On the Robustness of Idiosyncratic Volatility Effect

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Abstract

The idiosyncratic volatility effect of Ang et al. (2006) is robust to restricting the sample to NYSE firms (once proper listing indicator is used) and to excluding from the sample small, illiquid, and low-price stocks. The IVol effect is also unlikely to stem from the short-run reversal of Jegadeesh (1990), as the IVol effect stays significant for about six months and seems stronger for high turnover firms, which, as Medhat and Schmeling (2022) find, do not exhibit short-term reversal. The IVol effect also does not seem to weaken post-publication.

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1 Introduction

The idiosyncratic volatility (IVol) effect, discovered by Ang et al. (2006), records that high IVol firms earn roughly 1% per month less than low IVol firms. This evidence goes against the conventional wisdom that IVol should either be not priced in cross-section or priced positively if the marginal investor is underdiversified.

Ang et al. (2006) paper started a large literature on cross-sectional pricing of IVol and related variables; as of the end of June 2023, the paper amassed more than 7500 citations. Numerous explanations of the IVol effect were suggested (see, e.g., Hou and Loh, 2016, for a review and comprehensive evaluation), but two papers argued early on that the IVol effect is not robust.

Bali and Cakici (2008) record that the IVol effect disappears in the NYSE only sample; in the broader CRSP sample it also does not survive their price, size, and liquidity screens. Bali and Cakici conclude that the IVol effect is probably not tradable due to it being concentrated among small, illiquid, low-price NASDAQ stocks.

Fu (2009) and Huang et al. (2010) suggest that the IVol effect is just another manifestation of the short-term reversal of Jegadeesh (1990). In particular, Huang et al. find that in cross-sectional regressions past month return subsumes past month IVol. This observation is an important one, since if the IVol effect is nothing more than the short-term reversal in disguise, then the IVol effect should be a very short-lived phenomenon, just like the short-term reversal, which lasts for at most two months with the vast majority of gains concentrated in month one. The IVol effect suggests shorting very volatile and rather small firms, which are likely to have high shorting fees; if the 1% return in the first month after portfolio formation is all or nearly all the low-minus-high IVol strategy has to offer, the IVol effect is probably non-tradable.

The focus of this paper is to alleviate the concerns raised by Bali and Cakici (2008) and Huang et al. (2010). I find that the results in Bali and Cakici (2008) suffer from selection bias generated by their apparent use of the current listing indicator (`hexcd` from the CRSP returns file). While Bali and Cakici do not explicitly state that they use the hexcd listing indicator, I am able to replicate their results quite closely using `hexcd`, but not the historical listing indicator (`exchcd` from the CRSP events file).

The consequence of using the current listing indicator is that well-performing firms that were not traded on NYSE when IVol portfolios were being formed, but subsequently were promoted to NYSE and currently trade there, are erroneously included in the "NYSE only" sample in Bali and Cakici (2008). Similarly, badly-performing firms that were on NYSE as of portfolio formation, but were then demoted to a smaller exchange and are currently non-NYSE firms, are excluded from Bali and Cakici's "NYSE only" sample. Both the omissions and inclusions bias the returns in Bali and Cakici (2008) upward; I show that this bias is particularly strong among high IVol firms, as those firms are more likely to experience both extremely positive and extremely negative events that result in promotion to or demotion from NYSE. Once the correct, historical listing indicator (`exchcd`) is used, the alpha of the top IVol quintile declines by more than 50 bp per month compared to Bali and Cakici (2008), and the IVol effect in the NYSE only sample becomes almost as strong as it is in the full CRSP sample used by Ang et al. (2006). This observation also applies to sorts on IVol estimated from monthly returns in the past 60 months - Bali and Cakici (2008) argue that the IVol effect is weaker if a longer-term measure of IVol is used, but I show that this conclusion mostly comes from using the wrong listing indicator.

The fact that the IVol effect disappears in Bali and Cakici (2008) after they erroneously omit firms that are subsequently demoted from NYSE raises the possibility that the IVol effect can be driven by the inability of investors to price in the likelihood of losses should the firm head towards demotion. If so, then the IVol effect would be concentrated among a small number of firms going through the demotion; in other words, in the low-minus-high IVol strategy (that shorts the top and buys the bottom IVol quintile) all stocks on the long and short side will perform similarly, outside of a handful of stocks headed towards demotion. These few stocks would create the whole profit, assuming that the investor can short and keep shorting them during their downfall, and such a strategy may be seen as dangerous to trade.

An alternative source of the selection bias that destroys the IVol effect in Bali and Cakici (2008) are well-performing firms that should not be in the sample. My analysis reveals that such firms are more numerous than the firms described in the previous paragraph, and their contribution to the IVol effect is much larger. Hence, the results in Bali and Cakici (2008) do not imply that the IVol effect is the short seller's bet on a long shot.

I also address the finding of Bali and Cakici (2008) that the IVol effect is sensitive to omitting from the sample low-priced firms, small firms, and high price impact firms and discover that this finding is driven by how quintile breakpoints shift after Bali and Cakici omit those firms from the sample and then re-sort firms. While doing that, they inadvertently pool together firms originally in the third, fourth, and fifth quintile into what becomes their fifth IVol quintile. In other words, the result of Bali and Cakici that the IVol effect is vulnerable to omitting from the sample small and illiquid firms turns out to be restating the long-known fact that the IVol effect is driven by the top IVol quintile, and the fourth IVol quintile does not have a large negative alpha. When I stick to the full-sample quintile breakpoints while removing the same small and illiquid firms from the sample, I find that the IVol effect remains nearly as strong as it is in the full sample.

Turning to Huang et al. (2010), I extend their analysis of the IVol effect past the first month after portfolio formation. In portfolio sorts, I hold IVol quintile portfolios for a year after portfolio formation and find that while the alpha of the low-minus-high IVol strategy (long in bottom and short in top IVol quintile) does decline by one-third between months one and two, the IVol effect remains significant for roughly six months.[1] In cross-sectional regressions, I also find that the overlap between past month return and past month IVol is roughly one-third, and the overlap disappears completely if I lag the IVol variable by more than one month. The IVol variable stays significant if lagged by three to five months, and loses significance afterwards. I conclude that the IVol effect cannot be reduced to the short-term reversal, and the low-minus-high IVol strategy is likely to remain profitable for at least several months, long enough to recoup trading costs.

In a recent paper, Medhat and Schmeling (2022) find that short-term reversal turns into short-term momentum in the top turnover quintile. If Huang et al. (2010) are right and the IVol effect is just another manifestation of short-term reversal, Medhat and Schmeling's result suggests that the IVol effect should be absent for high turnover firms. However, in double sorts on IVol and turnover, I find that the IVol effect is, if anything, stronger in the top turnover quintile, which is inconsistent with short-term reversal driving the IVol effect.

Lastly, I look at performance of the IVol effect in the hold-out sample, which starts in 2005, since the Ang et al. (2006) paper first became publicly available as a NBER working paper in October 2004. I do not find any weakening of the IVol effect in 2005-2022; despite

[1] If I replace the past month IVol, computed using daily returns in the past month only, with a more long-term measure of IVol, computed from monthly returns in the past 36 months, I find that the overlap between the IVol effect and the short-term reversal is reduced to at most 10 bp per month, and after month two the remaining IVol effect stays flat at 50 bp per month and above for at least a year.

the sample being relatively short, the IVol effect is in most cases highly significant, and remains significant even after controlling both for the five factors from Fama and French (2015) and momentum.

2 Data

The main variable in the paper is idiosyncratic volatility. Following Ang et al. (2006), IVol is defined as standard deviation of residuals from the Fama-French (1993) model, fitted to daily data separately for each firm-month (at least 15 non-missing daily returns are required). An alternative, long-term measure of IVol from Bali and Cakici (2008) is also standard deviation of residuals from the Fama-French (1993) model, but the model is fitted in each firm-month to monthly returns in preceding 60 months (at least 24 non-missing observations are required). All returns are from CRSP; the five Fama-French factors, as well as the momentum factor and the short-term reversal factor, are from the website of Kenneth French; returns to the Q4 model factors are from the website of Lu Zhang. Definitions of all other variables are in the online appendix.

The sample period in the paper is from July 1963 to December 2022; in replications of Bali and Cakici (2008) and Huang et al. (2010) the sample is shortened to July 1963 to December 2004, which is the period both papers use.

3 "NYSE only" Sample

Bali and Cakici (2008) claim that the IVol effect is not robust to reasonable changes in the research design. Perhaps the strongest evidence against the IVol effect is presented in Table 4 of Bali and Cakici (2008), where IVol is calculated using monthly returns in the past 60 months and only NYSE firms are used. In equal-weighted returns in Panel B of their Table 4, Bali and Cakici find that the raw returns spread between bottom and top IVol quintile is -52 bp per month, t-statistic -1.94 (i.e., the IVol effect flips its sign), and the respective three-factor alpha differential is almost exactly zero.

When I try to mimic the results in Bali and Cakici (2008), I find that their results are contaminated by selection bias. My replication results suggest that when Bali and Cakici look at NYSE only firms, they define a NYSE firm using the current listing reported in the `hexcd` listing indicator from the CRSP returns file. That creates a strong selection bias, because only good performers remain NYSE firms from the portfolio formation date till now. Bad performers, even if they were NYSE firms at the portfolio formation date, are likely to be subsequently downgraded to OTC markets or regional stock exchanges, and therefore they do not make it into the Bali and Cakici "NYSE only" sample. On the other hand, good performers, even if they were on NASDAQ or a smaller exchange at the portfolio formation date, are likely to make it into the "NYSE only" sample, because they may have been upgraded to NYSE since then. This positive bias in returns is evidently stronger for high IVol firms, which are more likely to have extremely good performance (and be incorrectly included in the sample) or extremely bad performance (and be incorrectly excluded from the sample).

Table 1 presents evidence that highly volatile firms are more likely to be delisted or demoted from NYSE to a different stock exchange, but are also more likely to be upgraded from another stock exchange to NYSE. Panel A looks only at NYSE firms and uses the proper historical listing indicator (`exchcd` from the CRSP events file). Panel A1 looks at quintile sorts on IVol estimated from monthly data and shows that firms in the bottom IVol quintile have, on average, 0.118% probability to be delisted in the next month and 0.015% probability to be demoted from NYSE, vs. 0.834% and 0.101% probability in the top IVol quintile. Panel A2, with IVol estimated from daily returns in the previous month as in Ang et al. (2006), reports a similar decline in demotions from NYSE and performance-related delistings across IVol quintiles.[2]

Panel B uses the same, NYSE-based, breakpoints to sort firms into quintiles, but includes in the quintiles non-NYSE firms, which allows to add probability of promotion to NYSE to the analysis. Panel B1 uses monthly IVol estimates and finds again that firms in the top IVol quintile have twice higher probability to be demoted from NYSE – but also twice larger probability to be promoted to NYSE than firms in the bottom IVol quintile. Panel B2 uses IVol estimated from daily returns in the past month and arrives at qualitatively similar results.

In other words, the extreme volatility of firms in the top IVol quintile makes both positive and negative extreme outcomes more likely, and thus the selection bias introduced by the use of the current rather than historical listing indicator is more severe in the top IVol quintile. The top IVol quintile is, according to the IVol effect, a shorting target, and the strong positive bias in its returns introduced by using the current listing indicator makes the top IVol quintile undeservedly look like a poor shorting target and creates the false impression that the low-minus-high IVol strategy in the "NYSE only" sample does not deliver the alpha recorded by Ang et al. (2006).

Table 2 presents equal-weighted returns and alphas of quintile portfolios sorted on IVol estimated from monthly returns (the left part of the table) and from daily returns (the right part of the table). Panel A1 of Table 2 mimics results in Panel B of Table 4 in Bali and Cakici (2008): it comes rather close to their estimate of the low-minus-high spread

[2] All delistings decline between quintile two and quintile five, but experience a spike in the bottom IVol quintile. Table 4A in the online appendix shows that this spike is driven by M&A activity, is short-lived, and is substantially weakened once stocks with very low IVol (less than 10 bp per month) are excluded.

in raw returns (-41 bp in Table 2, -52 bp in Bali and Cakici, 2008) and in three-factor Fama and French (1993) alphas (7 bp in Table 2, 1 bp in Bali and Cakici, 2008). Panel A2 of Table 2 uses IVol estimated from daily data and mimics similarly closely Panel B of Table 2 in Bali and Cakici (2008). Both Panel A1 and Panel A2 in my Table 2 use the current listing indicator (`hexcd`), and the closeness of my results to Bali and Cakici (2008) suggests that Bali and Cakici used the same listing indicator.[3]

When I use the historical listing indicator, `exchcd`, to form the "NYSE only" sample in Panels B1 and B2, the results change dramatically, highlighting the selection bias in Bali and Cakici (2008) and its concentration in the top IVol quintile. Comparing Panels A1/A2 vs. Panels B1/B2, I observe that all alphas uniformly go down as I switch from using `hexcd` to `exchcd` listing indicator, but the decline is particularly notable in the top IVol quintile. Take three-factor Fama-French alphas in Panels A1 and B1 as an example: the alpha of the bottom IVol quintile declines from 5.4 bp to 3.5 bp per month, but the alpha of the top IVol quintile drops from -2 bp per month to -57 bp per month. As a result, the estimate of the idiosyncratic effect increases from 7 bp per month in Panel A1 (or 1 bp per month in Panel B of Table 4 in Bali and Cakici, 2008) to 60 bp per month, t-statistic 4.57. In raw returns, the IVol effect switches the sign from negative to positive between Panels A1 and B1 (both insignificant), but in Panel B1 the IVol effect survives controlling for momentum or the new Fama and French (2015) investment and profitability factors (CMA and RMW); in the Q4 model from Hou et al. (2015), the IVol effect in Panel B1 is relatively large (27 bp per month), but insignificant – one cannot reject that the IVol

[3]The small difference between my results and results of Bali and Cakici is probably coming from my use of delisting returns and using the correction from Shumway (1997) and Shumway and Warther (1999) for missing delisting returns: -30% for NYSE firms and -55% for NASDAQ firms. Bali and Cakici (2008) do not indicate whether they use the correction or delisting returns at all, but my results become even closer to theirs if I omit delisting returns entirely.

effect in the Q4 model is zero, but also cannot reject that it is, for example, 60 bp per month.

