Only Intraday Volatility Matters

Alexander Barinov

School of Business
University of California Riverside

E-mail: **abarinov@ucr.edu**
http://faculty.ucr.edu/~abarinov

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Abstract

Volatility of intraday returns is negatively related to future close-to-close returns. The part of overnight volatility that is orthogonal to intraday volatility is not priced. Controlling for intraday volatility also eliminates the disagreement effect from Diether et al. (2002) and the MAX effect from Bali et al. (2011), while controlling for overnight volatility does not weaken those effects. Intraday volatility also can serve as a limits-to-arbitrage proxy, even after being orthogonalized to overnight volatility. Overnight volatility does not seem to create limits to arbitrage once intraday volatility is controlled for.

JEL classification: G11, G12, G14

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1 Introduction

A growing recent literature looks at intraday and overnight returns and their determinants. Boudoukh et al. (2019) show that overnight returns are driven in large part by public news (e.g., after-the-bell earnings announcements and before-the-bell macro news), while only 12% of intraday volatility can be tied to public information, with the rest being noise trading and gleaning private information from prices. Barardehi et al. (2021) argue that overnight returns should be discarded when estimating the Amihud (2002) price impact measure, because overnight returns are primarily information-driven. Lou et al. (2019) show that institutions are more likely to trade during the day and near the close, while individuals tend to trade relatively more overnight or around the open, suggesting that intraday and overnight markets are driven by different clienteles.

Another strand of literature looks at intraday and overnight returns. Hendershott et al. (2020) find that the market beta is priced negatively in intraday (open-to-close) returns and positively in overnight (close-to-open) returns, which is suggestive of the intraday and overnight clienteles perceiving risks differently. Lou et al. (2019) and Akbas et al. (2022) establish the "tug-of-war" pattern, which is the tendency of positive intraday returns to be followed by negative overnight returns and vice versa. Lou et al. (2019) also illustrate "tug-of-war" by showing that most asset-pricing factors earn returns of different sign during the day and overnight.

This paper joins these two strands of literature by deriving a signal from intraday and overnight returns (return volatility) and using this signal in asset-pricing context. I define intraday/overnight volatility as standard deviation of open-to-close/close-to-open returns within a month.

The paper starts with looking into why high volatility firms are overpriced: Ang et al. (2006) establish this result using close-to-close volatility to sort firms into portfolios. I find that the Ang et al. result is driven completely by intraday volatility: the part of overnight volatility that is unrelated to intraday volatility has no ability to predict future returns, while the reverse is not true. My finding holds in conditional sorts, in sorts on overnight volatility orthogonalized to intraday volatility, and in cross-sectional regressions.

There are two potential explanations of the evidence that intraday volatility predicts returns and overnight volatility does not. First, these two volatilities can be different, though correlated, signals. As suggested by evidence in Boudoukh et al. (2019) and Barardehi et al. (2021), overnight volatility is driven by public information, while intraday volatility is driven by private information, noise trading, fads and sentiment, etc. If investors are clear where firm-specific volatility is coming from, they understand that it is diversifiable and should not be priced, as the textbook wisdom suggests, and this is why overnight volatility (or, more precisely, its part that is unrelated to intraday volatility) is not priced. However, investors tend to be overexcited about volatility of unclear origin that happens during the day, and this is why firms with high intraday volatility are overpriced.

Second, both intraday volatility and intraday returns can be driven by one clientele, while overnight volatility and overnight returns are driven by another clientele. The evidence in Hendershott et al. (2020) suggests that the overnight clientele is more long-term and risk-averse, while the intraday clientele is more profit-chasing and risk-seeking. Hence, the intraday clientele will primarily consider intraday volatility and overprice firms with high intraday volatility and the overnight clientele will consider overnight (fundamental volatility) more and require a risk premium for holding volatile firms. Of course, in the situation when investors hold stocks for longer than one day/night, the intraday clientele can also react to overnight volatility and vice versa.

The clientele hypothesis and the signal hypothesis are not mutually exclusive; yet looking at intraday and overnight returns in addition to intraday and overnight volatility can shed light on what role both mechanisms play. I find that intraday volatility is negatively related to intraday returns and positively related to overnight returns, similar to what Lou et al. (2019) find for close-to-close volatility. This evidence is inconsistent with the signal hypothesis, but consistent with the clientele hypothesis: intraday and overnight investors seem to disagree on what intraday volatility signals and how to price it. However, the part of overnight volatility that is orthogonal to intraday volatility is not priced in either intraday or overnight returns, which is consistent with the signal hypothesis, but not necessarily with the clientele hypothesis: both intraday and overnight investors agree that the signal in overnight volatility is different from the signal in intraday volatility, but they also treat overnight volatility the same way, as if they were one clientele, not two.

Taken together, the intraday and overnight returns results suggest that intraday and overnight clienteles agree on what overnight volatility means (it is likely to come from fundamental, publicly available information that creates diversifiable movements in stock prices), but disagree about the signal in intraday volatility: the intraday clientele takes higher intraday volatility as the chance to go for the long shot, and the overnight clientele thinks about intraday volatility as a risk deserving a premium. In the end, intraday volatility is negatively related to close-to-close returns, so the impact the intraday clientele has on pricing stocks with high intraday volatility is greater than the impact of the overnight clientele.

The paper also offers two additional pieces of evidence that intraday volatility matters and overnight volatility does not. First, controlling for intraday volatility eliminates the analyst disagreement effect from Diether et al. (2002) and the MAX effect from Bali et al. (2011), while controlling for overnight volatility does not materially weaken those two anomalies.

Second, mispricing (measured by the effect the composite mispricing measure from Stambaugh et al., 2015 has on future alphas) is stronger for firms with high intraday volatility (even if one holds overnight volatility fixed), but does not depend on overnight volatility (holding intraday volatility fixed). I conclude that the market views intraday volatility as one of limits-to-arbitrage proxies, while the part of overnight volatility that is unrelated to intraday volatility does not create limits to arbitrage.

The closest study to my paper is Barardehi et al. (2026), which finds that past intraday returns generate short-term reversal and momentum in close-to-close returns, while past overnight returns are related to the long-term reversal in close-to-close returns. My paper also uses the idea that intraday and overnight returns can send different signals, but looks at intraday/overnight volatility rather than cumulative past returns.

2 Data

Two main variables in the paper are intraday and overnight volatilities, defined as standard deviation of intraday/overnight returns within a month.

Intraday return is defined as $ID_t = \frac{prc_t - openprc_t}{openprc_t}$, where *prc* is the closing daily price from CRSP daily files and *openprc* is the opening daily price from CRSP daily files.

Overnight return is $ON_t = \frac{1+ret_t}{1+ID_t} - 1$, where *ret* is daily return from CRSP daily files.

Close-to-close total volatility is standard deviation of *ret* from CRSP daily files.

The sample starts in July 1992, when opening daily prices become available on CRSP, and ends in December 2022.

All other variables in the paper are defined in Data Appendix.

3 Intraday vs. Overnight Volatility

3.1 Portfolio Sorts

Table 1 sorts firms on intraday volatility in Panel A and on overnight volatility in Panel B. Sorts on intraday volatility produce a significant alpha spread between the bottom and top quintiles that ranges from 36 bp to 103 bp per month in value-weighted returns and from 59 bp to 110 bp per month in equal-weighted returns, depending on the model used to estimate the alphas. The alpha spread between is also statistically significant, with t-statistic of at least 2.08 (4.53) in value-weighted (equal-weighted) returns.

The volatility effect in intraday volatility sorts is quite similar to the same effect from sorts on close-to-close daily volatility (not tabulated to save space). For example, the equal-weighted five-factor Fama and French (2015) alpha of the low-minus-high portfolio is 61 bp per month, t-statistic 5.19, in sorts on close-to-close daily volatility vs. 59 bp per month, t-statistic 4.56 in Panel A2 of Table 1.

The sorts on overnight volatility in Panel B of Table 1 produce a significantly weaker alpha spread: compared to Panel A, it declines by 40-45 bp per month and becomes insignificant in five-factor alphas (6 bp per month, t-statistic 0.39, and 15 bp per month, t-statistic 1.41, in Panels B1 and B2, respectively) and marginally insignificant in value-weighted Carhart (1997) alphas. The decline in the volatility effect between Panel A and Panel B is driven primarily by the change in the alphas of the top volatility quintile, which become less negative by 25-40 bp per month and turn insignificant in almost all cases.

The results in Table 1 are consistent with intraday and overnight volatility picking up different things: firms with high intraday volatility are clearly overpriced, while the overpricing evidence is more muted for firms with high overnight volatility. However, many firms have both high intraday volatility and high overnight volatility: the average correlation between the two volatilities in my sample is around 0.7, with 50% of firms having the correlation in a tight range between 0.67 and 0.74. On the other hand, since the R-squared of a pairwise regression equals to the squared correlation between the two variables, the reported correlations imply that around 50% of variation in intraday volatility is unrelated to the variation in overnight volatility and vice versa, so there is definitely a significant independent variation in both.

To break the relation between intraday and overnight volatility, Table 2 performs conditional sorts. Panel A sorts firms on overnight volatility and then, in each overnight volatility quintile, sorts them into intraday volatility quintiles. The quintile alphas presented in Panel A are obtained by averaging returns of the respective intraday volatility quintile over all overnight volatility quintiles and then regressing the average returns on the standard asset-pricing factors. Conditional sorts intend to keep overnight volatility constant across intraday volatility quintiles, so Panel A shows the effect intraday volatility has on future returns holding overnight volatility the same.

Panel A of Table 2 reveals that conditional sorts on intraday volatility produce about the same magnitude of the volatility effect as the unconditional sorts in Panel A of Table 1. In other words, sorting on the part of intraday volatility that is unrelated to overnight volatility is as powerful as sorting on total intraday volatility – comparing Panels A of Table 1 and Table 2, we notice that value-weighted alphas of the top volatility quintile and the low-minus-high alpha spread declined by 10-20 bp per month, and the equal-weighted alphas stayed roughly the same.

Panel B of Table 2 does the opposite of what Panel A does and makes sorts on overnight volatility conditional on intraday volatility. The effect is striking: sorting on the part of overnight volatility that is unrelated to intraday volatility produces no effect on future returns. The alphas of the top overnight volatility quintile, which were as negative as -35 bp per month in Panel B of Table 1, are now predominantly positive and within 10 bp of zero; the low-minus-high alpha spread reached 61 bp per month in unconditional sorts, but now is at most 15 bp per month and turns insignificantly negative in the five-factor model. Overall, between unconditional and conditional sorts, the alphas of the top overnight volatility quintile become 15-35 bp per month (or by at least 94%) closer to zero and the low-minus-high alpha spread declines by 20-45 bp per month (or by at least 75%).

