Why Does Higher Variability of Trading Activity Predict Lower Expected Returns?

Alexander Barinov

Terry College of Business
University of Georgia
E-mail: **abarinov@terry.uga.edu**
http://abarinov.myweb.uga.edu/

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Abstract

The paper shows that controlling for the aggregate volatility risk factor eliminates the puzzling negative relation between variability of trading activity and future abnormal returns. I find that variability of other measures of liquidity and liquidity risk is largely unrelated to expected returns. Lastly, I show that the low returns to firms with high variability of trading activity are not explained by liquidity risk or mispricing theories.

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I Introduction

Chordia, Subrahmanyam, and Anshuman (2001) show that firms with higher variability of trading activity (measured by either volume or turnover) have lower expected returns. If one thinks of volume and turnover as measures of liquidity or liquidity risk, this regularity (referred henceforth as the volume/turnover variability effect) is puzzling. If anything, firms with higher variability of liquidity should be more risky, since, all else equal, higher variability of liquidity means that the firm will become illiquid with higher probability[1].

In this paper, I argue that higher variability of volume or turnover picks up higher firm-specific uncertainty, and this is the reason why higher variability of volume/turnover predicts lower future returns. I also refute the claim of Chordia et al. that liquidity variability appears to be negatively related to expected returns by considering multiple alternative liquidity measures and finding that their variability is unrelated to expected returns.

Higher firm-specific uncertainty predicts lower expected returns because high uncertainty firms tend to beat the CAPM when aggregate volatility in the economy unexpectedly increases.[2] More uncertainty about the underlying asset reduces the risk of the option-like firm[3] by making its value less responsive to the changes in the underlying asset value. The beta of an option is, by Ito's lemma, the product of the underlying asset beta and the option value elasticity with respect to the underlying asset value. While changes in

[1] In empirical tests, variability is measured as the coefficient of variation, the ratio of the standard deviation of the variable to the average value of the variable.

[2] For example, Barinov (2011) successfully uses an aggregate volatility risk factor to explain the idiosyncratic volatility discount of Ang et al. (2006). Barinov (2013a) does the same to explain the analyst disagreement effect of Diether et al. (2002).

[3] Equity can be option-like either because the firm has a lot of growth options (equity is a claim on the options) or because the firm has a lot of debt (equity itself is an option on the assets with the strike price equal to the debt value).

the uncertainty about the underlying asset do not influence its beta, they do make the elasticity and, hence, the option's beta smaller.

Both aggregate volatility and firm-specific uncertainty are high during recessions (see the results in Duarte et al., 2012, and Barinov, 2013a). According to the previous paragraph, when firm-specific uncertainty increases, the risk exposure of option-like stocks declines. All else equal, the lower risk exposure means lower expected return and higher stock price. Hence, during volatile periods option-like stocks lose less value than what the CAPM predicts. Also, holding everything else equal, option-like stocks increase in value when the uncertainty about the underlying asset increases[4]. These two effects of uncertainty on option-like stocks are stronger for high uncertainty firms[5]. Hence, high uncertainty firms with option-like equity should outperform the CAPM during volatile times.

Campbell (1993) and Chen (2002) show that investors would require a lower risk premium from the stocks, the value of which correlates least negatively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing and precautionary savings motives. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the notion of aggregate volatility risk. They show that the stocks with the least negative sensitivity to aggregate volatility increases have abnormally low expected returns. This paper builds on this literature and shows that the firms with high variability of volume/turnover have low expected returns because they have high uncertainty, and the high uncertainty makes them a hedge against aggregate volatility risk.

The paper proceeds as follows: Section II positions the paper in the related literature

[4] A recent analysis by Grullon, Lyandres, and Zhdanov (2012) suggest that changes in firm-level uncertainty have a substantial effect on the value of real options.

[5] The formal proofs and simulations are available from the author upon request.

and Section III presents the data. Section IV starts by showing that firms with high variability of trading activity are exactly of the type that is, according to my theory and prior research, the best hedge against aggregate volatility risk - high uncertainty firms. Section IV finds that firms with higher variability of trading activity have significantly higher idiosyncratic volatility, dispersion of analyst forecasts, analyst forecast error, and variability of earnings/cash flows.

Section IV also documents that while there exists a certain overlap between the volume/turnover variability effect and the uncertainty effects on expected returns, the volume/turnover variability effect weakens by at most one-quarter after controlling for the uncertainty effects and remains statistically and economically significant. Hence, the volume/turnover variability effect is an independent anomaly that merits a separate explanation.

In Section V, the main result of the paper is obtained by using the two-factor ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor). The FVIX factor tracks the daily changes in the CBOE VIX index. The VIX index measures the implied volatility of S&P 100 options.[6] Section V shows that the negative CAPM alphas of firms with high variability of trading activity are completely explained by their positive FVIX beta (the positive FVIX beta means relatively good performance when VIX increases).

According to my theory, higher firm-specific uncertainty reduces the risk of option-like firms. The natural prediction is that the effect of firm-specific uncertainty on expected returns is stronger for option-like firms. Section V confirms that in the double sorts on variability of trading activity and measures of equity option-likeness, the volume/turnover

[6] VIX was redefined as the implied volatility of S&P 500 options several years ago. The old series is currently called VXO and spans a longer time period. I use the old definition to increase the sample size. All results in the paper are robust to using the new definition of VIX.

variability effect is limited to the firms with high market-to-book or bad credit rating. Further analysis shows that these patterns are explained by the FVIX factor and that the link between the volume/turnover variability effect and equity option-likeness is also strong in Fama-MacBeth (1973) regressions. Section V also finds that the stronger relation between FVIX betas and volume/turnover variability for option-like firms is robust to switching from portfolio sorts to cross-sectional regressions.

I conclude that the volume/turnover variability effect does not suggest that variability of liquidity is negatively related to expected returns. The volume/turnover variability effect arises because variability of trading activity proxies for firm-specific uncertainty, and high uncertainty firms are hedges against aggregate volatility risk.

I also consider alternative explanations of the volume/turnover variability effect. Section VI looks at liquidity/liquidity risk explanations and finds that volume/turnover variability is unrelated to liquidity risk or its variability, but strongly related to variability of liquidity. However, further analysis shows that variability of liquidity itself is not priced, reinforcing the earlier conclusion that the reason why variability of volume/turnover is priced is because it picks up firm-specific uncertainty and therefore aggregate volatility risk.

Section VI also rejects the hypothesis of Pereira and Zhang (2010) that low returns to firms with highly variable trading activity are due to the fact that these firms have higher chance of becoming very liquid. Section VI finds that firms with high variability of volume/turnover are very illiquid and almost never become more liquid than firms with low variability of volume/turnover.

The strong negative relation between volume/turnover variability and liquidity also sheds light on why firms with high volume/turnover variability have high uncertainty. Liquidity drives variability of trading activity: illiquid firms are infrequently traded, and their trading volume witnesses frequent jumps due to the pent-up demand. Consistent with that, I discover in Section VI that the frequency of zero returns is 2.5 times higher in the highest volume/turnover variability quintile than in the lowest volume/turnover variability quintile. Liquidity, in turn, is driven by firm-specific uncertainty, as much of the microstructure literature suggests. Higher firm-specific uncertainty results in higher bid-ask spreads, stronger price impact, and, as a result, higher trading costs (which, in turn, result in infrequent trading and volatile trading activity).

Section VII studies the possibility that the volume/turnover variability effect is mispricing. One existing piece of evidence in favor of this view is the evidence from George and Hwang (2009) that the volume/turnover variability effect is stronger for the firms with lower analyst following. I also hypothesize that if the volume/turnover variability effect is mispricing, it will be stronger if short sale constraints are more severe, because the majority of the volume/turnover variability effect is driven by the negative alphas of firms with high variability of trading activity.

Section VII finds that the volume/turnover variability effect is indeed stronger for firms followed by few analysts, for firms with low institutional ownership, and for firms with high short interest. However, these regularities can be explained by the ICAPM with the FVIX factor, which makes the mispricing explanation redundant.

II Related Literature

The paper contributes to the growing volatility risk literature that establishes the importance of volatility risk (Ang et al., 2006, Chen and Petkova, 2012) and its role in explaining the negative relation between firm-specific uncertainty and expected returns (Barinov, 2011, 2013a, 2013b, Chen and Petkova, 2012). The paper thus adds to the list of the anomalies explained by aggregate volatility risk and strengthens the theory about the relation between firm-specific uncertainty and aggregate volatility risk by applying in to the anomaly it was not originally designed to explain (volume/turnover variability effect).

Ang et al. (2006) establish that FVIX, the aggregate volatility risk factor, is priced in the cross-section. They also perform double sorts on FVIX betas and idiosyncratic volatility and find that controlling for FVIX this way does not fully explain the negative cross-sectional relation between idiosyncratic volatility and future returns (the idiosyncratic volatility discount). Barinov (2011) contests this conclusion and finds that in a more direct test that looks at the alphas FVIX can explain the idiosyncratic volatility discount. Barinov (2011) also finds that the limited explanatory power of Ang et al.'s FVIX stems from the fact that they perform the factor-mimicking regression that creates FVIX separately in each month, estimating 6 parameters using 20-22 observations. The FVIX constructed using a full-sample regression (or, alternatively, using an expanding window regression) is shown to be less noisy, more strongly priced, and to explain the idiosyncratic volatility discount much better.

Chen and Petkova (2012) use the factor that mimics innovation to average firm-specific volatility rather than expected market volatility and find that this factor also explains the idiosyncratic volatility discount. In untabulated results, I find that their conclusion is not robust to minor changes in the factor-mimicking procedure. In particular, the base assets for the total volatility factor in Chen and Petkova are created by pre-sorting on sensitivity to changes in average total volatility and average correlation between all stocks, even though Chen and Petkova find that average correlation is not priced. I change the base assets for the total volatility factor to portfolios pre-sorted on sensitivity to changes in average total volatility only, and find a significant reduction in the factor risk premium and a complete disappearance of the link between the total volatility factor and the idiosyncratic volatility discount. I experiment with using other base assets, like size and book-to-market sorts or industry portfolios, but the conclusion stays the same.

Another paper close to the current one is Barinov (2013b), which argues that turnover is unrelated or even negatively related to liquidity, but positively related to firm-specific uncertainty, and uses FVIX to explain the negative relation between turnover and expected returns (the turnover effect). The focus of my paper is completely different though. While high turnover firms, studied by Barinov (2013b), are actively traded large firms, firms with high volume/turnover variability are small, infrequently traded firms. For example, in non-tabulated results I find that high (low) turnover variability firms have median monthly volume of \$1.7 million (\$266 million), and median market cap of \$37 million (\$2.3 billion). Thus, there is no a priori reason to believe that if FVIX explains the turnover effect, it will explain the volume/turnover variability effect. I also find, somewhat contrary to Barinov (2013b), that while average turnover is unrelated to liquidity, turnover and volume variability are related to variability of liquidity (though variability of liquidity is unrelated to expected returns).

III Data Sources

The data in the paper come from CRSP, Compustat, IBES, Thompson 13F, and the CBOE indexes databases. The sample period is from January 1966 to December 2010. Turnover is defined as trading volume divided by shares outstanding (both from CRSP). I follow Gao and Ritter (2010) in adjusting the NASDAQ turnover to eliminate double-counting. The NASDAQ turnover is divided by 2.0 prior to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003, and left unchanged thereafter. Firms are classified as NASDAQ firms if the exchcd historical listing indicator from the CRSP events file is equal to 3.

The volume/turnover variability is measured using the respective coefficient of variation. The coefficient of variation is the standard deviation over the average during the same period. The standard deviation of volume/turnover is measured using monthly volume/turnover data for the previous 36 months (at least 12 valid observations are required).

The proxy for expected aggregate volatility is the old VIX index. It is calculated by CBOE and measures the implied volatility of one-month options on S&P 100, available from January 1986 to December 2010. The values of the VIX index are from CBOE data on WRDS. Using the old version of the VIX provides a longer data series compared to newer CBOE indices.

I define FVIX, my aggregate volatility risk factor, as a factor-mimicking portfolio that tracks the daily changes in the VIX index. Following Ang, Hodrick, Xing, and Zhang (2006), I regress the daily changes in VIX on the daily excess returns to the five quintile portfolios sorted on past sensitivity to VIX changes. The sensitivity is the loading on the VIX change from the regression of daily stock returns in the past month on the market return and change in VIX. The fitted part of the factor-mimicking regression less the constant is the FVIX factor. I cumulate returns to the monthly level to get the monthly return to FVIX. All results in the paper are robust to changing the base assets from the volatility sensitivity quintiles to the ten industry portfolios (Fama and French, 1997) or the the six size and book-to-market portfolios (Fama and French, 1993).

The rest of the variables are discussed in detail in Data Appendix.

IV Variability of Trading Activity, Aggregate Volatility Risk, and Expected Returns

A Variability of Trading Activity, Firm-Specific Uncertainty, and Option-Like Equity

The central hypothesis of the paper is that variability of trading activity predicts lower expected returns because higher variability of trading activity proxies for higher firm-specific uncertainty. Higher firm-specific uncertainty, in turn, makes expected returns lower by lowering the risk of option-like equity. Therefore, the first step in testing the theory is to verify that the firms with higher variability of trading activity indeed have higher uncertainty.

Table 1 sorts firms on variability of turnover (Panel A) or volume (Panel B) and reports the median values of five uncertainty measures across the volume/turnover variability quintiles. The five uncertainty measures are idiosyncratic volatility, analyst disagreement, analyst forecast error, variability of cash flows, and variability of earnings. The detailed definitions of the uncertainty measures are in Data Appendix.

Panel A of Table 1 finds that the representative firm with high turnover variability has twice higher idiosyncratic volatility (2.8% per day versus 1.3% per day), twice higher dispersion of analyst forecasts (standard deviation of the forecast is 6.4 cents per $1 of EPS versus 3.4 cents per $1 of EPS), and twice higher analyst forecast error (18.6 cents per $1 of EPS versus 8.5 cents per $1 of EPS) than the representative firm with low turnover variability. The difference in the variability of earnings and cash flows (measured again as the coefficient of variation) of high and low turnover variability firms is even wider. Panel B looks at volume variability and arrives at very similar results.