Panel B2 of Table 2, where IVol is estimated from daily returns in the past month, as in Ang et al. (2006), reveals a similar picture: in the three-factor Fama-French alphas, used in Bali and Cakici (2008), the IVol effect stands at 40 bp per month when the current listing indicator, `hexcd`, is used, but improves to 83 bp per month when the historical listing indicator, `exchcd`, is used instead. The change in the IVol effect estimate is exclusively driven by the change in the alpha of the top IVol quintile, which changes from -33 bp per month in Panel A2 to -83 bp per month in Panel B2.[4]

Panels C1 and C2 extend the sample from 1963-2004 used in Bali and Cakici to 1963-2022 and confirm that in alphas (though not in raw returns[5]) the IVol effect among NYSE firms is alive and well in the longer sample once the proper exchange listing indicator is used. For example, in the alphas from the five-factor Fama and French (2015) model the IVol effect stands at 51 bp per month, t-statistic 3.22, if monthly returns from the past 60 months are used to estimate IVol, and at 68 bp per month, t-statistic 4.07, if IVol is estimated using daily returns in the most recent month. Extending the sample into the

[4]The effect of using the wrong listing indicator, `hexcd`, is less pronounced in value-weighted returns, which is the reason why my Table 2 looks at equal-weighted alphas and also the reason why in Bali and Cakici (2008) the IVol effect in NYSE only sample looks quite robust in value-weighted alphas (e.g., Panel A of their Table 2 estimates the IVol effect in value-weighted three-factor Fama and French (1993) alphas at 64 bp per month, t-statistic 4.4). As Table 3 below shows, the main result of using `hexcd` to classify firms as NYSE firms is including in the sample small firms that are not NYSE as of portfolio formation, but then do well and become NYSE firms. The effect of these small firms on value-weighted returns is limited; in untabulated results, I find that in value-weighted returns switching from `hexcd` to `exchcd` makes the IVol effect only 2-6 bp per month stronger.

[5]As Table 1A in the online appendix shows, the top IVol quintile has higher systematic risk: in the seven-factor model with the five Fama and French (2015) factors, momentum, and short-term reversal, the top IVol quintile in the NYSE only sample has 40% higher market beta and much more positive SMB beta than the bottom IVol quintile, and its loadings on all other factors, except for momentum, are insignificant. In the CAPM, the spread in market betas between the top and bottom IVol quintiles is even wider, 1.49 vs. 0.76. Thus, the positive and insignificant spread in raw returns between bottom and IVol top quintiles is surprising, and almost all asset pricing models confirm that by estimating a significant spread in the alphas.

post-publication period (the Ang et al. (2006) paper became publicly available as a NBER working paper in October 2004) also makes the IVol effect among NYSE firms significant in the Q4 model from Hou et al. (2015) by improving the power: e.g., in Panel B2, the Q4 model estimates the IVol effect at 29.7 bp per month, t-statistic 1.28, while in Panel C2 the estimate changes to 39.8 bp per month, t-statistic 2.19.

The fact that the lack of the IVol effect in Bali and Cakici (2008) can be due to omission from their sample firms that were NYSE firms as of portfolio formation date, but were later demoted to a smaller stock exchange suggests a possibility that the IVol effect is created exactly by those rare demotion events. In this case, if the arbitrageur forms the low-minus-high IVol strategy (in the NYSE only sample), almost all stocks on the long and short sides will perform similarly, and all gains from the strategy will arise when a handful of stocks on the short side are demoted from NYSE, which should probably be interpreted as a sign of caution for the arbitrageur.

That does not have to necessarily be the case, as the other group of firms that is creating the difference between my results and Bali and Cakici (2008) are firms that were not on NYSE as of portfolio formation date, but were later promoted to NYSE. I do not include those firms in the NYSE only sample, but Bali and Cakici seem to erroneously do, as they rely on the current listing indicator rather than the historical one. If the lack of the IVol effect in Bali and Cakici (2008) is caused by the erroneous inclusion of firms that should not be in the sample, then this fact has no material implications for trading on the IVol effect.

Table 3 looks into the source of difference between Panels A1/A2 and Panels B1/B2 in Table 2. Panel A of Table 3 reports equal-weighted returns and alphas of the first type of firms, the ones that were erroneously excluded by Bali and Cakici (2008), because `hexcd` current listing indicator classified them as non-NYSE firms, while they were traded on NYSE as of portfolio formation date, but were later demoted. Panel A of Table 3 shows that while the alphas of those firms are uniformly negative, those firms create the IVol effect of roughly the same magnitude as the one reported in full sample (Panel C of Table 2) and thus excluding them does not materially weaken our estimates of the IVol effect. Also, those demoted firms are not numerous: on average, each month the bottom IVol quintile in Bali and Cakici (2008) misses 8-9 such firms, while the top IVol quintile misses 18-19 (roughly 2.7% and 6% of all firms in those quintiles, respectively). I conclude from Panel A of Table 3 that the IVol effect in the NYSE only sample is unlikely to be driven by a small number of firms that are subsequently dropped by NYSE.

Panel B of Table 3 looks at the other type of firms that create the difference between my estimates of the IVol effect and the estimates in Bali and Cakici (2008): firms that are currently traded on NYSE, but were not traded there when the IVol quintiles were formed. Those firms (erroneously included in the "NYSE only" sample in Bali and Cakici, 2008) are more numerous: Panel B of Table 3 suggests that the bottom IVol quintile in Bali and Cakici (2008), on average, held 28-46 such firms (depending on whether IVol is measured using daily or monthly returns), and the top IVol quintile in Bali and Cakici (2008) seems to erroneously include, on average, 92-95 well-performing firms that start outside of NYSE, were non-NYSE when the quintiles were formed, and then were promoted to NYSE (those firms make up almost one-third of all firms in the top quintile). These firms in Panel B of Table 3 create a strongly negative IVol effect, of more that 1% per month if one looks at monthly IVol measure (Panel B1), and thus the erroneous inclusion of these firms seems to be the main reason why Bali and Cakici (2008) find no IVol effect in their "NYSE only" sample.

Panel C looks at average size of NYSE firms and the firms that erroneously included in/excluded from the "NYSE only" sample in Bali and Cakici (2008). Erroneously excluded firms are the firms that were NYSE firms as of portfolio formation, but by the end of the sample period were demoted from NYSE. Panel C shows that at the portfolio formation date those firms, in all IVol quintiles, were about the same size as other NYSE firms (which were also at NYSE as of portfolio formation date, but then stayed at NYSE at the end of the sample period). Erroneously included firms are the firms that were not NYSE firms at the portfolio formation date, but made it to NYSE by end of the sample period. Expectedly, those firms are several times smaller than NYSE firms at the portfolio formation date, which explains why in Bali and Cakici (2008) the IVol effect in value-weighted returns remains strong and is little affected by their use of the wrong indicator.

4 Screening Out Illiquid Stocks

Bali and Cakici (2008) also show in their Table 7 that the IVol effect is reduced to insignificant or barely significant values with three-factor Fama-French alphas ranging between 23 bp and 36 bp per month if two of three illiquidity screens are used: stocks priced below \$10 at portfolio formation date are dropped, or stocks that are in the bottom NYSE size decile as of portfolio formation date are dropped, or stocks in the top NYSE decile in terms of Amihud (2002) illiquidity measure are dropped.

Panel A of Table 4 applies all three filters at once using the 1963-2004 sample from Bali and Cakici (2008) and the IVol measure computed from daily returns, as Bali and Cakici do in their Table 7. In three-factor Fama-French alphas and Carhart alphas, Panel A finds larger IVol effect than Bali and Cakici (2008) do (47-49 bp and 40-47 bp per month, respectively, with t-statistics above 2.3 (3.2) in value-weighted (equal-weighted) returns).[6]However, with more modern risk-adjustment, the tenor of Bali and Cakici results is preserved in Panel A: controlling for the new Fama-French factors (CMA and RMW), the IVol effect is reduced to at most 15 bp per month (t-statistics mostly below 1), and Q4 model of Hou et al. (2015) yields similar results.

Panel B repeats Panel A in the longer, 1963-2022, sample. and finds that stronger IVol effect after small, illiquid, and low-price stocks are omitted. The significance of five-factor, six-factor, and Q4 alphas is restored in equal-weighted returns, and in value-weighted returns the five-factor and six-factor alphas of the top IVol quintile are negative and marginally significant.[7]

Panel C of Table 4 applies the screens differently: while Bali and Cakici (2008) state in the caption to their Table 7 that they first omit small, low-price, and illiquid stocks and then sort stocks into IVol quintiles, Panel C first performs the sorts and then removes small, low-price, and illiquid stocks from the sample. The magnitude and significance of the IVol effect increase greatly as a result: the five-factor and six-factor alphas, as well as Q4 alphas, now range between 51 and 62 bp per month, with t-statistics of 2.32 and above. Panel D reports, for comparison, IVol sorts in the full sample with no filters applied and finds that the IVol effect is, if anything, weakened by including small, illiquid, and low-price stocks in the sample. Of particular note are six-factor Fama-French alphas and

[6]I was unable to match the smaller spread in three-factor alphas from Bali and Cakici (2008), unless I restrict the sample to NYSE only firms using `hexcd` listing indicator (even though the caption of their Table 7 says that it uses all CRSP firms). Another issue that makes our results different is the calculation of the Amihud (2002) illiquidity measure in Bali and Cakici (2008): on p. 43, Bali and Cakici state: "...we measure stock illiquidity as the ratio of absolute stock return to its dollar volume, $ILLIQ_i = |R_i|/VOLD_i$, where R_i is the return on stock i in month t, and $VOLD_i$, is the respective monthly volume in dollars". It is unlikely that effects of price pressure will show up in monthly returns of most stocks (e.g., beginning-of-the-month volume, which is part of monthly volume, is unlikely to still affect end-of-the-month stock price). Amihud (2002) defines his monthly illiquidity measure as the average of similar ratios computed each day using daily returns and daily volume. The averaging also takes care of unavoidable noise.

[7]Chen et al. (2020) report similar evidence of the IVol effect robustness to size and price filters used one-by-one, but never reconcile their evidence with the opposite evidence reported by Bali and Cakici (2008).

Q4 alphas, which are reduced to insignificance in equal-weighted returns in Panel D, while in Panel C they were at 61.8 and 61.5 bp per month, respectively, and their t-statistics exceed 2.75.

The fact that the presence of small, illiquid, and low-price stocks in the sample weakens the IVol effect is consistent with the observation first made by Ang et al. (2006) that the IVol effect is stronger in value-weighted returns, which assign minuscule weight to such stocks. However, the comparison of Panel C and Panel D clearly contradicts the conclusion Bali and Cakici (2008) make on p. 45: "The IVol effect reported by AHXZ (2006) disappears in most cases after a screen for size, liquidity, and price, implying that small, illiquid, and low price stocks drive their results".

Panels E-H of Table 4 look into the impact size, price, and liquidity screens have on the composition of IVol quintiles and report, across the quintiles, average and median IVol, average and median number of firms in each quintile, as well as average and median weight of each quintile in the total market cap, with the whole CRSP population being 100%.

Panels E and F look at the role of breakpoint changes: in Panel E, the quintile breakpoints are determined after small, low-price, and illiquid stocks are omitted from the sample, as in Bali and Cakici (2008) and in Panel B, while Panel F follows Panel C and first forms the quintiles and then purges them of small, low-price, and illiquid stocks. The comparison of Panels E and F shows that breakpoints shift significantly: in Panel E, average and median IVol in the top IVol quintile are very similar to average and median IVol in the fourth quintile in Panel F. This is the main message of Panels E-H: sorting stocks on IVol after small, low-price, and illiquid stocks are removed from the sample shifts the quintile breakpoints so much that the weaker IVol effect in the new sorts (used in Bali and Cakici, 2008) essentially restates the well-known fact that the IVol effect is driven by the top IVol quintile and the alpha of the fourth IVol quintile is often small and insignificant.

