year *t*. Fund Controls include the natural log of assets, natural log of age, expense ratio, and turnover ratio all measured as of the end of calendar year *t* and the Fama-French four-factor exposures calculated from daily returns during calendar year *t*. We include year fixed effects and Lipper class fixed effects. All continuous variables are winsorized at the .5% and 99.5% levels. All continuous right-hand side variables are *z*-scored, i.e., demeaned and divided by their standard deviation. *p*-values from bootstrapped standard errors clustered on year are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Alpha	0.51			0.50
	[0.239]			[0.231]
Daily St. Dev.		-2.55*		-2.53*
		[0.069]		[0.092]
Daily Idio. St. Dev.			0.03	
			[0.963]	
Assets	-0.43***	-0.34**	-0.41**	-0.36**
	[0.010]	[0.022]	[0.021]	[0.019]
Age	0.25***	0.18**	0.23***	0.21***
	[0.001]	[0.018]	[0.008]	[0.002]
Expense	-0.38***	-0.35***	-0.40***	-0.34***
	[0.000]	[0.001]	[0.000]	[0.002]
Turnover	-0.38**	-0.41**	-0.43**	-0.36**
	[0.021]	[0.019]	[0.017]	[0.025]
Beta	-0.65**	-0.14	-0.69**	-0.11
	[0.043]	[0.741]	[0.026]	[0.787]
SMB	-0.17	0.44	-0.07	0.32
	[0.867]	[0.619]	[0.949]	[0.695]
HML	1.40**	0.83	1.38**	0.86
	[0.025]	[0.227]	[0.021]	[0.220]
UMD	-0.57	-0.54	-0.52	-0.59
	[0.241]	[0.292]	[0.322]	[0.235]
Observations	14,792	14,792	14,792	14,792
Time FE	Yes	Yes	Yes	Yes
Fund Type FE	Yes	Yes	Yes	Yes
Adjusted r^2	0.079	0.090	0.074	0.095

Table 6: Does stock selectivity explain the performance of low volatility mutual funds?
This table shows the monthly percentage alpha for portfolios sorted on one of two measures of stock selectivity (Active Share and r^2) and return volatility. Each month funds are first sorted into quintiles based on either (1) Active Share or (2) r^2. Active Share for a fund is measured following Petajisto (2013). We use the most recent value for Active Share available unless that value is more than three months old. A fund whose most recent value of Active Share is more than three months old is ineligible for inclusion in the portfolios that month. The r^2 for a fund is equal to the r^2 value resulting from the regression of fund monthly returns against the Fama-French four-factor model over the prior twenty four months. At least the prior twelve months of returns are required. After that sort, funds are then sorted within those quintiles into quintiles based on the standard deviation of fund daily returns in the prior calendar year. This double sort produces twenty five groups of funds that are used to form twenty five equal weighted portfolios. Alpha for the portfolios is measured from January 2001 through August 2009 using the Fama-French four-factor model (FF4). The All column and row are portfolios formed on only one of the two groupings after the original sorting procedure has occurred. *, **, and *** represent statistical significance using robust standard errors at the 10%, 5%, and 1% levels.

Panel A: Active Share Double Sort

	Active Share Rank						
St. Dev. Rank	Low	2	3	4	High	L-H	All
Low	-0.08	-0.09	-0.03	0.06	0.10	-0.18**	-0.01
2	-0.12***	-0.10*	-0.02	-0.02	0.01	-0.13	-0.05
3	-0.21***	-0.13***	-0.07	-0.13	-0.11	-0.11	-0.13***
4	-0.22***	-0.21***	-0.27***	-0.28***	-0.03	-0.18*	-0.20***
High	-0.28***	-0.39***	-0.40***	-0.35**	-0.44***	0.16	-0.37***
L-H	0.21	0.30*	0.37**	0.40**	0.54***	-0.33**	0.36**
All	-0.18***	-0.18***	-0.16***	-0.14*	-0.09	-0.09	-0.15***

Panel B: r^2 Double Sort

	r^2 Rank						
St. Dev. Rank	Low	2	3	4	High	L-H	All
Low	0.09	0.03	0.01	0.03	-0.06	0.15**	0.02
2	-0.06	-0.03	-0.08	-0.15***	-0.11***	0.05	-0.08
3	-0.06	-0.14**	-0.12*	-0.10	-0.24***	0.18	-0.14***
4	-0.02	-0.13*	-0.32***	-0.28***	-0.29***	0.27	-0.21***
High	-0.33**	-0.35***	-0.38***	-0.35***	-0.39***	0.06	-0.36***
L-H	0.41**	0.38**	0.39**	0.39**	0.33**	0.08	0.38***
All	-0.08	-0.12**	-0.18***	-0.17***	-0.22***	0.14	-0.15***

Table 7: Do low volatility mutual funds efficiently allocate their assets?

This table shows the stock return volatility of fund holdings and the effect of that volatility on fund performance. We measure the monthly standard deviation of returns for all stocks that pass our screens during each calendar year and match those values to the subsequent year's holdings data for our sample of active U.S. equity funds from 2003 through 2011. In Panel A, we measure the stock return volatility of fund holdings for groups sorted on fund return volatility. A low (high) volatility fund is among the 10% of mutual funds in the sample with the lowest (highest) standard deviation of daily returns in the year of the holdings. We calculate each statistic for each fund holdings snapshot and then average across all snapshots. Average SD is the annualized average standard deviation of monthly returns for all stocks held by a fund. Dollar Weighted SD is the annualized standard deviation of monthly returns for all stocks held by a fund weighted by investment size. We sort all stocks in the sample into deciles each calendar year based on the standard deviation of their returns and report the Average Decile for the stocks held by a fund. We also report the percentage of stocks held by a fund that fall into specific stock volatility deciles. In Panel B, we first sort funds into quintiles based on the standard deviation of their daily returns in the prior calendar year. We then sort funds within those quintiles into quintiles based on the dollar weighted standard deviation of returns from the funds' most recent holdings snapshot in the prior year. Alphas are calculated and reported as in Table 6. The time period for alpha measurement is January 2004 through December 2011.

Panel A: Fund Holdings

	Return SD Rank				
	Low	3	5	7	High
Dollar Weighted SD	25.3%	27.7%	29.8%	33.3%	41.2%
Average SD	26.3%	29.1%	31.2%	34.3%	41.9%
Average Decile	3.3	3.9	4.3	4.8	6.0
% Low	28.1%	20.3%	16.1%	11.6%	6.1%
% 3	14.1%	13.5%	13.2%	12.0%	8.5%
% 5	9.2%	11.1%	11.5%	11.9%	10.3%
% 7	4.3%	6.3%	7.6%	9.5%	11.7%
% High	1.3%	2.2%	3.3%	4.7%	11.1%

Panel B: Return SD and Holdings SD Double Sort

	Return SD Rank						
Holdings SD Rank	Low	2	3	4	High	L-H	All
Low	-0.03	-0.10*	-0.09	-0.18**	-0.18**	0.16	-0.11**
2	-0.01	-0.12***	-0.06	-0.16**	-0.10	0.09	-0.09***
3	-0.04	-0.06	-0.12**	-0.06	-0.12	0.07	-0.08*
4	-0.02	-0.06	-0.06	-0.10	-0.15	0.13	-0.08
High	-0.01	-0.05	-0.08	-0.16**	-0.32***	0.30**	-0.12**
L-H	-0.01	-0.05	-0.01	-0.01	0.13	-0.15	0.01
All	-0.02	-0.08*	-0.08**	-0.13**	-0.17**	0.15	-0.10***

Table 8: How do simulated funds that invest like high and low volatility funds perform? This table shows the performance of simulated mutual funds formed on the basis of stock return volatility. We first sort all stocks that pass our screens into deciles at the beginning of every year based on the standard deviation of their monthly returns during the previous calendar year. A simulated low (high) volatility fund then chooses 100 stocks based on the decile percentages for the low (high) volatility funds in Table 7. The percentages are constant but stocks are randomly selected from each decile. The same stocks remain in the fund for the full upcoming calendar year unless they fail a screen or leave the sample. At the beginning of the next year, 100 new stocks are chosen using the same procedure. We follow this procedure to create 1000 low and 1000 high volatility holdings histories. We use the holdings histories to construct portfolios that are either equal, value, and randomly weighted. Value weighted portfolios use market capitalization to generate weights and randomly weighted portfolios use the market capitalization weights but randomly assign them to stocks. We measure each simulated fund's performance from January 2000 through December 2011 and then average the results for the low and high volatility funds of each weighting. Each measure of performance presented is calculated as in Table 1. A *p*-value from a test of difference in means is provided for each characteristic. Panel A presents the equal weighted results. Panel B presents the value weighted results. Panel C presents the random weighted results.

