Online Appendix to
"On the Robustness of Idiosyncratic Volatility Effect"

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Abstract

The document contains supplementary tests for the paper "On the Robustness of Idiosyncratic Volatility Effect". Section 1 looks at factor betas and median firm characteristics across IVol quintiles. Section 2 tabulates median IVol and average number of firms in independent sorts on turnover and IVol. Section 3 looks at performance of several anomalies overlapping with the IVol effect and records this performance one, two, three, etc. months after portfolio formation to gauge the overlap of these anomalies with short-term reversal. Section 4 provides a more detailed look at delistings and demotions from NYSE across IVol quintiles, tabulating frequencies of different type of delistings and observing how frequency of delisting/demotions changes three, six, and twelve months after portfolio formation. Lastly, this document also contains Data Appendix to the paper with detailed definitions of all variables used and referred to in the paper.

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1 Factor Betas across IVol Quintiles

Table 1A records factor betas of idiosyncratic volatility (IVol) quintiles by fitting factor models to monthly returns of the quintile portfolios. Panel A uses all CRSP firms and CRSP breakpoints; Panel B uses NYSE-only (exchcd=1) firms. Panels A1 and B1 report the factor betas from the Q4 model of Hou et al. (2015); Panels A2 and B2 document the factor betas from the seven-factor model with five Fama and French (2015), factors, the momentum factor, MOM, based on Carhart (1997) and the short-term reversal factor, STR, based on Jegadeesh (1990) (both MOM and STR are from Kenneth French's website). Panels A3 and B3 additionally report median firm characteristics across IVol quintiles, focusing on the characteristics that serve as the basis of the factors in the Fama-French model (size, market-to-book, etc.); Panels A4 and B4 also present size-adjusted values of the firm characteristics.

Consistent with long-known negative correlation between size and IVol (which the first row of Panels A3 and B3 confirms), in Panels A2 and B2, both market beta and SMB beta increase in IVol sorts, whether one looks at the CRSP sample or NYSE-only sample (in Panels A1 and B1, the market beta and the size factor beta in the Q4 model behave similarly). Also, losses trigger an increase in volatility (probably due to increased leverage), hence the decrease in momentum betas going from bottom to top IVol quintile. The cumulative returns between months t-2 and t-12 (where t-1 is the portfolio formation month) decrease in all panels that tabulate firm characteristics, including the ones with size-adjustment.

The panels with firm characteristics also confirm the result in Fu (2009) that in the portfolio formation month, in contrast to months t-2 to t-12, high IVol firms tend to be winners in period t-1 (and hence may be exposed to short-term reversal). This is not surprising, since returns are bounded from below by -100%, whereas the upside is potentially unlimited. In the portfolio formation month, high IVol firms can be both big winners and big losers, but in the average (and even in the median) positive returns dominate. However, in Panels A2 and B2 of Table 1A, I do not see any relation between IVol and loadings on the short-term reversal factor. As mentioned in the paper (Section 5, p. 18), Huang et al. (2010) use a somewhat different short-term reversal factor (decile return spread) and do find a positive loading of the low-minus-high IVol portfolio on their short-term reversal factor, but the loading, while statistically significant, turns out to be numerically small, comparable to what I find in Panel A2.

The relation between IVol and three main Fama-French factors (HML, CMA, and RMW) is more complicated. In Panel A2 (CRSP sample), high IVol quintile loads negatively on HML, and the low-minus-high IVol strategy seems to overlap with the value-minus-growth strategy. In Panel B2 (NYSE-only sample), HML beta is largely flat across the IVol quintile. On the other hand, the firm characteristics in all but one panels (Panel B4 is an exception) show that high IVol firms have lower market-to-book that low IVol firms and hence high IVol firms are more likely to be value rather than growth. This is also consistent with what Ang et al. (2006) find in their Table 6.

I believe that the apparent contradiction between how IVol is related, in cross-section, with market-to-book and with HML beta is explained well in Barinov and Chabakauri (2023), who find, first, that the IVol effect the strongest among growth firms and absent among value firms and, second, that FVIX (the factor that mimics changes in VIX) can explain both the IVol effect and a large part of the value effect. The first piece of evidence suggests that while there can be more value firms among high IVol firms than among low IVol firms, it is high IVol growth firms that create the IVol effect, and this is what the HML factor picks up. The second piece of evidence is based on the intuition that higher volatility, all else equal, increases the value of growth options (hence the exposure of HML, which shorts growth firms, to volatility risk), and high IVol growth firms, which seem to drive the IVol effect, are the best hedges against volatility risk (i.e., they will outperform the CAPM prediction the most when VIX increases). Thus, both HML and the low-minus-high IVol strategy are exposed to volatility risk, and in Panel A2 of Table 1A HML just proxies for volatility risk exposure.

A similar contradiction arises between CMA betas of IVol quintiles and investment-to-assets ratios across those quintiles. CMA betas (as well as investment factor betas from the Q4 model) decline monotonically across IVol quintiles, suggesting that high IVol firms behave like high investment firms. However, Panels A3 and B3 of Table 1A show that high IVol firms actually have lower investment-to-asset ratios than low IVol firms, and the positive cross-sectional relation between IVol and investment-to-assets is only visible after size adjustment (Panels A4 and B4). Quite possibly, the same forces as in the case of HML betas are at work here: while some high IVol firms are value firms, and their low investment-to-asset ratios can obscure the relation between IVol and investment, the IVol effect is created by high IVol growth firms that do invest a lot, and this is what CMA betas are picking up. I also find in untabulated results that CMA loads significantly and negatively on FVIX, just like HML does in Barinov and Chabakauri (2023), even though the relation between CMA and FVIX is numerically smaller than the relation between HML and FVIX. So it is possible that CMA is picking up the volatility risk explanation of the IVol effect suggested by Barinov and Chabakauri (2023).