In untabulated results, I also look at the relation between volume/turnover variability and firm-specific uncertainty in multivariate context, regressing volume or turnover variability on known determinants of trading activity, such as market cap, firm age, number of analysts following the firm, etc.) I find that the strong positive relation between volume/turnover variability and firm-specific uncertainty remains intact in multivariate regressions.

To sum up, Table 1 strongly supports the hypothesis that in asset-pricing tests, volume/turnover variability picks up firm-specific uncertainty. I delay the discussion of the economic forces that drive the link between volume/turnover variability and firm-specific uncertainty to the end of Section VI.B, which looks at liquidity of the volume/turnover variability quintile portfolios.

B Volume/Turnover Variability Effect versus Uncertainty Effects

The close relation between variability of volume/turnover and several measures of firm-specific uncertainty established in Table 1 and the prevalent negative correlation between returns and these measures[7] suggest that the volume/turnover variability effect should overlap with the uncertainty effects found in the literature. To gauge the degree of the overlap, this subsection performs the horse race between those effects.

On the one hand, I expect the overlap to exist, because otherwise the central argument of the paper that the volume/turnover variability effect exists because volume/turnover variability picks up firm-specific uncertainty would lose plausibility. On the other hand, the overlap should be far from complete, because otherwise the volume/turnover variability effect would not merit an independent explanation.

My theory predicts that it is the volatility of fundamentals of the underlying asset behind valuable real options that is related to expected returns and aggregate volatility risk. Therefore, all empirical measures of firm-specific uncertainty are only proxies for this unobservable parameter. Hence, their impact on returns should overlap, but not necessarily overlap completely. Turnover variability, as outlined in the introduction and discussed in more detail in Section VI.B, is also associated to firm-specific uncertainty, and therefore its effects on returns should partially, but not completely overlap with the effects of other uncertainty measures.

[7] See, e.g., Ang et al. (2006) and Diether et al. (2002), among others

Table 2 runs Fama-MacBeth regressions of returns on standard asset-pricing controls, lagged volume/turnover variability, and several measures of firm-specific uncertainty. The standard controls used in all regressions are current beta, previous year size, previous year market-to-book, return in the past month, cumulative return between months t-2 and t-12, and average volume/turnover in the previous year. To save space, the coefficients on the controls and volume/turnover are not tabulated.

Panel A performs the horse race between the volume/turnover variability effect of Chordia et al. (2001) and the idiosyncratic volatility discount of Ang et al. (2006). The table reports the idiosyncratic volatility discount at 1.227% per month prior to controlling for the Chordia et al. effect, and at 1.076% (1.045%) per month after controlling for turnover (volume) variability. Likewise, the turnover (volume) variability effect stands at 41.4 bp (53.8 bp per month) prior to controlling for the idiosyncratic volatility discount, and at 32.4 bp (37.9 bp) per month after controlling for it. I conclude that while there is a visible overlap between the two effects, the Ang et al. and Chordia et al. anomalies are two empirically separate phenomena rather than one.

Panel B performs a very similar horse race between the Chordia et al. result and the analyst disagreement effect of Diether et al. (2002), replacing idiosyncratic volatility (IVol) by standard deviation of analyst forecasts (Disp). The conclusion is the same: the volume/turnover variability effect and the analyst disagreement effect do overlap, but the overlap is far from complete, suggesting that the volume/turnover variability effect merits a separate study.[8]

Untabulated results show that a similar measure of firm-specific uncertainty, analyst

[8] The visible difference between Panels A and B is that the volume/turnover variability effect is weaker, though still sizeable and significant, in the sample with non-missing standard deviation of analyst forecasts (i.e., with two or more analysts following the firm). The weaker volume/turnover variability effect for firms with better analyst coverage is consistent with the evidence in George and Hwang (2009), studied in more detail in Section VII.A.

forecast error, used in Table 1, is unrelated to expected returns and therefore cannot explain the volume/turnover variability effect.

Panel C replaces analysts disagreement with variability of earnings. The first column reports that the return differential between the firms with the lowest and the higher earnings variability is 32.6 bp per month, t-statistic 2.42. To my knowledge, this paper is the first one to document the negative relation between earnings variability and future returns.

The next columns of Panel C show that controlling for the earnings variability effect does not make the volume/turnover variability effect weaker, though the reverse is not true: controlling for the volume/turnover variability effect does weaken the earnings variability effect by about a third. Untabulated results show that the conclusions of Panel C are unchanged if one replaces variability of earnings by variability of cash flows, another measure from Table 1.

Also in untabulated results (available upon request), I try another way of gauging the overlap between the uncertainty effects and the volume/turnover variability effect. I orthogonalize volume/turnover variability to the uncertainty measures above by running Fama-MacBeth regressions of volume/turnover variability on the uncertainty measures and computing the residuals. I then use these orthogonalized measures of volume/turnover variability as explanatory variables in the regressions similar to the ones in columns two and four of Table 2. I find that the volume/turnover variability effect declines by about 20 bp per month after I orthogonalize volume/turnover variability to uncertainty measures, but remains statistically and economically significant at 20-30 bp per month.

Summing up the evidence in Table 2, I conclude that while there is a visible overlap between the volume/turnover variability effect and the uncertainty effects, consistent with the strong relation between volume/turnover variability and firm-specific uncertainty documented in Table 1, the volume/turnover variability effect is not subsumed by either of the uncertainty measures. Thus, the volume/turnover variability effect merits a separate explanation, which is the subject of the paper.

V Volume/Turnover Variability Effect and Aggregate Volatility Risk

A FVIX as an Aggregate Volatility Risk Factor

The main prediction of this paper is that the volume/turnover variability effect is explained by aggregate volatility risk, i.e., by the fact that firms with high (low) volume/turnover variability tend to perform relatively well (poorly) in response to unexpected increases in aggregate volatility.

In the tests of this hypothesis, I use the FVIX factor, the aggregate volatility risk factor that has been shown to be priced in a broad cross-section (see Ang, Hodrick, Xing, and Zhang, 2006, and Barinov, 2012) and has been shown to explain several important anomalies, including the idiosyncratic volatility discount of Ang et al. (2006) and the value effect (see Barinov, 2011), the analyst disagreement effect of Diether, Malloy, and Scherbina (2002) (see Barinov, 2013a), and the new issues puzzle (see Barinov, 2012).

FVIX is the factor-mimicking portfolio that mimics daily innovations to the VIX index (see Section 2 and Data Appendix for discussion of the factor-mimicking procedure). As such, it represents the combination of zero-investment portfolios (the base assets) that has the highest positive correlation with the VIX change (my proxy for innovations to VIX).

In order to be a valid and useful ICAPM factor, FVIX factor has to satisfy three requirements. First, it has to be significantly correlated with the variable it mimics (the change in VIX). In untabulated results, I find that the R-square of the factor-mimicking regression is 0.49, and the correlation between FVIX returns and VIX changes is then expectedly high at 0.69. I conclude that FVIX clears the first hurdle of being a good mimicking portfolio.

Second, FVIX has to earn sizeable and statistically significant risk premium, both in raw returns and, most importantly, on the risk-adjusted basis. Since FVIX is, by construction, positively correlated with VIX changes, FVIX represents an insurance against increases in aggregate volatility, and, as such, has to earn a negative risk premium. Untabulated results show that the average raw return to FVIX is -1.21 per month, t-statistic -3.4, and the CAPM alpha and the Fama-French alpha of FVIX are both at about -46 bp per month, t-statistics -3.86 and -3.26, respectively. I conclude that FVIX captures important risk investors care about, because the negative alphas suggest they are willing to pay a significant amount for the insurance against this risk provided by FVIX. Hence, FVIX clears the second hurdle for being a valid ICAPM factor.

Third, as Chen (2002) suggests, a valid volatility risk factor should be able to predict future volatility. Barinov (2013a) shows that FVIX returns indeed predict several measures of expected and realized market volatility. Thus, FVIX clears the third and final hurdle for being a valid volatility risk factor.

B Variability of Trading Activity and Aggregate Volatility Risk

Table 3 looks at the quintile sorts on volume/turnover variability. The quintiles are rebalanced monthly and use NYSE (exchcd=1) breakpoints. To eliminate microstructure issues, the sample excludes stocks priced below $5 at the portfolio formation date. The results are robust to using CRSP quintile breakpoints and including low-priced stocks back into the sample. The sample period is from January 1986 to December 2010 because of the availability of the FVIX factor.

The first row Panel A considers value-weighted CAPM alphas and confirms that the turnover (volume) variability effect is strong and significant at 48 bp (53 bp) per month, close to the estimates from the cross-sectional regressions in Table 2.[9] The second row looks at Fama-French (1993) alphas and brings similar numbers, just like the first two rows of Panel B that look at equal-weighted CAPM and Fama-French alphas.

The third row of Panels A and B add the FVIX factor to the CAPM and find that doing so completely eliminates the alpha differential between firms with the lowest and highest volume/turnover variability. The alpha differential flips the sign, loses significance and stands between -4 bp and -21 bp per month. Also, all alphas of volume/turnover variability quintiles become insignificant in the two-factor ICAPM with the market factor and FVIX, in contrast to the CAPM and Fama-French alphas that are normally significantly positive (negative) for firms with the lowest (highest) volume/turnover variability.

The driving force behind the success of the ICAPM with FVIX is revealed in the fourth row, which reports the FVIX betas. FVIX betas of firms with high volume/turnover variability are significantly more positive than FVIX betas of firms with low volume/turnover variability. This pattern in FVIX betas suggest that firms with high (low) volume/turnover variability do significantly better (worse) than the CAPM prediction when VIX increases, which is the reason why these firms earn low (high) expected returns.

Untabulated results add FVIX to the Fama-French model and the Carhart model and arrive at similar conclusions. Adding FVIX to either model substantially reduces the volume/turnover variability effect and reveals the ability of stocks with high volume/turnover variability to provide a hedge against aggregate volatility risk.

I conclude from Table 3 that volume/turnover variability is negatively related to expected returns not because liquidity variability is negatively related to expected returns (it is not, more on that in Section VI.C and Table 9), but because volume/turnover variability

[9] Table 3 uses the data from 1986-2010, whereas Table 2 uses the data from 1966-2010. The similar volume/turnover variability effect in both tables implies that the volume/turnover variability effect is stable.

picks up firm-specific uncertainty, which is in turn negatively related to aggregate volatility risk and therefore negatively related to expected returns, as prior research (Barinov, 2011, 2013a) suggests.[10]

In untabulated results (available upon request), I test whether the relation between volume/turnover variability and aggregate volatility risk can be due only to the overlap between volume/turnover variability and other uncertainty measures, documented in Section IV.B. My prior is that even after controlling for other uncertainty measures, there is a strong relation between volume/turnover variability and aggregate volatility risk: Table 2 shows that the other uncertainty measures subsume at most a third of the volume/turnover variability effect, while Table 3 demonstrates that FVIX explains the volume/turnover variability effect in its entirety.

The formal test I perform is the following: I construct a measure of volume/turnover variability orthogonalized to the uncertainty measures[11] and redo Table 3 using this new orthogonalized measure. I find that sorting on the orthogonalized volume/turnover variability still produces a significant (though slightly weaker) volume/turnover variability effect and a significant spread in FVIX betas, comparable to the one I observe in the original Table 3.

C Variability of Trading Activity, Growth Options, and Aggregate Volatility Risk

Table 4 looks at the abnormal return differential between low and high volume/turnover

[10] A referee suggested that the prediction of my theory that firms with high variability of trading activity react less negatively to increases in aggregate volatility is based on the assumption that when aggregate volatility goes up, the uncertainty of firms with highly variable trading activity increases at least just as much as the uncertainty of firms with stable trading activity. In untabulated results, I test this assumption and find that both in absolute and relative terms idiosyncratic volatility and analyst disagreement are more sensitive to increases in VIX for firms with high variability of volume/turnover.

[11] The orthogonalization involves performing Fama-MacBeth regressions of volume/turnover variability on the uncertainty measures and using the residuals as the orthogonalized measure.

variability firms across market-to-book quintiles. The hypothesis is that the abnormal return differential is stronger for high market-to-book firms, because variability of trading activity proxies for firm-specific uncertainty, and firm-specific uncertainty is more negatively related to returns for growth firms (see, e.g., Barinov, 2011, 2013a).

Panel A considers the turnover variability effect and shows that it is significantly different for growth and value firms only in equal-weighted returns. In value-weighted returns, the turnover variability effect is confined to three top market-to-book quintiles, but its value takes a sudden dip in the top market-to-book quintile, making the difference in the turnover variability effect between value and growth firms insignificant, though still economically large.

The second row of Panel A looks at the alphas and FVIX betas from the two-factor ICAPM and finds three results that strongly confirm my theory of the turnover variability effect. First, FVIX explains the turnover variability effect in all market-to-book quintiles. In particular, it explains the largest equal-weighted alpha of the low-minus-high turnover variability strategy in the growth quintile. The alpha is reduced from 63 bp per month in the CAPM to 9 bp per month in the ICAPM with FVIX.

Second, FVIX materially reduces and renders insignificant the difference in the turnover variability effect between value and growth firms. In equal-weighted returns, the difference declines from 73.3 bp per month, t-statistic 3.25, to 31.8 bp per month, t-statistic 1.16.

Third, the FVIX beta of the low-minus-high turnover variability strategy becomes significantly more negative as one goes from value firms to growth firms. The behavior of the FVIX beta suggests that shorting firms with high turnover variability means more exposure to aggregate volatility risk if done in the growth subsample, which is consistent with the prediction of my theory that firms with high turnover variability are better hedges against aggregate volatility risk if their equity is option-like.

Panel B of Table 4 considers the relation between market-to-book and the volume variability effect and arrives at the same conclusions. The volume variability effect is stronger for growth firms in both equal-weighted and value-weighted returns (78.2 bp and 97.9 bp per month difference, respectively, t-statistics 3.27 and 2.72), FVIX explains this regularity, and FVIX betas suggest that shorting firms with high volume variability produces the largest exposure to aggregate volatility risk if the shorting is done in the growth subsample.