Panel H reports, for comparison, characteristics of quintiles from the NYSE only subsample (same sample as the one in Panel C of Table 2). I observe that average and median IVol in the NYSE only sample are comparable to the ones reported in Panel F (first sort all stocks on IVol, then remove small, low-price, and illiquid stocks). Again, the top IVol quintile from Panel E seems similar to the fourth quintile in the NYSE only sample, which, according to Table 2, has small and often insignificant alpha. So, Bali and Cakici (2008) just rediscover that small and insignificant alpha, because the sorts in their Table 7 (remove small, low-price, and illiquid stocks, then sort remaining stocks on IVol) populate the top IVol quintile by firms that are in the fourth quintile in other sorts. Lastly, the portfolios in Panel F are very different in number of stocks, because filtering out small, low-price, and illiquid stocks affects high IVol quintiles more than low IVol quintiles, due to volatile firms being smaller, but still the top IVol quintile in Panel F is a balanced portfolio with number of stocks in it mostly in triple digits.[8]

5 Idiosyncratic Volatility Effect and Short-Term Reversal

Fu (2009) shows that sorting firms on IVol in the past month produces a strong sort on past month returns, because stocks have larger positive than negative swings due to limited liability. In his sample, during the portfolio formation month firms in the bottom

[8]The effect of applying the price, size, and liquidity screens is quite drastic: the comparison of Panel G (full CRSP population with no screens) with Panel F shows that all portfolios lose more than 50% of firms, and the top IVol quintile in Panel F loses 90% of firms because of the screens. In terms of market cap, the effect is smaller: the market share of omitted firms is about 1.5 percentage points for all portfolios, but for the top IVol quintile this change is about 50% of its (small) market cap. In untabulated findings, I find that the price screen (stocks with prices below $10 are omitted) is the most stringent: 80% of all firms in the top IVol quintile are gone because of this screen alone. If the price screen is loosened to keep stocks priced above $5, the number of remaining firms in the top IVol quintile doubles, and the results in Panel C are largely unaffected.

IVol quintile earn 44 bp, while firms in the top IVol quintile earn 411 bp. Fu hypothesizes therefore that the IVol effect of Ang et al. (2006) can be just another manifestation of the short-term reversal of Jegadeesh (1990).

Huang et al. (2010) formally test this hypothesis and seemingly confirm it. First, they find that the past-month return subsumes past-month IVol in Fama and MacBeth (1973) regressions. Second, they use a factor long in short-term winners (top decile) and short in losers (bottom decile) as of the portfolio formation month and show that adding this reversal factor to the three-factor Fama-French model or the Carhart model explains the IVol effect.

The hypothesis that the short-term reversal can be driving the IVol effect is not just a hypothesis that two anomalies are in fact one. Ang et al. (2006) sort firms on IVol each month, assuming that investors hold the resulting portfolios for a month and then rebalance. If the hypothesis in Fu (2009) and Huang et al. (2010) is true, then the low-minus-high IVol strategy based on the existence of the IVol effect should not be followed for longer than one or two months, because this is how long the short-term reversal lasts. The turnover and trading costs associated with this trading strategy will be substantial: two round-trip trades will be needed to chase 50-100 bp return in the first month and probably a much smaller return in the second month after portfolio formation, but no gains will accrue to the strategy after that.

In Table 5, I explore whether the low-minus-high IVol strategy indeed makes no gains two months after portfolio formation, as Fu (2009) and Huang et al. (2010) results would imply. I report the alpha spread between top and bottom IVol quintiles, using CRSP breakpoints and value-weighted returns. Panel A looks at the full sample period, 1963-2022, Panel B limits the sample period to 1963-2004, the one used in Huang et al. (2010).

The first column of Panel A reports the alphas of the strategy in the first month after portfolio formation and essentially repeats many numbers from the last column of Panel D1 in Table 4.

The second column in Table 5 records the alphas in the second month after portfolio formation without rebalancing (effectively, I sort on IVol in month t-2 and record alphas from month t). In both panels, I do observe a roughly 35 bp drop in the alphas, consistent with the overlap between the IVol effect and the short-term reversal discovered by Fu (2009) and Huang et al. (2010). However, the alphas in the second month after portfolio formation are still significant, ranging in Panel A from 49 bp in the five-factor Fama and French (2015) model to 97.5 bp in the three-factor Fama and French (1993) model, with t-statistics exceeding 3.2.[9] Similar alphas arise in Panel B, which covers the sample period from Huang et al. (2010). These second-month alphas are hard to attribute to the short-term reversal effect: sorts on IVol in month t-2 do create a strong sort on month t-2 returns, but they create an inverse sort on month t-1 returns by definition of the IVol effect. Thus, firms in the top IVol portfolio formed in month t-2 are no longer winners in the Jegadeesh (1990) sense by month t. By the start of month t, they are more likely to be recent losers, and the short-term reversal predicts high, not low returns for them.

In any case, the short-term reversal does not go beyond the second month after portfolio formation, but columns three and four in both panels of Table 5 show that the IVol effect ranges from 26 bp to 88 bp depending on risk-adjustment in the third and fourth month after portfolio formation (again, the Q4 model is the only exception). In the five-factor Fama-French model, the IVol effect significance is marginal in 1963-2004, but restored in

[9]The Q4 model from Hou et al. (2015) is the only exception: since it produces much lower alphas than other models, in the second month after portfolio formation the Q4 model estimates the IVol effect at statistically insignificant 26.5 bp per month.

the full sample; the Carhart model pegs the IVol effect at 61 bp and 82 bp in those two months (59.4 bp and 58.7 bp in the full sample), with t-statistics exceeding 2.3 (2.8 in the full sample).

According to the five-factor Fama-French model in Panel A (full sample), the IVol effect stays visible for five months, adding up to 2.23% (vs. 0.71% in the first month); the Carhart model suggests that the IVol effect keeps going for at least seven months (with a brief comeback to significance in month ten) and still sits at 26 bp per month in month twelve. This last number is not statistically significant, so we cannot reject the hypothesis it is zero, but we also cannot reject the hypothesis that it is 50 bp. Summing up only the first seven Carhart alphas puts the cumulative return to the low-minus-high IVol strategy at 4.14%; summing up all twelve months puts it at 5.61%, as compared to 0.95% in the first month.

One result in Panel B (1963-2004 sample) that contradicts Huang et al. (2010) is the large and significant alpha of the low-minus-high IVol strategy in the Carhart model augmented with the short-term reversal factor (STR) from the Kenneth French website. The STR factor is constructed similar to SMB and HML: it longs/shorts top/bottom three deciles formed on past month returns, does that separately for small and large firms, and then averages the long-short returns from large and small firms subsample. Huang et al. use a more extreme reversal factor that long/shorts extreme deciles only and does not separately look at large firms (almost all firms in the extreme deciles are probably small). I tried re-creating their factor and using it instead, but arrived at the same results as the ones in my Table 5, at odds with what Huang et al. report in their Table 4. The slopes on their reversal factor (WML) in their Table 4 are puzzling: the factor betas of -0.026 and -0.028 are statistically significant, but economically small (compared to, say, HML betas of the low-minus-high IVol strategy that Huang et al. report in the range between -0.38 and -0.46). Yet, even with those small betas adding WML to the Carhart model in Huang et al. changes the alpha of the low-minus-high IVol strategy from 106.5 bp per month to -27 bp per month, implying an enormous risk premium of WML.

Table 6 examines persistence of the IVol effect in the cross-sectional regressions setup by holding the traditional control variables the same, but lagging the IVol variable by an increasing number of months, as indicated in the first row of Table 6. Panel A performs the Fama-MacBeth regressions in the same sample (1963-2004) and with the same control variables Huang et al. (2010) used in their Table 1. The first column of Panel A in Table 6 lags IVol by one month, as traditionally done, and finds that controlling for short-term reversal (i.e., return in the past month) makes the IVol variable insignificant as in Huang et al. (2010) – the slope declines by almost 70% compared to the case (not tabulated) when the past month return control is omitted and the t-statistic in column one is only -1.21.

The second column, however, restores the size and significance of the slope on IVol. Comparing the slope to its value (not tabulated) without the short-term reversal control shows that the short-term reversal control has no impact on the IVol variable once it is lagged beyond one month: while with the one-month lag the slope on it is -13.41 without the control and -4.31 with it, with the two-month lag the slopes without and with the short-term reversal control are -10.17 and -8.92, respectively. This is not surprising: while IVol from t-1 and return from t-1 are positively correlated due to positive skewness of returns and limited liability of shareholders, IVol from t-2 and return from t-1 are negatively correlated by definition of the IVol effect. Hence, controlling for return from month t-1 will have opposite effects on IVol regressor from t-1 and from t-2.

Panel B expands the sample to 1963-2022 and performs similar regressions with IVol lagged by an increasing number of months. I observe that in the longer sample the short-term reversal control no longer subsumes IVol from month t-1, and the effect of the control on the IVol slope is more moderate: the slope changes from -15.12 without the short-term reversal control (not tabulated) to -8.36, t-statistic -2.95, in the first column of Panel B, as compared to -4.31, t-statistic -1.21 in the first column of Panel A. In other words, the result of Huang et al. (2010) that short-term reversal fully subsumes the IVol effect in cross-sectional regressions seems sample-dependent and does not hold in the longer sample. Also, in the 1963-2022 sample IVol remains marginally significant in months three to five, consistent with the conclusion I draw from the five-factor Fama-French alphas in Table 5: the IVol effect lasts for about five months.

In untabulated results, I also try repeating the regressions from Panel B changing the lag of the preceding month return (Rev) and omitting IVol. The results confirm that the short-term reversal persists only for two months: the slope on month t-1 return is -0.070, the slope on month t-2 return is -0.013, and after that the slopes alternate in sign and mostly come out positive.

Similarly, conditional sorts with CRSP breakpoints first on previous month return and then on IVol (untabulated) show limited overlap between the short-term reversal and IVol effect: e.g., the three-factor/five-factor Fama-French alphas are at 69 bp/50 bp per month before conditioning the sorts on previous month return and 54 bp/42 bp per month (t-statistics above 3.4) after the conditioning.

Overall, Table 6 is supportive of the conclusion from Table 5 that, while there exists a partial overlap between the IVol effect and short-term reversal, which causes the IVol effect to weaken by roughly one-third between month one and month two after portfolio formation, the overlap is far from complete and does not imply that the IVol effect is as short-lived as short-term reversal, which lasts for at most two months. The IVol effect lasts for roughly six months, and the total cumulative return to the low-minus-high IVol strategy is 4-5 times greater than the usually reported alpha from the first month after portfolio formation.

In a recent paper, Medhat and Schmeling (2022) find that short-term reversal turns into short-term momentum in the top turnover quintile. If Huang et al. (2010) are right and the IVol effect is just another manifestation of short-term reversal, Medhat and Schmeling's result suggests that the IVol effect should be absent for high turnover firms, since for such firms short-term reversal does not exist.

Table 7 presents the results of independent sorts on IVol (measured using daily returns in the past month) and past month turnover (which is the measure of turnover Medhat and Schmeling use).[10] Following Medhat and Schmeling (2022), the portfolios include all CRSP firms, but use NYSE breakpoints. Contrary to what the overlap between the IVol effect and short-term reversal would imply, I find in Table 7 that the IVol effect is, if anything, stronger in the top turnover quintile. In equal-weighted returns, the difference in the IVol effect between top and bottom turnover quintile is about 58 to 95 bp per month and strongly significant; in value-weighted returns, the IVol effect is similar in all turnover quintiles, but the main point of Table 7 is that there is no negative dependence of the IVol effect on turnover, as one would expect in the light of Medhat and Schmeling (2022) results and their implication for the main hypothesis of Huang et al. (2010) that the IVol effect is explained by short-term reversal.

[10] I use independent sorts to make sure that the spread in IVol between top and bottom IVol quintiles is the same across turnover quintiles and thus there is no mechanical relation between turnover and the IVol effect. Table 2A in the online appendix verifies that the IVol spread is indeed roughly constant across turnover quintiles and that portfolios from the independent sorts remain balanced.

In Table 3A of the online appendix, I also look at several anomalies that are known to overlap with the IVol effect: the MAX effect (Bali et al., 2011), the skewness effect (Boyer et al., 2010), and the analyst disagreement effect (Diether et al., 2002). The strong overlap between those anomalies and the IVol effect suggests that if IVol effect is largely subsumed by the short-term reversal, as Huang et al. (2010) argue, then those related anomalies should also at least strongly overlap with short-term reversal. However, I do not find such overlap: the analyst disagreement and skewness effects do not weaken between months one and two after portfolio formation, and the MAX effect declines by only one-third, as the IVol effect does in Table 5.