I also observe a strong decline in RMW betas across IVol quintiles, especially when I look at the CRSP sample, in which the top IVol quintile is likely to include more small and distressed firms. A very similar pattern emerges in the betas with respect to the ROE factor from the Q4 model. However, when I look at median profitability in Panels A3 and B3, I find it to be flat across IVol quintiles - but the pattern changes to the one consistent with the factor loadings once I perform the size adjustment in Panels A4 and B4.

Another reason, beyond the decline in size-adjusted profitability, why profitability factor betas decline across IVol quintiles can be that RMW is picking up volatility risk. Barinov (2023) finds RMW loads negatively on FVIX, and this loading, revealing RMW's exposure to volatility risk, stems from the fact that unprofitable firms tend to be distressed, their equity is similar to a call option on the assets, and the said option benefits from increases in volatility, as all options do. Juxtaposing the Barinov (2023) result with the result in Barinov and Chabakauri (2023) that the low-minus-high IVol strategy also loads negatively on FVIX yields the prediction that the low-minus-high IVol strategy will load positively on RMW and high IVol stocks (that load positively on FVIX in Barinov and Chabakauri, 2023) will load negatively on RMW, which is exactly what we see in Panels A2 and B2 of Table 1A.

I also find, in untabulated results, that the ROE factor from the Q4 model loads negatively and significantly on FVIX, and the logic from Barinov (2023) extends to ROE factor: its relation to FVIX can explain why ROE betas are negatively related to IVol.

2 Double Sorts on Turnover and IVol

Table 2A presents characteristics of portfolios double sorted on turnover and IVol. The sorts are independent sorts in order to keep the high-minus-low spread in IVol the same across turnover quintiles and make sure than any relation between turnover and the IVol effect is not mechanical. Panel A of Table 2A records median IVol for each of the double-sorted portfolios and finds that there is no reason to believe that the relation between turnover and the IVol effect in Table 7 of the paper is mechanical: the spread in IVol between the top and bottom IVol quintiles is 2.93% per day in the lowest turnover quintile and 2.92% per day in the highest turnover quintile. Likewise, IVol of the highest IVol firms is 3.67% per day in the lowest turnover quintile and 3.71% in the highest turnover quintile.

Panel B tabulates average number of firms in each of the double-sorted portfolios. Due to a strong positive relation between turnover and IVol (first predicted by Harris and Raviv, 1993, in their "disagreement creates trade"; see also Barinov, 2014, for empirical confirmation), most firms in the double sorts fall along the main diagonal, but the other corner portfolios are also relatively well-populated: for example, the intersection of the bottom turnover quintile and the top IVol quintile on average has 708 firms. The portfolio in the opposite corner (top turnover quintile and bottom IVol quintile) is more concerning with its 18 firms on average, but it neighbor (second highest turnover quintile and bottom IVol quintile) is again rather balanced with 43 firms on average - and one can see in Table 7 in the paper that the results stay the same if one compares the IVol effect in the top turnover quintile to the IVol effect in the second-lowest (not the bottom) turnover quintile. Overall, it seems that the relation between turnover and the IVol effect is unlikely to be obscured by extreme outlier returns coming from underdiversified portfolios.

In untabulated findings, I probe the results in Table 7 in several ways. First, I use CRSP breakpoints instead of NYSE breakpoints. Doing so deviates from what Medhat and Schmeling (2022) do to establish stronger reversal for low-turnover stocks, but solves the problem of scant number of stocks in the intersection of top turnover quintile and bottom IVol quintile, which increases to 39 on average. The result that the IVol effect is largely unrelated to turnover in value-weighted returns and strongly positively (not negatively) related to turnover in equal-weighted returns stays the same.

Second, I restrict the sample to NYSE firms, which keeps the breakpoints the same as in Table 7, but purges the sample of small and illiquid firms, which can impact returns of small portfolios too much. I find that in the NYSE-only sample the IVol effect increases across turnover quintiles both in value-weighted and equal-weighted returns.

Third, I perform conditional sorts, first on turnover and then on IVol, which completely resolves the problem of too few observations in the intersection of top turnover quintile and bottom IVol quintile, which now increases to 81 on average. The downside is that, since IVol and turnover are positively correlated, the IVol spread between top and bottom IVol quintiles is roughly 25% larger in the top turnover quintile than in the bottom turnover quintile. In the conditional sorts with all CRSP firms and NYSE breakpoints, the IVol effect increases across turnover quintiles both in value-weighted and equal-weighted returns, which is partly but not completely due to the larger IVol spread between top and bottom IVol in the top turnover quintile – after all, a similar IVol spread in the bottom turnover quintile is only 10% smaller than the IVol spread in unconditional sorts (roughly the same in all turnover quintiles).

3 Idiosyncratic Volatility Effect, Related Anomalies, and Short-Term Reversal

Several anomalies are known to have a significant overlap with the IVol effect of Ang et al. (2006). Ang et al. themselves note a strong, though incomplete overlap between the IVol effect and the analyst disagreement effect of Diether et al. (2002). Boyer et al.