Overall, the evidence in Table 4 is consistent the central idea of this paper that variability of trading activity is negatively related to expected returns because higher variability of trading activity means higher firm-specific uncertainty, and higher uncertainty means lower exposure of option-like firms (in this case, growth firms) to aggregate volatility risk.

D Variability of Trading Activity, Credit Rating, and Aggregate Volatility Risk

Table 5 repeats the analysis of Table 4 looking at the other dimension of equity option-likeness - the one that comes from the existence of risky debt. I use credit rating rather than leverage as a measure of equity option-likeness, because leverage is mechanically negatively correlated with market-to-book (market cap is in the denominator of leverage and in the numerator of market-to-book), but both leverage and market-to-book are expected to be positively related to the strength of the volume/turnover variability effect under my theory. Also, equity is option-like only when the firm is reasonably close to bankruptcy and limited liability can at least potentially play a role. Hence, the option-likeness of equity due to risky debt is best measured by distress risk measures like credit rating.

Table 5 looks at the CAPM and ICAPM alphas and the FVIX betas of the low-minus-high turnover/volume variability strategy followed separately for three groups of firms - with good (top 30%), medium (middle 40%), and bad (bottom 30%) credit rating. I resort to the three groups instead of quintiles because the number of rated firms that have enough data to compute volume/turnover variability is relatively small, and sorting into 25 portfolios instead of 9 produces some unbalanced portfolios with the number of stocks in low double-digits.

Panel A looks at the relation between the turnover variability effect and credit rating and finds that the turnover variability effect is indeed significant only for firms with the worst credit rating. The difference in the CAPM alphas of the low-minus-high turnover variability strategy between the worst and the best credit rating firms is 52.3 bp per month, t-statistic 2.22 in value-weighted returns and 44.4 bp per month, t-statistic 1.87 in equal-weighted returns.

After controlling for FVIX in the second row, the alpha differentials above decline to 17.1 bp per month, t-statistic 0.68, and 14.4 bp per month, t-statistic 0.68, respectively. Panel A also shows, consistent with my theory, that FVIX has no trouble explaining the turnover variability effect for bad credit rating firms, where the turnover variability effect is the strongest.

The FVIX betas also strongly align with my theory of the volume/turnover variability effect. Panel A finds that the low-minus-high turnover variability strategy has no exposure to aggregate volatility risk for firms with the best credit rating, the equity of which is not option-like. The FVIX beta of the low-minus-high turnover variability strategy then increases strongly and monotonically as one looks at the subsamples with medium and bad credit rating, revealing that shorting firms with high turnover variability and option-like equity means exposing oneself to aggregate volatility risk. This is consistent with the main prediction of my theory that turnover variability picks up firm-specific uncertainty, and higher firm-specific uncertainty makes expected returns lower by turning option-like equity into a hedge against aggregate volatility risk.

Panel B looks at the association between the volume variability effect and credit rating and reaches similar conclusions. According to Panel B, the volume variability effect is significantly stronger for firms with lower credit rating, FVIX explains its regularity, as well as the huge volume variability effect in the worst credit rating subsample (92 bp per month in value-weighted returns), and FVIX betas of the low-minus-high volume variability strategy become significantly more negative if the strategy is followed in the worst credit rating subsample.

In untabulated results, I corroborate the conclusions from Tables 4 and 5 by switching from portfolio sorts to cross-sectional regressions and adding more measures of equity option-likeness to the analysis. The regressions use the standard asset-pricing controls: market beta, market cap, market-to-book, return from the previous month (reversal), and cumulative return between months t-2 and t-12 (momentum). The regressions also include volume or turnover variability and the product of this variability with several option-likeness measures: market-to-book, sales growth, investment growth, credit rating, and Ohlson's (1980) O-score.

The untabulated regressions show that the volume/turnover variability effect is by 50 to 130 bp per month stronger for growth firms than for value firms. This link is large and statistically significant irrespective of whether one measures growth options with market-to-book, investment growth, or sales growth. Likewise, the volume/turnover variability effect is by about 90 bp per month stronger for distressed firms, even if distressed firms are defined using O-score and not credit rating (the effect of credit rating on the volume/turnover variability effect is even stronger).

I also verify that the effects of volume/turnover variability and its product with the measures of equity option-likeness on expected returns are mirrored by similar effect on FVIX betas. To that end, I change the dependent variable from returns to firm-level FVIX betas and re-run the regressions above. The control variables stay the same.

The regression with FVIX betas shows that FVIX beta of the low-minus-high volume/turnover variability strategy strongly increases in measures of growth options, and in several cases the FVIX beta of the low-minus-high volume/turnover variability portfolio becomes insignificant for value firms. Likewise, the regressions with FVIX betas confirm that the FVIX beta of the low-minus-high volume/turnover variability portfolio is significantly greater for distressed firms, irrespective of whether distress is measured by credit rating or by O-score.

I conclude that the link between the volume/turnover variability effect and equity option-likeness is just as strong in cross-sectional regressions as in double sorts and robust to using different measures of growth options and financial distress. The same is true about the aggregate volatility risk explanation of this link.

VI Can the Volume/Turnover Variability Effect Be a Liquidity or Liquidity Risk Phenomenon?

A Variability of Trading Activity and Liquidity Risk

Chordia et al. (2001) suggest that the negative relation between volume/turnover variability and expected returns is puzzling because firms with high variability of volume/turnover have a higher chance of experiencing low volume/turnover and hence higher trading costs. Higher probability of being illiquid should then make these firms more risky and less attractive to investors, resulting in higher, not lower expected returns.

In a covariance-based world, such tendency will only matter if the high-trading-costs states of firms with high volume/turnover variability are related to market-wide illiquidity. If firms with high volume/turnover variability tend to hit those high-trading-costs states when market illiquidity is high (low), then such firms have high (low) liquidity risk, which would make their low returns more (less) puzzling.

Table 6 checks whether higher variability of trading activity implies higher or lower liquidity risk. Following Acharya and Pedersen (2005), Table 6 defines liquidity risk in two ways: as the tendency to experience low returns in response to increases in market illiquidity and as the tendency to experience high trading costs during market declines.[12]

Panels A to C of Table 6 focus on the first, more conventional, definition of liquidity risk. Panel A looks at the quintile sorts on turnover/volume variability and reports the alpha from the Fama-French model and the four-factor models with the three Fama-French factors and one of the liquidity factors.

Panel A suggests that firms with higher variability of trading activity have slightly lower, not higher liquidity risk. The impact of controlling for liquidity risk on the alpha of the low-minus-high variability portfolio ranges from a few basis points (in the case of the Pastor-Stambaugh factor) to one-third of the alpha (in the case of the traded Amihud factor). The volume/turnover variability effect, however, remains economically strong, at at least 27.6 bp per month and statistically significant.[13]

Panel B reports the liquidity betas from the regressions in Panel A. Consistent with Panel A, the spread in liquidity betas between firms with high and low variability of trading activity is numerically small (on average, about 0.1-0.15 for the factors with the Fama-French alpha of about 60 bp per month) and often statistically insignificant. Also,

[12] Acharya and Pedersen also analyze the third type of liquidity risk, the tendency to experience high trading costs in an illiquid market, but find that the two types above are more important. In untabulated results, I also consider the third type of liquidity risk and arrive to the conclusions similar to that from Panel D (see below).

[13] The volume variability effect loses statistical significance after controlling for the Sadka and Amihud factors, but the alphas stay around 30 bp per month with t-statistics of roughly 1.5, which imply that while we cannot, strictly speaking, reject the hypothesis that the volume variability effect, controlling for liquidity risk, is zero, we also cannot reject the hypothesis that the volume variability effect, controlling for liquidity risk, is as high as 70 bp per month.

while the volume/turnover variability effect comes primarily from the short side, [14] the liquidity betas are generally larger and more significant for firms with low volume/turnover variability.

Panel C looks at the loadings on the non-traded liquidity factors and finds even more evidence undermining the relation between variability of trading activity and liquidity risk. Despite the evidence in Panels A and B that the Pastor-Stambaugh and Sadka factors help somewhat in explaining the volume/turnover variability effect, Panel C finds that the loading on Pastor-Stambaugh factor is positively related to variability of trading activity (suggesting higher liquidity risk for firms with more variable volume/turnover) and that the relation between the Sadka factor and volume/turnover variability, significant in Panel B, loses significance in Panel C.

Lastly, Panel D performs firm-level regressions of changes in several liquidity measures on the market return and reports the median slope (type-two liquidity risk beta from Acharya and Pedersen, 2005). The regressions are run every month using monthly data from the past 36 months. The liquidity measures are three measures of spread: the Roll (1984) measure, the effective tick estimate of Holden (2009), and the effective spread estimate from Corwin and Schultz (2012), two measures of price impact: the Amihud (2002) measure and the Pastor-Stambaugh (2003) gamma, and the general measure of trading costs: the frequency of zero returns, suggested by Lesmond, Ogden, and Trczinka (1999). I multiply the Pastor-Stambaugh gamma by -1 to make sure that high values of all measures mean lower liquidity.

The sensitivity of trading costs to market returns is uniformly negative in all quintiles, suggesting that all quintiles have some liquidity risk in the form of higher trading costs

[14] Firms with high variability of trading activity have significantly negative alphas, much larger in absolute magnitude than the positive alphas of firms with low variability of trading activity, see the first row of Panel A.

when the market drops. However, the spread in the trading costs sensitivity between firms with low and high variability of trading activity takes different sings depending on the liquidity measure. For example, out of three spread measures, the Roll measure and the Holden effective tick estimate suggest that firms with more variable trading activity have lower liquidity risk, but the effective spread estimate of Corwin and Schultz suggests otherwise. Both measures of price impact indicate higher liquidity risk for firms with more variable volume/turnover, but the catch-all trading costs measure from Lesmond et al. finds that the similar relation is statistically weak. On the balance though, the spreads in liquidity risk that suggest higher liquidity risk for high volume/turnover variability firms are more common and more statistically significant. This is in contrast to the conclusion from Panels A to C that firms with higher variability of trading activity have, if anything, lower liquidity risk.

To sum up the evidence in Table 6, I do not find a clear relation between volume/turnover variability and liquidity risk. I conclude that liquidity risk does not help significantly to explain the volume/turnover variability effect of Chordia et al. (2001), but is also unlikely to make it more puzzling.

B Variability of Trading Activity and Variability of Liquidity/Liquidity Risk

Pereira and Zhang (2010) argue that the variability of trading activity is negatively related to future returns because higher variability of trading activity implies higher variability of price impact, and higher variability of price impact means a higher chance to sell with a lower price impact. In other words, Pereira and Zhang (2010) argue that investors in firms with high volume/turnover variability can wait out the periods of low liquidity and use the periods of high liquidity that firms with more variable liquidity are more likely to have.

Table 7 tests whether higher variability of trading activity is indeed related to variability of liquidity. Similar to Table 1, Table 7 performs quintile sorts on variability of turnover (Panel A) or variability of volume (Panel B) and reports median coefficient of variation of several liquidity measures across the quintiles.

Expectedly, Table 7 finds that firms with more variable volume/turnover also have more variable trading costs (the Pastor-Stambaugh gamma and the frequency of zero returns are the only liquidity measures that suggest otherwise). The relation is also strictly monotonic and economically significant in most cases. For example, according to the Amihud measure, the price impact becomes about two times more variable for high rather than low volume/turnover variability firms. The increase in the variability of spread measures from low to high volume/turnover variability firms is between one-third and one-half (with the exception of the Roll measure, which yields a smaller, 10-15%, increase).

One obvious condition for the Pereira and Zhang explanation of the volume/turnover variability effect is a relatively high probability that a significant number of firms with highly variable volume/turnover will have higher liquidity than a significant number of firms with low variability of volume/turnover. If firms with high variability of trading activity are, on average, very illiquid, and despite higher variability, their liquidity is very rarely higher than the liquidity of firms with low variability of trading activity, then it is unlikely that investors will be able to wait out the periods of relative illiquidity of firms with high volume/turnover variability: such periods will take almost the whole sample.

Table 8 shows that this is exactly the case. Panel A (B) sorts firms into quintiles based on their variability of turnover (volume) and reports median values of several liquidity characteristics in each of these quintiles. Panels A and B find that firms with the highest variability of volume/turnover have 2 to 4 times higher spread (as measured by the Roll measure, the effective tick, the Gibbs sampler of Hasbrouck, 2009, or the spread estimator of Corwin and Schultz, 2012), 15 times higher price impact (as measured by the Amihud (2002) measure), 2 to 4 times higher price impact if one is willing to accept the "bounce-back-based" Roll measure and Gibbs sampler as measures of price impact, and more than twice higher total trading costs, as proxied by the frequency of zero returns.

Panel C (D) tabulates the probability that the liquidity of firms with higher variability of turnover (volume), as measured by the liquidity measure in the respective column, will beat the liquidity of firms with lower variability of turnover (volume). Panels C and D run the median against the median in the top row, and the 25th percentile of liquidity in the highest volume/turnover variability quintile against the 75th percentile of liquidity in the lowest volume/turnover variability quintile in the bottom row.

Panels C and D show that the probability of the median firm with high variability of volume/turnover being more liquid than the median firm with low variability of volume/turnover is exactly 0 for three out of the six liquidity measures (the effective tick, the Amihud measure, and the Gibbs spread estimator) and below 1.5% (3 months or less out of the sample of 540 months) for the other three measures.

When one compares the cut-off of the most liquid 25% in the highest volume/turnover variability quintile to the cut-off of the least liquid 25% in the lowest volume/turnover variability quintile, one finds that the probability that the former beats the latter in about 40% of sample months (in 4 out of 12 cases the probability is below 15%, in 2 out of 12 cases the probability exceeds 50%).