6 Idiosyncratic Volatility Effect, RMW Factor, and the Hold-Out Sample

Ang et al. (2006), the paper the IVol effect originates from, discovered the effect in 1963-2000 sample and used the three-factor Fama and French (1993) model as the benchmark. Subsequent studies mostly kept using the three-factor model as the benchmark and gradually expanded the sample, but no study, to the best of my knowledge, has considered the post-publication sample separately.[11]

In Table 8, I look at the role the two new factors introduced in Fama and French (2015) play in explaining the IVol discount. Panel A follows Ang et al. (2006) in using breakpoints from the full CRSP sample to allocate stocks into IVol quintiles. Panel B uses a more conservative approach of using NYSE breakpoints and excluding from the sample stocks priced below $5 at the portfolio formation date.

[11]Several papers that looked at post-publication performance of dozens of anomalies at a time (e.g., McLean and Pontiff, 2016) considered the IVol effect together with other anomalies, but did not report its post-publication performance separately).

Panels A1/A2 and B1/B2 report alphas from several baseline models, starting with the traditionally used three-factor Fama-French model and ending with the six-factor model that includes, along with the traditional three factors (the market return, SMB, and HML), the two new factors: CMA (the investment factor) and RMW (the profitability factor), as well as the momentum factor from the Carhart (1997) model.

The first conclusion I draw from Panels A1/A2 and B1/B2 is that for the vast majority of models, the negative alpha of the top IVol quintile, which essentially creates the IVol discount, is economically large and highly significant with t-statistics exceeding 2.7 by absolute magnitude, with several exceptions.[12] Consequently, the IVol effect is consistently strong and significant, with the exception of the aforementioned cases.[13]

The second conclusion I draw is that the long-known fact that the IVol effect is stronger in value-weighted returns holds only in Panel A. Once the price screen and NYSE breakpoints are used, the IVol effect in equal-weighted returns starts to compare favorably with that in value-weighed returns, especially controlling for the new factors, RMW and CMA. Consequently, when we compare Panel A1 with Panel B1, we see that in value-weighted returns applying the price screen and NYSE breakpoints leads to declines in the alphas: the Carhart/five-factor alphas decline from 95/71 bp per month to 48/23 bp per month (still significant); in equal-weighted returns (Panel A2 vs. Panel B2), somewhat surprisingly, the same change leads to increases in the same Carhart/five-factor alphas, from 45/31 bp per month (the latter marginally significant at the 10% level) to 60/40 bp per month (both t-statistics exceed 5).

[12]The exceptions are the equal-weighted five-factor, six-factor, and Q4 alphas in the sorts with CRSP breakpoints (Panel A2) and the value-weighted Q4 and six-factor alphas in the sorts with the price screen and NYSE breakpoints in Panel B1 (the latter is still marginally significant at -17 bp per month, t-statistic -1.99).

[13]Recent papers, such as Chen et al. (2020) and Cao et al. (2021), also confirm the existence of the IVol effect in the five-factor alphas, while Hou et al. (2020) find no IVol effect in raw returns.

Turning to the role of the two new factors, CMA and RMW, in explaining the IVol effect, the first thing of note is that adding those two factors reduces the alpha of the low-minus-high IVol strategy perhaps more than controlling for any other factor. Panels B1 and B2 in Table 8 show that adding the momentum factor to the three-factor model reduces the estimate of the IVol effect by less than 10 bp per month. However, adding CMA and RMW instead shaves off full 27-34 bp per month.

The bottom row of each panel adds RMW to the three-factor model and finds that 68-75% of the difference in alphas between the three-factor and five-factor models is explained by RMW. The role of RMW is also consistent with the aggregate volatility risk explanation of the IVol effect in Barinov and Chabakauri (2023), who find that a factor-mimicking portfolio for change in the VIX index, FVIX, can explain the alpha of the low-minus-high IVol strategy, and the aggregate volatility risk explanation of the profitability anomaly in Barinov (2023), who finds that FVIX can explain the alpha of RMW, but not the other way around. Barinov and Chabakauri (2023) present a model suggesting that growth options perform better than expected when VIX increases due to their convexity and higher IVol makes growth options take a larger fraction of the firm value – thus high IVol firms load positively on FVIX. Barinov (2023) argues that distressed firms perform better than expected when VIX increases due to their equity being effectively a call option on the assets, and since RMW tends to buy profitable (healthy) firms and short unprofitable (distressed) firms, Barinov (2023) finds that RMW loads negatively on FVIX. Table 1A in the online appendix looks at factor loadings across IVol quintiles and finds, among other things, that in the full CRSP sample high IVol firms indeed load very negatively on RMW (or the similar ROE factor from the Q4 model).

The main message of Panels A1/A2 and B1/B2 in Table 8 is that the IVol effect is generally robust to controlling for the new factors, RMW and CMA, is robust to using NYSE breakpoints to form IVol quintiles, and is also robust to exclusion of penny stocks. Even after the six common asset-pricing factors are controlled for and liquidity/microstructure concerns are largely addressed, the IVol effect represents an anomaly to be explained.

Panels A3/A4 and B3/B4 repeat Panels A1/A2 and B1/B2 in the post-publication sample, 2005-2022 (the Ang et al., 2006, paper first became publicly available as a NBER working paper in October 2004). The sample is only 18 years long and includes some high-volatility episodes like the Great Recession and the Covid pandemic, so some power issues are expected. However, Panels A3/A4 and B3/B4 repeat Panels A1/A2 and B1/B2 very closely both in terms of alpha magnitudes and their significance. Five asset-pricing models (the three-factor and five-factor models of Fama and French (1993, 2015), the Carhart (1997) model, the six-factor model from Fama and French, 2016, and the Q4 model from Hou et al., 2015) and four ways of measuring the alpha (value/equal-weighted returns, CRSP/NYSE breakpoints) produce 20 estimates of the IVol effect in Panels A1/A2 and B1/B2 and another 20 in Panels A3/A4 and B3/B4. Panels A1/A2 and B1/B2 have 15 significant estimates, with t-statistics exceeding 3 in 12 cases; Panels A3/A4 and B3/B4 have 17 significant estimates, one more marginally significant at the 5% level, and 8 estimates with t-statistics above 3. The average five-factor alpha of the low-minus-high IVol strategy from Panels A1/A2 and B1/B2 is 41 bp per month, while all 20 alphas (from all models) in Panels A1/A2 and B1/B2 average to 47 bp per month; the same averages from Panels A3/A4 and B3/B4 come to 67 bp and 69 bp per month, with the increase driven primarily by Panel B (NYSE breakpoints, stocks priced below $5 at the portfolio formation date excluded).

Overall, my analysis of the post-publication sample shows that the IVol effect is as strong as ever in the most recent 18 years, and the circulation and publication of the Ang et al. (2006) paper did not cause the anomaly to weaken (which may suggest that the IVol effect is not mispricing and is likely to have a risk explanation, e.g., the one Barinov and Chabakauri, 2023, suggest).

7 Conclusion

The main conclusion of the paper is that the IVol effect of Ang et al. (2006) is robust to numerous tweaks in research design. The paper largely dispels two most serious concerns about robustness of the IVol effect brought up in the literature. I find that the evidence in Bali and Cakici (2008) that the IVol effect disappears in the "NYSE only" sample is caused by selection bias arising from Bali and Cakici's use of the current listing indicator (`hexcd` from the CRSP returns file) to classify firms as NYSE firms. This selection bias causes many well-performing firms that were not NYSE firms as of portfolio formation, but were subsequently promoted to NYSE, enter Bali and Cakici's sample, while bad-performing firms (that used to by on NYSE when the IVol portfolios were formed, but were subsequently dropped by NYSE) are erroneously excluded from the sample. This positive bias in returns disproportionately affects high IVol firms, which, as I show in this paper, are more likely to be either promoted to or demoted from NYSE.

Once the selection bias is corrected by using the historical listing indicator (`exchcd` from the CRSP events file), the IVol effect emerges as strong in the NYSE only sample as in the full CRSP sample. I find that the vast majority of the selection bias is created by firms that are misclassified as NYSE firms by the current listing indicator (rather than the ones that are misclassified as non-NYSE), which alleviates the concern that the IVol effect in the NYSE only sample can be created by rare negative events of demotion from

NYSE.

I also find that the evidence in Bali and Cakici (2008) that the IVol effect disappears after small, low-price, and illiquid stocks are dropped from the sample arises because Bali and Cakici first drop those firms from the sample and then sort firms on IVol, which significantly shifts the IVol breakpoints. Using the breakpoints from the sample of relatively large and liquid stocks, Bali and Cakici populate their top IVol quintile with stocks that would have fallen in the fourth quintile even in the NYSE only sample. When I first sort firms on IVol and then purge IVol quintiles of small, low-price, and illiquid stocks, the IVol effect turns out to be as strong as it is in the full CRSP sample.

The concern raised by Huang et al. (2010) that the IVol effect can be the short-term reversal repackaged also turns out to be a false alarm. If true, that would imply that the IVol effect is as short-lived as the short-term reversal (which lasts for one or two months) and probably non-tradable. I find, however, that the IVol effect remains significant for at least six months; if monthly returns are used to estimate IVol, the IVol effect remains significant for more than a year and does not show any signs of weakening in the first year, similar to other anomalies that are known to overlap with the IVol effect. The short-term reversal does explain about one-third of the IVol effect in the first month after portfolio formation, but in subsequent months, which generate the vast majority of abnormal returns to the low-minus-high IVol strategy, controlling for the short-term reversal does not decrease the alpha of the said strategy at all.

Lastly, I find that the IVol effect is stronger for high turnover firms, which, in the light of the recent Medhat and Schmeling (2022) result that short-term reversal does not exist for high turnover firms, is inconsistent with the IVol effect being driven by short-term reversal.

I also find that while the literature usually estimates the IVol effect using the three-factor Fama and French (1993) model as the benchmark, the IVol effect survives controlling for momentum and the two new factors from Fama and French (2015), RMW and CMA. Of the extra factors, RMW has the most overlap with the IVol effect, consistent with the joint aggregate volatility risk explanation of the IVol effect (see Barinov and Chabakauri, 2023) and the profitability effect (see Barinov, 2023).

Lastly, I find that if I restrict the sample to the post-publication years, 2005-2022, the IVol effect remains as strong as it is in the full sample. This hold-out sample test suggests, first, that the IVol effect is not just a "lucky" strategy that delivers a significant alpha due to a 5% level test rejecting the null of zero alpha 5% of the time even if the null is true. Second, the strong IVol effect in the post-publication sample suggests that the IVol effect was not arbitraged away (and, in fact, hardly declined) post-discovery, making more likely that the IVol effect has a risk-based explanation.

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Table 1. Idiosyncratic Volatility, Delisting Frequency, and Frequency of Promotion to/Demotion from NYSE

The table reports average percentage frequency of firms in different IVol quintiles being delisted (Delist row), being delisted for performance reasons (PerfDelist row), being demoted from NYSE (Demotion row) or promoted to NYSE from a different exchange (Promotion row). The percentage frequencies are measured in the month after portfolio formation. A firm is delisted (for performance reasons) if dlstcd code from CRSP events file is 200 and above (is between 500 and 599). A firm is demoted from NYSE if $exchcd \neq 1$ in the current month, but $exchcd = 1$ in the previous (portfolio formation) month. A firm is promoted to NYSE if $exchcd = 1$ in the current month, but $exchcd \neq 1$ in the previous (portfolio formation) month. In Panel A, the sample is restricted to NYSE (exchcd=1) firms only, in Panel B, all CRSP firms are included, but the quintile breakpoints still come from NYSE firms sample. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022.