(2010) suggest that the negative relation between expected skewness and future returns, arising from lottery preference by individual investors, can explain the IVol effect. Bali et al. (2011) argues that a similar negative relation between maximum daily return in the past month and future return can explain both the IVol effect of Ang et al. (2006) and the skewness effect of Boyer et al. (2010). Barinov (2015) adds to this list the negative relation between future returns and variability of monthly turnover in the past 36 months from Chordia et al. (2001) and argues that both the IVol effect of Ang et al. (2006) and the turnover variability effect of Chordia et al. (2001) are driven by the same aggregate volatility risk factor.

The claim of Huang et al. (2010) that the IVol effect is subsumed by the short-term reversal of Jegadeesh (1990) and the more moderate evidence in my Tables 5 and 6 that those two anomalies have an overlap of roughly one-third, invites the question about the role the short-term reversal plays in the other anomalies related to the IVol effect. Again, this is not an abstract question of whether two anomalies overlap and to what extent; rather, this is an issue of practical importance: if any of the anomalies from the previous paragraph are subsumed by the short-term reversal, then trading on such anomalies is not practical, since the respective low-minus-high strategy will only deliver gains for one month, or at most two.

Table 3A repeats the analysis in Table 5 in the paper for the anomalies from the first paragraph of this section: I tabulate the alphas of the low-minus-high strategies implied by those anomalies in twelve months after portfolio formation. For example, Panel A of Table 3A considers the analyst disagreement effect of Diether et al. (2002). The first column reports the CAPM, three-factor Fama-French, and Carhart alphas of the portfolio that is long in the bottom and short in the top analyst disagreement quintile and is held during the first month after portfolio formation. These are the alphas that are always reported in papers on the analyst disagreement effect, as portfolios in the analyst disagreement sorts are rebalanced monthly. The second column of Panel A reports alphas of the same portfolio held in the second month after the quintile portfolios representing its long and short legs are formed, the third column presents the alphas from the third month after portfolio formation, etc.

Table 3A shows that the only other anomaly that has some overlap with short-term reversal, represented by a dip in the alpha between months one and two after portfolio formation, is the maximum effect of Bali et al. (2011). For all other anomalies considered in this section, including the version of the IVol effect based on IVol computed from monthly returns in the past 60 months (analyzed in Panel E of Table 3A), the dip in the alpha between months one and two is around 5-10 bp.[1]

I also observe that all anomalies in Table 3A, except for, probably, the skewness effect of Boyer et al. (2010), continue to be significant for twelve months after portfolio formation and one cannot reject the null that any of the anomalies in Table 3A, including the IVol effect with monthly IVol measure, do not decay at all during the first year after portfolio formation. The exception is the maximum effect that does see a drop in its value between months one and two, and then again between months two and twelve.

[1]The result in Panel E is somewhat mechanical, because the measure of IVol in Panel E is very autocorrelated: at t, it uses returns from t-1 to t-60; at t+1, it uses returns from t to t-59, which have 58 out of 60 returns in common. The point of Panel E, however, is that it is possible to form a tradable low-minus-high IVol strategy that works for an extended period of time. The fact that the IVol measure calculated from returns in the past 60 months produces a profitable trading strategy is in itself an indication that not only IVol in month t-1 matters, but IVol in t-2, t-3, etc. matters, in contrast to the short-term reversal explanation of the IVol effect in Huang et al. (2010).

4 Exploring the Delisting Spike in the Bottom IVol Quintile

Panel A2 of Table 1 in the paper sorts firms on IVol calculated from daily returns (as in Ang et al., 2006) and finds a sharp spike in delisting frequency in the bottom IVol quintile, which sees more delistings than the top IVol quintile. A similar, though much weaker, spike is observed in performance delistings and demotions, which in the bottom IVol quintile are more frequent than in the second and third (middle) quintile, but much less frequent than in the top IVol quintile. The spikes are counterintuitive, and thus in Table 4A I look into potential reasons of why the spikes occur.

In Panel A, I split delistings according to CRSP manual. Delisting codes (dlstcd) between 100 and 199 mean either the security is still trading (code 100) or trading is halted temporarily. Delisting codes that exceed 100 but do not exceed 199 are very rare, I found only 3 instances in my sample period (if trading is halted and not renewed, CRSP counts the issue as liquidated for unknown reason and assigns codes in the 400s) – therefore, I do not count delisting codes between 100 and 199 as delistings. Delisting codes between 200 and 299 stand for mergers; delisting codes between 300 and 399 are used when stock is exchanged for something (e.g., cash if the company is bought out and taken private). Delisting codes between 400 and 499 imply liquidation, with bankruptcy being one reason among many. Delisting codes between 500 and 599 mean that the stock was dropped by the stock exchange for performance reasons (stock price too low, equity too low, number of shareholders too low).

Panel A of Table 4A creates four separate dummy variables for mergers, stock being exchanged for something, firm being liquidated, stock dropped by stock exchange. The four dummies add up to the delisting (Delist) dummy used in Table 1 in the paper and in Panels B-D of Table 4A. Panel A reveals that the counterintuitive spike in delisting frequencies in the bottom IVol quintile comes almost entirely from delisting caused by mergers. Other types of delistings show much smaller similar spikes.