The conclusion from Table 2 is that only intraday volatility is priced: subtracting the impact of overnight volatility from intraday volatility does not impact the ability of intraday volatility to predict future returns, while the part of overnight volatility that is unrelated to intraday volatility is clearly not priced, so the pricing of overnight volatility in unconditional sorts (Panel B of Table 1) is completely driven by intraday volatility.

This conclusion is reinforced by Table 3, which orthogonalizes intraday and overnight volatility to each other. In Panel A, I perform, in each month, a cross-sectional regression of log intraday volatility on log overnight volatility and the squared log of overnight volatility – and then sort firms on the residual from this regression. The sort on the part of intraday volatility that is orthogonal to overnight volatility produces slightly larger alphas compared even to Panel A of Table 1. A particular improvement in precision can be observed in value-weighted five-factor alphas of the top volatility quintile and the low-minus-high portfolio, which have t-statistics of -1.88 and 2.08, respectively, in Panel A of Table 1 and t-statistics of -2.34 and 3.0 in Panel A of Table 3.

In Panel B, I perform a similar cross-sectional regression of log overnight volatility on log intraday volatility and the squared log of intraday volatility and then sort firms on the residual, which captures the part of overnight volatility that is unrelated to intraday volatility. This part of overnight volatility is positively, not negatively priced: it is now the bottom volatility quintile that produces negative and (marginally) significant alphas, and the low-minus-high alpha spread ranges between -20 bp and -30 bp per month (statistically significant in equal-weighted alphas), suggesting that high volatility firms tend to earn higher returns than low volatility firms, in contrast to the Ang et al. (2006) result and the rest of Tables 1-3.

The totality of evidence in Tables 1-3 suggests that there are two parts of total volatility that was shown to be negatively priced in Ang et al. (2006). One part is intraday volatility – it is negatively priced and its pricing drives the negative pricing of total volatility in Ang et al. (2006). The second part is the part of overnight volatility orthogonal to intraday volatility, and this part is either not priced or weakly positively priced. Intraday volatility can be further partitioned into the part that is orthogonal to overnight volatility and strongly negatively priced, as Panels A of Tables 2 and 3 show, and the part that is related to overnight volatility and explains why overnight volatility is negatively priced in unconditional sorts (Panel B of Table 1).

There are two plausible economic mechanisms behind the different relation between future returns and intraday/overnight volatility. First, investors can agree that intraday and overnight volatility signal different things. Intraday volatility can make them excited and willing to overbuy high volatility stocks, and overnight volatility can seem to investors to be a more fundamental thing, which has to either be positively priced, as in, e.g., Merton (1987), or be diversifiable and thus not priced. Second, there could be two types of investors: intraday investors (speculators), who are excited about both intraday and overnight volatility (and thus tend to overprice all volatile stocks) and overnight investors (long-term investors), who perceive intraday volatility as transient noise that should not be priced and overnight volatility as fundamental risk that has to be positively priced. The resulting force of both groups of investors trading is that intraday volatility is negatively priced (because long-term investors do not battle speculators) and overnight volatility is not priced (because the strong demand for volatile stocks from speculators is counterbalanced by weak demand for those stocks by long-term investors).

3.2 Intraday/Overnight Idiosyncratic Volatility

Ang et al. (2006) show that sorting firms on total volatility and on idiosyncratic volatility produces roughly the same spread in future alphas. This is not surprising: in my sample period, the median R-square of the three-factor Fama and French (1993) model fitted to daily returns in the past month (which is the model Ang et al. use to measure idiosyncratic volatility) is 0.259; the 25th/75th percentile of the R-squared distribution is roughly 18%/36%. Hence, firm-level total volatility is primarily idiosyncratic, and sorting on total or idiosyncratic volatility expectedly produces similar results.

The reason why I chose total volatility for the main tests is that it is unclear how to measure idiosyncratic volatility for intraday/overnight returns. From the point of view of equilibrium models, both intraday and overnight returns should be regressed on close-to-close returns to standard asset-pricing factors (e.g., the five factors from Fama and French, 2015). On the other hand, Hendershott et al. (2020) find that the market beta is priced negatively during the day and positively at night, while Lou et al. (2019) find that the factor risk premia are different in intraday and overnight returns: most Fama-French factors earn all their premia intraday (and the premia become negative overnight), while the market factor and SMB earn the majority of their premia overnight. Thus, it might be warranted to estimate intraday idiosyncratic volatility by regressing intraday (overnight) stock returns on intraday (overnight) factor returns (and then calculate the standard deviation of residuals).

Table 4 tries calculating idiosyncratic volatility both ways: in Panel A (C), intraday (overnight) stock returns are regressed on close-to-close factor returns to obtain the residuals, the standard deviation of which will become idiosyncratic volatility; in Panel B (D), intraday (overnight) stock returns are regressed on intraday (overnight) factor returns and the residuals are used to estimated idiosyncratic volatility. The results in Panels A and B (sorts on intraday idiosyncratic volatility) are similar to each other and somewhat weaker than the baseline results in Panel A of Table 1 (unconditional sorts on total intraday volatility). Similarly, the results in Panels C and D (sorts on overnight idiosyncratic volatility) are also similar to each other and slightly weaker than the baseline results in Panel A of Table 1 (unconditional sorts on total overnight volatility).

I make two conclusions: first, it does not matter much for idiosyncratic volatility sorts whether idiosyncratic volatility was calculated using the model with close-to-close factor returns or intraday/overnight factor returns to match the stock returns. Second, the total volatility effect and the idiosyncratic volatility effect are similar in magnitude, and it makes sense to consider the latter if I need to pick one, because the total volatility effect is marginally stronger.

3.3 Cross-Sectional Regressions

Table 5 runs cross-sectional regressions to corroborate the results in the previous subsections. The regressions are run at the firm-level, Fama-MacBeth style and use standard asset-pricing controls (beta, log of market cap, log of market-to-book, momentum, short-term reversal, investment-to-assets, and gross profitability). In my sample size, I observe that the market beta is not priced (though the slope is positive), the size effect and the short-term reversal exist (controlling for volatility seems essential for discovering the size effect), the investment and profitability effects are also significant, but momentum is weak (because of its 2009 crush) and the value effect is also weak (the value strategy did poorly in 1990s and 2010s and crushed in 2020). The main variables of interest though are log of total volatility (defined as in Ang et al., 2006) and logs of intraday and overnight volatilities (defined as in Table 1).

The first three columns of Panel A confirm the finding of Table 1 that future returns are negatively and significantly related to total (close-to-close) volatility and to intraday volatility, but insignificantly related to overnight volatility. Even prior to controlling for intraday volatility, the slope on overnight volatility is more than twice smaller than the slope on total volatility and almost three times smaller than the slope on intraday volatility.

In the fourth column, intraday and overnight volatility are used together – consistent with Table 3, the slope on intraday volatility slightly increases when overnight volatility is controlled for, and the slope on overnight volatility becomes positive and marginally significant in the presence of the intraday volatility control. Thus, column four confirms that the part of intraday volatility that is orthogonal to overnight volatility is strongly negatively priced and the part of overnight volatility that is orthogonal to intraday volatility is weakly positively priced – so the total volatility effect in Ang et al. (2006) is driven by intraday volatility only.

The latter statement is further confirmed by column five, which uses close-to-close volatility and intraday volatility together. Intraday volatility is part of close-to-close volatility, so the two variables are strongly related. Column five shows that both become marginally significant when used together; the slope on close-to-close volatility drops by 55% and the slope on intraday volatility drops by 35% (compared to columns one and two), confirming that close-to-close volatility and intraday volatility essentially pick up the same thing.

Panel B makes two changes in the variables: first, total volatility is replaced by idiosyncratic volatility in all three cases, and second, the reversal control now records only intraday returns in the past month, since, as Barardehi et al. (2026) show, short-term reversal is driven only by intraday returns.

Panel B of Table 5 confirms the results in Table 4: replacing total volatility with idiosyncratic volatility does not change either the conclusion that the negative cross-sectional relation between volatility and future returns is driven by intraday volatility only or the conclusion that the part of overnight volatility that is unrelated to intraday volatility is positively, rather than negatively, priced. The results are even stronger than those in Panel A: the slope on overnight idiosyncratic volatility, when used alone in column three, is four times smaller than the slope on close-to-close idiosyncratic volatility and almost five times smaller than the slope on intraday idiosyncratic volatility (columns one and two, respectively). In column four of Panel B, where intraday and overnight volatility are used together, the positive effect of overnight volatility on future returns (controlling for intraday volatility) is now highly significant with t-statistic 2.89. In column five, where close-to-close and intraday volatility are used together, close-to-close volatility now loses significance even at the 10% level.

I also discover in Panel B that the short-term reversal based on intraday returns only indeed works, but the volatility effect is unaffected by controlling for the short-term reversal, in contrast to Huang et al. (2010), but consistent with Barinov (2025).

3.4 Volatility Effect in Intraday and Overnight Returns

So far, the paper used close-to-close returns to evaluate effects of intraday and overnight volatility on future returns. Several papers argue that overnight and intraday trading is done by different clienteles: Berkman et al. (2012) suggest that overnight trading is done primarily by individual investors, and Bogousslavsky (2021) argues that many arbitrageurs are wary of leaving positions overnight. Hendershott et al. (2020) use this evidence to argue that overnight investors are more long-term and look more at fundamentals, which could be the reason why the market beta is priced positively in overnight returns and negatively in intraday returns; Lou et al. (2019) and Akbas et al. (2022) present "tug-of-war" evidence suggesting that the intraday clientele and the overnight clientele trade against each other. It is thus possible that intraday and overnight volatility are created by different clienteles and thus have different effect on intraday and overnight returns.

It is also possible that the signal in intraday and overnight volatilities is different. Boudoukh et al. (2019) find that 12% (50%) of intraday (overnight) volatility is driven by publicly available information; Barardehi et al. (2021) show that the Amihud (2002) price impact measure is better at measuring trading costs when overnight return is dropped from the calculation, because overnight returns are information-driven, while intraday returns are affected relatively more by noise trading and microstructure effects. Hence, both the intraday and overnight clienteles can view intraday volatility as desirable (and thus the negative relation between intraday volatility and future returns in the previous subsections) and view overnight volatility as purely firm-specific and thus diversifiable (and hence no relation between future returns and overnight volatility once intraday volatility is controlled for).

The clientele explanation of the evidence in the paper and the signal hypothesis are not mutually exclusive. Table 6 looks at what role both mechanisms play in pricing of intraday and overnight volatility and switches from close-to-close returns to considering intraday and overnight returns separately.