IVol from Monthly Returns in the Past 5 Years

Panel A1. NYSE only Sample

	Low	IVol2	IVol3	IVol4	High	H-L
Delist	0.118	0.235	0.345	0.492	0.834	0.715
t-stat	*8.10*	*12.32*	*15.19*	*17.50*	*20.53*	*19.8*
PerfDelist	0.003	0.003	0.009	0.026	0.290	0.287
t-stat	*2.51*	*2.48*	*3.93*	*5.75*	*10.3*	*10.1*
Demotion	0.015	0.014	0.023	0.040	0.101	0.086
t-stat	*3.17*	*4.42*	*5.92*	*7.92*	*10.2*	*8.76*

Panel B1. Full Sample, NYSE breakpoints

	Low	IVol2	IVol3	IVol4	High	H-L
Demotion	0.008	0.008	0.013	0.016	0.017	0.009
t-stat	*3.12*	*4.54*	*5.44*	*7.73*	*9.19*	*3.19*
Promotion	0.030	0.047	0.061	0.082	0.061	0.032
t-stat	*8.56*	*9.07*	*10.1*	*14.2*	*12.2*	*5.25*

IVol from Daily Returns in the Past Month

Panel A2. NYSE only Sample

	Low	IVol2	IVol3	IVol4	High	H-L
Delist	0.914	0.197	0.186	0.167	0.542	-0.371
t-stat	*15.3*	*12.8*	*13.5*	*12.2*	*15.4*	*-6.35*
PerfDelist	0.015	0.007	0.006	0.010	0.284	0.269
t-stat	*4.93*	*3.33*	*3.10*	*3.76*	*10.2*	*9.67*
Demotion	0.025	0.014	0.018	0.028	0.102	0.077
t-stat	*4.97*	*4.39*	*4.87*	*6.57*	*10.3*	*7.68*

Panel B2. Full Sample, NYSE breakpoints

	Low	IVol2	IVol3	IVol4	High	H-L
Demotion	0.013	0.007	0.008	0.010	0.018	0.006
t-stat	*4.78*	*4.43*	*5.01*	*6.46*	*9.80*	*2.05*
Promotion	0.035	0.045	0.078	0.098	0.050	0.015
t-stat	*10.3*	*10.6*	*12.1*	*14.8*	*13.0*	*3.05*

Table 2. Idiosyncratic Volatility Effect and Exchange Listing

The table presents, across IVol quintiles, equal-weighted raw returns and alphas from the CAPM, the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the Q4 model from Hou et al. (2015). The sample is restricted to NYSE firms only: Panels A1 and A2 use current listing indicator (hexcd) from the CRSP monthly file, Panels B1 and beyond use historical listing indicator (exchcd) from the CRSP events file. IVol is standard deviation of the FF model residuals. In panels on the left (A1-C1), the FF model is fitted, in each firm-month, to monthly stock returns in the past 60 months (at least 24 valid observations are required). In panels on the right (A2-C2), the FF model is fitted, in each firm-month, to daily stock returns in the past month (at 15 valid observations are required). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2004 (Panels A1-B2) and from July 1963 to December 2022 (Panels C1 and C2).

IVol from Monthly Returns in the Past 5 Years

Panel A1. 1963-2004 Sample, hexcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.165	1.327	1.433	1.457	1.577	-0.411
t-stat	*6.72*	*6.24*	*5.60*	*4.85*	*4.22*	*-1.53*
$\boldsymbol{\alpha}_{CAPM}$	0.353	0.409	0.449	0.402	0.433	-0.080
t-stat	*3.35*	*3.60*	*3.22*	*2.49*	*1.99*	*-0.38*
$\boldsymbol{\alpha}_{FF}$	0.054	0.104	0.070	0.006	-0.020	0.074
t-stat	*0.79*	*1.50*	*0.88*	*0.07*	*-0.18*	*0.62*
$\boldsymbol{\alpha}_{Carhart}$	0.121	0.194	0.183	0.155	0.208	-0.087
t-stat	*1.73*	*3.05*	*2.66*	*1.99*	*1.97*	*-0.65*
$\boldsymbol{\alpha}_{FF5}$	-0.060	-0.057	-0.081	-0.100	-0.046	-0.014
t-stat	*-0.96*	*-1.04*	*-1.21*	*-1.10*	*-0.33*	*-0.09*
$\boldsymbol{\alpha}_{Q4}$	-0.050	-0.031	-0.011	-0.016	0.173	-0.223
t-stat	*-0.46*	*-0.28*	*-0.08*	*-0.11*	*0.81*	*-1.05*

IVol from Daily Returns in the Past Month

Panel A2. 1963-2004 Sample, hexcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.182	1.389	1.553	1.611	1.309	-0.128
t-stat	*6.31*	*6.27*	*6.17*	*5.45*	*3.56*	*-0.54*
$\boldsymbol{\alpha}_{CAPM}$	0.353	0.462	0.563	0.551	0.174	0.178
t-stat	*3.36*	*4.09*	*4.30*	*3.51*	*0.81*	*0.96*
$\boldsymbol{\alpha}_{FF}$	0.070	0.158	0.236	0.192	-0.333	0.402
t-stat	*1.03*	*2.16*	*2.99*	*2.23*	*-3.07*	*3.46*
$\boldsymbol{\alpha}_{Carhart}$	0.104	0.228	0.320	0.339	-0.024	0.128
t-stat	*1.57*	*3.14*	*4.00*	*4.65*	*-0.23*	*0.96*
$\boldsymbol{\alpha}_{FF5}$	-0.067	0.012	0.072	0.061	-0.327	0.260
t-stat	*-1.21*	*0.20*	*1.05*	*0.71*	*-2.22*	*1.69*
$\boldsymbol{\alpha}_{Q4}$	-0.071	0.011	0.072	0.155	0.011	-0.082
t-stat	*-0.70*	*0.10*	*0.62*	*1.11*	*0.05*	*-0.37*

IVol from Monthly Returns in the Past Month

Panel B1. 1963-2004 Sample, exchcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.137	1.243	1.350	1.295	1.026	0.111
t-stat	*6.64*	*5.96*	*5.42*	*4.49*	*2.83*	*0.42*
$\boldsymbol{\alpha}_{CAPM}$	0.329	0.324	0.369	0.249	-0.103	0.432
t-stat	*3.16*	*2.94*	*2.77*	*1.60*	*-0.49*	*2.05*
$\boldsymbol{\alpha}_{FF}$	0.035	0.031	0.000	-0.139	-0.568	0.603
t-stat	*0.51*	*0.45*	*0.00*	*-1.56*	*-5.03*	*4.57*
$\boldsymbol{\alpha}_{Carhart}$	0.102	0.116	0.129	0.030	-0.296	0.398
t-stat	*1.39*	*1.84*	*1.90*	*0.39*	*-2.73*	*2.84*
$\boldsymbol{\alpha}_{FF5}$	-0.070	-0.132	-0.142	-0.240	-0.580	0.510
t-stat	*-1.05*	*-2.42*	*-2.06*	*-2.49*	*-4.05*	*3.22*
$\boldsymbol{\alpha}_{Q4}$	-0.067	-0.115	-0.053	-0.133	-0.336	0.270
t-stat	*-0.60*	*-1.12*	*-0.41*	*-0.85*	*-1.59*	*1.26*

IVol from Daily Returns in the Past 5 Years

Panel B2. 1963-2004 Sample, exchcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.094	1.303	1.400	1.425	0.815	0.279
t-stat	*6.08*	*6.08*	*5.78*	*5.07*	*2.28*	*1.17*
$\boldsymbol{\alpha}_{CAPM}$	0.268	0.382	0.419	0.375	-0.305	0.574
t-stat	*2.66*	*3.58*	*3.34*	*2.57*	*-1.44*	*2.99*
$\boldsymbol{\alpha}_{FF}$	-0.003	0.084	0.093	0.013	-0.832	0.829
t-stat	*-0.05*	*1.21*	*1.20*	*0.15*	*-7.06*	*6.23*
$\boldsymbol{\alpha}_{Carhart}$	0.027	0.153	0.187	0.182	-0.468	0.495
t-stat	*0.42*	*2.15*	*2.42*	*2.69*	*-4.29*	*3.55*
$\boldsymbol{\alpha}_{FF5}$	-0.135	-0.057	-0.052	-0.101	-0.819	0.684
t-stat	*-2.41*	*-0.94*	*-0.74*	*-1.13*	*-5.19*	*4.07*
$\boldsymbol{\alpha}_{Q4}$	-0.155	-0.066	-0.024	0.004	-0.451	0.297
t-stat	*-1.59*	*-0.62*	*-0.20*	*0.03*	*-1.84*	*1.28*

Panel C1. 1963-2022 Sample, exchcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.070	1.152	1.213	1.234	0.997	0.073
t-stat	*7.35*	*6.37*	*5.59*	*4.81*	*2.97*	*0.30*
$\boldsymbol{\alpha}_{CAPM}$	0.301	0.253	0.235	0.169	-0.178	0.479
t-stat	*3.55*	*2.80*	*2.08*	*1.27*	*-0.92*	*2.54*
$\boldsymbol{\alpha}_{FF}$	0.150	0.084	0.006	-0.086	-0.514	0.664
t-stat	*2.59*	*1.59*	*0.09*	*-1.14*	*-4.63*	*5.12*
$\boldsymbol{\alpha}_{Carhart}$	0.182	0.150	0.123	0.090	-0.260	0.443
t-stat	*3.16*	*3.19*	*2.06*	*1.11*	*-2.28*	*3.18*
$\boldsymbol{\alpha}_{FF5}$	0.038	-0.052	-0.111	-0.163	-0.506	0.545
t-stat	*0.70*	*-1.10*	*-1.94*	*-2.00*	*-4.04*	*3.86*
$\boldsymbol{\alpha}_{Q4}$	0.059	-0.015	-0.016	-0.023	-0.278	0.337
t-stat	*0.70*	*-0.19*	*-0.16*	*-0.18*	*-1.72*	*2.02*

Panel C2. 1963-2022 Sample, exchcd Listing Indicator

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.047	1.199	1.280	1.287	0.776	0.271
t-stat	*6.91*	*6.45*	*6.05*	*5.11*	*2.26*	*1.12*
$\boldsymbol{\alpha}_{CAPM}$	0.265	0.299	0.305	0.224	-0.404	0.669
t-stat	*3.21*	*3.38*	*2.90*	*1.74*	*-2.04*	*3.65*
$\boldsymbol{\alpha}_{FF}$	0.125	0.129	0.107	-0.015	-0.765	0.890
t-stat	*2.19*	*2.46*	*1.79*	*-0.20*	*-6.51*	*6.72*
$\boldsymbol{\alpha}_{Carhart}$	0.134	0.176	0.186	0.141	-0.399	0.533
t-stat	*2.39*	*3.47*	*3.07*	*1.88*	*-3.15*	*3.63*
$\boldsymbol{\alpha}_{FF5}$	0.005	0.019	-0.004	-0.095	-0.730	0.735
t-stat	*0.10*	*0.37*	*-0.06*	*-1.25*	*-5.32*	*5.00*
$\boldsymbol{\alpha}_{Q4}$	0.023	0.032	0.031	0.032	-0.375	0.398
t-stat	*0.29*	*0.40*	*0.35*	*0.29*	*-2.00*	*2.19*

Table 3. Source of Selection Bias: Wrongfully Excluded or Wrongfully Included Firms?

Panel A presents equal-weighted returns and alphas of NYSE firms excluded from Bali and Cakici (2008) analysis (firms that were traded on NYSE as of portfolio formation date ($exchcd = 1$), but are not currently traded on NYSE ($hexcd \neq 1$)), while Panel B presents average returns and alphas of non-NYSE firms included by Bali and Cakici (2008) into NYSE only sample (firms that are currently traded on NYSE ($hexcd = 1$), but were not NYSE firms as of the portfolio formation date ($exchcd \neq 1$)). The alphas are from the CAPM, the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the Q4 model from Hou et al. (2015). The last two rows of each panel report the average number of firms in each quintile, as well as the fraction they take in the true NYSE (exchcd=1) sample. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022.

IVol from Monthly Returns in the Past 5 Years

Panel A1. Wrongfully Excluded Stocks

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	0.869	0.874	0.718	0.858	0.840	-0.026
t-stat	*5.02*	*4.04*	*2.81*	*2.49*	*2.15*	*-0.08*
$\boldsymbol{\alpha}_{CAPM}$	0.092	-0.019	-0.292	-0.289	-0.445	0.490
t-stat	*0.82*	*-0.14*	*-1.84*	*-1.29*	*-1.72*	*1.81*
$\boldsymbol{\alpha}_{FF}$	-0.020	-0.242	-0.526	-0.551	-0.764	0.692
t-stat	*-0.20*	*-2.29*	*-3.90*	*-2.98*	*-3.91*	*3.19*
$\boldsymbol{\alpha}_{Carhart}$	0.016	-0.149	-0.314	-0.314	-0.404	0.358
t-stat	*0.16*	*-1.35*	*-2.47*	*-1.56*	*-1.97*	*1.56*
$\boldsymbol{\alpha}_{FF}$	-0.048	-0.399	-0.564	-0.563	-0.631	0.511
t-stat	*-0.45*	*-3.96*	*-4.24*	*-2.95*	*-2.78*	*2.09*
$\boldsymbol{\alpha}_{Q4}$	-0.017	-0.347	-0.260	-0.266	-0.255	0.162
t-stat	*-0.14*	*-2.54*	*-1.51*	*-1.14*	*-0.88*	*0.54*
# Firms	11	10	11	14	19	
% Firms	3.7%	3.3%	3.9%	4.9%	6.6%	