In order to understand why the spike in delistings exists in the first place and is limited to sorts on IVol estimated from daily returns in the past month (delisting frequency monotonically increases with IVol in the IVol sorts if IVol is estimated from monthly returns in the past 36 months, as Panels A1 and B1 of Table 1 in the paper show), I probe the results in Panel A of Table 4A and in Panel A2 of Table 1 in the paper in a variety of ways. First, in untabulated results, I discover that the spike in delistings in the bottom IVol quintile becomes smaller if I exclude small firms and/or low-price stocks. The spike also subsides if I drop from the sample stocks with zero IVol and stocks with very small IVol (below 10 bp per month).

Second, in Panels B-D of Table 1R, I look at IVol quintile portfolios three, six, and twelve months after portfolio formation and tabulate frequency of delisting across the quintiles. I find that while a slight uptick in frequencies of demotions and performance delistings between IVol quintiles one and two remains in months three and six (in both cases, the top IVol quintile still has order of magnitude more performance-related delistings and four times higher frequency of demotion). However, when it comes to all delistings, I find that the U-shape in their frequency materially subsides as I look at months further from portfolio formation. In month three, the bottom IVol quintile already has significantly less delistings than the top IVol quintile, consistent with my expectation. By month twelve (Panel D), frequency of delistings monotonically increases with IVol, which both what I expect and what I was able to find in Panel A1 of Table 1 in the paper (where IVol sorts are based on IVol estimated from monthly returns in the past 36 months).

The totality of the evidence seems to suggest that the spike in delisting frequency in Panel A2 of Table 1 is short-lived and driven primarily by small, low IVol firms that are being acquired. The low IVol of these firms may be caused by illiquidity and infrequent trading.

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A Data Appendix

Amihud price impact measure - average ratio of absolute return to dollar volume, both from CRSP. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return/volume observations in a year or with the stock price of less than \$5 at the end of the previous year are excluded).

Analyst forecast dispersion - standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst are excluded). Earnings forecasts are from the IBES summary file.

Expected skewness - the expected value from

$$\begin{aligned} ISkew_t = \quad & \gamma_0 + \gamma_1 \cdot ISkew_{t-60} + \gamma_2 IVol_{t-60} + \gamma_3 \cdot Mom_{t-60} + \gamma_4 \cdot Turn_{t-60} + \\ & + \gamma_5 \cdot NASD_{t-60} + \gamma_6 \cdot Small_{t-60} + \gamma_7 \cdot Med_{t-60} + \Gamma \cdot IndDum \end{aligned} \tag{A-1}$$

The regression is performed in cross-section every month. ISkew is idiosyncratic skewness, computed from daily firm-level residuals (ϵ) of the Fama-French model in the past 60 months. ISkew is scaled by idiosyncratic volatility (IVol), computed the same way in the same period, raised to the power of 3/2:

$$ISkew = \frac{\sum_{t\in D} \epsilon_t^3}{(\sum_{t\in D} \epsilon_t^2)^{3/2}} \tag{A-2}$$

where D is the set of non-missing daily returns in the past 60 months. IVol on the right-hand side of (A-1) is, as above, $IVol = \sum_{t\in D} \epsilon_t^2$. Mom is cumulative monthly return in the past 12 months excluding the most recent one, Turn is average monthly turnover in the past year. NASD is NASDAQ dummy - 1 if the firm is from NASDAQ (exchcd from CRSP events file is equal to 3), and 0 otherwise. Small is small firms dummy - 1 if the firm is from the bottom three size deciles, 0 otherwise. Med is medium firms dummy - 1 if the firm is in one of the size deciles between fourth and seventh, 0 otherwise. Ind are industry dummies - 1 if the firm belongs to a certain industry, 0 otherwise. The industries are 30 industries from Fama and French (1997).

Inv (investment-to-assets) - annual change in capital expenditures (capx item from the annual Compustat file) divided by total assets (at item from Compustat) in the preceding year.

Idiosyncratic volatility (daily) - standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily data within each firm-month (at least 15 valid observations are required).

Idiosyncratic volatility (monthly) - standard deviation of residuals from the three-factor Fama and French (1993) model, fitted each firm-month to monthly returns in the preceding 60 months (at least 24 valid observations are required).

GProf (gross profitability) - total revenue (*sale* item) minus cost of goods sold (*cogs* item) divided by book value of equity (*ceq* plus *txdb*), all items from the Compustat annual file.

MAX (maximum daily return) - maximum daily return (from CRSP) in the previous month.

MB (market-to-book) - equity value (*csho* item times *prcc_f* item) divided by book equity (*ceq*) plus deferred taxes if available (*txdb*), all items from the Compustat annual file.

Mom (cumulative past return) - cumulative monthly return between months t-2 and t-12, monthly returns are from CRSP.

Rev (short term reversal) - stock return (from CRSP) in month t-1.

Size (market capitalization) - shares outstanding times price, both from the CRSP monthly returns file.

Turn (turnover) – monthly dollar trading volume from CRSP divided by end-of-the month market capitalization.

Turnover variability - coefficient of variation (standard deviation over the average) of monthly turnover measured between months t-2 and t-36. Turnover is dollar volume over market cap, both dollar volume and market cap are from CRSP.