Table 6 starts with sorts on close-to-close volatility in Panel A and reports intraday and overnight alphas in the left part (Panel A1) and the right part (Panel A2), respectively. The alphas are computed the conventional way, i.e., by regressing intraday or overnight returns to volatility quintiles on close-to-close factor returns. Panel A confirms the result in Lou et al. (2019) that close-to-close volatility is negatively priced in intraday returns and positively priced in overnight returns. One possible interpretation can be that the intraday clientele goes for the long shot and thus overprices volatile stocks, while the overnight clientele is wary of volatile stocks and demands a risk premium for holding them. (This interpretation would be completely true if the intraday/overnight clientele held stocks only during the day/night; in reality, low intraday returns to volatile stocks will also accrue to overnight investors who hold stocks for longer than one night, and vice versa).

Panel B recomputes alphas regressing intraday quintile (overnight) returns on intraday (overnight) factor returns, because all factors are priced differently during the night and during the day: as Table A in Factor Appendix shows, MKT and SMB earn most of their returns overnight, while HML, CMA, RMW, MOM earn all their returns during the day (and earn significantly negative returns at night). Matching the observation period for quintile returns and factors reduces the alphas, but still leaves them significant: for example, intraday (overnight) five-factor alpha spread between bottom and top quintile is

1.64% (-1.51%) per month in Panel A vs. 1.25% (-0.47%) in Panel B.

Panel C of Table 6 performs sorts on the part of intraday volatility that is orthogonal to overnight volatility. This is what Panel A of Table 3 did, but this time I look at intraday/overnight returns separately and use intraday/overnight factors to compute the alphas. The alphas in Panel C are very close to the ones in Panel B, expanding the conclusion of Panel A of Table 3 that the part of intraday volatility that is unrelated to overnight volatility is priced the same way as close-to-close volatility. Panel A of Table 3 establishes this is true for close-to-close returns; Panel C of Table 6 shows the same is true about both overnight and intraday returns.

The evidence in Panel C is consistent with the clientele hypothesis, but not with the signal hypothesis: clearly, the intraday clientele and the overnight clientele disagree on what the signal in intraday volatility means. The intraday clientele probably views high intraday volatility as a chance to go for the long shot (and therefore during the day firms with high intraday volatility look overpriced). The overnight clientele seems to view intraday volatility as a source of risk that happens during the day and needs to be compensated for by higher returns at night, and overnight alphas of firms with high intraday volatility are indeed large and positive (between 35 bp and 66 bp per month in Panel C, t-statistics above 3.9).

Panel D of Table 6 looks at sorts on the part of overnight volatility that is orthogonal to intraday volatility – the sorts are similar to the ones in Panel B of Table 3, but Panel D of Table 6 looks at intraday and overnight returns separately. I find a slightly negative volatility effect in intraday returns (-38 bp per month, t-statistic -2.82 in Carhart alphas and -20 bp per month, t-statistic -1.39 in five-factor alphas) and virtually no effect in overnight returns (though in both intraday and overnight returns the relation between overnight volatility and future alphas is U-shaped rather than linear, but that may be a consequence of orthogonalization).

I conclude that both intraday and overnight investors view the part of overnight volatility that is unrelated to intraday volatility as a largely diversifiable risk that should not be priced, consistent with the signal hypothesis, but not necessarily the clientele hypothesis. Both intraday and overnight clienteles agree that intraday and overnight volatility should be priced differently, because they allegedly pick up different things, but somehow the two clienteles disagree about how to price intraday volatility, but agree on how to price overnight volatility.

In untabulated results, I also perform conditional sorts first on intraday volatility and then on overnight volatility in an effort to escape the U-shaped relation between future alphas and the part of overnight volatility that is unrelated to intraday volatility. I find that the U-shape in the alphas is gone and in the conditional sorts overnight volatility is slightly positively (negatively) related to future intraday (overnight) returns, but the relation is several times weaker that a similar one between intraday volatility and intraday/overnight returns (see Panel C of Table 6) and is completely absent in five-factor alphas.

Also in untabulated results, I perform unconditional sorts on overnight volatility and find the results similar in spirit, but roughly twice weaker than the ones in Panel C. I conclude that intraday volatility (both its common part with overnight volatility and its part that is independent of overnight volatility) is negatively related to intraday returns and positively related to overnight returns, i.e., intraday investors overprice firms with high intraday volatility, and overnight investors view firms with high intraday volatility as dangerous and require higher returns from them. The part of overnight volatility that is unrelated to intraday volatility is not priced – be it in close-to-close, intraday, or overnight returns, only intraday volatility matters.

4 Intraday/Overnight Volatility and Other Anomalies

4.1 Intraday/Overnight Volatility and Short-Term Reversal

Huang et al. (2010) claim that the short-term reversal in Jegadeesh (1990) is behind the idiosyncratic volatility effect in Ang et al. (2006), because highly volatile firms are more likely to be recent winners due to positive skewness of individual firms returns. Medhat and Schmeling (2022) show that short-term reversal is concentrated among low-turnover stocks, while high-turnover stocks exhibit short-term momentum. Barinov (2025) used the evidence in Medhat and Schmeling (2022) to refute the hypothesis of Huang et al. (2010) that the idiosyncratic volatility effect is short-term reversal in disguise: as Barinov (2025) shows, the idiosyncratic volatility effect is equally strong for low- and high-turnover firms.

In Panel A of Table 7, I extend the evidence in Medhat and Schmeling (2022) to short-term reversal based on intraday returns (first documented by Barardehi et al., 2026). I report the magnitude of this version of short-term reversal across turnover quintiles and find that the short-term reversal based on intraday returns is strong in the bottom two turnover quintiles and turns negative (i.e., becomes short-term momentum) in the top turnover quintile. The difference in the short-term reversal between bottom and top turnover quintiles is at 1% per month in value-weighted returns and at 1.3% in equal-weighted returns, similar to the difference Medhat and Schmeling find in their Table 1.

In Panel B of Table 7, I similarly extend the evidence in Barinov (2025) to the intraday volatility effect. Panel B reports alphas of the low-minus-high intraday volatility strategy across turnover quintiles and shows that, in contrast to the short-term reversal, the intraday volatility effect is largely flat across turnover quintiles and thus it is unlikely to be the short-term reversal repackaged, even though both the short-term reversal and the volatility effect in returns seem to be driven by the signals that come from intraday returns (cumulative intraday returns in the past month and intraday return volatility, respectively).

Another point of Table 7 is that the results in the paper are not a juxtaposition of Huang et al. (2010) and Barardehi et al. (2026): the former paper argues that the idiosyncratic volatility effect is driven by the short-term reversal, while the latter points out that the short-term reversal is driven by intraday returns. If one believes both papers, one would not be surprised that the idiosyncratic volatility effect is also driven by intraday returns (i.e., their volatility). Table 7 breaks the link between the short-term reversal and the volatility effect, showing that they behave differently across turnover quintiles – so the fact that the short-term reversal is driven by intraday returns in Barardehi et al. (2026) does not imply that the volatility effect will be driven by intraday volatility.

In untabulated results, I also look at the impact overnight volatility (in particular, its part unrelated to intraday volatility, as in Panel B of Table 3) has on future alphas across turnover quintiles. I find that the overnight volatility effect is largely absent in all turnover quintiles and sometimes turns out negative, not positive in the bottom turnover quintiles (for example, in equal-weighted CAPM and Carhart alphas). Hence, the impact of overnight volatility on returns also does not overlap with the short-term reversal.

Also in untabulated results, I check how long the effect of intraday volatility on future alphas lasts. In equal-weighted returns, as well as value-weighted CAPM and Carhart alphas, the effect stays significant for more than 12 months – its magnitude drops by half by month 12, but I observe no sharp decrease in the alphas after one or two months, as should be the case if there was a strong overlap between the short-term reversal (that lasts at most one or two months) and the intraday volatility effect.

4.2 Intraday Volatility Explains Other Anomalies

It is known since Ang et al. (2006) that the idiosyncratic volatility effect has a strong, though incomplete overlap with the analyst disagreement effect of Diether et al. (2002). Bali et al. (2011) also point out a very strong overlap between their MAX effect and the idiosyncratic volatility effect. In this subsection, I study the ability of intraday volatility to explain the analyst disagreement effect and the MAX effect in addition to explaining the volatility effect based on close-to-close volatility.

Panel A of Table 8 shows that the analyst disagreement effect still exists in my sample period (1992-2022, the majority of it is the post-publication sample). In equal-weighted returns (Panel A2), it is between 41 bp and 73 bp per month, depending on the model used to estimate the alphas, and the t-statistics are always above 4. In value-weighted returns (Panel A1), the analyst disagreement effect loses statistical significance in the five-factor alphas, but stands at above 50 bp per month with t-statistics above 3 in the CAPM and the Carhart model.

Panel B of Table 8 orthogonalizes analyst disagreement to intraday volatility by regressing, cross-sectionally, log of analyst disagreement on log of intraday volatility and squared log of intraday volatility and then taking the residual from the regression and sorting firms into quintiles on the residual. The sorts in Panel B produce no difference in the alphas between low and high disagreement firms – the difference in the alphas is between -10.2 bp and 16.5 bp per month, and all t-statistics but one are below 1.2 by absolute magnitude. I conclude from Panel B that intraday volatility explains the analyst disagreement effect.

In unreported results, I orthogonalize analyst disagreement to overnight volatility and find that the analyst disagreement effect remains about as strong as in Panel A. I conclude that it is intraday volatility, not overnight volatility (and not the part they have in common) that explains the analyst disagreement effect.

Panel C of Table 8 sorts firms on the maximum daily return in the past month and shows that the MAX effect of Bali et al. (2011) is alive and well in 1992-2022. In equal-weighted returns (Panel C2), it exceeds 60 bp per month with t-statistics above 4.9. In value-weighted CAPM and Carhart alphas (Panel C1), it is also above 60 bp per month with t-statistics above 3.6, and in value-weighted five-factor alphas it is still at 30 bp per month, t-statistic 2.25.

Panel D orthogonalizes MAX to intraday volatility the same way Panel B did: I regress, in cross-section, log of MAX on log of intraday volatility and squared log of intraday volatility, take the residual, sort firms into quintiles and report the quintiles alphas in Panel D. As was the case in Panel B with the analyst disagreement effect, I find in Panel D that there is no MAX effect controlling for intraday volatility: sorting firms on the part of MAX that is unrelated to intraday volatility produces low-minus-high quintile alpha spreads between -17 bp and 13 bp per month, with t-statistics at most 1.5 by absolute magnitude. Hence, intraday volatility explains the MAX effect.

In untabulated results, I find that overnight volatility does not explain the MAX effect, because sorting on the part of MAX that is orthogonal to overnight volatility produces the MAX effect almost as strong as the one in Panel C (unconditional sorts on MAX). I also find that the MAX effect is explained by intraday MAX, but the effect of intraday MAX on future returns is in turn explained by intraday volatility.