IVol from Daily Returns in the Past Month

Panel A2. Wrongfully Excluded Stocks

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	0.682	0.933	0.931	0.939	0.526	0.157
t-stat	*3.58*	*4.48*	*3.30*	*3.08*	*1.32*	*0.49*
$\boldsymbol{\alpha}_{CAPM}$	-0.070	-0.034	-0.082	-0.204	-0.714	0.624
t-stat	*-0.54*	*-0.26*	*-0.40*	*-1.15*	*-2.57*	*2.20*
$\boldsymbol{\alpha}_{FF}$	-0.188	-0.159	-0.324	-0.441	-1.088	0.875
t-stat	*-1.63*	*-1.40*	*-1.77*	*-3.16*	*-5.21*	*3.55*
$\boldsymbol{\alpha}_{Carhart}$	-0.209	-0.108	-0.186	-0.257	-0.627	0.393
t-stat	*-1.82*	*-0.96*	*-1.03*	*-1.73*	*-2.72*	*1.47*
$\boldsymbol{\alpha}_{FF}$	-0.299	-0.261	-0.401	-0.449	-0.948	0.626
t-stat	*-2.55*	*-2.50*	*-2.19*	*-3.01*	*-4.10*	*2.31*
$\boldsymbol{\alpha}_{Q4}$	-0.279	-0.178	-0.305	-0.241	-0.436	0.133
t-stat	*-2.19*	*-1.38*	*-1.35*	*-1.34*	*-1.42*	*0.40*
# Firms	11	11	12	15	20	
% Firms	3.5%	3.4%	3.8%	4.6%	6.3%	

IVol from Monthly Returns in the Past 5 Years

Panel B1. Wrongfully Included Stocks

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.192	1.540	1.787	1.937	2.722	-1.540
t-stat	*7.04*	*7.23*	*7.41*	*6.35*	*7.76*	*-5.72*
$\boldsymbol{\alpha}_{CAPM}$	0.466	0.705	0.862	0.883	1.541	-1.080
t-stat	*3.65*	*4.62*	*5.03*	*4.61*	*6.97*	*-5.08*
$\boldsymbol{\alpha}_{FF}$	0.280	0.497	0.681	0.602	1.249	-0.976
t-stat	*2.95*	*4.67*	*5.25*	*4.71*	*8.10*	*-5.50*
$\boldsymbol{\alpha}_{Carhart}$	0.281	0.513	0.703	0.649	1.387	-1.110
t-stat	*3.04*	*4.72*	*5.99*	*4.55*	*8.41*	*-5.84*
$\boldsymbol{\alpha}_{FF5}$	0.208	0.385	0.509	0.457	1.300	-1.098
t-stat	*2.23*	*3.91*	*4.07*	*3.86*	*7.44*	*-5.45*
$\boldsymbol{\alpha}_{Q4}$	0.179	0.415	0.539	0.524	1.514	-1.334
t-stat	*1.42*	*3.01*	*3.55*	*2.90*	*7.03*	*-5.82*
# Firms	25	31	41	50	89	
% Firms	8.6%	10.4%	13.7%	17.0%	30.2%	

IVol from Daily Returns in the Past Month

Panel B2. Wrongfully Included Stocks

	Low	IVol2	IVol3	IVol4	High	L-H
Raw	1.500	1.842	1.909	2.269	2.596	-1.121
t-stat	*7.50*	*8.05*	*7.33*	*7.05*	*7.22*	*-4.52*
$\boldsymbol{\alpha}_{CAPM}$	0.660	0.936	0.915	1.178	1.380	-0.728
t-stat	*4.71*	*6.31*	*5.20*	*5.84*	*5.63*	*-3.40*
$\boldsymbol{\alpha}_{FF}$	0.463	0.764	0.753	0.959	1.070	-0.609
t-stat	*4.36*	*6.46*	*5.74*	*6.79*	*6.45*	*-3.28*
$\boldsymbol{\alpha}_{Carhart}$	0.496	0.786	0.695	1.030	1.232	-0.736
t-stat	*4.68*	*6.99*	*5.30*	*5.99*	*6.68*	*-3.64*
$\boldsymbol{\alpha}_{FF5}$	0.346	0.631	0.624	0.854	1.115	-0.766
t-stat	*3.43*	*5.44*	*5.00*	*6.19*	*5.65*	*-3.56*
$\boldsymbol{\alpha}_{Q4}$	0.373	0.658	0.509	0.985	1.360	-0.980
t-stat	*2.66*	*4.40*	*3.43*	*4.34*	*5.32*	*-4.06*
# Firms	43	37	46	62	92	
% Firms	13.2%	11.4%	14.2%	19.4%	28.7%	

Panel C. Average Size

	Low	IVol2	IVol3	IVol4	High		Low	IVol2	IVol3	IVol4	High
Wrongfully excluded	12.258	5.881	3.142	2.448	0.913	**Wrongfully excluded**	9.047	6.012	3.916	2.312	1.047
Wrongfully included	3.420	1.541	0.822	0.940	0.520	**Wrongfully included**	2.325	1.452	1.041	0.742	0.472
NYSE only	13.334	5.835	3.055	1.619	0.850	**NYSE only**	9.988	6.110	3.843	2.245	1.074

Table 4. Idiosyncratic Volatility Effect and Size, Liquidity, and Price Screens

Panels A-D present, across IVol quintiles, average raw returns and alphas from the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, the five-factor and six-factor Fama and French (2015, 2016) models (FF5, FF6), and the Q4 model from Hou et al. (2015). Panels A-C remove from the sample all stocks that, as of the portfolio formation date, are priced below \$10, or fall into the bottom NYSE size decile, or fall into the top NYSE decile in terms of Amihud (2002) illiquidity measure. Panels A and B perform the quintile sorts after removing the aforementioned stocks, and Panel C uses full-sample breakpoints to form the quintiles. Panel D keeps all CRSP stocks before and after the sorting. Panels E-H report average and median IVol across IVol quintiles, as well as average and median number of firms in each quintile and their average and median total market share. IVol is standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily data for each firm-month (at least 15 valid observations are required). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2004 (Panels A and B) and from July 1963 to December 2022 (Panels C-H).

Panel A. 1963-2004 Sample, Size above NYSE bottom decile, Price > \$10, Amihud measure below NYSE top decile, breakpoints from truncated sample

Panel A1. Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.111	0.100	0.136	0.129	-0.343	0.454
t-stat	*1.83*	*1.52*	*1.79*	*1.31*	*-2.13*	*2.51*
$\alpha_{Carhart}$	0.035	0.028	0.111	0.055	-0.428	0.462
t-stat	*0.55*	*0.40*	*1.46*	*0.56*	*-2.78*	*2.47*
α_{FF5}	-0.008	0.001	0.112	0.239	-0.068	0.060
t-stat	*-0.12*	*0.01*	*1.32*	*2.21*	*-0.44*	*0.38*
α_{FF6}	-0.058	-0.048	0.094	0.160	-0.180	0.121
t-stat	*-0.94*	*-0.65*	*1.09*	*1.50*	*-1.17*	*0.69*
α_{Q4}	-0.077	-0.114	0.070	0.205	-0.084	0.007
t-stat	*-1.03*	*-1.42*	*0.67*	*1.60*	*-0.42*	*0.03*

Panel A2. Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.062	0.184	0.258	0.183	-0.253	0.315
t-stat	*0.76*	*2.33*	*3.96*	*2.62*	*-1.93*	*1.88*
$\alpha_{Carhart}$	0.072	0.199	0.242	0.122	-0.353	0.425
t-stat	*0.94*	*2.57*	*3.69*	*1.68*	*-2.66*	*2.54*
α_{FF5}	-0.075	0.049	0.178	0.230	-0.020	-0.055
t-stat	*-1.09*	*0.73*	*2.65*	*2.75*	*-0.15*	*-0.38*
α_{FF6}	-0.047	0.082	0.176	0.171	-0.139	0.093
t-stat	*-0.69*	*1.21*	*2.73*	*2.12*	*-1.04*	*0.61*
α_{Q4}	-0.102	0.002	0.121	0.209	-0.038	-0.064
t-stat	*-0.95*	*0.02*	*1.55*	*2.36*	*-0.23*	*-0.28*

Panel B. 1963-2022 Sample, Size above NYSE bottom decile, Price > \$10, Amihud measure below NYSE top decile, breakpoints from truncated sample

Panel B1. Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.354	0.303	0.302	0.263	-0.146	0.501
t-stat	*3.93*	*3.36*	*2.99*	*2.00*	*-0.89*	*3.33*
$\alpha_{Carhart}$	0.305	0.255	0.281	0.216	-0.188	0.492
t-stat	*3.19*	*2.59*	*2.55*	*1.56*	*-1.11*	*3.27*
α_{FF5}	0.272	0.240	0.309	0.383	0.133	0.139
t-stat	*2.78*	*2.36*	*2.66*	*2.77*	*0.81*	*1.05*
α_{FF6}	0.237	0.203	0.290	0.332	0.072	0.165
t-stat	*2.32*	*1.87*	*2.33*	*2.28*	*0.42*	*1.16*
α_{Q4}	0.208	0.132	0.223	0.279	0.053	0.155
t-stat	*1.96*	*1.11*	*1.67*	*1.77*	*0.26*	*0.91*

Panel B2. Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.385	0.471	0.484	0.372	-0.062	0.447
t-stat	*3.50*	*4.26*	*4.45*	*3.16*	*-0.42*	*3.31*
$\alpha_{Carhart}$	0.377	0.460	0.452	0.322	-0.116	0.493
t-stat	*3.38*	*4.01*	*3.89*	*2.52*	*-0.74*	*3.82*
α_{FF5}	0.289	0.380	0.445	0.438	0.171	0.118
t-stat	*2.37*	*3.07*	*3.52*	*3.14*	*1.04*	*0.89*
α_{FF6}	0.290	0.378	0.420	0.389	0.103	0.188
t-stat	*2.36*	*2.97*	*3.20*	*2.68*	*0.60*	*1.46*
α_{Q4}	0.258	0.320	0.357	0.359	0.101	0.157
t-stat	*1.85*	*2.22*	*2.47*	*2.26*	*0.51*	*0.85*

Panel C. 1963-2022 Sample, Size above NYSE bottom decile, Price > \$10, Amihud measure below NYSE top decile, breakpoints from full sample

Panel C1. Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.277	0.366	0.295	-0.018	-0.656	0.934
t-stat	*3.08*	*3.99*	*2.59*	*-0.12*	*-3.04*	*4.51*
$\alpha_{Carhart}$	0.225	0.333	0.281	-0.014	-0.671	0.896
t-stat	*2.35*	*3.37*	*2.29*	*-0.09*	*-2.95*	*4.22*
α_{FF5}	0.184	0.302	0.344	0.169	-0.322	0.506
t-stat	*1.83*	*2.93*	*2.73*	*1.08*	*-1.46*	*2.59*
α_{FF6}	0.147	0.279	0.326	0.155	-0.366	0.513
t-stat	*1.40*	*2.57*	*2.41*	*0.94*	*-1.56*	*2.46*
α_{Q4}	0.117	0.203	0.251	0.089	-0.417	0.535
t-stat	*1.01*	*1.74*	*1.74*	*0.48*	*-1.65*	*2.32*

Panel C2. Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.357	0.495	0.462	0.096	-0.607	0.964
t-stat	*3.51*	*4.49*	*4.08*	*0.72*	*-3.13*	*5.48*
$\alpha_{Carhart}$	0.345	0.489	0.443	0.068	-0.643	0.988
t-stat	*3.36*	*4.22*	*3.63*	*0.48*	*-3.16*	*5.73*
α_{FF5}	0.264	0.407	0.446	0.237	-0.297	0.561
t-stat	*2.45*	*3.23*	*3.40*	*1.51*	*-1.48*	*3.34*
α_{FF6}	0.262	0.409	0.430	0.199	-0.357	0.618
t-stat	*2.39*	*3.16*	*3.14*	*1.21*	*-1.69*	*3.65*
α_{Q4}	0.241	0.330	0.366	0.159	-0.374	0.615
t-stat	*1.98*	*2.25*	*2.45*	*0.87*	*-1.56*	*2.79*

Panel D. 1963-2022 Sample, All Firms

Panel D1. Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.080	0.106	0.000	-0.340	-1.121	1.201
t-stat	*1.29*	*2.75*	*0.00*	*-3.92*	*-8.07*	*6.98*
$\boldsymbol{\alpha}_{Carhart}$	0.034	0.106	0.045	-0.223	-0.919	0.953
t-stat	*0.57*	*2.74*	*0.81*	*-2.58*	*-6.47*	*5.41*
$\boldsymbol{\alpha}_{FF5}$	0.008	0.031	0.073	-0.109	-0.706	0.714
t-stat	*0.14*	*0.76*	*1.31*	*-1.46*	*-5.89*	*4.74*
$\boldsymbol{\alpha}_{FF6}$	-0.025	0.037	0.105	-0.028	-0.566	0.541
t-stat	*-0.42*	*0.90*	*1.84*	*-0.34*	*-4.39*	*3.35*
$\boldsymbol{\alpha}_{Q4}$	-0.029	0.007	0.063	-0.011	-0.510	0.481
t-stat	*-0.41*	*0.15*	*0.95*	*-0.11*	*-3.51*	*2.63*