The meaning of this last comparison is the following: suppose one bought stock A from the lowest and stock B from the highest volume (or turnover) variability quintile. Then, conditional on the fact that A fell in the bottom liquidity quartile among low volume/turnover variability firms and B fell in the top liquidity quartile among high volume/turnover variability firms (which is itself an event with probability 6.25%), the probability of B being more liquid than A is about 40%.[15] The unconditional probability of B becoming more liquid than A is then about $40\% \cdot 6.25\% = 2.5\%$ - that is, it is virtually impossible to wait until a firm with high volume/turnover variability becomes more liquid than a firm with low volume/turnover variability.

Panels A and B of Table 8 also shed light on the driving force behind the relation between volume/turnover variability and uncertainty. Panel A and B suggest that firms with high volume/turnover variability are extremely illiquid. One consequence is the infrequent trading of these firms: the zero frequency measure in the last row of Panels A and B suggests that a representative firm with low volume/turnover variability is not traded on 10% of trading days, and a representative firm with high volume/turnover variability is not traded on 23% of trading days. It appears that the infrequent trading is the force that creates the high variability of trading activity: if instead of moving smoothly, trading volume jumps between zero and a multi-period volume that includes the pent-up demand from the prior periods with no trading, trading activity will naturally be more volatile. Infrequent trading and low liquidity is, in turn, brought about by high uncertainty. Hence, the economic mechanism that links uncertainty to variability of trading activity works this way: high uncertainty results in low liquidity, low liquidity implies infrequent trading, and infrequent trading causes higher volume/turnover variability.

C Liquidity Variability and Expected Returns

Table 7 establishes that firms with higher variability of volume/turnover have higher variability of other liquidity measures. Panel A of Table 9 considers the relation between expected returns and the variability of the six measures of liquidity from Panel A of Table 7. Panel A of Table 9 performs firm-level Fama-MacBeth regressions of returns on the

[15] According to the numbers in Panel D, the conditional probability of B having lower Amihud measure is 12.2% and the conditional probability of B having lower Roll measure is 45.2%.

liquidity variability measures lagged by two months and the standard controls (untabulated to save space): market beta, previous year size, previous year market-to-book, previous month return, cumulative return between months t-2 and t-12. Also, the untabulated controls include of the level of the liquidity variable, the variability of which is used in the regression. When Panel A of Table 9 performs the horse race between variability of liquidity and variability of volume/turnover, the controls also include average value of volume/turnover in the past year. All independent variables are ranks confined between 0 and 1.

The first row of Panel A reports the slopes of the variability of liquidity variables, used separately from each other. The slopes show that neither of the measures of liquidity variability is significantly related to expected returns. The magnitude of the slopes suggests that the effects of liquidity variability are from -17 bp to 6 bp per month. Four out of six slopes are negative, but none of them is statistically significant. Similar to results in Pereira and Zhang (2010), the effect of variability of the Amihud measure on expected returns is at -10 bp per month, but lacks statistical significance.

The second and third rows of Panel A report the slopes of turnover variability and liquidity variability from the regressions that pair up turnover variability and different liquidity variability measures, used separately from each other. The slopes show that turnover variability is a strong and significant predictor of expected returns no matter how one controls for variability of liquidity, and variability of liquidity is still insignificant in the presence of turnover variability.

The fourth and fifth row replace turnover variability with volume variability. The results are the same: controlling for liquidity variability leaves the negative relation between volume variability and future returns strong and significant, and controlling for volume variability does not change the fact that liquidity variability is unrelated to expected returns.[16]

Panel B repeats Panel A replacing liquidity variability by variability of liquidity risk, measured as variability of firm-level monthly loadings on the traded and non-traded versions of the Pastor-Stambaugh, Sadka, and Amihud factors.[17] The liquidity risk loadings are re-estimated each month using individual firms' returns in the past 36 months.

Panel B shows, similar to Panel A, that variability of liquidity risk is largely unrelated to expected returns, and this conclusion does not change when one controls for volume or turnover variability. Likewise, the relation between expected returns and volume/turnover variability is unaffected by the presence of variability of liquidity risk. Panel B finds some traces of weak positive relation between expected returns and variability of liquidity risk exposures (see non-traded Sadka factor and traded Amihud factor), in contrast to the strong and negative relation between expected returns and volume/turnover variability.

I conclude that variability of either liquidity or liquidity risk is clearly unrelated to expected returns: none of the long list of variables I used was able to tease out the relation between liquidity or liquidity risk variability and expected returns. This evidence lends further support to the central hypothesis of the paper that volume/turnover variability is related to expected returns only because volume/turnover variability is related to firm-specific uncertainty and therefore to aggregate volatility risk.

D Daily Variability of Liquidity

Akbas et al. (2010) measure variability of liquidity using daily data within one month, and find that higher variability of the "Amihud ratio"[18] this month predicts higher, not

[16] In untabulated results, Panel A was repeated using all measures of liquidity variability in joint regressions, which also included turnover variability, or volume variability, or none. The results were very similar to Panel A.

[17] Unreported results show that variability of volume/turnover is unrelated to variability of liquidity risk.

[18] Akbas et al. (2010) use variability of the daily ratio of absolute return to dollar trading volume,

lower expected returns next month. While this result seems to be at odds with the volume/turnover variability effect of Chordia et al. (2001), Akbas et al. (2010) show that both their result and the Chordia et al. (2001) coexist in cross-sectional regressions, and conclude that the "finding that the volatility of liquidity is positively related to returns should be viewed as complementary rather than contradictory to the results documented by Chordia et al." Indeed, the Chordia et al. result will remain an anomaly and will need an explanation even if the Akbas et al. measure of liquidity variability turns out to be "better".

In untabulated results, I verify whether FVIX can also explain the Akbas et al. result. The findings are the following: first, FVIX betas are unrelated to daily volatility of liquidity. Second, and most surprisingly, daily volatility of liquidity, as measured in Akbas et al., is negatively rather than positively related to both firm-specific uncertainty measures and monthly measures of liquidity variability from Table 7. Third, if one switches from the variability of the "Amihud ratio" in Akbas et al. to variability of daily volume or turnover, the Chordia et al. result and its aggregate volatility explanation are back (though the volume/turnover variability effect is noticeably smaller using daily volume/turnover).

I conclude that the Akbas et al. (2010) result is not driven by either the relation between firm-specific uncertainty and expected return, or aggregate volatility risk, or even the relation between variability of liquidity and expected returns, and therefore is beyond the scope of my paper.

VII Can the Volume/Turnover Variability Effect Be Mispricing?

A The Volume/Turnover Variability Effect and Analyst Coverage

One possible explanation of the volume/turnover variability effect is that it is mis-

which is similar to variability of the Amihud measure, but technically is not that, because the Amihud measure is the average of this ratio within a month/year, not the ratio per se.

pricing. George and Hwang (2009) suggest that the volume/turnover variability effect can exist because betting against it implies trading in firms with high uncertainty and information asymmetry, and arbitrageurs are usually unwilling to do that. George and Hwang use analyst coverage as a proxy for uncertainty and information asymmetry, and successfully test the prediction that the volume/turnover variability effect is significantly stronger for firms with low analyst coverage.

Panel A of Table 10 confirms that the volume/turnover variability effect is indeed stronger when analyst coverage is low. The difference in the turnover (volume) variability effect between low and high coverage firms is 27.1 bp per month, t-statistic 1.78 (35.2 bp per month, t-statistic 2.29), which is consistent with the volume/turnover variability effect being mispricing.

My theory of the volume/turnover variability effect does not exclude the possibility that the volume/turnover variability effect is related, in the cross-section, to various firm characteristics, including analyst coverage. The prediction my theory makes is that the relation between the strength of the volume/turnover variability effect and any firm characteristic should be explained by aggregate volatility risk and that the volume/turnover variability effect should be explained by FVIX in any subsample.

This is exactly what the second row of Panel A shows. When one controls for FVIX, the relation between the volume/turnover variability effect and analyst coverage disappears, and the stronger volume/turnover variability effect for firms with low analyst coverage is reduced to almost zero. As usual, the third row shows that these changes are accompanied by more negative FVIX betas of the low-minus-high volume/turnover variability strategy in the low analyst coverage subsample.

I conclude from Panel A that the stronger volume/turnover variability effect for low analyst coverage stocks does not imply that the volume/turnover variability effect is mispricing, because the FVIX factor provides an adequate explanation of the relation between the volume/turnover variability effect and analyst coverage.

B The Volume/Turnover Variability Effect and Institutional Ownership

The previous analysis (Table 1) shows that variability of trading activity is closely related to firm-specific uncertainty. The obvious mispricing story for the volume/turnover variability effect is then the Miller (1977) theory. Miller suggests that in the presence of short sale constraints, stocks will be overpriced because the short sale constraints keep pessimists out of the market and the prices then reflect the average valuation of optimists. The higher is the uncertainty about the firm and the disagreement between pessimists and optimists, the larger is the mispricing caused by keeping the pessimists out of the market and the lower are the future returns. The empirical hypothesis from the Miller theory is that the volume/turnover variability effect will be stronger if short sale constraints are stronger.

Panel B of Table 10 tests the Miller theory by looking at the volume/turnover variability effect across the institutional ownership quintiles. I treat institutional ownership as the measure of supply of shares available to sell short. If institutional ownership is low, stocks for shorting will be hard to find, short sales will be costly and, according to the Miller story, the volume/turnover variability effect will be stronger due to short sale constraints. To make sure that institutional ownership is not capturing any size effects, I follow Nagel (2005) and orthogonalize institutional ownership to size, making it residual institutional ownership (RI).

The first row of Panel B shows that the turnover (volume) variability effect is indeed stronger for firms with lower institutional ownership - by 39 bp per month, t-statistic 1.91 (64.5 bp per month, t-statistic 3.50), which is consistent with the volume/turnover variability effect being mispricing.

The difference in the turnover (volume) variability effect between low and high institutional ownership firms declines to 16.7 bp per month, t-statistic 0.99 (45.8 bp per month, t-statistic 2.82) after one controls for FVIX. Panel B also finds that the volume/turnover variability effect is explained by FVIX in all institutional ownership quintiles, and the still significant difference in the the volume variability effect between high and low institutional ownership firms is driven by the negative volume variability effect (in the ICAPM alphas) for high institutional ownership firms.

To sum up, Panel B of Table 10 shows that the volume/turnover variability effect is indeed stronger for low institutional ownership firms, as the Miller theory would suggest, but this pattern is largely explained by the FVIX factor, thus making the mispricing explanation redundant and suggesting that the volume/turnover variability effect can be a purely rational phenomenon.

C The Volume/Turnover Variability Effect and Relative Short Interest

Panel C of Table 10 studies the volume/turnover variability effect across relative short interest quintiles. Relative short interest is defined as the percentage of shares outstanding that have been shorted and proxies for the demand for shorting. If short interest is already high, it is likely that shorting additional shares would be costly. Under the Miller theory, the volume/turnover variability effect will be stronger for the firms with high short interest, because these stocks are likely to be costly to short.

The first row of Panel C of Table 10 demonstrates that the volume/turnover variability effect is significantly stronger for heavily shorted firms. However, controlling for aggregate volatility risk in the second row reduces the difference in the turnover (volume) variability effect between between firms with high and low short interest from 67 bp per month, t-statistic 2.99, to 31.1 bp per month, t-statistic 1.46 (from 41.6 bp per month, t-statistic 1.67, to 9 bp per month, t-statistic 0.32). Likewise, the FVIX factor explains the large CAPM alphas of 86 bp and 62 bp per month that the low-minus-high volume/turnover variability strategy has in the highest short interest quintile.

Overall, Panel C of Table 10 suggests that the evidence that the volume/turnover variability effect is stronger for high relative short interest firms does not suggest that the volume/turnover variability effect is mispricing, because the stronger volume/turnover variability effect for heavily shorted firms is still explained by FVIX.

VIII Conclusion

The result in Chordia, Subrahmanyam, and Anshuman (2001) that variability of trading activity is negatively related to expected returns (the volume/turnover variability effect) creates the impression that liquidity variability bears a negative risk premium. The paper disputes this conclusion and shows that the volume/turnover variability effect can be explained by the fact that variability of trading activity is positively correlated with firm-specific uncertainty, and higher firm-specific uncertainty means lower aggregate volatility risk. The paper also shows that variability of other liquidity measures is unrelated to expected returns.

Higher uncertainty lowers the systematic risk of option-like equity[19] by making it less responsive to the changes in the value of the underlying assets. This property becomes particularly useful in recessions, when firm-specific uncertainty increases, and the risk exposure of option-like equity drops, causing its value to drop less in response to higher future expected returns. Also, all else equal, option-like equity increases in value when the uncertainty about the underlying asset increases during recessions, and this effect is

[19] Equity can be option-like either because it is a claim on options, such as growth options, or because it is similar to an option on the assets due to high indebtedness and limited liability.

naturally stronger for high uncertainty firms.

The paper starts by showing that variability of trading activity is strongly and positively related to several measures of uncertainty, such as idiosyncratic volatility, analyst disagreement, analyst forecast error, and the variability of earnings and cash flows. Further tests show that firm-specific uncertainty is linked to volume/turnover variability through liquidity. High firm-specific uncertainty implies lower liquidity, lower liquidity brings about infrequent trading, and infrequent trading makes volume and turnover more volatile. This argument is supported by the finding that firms with high variability of volume/turnover are indeed several times less liquid and witness no-trade days several times more often than firms with low variability of volume/turnover.

The paper proceeds to show that the volume/turnover variability effect disappears in the ICAPM with the market factor and the aggregate volatility risk factor. Consistent with my hypothesis that higher variability of trading activity predicts lower expected returns, because it is positively correlated to firm-specific uncertainty, and higher uncertainty lowers the risk of option-like equity, I find that the volume/turnover variability effect is significantly stronger for growth firms and firms with bad credit rating. I also find that the aggregate volatility risk factor explains why the volume/turnover variability effect is stronger for growth firms and firms with bad credit rating, lending further support that volume/turnover variability is related to firm-specific uncertainty and therefore to aggregate volatility risk.