Table 1A. Factor Betas across Idiosyncratic Volatility Quintiles

The table presents factor betas of quintile portfolios sorted on last month idiosyncratic volatility (calculated from daily returns). Panel A (B) sorts all CRSP (NYSE) firms using CRSP (NYSE) quintile breakpoints. NYSE firms are defined using historical listing indicator (exchcd from the CRSP events file). Panels A1 and B1 fit the Q4 model from Hou et al. (2015) to monthly quintile returns; Panels A2 and B2 fit the five-factor Fama and French (2015) model augmented with the momentum factor from Carhart (1997) and the short-term reversal factor based on Jegadeesh (1990). The factor returns for the Q4 model are from Lu Zhang's website; the factor returns used in Panels A2 and B2 are from the website of Kenneth French. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022. Panels A3 and B3 present median firm characteristics for each quintile by first taking the median within each quintile each month, and then averaging across months within a quintile. Panels A4 and B4 perform size-adjustment before computing the medians by assigning each firm to a size decile (NYSE breakpoints are used in forming the quintiles) and then deducting from each of its characteristic the average of that characteristic in the size decile the firm was assigned to this year.

Panel A. All CRSP Firms, CRSP Breakpoints

Panel A1. Betas from the Q4 Model

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
$\boldsymbol{\beta}_{MKT}$	0.833	1.027	1.131	1.201	1.199	-0.366
t-stat	*32.7*	*71.8*	*65.8*	*50.3*	*27.5*	*-6.20*
$\boldsymbol{\beta}_{ME}$	-0.123	-0.034	0.214	0.534	0.818	-0.941
t-stat	*-4.02*	*-0.93*	*5.57*	*9.86*	*10.8*	*-9.76*
$\boldsymbol{\beta}_{I/A}$	0.218	0.096	-0.177	-0.475	-0.597	0.815
t-stat	*3.54*	*2.27*	*-2.76*	*-6.00*	*-5.43*	*5.29*
$\boldsymbol{\beta}_{ROE}$	0.125	0.125	-0.059	-0.383	-0.826	0.951
t-stat	*2.80*	*4.33*	*-1.37*	*-5.73*	*-8.65*	*7.33*

Panel B. NYSE-only Firms, NYSE Breakpoints

Panel B1. Betas from the Q4 Model

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
$\boldsymbol{\beta}_{MKT}$	0.874	1.018	1.106	1.197	1.281	-0.407
t-stat	*59.6*	*64.3*	*54.8*	*47.3*	*28.9*	*-8.34*
$\boldsymbol{\beta}_{ME}$	-0.186	-0.086	0.059	0.182	0.421	-0.607
t-stat	*-6.32*	*-2.60*	*1.06*	*2.53*	*4.70*	*-7.41*
$\boldsymbol{\beta}_{I/A}$	0.318	0.301	0.272	0.106	-0.033	0.351
t-stat	*6.41*	*5.13*	*4.82*	*1.44*	*-0.34*	*3.30*
$\boldsymbol{\beta}_{ROE}$	0.156	0.171	0.058	-0.104	-0.385	0.541
t-stat	*4.09*	*3.93*	*1.42*	*-1.73*	*-4.09*	*5.26*

Panel A2. Betas from the 7-factor Fama-French model

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\beta}_{MKT}$	0.841	1.019	1.115	1.185	1.179	-0.338
t-stat	*33.0*	*81.2*	*74.5*	*49.3*	*26.6*	*-5.51*
$\boldsymbol{\beta}_{SMB}$	-0.152	-0.017	0.235	0.592	0.918	-1.071
t-stat	*-6.87*	*-0.72*	*7.59*	*13.5*	*14.9*	*-15.0*
$\boldsymbol{\beta}_{HML}$	0.151	0.035	-0.019	-0.199	-0.215	0.366
t-stat	*3.03*	*1.37*	*-0.59*	*-4.55*	*-2.74*	*3.30*
$\boldsymbol{\beta}_{CMA}$	0.055	0.038	-0.158	-0.256	-0.341	0.396
t-stat	*0.88*	*1.02*	*-3.41*	*-3.61*	*-2.81*	*2.55*
$\boldsymbol{\beta}_{RMW}$	0.144	0.195	-0.079	-0.429	-0.856	1.000
t-stat	*3.04*	*4.35*	*-1.60*	*-7.93*	*-10.03*	*8.57*
$\boldsymbol{\beta}_{MOM}$	0.049	-0.004	-0.040	-0.117	-0.201	0.250
t-stat	*2.51*	*-0.28*	*-1.61*	*-2.64*	*-3.04*	*3.12*
$\boldsymbol{\beta}_{REV}$	0.012	0.021	0.023	-0.024	-0.040	0.053
t-stat	*0.41*	*0.94*	*0.82*	*-0.51*	*-0.60*	*0.62*