Panel D2. Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.212	0.237	0.180	-0.055	-0.552	0.764
t-stat	*2.65*	*4.03*	*3.65*	*-0.85*	*-3.76*	*4.41*
$\boldsymbol{\alpha}_{Carhart}$	0.205	0.270	0.256	0.111	-0.244	0.449
t-stat	*2.70*	*4.84*	*5.08*	*1.45*	*-1.37*	*2.33*
$\boldsymbol{\alpha}_{FF5}$	0.119	0.148	0.171	0.099	-0.190	0.309
t-stat	*1.40*	*2.80*	*3.24*	*1.28*	*-1.15*	*1.72*
$\boldsymbol{\alpha}_{FF6}$	0.122	0.185	0.238	0.231	0.047	0.076
t-stat	*1.53*	*4.02*	*5.24*	*2.78*	*0.24*	*0.36*
$\boldsymbol{\alpha}_{Q4}$	0.144	0.165	0.230	0.297	0.189	-0.045
t-stat	*1.45*	*2.06*	*3.07*	*2.66*	*0.80*	*-0.18*

Panel E. 1963-2022 Sample, Size above NYSE bottom decile, Price > $10, Amihud measure below NYSE top decile, breakpoints from truncated sample

Panel E1. Mean IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.011	0.014	0.017	0.020	0.025
NObs	371	370	370	370	370
MktShare	40.2%	23.9%	15.2%	9.6%	5.7%

Panel E2. Median IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.010	0.013	0.015	0.018	0.023
NObs	391	390	390	390	390
MktShare	41.2%	23.3%	14.7%	9.3%	5.4%

Panel F. 1963-2022 Sample, Size above NYSE bottom decile, Price > $10, Amihud measure below NYSE top decile, breakpoints from full sample

Panel F1. Mean IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.011	0.015	0.019	0.024	0.030
NObs	375	545	489	319	124
MktShare	39.1%	31.8%	15.9%	6.2%	1.6%

Panel F2. Median IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.010	0.014	0.018	0.022	0.027
NObs	337	541	507	273	94
MktShare	42.5%	31.1%	12.8%	4.9%	1.2%

Panel G. 1963-2022 Sample, All Firms

Panel G1. Mean IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.010	0.016	0.021	0.030	0.048
NObs	1214	1217	1218	1218	1214
MktShare	40.0%	32.8%	17.0%	7.5%	2.5%

Panel G2. Median IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.009	0.014	0.019	0.026	0.041
NObs	1335	1339	1340	1340	1337
MktShare	43.9%	32.4%	14.4%	6.4%	2.2%

Panel H. 1963-2022 Sample, NYSE Firms only, NYSE breakpoints

Panel H1. Mean IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.011	0.014	0.017	0.020	0.031
NObs	280	280	280	280	279
MktShare	35.5%	20.6%	13.0%	7.7%	3.8%

Panel H2. Median IVol and # of Firms

	Low	IVol2	IVol3	IVol4	High
IVol	0.010	0.013	0.015	0.019	0.026
NObs	276	276	276	276	275
MktShare	35.0%	20.4%	12.7%	7.5%	3.5%

Table 5. Idiosyncratic Volatility Effect in Event Time

The table reports alphas of the low-minus-high IVol strategy one, two, three, etc. months after portfolio formation, as indicated by the name of the column. The models that estimate the alphas include the CAPM, the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, and the five-factor Fama and French (2015) model (FF5), as well as the Carhart model augmented with the Fama-French short-term reversal factor (STR factor) and the Q4 model from Hou et al. (2015). The rightmost three columns report the difference in the IVol effect between the first and the twelfth (the first and the second, the second and the twelfth) month after portfolio formation. IVol is standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily data for each firm-month (at least 15 valid observations are required). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022.

Panel A. Full Sample, 1963-2022

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**	**1-2**	**2-12**
$\boldsymbol{\alpha}_{CAPM}$	1.213	0.968	0.858	0.876	0.818	0.763	0.636	0.529	0.633	0.677	0.537	0.538	0.654	0.243	0.406
t-stat	*5.09*	*4.28*	*3.77*	*3.64*	*3.48*	*3.33*	*2.78*	*2.23*	*2.63*	*2.77*	*2.11*	*2.21*	*5.05*	*2.10*	*3.13*
$\boldsymbol{\alpha}_{FF}$	1.201	0.975	0.851	0.904	0.825	0.790	0.664	0.539	0.640	0.669	0.563	0.547	0.657	0.225	0.428
t-stat	*6.98*	*5.67*	*5.21*	*5.55*	*5.39*	*5.15*	*4.10*	*3.34*	*3.87*	*4.15*	*3.32*	*3.24*	*4.76*	*1.77*	*2.98*
$\boldsymbol{\alpha}_{Carhart}$	0.953	0.717	0.547	0.561	0.504	0.504	0.351	0.216	0.304	0.405	0.291	0.259	0.698	0.235	0.461
t-stat	*5.41*	*4.31*	*3.15*	*3.28*	*3.19*	*3.07*	*2.17*	*1.26*	*1.75*	*2.48*	*1.64*	*1.51*	*4.76*	*1.77*	*3.08*
$\boldsymbol{\alpha}_{Carhart+STR}$	0.926	0.727	0.594	0.587	0.531	0.540	0.416	0.235	0.311	0.445	0.343	0.309	0.622	0.198	0.420
t-stat	*4.78*	*4.13*	*3.23*	*2.87*	*2.89*	*2.95*	*2.52*	*1.24*	*1.62*	*2.58*	*1.77*	*1.68*	*4.14*	*1.51*	*2.83*
$\boldsymbol{\alpha}_{FF5}$	0.714	0.488	0.321	0.343	0.365	0.285	0.159	0.066	0.121	0.161	0.100	0.027	0.679	0.225	0.452
t-stat	*4.74*	*3.26*	*2.20*	*2.21*	*2.54*	*1.88*	*1.04*	*0.45*	*0.74*	*1.08*	*0.64*	*0.17*	*5.08*	*1.77*	*2.95*
$\boldsymbol{\alpha}_{Q4}$	0.481	0.265	0.033	0.049	0.126	-0.004	-0.145	-0.274	-0.178	-0.092	-0.159	-0.278	0.758	0.215	0.543
t-stat	*2.63*	*1.48*	*0.17*	*0.27*	*0.72*	*-0.02*	*-0.74*	*-1.33*	*-0.82*	*-0.45*	*-0.78*	*-1.33*	*4.77*	*1.48*	*2.99*

Panel B. Huang et al. (2010) Sample, 1963-2004

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**	**1-2**	**2-12**
$\boldsymbol{\alpha}_{CAPM}$	1.320	0.946	0.881	0.997	0.914	0.763	0.631	0.606	0.676	0.646	0.520	0.612	0.681	0.373	0.299
t-stat	*4.49*	*3.24*	*3.04*	*3.42*	*3.04*	*2.65*	*2.16*	*2.07*	*2.32*	*2.10*	*1.69*	*2.08*	*5.14*	*3.01*	*2.15*
$\boldsymbol{\alpha}_{FF}$	1.353	0.933	0.862	1.021	0.947	0.825	0.698	0.700	0.730	0.711	0.639	0.714	0.649	0.418	0.225
t-stat	*6.70*	*4.31*	*4.21*	*5.29*	*5.21*	*4.49*	*3.32*	*3.62*	*3.80*	*3.79*	*3.30*	*3.55*	*4.87*	*3.11*	*1.49*
$\boldsymbol{\alpha}_{Carhart}$	1.100	0.671	0.534	0.706	0.609	0.531	0.312	0.335	0.367	0.366	0.277	0.364	0.745	0.428	0.314
t-stat	*5.10*	*3.15*	*2.24*	*3.52*	*3.19*	*2.55*	*1.39*	*1.44*	*1.71*	*1.68*	*1.23*	*1.55*	*4.66*	*2.91*	*1.82*
$\boldsymbol{\alpha}_{Carhart+STR}$	1.109	0.714	0.613	0.818	0.716	0.621	0.403	0.403	0.391	0.424	0.366	0.467	0.652	0.393	0.254
t-stat	*4.56*	*3.02*	*2.34*	*3.39*	*3.21*	*2.54*	*1.66*	*1.53*	*1.63*	*1.75*	*1.37*	*1.78*	*4.24*	*2.96*	*1.58*
$\boldsymbol{\alpha}_{FF5}$	0.745	0.360	0.264	0.392	0.417	0.266	0.089	0.163	0.142	0.140	0.096	0.132	0.602	0.381	0.220
t-stat	*4.07*	*1.96*	*1.38*	*2.04*	*2.43*	*1.45*	*0.45*	*0.94*	*0.70*	*0.74*	*0.51*	*0.67*	*4.15*	*2.62*	*1.32*
$\boldsymbol{\alpha}_{Q4}$	0.469	0.088	-0.120	0.028	0.117	-0.067	-0.322	-0.286	-0.262	-0.273	-0.271	-0.292	0.761	0.381	0.380
t-stat	*1.95*	*0.38*	*-0.43*	*0.12*	*0.52*	*-0.27*	*-1.15*	*-1.05*	*-0.95*	*-0.99*	*-1.01*	*-1.03*	*4.16*	*2.14*	*1.72*

Table 6. Idiosyncratic Volatility Effect in Cross-Sectional Regressions

The table presents slopes from cross-sectional Fama-MacBeth (1973) regressions of month t returns on IVol and controls. Panel A uses the controls from Huang et al. (2010) (market beta, log size, log market-to-book (MB), cumulative return in months t-2 to t-12 (MOM), and returns from the past (t-1) month (Rev), and Panel B employs a longer list of controls that adds investment-to-assets (Inv) and gross profitability (GProf). IVol is lagged by the number of months indicated in the name of each column (all other variables are always from the same period as in column one). Detailed definitions of all variables are in Data Appendix. The models that estimate the alphas include the CAPM, the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, and the five-factor Fama and French (2015) model (FF5), as well as the Carhart model augmented with the Fama-French short-term reversal factor (STR factor) and the Q4 model from Hou et al. (2015). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2004 (Panel A) and from July 1963 to December 2022 (Panel B).

Panel A. 1963-2004 Sample

IVol lag=	**1**	**2**	**3**	**4**	**5**	**6**
Beta	0.066	0.089	0.046	0.066	0.058	0.044
t-stat	*0.61*	*0.83*	*0.43*	*0.60*	*0.53*	*0.41*
log(Size)	-0.144	-0.171	-0.151	-0.160	-0.146	-0.139
t-stat	*-3.83*	*-4.54*	*-4.02*	*-4.24*	*-3.83*	*-3.66*
log(MB)	-0.317	-0.304	-0.318	-0.319	-0.325	-0.329
t-stat	*-5.57*	*-5.35*	*-5.61*	*-5.63*	*-5.72*	*-5.77*
Mom	0.711	0.686	0.698	0.696	0.698	0.689
t-stat	*5.30*	*4.97*	*4.99*	*4.98*	*4.99*	*4.88*
Rev	-0.067	-0.067	-0.067	-0.067	-0.067	-0.067
t-stat	*-15.9*	*-16.9*	*-16.8*	*-16.6*	*-16.6*	*-16.5*
IVol	-4.310	-10.17	-2.875	-4.373	-1.252	1.708
t-stat	*-1.21*	*-2.84*	*-0.78*	*-1.32*	*-0.37*	*0.49*

Panel B. 1963-2022 Sample

IVol lag=	**1**	**2**	**3**	**4**	**5**	**6**
Beta	0.071	0.083	0.051	0.064	0.062	0.054
t-stat	*0.84*	*0.98*	*0.60*	*0.75*	*0.73*	*0.63*
log(Size)	-0.116	-0.134	-0.111	-0.112	-0.108	-0.108
t-stat	*-3.85*	*-4.43*	*-3.70*	*-3.75*	*-3.54*	*-3.53*
log(MB)	-0.247	-0.238	-0.250	-0.254	-0.256	-0.259
t-stat	*-5.29*	*-5.10*	*-5.36*	*-5.44*	*-5.48*	*-5.52*
Mom	0.503	0.498	0.508	0.510	0.509	0.504
t-stat	*4.37*	*4.23*	*4.30*	*4.31*	*4.28*	*4.20*
Rev	-0.050	-0.052	-0.051	-0.051	-0.051	-0.051
t-stat	*-13.8*	*-15.3*	*-15.2*	*-15.1*	*-15.1*	*-15.1*
IVol	-8.361	-12.22	-5.471	-5.101	-4.239	-3.067
t-stat	*-2.95*	*-4.48*	*-1.92*	*-1.94*	*-1.65*	*-1.15*

Table 7. Idiosyncratic Volatility Effect across Turnover Quintiles

The table presents alphas of the zero-investment strategy that buys/shorts the lowest/hishest IVol quintile across turnover quintiles. Both IVol and turnover sorts use NYSE (exchcd=1) breakpoints, but include all CRSP firms. IVol is estimated from daily returns in the past month. Turnover is past month's dollar trading volume from CRSP divided by end-of-the month market capitalization. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022.