Panel A: Equal Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	10.2%	8.3%	1.9%	<0.001
Geometric Return	9.1%	5.3%	3.8%	<0.001
SD of Returns	17.1%	25.1%	-8.0%	<0.001
Sharpe Ratio	0.46	0.24	0.22	<0.001
Treynor Ratio	0.09	0.05	0.04	<0.001

Panel B: Value Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	4.4%	3.0%	1.4%	<0.001
Geometric Return	3.2%	0.8%	2.4%	<0.001
SD of Returns	15.7%	21.0%	-5.3%	<0.001
Sharpe Ratio	0.14	0.04	0.10	<0.001
Treynor Ratio	0.03	0.01	0.02	<0.001

Panel C: Random Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	10.2%	8.4%	1.8%	<0.001
Geometric Return	8.4%	4.0%	4.4%	<0.001
SD of Returns	20.8%	30.4%	-9.6%	<0.001
Sharpe Ratio	0.38	0.20	0.18	<0.001
Treynor Ratio	0.09	0.05	0.04	<0.001

Table 9: Characteristics of the LVH (low volatility versus high volatility) factor

This table presents summary statistics and correlations for the Fama-French four-factors, the Pastor and Stambaugh (2003) liquidity factor, and our LVH (low volatility versus high volatility) factor from January 2000 through December 2011. The LVH factor is equal to the return to a value weighted portfolio of all stocks that pass our screens that are in the lowest decile of standard deviation of monthly returns during the previous calendar year less the return to a value weighted portfolio of all stocks that pass our screens in the highest decile. Panel A reports the mean and median monthly return for each factor, the standard deviation of the monthly factor returns, and the 10^{th} and 90^{th} percentile factor returns. Panel B reports the correlations between the monthly factor returns.

Panel A: Factor Summary Statistics

Factor	Mean	Median	St. Dev.	10%	90%
LVH	1.16%	0.16%	11.66%	-9.97%	13.96%
Mktrf	0.06%	0.76%	4.98%	-7.16%	6.26%
SMB	0.46%	0.08%	3.79%	-3.24%	4.34%
HML	0.53%	0.34%	3.63%	-2.93%	4.39%
UMD	0.17%	0.41%	6.32%	-6.85%	6.19%
PS Liquidity	0.91%	0.71%	4.31%	-4.17%	5.44%

Panel B: Factor Correlations

	LVH	Mktrf	SMB	HML	UMD	PS Liq
LVH	1					
Mktrf	-0.71	1				
SMB	-0.66	0.30	1			
HML	0.52	-0.11	-0.37	1		
UMD	0.24	-0.38	0.13	-0.10	1	
PS Liquidity	-0.05	0.11	0.13	-0.14	0.08	1

Table 10: Does the vol anomaly explain the difference in performance between low and high volatility mutual funds?
This table replicates the Fama-French factor results of Table 2, but adds new variables to the model specification. Models (1) through (3) analyze the low volatility portfolio from Table 2, Models (4) through (6) the high volatility portfolio from Table 2, and Models (7) through (9) the differences between the low and high volatility portfolios. Models (1), (2), and (3) in Table 2 are identical to Models (1), (4), and (7) in this table. The first new factor added to the specification is the LVH (low volatility versus high volatility) factor. The LVH factor is equal to the return to a value weighted portfolio of all stocks that pass our screens that are in the lowest decile of standard deviation of monthly returns during the previous calendar year less the return to a value weighted portfolio of all stocks that pass our screens in the highest decile. The second new factor is the Pastor and Stambaugh (2003) liquidity factor. *p*-values from robust standard errors are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

	Low Volatility			High Volatility			Low - High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta	0.79***	0.92***	0.90***	1.24***	0.99***	1.01***	-0.45***	-0.08*	-0.11***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.057]	[0.006]
SMB	0.08***	0.22***	0.20***	0.54***	0.28***	0.29***	-0.46***	-0.06	-0.09
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.385]	[0.197]
HML	0.25***	0.14***	0.15***	-0.28***	-0.06	-0.07	0.54***	0.20***	0.23***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.226]	[0.136]	[0.000]	[0.001]	[0.000]
UMD	0.02	-0.01	-0.01	0.04	0.09***	0.09***	-0.02	-0.10***	-0.10***
	[0.356]	[0.505]	[0.453]	[0.479]	[0.010]	[0.008]	[0.758]	[0.003]	[0.001]
LVH		0.11***	0.10***		-0.21***	-0.20***		0.32***	0.30***
		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]
PS Liquidity			0.04**			-0.04			0.09***
			[0.017]			[0.101]			[0.002]
Alpha	0.16%**	0.03%	0.00%	-0.30%**	-0.05%	-0.02%	0.45%***	0.07%	0.01%
	[0.044]	[0.669]	[0.982]	[0.020]	[0.625]	[0.879]	[0.008]	[0.519]	[0.902]
Observations	144	144	144	144	144	144	144	144	144
Adjusted r^2	0.94	0.95	0.96	0.95	0.97	0.97	0.79	0.90	0.91

Appendix A – The long run performance of low and high volatility mutual funds

The time period we study is January 2000 through December 2011. We choose that time period because of (1) the availability of data for constraints we impose to form our sample of active U.S. equity mutual funds and (2) the availability of daily mutual fund returns to measure volatility. We relax those constraints here to study the performance of low and high volatility mutual funds over a longer time period. We discuss the performance of low and high volatility mutual funds in our new sample here, but include additional discussion of the effect of switching from daily to monthly return volatility in Appendix B.

We still use the CRSP Survivor-Bias-Free U.S. Mutual Fund database to build our new sample of active U.S. equity funds. We also keep our original constraints that (1) CRSP not identify a fund as an index fund, ETF, or variable annuity and (2) a fund not have a term in its name not associated with unleveraged, active management or equity investment. Lipper class codes and equity holdings percentage are missing in large portions of our expanded sample, so we now keep only funds that have CRSP objective codes that identify domestic equity funds associated with market cap and value/growth tilt.[1] We no longer require funds to reach a minimum age or size, nor do we require them to have any past data available except for monthly return volatility in the prior calendar year.[2]

We use the CRSP monthly return file to calculate return volatility for each fund each calendar year. After measuring past return volatility for our new sample, we choose to set our start year for the portfolios as 1992. Beginning the sample in earlier years would place few funds into each volatility decile. By first measuring volatility in 1991 and beginning the portfolios in

[1] The CRSP objective codes we use are: EDCM, EDCS, EDCI, EDYG, EDYB, and EDYI.
[2] Results are not significantly changed if we do impose a requirement that funds have at least $20 million in assets in the month prior to entering the sample.

January 1992, we have at least fifty mutual funds in each decile each month. Our new sample ends at the same point as our original sample, December 2011.