The paper also considers the explanations of the volume/turnover variability effect that are based on liquidity and liquidity risk. I find that variability of trading activity is largely unrelated to liquidity risk. My results also show that variability of volume/turnover is strongly and positively associated with variability of other liquidity measures, but the variability of other liquidity measures is unrelated to expected returns.

I also reject the hypothesis of Pereira and Zhang (2010) that firms with high variability of volume/turnover are desired by investors because such firms have higher probability to become very liquid. My results show that variability of volume/turnover is strongly and negatively associated with liquidity, and in the data firms with highly variable volume/turnover are almost always less liquid than firms with low variability of volume/turnover.

I entertain the possibility that the volume/turnover variability effect may be mispricing. I find that the volume/turnover variability effect is stronger for the firms with higher limits to arbitrage, but the aggregate volatility risk factor explains a significant part of this relation.

References

Acharya, V.; and L. H. Pedersen. "Asset Pricing with Liquidity Risk." *Journal of Financial Economics*, 77 (2005), 375–410.

Akbas, F.; W. J. Armstrong; and R. Petkova. "The Volatility of Liquidity and Expected Stock Returns." Working Paper, Texas A&M University (2010).

Amihud, Y. "Illiquidity and Stock Returns: Cross-Section and Time–Series Effects." *Journal of Financial Markets*, 5 (2002), 31–56.

Ang, A.; R. J. Hodrick; Y. Xing; and X. Zhang. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, 61 (2006), 259–299.

Barinov, A. "Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns." Working Paper, University of Georgia (2011).

Barinov, A."Aggregate Volatility Risk: Explaining the Small Growth Anomaly and the New Issues Puzzle." *Journal of Corporate Finance* 18 (2012), 763–781.

Barinov, A. "Analyst Disagreement and Aggregate Volatility Risk." *Journal of Financial and Quantitative Analysis*, forthcoming (2013a).

Barinov, A. "Turnover: Liquidity or Uncertainty?" Working Paper, University of Georgia (2013b).

Campbell, J. Y. "Intertemporal Asset Pricing without Consumption Data." *American Economic Review*, 83 (1993), 487–512.

Chen, J. "Intertemporal CAPM and the Cross-Section of Stock Returns." Working Paper, University of Southern California (2002).

Chen, Z.; and R. Petkova. "Does Idiosyncratic Volatility Proxy for Risk Exposure?" *Review of Financial Studies*, 25 (2012), 2745–2787.

Chordia, T.; A. Subrahmanyam; and V. R. Anshuman. "Trading Activity and Expected Stock Returns." *Journal of Financial Economics*, 59 (2001), 3–32.

Corwin, S. A.; and P. Schultz. "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices." *Journal of Finance*, 67 (2012), 719–759.

Diether, K.; C. Malloy; and A. Scherbina. "Differences of Opinion and the Cross-Section of Returns." *Journal of Finance*, 57 (2002), 2113–2141.

Duarte, J.; A. Kamara; S. Siegel; and C. Sun. "The Common Components of Idiosyncratic Volatility." Working paper, University of Washington (2012).

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and K. R. French. "Industry Costs of Equity." *Journal of Financial Economics*, 43 (1997), 153–193.

Fama, E. F., and J. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Gao, X.; and J. R. Ritter. "The Marketing of Seasoned Equity Offerings." *Journal of Financial Economics*, 97 (2010), 33–52.

George, T. J.; and C.-Y. Hwang. "Why Do Firms with High Idiosyncratic Volatility and High Trading Volume Volatility Have Low Returns?" Working Paper, University of Houston (2009).

Grullon, G.; E. Lyandres; and A. Zhdanov. "Real Options, Volatility, and Stock Returns." *Journal of Finance*, 2012, forthcoming.

Hasbrouck, J. "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data." *Journal of Finance*, 64 (2009), 1445–1477.

Holden, C. W. "New Low-Frequency Spread Measures." *Journal of Financial Markets*, 12 (2009), 778–813.

Lesmond, D. A.; J. Ogden; and C. Trzcinka. "A New Estimate of Transaction Costs." *Review of Financial Studies*, 12 (1999), 1113-1141.

Merton, R. C. "An Intertemporal Capital Asset Pricing Model." *Econometrica*, 41 (1973), 867–887.

Miller, E. M. "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance*, 32 (1977), 1151–1168.

Nagel, S. "Short Sales, Institutional Investors, and the Cross-Section of Stock Returns." *Journal of Financial Economics*, 78 (2005), 277–309.

Newey, W.; and K. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.

Ohlson, J. A. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research*, 18 (1980), 109–131.

Pastor, L.; and R. F. Stambaugh. "Liquidity Risk and Ecpected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.

Pereira, J. P.; and H. H. Zhang. "Stock Returns and the Volatility of Liquidity." *Journal of Financial and Quantitative Analysis*, 45 (2010), 1077–1110.

Roll, R. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance*, 39 (1984), 1127–1139.

Sadka, R. "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk." *Journal of Financial Economics*, 80 (2006), 309–349.

A Data Appendix

The variables are arranged in the alphabetical order according to the abbreviated variable name used in the tables.

Amihud (Amihud illiquidity measure) - the 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 observations in a year and the stock price of less than $5 at the end of the previous year are excluded).

$\boldsymbol{\beta_{PS}}$ and $\boldsymbol{\beta_{PS-T}}$ (Pastor-Stambaugh beta wrt the non-traded/traded factor) - the loading from the regression of returns on the three Fama-French factors (MKT, SMB, HML from the website of Kenneth French) and the Pastor-Stambaugh factor

(A-1)

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{PS} \cdot PS_t.$$

In Table 6, the regression is performed at the portfolio level using monthly returns in 1986–2010. In Table 9, the regression is performed at the firm level, using monthly returns in months t-1 to t-36.

The Pastor-Stambaugh non-traded factor is the innovation to the market-wide monthly average of the Pastor-Stambaugh gamma, γ_{PS} (available from WRDS). The Pastor-Stambaugh traded factor (also available from WRDS) is the value-weighted return differential between the top and bottom deciles from the sorts on the expected value of β_{PS} - the Pastor-Stambaugh beta wrt the non-traded factor described above.

$\boldsymbol{\beta_{Sad}}$ and $\boldsymbol{\beta_{Sad-T}}$ (Sadka beta wrt the non-traded/traded factor) - the loading from the regression of returns on the three Fama-French factors (MKT, SMB, HML from the website of Kenneth French) and the Sadka factor

(A-2)

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{Sad} \cdot Sad_t.$$

In Table 6, the regression is performed at the portfolio level using monthly returns in 1986–2010. In Table 9, the regression is performed at the firm level, using monthly returns in months t-1 to t-36.

The Sadka non-traded factor is the innovation to the market-wide average of the variable (information-based) price impact or Kyle's λ (available from CRSP). The Sadka traded factor is the factor-mimicking portfolio that mimics the innovation to the market-wide average of the variable (information-based) price impact or Kyle's λ (that is, the Sadka non-traded factor) by regressing the innovation on the excess returns to the five quintile portfolios sorted on β_{Sad}, which is estimated at the firm level in month t-1

$$\Delta\lambda_t = \gamma_0 + \gamma_1 \cdot (Sad1_t - RF_t) + \gamma_2 \cdot (Sad2_t - RF_t) +$$

$$+\gamma_3 \cdot (Sad3_t - RF_t) + \gamma_4 \cdot (Sad4_t - RF_t) + \gamma_5 \cdot (Sad5_t - RF_t). \tag{A-3}$$

where $Sad1_t, \ldots, Sad5_t$ are the β_{Sad} quintiles described above, with $Sad1_t$ being the quintile with the most negative β_{Sad}. The Sadka traded factor is the fitted part of this regression less the constant.

$\boldsymbol{\beta_{Ami}}$ **and** $\boldsymbol{\beta_{Ami-T}}$ **(Amihud beta wrt the non-traded/traded factor)** - the loading from the regression of returns on the three Fama-French factors (MKT, SMB, HML from the website of Kenneth French) and the Amihud factor

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{Ami} \cdot Ami_t. \tag{A-4}$$

In Table 6, the regression is performed at the portfolio level using monthly returns in 1986–2010. In Table 9, the regression is performed at the firm level, using monthly returns in months t-1 to t-36.

The Amihud non-traded factor is the innovation to the monthly market-wide average of the Amihud measure (Illiq). Illiq is computed separately for each firm-month (at least 15 valid return and volume observations within each firm-month are required). The innovation is from the AR(1) model fitted to the average Amihud measure.

The Amihud traded factor is the factor-mimicking portfolio that mimics the innovation to the market-wide average of the Amihud measure (that is, the Amihud non-traded factor) by regressing the innovation on the excess returns to the five β_{Ami} quintiles, as in (A-3). The Amihud traded factor is the fitted part of this regression less the constant.

Cred (credit rating) - Standard and Poor's rating (spdr variable in the Compustat quarterly file). The credit rating is coded as 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D.

CVEarn/CVCFO (earnings/cash flows volatility) - coefficient of variation (standard deviation over the average) of quarterly earnings/cash flows measured in the past twelve quarters. Earnings are EPS (epspiq over prccq lagged by one quarter). Cash flows are operating income before depreciation (oibdpq) less the change in current assets (actq) plus the change in current liabilities (lctq) less the change in short-term debt (dlcq) plus the change in cash (cheq). The cash flows are scaled by average total assets (atq) in the past two years. All variables are from the Compustat quarterly file.

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

CVLiq (variability of liquidity or liquidity risk) - coefficient of variation (standard deviation over the average) of monthly liquidity/liquidity risk measures. The coefficient of variation is measured between months t-2 and t-36. The liquidity/liquidity risk measures include Amihud, EffTick, Gamma, Roll, Spread, Zero (liquidity), β_{Ami}, β_{Ami-T}, β_{PS}, β_{PS-T}, β_{Sad}, β_{Sad-T} (liquidity risk). The detailed definitions of the liquidity/liquidity risk measures can be found in this Appendix.

Disp (analyst forecast dispersion) - the 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 excluded). Earnings forecasts are from the IBES Summary file.

EffTick (effective tick size) - measure of effective spread from Holden (2009). On the simple $\$\frac{1}{8}$ grid, frequency of odd $\frac{1}{8}$s prices (prices that end with $\frac{1}{8}$, $\frac{3}{8}$, $\frac{5}{8}$, or $\frac{7}{8}$) measures the probability of the bid-ask spread being equal to $\$\frac{1}{8}$, the frequency of odd $\frac{1}{4}$s prices measures the probability of the bid-ask spread being equal to $\$\frac{1}{4}$, the frequency of the prices that end $\frac{1}{2}$ measures the probability of the bid-ask spread being $\$\frac{1}{2}$, and the frequency of whole-dollar prices measures the probability of the spread being \$1. For each firm-month, I estimate the probabilities of the spread as above and compute its expected value by multiplying the probabilities by the respective spread values. I use the $\$\frac{1}{16}$ grid before 2001 (decimalization) and the grid with clustering on dollars, half-dollars, quarters, dimes, nickels, and cents from 2001 on.

Error (analyst forecast error) - the absolute value of the difference between the one-year-ahead consensus forecast and actual earnings divided by actual earnings. All variables are from the IBES Summary file.

FVIX (aggregate volatility risk factor - factor-mimicking portfolio that tracks the daily changes in the VIX index. Following Ang, Hodrick, Xing, and Zhang (2006), I regress the daily changes in VIX on the daily excess returns to the five portfolios sorted on past sensitivity to VIX changes:

$$\begin{aligned} \Delta VIX_t = \gamma_0 + \gamma_1 \cdot (VIX1_t - RF_t) + \gamma_2 \cdot (VIX2_t - RF_t) + \\ + \gamma_3 \cdot (VIX3_t - RF_t) + \gamma_4 \cdot (VIX4_t - RF_t) + \gamma_5 \cdot (VIX5_t - RF_t), \end{aligned} \tag{A-5}$$

where $VIX1_t, \ldots, VIX5_t$ are the VIX sensitivity quintiles described above, with $VIX1_t$

being the quintile with the most negative sensitivity.

The fitted part of the regression above less the constant is my aggregate volatility risk factor (FVIX factor):

$$FVIX_t = \hat{\gamma_1} \cdot (VIX1_t - RF_t) + \hat{\gamma_2} \cdot (VIX2_t - RF_t) + \hat{\gamma_3} \cdot (VIX3_t - RF_t) +$$

$$+ \hat{\gamma_4} \cdot (VIX4_t - RF_t) + \hat{\gamma_5} \cdot (VIX5_t - RF_t). \tag{A-6}$$

The returns are then cumulated to the monthly level to get the monthly return to FVIX.

Gamma (Pastor-Stambaugh gamma) - the firm return sensitivity to the firm previous day dollar volume times the sign of the previous date return, from

$$R_{t+1} = \theta + \phi R_t + \gamma_{PS} \cdot \mathrm{sign(R_t)} \cdot \mathrm{Vol_t}. \tag{A-7}$$

Both the returns and the volume are from CRSP. The dollar volume is scaled by the ratio of the current total market value of NYSE and AMEX shares to the total market value of NYSE and AMEX shares in January 1963. γ_{PS} is computed only for NYSE (exchcd=1) and AMEX (exchcd=2) shares.

Gibbs (Gibbs measure) - the slope from the regression $\Delta P_t = a + c\Delta Q_t$, where P_t is the stock price and Q_t is the trade direction indicator. The values of the Gibbs measure come from the website of Joel Hasbrouck.

IG (investment growth) - the change in capital expenditures (capx item from Compustat) in percentage of last year capital expenditures: $IG_t = \dfrac{capx_t - capx_{t-1}}{capx_{t-1}}$

IVol (idiosyncratic volatility) - the standard deviation of residuals from the Fama-French model, fitted to the daily data for each month (at least 15 valid observations are required).

MB (market-to-book) - equity value (share price, prcc, times number of shares outstanding, csho) divided by book equity (ceq) plus deferred taxes (txdb), all items from Compustat annual files.

Mom (cumulative past return) - cumulative return to the stock between month t-2 and t-12.

Lev (leverage) - long-term debt (dltt) plus short-term debt (dlc) divided by equity value, all items from Compustat annual.