Panel B2. Betas from the 7-factor Fama-French model

	Low	IVol2	IVol3	IVol4	High	L-H
$\boldsymbol{\beta}_{MKT}$	0.880	1.015	1.091	1.169	1.249	-0.369
t-stat	*64.0*	*58.1*	*70.4*	*58.2*	*33.2*	*-7.81*
$\boldsymbol{\beta}_{SMB}$	-0.198	-0.089	0.090	0.263	0.540	-0.738
t-stat	*-11.4*	*-4.50*	*3.65*	*7.39*	*9.72*	*-12.0*
$\boldsymbol{\beta}_{HML}$	0.125	0.152	0.161	0.126	0.077	0.049
t-stat	*4.44*	*5.72*	*4.79*	*2.55*	*0.95*	*0.50*
$\boldsymbol{\beta}_{CMA}$	0.167	0.106	0.069	-0.047	-0.117	0.284
t-stat	*4.55*	*2.40*	*1.73*	*-0.85*	*-1.15*	*2.33*
$\boldsymbol{\beta}_{RMW}$	0.243	0.244	0.214	0.144	-0.088	0.331
t-stat	*8.59*	*5.57*	*4.01*	*2.08*	*-1.04*	*3.80*
$\boldsymbol{\beta}_{MOM}$	0.009	0.021	-0.036	-0.119	-0.227	0.236
t-stat	*0.42*	*0.91*	*-1.66*	*-3.57*	*-3.35*	*2.85*
$\boldsymbol{\beta}_{REV}$	-0.001	0.006	0.040	0.053	0.028	-0.029
t-stat	*-0.06*	*0.26*	*1.25*	*1.30*	*0.45*	*-0.38*

Panel A3. Median Firm Characteristics

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Size	0.968	0.921	0.439	0.168	0.048	0.921	6.95
MB	1.692	1.799	1.745	1.747	1.780	-0.088	-1.35
Inv	0.042	0.045	0.046	0.043	0.034	0.008	5.32
Prof	0.273	0.314	0.328	0.322	0.279	-0.006	-0.93
MOM	0.119	0.114	0.094	0.039	-0.124	0.243	10.3
Rev	0.210	0.367	0.179	-0.190	0.369	-0.159	-0.35

Panel B3. Median Firm Characteristics

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Size	2.563	1.734	1.138	0.694	0.327	2.235	8.77
MB	1.925	1.805	1.709	1.599	1.415	0.510	8.61
Inv	0.047	0.046	0.045	0.045	0.038	0.009	4.72
Prof	0.298	0.313	0.318	0.316	0.299	-0.001	-0.10
MOM	0.121	0.112	0.101	0.078	-0.027	0.148	7.46
Rev	0.595	0.634	0.705	0.774	1.027	-0.433	-1.27

Panel A4. Median Firm Characteristics: Size-Adjusted

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
MB	-1.577	-1.564	-1.574	-1.605	-1.808	0.234	3.52
Inv	-0.059	-0.042	-0.034	-0.034	-0.047	-0.012	-2.77
Prof	-0.041	-0.043	-0.045	-0.048	-0.072	0.031	5.35
MOM	-0.075	-0.084	-0.095	-0.110	-0.181	0.106	7.75
Rev	-1.016	-1.011	-0.972	-0.880	-0.405	-0.610	-2.19

Panel B3. Median Firm Characteristics: Size-Adjusted

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H
MB	-1.916	-1.601	-1.588	-1.644	-1.988	0.073	0.23
Inv	-0.073	-0.027	-0.011	-0.010	-0.043	-0.030	-6.27
Prof	-0.052	-0.049	-0.066	-0.186	-0.257	0.204	4.34
MOM	-0.058	-0.060	-0.060	-0.084	-0.198	0.140	7.60
Rev	-0.951	-1.068	-1.120	-1.245	-0.176	-0.775	-1.97

Table 2A. Double Sorts on Turnover and Idiosyncratic Volatility

The table performs independent sorts on past month turnover (monthly dollar trading volume from CRSP divided by end-of-the month market capitalization) and past month idiosyncratic volatility (calculated from daily returns). Panel A presents median values of idiosyncratic volatility (the medians are calculated each month for each portfolio, and then averaged over months), Panel B presents average number of stocks in each portfolio. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from July 1963 to December 2022.

Panel A. Median Idiosyncratic Volatility

	LoIVol	IVol2	IVol3	IVol4	HiIVol	H-L	t(H-L)
LoTurn	0.75%	1.18%	1.54%	2.05%	3.67%	2.93%	36.2
Q2	0.83%	1.18%	1.53%	2.05%	3.58%	2.75%	38.7
Q3	0.85%	1.19%	1.54%	2.04%	3.51%	2.66%	38.4
Q4	0.86%	1.20%	1.55%	2.05%	3.46%	2.60%	40.0
HiTurn	0.80%	1.21%	1.57%	2.08%	3.71%	2.92%	40.1
H-L	0.05%	0.03%	0.03%	0.03%	0.04%	-0.01%	-0.14

Panel B. Number of Observations

	LoIVol	IVol2	IVol3	IVol4	HiIVol
LoTurn	262	182	205	276	708
Q2	112	105	99	113	250
Q3	75	93	99	111	213
Q4	43	72	101	131	245
HiTurn	18	32	68	143	439
H-L	-245	-149	-136	-133	-269

Table 3A. Related Anomalies in Event Time

The table reports alphas of the strategy that buys bottom and shorts top quintile based on the variable indicated in the heading of the panel. The rightmost three columns report the difference in the alphas of the respective strategy between the first and the twelfth (the first and the second, the second and the twelfth) month after portfolio formation. The alphas are measured 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), and the Carhart (1997) model. Detailed definitions of all variables are in Data Appendix. 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 2019 (Panel B).