Figure A-1 replicates Figure 1 from the paper using our new sample and time period. It shows the value of one dollar invested in the low and high volatility portfolios starting in January 1992 and ending December 2011. The comparative performance of the low and high volatility portfolios has three distinct time periods: January 1992 through December 1998, January 1999 through September 2002, and October 2002 through December 2011.

During the first time period, January 1992 through December 1998, the portfolios have about the same performance. At the end of 1998 the low volatility portfolio is worth \$2.38 and the high volatility portfolio is worth \$2.43. The correlation of their returns is about .96. Any differences in risk between the portfolios over that time period did not result in different outcomes for investors.

The performance of the low and high volatility portfolios does differ significantly during the second time period, January 1999 through September 2002. As the famous tech bubble neared its end, the high volatility portfolio doubled in value in a little over a year; however, its value at the end of the period is less than when the period began. The high volatility portfolio is worth \$5.35 in February 2000, but by the end of 2000 its value falls to \$3.48. By September 2002, its value is only \$1.57. At that same time, the low volatility portfolio experienced little turbulence. It is worth \$2.40 in February 2000, up \$0.02 from the start of the second period. In September 2002, the low volatility portfolio's value is down from the start of the period but by only \$0.20. The correlation of the returns of the low and high volatility portfolios is only about .24 during the second time period.

During the remaining time in our sample, October 2002 through December 2011, the low volatility portfolio is never worth less than the high volatility portfolio. While the difference in their respective values fluctuates over time, the high volatility portfolio never recovers from its large loss in the second period. The gap between the portfolios in the third time period is smallest in March 2006 ($0.12) and largest in November 2008 ($0.81). But by the end of 2011, the low volatility portfolio is worth $3.78, and the high volatility portfolio is worth $3.24. The correlation between the returns on the low and high volatility portfolios during the third time period (.97) is similar to first time period correlation.

In additional to a higher terminal value, the low volatility portfolio also has much higher risk-adjusted returns. Table A-1 replicates Table 1, Panel A, from the paper using the new sample and time period. It shows the average return and performance evaluation measures for the high and low volatility portfolios from January 1992 through December 2011. The high volatility portfolio does have a higher arithmetic average return than the low volatility portfolio, but the low volatility portfolio has the higher geometric average return. The key difference between the two portfolios is their variability. The low volatility portfolio has an annualized standard deviation of about half that of the high volatility portfolio. The lower variability results in a Sharpe (Treynor) ratio for the low volatility portfolio of .36 (.06) compared to .24 (.04) for the high volatility portfolio. Overall, an investor over this twenty year period would have accumulated more wealth from substantially less risky investments with the portfolio of low volatility mutual funds.

Figure A-1: The return on one dollar invested in mutual funds sorted on past return volatility – Extended sample

This figure shows the changing value of $1 invested in January 1992 through December 2011 in two equal weighted portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of monthly returns in the prior calendar year.

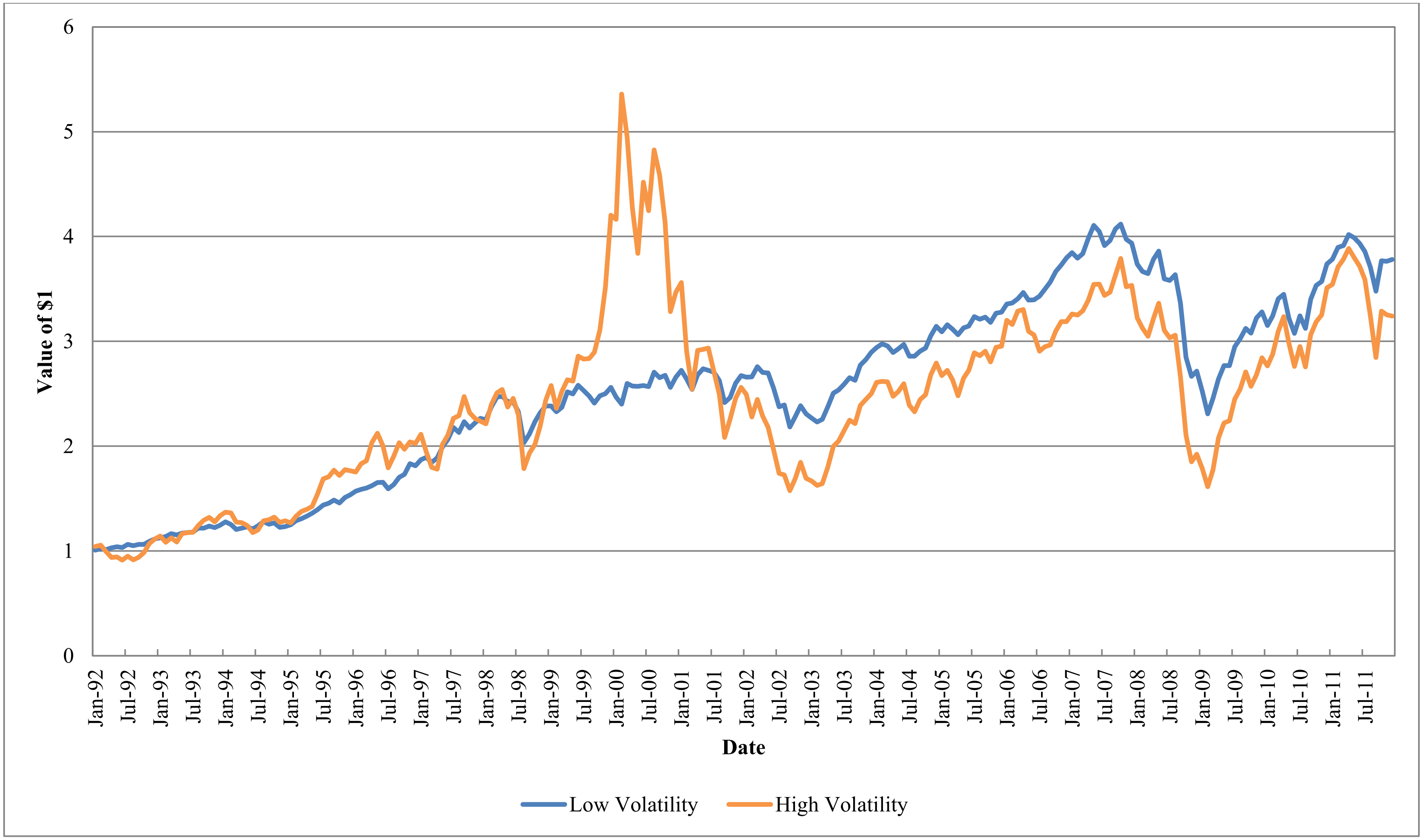


Table A-1: The returns on portfolios of mutual funds sorted on past return volatility – Extended sample

This table shows the returns on two portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of monthly returns in the prior calendar year. Performance for each portfolio is measured from January 1992 through December 2011. Average Return is the mean monthly return for the portfolio multiplied by twelve. Geometric Return is the annualized monthly compound return. Standard Deviation is the annualized standard deviation of monthly portfolio returns. Sharpe (Treynor) Ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized portfolio standard deviation (CAPM beta).

	Low	High	L - H
Average Return	7.4%	8.8%	-1.5%
Geometric Return	6.9%	6.1%	0.8%
SD of Returns	11.8%	24.2%	-12.4%
Sharpe Ratio	0.36	0.24	0.12
Treynor Ratio	0.06	0.04	0.02

Appendix B – Measuring mutual fund volatility using monthly returns

Throughout the paper, we measure fund volatility using the standard deviation of daily returns during the prior calendar year. Our goal was to select a measure of volatility that (1) requires a relatively small time frame to measure and (2) is predictive of future volatility. Using monthly returns over the previous three to five years may accurately predict future volatility but would require funds to operate for many years before entering the sample. Using monthly returns over a single year solves that problem, but we find that it is a weak predictor of future volatility compared to daily return volatility. Furthermore, we find using this less persistent measure greatly affects the results in the paper.