#An (number of analysts; analyst coverage) - the number of analysts covering the firm (from IBES).

O-score - the probability of bankruptcy measure from Ohlson (1980), computed as

$$\begin{aligned} O = -1.32 - 0.407 \cdot \ln TA + 6.03 \cdot \frac{TL}{TA} - 1.43 \cdot \frac{WC}{TA} + 0.076 \cdot \frac{CL}{CA} - \\ -1.72 \cdot I(TL > TA) - 2.37 \cdot \frac{NI}{TA} - 1.83 \cdot \frac{FFO}{TA} + \\ +0.285 \cdot I(NI < 0\ \&\ NI_{-1} < 0) - 0.521 \cdot \frac{NI - NI_{-1}}{|NI| + |NI_{-1}|}. \end{aligned} \tag{A-8}$$

where TA is the book value of total assets (Compustat item at), TL is the book value of total liabilities (lt), WC is working capital (wcap), CL are current liabilities (lct), CA are current assets (act), NI is net income (ni), NI_{-1} is the previous year net income, FFO are funds from operation (pi plus dp), $I(TL > TA)$ is the dummy variable equal to 1 if the book value of total liabilities exceeds the book value of total assets, and equal to 0 otherwise, $I(NI < 0\ \&\ NI_{-1} < 0)$ is the dummy variable equal to 1 if the net income was negative in the two most recent years, and equal to 0 otherwise.

RI (residual IO) - the residual (ϵ) from the logistic regression of IO on log Size and its square

$$log(\frac{Inst}{1 - Inst}) = \gamma_0 + \gamma_1 \cdot log(Size) + \gamma_2 \cdot log^2(Size) + \epsilon. \tag{A-9}$$

IO is the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. All stocks below the 20th NYSE/AMEX size percentile are dropped. If the stock is not dropped, appears on CRSP, but not on Thompson Financial 13Fs, it is assumed to have zero IO.

Roll (Roll measure) - $\mathrm{Roll_t} = 200 \cdot \sqrt{-\mathrm{Cov}(\mathrm{R_t}, \mathrm{R_{t-1}})}$ if the covariance is positive and 0 otherwise.

RSI (relative short interest) – outstanding shorts reported by NYSE and NASDAQ divided by the number of shares outstanding. The data are monthly and reported on the 15th calendar day of each month.

SG (sales growth) - the change in sales (sale item from Compustat) in percentage of last year sales: $SG_t = \dfrac{Sales_t - Sales_{t-1}}{Sales_{t-1}}$

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

Spread - the spread implied by the daily high and low prices. Spread is calculated by the formula from Corwin and Schultz (2011):

$$\text{Spread} = \frac{2 \cdot (\exp^{\alpha} - 1)}{1 + \exp^{\alpha}}, \tag{A-10}$$

where

$$\alpha = \frac{\sqrt{\beta} \cdot (\sqrt{2} - 1)}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \tag{A-11}$$

where

$$\beta = \log^2\left(\frac{HI_t}{LO_t}\right) + \log^2\left(\frac{HI_{t+1}}{LO_{t+1}}\right) \tag{A-12}$$

and

$$\gamma = \log^2\left(\frac{\max(HI_t,\ HI_{t+1})}{\min(LO_t,\ LO_{t+1})}\right), \tag{A-13}$$

where HI_t (LO_t) is the highest (lowest) price of the stock in day t.

Turn (turnover) - monthly dollar trading volume over market capitalization at the end of the month (both from CRSP), averaged in each firm-year.

Volume (dollar trading volume) - price per share at the end of a month times shares traded during the month (both from CRSP), averaged in each firm-year. Following Gao and Ritter (2010), the NASDAQ volume is divided by 2 before February 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and are unchanged after that. A firm is classified as a NASDAQ firm if its CRSP events file listing indicator - exchcd - is equal to 3.

Zero (zero frequency) - the fraction of zero-return days within each month.

Table 1. Variability of Trading Activity and Firm-Specific Uncertainty

The table presents the median values of uncertainty measures across quintile sorts on variability of volume/turnover. The quintiles are rebalanced monthly and use NYSE (exchcd=1) breakpoints. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Turnover Variability

	Low	**CV2**	**CV3**	**CV4**	**High**	**H-L**
IVol	0.013	0.016	0.020	0.023	0.028	0.015
t-stat	*27.7*	*31.5*	*28.8*	*26.2*	*25.7*	*16.7*
Disp	0.034	0.043	0.050	0.058	0.064	0.030
t-stat	*14.9*	*14.7*	*14.6*	*16.5*	*17.8*	*13.4*
Error	0.085	0.110	0.141	0.168	0.186	0.106
t-stat	*8.09*	*10.86*	*10.57*	*11.14*	*13.2*	*12.2*
CV Earn	0.477	0.625	0.834	0.999	1.144	0.667
t-stat	*15.2*	*18.0*	*18.0*	*18.7*	*21.8*	*18.5*
CV CF	0.584	0.791	1.039	1.238	1.457	0.873
t-stat	*36.6*	*34.1*	*27.3*	*27.0*	*26.6*	*15.1*

Panel B. Volume Variability

	Low	**CV2**	**CV3**	**CV4**	**High**	**H-L**
IVol	0.013	0.015	0.019	0.023	0.030	0.017
t-stat	*28.3*	*33.4*	*32.0*	*28.5*	*25.8*	*17.5*
Disp	0.034	0.041	0.049	0.057	0.067	0.034
t-stat	*12.9*	*13.8*	*15.0*	*16.0*	*18.4*	*12.2*
Error	0.081	0.116	0.128	0.156	0.191	0.113
t-stat	*9.00*	*7.33*	*12.2*	*13.5*	*13.6*	*13.2*
CV Earn	0.447	0.563	0.752	0.972	1.200	0.753
t-stat	*17.4*	*20.1*	*20.6*	*18.0*	*22.7*	*17.9*
CV CF	0.574	0.767	0.989	1.212	1.473	0.904
t-stat	*34.3*	*36.0*	*27.8*	*28.4*	*25.3*	*15.3*

Table 2. Variability of Trading Activity, Firm-Specific Uncertainty and Expected Returns

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. All independent variables, except for the market beta, are ranks between 0 and 1. The controls used in all regressions (coefficients not reported) are market beta, market-to-book, size, cumulative return between month t-2 and t-12 (MOM), return in the past month (REV) and either turnover (Turn), or trading volume (Vol), depending on whether CVTurn or CVVol are used. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Variability of Trading Activity versus Idiosyncratic Volatility

	1	**2**	**3**	**4**	**5**
IVol	-1.227		-1.076		-1.045
t-stat	*-5.09*		*-5.41*		*-5.28*
CVTurn		-0.414	-0.324		
t-stat		*-4.34*	*-3.84*		
CVVol				-0.538	-0.379
t-stat				*-3.45*	*-2.92*

Panel B. Variability of Trading Activity versus Analyst Disagreement

	1	**2**	**3**	**4**	**5**
Disp	-0.473		-0.347		-0.332
t-stat	*-2.35*		*-1.87*		*-1.82*
CVTurn		-0.330	-0.293		
t-stat		*-2.58*	*-2.37*		
CVVol				-0.430	-0.383
t-stat				*-2.12*	*-2.02*

Panel C. Variability of Trading Activity versus Variability of Earnings

	1	**2**	**3**	**4**	**5**
CVEarn	-0.326		-0.247		-0.215
t-stat	*-2.42*		*-2.34*		*-2.03*
CVTurn		-0.437	-0.415		
t-stat		*-3.70*	*-3.54*		
CVVol				-0.570	-0.537
t-stat				*-2.94*	*-2.85*

Table 3. Variability of Trading Activity, Aggregate Volatility Risk, and Expected Returns

The table presents the alphas and FVIX betas for the quintile portfolios sorted on turnover variability (left part) and volume variability (right part). Detailed definitions of volume/turnover variability are in Data Appendix. The following models are used for measuring the alphas and the FVIX betas: the CAPM, the Fama-French model, and the CAPM augmented with FVIX (ICAPM). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. The sorts on volume/turnover variability are performed monthly and use NYSE (exchcd=1) breakpoints. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Value-Weighted Returns to Variability of Trading Activity Quintile Portfolios

Panel A1. Turnover Variability

	Low	CV2	CV3	CV4	High	L-H
α_{CAPM}	0.126	-0.013	-0.053	-0.267	-0.353	0.479
t-stat	*2.06*	*-0.19*	*-0.52*	*-2.09*	*-2.34*	*2.46*
α_{FF}	0.154	-0.016	-0.065	-0.274	-0.459	0.613
t-stat	*2.79*	*-0.22*	*-0.71*	*-2.39*	*-3.08*	*3.31*
α_{ICAPM}	-0.082	-0.084	-0.075	-0.110	-0.039	-0.043
t-stat	*-1.06*	*-1.02*	*-0.72*	*-0.81*	*-0.23*	*-0.19*
β_{FVIX}	-0.450	-0.155	-0.047	0.341	0.682	-1.131
t-stat	*-4.68*	*-2.16*	*-0.68*	*2.38*	*4.44*	*-4.99*

Panel A2. Volume Variability

	Low	CV2	CV3	CV4	High	L-H
α_{CAPM}	0.225	0.040	-0.081	-0.238	-0.306	0.531
t-stat	*2.07*	*0.52*	*-0.98*	*-1.87*	*-1.76*	*2.01*
α_{FF}	0.166	0.035	-0.111	-0.241	-0.242	0.407
t-stat	*2.05*	*0.41*	*-1.47*	*-2.18*	*-1.65*	*2.01*
α_{ICAPM}	-0.070	-0.124	-0.145	-0.069	0.137	-0.208
t-stat	*-0.76*	*-1.38*	*-1.58*	*-0.52*	*0.87*	*-0.91*
β_{FVIX}	-0.639	-0.356	-0.138	0.367	0.962	-1.602
t-stat	*-3.57*	*-3.20*	*-0.91*	*2.09*	*3.89*	*-3.94*

Panel B. Equal-Weighted Returns to Variability of Trading Activity Quintile Portfolios

Panel B1. Turnover Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	0.272	0.165	0.083	-0.008	-0.099	0.371
t-stat	*2.35*	*1.08*	*0.51*	*-0.05*	*-0.57*	*2.15*
$\boldsymbol{\alpha}_{FF}$	0.152	0.017	-0.066	-0.144	-0.207	0.359
t-stat	*1.96*	*0.18*	*-0.90*	*-2.03*	*-2.36*	*3.10*
$\boldsymbol{\alpha}_{ICAPM}$	0.154	0.110	0.181	0.193	0.217	-0.063
t-stat	*1.37*	*0.76*	*1.06*	*1.05*	*1.06*	*-0.29*
$\boldsymbol{\beta}_{FVIX}$	-0.255	-0.120	0.214	0.436	0.685	-0.941
t-stat	*-1.25*	*-0.87*	*2.16*	*4.12*	*5.17*	*-3.08*

Panel B2. Volume Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	0.233	0.165	0.121	0.078	-0.133	0.366
t-stat	*1.47*	*0.98*	*0.65*	*0.45*	*-0.80*	*1.73*
$\boldsymbol{\alpha}_{FF}$	0.061	-0.020	-0.067	-0.093	-0.197	0.258
t-stat	*0.61*	*-0.22*	*-0.71*	*-1.21*	*-2.57*	*2.01*
$\boldsymbol{\alpha}_{ICAPM}$	0.024	0.058	0.146	0.243	0.237	-0.213
t-stat	*0.18*	*0.38*	*0.79*	*1.27*	*1.18*	*-0.94*
$\boldsymbol{\beta}_{FVIX}$	-0.454	-0.232	0.055	0.358	0.803	-1.257
t-stat	*-1.88*	*-1.31*	*0.37*	*3.23*	*4.76*	*-3.27*

Table 4. Variability of Trading Activity, Growth Options, and Aggregate Volatility Risk

The table reports the CAPM and ICAPM alphas and the FVIX betas for the volume/turnover variability arbitrage portfolio formed separately within each market-to-book quintile. The volume/turnover variability arbitrage portfolio is long in the lowest volume/turnover variability quintile and short in the highest volume/turnover variability quintile. Volume/turnover variability quintiles are rebalanced monthly, market-to-book quintiles are rebalanced annually. All quintiles use NYSE (exchcd=1) breakpoints. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Turnover Variability Effect and Growth Options

	Value-Weighted Returns							Equal-Weighted Returns					
	Value	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**		**Value**	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**
α_{CAPM}	0.013	0.084	0.611	0.654	0.354	0.341	α_{CAPM}	-0.102	0.234	0.484	0.425	0.631	0.733
t-stat	*0.03*	*0.29*	*2.07*	*2.33*	*1.62*	*0.92*	**t-stat**	*-0.57*	*1.24*	*2.40*	*1.74*	*2.57*	*3.25*
α_{ICAPM}	-0.133	-0.227	0.303	0.229	-0.185	-0.052	α_{ICAPM}	-0.228	-0.121	0.146	0.019	0.090	0.318
t-stat	*-0.38*	*-0.74*	*1.07*	*0.73*	*-0.79*	*-0.14*	**t-stat**	*-1.32*	*-0.61*	*0.82*	*0.08*	*0.34*	*1.16*
β_{FVIX}	-0.351	-0.648	-0.637	-0.941	-1.169	-0.818	β_{FVIX}	-0.306	-0.778	-0.732	-0.906	-1.179	-0.874
t-stat	*-0.96*	*-2.06*	*-3.25*	*-2.38*	*-3.77*	*-1.70*	**t-stat**	*-1.91*	*-2.85*	*-2.76*	*-1.83*	*-2.4*	*-1.98*