Panel A. Analyst Disagreement Effect

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**	**1-2**	**2-12**
$\boldsymbol{\alpha}_{CAPM}$	0.695	0.635	0.583	0.659	0.508	0.419	0.552	0.443	0.491	0.582	0.553	0.557	0.138	0.060	0.078
t-stat	*3.70*	*3.52*	*3.22*	*3.52*	*2.55*	*2.37*	*2.89*	*2.39*	*2.53*	*3.13*	*2.84*	*2.89*	*1.37*	*1.05*	*0.73*
$\boldsymbol{\alpha}_{FF}$	0.759	0.689	0.641	0.717	0.558	0.450	0.583	0.478	0.520	0.593	0.582	0.582	0.177	0.070	0.107
t-stat	*4.27*	*4.08*	*3.86*	*4.11*	*2.96*	*2.84*	*3.36*	*2.84*	*3.00*	*3.48*	*3.28*	*3.27*	*1.72*	*1.08*	*0.97*
$\boldsymbol{\alpha}_{Carhart}$	0.518	0.463	0.415	0.501	0.353	0.261	0.391	0.303	0.363	0.432	0.376	0.376	0.142	0.055	0.087
t-stat	*2.97*	*2.82*	*2.59*	*2.89*	*1.87*	*1.61*	*2.19*	*1.77*	*1.97*	*2.44*	*1.98*	*2.05*	*1.31*	*0.81*	*0.74*

Panel B. Skewness Effect

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**	**1-2**	**2-12**
$\boldsymbol{\alpha}_{CAPM}$	0.267	0.200	0.232	0.162	0.061	0.155	0.219	0.383	0.289	0.233	0.262	0.262	0.006	0.068	-0.062
t-stat	*1.39*	*1.01*	*1.16*	*0.85*	*0.32*	*0.78*	*1.16*	*1.98*	*1.54*	*1.27*	*1.42*	*1.37*	*0.04*	*0.85*	*-0.49*
$\boldsymbol{\alpha}_{FF}$	0.309	0.273	0.335	0.239	0.125	0.249	0.298	0.472	0.377	0.309	0.321	0.343	-0.034	0.036	-0.070
t-stat	*2.59*	*2.17*	*2.32*	*1.77*	*0.91*	*1.54*	*2.13*	*3.33*	*2.40*	*2.27*	*2.29*	*2.33*	*-0.23*	*0.47*	*-0.52*
$\boldsymbol{\alpha}_{Carhart}$	0.309	0.284	0.335	0.208	0.058	0.179	0.249	0.391	0.209	0.134	0.134	0.172	0.137	0.025	0.112
t-stat	*2.46*	*2.16*	*2.26*	*1.47*	*0.42*	*1.15*	*1.72*	*2.78*	*1.43*	*0.95*	*0.91*	*1.10*	*0.88*	*0.30*	*0.79*

Panel C. MAX Effect

	1	2	3	4	5	6	7	8	9	10	11	12	1-12	1-2	2-12
$\boldsymbol{\alpha}_{CAPM}$	0.925	0.686	0.559	0.690	0.625	0.527	0.611	0.521	0.465	0.570	0.309	0.352	0.556	0.238	0.315
t-stat	*4.30*	*3.13*	*2.59*	*3.51*	*2.83*	*2.67*	*2.80*	*2.36*	*2.07*	*2.40*	*1.46*	*1.54*	*4.20*	*2.23*	*2.34*
$\boldsymbol{\alpha}_{FF}$	0.843	0.582	0.461	0.650	0.569	0.482	0.535	0.453	0.378	0.512	0.274	0.335	0.512	0.259	0.251
t-stat	*5.10*	*3.29*	*2.59*	*4.25*	*3.47*	*3.22*	*3.41*	*2.80*	*2.24*	*2.81*	*1.82*	*2.09*	*3.87*	*2.23*	*1.69*
$\boldsymbol{\alpha}_{Carhart}$	0.659	0.422	0.278	0.494	0.385	0.302	0.342	0.238	0.212	0.350	0.078	0.109	0.555	0.235	0.319
t-stat	*3.96*	*2.45*	*1.55*	*3.07*	*2.33*	*1.90*	*2.18*	*1.34*	*1.29*	*1.73*	*0.51*	*0.65*	*3.82*	*1.91*	*2.21*

Panel D. Turnover Variability Effect

	1	2	3	4	5	6	7	8	9	10	11	12	1-12	1-2	2-12
$\boldsymbol{\alpha}_{CAPM}$	0.295	0.293	0.277	0.350	0.295	0.244	0.238	0.314	0.282	0.291	0.252	0.223	0.072	0.002	0.070
t-stat	*1.91*	*1.71*	*1.69*	*1.85*	*1.80*	*1.58*	*1.59*	*2.05*	*1.83*	*1.77*	*1.65*	*1.57*	*0.72*	*0.06*	*0.63*
$\boldsymbol{\alpha}_{FF}$	0.428	0.436	0.414	0.507	0.452	0.405	0.392	0.470	0.431	0.448	0.409	0.376	0.053	-0.007	0.060
t-stat	*2.74*	*2.51*	*2.55*	*2.55*	*2.75*	*2.82*	*3.03*	*3.44*	*3.07*	*2.78*	*2.85*	*2.99*	*0.46*	*-0.20*	*0.48*
$\boldsymbol{\alpha}_{Carhart}$	0.412	0.425	0.394	0.469	0.381	0.310	0.295	0.367	0.330	0.345	0.310	0.263	0.149	-0.012	0.161
t-stat	*2.67*	*2.44*	*2.31*	*2.28*	*2.19*	*2.03*	*2.07*	*2.50*	*2.10*	*1.79*	*1.73*	*1.67*	*1.22*	*-0.32*	*1.26*