Table 9 corroborates the results in Table 8 by running cross-sectional regressions of future returns on standard asset-pricing controls (beta, log of market cap, log of market-to-book, momentum, short-term reversal, investment-to-assets, and gross profitability) and, in Panel A, on log of MAX and logs of close-to-close and intraday volatility. The first column of Panel A establishes a strong MAX effect (t-statistic -2.59). In columns two and three, I find that controlling for either close-to-close or intraday volatility kills off the MAX effect (the slope on MAX becomes positive and insignificant), while both close-to-close or intraday volatility remain significant with t-statistics -4.51 and -4.21 in the presence of MAX.

In Panel B, I use log of analyst forecast dispersion (Disp) instead of MAX. In column one, the analyst disagreement effect is strong with t-statistic -2.34. In columns two and three, which control for close-to-close and intraday volatility, respectively, the slope on Disp shrinks by a factor of 7 and 8.5 and the t-statistics dip below 0.4 by absolute magnitude. Close-to-close and intraday volatility remain significant in the presence of Disp and have t-statistics exceeding 2.15 by absolute magnitude. The t-statistics are lower, because the sample of firms covered by at least two analysts on IBES (which is needed to compute DISP) is much smaller than the sample of firms with enough daily returns to compute MAX.

4.3 Intraday Volatility as a Limits-to-Arbitrage Measure

Bogousslavsky (2021) shows that arbitrageurs are wary of leaving their positions open overnight, and even when they carry a position for multiple days, they definitely want to close it during the day and thus are concerned about the price at which they will close. It seems natural then to assume that when arbitrageurs think of volatility as a limit to arbitrage, they are thinking about intraday volatility and not close-to-close or overnight volatility. On the other hand, one can also argue that the fact that arbitrageurs do not want to leave their positions open overnight implies that arbitrageurs are very concerned about overnight volatility.

Table 10 tests this prediction using the mispricing measure of Stambaugh et al. (2015) that unites 11 most popular anomalies into a single mispricing score. In Panel A, I look at the alphas of the long-short strategy based on the Stambaugh et al. mispricing measure across intraday volatility quintiles. The strategy buys/shorts firms in the bottom/top quintile based on the cumulative mispricing measure. The intraday volatility is orthogonalized to overnight volatility before the intraday volatility quintiles are formed, as in Panel A of Table 3.

In value-weighted returns (Panel A1), the alphas of the long-short strategy are largely flat across the bottom four volatility quintiles and then spike sharply in the quintile with the highest intraday volatility. The difference in the alphas of the strategy between top and bottom volatility quintiles is substantial and varies from 66 bp to 90 bp per month depending on what model is used to estimate the alphas. In equal-weighted returns (Panel A2), the increase in the alphas across the volatility quintiles is more monotonic, but the 50-65 bp per month spike in the top volatility quintile is still very visible. The difference in the alphas between top and bottom volatility quintiles is between 78 bp and 105 bp per month, with t-statistics exceeding 4.3.

Panel B presents the alphas of the same long-short strategy based on the mispricing measure of Stambaugh et al. (2015) across overnight volatility quintiles, with overnight volatility orthogonalized to intraday volatility (as in Panel B of Table 3). In Panel B, the alphas are largely flat across overnight volatility quintiles, with the alpha differential between the top and bottom quintiles being between -23 bp and 17 bp per month and the t-statistics below 1.1 in absolute magnitude.

I conclude from Table 10 that intraday volatility is a good limits-to-arbitrage measure: even after I orthogonalize it to overnight volatility, mispricing is stronger in the high intraday volatility subsample. Overnight volatility, on the other hand, is unrelated to the strength of mispricing once orthogonalized to intraday volatility, so overnight volatility is unrelated to limits to arbitrage.

Bogousslavsky (2021) uses overnight volatility as a limits-to-arbitrage proxy in his Table 2, but he is looking at changes in overnight variance of a large mispricing-based portfolio rather than at the level of overnight volatility for the firms making up the portfolio. Also, Table 10 is careful to orthogonalize overnight volatility to intraday volatility; in untabulated results, I redo Panel B of Table 10 with untransformed overnight volatility and find that it is related to mispricing – which only means that the part intraday and overnight volatility have in common is related to mispricing, because the other part (unrelated to intraday volatility) is not related to mispricing in Panel B. Hence, my results are not at odds with the test Bogousslavsky runs in his Table 2 (though his test may be picking up the effect of intraday rather than overnight volatility).

5 Conclusion

Only intraday volatility matters, and overnight volatility, once orthogonalized to intraday volatility, does not matter.

Intraday volatility matters in several ways: first, it seems to be the driving force behind the idiosyncratic volatility effect of Ang et al. (2006).

Second, intraday volatility can explain the analyst disagreement effect from Diether et al. (2002) and the MAX effect from Bali et al. (2011): once intraday volatility is controlled for, both effects are gone.

Third, intraday volatility is negatively priced in intraday returns and positively priced in overnight returns, suggesting that intraday traders are overexcited about firms with high intraday volatility and overnight traders require a premium for holding firms with high intraday volatility (potentially due to the impact intraday volatility has on overnight volatility). On the other hand, the part of overnight volatility that is unrelated to intraday volatility is not priced in either intraday or overnight returns.

Fourth, intraday volatility works as a limits-to-arbitrage proxy, while overnight volatility, once orthogonalized to intraday volatility, does not.

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A Data Appendix

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.

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.

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.

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.

Stambaugh et al. mispricing measure – average percentage ranking from ranking firms on 11 priced characteristics (accruals, momentum, ROA, asset growth, gross profitability, investment-to-assets, net stock issuance, cumulative stock issuance, net operating assets, O-score, expected probability of bankruptcy) in a way that ranks the most overpriced firm (highest accruals or lowest momentum) as 100, the most underpriced firm as 1, and firms in between get a corresponding percentage rank (e.g., a firm ranked 50th most overpriced in a sample of 2000 will get a rank of 97.5). The average is taken for all firms with at least five rankings available, otherwise Over is set to missing. Detailed description of the process and the sorting variables is in Stambaugh, Yu, and Yuan (2015).

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

A Factor Appendix

I follow Fama and French (2015) approach in constructing intraday and overnight factor returns. I split all firms into six bins: two on size (large and small) and three on either market-to-book or momentum or investment-to-assets or profitability (high, medium, and low). I then compute value-weighted high-minus-low (or low-minus-high) returns separately for large and small firms (e.g., low investment group minus high investment group) and take simple average between the two high-minus-low (or low-minus-high) spreads (among small and large firms) – that produces the factor returns. Using intraday/overnight returns this way yields intraday/overnight factor returns at daily frequency; the returns are then cumulated to the monthly level if needed.

Panels A and B report intraday and overnight value-weighted alphas of the factors, as well as their market betas and the average market return. Consistent with previous findings (Lou et al., 2019; Hendershott et al., 2020), the market factor and the SMB factor earn their returns primarily overnight, while all other factors are intraday phenomena, with overnight alphas being significantly negative (as an aside, the intraday and overnight alphas do not have to add up to the close-to-close alpha, because the calculation of the close-to-close alpha implicitly forces the beta to be the same during the day and the night, and Panels A and B show that the market betas of the factors are different in intraday and overnight returns).

Panel C reports correlations between intraday factor returns (above the main diagonal) and overnight factor returns (below the main diagonal). With the exception of the correlations with the market, the correlations between factors are usually similar in intraday and overnight returns. For example, during the day the correlation between SMB and HML is 0.225, and during the night the same correlation is 0.157. HML and RMW, as another example, are more tightly related with the correlation at 0.374 (0.376) in intraday (overnight) returns. The stability of factor correlations suggests that factors pick up similar things intraday and overnight, and one would be justified to use the same factors for explaining intraday and overnight returns (while allowing factor loadings to be different during the day and during the night).

Panel D reports correlations between close-to-close, intraday, and overnight returns to the same factor. I find that intraday and overnight factor returns are generally unrelated, which is an implication of market efficiency: in a perfectly efficient market, intraday returns to any portfolio should be unpredictable using its overnight returns and vice versa. For the market factor, the correlation between intraday and overnight returns is 0.004, for other factors the correlations are slightly negative, picking up the tug-of-war effect of Lou et al. (2019). SMB factor has the most negative correlation between intraday and overnight returns (-0.236), HML has the least negative (-0.046).

Another thing I find is that close-to-close factor returns are much more correlated with the intraday returns than with overnight returns, irrespective of when the alpha accrues to the factor. For the market factor, the correlations between close-to-close returns and intraday/overnight factor returns are close (0.790 vs. 0.615); for SMB and HML they are much further apart (0.828 vs. 0.191 and 0.76 vs. 0.263).

Overall, factor returns do look rather different during the day and during the night, which suggests using intraday factor returns when the left-hand side variable is an intraday return and overnight factor returns if the goal is to compute overnight alphas from overnight quintile/firm returns.

Table 1. Intraday and Overnight Volatility Sorts

The table presents quintile alphas from quintile sorts on total volatility of intraday (Panel A) and overnight (Panel B) returns. Intraday returns are defined as $ID_t = \frac{prc_t - openprc_t}{openprc_t}$, where *prc* is the closing daily price from CRSP daily files and *openprc* is the opening daily price from CRSP daily files. Overnight returns are $ON_t = \frac{1+ret_t}{1+ID_t} - 1$, where *ret* is daily return from CRSP daily files. Intraday/overnight volatility is standard deviation of intraday/overnight returns in the preceding month. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below \$5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Intraday Total Volatility Sorts

A1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.340	0.222	-0.029	-0.111	-0.688	1.027
t-stat	*3.66*	*2.28*	*-0.28*	*-0.95*	*-3.28*	*3.62*
$\alpha_{Carhart}$	0.245	0.159	-0.003	-0.007	-0.485	0.729
t-stat	*3.46*	*2.22*	*-0.04*	*-0.06*	*-2.84*	*3.40*
α_{FF5}	0.104	0.013	-0.123	-0.036	-0.257	0.361
t-stat	*1.67*	*0.21*	*-1.50*	*-0.35*	*-1.88*	*2.08*

A2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.498	0.402	0.332	0.173	-0.597	1.095
t-stat	*3.48*	*2.56*	*1.96*	*1.04*	*-2.87*	*4.53*
$\alpha_{Carhart}$	0.412	0.318	0.277	0.167	-0.485	0.897
t-stat	*4.65*	*4.21*	*3.34*	*2.28*	*-4.41*	*5.63*
α_{FF5}	0.282	0.149	0.106	0.041	-0.305	0.587
t-stat	*3.13*	*2.13*	*1.39*	*0.66*	*-3.56*	*4.56*