Panel B. Volume Variability Effect and Growth Options

	Value-Weighted Returns							Equal-Weighted Returns					
	Value	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**		**Value**	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**
α_{CAPM}	-0.461	-0.072	0.651	0.612	0.519	0.979	α_{CAPM}	-0.246	0.172	0.404	0.367	0.537	0.782
t-stat	*-1.15*	*-0.23*	*1.95*	*1.82*	*1.63*	*2.72*	**t-stat**	*-1.26*	*0.84*	*1.64*	*1.43*	*1.92*	*3.27*
α_{ICAPM}	-0.706	-0.513	0.127	-0.038	-0.176	0.530	α_{ICAPM}	-0.603	-0.233	-0.064	0.079	-0.345	0.258
t-stat	*-1.91*	*-1.41*	*0.45*	*-0.12*	*-0.62*	*1.60*	**t-stat**	*-2.98*	*-1.08*	*-0.26*	*0.27*	*-0.92*	*0.91*
β_{FVIX}	-0.556	-0.921	-1.062	-1.436	-1.505	-0.949	β_{FVIX}	-0.674	-0.979	-1.125	-1.182	-1.625	-0.951
t-stat	*-1.63*	*-1.99*	*-3.70*	*-2.38*	*-2.70*	*-2.49*	**t-stat**	*-3.23*	*-3.47*	*-2.96*	*-2.21*	*-2.50*	*-1.93*

Table 5. Variability of Trading Activity, Credit Rating, and Aggregate Volatility Risk

The table reports the CAPM and ICAPM alphas and the FVIX betas for the volume/turnover variability arbitrage portfolio formed separately within each credit rating quintile. The volume/turnover variability arbitrage portfolio is long in the lowest volume/turnover variability quintile and short in the highest volume/turnover variability quintile. Volume/turnover variability quintiles are rebalanced monthly, credit rating quintiles are rebalanced quarterly. All quintiles use NYSE (exchcd=1) breakpoints. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Turnover Variability Effect and Credit Rating

	Value-Weighted Returns					Equal-Weighted Returns			
	Best	**Med**	**Worst**	**W-B**		**Best**	**Med**	**Worst**	**W-B**
$\boldsymbol{\alpha}_{CAPM}$	-0.044	0.062	0.479	0.523	$\boldsymbol{\alpha}_{CAPM}$	-0.048	0.076	0.396	0.444
t-stat	*-0.35*	*0.45*	*2.35*	*2.22*	**t-stat**	*-0.37*	*0.65*	*1.69*	*1.87*
$\boldsymbol{\alpha}_{ICAPM}$	0.048	0.059	0.218	0.171	$\boldsymbol{\alpha}_{ICAPM}$	-0.040	-0.112	0.104	0.144
t-stat	*0.35*	*0.42*	*1.08*	*0.68*	**t-stat**	*-0.30*	*-0.89*	*0.52*	*0.68*
$\boldsymbol{\beta}_{FVIX}$	0.199	-0.007	-0.567	-0.766	$\boldsymbol{\beta}_{FVIX}$	0.018	-0.409	-0.633	-0.651
t-stat	*2.51*	*-0.06*	*-2.94*	*-3.17*	**t-stat**	*0.17*	*-3.27*	*-2.03*	*-2.13*

Panel B. Volume Variability Effect and Credit Rating

	Value-Weighted Returns					Equal-Weighted Returns			
	Best	**Med**	**Worst**	**W-B**		**Best**	**Med**	**Worst**	**W-B**
$\boldsymbol{\alpha}_{CAPM}$	0.167	0.258	0.917	0.750	$\boldsymbol{\alpha}_{CAPM}$	-0.081	0.082	0.549	0.630
t-stat	*0.84*	*0.94*	*1.84*	*1.79*	**t-stat**	*-0.53*	*0.52*	*1.71*	*2.34*
$\boldsymbol{\alpha}_{ICAPM}$	-0.168	-0.297	0.223	0.390	$\boldsymbol{\alpha}_{ICAPM}$	-0.233	-0.194	0.022	0.255
t-stat	*-0.89*	*-1.20*	*0.56*	*1.00*	**t-stat**	*-1.41*	*-1.21*	*0.08*	*1.03*
$\boldsymbol{\beta}_{FVIX}$	-0.722	-1.186	-1.500	-0.779	$\boldsymbol{\beta}_{FVIX}$	-0.330	-0.598	-1.144	-0.813
t-stat	*-2.87*	*-6.68*	*-2.17*	*-1.61*	**t-stat**	*-2.00*	*-4.40*	*-2.91*	*-3.06*

Table 6. Variability of Trading Activity and Liquidity Risk

Panel A presents the alphas from the Fama-French (FF) model (α_{FF}) and the alphas from the FF model augmented by a liquidity risk factor (for example, α_{FF+Sad} is the alpha from the FF model with the Sadka factor added) across the quintile sorts on volume/turnover variability. Panel B reports the liquidity betas from the augmented FF models from Panel A. Panel C replaces the traded factors with their non-traded versions and reports the loadings on the non-traded factors across the same quintile sorts. Panel D looks at median sensitivity of several liquidity measures to market returns across the same quintiles. The sensitivity is measured separately in each firm-month by regressing the monthly change in the respective liquidity on the market return using monthly data between month t-1 and month t-36. Detailed definitions of all liquidity measures and liquidity factors are in Data Appendix. All explanatory variables are ranks between 0 and 1. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Fama-French and Liquidity-Augmented Alphas

Panel A1. Turnover Variability

	Low	**CV2**	**CV3**	**CV4**	**High**	**L-H**
$\boldsymbol{\alpha}_{FF}$	0.154	-0.016	-0.065	-0.274	-0.459	0.613
t-stat	*2.79*	*-0.22*	*-0.71*	*-2.39*	*-3.08*	*3.31*
$\boldsymbol{\alpha}_{FF+PS}$	0.152	-0.023	-0.086	-0.311	-0.402	0.554
t-stat	*2.70*	*-0.34*	*-0.92*	*-2.74*	*-3.01*	*3.27*
$\boldsymbol{\alpha}_{FF+Sad}$	0.135	-0.065	-0.059	-0.267	-0.340	0.475
t-stat	*2.07*	*-0.80*	*-0.66*	*-2.04*	*-1.97*	*2.25*
$\boldsymbol{\alpha}_{FF+Ami}$	0.071	0.010	-0.053	-0.130	-0.333	0.405
t-stat	*1.72*	*0.19*	*-0.95*	*-1.59*	*-3.36*	*3.30*

Panel A2. Volume Variability

	Low	**CV2**	**CV3**	**CV4**	**High**	**L-H**
$\boldsymbol{\alpha}_{FF}$	0.166	0.035	-0.111	-0.241	-0.242	0.407
t-stat	*2.05*	*0.41*	*-1.47*	*-2.18*	*-1.65*	*2.01*
$\boldsymbol{\alpha}_{FF+PS}$	0.179	0.013	-0.113	-0.246	-0.226	0.405
t-stat	*2.14*	*0.15*	*-1.49*	*-2.16*	*-1.71*	*2.12*
$\boldsymbol{\alpha}_{FF+Sad}$	0.130	0.015	-0.136	-0.280	-0.165	0.295
t-stat	*1.53*	*0.17*	*-1.67*	*-2.27*	*-1.14*	*1.48*
$\boldsymbol{\alpha}_{FF+Ami}$	0.107	0.003	-0.160	-0.271	-0.169	0.276
t-stat	*1.47*	*0.03*	*-2.18*	*-2.25*	*-1.23*	*1.51*

Panel B. Liquidity Betas: Traded Factors

Panel B1. Turnover Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\beta}_{PS-T}$	0.004	0.015	0.034	0.063	-0.094	0.098
t-stat	*0.29*	*0.67*	*1.34*	*1.90*	*-1.43*	*1.35*
$\boldsymbol{\beta}_{Sad-T}$	0.016	0.015	-0.032	-0.025	-0.054	0.070
t-stat	*1.40*	*0.90*	*-1.68*	*-0.99*	*-1.67*	*2.02*
$\boldsymbol{\beta}_{Ami-T}$	0.076	0.098	0.055	0.036	-0.073	0.148
t-stat	*3.38*	*3.31*	*1.21*	*0.54*	*-0.92*	*1.67*

Panel B2. Volume Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\beta}_{PS-T}$	-0.022	0.046	0.002	0.009	-0.031	0.008
t-stat	*-1.07*	*1.47*	*0.07*	*0.28*	*-0.46*	*0.11*
$\boldsymbol{\beta}_{Sad-T}$	0.020	0.009	0.027	0.016	-0.036	0.056
t-stat	*1.75*	*0.87*	*2.25*	*0.85*	*-2.25*	*2.67*
$\boldsymbol{\beta}_{Ami-T}$	0.129	0.085	0.109	0.067	-0.167	0.296
t-stat	*4.69*	*3.84*	*2.54*	*1.17*	*-2.85*	*5.23*

Panel C. Liquidity Betas: Non-Traded Factors

Panel C1. Turnover Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\beta}_{PS}$	-0.011	-0.017	0.013	0.045	0.056	-0.067
t-stat	*-1.03*	*-1.37*	*1.10*	*1.75*	*2.04*	*-2.02*
$\boldsymbol{\beta}_{Sad}$	0.000	-0.001	-0.004	-0.001	-0.004	0.004
t-stat	*0.32*	*-0.84*	*-2.14*	*-0.49*	*-1.10*	*1.01*
$\boldsymbol{\beta}_{Ami}$	0.005	0.009	0.005	0.002	-0.021	0.026
t-stat	*2.37*	*3.95*	*1.09*	*0.29*	*-2.03*	*2.28*

Panel C2. Volume Variability

	Low	CV2	CV3	CV4	High	L-H
$\boldsymbol{\beta}_{PS}$	-0.018	-0.002	0.009	0.035	0.034	-0.052
t-stat	*-0.97*	*-0.13*	*0.41*	*1.40*	*1.12*	*-1.25*
$\boldsymbol{\beta}_{Sad}$	0.000	-0.002	0.002	0.000	-0.007	0.007
t-stat	*-0.25*	*-1.53*	*0.99*	*0.02*	*-2.15*	*1.58*
$\boldsymbol{\beta}_{Ami}$	0.008	0.007	0.004	-0.001	-0.022	0.030
t-stat	*3.59*	*1.80*	*0.99*	*-0.26*	*-2.05*	*2.50*

Panel D. Trading Cost Sensitivity to Market Returns

Panel D1. Turnover Variability

	Low	CV2	CV3	CV4	High	L-H
Roll	-0.003	-0.003	-0.003	-0.002	-0.002	0.001
t-stat	*-2.50*	*-1.97*	*-1.57*	*-1.41*	*-1.61*	*2.42*
Spread	-0.003	-0.005	-0.015	-0.016	-0.039	-0.036
t-stat	*-0.20*	*-0.31*	*-0.81*	*-0.75*	*-2.02*	*-2.46*
EffTick	-1.354	-1.421	-1.475	-1.321	-1.012	0.342
t-stat	*-3.59*	*-3.98*	*-4.30*	*-3.60*	*-3.09*	*1.79*
- Gamma	-0.002	-0.005	-0.009	-0.021	-0.032	-0.030
t-stat	*-2.10*	*-2.43*	*-2.95*	*-3.32*	*-2.17*	*-2.15*
Amihud	-0.007	-0.010	-0.013	-0.015	-0.018	-0.011
t-stat	*-4.07*	*-4.76*	*-5.08*	*-4.89*	*-5.60*	*-6.62*
Zero	-0.033	-0.094	-0.188	-0.302	-0.418	-0.385
t-stat	*-1.76*	*-1.85*	*-1.77*	*-1.82*	*-1.78*	*-1.81*

Panel D2. Volume Variability

	Low	CV2	CV3	CV4	High	L-H
Roll	-0.003	-0.003	-0.003	-0.002	-0.003	0.001
t-stat	*-2.48*	*-1.75*	*-1.57*	*-1.47*	*-1.69*	*1.38*
Spread	-0.001	-0.004	-0.015	-0.017	-0.039	-0.038
t-stat	*-0.06*	*-0.24*	*-0.75*	*-0.82*	*-1.99*	*-2.75*
EffTick	-1.212	-1.418	-1.458	-1.315	-1.107	0.105
t-stat	*-2.99*	*-4.09*	*-4.28*	*-3.83*	*-3.34*	*0.49*
- Gamma	-0.002	-0.005	-0.010	-0.021	-0.034	-0.033
t-stat	*-2.23*	*-2.66*	*-3.08*	*-2.61*	*-2.50*	*-2.51*
Amihud	-0.007	-0.010	-0.012	-0.015	-0.020	-0.013
t-stat	*-3.81*	*-4.47*	*-4.91*	*-4.87*	*-5.55*	*-6.37*
Zero	-0.029	-0.086	-0.177	-0.295	-0.465	-0.437
t-stat	*-1.96*	*-1.89*	*-1.80*	*-1.65*	*-1.70*	*-1.70*

Table 7. Variability of Trading Activity and Variability of Liquidity

The table presents the median variability of several liquidity measures across quintile sorts on variability of volume/turnover. The quintiles are rebalanced monthly and use NYSE (exchcd=1) breakpoints. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010. The sample excludes stocks with price below $5 at the portfolio formation date.