Table B-1 shows the percentage of funds in our sample that fall into each mutual fund volatility decile in year $t+1$ given their year t decile. We use daily returns to measure volatility in Panel A and monthly returns in Panel B. Daily return volatility is a better indicator of future fund volatility than monthly return volatility regardless of decile. Using daily returns, 54.1% of funds in the lowest volatility decile in year t remain in the lowest volatility decile in year $t+1$, and 55.5% of funds in the highest volatility in year t decile remain in the highest volatility decile in year $t+1$. Using monthly returns, only 34.7% of funds that are in the lowest volatility remain in the lowest volatility decile, and only 47.9% of funds that are in the highest volatility remain in the highest volatility decile.

The less predictive monthly return volatility measure has a significant effect on the outcome of our tests. We first repeat Figure 1 and Panel A of Table 1 from our paper using monthly returns in Figure B-1 and Table B-2. Using monthly return volatility the low volatility portfolio is worth about $1.46 at the end of 2011, and the high volatility portfolio is worth only $0.80. Using daily return volatility the low volatility portfolio was worth about $2.00 at the end of 2011, and the high volatility portfolio was worth only \$0.73. The high volatility portfolio has poor performance regardless of volatility measure, but the low volatility has significantly worse performance using monthly return volatility. The average return for the low volatility portfolio using monthly return volatility is 2.6% less per year than the same portfolio using daily return volatility. The Sharpe and Treynor ratios for the monthly return low volatility portfolio are less than half of the value of those for the daily return low volatility portfolio.

The use of monthly return volatility also effects our measurement of portfolio alpha. We repeat Table 2 from our paper using monthly return volatility in Table B-3. Using monthly return volatility the alpha for the low volatility portfolio is .04% per month, a decrease of .12% per month from the low volatility portfolio formed using daily return volatility. Alpha for the high volatility portfolio is about the same regardless of the volatility measure. The difference in alpha between the portfolios created using monthly return volatility is now .31% per month, compared to .45% per month using daily return volatility. The results are similar if we compare the portfolios in first or last six months of the each year. Overall, the impact of past volatility on future fund returns is much more pronounced when we use daily return volatility.

We further demonstrate the reduced capability of monthly return volatility by repeating Table 5 from our paper in Table B-4. Replacing our daily return volatility measure with the monthly return volatility measure in our panel regression causes a significant decrease in the ability of past volatility to predict future alpha. In our original daily return volatility specification, a one standard deviation increase in return volatility in the prior year predicted alpha would decrease by about 2.5% in the subsequent year. In our monthly return volatility specification, a one standard deviation increase in monthly return volatility in the prior year predicts alpha will decrease by about 1.2% (statistically insignificant) in the subsequent year.

Figure B-1: The return on one dollar invested in mutual funds sorted on past return volatility – Monthly return volatility

This figure shows the changing value of $1 invested in January 2000 through December 2011 in five equal weighted portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of *monthly* returns in the prior calendar year. For clarity, we present only the 1st (low volatility), 3rd, 5th, 7th, and 10th (high volatility) deciles.

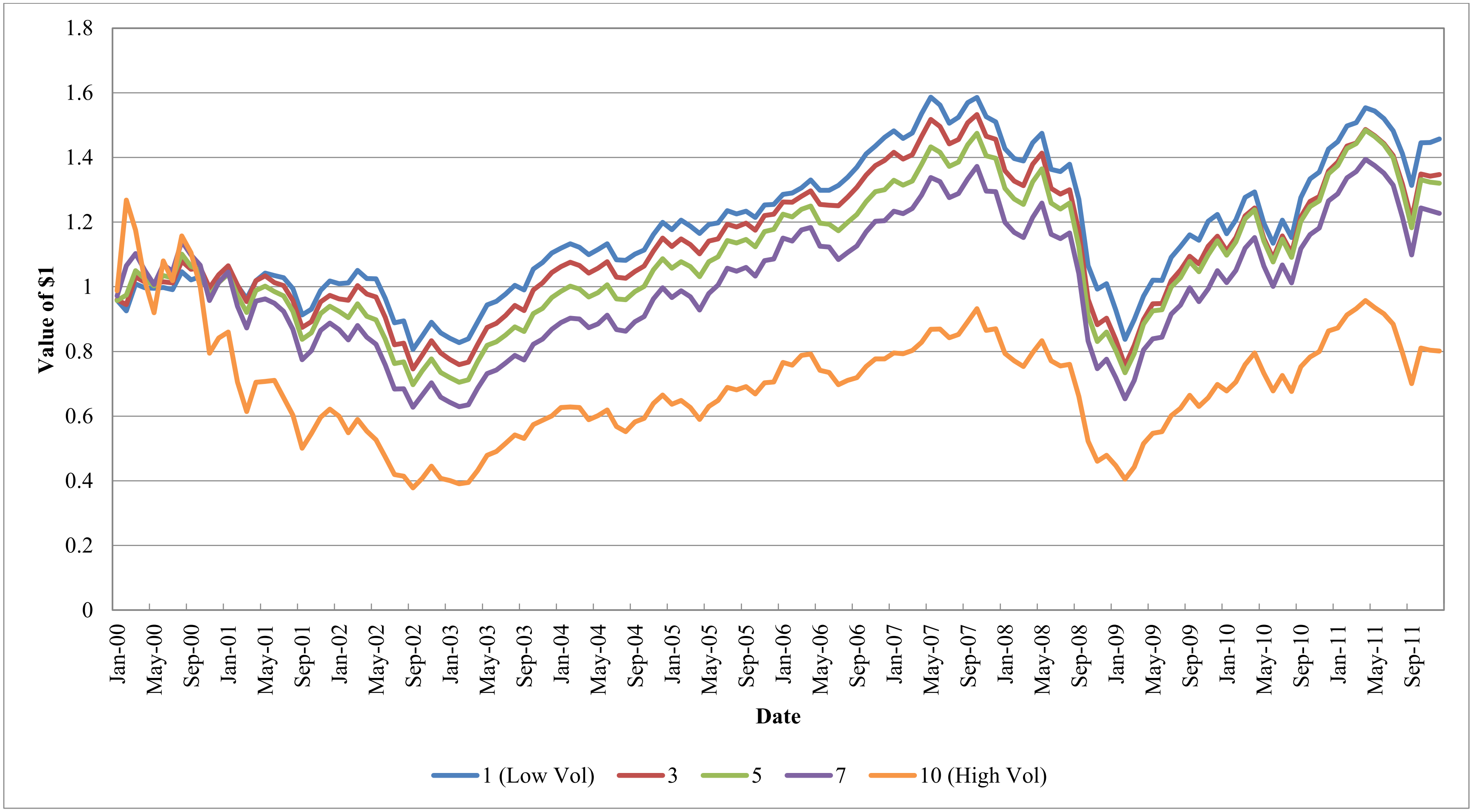


Table B-1: The persistence of mutual fund volatility - Daily vs. monthly returns
This table shows the percentage of funds in our sample that fall into different mutual fund volatility deciles in year *t+1* given their year *t* decile. Volatilities are measured each calendar year from 1999 through 2011. We use daily returns to measure volatility in Panel A and monthly returns in Panel B. We bold the diagonal of the table to ease the identification of matching deciles in different years.