Panel B. Overnight Total Volatility Sorts

B1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.260	0.088	0.103	-0.055	-0.353	0.613
t-stat	*2.18*	*0.91*	*1.13*	*-0.65*	*-2.44*	*2.53*
$\alpha_{Carhart}$	0.156	0.008	0.031	-0.044	-0.169	0.326
t-stat	*1.58*	*0.11*	*0.42*	*-0.50*	*-1.34*	*1.64*
α_{FF5}	0.003	-0.148	-0.037	-0.057	-0.058	0.060
t-stat	*0.03*	*-2.26*	*-0.52*	*-0.71*	*-0.57*	*0.39*

B2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.337	0.225	0.175	0.102	-0.217	0.553
t-stat	*2.47*	*1.33*	*1.04*	*0.60*	*-1.26*	*2.78*
$\alpha_{Carhart}$	0.242	0.139	0.111	0.094	-0.144	0.386
t-stat	*2.83*	*1.52*	*1.34*	*1.22*	*-1.77*	*3.01*
α_{FF5}	0.108	-0.034	-0.032	-0.003	-0.045	0.153
t-stat	*1.27*	*-0.42*	*-0.47*	*-0.04*	*-0.61*	*1.41*

Table 2. Conditional Sorts on Intraday and Overnight Volatility

Panel A performs quintile sorts first on overnight volatility and then, within each overnight volatility quintile, on intraday volatility and reports alphas of each intraday volatility quintile. Panel B reverses the order and sorts first on intraday volatility and then, within each intraday volatility quintile, on overnight volatility and reports alphas of each overnight volatility quintile. Overnight and intraday volatility are defined in the header of Table 1. The models to compute the alphas are the CAPM, the four-factor Carhart (1997) model, and the five-factor Fama and French (2015) model. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Intraday Volatility Conditional on Overnight Volatility

A1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.314	0.125	0.065	-0.201	-0.500	0.814
t-stat	*3.30*	*1.79*	*0.90*	*-2.62*	*-3.04*	*3.35*
$\alpha_{Carhart}$	0.241	0.111	0.077	-0.150	-0.380	0.622
t-stat	*3.29*	*2.02*	*1.20*	*-1.91*	*-3.34*	*3.73*
α_{FF5}	0.102	-0.010	0.007	-0.091	-0.105	0.207
t-stat	*1.68*	*-0.18*	*0.11*	*-1.20*	*-1.15*	*1.63*

A2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.537	0.416	0.284	0.020	-0.603	1.140
t-stat	*3.49*	*2.69*	*1.89*	*0.13*	*-3.18*	*5.00*
$\alpha_{Carhart}$	0.459	0.372	0.249	0.022	-0.523	0.982
t-stat	*5.23*	*5.43*	*3.62*	*0.32*	*-6.37*	*7.25*
α_{FF5}	0.327	0.225	0.108	-0.036	-0.321	0.648
t-stat	*3.62*	*3.23*	*1.84*	*-0.61*	*-4.95*	*5.62*

Panel B. Overnight Volatility Conditional on Intraday Volatility

B1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.130	0.052	-0.012	-0.069	-0.023	0.153
t-stat	*1.17*	*0.60*	*-0.18*	*-1.22*	*-0.30*	*0.90*
$\alpha_{Carhart}$	0.061	-0.031	-0.053	-0.099	0.032	0.029
t-stat	*0.60*	*-0.41*	*-0.93*	*-1.58*	*0.46*	*0.19*
α_{FF5}	-0.049	-0.115	-0.120	-0.081	0.089	-0.138
t-stat	*-0.58*	*-1.50*	*-2.24*	*-1.38*	*1.29*	*-1.01*

B2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.127	0.086	0.045	0.060	0.026	0.102
t-stat	*0.84*	*0.57*	*0.30*	*0.41*	*0.17*	*0.76*
$\alpha_{Carhart}$	0.058	0.035	0.007	0.054	0.046	0.012
t-stat	*0.62*	*0.44*	*0.11*	*0.95*	*0.64*	*0.11*
α_{FF5}	-0.063	-0.075	-0.074	0.028	0.098	-0.161
t-stat	*-0.70*	*-1.13*	*-1.41*	*0.59*	*1.28*	*-1.51*

Table 3. Sorts on Intraday and Overnight Volatility Orthogonalized to Each Other

Panel A presents quintile alphas from sorts on residual, ϵ_i, from $\log(VolID_i) = a + b \cdot \log(VolON_i) + c \cdot \log^2(VolON_i) + \epsilon_i$. Panel B presents quintile alphas from sorts on residual, ϵ_i, from $\log(VolON_i) = a + b \cdot \log(VolID_i) + c \cdot \log^2(VolID_i) + \epsilon_i$. The regressions are performed cross-sectionally within each month. $VolID$ and $VolON$ are intraday and overnight volatilities defined as in the header of Table 1. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below \$5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Intraday Volatility Orthogonalized to Overnight Volatility

	A1. Value-Weighted Returns							A2. Equal-Weighted Returns					
	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**		**Low**	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**
α_{CAPM}	0.310	0.101	0.030	-0.204	-0.641	0.950	α_{CAPM}	0.439	0.312	0.198	0.040	-0.602	1.041
t-stat	*4.49*	*1.78*	*0.38*	*-2.37*	*-3.63*	*4.25*	**t-stat**	*2.99*	*2.21*	*1.42*	*0.28*	*-3.06*	*5.59*
$\alpha_{Carhart}$	0.276	0.073	0.010	-0.166	-0.526	0.801	$\alpha_{Carhart}$	0.396	0.262	0.159	0.025	-0.546	0.942
t-stat	*4.20*	*1.67*	*0.14*	*-1.90*	*-3.64*	*4.34*	**t-stat**	*5.30*	*4.01*	*2.54*	*0.40*	*-6.19*	*7.73*
α_{FF5}	0.186	-0.023	-0.047	-0.121	-0.289	0.476	α_{FF5}	0.316	0.153	0.053	-0.029	-0.382	0.698
t-stat	*3.07*	*-0.53*	*-0.67*	*-1.46*	*-2.34*	*3.00*	**t-stat**	*3.85*	*2.36*	*0.81*	*-0.45*	*-5.18*	*5.89*

Panel B. Overnight Volatility Orthogonalized to Intraday Volatility

	A1. Value-Weighted Returns							A2. Equal-Weighted Returns					
	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**		**Low**	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**
α_{CAPM}	-0.187	0.048	0.044	0.015	0.014	-0.202	α_{CAPM}	-0.199	0.160	0.205	0.147	0.046	-0.245
t-stat	*-1.94*	*0.57*	*0.67*	*0.30*	*0.17*	*-1.42*	**t-stat**	*-1.16*	*1.17*	*1.51*	*1.13*	*0.34*	*-2.67*
$\alpha_{Carhart}$	-0.208	-0.030	-0.021	-0.029	0.090	-0.298	$\alpha_{Carhart}$	-0.223	0.113	0.174	0.121	0.080	-0.303
t-stat	*-2.43*	*-0.38*	*-0.31*	*-0.51*	*1.05*	*-2.10*	**t-stat**	*-2.91*	*1.90*	*3.23*	*2.39*	*1.29*	*-3.77*
α_{FF5}	-0.119	-0.070	-0.064	-0.057	0.117	-0.236	α_{FF5}	-0.138	0.065	0.104	0.045	0.087	-0.226
t-stat	*-1.31*	*-0.89*	*-1.18*	*-1.06*	*1.51*	*-1.67*	**t-stat**	*-1.96*	*1.10*	*1.90*	*0.84*	*1.28*	*-2.55*

Table 4. Sorts on Intraday and Overnight Idiosyncratic Volatility

The table presents quintile alphas from sorts on intraday and overnight idiosyncratic volatility. Idiosyncratic volatility is standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily returns in the previous month. To calculate the residuals, Panel A (C) regresses intraday (overnight) stock returns on daily returns to the three Fama-French factors from the website of Kenneth French; Panel B (D) regresses intraday (overnight) stock returns on intraday (overnight) factor returns (constructed as described in the Factors Appendix). Overnight and intraday returns are defined in the header of Table 1. The models to compute the alphas are the CAPM, the four-factor Carhart (1997) model, and the five-factor Fama and French (2015) model. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Intraday IVol Sorts: IVol from Intraday Returns Regressed on Conventional Factors

	A1. Value-Weighted Returns							**A2. Equal-Weighted Returns**					
	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**		**Low**	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**
$\boldsymbol{\alpha_{CAPM}}$	0.334	0.077	0.065	-0.157	-0.575	0.909	$\boldsymbol{\alpha_{CAPM}}$	0.479	0.372	0.316	0.225	-0.458	0.937
t-stat	*3.67*	*0.84*	*0.70*	*-1.74*	*-2.82*	*3.31*	**t-stat**	*3.36*	*2.31*	*1.95*	*1.42*	*-2.34*	*4.25*
$\boldsymbol{\alpha_{Carhart}}$	0.249	0.011	0.040	-0.079	-0.395	0.644	$\boldsymbol{\alpha_{Carhart}}$	0.397	0.274	0.252	0.200	-0.370	0.767
t-stat	*3.58*	*0.16*	*0.55*	*-0.83*	*-2.74*	*3.48*	**t-stat**	*4.81*	*3.58*	*3.40*	*2.83*	*-4.33*	*6.05*
$\boldsymbol{\alpha_{FF5}}$	0.126	-0.118	-0.007	-0.068	-0.207	0.333	$\boldsymbol{\alpha_{FF5}}$	0.262	0.121	0.098	0.072	-0.221	0.483
t-stat	*2.32*	*-1.93*	*-0.10*	*-0.81*	*-1.72*	*2.21*	**t-stat**	*3.03*	*1.79*	*1.33*	*1.22*	*-3.09*	*4.50*

Panel B. Intraday IVol Sorts: IVol from Intraday Returns Regressed on Intraday Factors

B1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.298	0.094	0.000	-0.187	-0.581	0.879
t-stat	*3.26*	*1.21*	*-0.01*	*-1.99*	*-3.00*	*3.34*
$\alpha_{Carhart}$	0.204	0.042	0.015	-0.136	-0.410	0.614
t-stat	*3.08*	*0.65*	*0.22*	*-1.47*	*-3.01*	*3.47*
α_{FF5}	0.112	-0.086	-0.035	-0.116	-0.216	0.327
t-stat	*1.78*	*-1.44*	*-0.52*	*-1.33*	*-1.84*	*2.07*

B2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.481	0.384	0.310	0.215	-0.442	0.923
t-stat	*3.39*	*2.43*	*1.90*	*1.37*	*-2.28*	*4.19*
$\alpha_{Carhart}$	0.400	0.287	0.246	0.192	-0.357	0.757
t-stat	*4.90*	*3.77*	*3.41*	*2.78*	*-4.20*	*6.00*
α_{FF5}	0.261	0.126	0.098	0.074	-0.208	0.470
t-stat	*3.05*	*1.93*	*1.36*	*1.20*	*-3.03*	*4.50*