Panel A. Value-Weighted Returns

	LoTurn	**Q2**	**Q3**	**Q4**	**HiTurn**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.807	0.722	0.680	0.670	1.066	-0.259
t-stat	*3.77*	*3.61*	*3.77*	*3.75*	*5.00*	*-1.11*
$\boldsymbol{\alpha}_{FF}$	0.892	0.775	0.681	0.632	0.963	-0.071
t-stat	*5.51*	*5.02*	*4.75*	*4.33*	*4.80*	*-0.32*
$\boldsymbol{\alpha}_{Carhart}$	0.660	0.559	0.467	0.449	0.778	-0.119
t-stat	*4.07*	*3.15*	*2.86*	*2.78*	*4.03*	*-0.53*
$\boldsymbol{\alpha}_{Carh+STR}$	0.692	0.542	0.499	0.482	0.796	-0.104
t-stat	*3.85*	*2.68*	*2.64*	*2.69*	*4.05*	*-0.45*
$\boldsymbol{\alpha}_{FF5}$	0.603	0.481	0.418	0.390	0.541	0.062
t-stat	*4.08*	*3.21*	*2.65*	*3.01*	*2.91*	*0.27*
$\boldsymbol{\alpha}_{FF6}$	0.429	0.322	0.258	0.255	0.421	0.008
t-stat	*3.01*	*1.91*	*1.53*	*1.70*	*2.18*	*0.03*
$\boldsymbol{\alpha}_{Q4}$	0.387	0.352	0.221	0.143	0.330	0.057
t-stat	*2.39*	*1.82*	*1.18*	*0.88*	*1.41*	*0.21*

Panel B. Equal-Weighted Returns

	LoTurn	**Q2**	**Q3**	**Q4**	**HiTurn**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.133	0.266	0.517	0.648	1.079	-0.946
t-stat	*0.65*	*1.07*	*2.26*	*3.18*	*4.81*	*-4.59*
$\boldsymbol{\alpha}_{FF}$	0.191	0.315	0.533	0.649	1.052	-0.861
t-stat	*1.17*	*1.81*	*3.17*	*4.36*	*5.07*	*-3.94*
$\boldsymbol{\alpha}_{Carhart}$	-0.050	-0.078	0.169	0.289	0.723	-0.773
t-stat	*-0.31*	*-0.39*	*0.85*	*1.54*	*3.11*	*-3.20*
$\boldsymbol{\alpha}_{Carh+STR}$	-0.024	-0.041	0.211	0.388	0.788	-0.812
t-stat	*-0.14*	*-0.18*	*0.95*	*2.00*	*3.31*	*-3.35*
$\boldsymbol{\alpha}_{FF5}$	-0.031	-0.070	0.132	0.237	0.604	-0.635
t-stat	*-0.20*	*-0.38*	*0.79*	*1.43*	*2.82*	*-2.75*
$\boldsymbol{\alpha}_{FF6}$	-0.219	-0.372	-0.145	-0.035	0.360	-0.578
t-stat	*-1.43*	*-1.81*	*-0.72*	*-0.18*	*1.50*	*-2.34*
$\boldsymbol{\alpha}_{Q4}$	-0.283	-0.407	-0.219	-0.147	0.307	-0.590
t-stat	*-1.66*	*-1.77*	*-0.92*	*-0.62*	*1.11*	*-2.21*

Table 8. Idiosyncratic Volatility Effect, RMW Factor, and the Post-Publication Sample

The table presents, across IVol quintiles, alphas from the three-factor Fama and French (1993) model (FF), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), the five-factor Fama and French (2015) model augmented with the momentum factor (FF6), as well as alphas from the three-factor Fama and French (1993) model augmented with the profitability factor (FF+RMW) and the Q4 model from Hou et al. (2015). IVol is standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily data for each firm-month (at least 15 valid observations are required). Quintile sorts in Panel A use CRSP breakpoints and all stocks in the sample, while quintiles sorts in Panel B use NYSE breakpoints and exclude stocks priced below $5 at the portfolio formation date. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022 (Panels A1, A2, B1, B2) and from January 2005 to December 2022 (Panels A3, A4, B3, B4).

Panel A. CRSP Breakpoints, All Stocks

Panel A1. 1963-2022 Sample, Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.080	0.106	0.000	-0.340	-1.121	1.201
t-stat	1.29	2.75	0.00	-3.92	-8.07	6.98
$\boldsymbol{\alpha}_{Carhart}$	0.034	0.106	0.045	-0.223	-0.919	0.953
t-stat	0.57	2.74	0.81	-2.58	-6.47	5.41
$\boldsymbol{\alpha}_{FF5}$	0.008	0.031	0.073	-0.109	-0.706	0.714
t-stat	0.14	0.76	1.31	-1.46	-5.89	4.74
$\boldsymbol{\alpha}_{FF6}$	-0.025	0.037	0.105	-0.028	-0.566	0.541
t-stat	-0.42	0.90	1.84	-0.34	-4.39	3.35
$\boldsymbol{\alpha}_{Q4}$	-0.029	0.007	0.063	-0.011	-0.510	0.481
t-stat	-0.41	0.15	0.95	-0.11	-3.51	2.63
$\boldsymbol{\alpha}_{FF+RMW}$	0.027	0.039	0.026	-0.187	-0.814	0.840
t-stat	0.42	0.97	0.45	-2.53	-6.86	5.50

Panel A2. 1963-2022 Sample, Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.212	0.237	0.180	-0.055	-0.552	0.764
t-stat	2.65	4.03	3.65	-0.85	-3.76	4.41
$\boldsymbol{\alpha}_{Carhart}$	0.205	0.270	0.256	0.111	-0.244	0.449
t-stat	2.70	4.84	5.08	1.45	-1.37	2.33
$\boldsymbol{\alpha}_{FF5}$	0.119	0.148	0.171	0.099	-0.190	0.309
t-stat	1.40	2.80	3.24	1.28	-1.15	1.72
$\boldsymbol{\alpha}_{FF6}$	0.122	0.185	0.238	0.231	0.047	0.076
t-stat	1.53	4.02	5.24	2.78	0.24	0.36
$\boldsymbol{\alpha}_{Q4}$	0.144	0.165	0.230	0.297	0.189	-0.045
t-stat	1.45	2.06	3.07	2.66	0.80	-0.18
$\boldsymbol{\alpha}_{FF+RMW}$	0.159	0.151	0.161	0.059	-0.250	0.409
t-stat	1.88	2.83	3.11	0.85	-1.64	2.52

Panel A3. 2005-2022 Sample, Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.145	0.140	-0.066	-0.168	-0.744	0.889
t-stat	1.13	2.39	-0.81	-1.06	-3.21	3.12
$\alpha_{Carhart}$	0.119	0.136	-0.059	-0.103	-0.638	0.757
t-stat	0.94	2.33	-0.71	-0.63	-2.66	2.62
α_{FF5}	0.162	0.087	-0.022	-0.091	-0.528	0.690
t-stat	1.18	1.67	-0.30	-0.57	-2.49	2.51
α_{FF6}	0.142	0.085	-0.018	-0.045	-0.449	0.590
t-stat	1.02	1.64	-0.24	-0.28	-2.13	2.17
α_{Q4}	0.096	0.082	-0.076	0.018	-0.347	0.443
t-stat	0.67	1.61	-0.86	0.11	-1.55	1.50
α_{FF+RMW}	0.159	0.101	-0.031	-0.131	-0.547	0.706
t-stat	1.08	1.81	-0.41	-0.87	-2.65	2.53

Panel A4. 2005-2022 Sample, Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.372	0.250	0.167	-0.073	-0.736	1.108
t-stat	3.17	3.29	2.28	-0.59	-2.56	3.71
$\alpha_{Carhart}$	0.361	0.251	0.197	0.004	-0.598	0.959
t-stat	3.11	3.34	2.76	0.03	-2.43	3.85
α_{FF}	0.426	0.242	0.185	0.036	-0.399	0.826
t-stat	4.33	3.63	2.65	0.31	-1.41	2.74
α_{FF6}	0.420	0.240	0.206	0.092	-0.294	0.714
t-stat	4.22	3.67	3.12	0.94	-1.24	2.80
α_{Q4}	0.380	0.186	0.175	0.131	-0.274	0.654
t-stat	3.31	2.09	2.49	1.27	-1.16	2.34
α_{FF+RMW}	0.462	0.220	0.164	0.015	-0.404	0.866
t-stat	4.29	3.00	2.43	0.14	-1.41	2.84

Panel B. NYSE Breakpoints, Stocks Priced Below $5 Excluded

Panel B1. 1963-2022 Sample, Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.150	0.096	-0.001	-0.052	-0.416	0.566
t-stat	3.35	2.28	-0.03	-0.83	-4.69	4.66
$\alpha_{Carhart}$	0.128	0.061	0.009	-0.002	-0.347	0.476
t-stat	2.85	1.32	0.21	-0.04	-3.88	3.94
α_{FF5}	0.023	0.009	-0.062	-0.015	-0.208	0.231
t-stat	0.59	0.21	-1.18	-0.23	-2.66	2.25
α_{FF6}	0.015	-0.013	-0.048	0.024	-0.167	0.182
t-stat	0.35	-0.27	-0.98	0.39	-1.99	1.63
α_{Q4}	0.007	-0.036	-0.094	0.032	-0.130	0.137
t-stat	0.13	-0.74	-1.84	0.46	-1.29	1.00
α_{FF+RMW}	0.070	0.024	-0.050	-0.061	-0.276	0.347
t-stat	1.89	0.58	-0.96	-0.89	-3.58	3.44

Panel B2. 1963-2022 Sample, Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
α_{FF}	0.207	0.235	0.216	0.133	-0.460	0.667
t-stat	3.06	3.94	3.77	2.49	-8.25	7.01
$\alpha_{Carhart}$	0.207	0.257	0.245	0.186	-0.397	0.604
t-stat	3.27	4.79	4.70	3.50	-6.83	6.57
α_{FF5}	0.096	0.116	0.117	0.075	-0.299	0.395
t-stat	1.51	2.25	2.23	1.44	-5.75	5.01
α_{FF6}	0.106	0.146	0.151	0.125	-0.257	0.363
t-stat	1.74	3.21	3.58	3.08	-4.96	4.43
α_{Q4}	0.138	0.131	0.112	0.116	-0.211	0.349
t-stat	1.55	1.57	1.44	1.58	-2.95	3.11
α_{FF+RMW}	0.130	0.134	0.125	0.074	-0.340	0.470
t-stat	2.15	2.64	2.33	1.36	-6.38	6.29

Panel B3. 2005-2022 Sample, Value-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.226	0.026	-0.053	-0.238	-0.445	0.671
t-stat	3.12	0.50	-0.75	-2.23	-2.46	2.80
$\boldsymbol{\alpha}_{Carhart}$	0.213	0.018	-0.054	-0.219	-0.401	0.614
t-stat	2.85	0.34	-0.77	-2.00	-2.14	2.47
$\boldsymbol{\alpha}_{FF5}$	0.161	0.010	-0.041	-0.167	-0.298	0.459
t-stat	2.48	0.19	-0.55	-1.61	-1.85	2.19
$\boldsymbol{\alpha}_{FF6}$	0.153	0.003	-0.041	-0.157	-0.267	0.420
t-stat	2.30	0.05	-0.55	-1.47	-1.63	1.96
$\boldsymbol{\alpha}_{Q4}$	0.168	-0.028	-0.067	-0.125	-0.172	0.340
t-stat	2.36	-0.53	-0.96	-1.26	-0.97	1.45
$\boldsymbol{\alpha}_{FF+RMW}$	0.179	0.009	-0.028	-0.202	-0.316	0.495
t-stat	2.72	0.17	-0.39	-1.92	-2.06	2.45

Panel B4. 2005-2022 Sample, Equal-Weighted Returns

	Low	IVol2	IVol3	IVol4	High	L-H
FF	0.376	0.204	0.142	-0.027	-0.532	0.908
t-stat	4.85	3.60	2.59	-0.43	-4.42	5.62
$\boldsymbol{\alpha}_{Carhart}$	0.366	0.205	0.153	-0.003	-0.493	0.859
t-stat	4.58	3.52	2.77	-0.05	-4.23	5.44
$\boldsymbol{\alpha}_{FF5}$	0.345	0.191	0.157	0.025	-0.342	0.687
t-stat	4.25	3.69	2.96	0.43	-4.02	5.21
$\boldsymbol{\alpha}_{FF6}$	0.337	0.189	0.163	0.041	-0.316	0.653
t-stat	4.10	3.62	3.07	0.72	-3.88	5.17
$\boldsymbol{\alpha}_{Q4}$	0.336	0.151	0.129	0.048	-0.285	0.621
t-stat	3.42	1.91	2.04	0.76	-2.81	3.80
$\boldsymbol{\alpha}_{FF+RMW}$	0.341	0.169	0.142	0.008	-0.365	0.706
t-stat	4.14	3.07	2.73	0.14	-3.84	5.16