Panel A. Turnover Variability and Variability of Liquidity

	Low	**CV2**	**CV3**	**CV4**	**High**	**H-L**
EffTick	0.381	0.400	0.426	0.456	0.504	0.123
t-stat	*14.1*	*15.7*	*17.6*	*19.5*	*21.3*	*15.5*
Spread	0.381	0.410	0.440	0.479	0.544	0.163
t-stat	*55.3*	*48.4*	*46.5*	*49.5*	*70.0*	*26.8*
Roll	0.541	0.547	0.554	0.563	0.595	0.054
t-stat	*78.1*	*81.8*	*81.8*	*77.0*	*56.5*	*7.18*
Gamma	7.155	7.189	7.159	7.130	6.732	-0.423
t-stat	*57.5*	*69.5*	*86.4*	*97.2*	*71.5*	*-2.93*
Amihud	0.448	0.551	0.661	0.787	0.962	0.515
t-stat	*32.8*	*44.0*	*45.3*	*39.0*	*30.0*	*14.7*
Zero	0.958	0.863	0.792	0.711	0.581	-0.377
t-stat	*8.60*	*8.24*	*8.02*	*8.66*	*12.7*	*-5.56*

Panel B. Volume Variability and Variability of Liquidity

	Low	**CV2**	**CV3**	**CV4**	**High**	**H-L**
EffTick	0.388	0.409	0.441	0.484	0.566	0.178
t-stat	*14.9*	*16.4*	*18.4*	*20.0*	*22.5*	*18.0*
Spread	0.422	0.449	0.487	0.526	0.578	0.156
t-stat	*49.9*	*49.2*	*54.2*	*64.8*	*78.3*	*23.5*
Roll	0.558	0.567	0.575	0.589	0.633	0.075
t-stat	*67.2*	*71.9*	*67.9*	*60.5*	*42.6*	*6.53*
Gibbs	7.211	7.183	7.142	7.106	6.714	-0.496
t-stat	*52.1*	*65.9*	*85.9*	*101.3*	*77.6*	*-3.29*
Amihud	0.437	0.570	0.707	0.874	1.119	0.682
t-stat	*34.6*	*44.5*	*49.7*	*42.3*	*30.8*	*16.7*
Zero	1.009	0.918	0.848	0.760	0.646	-0.362
t-stat	*8.01*	*7.79*	*7.87*	*8.62*	*11.3*	*-5.11*

Table 8. Variability of Trading Activity and Liquidity

Panel A (B) presents the median values of several liquidity measures across turnover (volume) variability quintiles. The liquidity measures include spread measures (EffTick, Spread, Roll, Gibbs) that estimate the effective bid-ask spread in percents of the stock price, the price impact measure (Amihud) that estimates the movement of the price (in percents) in response to trading $1 million in a day, and the cumulative liquidity measure - the frequency of zero returns (Zero). Detailed definitions of all variables are in Data Appendix.

Panels C (D) present the estimated frequency of the median liquidity of the highest turnover (volume) variability quintile being better than the median liquidity of the lowest turnover (volume) variability quintile (50vs50) and the estimated frequency of the 25th liquidity percentile in the highest turnover (volume) variability quintile being better than the the 75th liquidity percentile in the lowest turnover (volume) variability quintile (75vs25). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010.

Panel A. Turnover Variability and Liquidity

	Low	**CV2**	**CV3**	**CV4**	**High**	**H-L**
EffTick	1.274	1.778	2.512	3.449	5.087	3.813
t-stat	*11.4*	*11.8*	*11.2*	*11.0*	*12.7*	*11.2*
Spread	0.529	0.591	0.749	0.958	1.421	0.891
t-stat	*15.8*	*17.6*	*16.1*	*13.2*	*9.86*	*6.21*
Roll	1.005	1.192	1.452	1.807	2.356	1.350
t-stat	*20.4*	*27.3*	*26.3*	*20.3*	*15.7*	*8.88*
Gibbs	0.299	0.396	0.552	0.797	1.159	0.860
t-stat	*28.7*	*25.9*	*17.1*	*12.1*	*11.6*	*8.83*
Amihud	0.016	0.044	0.080	0.133	0.259	0.243
t-stat	*4.23*	*4.41*	*4.81*	*4.85*	*6.60*	*6.76*
Zero	0.100	0.131	0.161	0.186	0.234	0.135
t-stat	*8.98*	*9.62*	*9.77*	*10.2*	*11.2*	*9.33*

Panel B. Volume Variability and Liquidity

	Low	CV2	CV3	CV4	High	H-L
EffTick	1.269	1.765	2.515	3.475	5.003	3.735
t-stat	*10.8*	*11.3*	*10.7*	*10.3*	*11.9*	*10.3*
Spread	0.527	0.595	0.748	0.953	1.359	0.833
t-stat	*17.7*	*17.7*	*15.8*	*12.7*	*9.87*	*6.13*
Roll	1.010	1.193	1.458	1.820	2.352	1.343
t-stat	*21.0*	*26.7*	*25.3*	*19.2*	*15.5*	*8.84*
Gibbs	0.299	0.396	0.552	0.797	1.159	0.860
t-stat	*28.7*	*25.9*	*17.1*	*12.1*	*11.6*	*8.83*
Amihud	0.015	0.041	0.076	0.123	0.234	0.218
t-stat	*4.09*	*4.24*	*4.37*	*4.72*	*6.47*	*6.65*
Zero	0.098	0.131	0.159	0.184	0.225	0.127
t-stat	*8.72*	*9.28*	*9.45*	*9.92*	*11.0*	*9.27*

Panel C. Turnover Variability and Chances of Lower Liquidity

	EffTick	Spread	Roll	Gibbs	Amihud	Zero
50vs50	0.00%	0.93%	0.37%	0.00%	0.00%	0.74%
75vs25	8.15%	60.7%	58.0%	22.2%	2.41%	37.8%

Panel D. Volume Variability and Chances of Lower Liquidity

	EffTick	Spread	Roll	Gibbs	Amihud	Zero
50vs50	0.00%	1.11%	0.19%	0.00%	0.00%	1.48%
75vs25	9.44%	45.0%	45.2%	23.3%	12.2%	44.6%

Table 9. Variability of Liquidity, Variability of Liquidity Risk, and Expected Returns

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. All independent variables are ranks between 0 and 1. The top row of each panel reports the slopes on variability of liquidity/liquidity risk measures, used one at a time. The next two pair of rows add either the variability of turnover or variability of volume to the list of controls. The controls (not tabulated) include the market beta, size, market-to-book, cumulative return in the past 12 months, and turnover/volume depending on whether the variability of turnover or volume is used as the additional control. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1966 to December 2010.

Panel A. Variability of Liquidity and Expected Returns

A1: γs from $Ret_t - RF_t = \gamma \cdot CVLiq_t + X'\beta$

	EffTick	Spread	Roll	Amihud	Gamma	Zero
CVLiq	-0.005	-0.173	0.034	-0.099	0.056	-0.045
t-stat	*-0.03*	*-1.17*	*0.39*	*-0.58*	*1.15*	*-0.24*

A2: γs from $Ret_t - RF_t = \gamma_1 \cdot CVTurn_t + \gamma_2 \cdot CVLiq_t + X'\beta$

	EffTick	Spread	Roll	Amihud	Gamma	Zero
CVTurn	-0.558	-0.466	-0.530	-0.571	-0.560	-0.561
t-stat	*-5.55*	*-4.59*	*-5.05*	*-5.72*	*-5.67*	*-5.53*
CVLiq	0.038	-0.075	0.094	0.049	0.053	-0.064
t-stat	*0.25*	*-0.50*	*1.04*	*0.29*	*1.09*	*-0.34*

A3: γs from $Ret_t - RF_t = \gamma_1 \cdot CVVol_t + \gamma_2 \cdot CVLiq_t + X'\beta$

	EffTick	Spread	Roll	Amihud	Gamma	Zero
CVVol	-0.383	-0.506	-0.343	-0.385	-0.401	-0.377
t-stat	*-2.40*	*-3.10*	*-2.04*	*-2.40*	*-2.73*	*-2.41*
CVLiq	0.029	-0.128	0.061	0.019	0.053	-0.113
t-stat	*0.20*	*-0.85*	*0.68*	*0.12*	*1.08*	*-0.64*

Panel B. Variability of Liquidity Risk Loadings and Expected Returns

B1: γs from $Ret_t - RF_t = \gamma \cdot CVLiq_t + X'\beta$

	Non-Tradable			Tradable		
	β_{PS}	β_{Sad}	β_{Ami}	β_{PS-T}	β_{Sad-T}	β_{Ami-T}
CVLiq	0.009	0.130	0.039	-0.028	0.011	0.081
t-stat	*0.18*	*1.84*	*0.66*	*-0.59*	*0.13*	*1.49*

B2: γs from $Ret_t - RF_t = \gamma_1 \cdot CVTurn_t + \gamma_2 \cdot CVLiq_t + X'\beta$

	Non-Tradable			Tradable		
	β_{PS}	β_{Sad}	β_{Ami}	β_{PS-T}	β_{Sad-T}	β_{Ami-T}
CVTurn	-0.599	-0.733	-0.596	-0.569	-0.838	-0.594
t-stat	*-5.69*	*-4.44*	*-5.66*	*-5.00*	*-4.22*	*-5.52*
CVLiq	0.003	0.122	0.036	-0.028	-0.006	0.076
t-stat	*0.06*	*1.75*	*0.61*	*-0.59*	*-0.07*	*1.41*

B3: γs from $Ret_t - RF_t = \gamma_1 \cdot CVVol_t + \gamma_2 \cdot CVLiq_t + X'\beta$

	Non-Tradable			Tradable		
	β_{PS}	β_{Sad}	β_{Ami}	β_{PS-T}	β_{Sad-T}	β_{Ami-T}
CVVol	-0.462	-0.456	-0.460	-0.386	-0.428	-0.478
t-stat	*-2.69*	*-1.64*	*-2.69*	*-2.09*	*-1.23*	*-2.74*
CVLiq	0.001	0.128	0.044	-0.027	0.000	0.076
t-stat	*0.02*	*1.82*	*0.76*	*-0.56*	*0.00*	*1.42*

Table 10. Variability of Trading Activity, Limits to Arbitrage, and Expected Returns

The table reports the CAPM and ICAPM alphas and the FVIX betas for the volume/turnover variability arbitrage portfolio formed separately in each limits-to-arbitrage quintile. The volume/turnover variability arbitrage portfolio is long in the lowest volume/turnover variability quintile and short in the highest volume/turnover variability quintile. The limits to arbitrage measures are residual institutional ownership, number of analysts following the firm, and relative short interest. Detailed definitions of all variables are in Data Appendix. All quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Panel A. Variability of Trading Activity and the Number of Analysts Following the Firm

Panel A1. Turnover Variability / Panel A2. Volume Variability

	Low	**#An2**	**#An3**	**#An4**	**High**	**L-H**		**Low**	**#An2**	**#An3**	**#An4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.423	0.440	0.363	0.327	0.152	0.271	$\boldsymbol{\alpha}_{CAPM}$	0.521	0.479	0.347	0.282	0.168	0.352
t-stat	*2.18*	*2.34*	*2.15*	*2.02*	*0.84*	*1.78*	**t-stat**	*1.89*	*2.00*	*1.63*	*1.36*	*0.69*	*2.29*
$\boldsymbol{\alpha}_{ICAPM}$	-0.017	0.080	-0.043	0.092	-0.033	0.016	$\boldsymbol{\alpha}_{ICAPM}$	-0.024	-0.062	-0.093	-0.079	-0.206	0.182
t-stat	*-0.09*	*0.44*	*-0.22*	*0.58*	*-0.20*	*0.11*	**t-stat**	*-0.09*	*-0.28*	*-0.37*	*-0.41*	*-0.95*	*1.13*
$\boldsymbol{\beta}_{FVIX}$	-0.977	-0.776	-0.874	-0.503	-0.429	-0.548	$\boldsymbol{\beta}_{FVIX}$	-1.195	-1.173	-0.969	-0.797	-0.831	-0.364
t-stat	*-2.52*	*-2.11*	*-2.64*	*-1.98*	*-1.55*	*-2.50*	**t-stat**	*-2.26*	*-2.77*	*-2.37*	*-2.62*	*-2.10*	*-1.71*

Panel B. Variability of Trading Activity and Residual Institutional Ownership

Panel B1. Turnover Variability

	Low	**RI 2**	**RI 3**	**RI 4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.598	0.512	0.404	0.145	0.208	0.390
t-stat	*2.84*	*2.57*	*2.59*	*0.85*	*1.74*	*1.91*
$\boldsymbol{\alpha}_{ICAPM}$	0.142	0.208	0.051	-0.161	-0.025	0.167
t-stat	*0.83*	*1.51*	*0.24*	*-0.82*	*-0.19*	*0.99*
$\boldsymbol{\beta}_{FVIX}$	-1.015	-0.669	-0.782	-0.668	-0.508	-0.507
t-stat	*-2.53*	*-2.22*	*-2.20*	*-2.50*	*-3.97*	*-1.65*

Panel B2. Volume Variability

	Low	**RI 2**	**RI 3**	**RI 4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.761	0.491	0.252	0.147	0.116	0.645
t-stat	*2.63*	*1.87*	*1.06*	*0.64*	*0.60*	*3.50*
$\boldsymbol{\alpha}_{ICAPM}$	0.167	0.039	-0.233	-0.308	-0.291	0.458
t-stat	*0.67*	*0.17*	*-0.87*	*-1.34*	*-1.43*	*2.82*
$\boldsymbol{\beta}_{FVIX}$	-1.306	-1.003	-1.071	-1.009	-0.884	-0.422
t-stat	*-2.58*	*-2.22*	*-2.55*	*-2.65*	*-2.43*	*-2.28*

Panel C. Variability of Trading Activity and Relative Short Interest

Panel C1. Turnover Variability

	Low	**RSI2**	**RSI3**	**RSI4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.194	0.271	0.199	0.654	0.864	0.670
t-stat	*1.30*	*1.48*	*0.79*	*2.66*	*3.33*	*2.99*
$\boldsymbol{\alpha}_{ICAPM}$	-0.027	-0.077	-0.290	0.180	0.285	0.311
t-stat	*-0.20*	*-0.52*	*-1.53*	*0.91*	*1.33*	*1.46*
$\boldsymbol{\beta}_{FVIX}$	-0.566	-0.892	-1.254	-1.213	-1.484	-0.919
t-stat	*-4.14*	*-6.07*	*-5.96*	*-4.90*	*-4.62*	*-2.64*

Panel C2. Volume Variability

	Low	**RSI2**	**RSI3**	**RSI4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.208	0.391	0.272	0.490	0.624	0.416
t-stat	*1.25*	*1.88*	*1.05*	*1.75*	*1.98*	*1.67*
$\boldsymbol{\alpha}_{ICAPM}$	-0.079	-0.034	-0.240	-0.089	0.011	0.090
t-stat	*-0.52*	*-0.19*	*-1.03*	*-0.30*	*0.04*	*0.32*
$\boldsymbol{\beta}_{FVIX}$	-0.603	-0.894	-1.076	-1.219	-1.289	-0.686
t-stat	*-4.13*	*-4.24*	*-2.28*	*-2.57*	*-2.09*	*-1.33*