Panel C. Overnight IVol Sorts: IVol from Overnight Returns Regressed on Conventional Factors

C1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.245	0.111	0.119	0.068	-0.356	0.601
t-stat	*2.01*	*1.19*	*1.25*	*0.81*	*-2.80*	*2.71*
$\alpha_{Carhart}$	0.136	0.020	0.047	0.069	-0.228	0.364
t-stat	*1.43*	*0.26*	*0.62*	*0.81*	*-1.86*	*1.98*
α_{FF5}	-0.011	-0.112	-0.044	0.021	-0.134	0.123
t-stat	*-0.14*	*-1.67*	*-0.66*	*0.26*	*-1.35*	*0.86*

C2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.346	0.197	0.188	0.130	-0.178	0.524
t-stat	*2.57*	*1.18*	*1.08*	*0.76*	*-1.04*	*2.79*
$\alpha_{Carhart}$	0.254	0.102	0.110	0.101	-0.116	0.370
t-stat	*2.93*	*1.20*	*1.34*	*1.20*	*-1.47*	*2.95*
α_{FF5}	0.118	-0.057	-0.033	-0.008	-0.031	0.149
t-stat	*1.37*	*-0.74*	*-0.51*	*-0.12*	*-0.43*	*1.40*

Panel D. Overnight IVol Sorts: IVol from Overnight Returns Regressed on Overnight Factors

D1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.211	0.122	0.080	-0.031	-0.331	0.543
t-stat	*1.95*	*1.61*	*1.16*	*-0.40*	*-2.74*	*2.60*
$\alpha_{Carhart}$	0.108	0.050	0.026	-0.003	-0.208	0.316
t-stat	*1.21*	*0.88*	*0.42*	*-0.04*	*-1.98*	*1.83*
α_{FF5}	-0.011	-0.020	-0.025	-0.075	-0.103	0.093
t-stat	*-0.14*	*-0.31*	*-0.41*	*-0.93*	*-1.19*	*0.72*

D2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.274	0.250	0.170	0.088	-0.141	0.415
t-stat	*1.95*	*1.52*	*1.07*	*0.56*	*-0.86*	*2.29*
$\alpha_{Carhart}$	0.171	0.157	0.101	0.070	-0.090	0.261
t-stat	*2.20*	*1.96*	*1.32*	*0.97*	*-1.21*	*2.36*
α_{FF5}	0.035	-0.006	-0.030	-0.020	0.001	0.034
t-stat	*0.43*	*-0.09*	*-0.46*	*-0.30*	*0.01*	*0.34*

Table 5. Intraday (ID) and Overnight (ON) Volatility in Cross-Sectional Regressions

The table presents Fama-MacBeth cross-sectional regressions of monthly stock returns on standard asset-pricing controls and, in Panel A, logs of total volatility (standard deviation of daily returns in the past month) and intraday/overnight total volatility (defined as in the header of Table 1) or, in Panel B, on logs of idiosyncratic volatility (standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily returns in the previous month) and intraday/overnight idiosyncratic volatility (defined as in the header of Table 4). Detailed definitions of the controls are in the Data Appendix. RevID in Panel B is cumulative intraday return in the past month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. ID vs. ON vs. Close-to Close Volatility

	1	**2**	**3**	**4**	**5**
Beta	0.156	0.165	0.119	0.168	0.167
t-stat	*1.09*	*1.25*	*0.78*	*1.28*	*1.27*
log(Size)	-0.083	-0.096	-0.047	-0.084	-0.098
t-stat	*-2.21*	*-2.55*	*-1.07*	*-2.25*	*-2.62*
log(MB)	-0.128	-0.112	-0.158	-0.113	-0.113
t-stat	*-1.27*	*-1.14*	*-1.52*	*-1.15*	*-1.14*
Mom	0.303	0.293	0.308	0.309	0.291
t-stat	*1.22*	*1.19*	*1.20*	*1.27*	*1.20*
Rev	-0.027	-0.027	-0.025	-0.026	-0.026
t-stat	*-5.34*	*-5.37*	*-5.09*	*-5.19*	*-5.27*
Inv	-1.140	-1.119	-1.225	-1.114	-1.109
t-stat	*-3.25*	*-3.22*	*-3.40*	*-3.20*	*-3.20*
Prof	0.523	0.489	0.584	0.492	0.489
t-stat	*2.43*	*2.28*	*2.69*	*2.30*	*2.28*
log(TVol)	-17.58				-7.960
t-stat	*-3.06*				*-1.90*
log(TVolID)		-20.49		-23.97	-13.21
t-stat		*-2.88*		*-3.36*	*-1.74*
log(TVolON)			-7.459	7.814	
t-stat			*-1.43*	*1.96*	

Panel B. Intraday Returns as a Reversal Control

	1	**2**	**3**	**4**	**5**
Beta	0.133	0.150	0.111	0.163	0.149
t-stat	*1.00*	*1.21*	*0.77*	*1.32*	*1.20*
log(Size)	-0.103	-0.107	-0.039	-0.080	-0.113
t-stat	*-2.85*	*-3.12*	*-0.95*	*-2.33*	*-3.29*
log(MB)	-0.167	-0.161	-0.196	-0.158	-0.159
t-stat	*-1.81*	*-1.79*	*-2.07*	*-1.76*	*-1.77*
Mom	0.207	0.225	0.262	0.271	0.220
t-stat	*0.91*	*1.01*	*1.14*	*1.24*	*1.00*
IDRev	-0.016	-0.016	-0.016	-0.016	-0.016
t-stat	*-4.66*	*-4.62*	*-4.95*	*-4.58*	*-4.61*
Inv	-0.224	-0.232	-0.251	-0.230	-0.223
t-stat	*-1.58*	*-1.65*	*-1.74*	*-1.64*	*-1.58*
Prof	0.528	0.488	0.579	0.487	0.487
t-stat	*2.57*	*2.39*	*2.80*	*2.39*	*2.39*
log(IVol)	-14.77				-5.516
t-stat	*-2.88*				*-1.53*
log(IVolID)		-17.33		-22.39	-12.49
t-stat		*-2.69*		*-3.63*	*-1.88*
log(IVolON)			-3.681	10.38	
t-stat			*-0.72*	*2.89*	

Table 6. Total Volatility Effect in Intraday and Overnight Returns

The table presents intraday and overnight alphas of quintile portfolios sorted on close-to-close total volatility (standard deviation of daily returns in the past month) in Panels A and B, on residual, ϵ_i, from $\log(VolID_i) = a + b \cdot \log(VolON_i) + c \cdot \log^2(VolON_i) + \epsilon_i$ in Panel C, and on residual, ϵ_i, from $\log(VolON_i) = a + b \cdot \log(VolID_i) + c \cdot \log^2(VolID_i) + \epsilon_i$ in Panel D. The regressions are performed cross-sectionally within each month. $VolID$ and $VolON$ are intraday and overnight volatilities defined as in the header of Table 1. In Panel A, alphas are calculated by regressing intraday/overnight quintile portfolio returns (cumulated within a month) on monthly returns to standard asset-pricing factors from the website of Kenneth French. In Panels B-D, alphas are calculated by regressing intraday/overnight quintile portfolio returns (cumulated within a month) on monthly intraday/overnight returns to the same factors (constructed as described in the Factors Appendix). The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below \$5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Sorts on Close-to-Close Volatility: Alphas Based on Close-to-Close Factors

A1. Intraday Value-Weighted Returns

	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**
$\boldsymbol{\alpha_{CAPM}}$	0.368	0.064	-0.376	-0.654	-1.834	2.201
t-stat	*2.64*	*0.45*	*-2.40*	*-3.57*	*-7.22*	*8.02*
$\boldsymbol{\alpha_{Carhart}}$	0.315	0.072	-0.306	-0.535	-1.597	1.912
t-stat	*2.16*	*0.45*	*-1.84*	*-2.73*	*-5.97*	*6.85*
$\boldsymbol{\alpha_{FF5}}$	0.164	-0.053	-0.458	-0.650	-1.476	1.640
t-stat	*1.33*	*-0.38*	*-2.78*	*-3.22*	*-5.11*	*6.33*

A2. Overnight Value-Weighted Returns

	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**L-H**
$\boldsymbol{\alpha_{CAPM}}$	-0.152	-0.047	0.239	0.531	1.293	-1.445
t-stat	*-1.46*	*-0.41*	*1.79*	*3.30*	*5.04*	*-5.52*
$\boldsymbol{\alpha_{Carhart}}$	-0.196	-0.117	0.168	0.478	1.253	-1.448
t-stat	*-1.72*	*-0.94*	*1.14*	*2.81*	*4.85*	*-5.71*
$\boldsymbol{\alpha_{FF5}}$	-0.219	-0.133	0.198	0.504	1.294	-1.512
t-stat	*-2.04*	*-1.07*	*1.44*	*2.92*	*4.49*	*-5.37*

Panel B. Sorts on Close-to-Close Volatility: Alphas Based on Intraday/Overnight Factors

B1. Intraday Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.467	0.222	-0.182	-0.412	-1.492	1.959
t-stat	*4.87*	*2.51*	*-2.08*	*-4.03*	*-8.18*	*7.65*
$\alpha_{Carhart}$	0.374	0.135	-0.217	-0.459	-1.352	1.726
t-stat	*4.04*	*1.51*	*-2.34*	*-4.84*	*-9.14*	*7.99*
α_{FF5}	0.174	-0.033	-0.330	-0.433	-1.073	1.247
t-stat	*2.08*	*-0.39*	*-3.74*	*-4.30*	*-6.04*	*5.58*

B2. Overnight Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	-0.319	-0.274	-0.009	0.230	0.976	-1.295
t-stat	*-4.04*	*-4.24*	*-0.14*	*2.91*	*5.93*	*-5.71*
$\alpha_{Carhart}$	-0.238	-0.173	0.035	0.242	0.695	-0.933
t-stat	*-4.43*	*-3.71*	*0.60*	*3.44*	*5.92*	*-5.89*
α_{FF5}	-0.103	-0.047	0.158	0.229	0.369	-0.472
t-stat	*-1.89*	*-1.03*	*2.59*	*3.09*	*2.87*	*-2.83*

Panel C. Sorts on ID Volatility Orthogonalized to ON Volatility: Alphas Based on Intraday/Overnight Factors