Panel A: Daily Return Volatility

	Rank - Year *t+1*									
Rank - Year *t*	1	2	3	4	5	6	7	8	9	10
1	**54.1%**	20.0%	10.2%	5.6%	3.9%	2.8%	1.8%	0.7%	0.6%	0.3%
2	20.1%	**29.0%**	17.3%	14.6%	7.2%	5.3%	3.5%	1.7%	0.9%	0.5%
3	9.3%	21.0%	**22.5%**	16.4%	13.0%	6.9%	5.7%	2.8%	1.8%	0.5%
4	5.5%	13.1%	19.9%	**20.3%**	16.2%	11.0%	6.5%	3.8%	2.1%	1.7%
5	3.0%	7.8%	13.8%	17.9%	**17.9%**	18.0%	9.3%	5.9%	4.2%	2.1%
6	1.5%	4.1%	7.5%	13.0%	17.8%	**19.2%**	16.6%	11.9%	6.2%	2.3%
7	1.2%	2.8%	4.5%	6.7%	13.2%	18.0%	**19.7%**	18.2%	11.1%	4.5%
8	0.5%	1.5%	2.6%	3.0%	7.1%	11.2%	20.0%	**24.3%**	19.4%	10.5%
9	0.4%	1.5%	1.4%	1.9%	2.4%	5.6%	12.7%	20.8%	**30.7%**	22.6%
10	0.7%	0.0%	0.7%	0.5%	1.6%	2.0%	4.7%	10.4%	23.8%	**55.5%**

Panel B: Monthly Return Volatility

	Rank - Year *t+1*									
Rank - Year *t*	1	2	3	4	5	6	7	8	9	10
1	**34.7%**	19.7%	14.7%	9.9%	7.2%	5.6%	3.7%	2.5%	1.2%	0.8%
2	18.5%	**18.3%**	18.8%	14.4%	9.9%	8.1%	5.8%	3.2%	2.0%	1.0%
3	12.0%	20.0%	**17.9%**	16.3%	11.9%	7.9%	5.7%	4.1%	2.9%	1.2%
4	10.5%	13.3%	13.6%	**16.2%**	16.0%	12.3%	7.6%	5.1%	3.7%	1.6%
5	8.3%	9.6%	12.5%	13.5%	**15.4%**	13.9%	11.3%	7.6%	5.3%	2.5%
6	6.7%	7.4%	8.4%	10.2%	13.5%	**18.1%**	14.1%	11.4%	6.2%	4.0%
7	4.3%	5.2%	5.4%	8.1%	9.3%	13.7%	**17.0%**	18.5%	12.1%	6.2%
8	2.4%	3.3%	4.0%	5.5%	7.3%	11.4%	15.4%	**19.5%**	19.4%	11.9%
9	1.3%	2.0%	2.5%	4.3%	5.7%	6.1%	12.8%	17.0%	**25.4%**	22.9%
10	0.9%	1.1%	1.5%	2.3%	3.2%	4.0%	6.3%	11.0%	21.8%	**47.9%**

Table B-2: The returns on portfolios of mutual funds sorted on past return volatility – Monthly return volatility

This table shows the return on five equal weighted portfolios of active U.S. equity mutual funds. The low (high) volatility portfolio buys the 10% of mutual funds in the sample with the lowest (highest) standard deviation of *monthly* returns in the prior calendar year. We present only the 1st (low volatility), 3rd, 5th, 7th, and 10th (high volatility) deciles. To save space, we show the performance of each portfolio from January 2000 through December 2011. Average Return is the mean monthly return for the portfolio multiplied by twelve. Geometric Return is the annualized monthly compound return. Standard Deviation is the annualized standard deviation of monthly portfolio returns. Sharpe (Treynor) Ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized portfolio standard deviation (CAPM beta).

	Low	3	5	7	High	L - H
Average Return	4.2%	3.8%	3.7%	3.5%	1.6%	2.6%
Geometric Return	3.2%	2.5%	2.3%	1.7%	-1.8%	5.0%
SD of Returns	14.5%	15.9%	16.7%	18.7%	26.2%	-11.7%
Sharpe Ratio	0.13	0.09	0.09	0.06	-0.03	0.16
Treynor Ratio	0.02	0.02	0.02	0.01	-0.01	0.03

Table B-3: Do low volatility mutual funds outperform high volatility mutual funds? – Monthly return volatility
This table shows the Fama-French four-factor regression results for monthly returns on portfolios of low and high volatility mutual funds from January 2000 through December 2011. The low (high) volatility portfolio is an equal weighted portfolio of active U.S. equity funds with the lowest (highest) 10% of standard deviation of *monthly* returns in the prior calendar year. We divide the sample into equal time periods and test the portfolios only in the first six months of the year in Models (4) through (6) and only in the last six months in Models (7) through (9). *p*-values from robust standard errors are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

	Full Sample			January - June			July - December		
	(1) Low	(2) High	(3) L - H	(4) Low	(5) High	(6) L - H	(7) Low	(8) High	(9) L - H
Beta	0.84***	1.23***	-0.38***	0.81***	1.27***	-0.46***	0.83***	1.22***	-0.39***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SMB	-0.09***	0.63***	-0.72***	-0.13***	0.63***	-0.76***	0.05	0.59***	-0.54***
	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.262]	[0.000]	[0.000]
HML	0.20***	-0.30***	0.51***	0.23***	-0.36***	0.59***	0.13***	-0.23***	0.36***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.003]	[0.000]
UMD	0.01	0.06	-0.06	0.02	0.05	-0.04	0.01	0.10*	-0.10
	[0.643]	[0.229]	[0.394]	[0.454]	[0.501]	[0.695]	[0.805]	[0.065]	[0.162]
Alpha	0.04%	-0.26%**	0.31%*	0.06%	-0.26%	0.31%	0.10%	-0.31%**	0.41%*
	[0.560]	[0.033]	[0.069]	[0.495]	[0.108]	[0.134]	[0.323]	[0.041]	[0.060]
Observations	144	144	144	72	72	72	72	72	72
Adjusted r^2	0.95	0.96	0.82	0.96	0.95	0.88	0.96	0.96	0.75

Table B-4: Does fund volatility predict future performance? – Monthly return volatility
This table presents results from the following panel model:

$$\text{Alpha}_{i,t+1} = \text{Alpha}_{i,t} + \text{SD}_{i,t} + \text{Idio}_{i,t} + \text{Fund Controls}_{i,t} + \text{Obj FE} + \text{Time FE} + \epsilon_{i,t}$$

The dependent variable is the annualized percentage alpha for fund *i* in calendar year *t+1* calculated from the Fama-French four-factor model using daily returns. Month St. Dev. is the standard deviation of *monthly* returns during calendar year *t*. Daily Idio. St. Dev. is the idiosyncratic standard deviation of daily returns during calendar year *t*. Fund Controls include the natural log of fund assets, natural log of age, expense ratio, and turnover ratio all measured as of the end of calendar year *t* and the Fama-French four-factor exposures calculated from daily returns during calendar year *t*. We include year fixed effects and Lipper class fixed effects. All continuous variables are winsorized at the .5% and 99.5% levels. All continuous right-hand side variables are z-scored, i.e., demeaned and divided by their standard deviation. *p*-values from bootstrapped standard errors clustered on year are reported below the coefficients in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Alpha	0.51			0.51
	[0.239]			[0.253]
SD Return		-1.21		-1.20
		[0.281]		[0.295]
Idio SD Return			0.03	
			[0.963]	
Assets	-0.43***	-0.35***	-0.41**	-0.38***
	[0.010]	[0.007]	[0.021]	[0.006]
Age	0.25***	0.20**	0.23***	0.22***
	[0.001]	[0.015]	[0.008]	[0.001]
Expense	-0.38***	-0.35***	-0.40***	-0.34***
	[0.000]	[0.001]	[0.000]	[0.001]
Turnover	-0.38**	-0.41**	-0.43**	-0.36**
	[0.021]	[0.019]	[0.017]	[0.024]
Beta	-0.65**	-0.43	-0.69**	-0.39
	[0.043]	[0.210]	[0.026]	[0.237]
SMB	-0.17	0.48	-0.07	0.36
	[0.867]	[0.583]	[0.949]	[0.658]
HML	1.40**	1.13*	1.38**	1.16*
	[0.025]	[0.062]	[0.021]	[0.065]
UMD	-0.57	-0.58	-0.52	-0.63
	[0.241]	[0.279]	[0.322]	[0.223]
Observations	14,792	14,792	14,792	14,792
Time FE	Yes	Yes	Yes	Yes
Fund Type FE	Yes	Yes	Yes	Yes
Adjusted r^2	0.079	0.081	0.074	0.086