Panel E. Idiosyncratic Volatility Effect, Monthly Measure

	1	2	3	4	5	6	7	8	9	10	11	12	1-12	1-2	2-12
$\boldsymbol{\alpha}_{CAPM}$	0.767	0.687	0.721	0.729	0.746	0.794	0.766	0.759	0.769	0.766	0.767	0.755	0.003	0.079	-0.079
t-stat	*3.18*	*2.79*	*3.01*	*3.08*	*3.08*	*3.28*	*3.12*	*3.10*	*3.06*	*3.05*	*3.07*	*3.03*	*0.03*	*2.91*	*-0.96*
$\boldsymbol{\alpha}_{FF}$	0.661	0.585	0.633	0.636	0.667	0.714	0.700	0.690	0.697	0.702	0.710	0.703	-0.025	0.075	-0.102
t-stat	*3.97*	*3.46*	*4.01*	*4.16*	*4.35*	*4.69*	*4.59*	*4.54*	*4.45*	*4.38*	*4.39*	*4.41*	*-0.25*	*2.77*	*-1.09*
$\boldsymbol{\alpha}_{Carhart}$	0.606	0.501	0.522	0.510	0.507	0.542	0.505	0.477	0.469	0.468	0.463	0.437	0.184	0.103	0.078
t-stat	*3.80*	*3.09*	*3.34*	*3.34*	*3.32*	*3.56*	*3.34*	*3.14*	*3.04*	*3.01*	*2.98*	*2.82*	*1.91*	*3.71*	*0.85*

Table 4A. Delisting Reasons across IVol Quintiles

Panel A reports average percentage frequency of firms in different IVol quintiles being delisted for different reasons. "Merger" row looks at delistings due to the firm being acquired (dlstcd code between 200 and 299), "Exchange" row looks at delistings due to company's stock exchanged for something (e.g., for cash if a firm is taken private) with dlstcd code between 300 and 399, "Liquid" row looks at delistings due to liquidation (dlstcd code between 400 and 499), "PerfDelist" row looks at delistings due to performance reasons (dlstcd code between 500 and 599). Panels B-D report 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). A firm is delisted if dlstcd code from CRSP events file is 200 and above. A firm is demoted from NYSE if $exchcd \neq 1$ in the current month, but $exchcd = 1$ in the portfolio formation month. The percentage frequencies in Panel A are measured in the month after portfolio formation; the headings of Panels B-D report the number of months between portfolio formation and the measurement of delisting/demotion frequencies. IVol is volatility of the three-factor FF model residuals; the FF model is fitted, in each firm-month, to daily stock returns in the past month (at 15 valid observations are required). The sample is restricted to NYSE firms only (exchcd=1). 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. Different Delisting Events

	Low	IVol2	IVol3	IVol4	High	H-L
Merger	0.847	0.178	0.164	0.145	0.212	-0.635
t-stat	*15.1*	*12.4*	*12.3*	*11.2*	*14.3*	*-12.3*
Exchange	0.028	0.011	0.012	0.010	0.038	0.011
t-stat	*3.15*	*3.89*	*3.82*	*4.34*	*5.30*	*1.77*
Liquid	0.024	0.001	0.004	0.002	0.008	-0.016
t-stat	*1.85*	*1.43*	*2.50*	*2.03*	*2.80*	*-1.17*
PerfDelist	0.015	0.007	0.006	0.010	0.284	0.269
t-stat	*4.93*	*3.33*	*3.10*	*3.76*	*10.23*	*9.67*

Panel B. IVol lagged by 3 months

	Low	IVol2	IVol3	IVol4	High	H-L
Delist	0.626	0.212	0.216	0.230	0.749	0.123
t-stat	*14.0*	*13.3*	*13.8*	*14.9*	*19.2*	*2.77*
PerfDelist	0.016	0.005	0.010	0.018	0.276	0.259
t-stat	*4.53*	*2.66*	*4.26*	*4.97*	*10.0*	*9.22*
Demotion	0.024	0.018	0.020	0.027	0.099	0.075
t-stat	*5.16*	*5.13*	*4.69*	*6.81*	*10.5*	*7.55*

Panel C. IVol lagged by 6 months

	Low	IVol2	IVol3	IVol4	High	H-L
Delist	0.373	0.258	0.283	0.359	0.785	0.412
t-stat	*11.6*	*16.0*	*15.6*	*17.1*	*19.4*	*10.5*
PerfDelist	0.012	0.008	0.011	0.024	0.279	0.267
t-stat	*3.65*	*3.57*	*4.22*	*5.57*	*10.1*	*9.43*
Demotion	0.023	0.015	0.025	0.035	0.093	0.070
t-stat	*5.17*	*4.32*	*6.08*	*7.65*	*10.4*	*7.33*

Panel D. IVol lagged by 12 months

	Low	IVol2	IVol3	IVol4	High	H-L
Delist	0.295	0.314	0.361	0.426	0.691	0.395
t-stat	*11.8*	*14.3*	*15.2*	*19.3*	*18.4*	*10.7*
PerfDelist	0.009	0.016	0.020	0.042	0.260	0.251
t-stat	*3.81*	*4.81*	*5.08*	*6.69*	*10.2*	*9.78*
Demotion	0.024	0.018	0.030	0.037	0.087	0.063
t-stat	*4.76*	*5.45*	*7.12*	*7.85*	*11.0*	*7.28*