C1. Intraday Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.411	0.228	0.021	-0.235	-1.158	1.569
t-stat	*4.67*	*3.26*	*0.41*	*-4.00*	*-9.04*	*9.50*
$\alpha_{Carhart}$	0.395	0.226	0.005	-0.276	-1.094	1.489
t-stat	*5.11*	*3.37*	*0.08*	*-5.21*	*-9.11*	*9.03*
α_{FF5}	0.321	0.140	-0.055	-0.253	-0.919	1.241
t-stat	*3.54*	*2.23*	*-0.95*	*-4.13*	*-7.84*	*7.75*

C2. Overnight Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	-0.247	-0.124	-0.097	0.054	0.655	-0.902
t-stat	*-3.64*	*-2.24*	*-2.61*	*1.57*	*5.92*	*-5.83*
$\alpha_{Carhart}$	-0.318	-0.092	-0.068	0.117	0.555	-0.873
t-stat	*-6.16*	*-1.82*	*-1.88*	*3.68*	*6.12*	*-7.27*
α_{FF5}	-0.319	-0.047	0.021	0.105	0.345	-0.664
t-stat	*-5.43*	*-0.92*	*0.65*	*3.17*	*3.96*	*-5.36*

Panel D. Sorts on ON Volatility Orthogonalized to ID Volatility: Alphas Based on Intraday/Overnight Factors

D1. Intraday Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	-0.605	-0.159	-0.009	-0.023	-0.274	-0.331
t-stat	*-4.86*	*-2.23*	*-0.16*	*-0.45*	*-4.21*	*-2.37*
$\alpha_{Carhart}$	-0.615	-0.172	-0.063	-0.018	-0.238	-0.377
t-stat	*-5.68*	*-2.28*	*-1.21*	*-0.38*	*-3.72*	*-2.82*
α_{FF5}	-0.416	-0.178	-0.127	-0.074	-0.211	-0.204
t-stat	*-4.04*	*-2.41*	*-2.36*	*-1.63*	*-2.78*	*-1.39*

D2. Overnight Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.363	0.005	-0.125	-0.098	0.302	0.061
t-stat	*3.74*	*0.12*	*-3.29*	*-2.63*	*5.24*	*0.57*
$\alpha_{Carhart}$	0.268	0.052	-0.080	-0.086	0.213	0.055
t-stat	*3.58*	*1.21*	*-2.29*	*-2.44*	*5.17*	*0.68*
α_{FF5}	0.072	0.050	-0.019	-0.039	0.130	-0.057
t-stat	*1.04*	*1.06*	*-0.59*	*-1.06*	*2.91*	*-0.65*

Table 7. Short-Term Reversal and Idiosyncratic Volatility Effect across Turnover Quintiles

Panel A (B) presents, across monthly turnover quintiles, alpha spreads between bottom and top quintile sorted on cumulative intraday return (intraday idiosyncratic volatility) in the previous month. Turnover is past month's dollar trading volume from CRSP divided by end-of-the month market capitalization. Intraday idiosyncratic volatility is defined in the header of Table 4 (Panel B). The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Short-Term Reversal Based on Intraday Returns across Turnover Quintiles

A1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.416	0.606	0.086	0.176	-0.608	1.025
t-stat	*1.80*	*2.72*	*0.40*	*0.73*	*-2.32*	*3.25*
$\alpha_{Carhart}$	0.383	0.499	0.031	0.215	-0.580	0.963
t-stat	*1.63*	*2.27*	*0.15*	*0.85*	*-2.23*	*3.08*
α_{FF5}	0.539	0.736	0.241	0.307	-0.575	1.114
t-stat	*2.38*	*3.29*	*1.12*	*1.34*	*-2.18*	*3.51*

A2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.783	0.598	0.280	0.119	-0.578	1.362
t-stat	*6.85*	*3.95*	*1.93*	*0.70*	*-2.96*	*6.35*
$\alpha_{Carhart}$	0.856	0.641	0.317	0.190	-0.468	1.324
t-stat	*7.43*	*4.06*	*2.08*	*1.06*	*-2.20*	*5.91*
α_{FF5}	0.864	0.698	0.421	0.244	-0.512	1.376
t-stat	*7.87*	*4.75*	*2.59*	*1.39*	*-2.17*	*5.74*

Panel B. Idiosyncratic Volatility Effect Based on Intraday Returns across Turnover Quintiles

B1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.946	0.842	0.707	1.103	1.221	-0.275
t-stat	*3.90*	*2.94*	*2.54*	*4.38*	*3.42*	*-0.77*
$\alpha_{Carhart}$	0.800	0.637	0.455	0.944	0.922	-0.122
t-stat	*4.29*	*2.97*	*1.87*	*4.23*	*3.13*	*-0.40*
α_{FF5}	0.599	0.513	0.184	0.724	0.592	0.008
t-stat	*3.25*	*2.52*	*0.77*	*3.57*	*2.02*	*0.02*

B2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	L-H
α_{CAPM}	0.868	0.708	0.695	0.850	1.104	-0.236
t-stat	*5.75*	*2.91*	*2.86*	*3.40*	*3.97*	*-0.98*
$\alpha_{Carhart}$	0.766	0.491	0.502	0.660	0.877	-0.111
t-stat	*5.62*	*2.81*	*3.18*	*3.67*	*4.62*	*-0.52*
α_{FF5}	0.634	0.298	0.239	0.427	0.585	0.049
t-stat	*5.30*	*2.02*	*2.02*	*2.78*	*3.34*	*0.23*

Table 8. Intraday Volatility Explains the Analyst Disagreement Effect and the MAX Effect in Portfolio Sorts

Panel A presents alphas of quintile portfolios sorted on analyst disagreement (AD), defined as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecasts. Panel B reports alphas of quintile portfolios sorted on residual, ϵ_i, from $\log(AD_i) = a + b \cdot \log(VolID_i) + c \cdot \log^2(VolID_i) + \epsilon_i$, where $VolID$ is intraday volatility defined as in the header of Table 1. Panel C records alphas of quintile portfolios sorted on maximum daily return in the past month (MAX). Panel D shows alphas of quintile portfolios sorted on residual, ϵ_i, from $\log(MAX_i) = a + b \cdot \log(VolID_i) + c \cdot \log^2(VolID_i) + \epsilon_i$. The models to compute the alphas are the CAPM, the four-factor Carhart (1997) model, and the five-factor Fama and French (2015) model. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Sorts on Analyst Disagreement

	A1. Value-Weighted Returns							A2. Equal-Weighted Returns					
	Low	**Quint2**	**Quint3**	**Quint4**	**High**	**H-L**		**Low**	**Quint2**	**Quint3**	**Quint4**	**High**	**H-L**
α_{CAPM}	0.305	0.089	-0.001	0.081	-0.404	0.709	α_{CAPM}	0.443	0.153	0.112	0.034	-0.301	0.743
t-stat	*3.56*	*1.64*	*-0.02*	*0.92*	*-2.87*	*3.61*	**t-stat**	*3.26*	*1.18*	*0.84*	*0.25*	*-1.64*	*4.31*
$\alpha_{Carhart}$	0.239	0.110	0.000	0.057	-0.297	0.536	$\alpha_{Carhart}$	0.372	0.129	0.120	0.073	-0.205	0.577
t-stat	*3.42*	*1.92*	*0.00*	*0.71*	*-2.24*	*3.06*	**t-stat**	*4.19*	*1.78*	*1.75*	*1.24*	*-2.42*	*4.38*
α_{FF5}	0.078	0.018	-0.026	0.202	-0.137	0.216	α_{FF5}	0.259	-0.007	0.035	0.067	-0.153	0.411
t-stat	*1.51*	*0.32*	*-0.36*	*2.32*	*-1.14*	*1.52*	**t-stat**	*4.38*	*-0.11*	*0.57*	*1.01*	*-1.78*	*4.00*

Panel B. Sorts on Analyst Disagreement Orthogonalized to Intraday Volatility

B1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	-0.188	0.091	0.201	0.224	-0.087	-0.102
t-stat	*-1.70*	*1.14*	*2.65*	*3.31*	*-0.95*	*-0.69*
$\alpha_{Carhart}$	-0.053	0.071	0.128	0.161	-0.053	0.000
t-stat	*-0.54*	*0.96*	*2.03*	*2.60*	*-0.58*	*0.00*
α_{FF5}	0.009	-0.008	0.032	0.109	0.053	-0.045
t-stat	*0.09*	*-0.11*	*0.51*	*1.56*	*0.58*	*-0.33*

B2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	-0.086	0.201	0.269	0.250	-0.160	0.075
t-stat	*-0.55*	*1.43*	*1.90*	*1.81*	*-1.00*	*0.74*
$\alpha_{Carhart}$	0.005	0.174	0.200	0.206	-0.107	0.112
t-stat	*0.07*	*2.43*	*2.78*	*3.07*	*-1.40*	*1.17*
α_{FF5}	0.049	0.035	0.079	0.109	-0.116	0.165
t-stat	*0.70*	*0.50*	*1.21*	*1.55*	*-1.55*	*1.89*

Panel C. Sorts on Past Maximum Daily Return (MAX)

C1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	0.391	0.211	0.003	-0.252	-0.456	0.846
t-stat	*3.92*	*2.55*	*0.03*	*-2.89*	*-3.13*	*3.67*
$\alpha_{Carhart}$	0.286	0.147	-0.024	-0.192	-0.320	0.607
t-stat	*3.62*	*2.53*	*-0.32*	*-1.95*	*-3.03*	*3.72*
α_{FF5}	0.150	0.010	-0.097	-0.191	-0.154	0.304
t-stat	*2.10*	*0.22*	*-1.43*	*-2.05*	*-1.78*	*2.25*

C2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	0.562	0.423	0.301	0.078	-0.503	1.065
t-stat	*3.84*	*2.74*	*1.80*	*0.46*	*-2.74*	*4.93*
$\alpha_{Carhart}$	0.480	0.353	0.241	0.057	-0.417	0.898
t-stat	*5.45*	*4.86*	*3.20*	*0.84*	*-5.24*	*7.03*
α_{FF5}	0.351	0.187	0.101	-0.027	-0.261	0.613
t-stat	*3.99*	*2.79*	*1.55*	*-0.39*	*-4.30*	*6.06*

Panel D. Sorts on MAX Orthogonalized to Intraday Volatility

D1. Value-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	-0.282	0.248	0.105	-0.015	-0.138	-0.145
t-stat	*-2.27*	*2.70*	*1.67*	*-0.29*	*-1.46*	*-0.83*
$\alpha_{Carhart}$	-0.268	0.226	0.063	-0.040	-0.097	-0.171
t-stat	*-2.21*	*2.85*	*1.20*	*-0.83*	*-1.08*	*-1.03*
α_{FF5}	-0.092	0.160	-0.006	-0.100	-0.102	0.010
t-stat	*-0.93*	*2.45*	*-0.12*	*-2.02*	*-1.08*	*0.06*