Appendix C – Alpha *t*-statistic distributions using the KTWW (2006) method

In Figures 3 and 4 in the paper, we present plots of the cumulative distribution of alpha *t*-statistics for low and high volatility funds. We compare those distributions to a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. The distributions in those figures were calculated following Fama and French (2010), but a similar method is proposed in Kosowski, Timmerman, Wermers, and White (KTWW) (2006). We defer a full discussion of each method to their respective papers, but in brief, two key differences are that the Fama and French method (1) randomly samples from the calendar months in the sample and (2) requires eight months of returns while the KTWW method (1) performs a separate sampling of calendar months for each fund and (2) requires sixty months of returns.

In Figure C-1 and Figure C-2, we replicate Figure 3 and 4 using the KTWW method instead of the Fama and French method. As in Figure 3, Figure C-1 indicates that there is a substantial difference in skill between low and high volatility funds based on the Fama-French four-factor model alone. Low (high) volatility funds have better (worse) performance than would be expected by luck alone. But as in Figure 4, Figure C-2 indicates that there is no discernable difference in skill between low and high volatility funds after including the LVH factor in the model. Figure C-2 only differs from Figure 4 in that it indicates that both low and high volatility funds do have some funds that perform better than would be expected by luck alone. However, if we change the sixty months requirement to the eight months, the performance that is better than would be expected by luck alone is significantly lessened. Overall, the results in our paper do not appear very sensitive to choice of model we use to calculate the no skill distributions.

Figure C-1: How does the distribution of mutual fund alpha differ with respect to fund volatility? KTWW method
This figure shows (1) a plot of the cumulative distribution of the alpha *t*-statistics for the low volatility mutual funds, (2) a plot of the cumulative distribution of the alpha *t*-statistics for the high volatility mutual funds, and (3) a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. A mutual fund is considered low (high) volatility in every month after the standard deviation of its daily returns first falls into the lowest (highest) 10% among funds in the prior calendar year. Only fund months between January 2000 and December 2011 and after a fund is labeled low or high volatility are used. We follow the Kosowski, Timmerman, Wermers, and White (2006) bootstrap procedure with one thousand simulations to calculate alpha for the low and high volatility funds under the restriction of no manager skill. We use the Fama-French four-factor model to calculate fund alphas using gross returns. We define a fund's gross return for a month as the net return plus one twelfth the annual expense ratio.

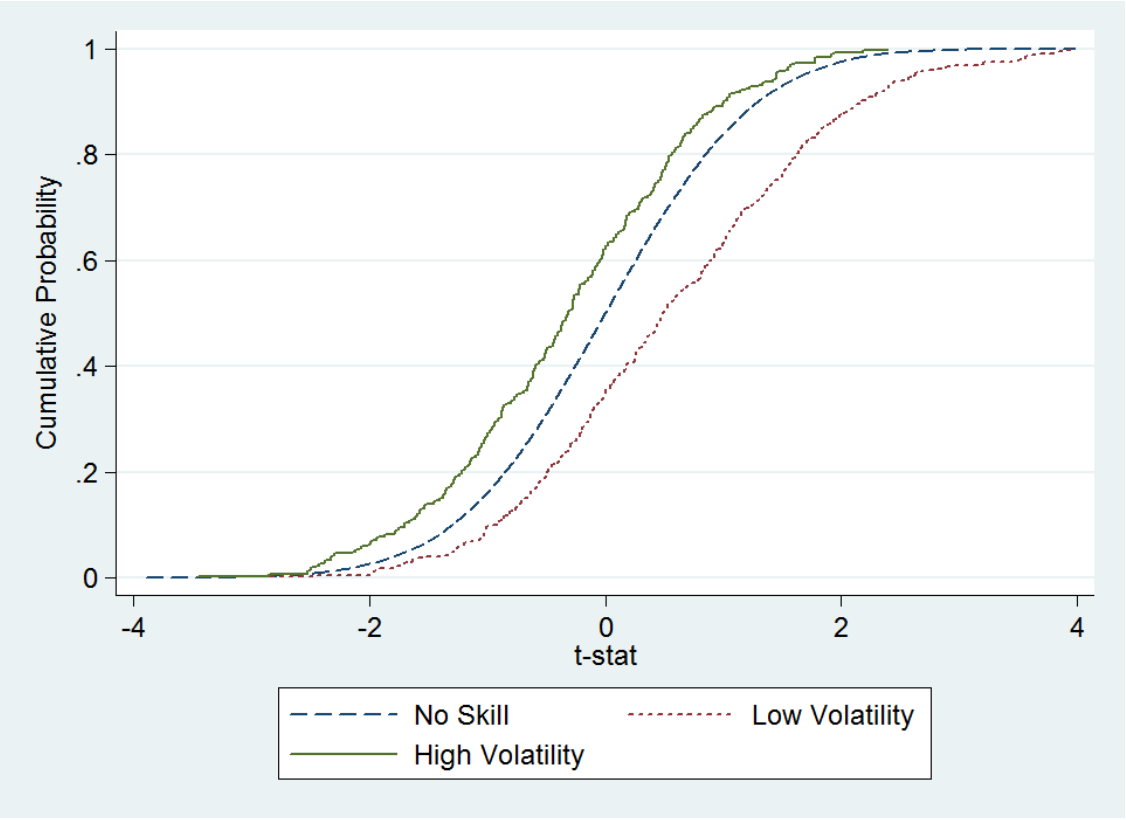
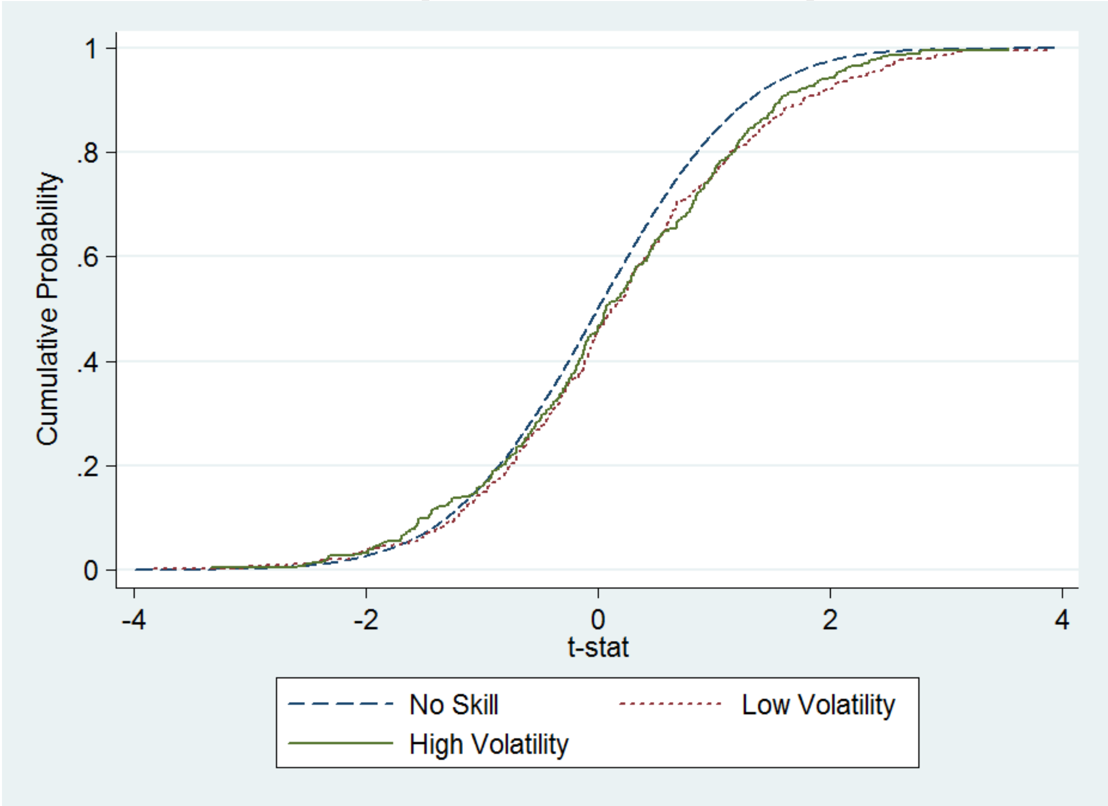


Figure C-2: How is the distribution of mutual fund alpha affected by accounting for the vol anomaly? KTWW method
This figure shows (1) a plot of the cumulative distribution of the alpha *t*-statistics for the low volatility mutual funds, (2) a plot of the cumulative distribution of the alpha *t*-statistics for the high volatility mutual funds, and (3) a combined cumulative distribution of low and high volatility fund alpha *t*-statistics calculated under the restriction that fund managers have no skill. A mutual fund is considered low (high) volatility in every month after the standard deviation of its daily returns first falls into the lowest (highest) 10% among funds in the prior calendar year. Only fund months between January 2000 and December 2011 and after a fund is labeled low or high volatility are used. We follow the Kosowski, Timmerman, Wermers, and White (2006) bootstrap procedure with one thousand simulations to calculate alpha for the low and high volatility funds under the restriction of no manager skill. We use the Fama-French four-factor model along with the LVH factor to calculate fund alphas using gross returns. The LVH factor is equal to the return to a value weighted portfolio of all stocks that pass our screens that are in the lowest decile of standard deviation of monthly returns during the previous calendar year less the return to a value weighted portfolio of all stocks that pass our screens in the highest decile. We define a fund's gross return for a month as the net return plus one twelfth the annual expense ratio.



Appendix D – The long run performance of simulated low and high volatility mutual funds

We report the performance of simulated mutual funds that invest like actual low and high volatility mutual funds in Table 8 of the paper. The time period used for those simulations is the same as the period used for the actual funds, January 2000 through December 2011. We match those periods to allow for a direct comparison of the performance of the simulated and real mutual funds. Here we report the performance of simulated low and high volatility funds over a longer time period, January 1980 through December 2009, to further evaluate our overall conclusions. Using this extended time period, we can examine the long run performance of a low volatility investing style and test performance in periods not covered (due to data availability) in the paper and Appendix A.

Our procedure to create the simulated funds in this section is identical to that used in Table 8. The only difference is the time period. Each year a simulated low (high) volatility fund chooses 100 stocks based on the decile percentages for the actual low (high) volatility funds in Table 7. For example, 6 of the stocks chosen for a simulated high volatility fund each year are from the low stock volatility decile and 11 are from the high stock volatility decile. We create 1000 different simulated fund holdings histories for both the low and high volatility funds. From those holdings histories we then construct fund portfolios that are either equal, value, or random weighted.

Table D-1 shows the performance of our simulated low and high volatility funds from January 1980 through December 2009. The simulated low volatility funds outperform the simulated high volatility funds on all measures regardless of portfolio weighting. Focusing on the value weighted results, the simulated low volatility funds have an arithmetic (geometric) annual return .6% (1.4%) per year greater than the simulated high volatility funds. That difference occurs despite the simulated low volatility funds having an annualized standard deviation of returns of 15.3%, compared to 19.0% for the simulated high volatility funds. The combined effect is the simulated low volatility funds have Sharpe and Treynor ratios about 40% greater than those of the simulated high volatility funds.

The differential performance of the simulated funds does vary over time. Table D-2 shows the performance from January 1980 through December 1989. As in the full sample, the simulated low volatility funds outperform the simulated high volatility funds, but to a greater degree. Again focusing on the value weighted results, the simulated low volatility funds have an arithmetic (geometric) annual return 2.6% (3.3%) per year greater than the simulated high volatility funds. The Sharpe and Treynor ratios of the simulated low volatility funds are also about 55% greater than those of the simulated high volatility funds.

However, that across-the-board outperformance does not hold in the subsequent decade. Table D-3 shows the performance from January 1990 through December 1999. The value weighted results show the simulated high volatility funds outperforming the simulated low volatility funds by about 2% per year, with the Sharpe and Treynor ratios of the groups about the same. Using equal or random weighting, the simulated low volatility funds do outperform the simulated high volatility funds, but to a lesser degree. The arithmetic annual returns are about equal, with Sharpe and Treynor ratios about 40% greater for the simulated low volatility funds. Overall, even though this period ends only a few months before the peak of the "dot-com" bubble, the simulated low volatility funds still perform well compared to the simulated high volatility funds.

The simulated low volatility funds again outperform the simulated high volatility funds across-the-board in the final decade of the sample. Table D-3 shows the performance from

January 2000 through December 2009. The simulated low volatility funds outperform the simulated high volatility funds over that time on all measures regardless of portfolio weighting. While the return on the value weighted portfolios are small for both groups, the arithmetic annual return for the simulated low volatility funds is almost double that of the simulated high volatility funds. Likewise, the Sharpe and Treynor ratios are low for the simulated low volatility funds, but both are negative for the simulated high volatility funds.

The totality of these results suggests that low volatility fund managers are benefiting from a long-term, mechanical effect. Over the 30 year period tested in this section, investing following a low volatility style produced not only superior risk-adjusted returns, but also higher raw returns. The performance of the simulated low volatility funds did vary over time, but at worst it was about as good as the simulated high volatility funds. The simulated low volatility funds did generate lower raw returns than the simulated high volatility funds using the value weighted portfolios in the 1990s, but even in that instance, the risk-adjusted returns of the simulated low volatility funds were slightly higher than those of the simulated high volatility funds.

Table D-1: The performance of simulated low and high volatility funds – 1980-2009
This table shows the performance of simulated mutual funds formed on the basis of stock return volatility. We first sort all stocks that pass our screens into deciles at the beginning of every year based on the standard deviation of their monthly returns during the previous calendar year. A simulated low (high) volatility fund then chooses 100 stocks based on the decile percentages for the low (high) volatility funds in Table 7. The percentages are constant but stocks are randomly selected from each decile. The same stocks remain in the fund for the full upcoming calendar year unless they fail a screen or leave the sample. At the beginning of the next year, 100 new stocks are chosen using the same procedure. We follow this procedure to create 1000 low and 1000 high volatility holdings histories. We use the holdings histories to construct portfolios that are either equal, value, and randomly weighted. Value weighted portfolios use market capitalization to generate weights and randomly weighted portfolios use the market capitalization weights but randomly assign them to stocks. We measure each simulated fund's performance from January 1980 through December 2009 and then average the results for the low and high volatility funds of each weighting. Each measure of performance presented is calculated as in Table 1. A *p*-value from a test of difference in means is provided for each characteristic. Panel A presents the equal weighted results. Panel B presents the value weighted results. Panel C presents the random weighted results.