D2. Equal-Weighted Returns

	Low	Quint2	Quint3	Quint4	High	H-L
α_{CAPM}	-0.126	0.217	0.295	0.113	-0.166	0.040
t-stat	*-0.75*	*1.52*	*2.22*	*0.87*	*-1.16*	*0.47*
$\alpha_{Carhart}$	-0.077	0.184	0.239	0.072	-0.174	0.097
t-stat	*-0.94*	*3.04*	*4.42*	*1.25*	*-2.70*	*1.08*
α_{FF5}	-0.010	0.107	0.157	0.002	-0.140	0.130
t-stat	*-0.14*	*1.85*	*3.08*	*0.03*	*-2.12*	*1.51*

Table 9. Intraday Volatility Explains the Analyst Disagreement Effect and the MAX Effect in Cross-Sectional Regressions

The table presents Fama-MacBeth cross-sectional regressions of monthly stock returns on standard asset-pricing controls and logs of total volatility (standard deviation of daily returns in the past month) and intraday total volatility (defined as in the header of Table 1), and maximum daily return in the past month (MAX, Panel A) or analyst disagreement (AD, Panel B). AD is defined in the header of Table 8. Detailed definitions of the controls are in the Data Appendix. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Explaining the MAX Effect | **Panel B. Explaining the AD Effect**

	1	**2**	**3**		**1**	**2**	**3**
Beta	0.126	0.141	0.174	**Beta**	-0.387	-0.232	-0.185
t-stat	*1.02*	*1.15*	*1.48*	**t-stat**	*-3.12*	*-2.00*	*-1.72*
log(Size)	-0.057	-0.093	-0.099	**log(Size)**	-0.287	-0.438	-0.443
t-stat	*-1.45*	*-2.36*	*-2.46*	**t-stat**	*-5.87*	*-9.40*	*-9.63*
log(MB)	-0.196	-0.125	-0.113	**log(MB)**	-0.229	-0.131	-0.134
t-stat	*-2.71*	*-1.58*	*-1.45*	**t-stat**	*-2.50*	*-1.48*	*-1.53*
Mom	0.241	0.301	0.297	**Mom**	-0.481	-0.518	-0.461
t-stat	*1.35*	*1.53*	*1.52*	**t-stat**	*-2.22*	*-2.46*	*-2.26*
Rev	-0.022	-0.030	-0.029	**Rev**	0.014	0.013	0.013
t-stat	*-3.93*	*-5.65*	*-5.91*	**t-stat**	*2.74*	*2.72*	*2.77*
Inv	-0.209	-1.088	-1.060	**Inv**	-2.335	-2.110	-2.088
t-stat	*-1.57*	*-3.56*	*-3.48*	**t-stat**	*-7.82*	*-7.17*	*-7.19*
Prof	0.521	0.504	0.457	**Prof**	1.634	1.541	1.476
t-stat	*2.88*	*2.54*	*2.33*	**t-stat**	*7.97*	*7.54*	*7.26*
log(TVol)		-24.40		**log(TVol)**		-12.61	
t-stat		*-4.51*		**t-stat**		*-2.73*	
log(TVolID)			-25.32	**log(TVolID)**			-13.41
t-stat			*-4.21*	**t-stat**			*-2.18*
log(Max)	-3.973	1.752	1.138	**log(Disp)**	-0.537	-0.078	-0.063
t-stat	*-2.59*	*1.36*	*1.24*	**t-stat**	*-2.34*	*-0.36*	*-0.30*

Table 10. Intraday and Overnight Volatility as Limits-to-Arbitrage Proxies: Stambaugh et al. (2012) Overpricing Effect across Volatility Quintiles

The table presents alpha spreads between top and bottom quintile sorted on Stambaugh et al. (2012) mispricing measure, which combines 11 well-known anomalies (see Data Appendix for detailed definition). The alpha spreads are reported separately in each residual intraday/overnight volatility quintile. The quintiles are formed as described in Table 3. The quintile portfolios use NYSE (exchcd=1) breakpoints and are rebalanced each month. Stocks priced below $5 at the beginning of the month are excluded. The sample is from August 1992 to December 2022.

Panel A. Intraday Volatility Orthogonalized to Overnight Volatility as Limits-to-Arbitrage Proxy

A1. Value-Weighted Returns

	LoVol	Quint2	Quint3	Quint4	HiVol	H-L
α_{CAPM}	0.928	0.854	1.014	0.739	1.826	0.898
t-stat	*3.56*	*3.59*	*3.47*	*3.00*	*5.67*	*2.71*
$\alpha_{Carhart}$	0.607	0.569	0.679	0.396	1.270	0.662
t-stat	*2.63*	*2.58*	*2.62*	*1.75*	*4.15*	*2.03*
α_{FF5}	0.713	0.503	0.665	0.481	1.404	0.691
t-stat	*2.50*	*2.30*	*2.29*	*1.84*	*4.54*	*1.95*

A2. Equal-Weighted Returns

	LoVol	Quint2	Quint3	Quint4	HiVol	H-L
α_{CAPM}	0.670	0.981	1.040	1.086	1.723	1.053
t-stat	*4.89*	*6.02*	*6.03*	*6.07*	*7.45*	*5.77*
$\alpha_{Carhart}$	0.441	0.713	0.736	0.722	1.224	0.783
t-stat	*3.82*	*5.45*	*4.98*	*4.74*	*6.23*	*4.33*
α_{FF5}	0.474	0.815	0.794	0.811	1.363	0.889
t-stat	*2.89*	*5.08*	*4.25*	*4.48*	*5.25*	*4.62*

Panel B. Overnight Volatility Orthogonalized to Intraday Volatility as Limits-to-Arbitrage Proxy

B1. Value-Weighted Returns

	LoVol	Quint2	Quint3	Quint4	HiVol	H-L
α_{CAPM}	1.424	0.906	1.076	1.150	1.379	-0.044
t-stat	*4.66*	*3.62*	*4.82*	*4.58*	*5.12*	*-0.17*
$\alpha_{Carhart}$	1.069	0.584	0.809	0.756	0.837	-0.232
t-stat	*4.17*	*2.67*	*4.15*	*3.31*	*3.68*	*-0.81*
α_{FF5}	1.064	0.565	0.729	0.863	0.841	-0.223
t-stat	*4.19*	*2.61*	*3.41*	*3.83*	*3.39*	*-0.78*

B2. Equal-Weighted Returns

	LoVol	Quint2	Quint3	Quint4	HiVol	H-L
α_{CAPM}	1.307	1.021	1.089	1.195	1.478	0.172
t-stat	*8.45*	*5.32*	*6.23*	*6.55*	*6.95*	*1.07*
$\alpha_{Carhart}$	1.067	0.677	0.782	0.848	0.969	-0.098
t-stat	*7.12*	*4.50*	*5.33*	*5.48*	*5.46*	*-0.65*
α_{FF5}	1.128	0.731	0.880	0.927	1.117	-0.011
t-stat	*6.44*	*3.76*	*5.30*	*5.15*	*4.83*	*-0.07*

Table A. Intraday and Overnight Factor Returns

Panel A (B) reports CAPM alphas of standard asset-pricing factors and average market intraday (overnight) return. The alphas are calculated by regressing intraday (overnight) factor returns on close-to-close market return. Panel C shows pairwise correlation between intraday (overnight) factor returns above (below) the main diagonal. Panel D presents correlations between close-to-close (CtC), intraday (ID), and overnight (ON) returns to the same factor (named in the subpanel header). The construction of factors follows Fama and French (2015). Intraday and overnight returns are defined in the header of Table 1. The sample is from August 1992 to December 2022.

Panel A. Intraday Value-Weighted Alphas

	SMB	HML	MOM	CMA	RMW	MKT
$\boldsymbol{\alpha}$	0.157	0.461	0.859	0.697	0.873	0.227
t-stat	*0.76*	*1.87*	*3.76*	*4.73*	*4.07*	*1.30*
$\boldsymbol{\beta}$	0.224	-0.014	-0.402	-0.130	-0.238	
t-stat	*4.81*	*-0.20*	*-4.67*	*-2.91*	*-3.78*	

Panel B. Overnight Value-Weighted Alphas

	SMB	HML	MOM	CMA	RMW	MKT
$\boldsymbol{\alpha}$	0.404	-0.266	-0.806	-0.423	-0.871	0.693
t-stat	*3.05*	*-2.15*	*-2.19*	*-3.84*	*-5.81*	*4.21*
$\boldsymbol{\beta}$	-0.004	-0.008	-0.075	-0.034	-0.020	
t-stat	*-0.13*	*-0.25*	*-0.69*	*-1.79*	*-0.74*	

Panel C. Intraday Correlations (top) vs. Overnight Correlations (bottom)

	MKT	SMB	HML	MOM	CMA	RMW
MKT		0.244	-0.128	-0.390	-0.262	-0.398
t-stat		*4.78*	*-2.45*	*-8.08*	*-5.16*	*-8.26*
SMB	-0.015		0.157	-0.288	-0.020	-0.329
t-stat	*-0.28*		*3.03*	*-5.72*	*-0.38*	*-6.64*
HML	-0.011	0.225		-0.044	0.433	0.376
t-stat	*-0.21*	*4.40*		*-0.83*	*9.14*	*7.74*
MOM	-0.109	-0.342	0.038		0.286	0.425
t-stat	*-2.09*	*-6.94*	*0.72*		*5.70*	*8.95*
CMA	-0.137	0.058	0.390	0.124		0.432
t-stat	*-2.64*	*1.11*	*8.08*	*2.39*		*9.12*
RMW	-0.129	-0.085	0.374	0.366	0.374	
t-stat	*-2.47*	*-1.63*	*7.69*	*7.48*	*7.69*	

Panel D. Correlations between Close-to-Close (CtC), Intraday (ID), and Overnight (ON) Factor Returns

Panel D1. Market Factor

	CtC	ID	ON
CtC		0.790	0.615
ID	0.790		0.004
ON	0.615	0.004	

Panel D2. SMB Factor

	CtC	ID	ON
CtC		0.828	0.191
ID	0.828		-0.236
ON	0.191	-0.236	

Panel D3. HML Factor

	CtC	ID	ON
CtC		0.760	0.263
ID	0.760		-0.046
ON	0.263	-0.046	

Panel D4. MOM Factor

	CtC	ID	ON
CtC		0.787	0.366
ID	0.787		-0.126
ON	0.366	-0.126	

Panel D5. CMA Factor

	CtC	ID	ON
CtC		0.476	0.095
ID	0.476		-0.194
ON	0.095	-0.194	

Panel D6. RMW Factor

	CtC	ID	ON
CtC		0.739	0.219
ID	0.739		-0.112
ON	0.219	-0.112	