Panel A: Equal Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	14.2%	12.2%	2.0%	<0.001
Geometric Return	13.8%	10.4%	3.4%	<0.001
SD of Returns	15.3%	21.2%	-5.9%	<0.001
Sharpe Ratio	0.58	0.32	0.26	<0.001
Treynor Ratio	0.10	0.06	0.05	<0.001

Panel B: Value Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	12.6%	12.0%	0.6%	<0.001
Geometric Return	12.1%	10.7%	1.4%	<0.001
SD of Returns	15.3%	19.0%	-3.7%	<0.001
Sharpe Ratio	0.48	0.35	0.13	<0.001
Treynor Ratio	0.09	0.06	0.03	<0.001

Panel C: Random Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	14.2%	12.3%	1.9%	<0.001
Geometric Return	13.3%	9.4%	3.9%	<0.001
SD of Returns	18.3%	25.8%	-7.5%	<0.001
Sharpe Ratio	0.48	0.27	0.21	<0.001
Treynor Ratio	0.10	0.06	0.04	<0.001

Table D-2: The performance of simulated low and high volatility funds – 1980-1989

This table shows the performance of simulated mutual funds formed on the basis of stock return volatility. We first sort all stocks that pass our screens into deciles at the beginning of every year based on the standard deviation of their monthly returns during the previous calendar year. A simulated low (high) volatility fund then chooses 100 stocks based on the decile percentages for the low (high) volatility funds in Table 7. The percentages are constant but stocks are randomly selected from each decile. The same stocks remain in the fund for the full upcoming calendar year unless they fail a screen or leave the sample. At the beginning of the next year, 100 new stocks are chosen using the same procedure. We follow this procedure to create 1000 low and 1000 high volatility holdings histories. We use the holdings histories to construct portfolios that are either equal, value, and randomly weighted. Value weighted portfolios use market capitalization to generate weights and randomly weighted portfolios use the market capitalization weights but randomly assign them to stocks. We measure each simulated fund's performance from January 1980 through December 1989 and then average the results for the low and high volatility funds of each weighting. Each measure of performance presented is calculated as in Table 1. A *p*-value from a test of difference in means is provided for each characteristic. Panel A presents the equal weighted results. Panel B presents the value weighted results. Panel C presents the random weighted results.

Panel A: Equal Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	19.5%	15.6%	3.9%	<0.001
Geometric Return	19.4%	14.5%	4.9%	<0.001
SD of Returns	15.6%	19.7%	-4.1%	<0.001
Sharpe Ratio	0.70	0.36	0.34	<0.001
Treynor Ratio	0.12	0.06	0.06	<0.001

Panel B: Value Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	19.3%	16.7%	2.6%	<0.001
Geometric Return	19.2%	16.0%	3.3%	<0.001
SD of Returns	15.9%	18.6%	-2.7%	<0.001
Sharpe Ratio	0.68	0.44	0.24	<0.001
Treynor Ratio	0.12	0.08	0.04	<0.001

Panel C: Random Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	19.5%	15.6%	3.9%	<0.001
Geometric Return	19.5%	14.1%	5.5%	<0.001
SD of Returns	17.3%	21.6%	-4.3%	<0.001
Sharpe Ratio	0.63	0.33	0.31	<0.001
Treynor Ratio	0.12	0.06	0.06	<0.001

Table D-3: The performance of simulated low and high volatility funds – 1990-1999
This table shows the performance of simulated mutual funds formed on the basis of stock return volatility. We first sort all stocks that pass our screens into deciles at the beginning of every year based on the standard deviation of their monthly returns during the previous calendar year. A simulated low (high) volatility fund then chooses 100 stocks based on the decile percentages for the low (high) volatility funds in Table 7. The percentages are constant but stocks are randomly selected from each decile. The same stocks remain in the fund for the full upcoming calendar year unless they fail a screen or leave the sample. At the beginning of the next year, 100 new stocks are chosen using the same procedure. We follow this procedure to create 1000 low and 1000 high volatility holdings histories. We use the holdings histories to construct portfolios that are either equal, value, and randomly weighted. Value weighted portfolios use market capitalization to generate weights and randomly weighted portfolios use the market capitalization weights but randomly assign them to stocks. We measure each simulated fund's performance from January 1990 through December 1999 and then average the results for the low and high volatility funds of each weighting. Each measure of performance presented is calculated as in Table 1. A *p*-value from a test of difference in means is provided for each characteristic. Panel A presents the equal weighted results. Panel B presents the value weighted results. Panel C presents the random weighted results.

Panel A: Equal Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	13.7%	13.5%	0.2%	0.003
Geometric Return	13.6%	12.5%	1.1%	<0.001
SD of Returns	13.1%	18.1%	-5.0%	<0.001
Sharpe Ratio	0.68	0.48	0.20	<0.001
Treynor Ratio	0.11	0.08	0.03	<0.001

Panel B: Value Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	15.6%	17.7%	-2.1%	<0.001
Geometric Return	15.6%	17.6%	-2.1%	<0.001
SD of Returns	13.8%	16.7%	-2.9%	<0.001
Sharpe Ratio	0.79	0.77	0.01	0.038
Treynor Ratio	0.12	0.12	0.00	0.003

Panel C: Random Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	13.7%	13.8%	-0.1%	0.500
Geometric Return	13.1%	11.8%	1.4%	<0.001
SD of Returns	16.2%	23.4%	-7.2%	<0.001
Sharpe Ratio	0.55	0.38	0.17	<0.001
Treynor Ratio	0.11	0.08	0.03	<0.001

Table D-4: The performance of simulated low and high volatility funds – 2000-2009

This table shows the performance of simulated mutual funds formed on the basis of stock return volatility. We first sort all stocks that pass our screens into deciles at the beginning of every year based on the standard deviation of their monthly returns during the previous calendar year. A simulated low (high) volatility fund then chooses 100 stocks based on the decile percentages for the low (high) volatility funds in Table 7. The percentages are constant but stocks are randomly selected from each decile. The same stocks remain in the fund for the full upcoming calendar year unless they fail a screen or leave the sample. At the beginning of the next year, 100 new stocks are chosen using the same procedure. We follow this procedure to create 1000 low and 1000 high volatility holdings histories. We use the holdings histories to construct portfolios that are either equal, value, and randomly weighted. Value weighted portfolios use market capitalization to generate weights and randomly weighted portfolios use the market capitalization weights but randomly assign them to stocks. We measure each simulated fund's performance from January 2000 through December 2009 and then average the results for the low and high volatility funds of each weighting. Each measure of performance presented is calculated as in Table 1. A *p*-value from a test of difference in means is provided for each characteristic. Panel A presents the equal weighted results. Panel B presents the value weighted results. Panel C presents the random weighted results.

Panel A: Equal Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	9.4%	7.5%	1.9%	<0.001
Geometric Return	8.3%	4.4%	3.9%	<0.001
SD of Returns	16.9%	25.3%	-8.4%	<0.001
Sharpe Ratio	0.40	0.19	0.21	<0.001
Treynor Ratio	0.08	0.04	0.04	<0.001

Panel B: Value Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	3.0%	1.6%	1.3%	<0.001
Geometric Return	1.7%	-0.6%	2.3%	<0.001
SD of Returns	15.7%	21.1%	-5.4%	<0.001
Sharpe Ratio	0.02	-0.05	0.07	<0.001
Treynor Ratio	0.00	-0.01	0.01	<0.001

Panel C: Random Weighted Portfolios

	Low Volatility	High Volatility	Difference	*p*-value
Average Return	9.5%	7.6%	1.9%	<0.001
Geometric Return	7.6%	3.0%	4.6%	<0.001
SD of Returns	20.9%	31.1%	-10.2%	<0.001
Sharpe Ratio	0.32	0.15	0.17	<0.001
Treynor Ratio	0.08	0.04	0.04	<0.001