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

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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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# 1 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 turnover as a measure of liquidity or liquidity risk, this regularity (referred henceforth as the 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 turnover variability picks up higher idiosyncratic risk, and this is the reason why higher turnover variability predicts lower future returns[2]. 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.

The main question of this paper is also broader than "what explains the turnover variability effect?". Similar to the initial study of Chordia et al. (2001), I try to find out if liquidity variability is priced. The turnover variability effect, which states that the relation between liquidity variability and expected returns is backwards, is the obstacle one has to remove before answering the bigger question. In this paper, I use a battery of alternative liquidity measures and find that the relation between liquidity variability and expected returns is zero rather than negative. The zero relation, in contrast to the negative one, opens the gate to future studies of liquidity variability pricing, because the zero relation might arise because proxies for liquidity variability are imprecise.

[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] All tests in the paper use turnover variability only, but using volume variability instead brings about very similar results (available upon request)

Prior research shows that high idiosyncratic risk firms have negative CAPM alphas because they outperform the CAPM when aggregate volatility increases.[3] The outperformance happens for two reasons. First, aggregate volatility and average idiosyncratic risk in the economy comove (see Duarte et al., 2012, Barinov, 2011, 2013). Holding all else equal, when idiosyncratic risk increases, the value of option-like firms[4] also increases, which means that such firms react less negatively to increases in aggregate volatility. This effect is naturally stronger for high idiosyncratic risk firms, which are more likely to witness large increases in idiosyncratic risk.[5]

Second, as Johnson (2004) shows, all else equal, for option-like firms higher idiosyncratic risk implies lower beta. By Ito's lemma, option's beta is equal to the product of the beta of the underlying asset and the elasticity of the option's value with respect to the value of the underlying asset. If the idiosyncratic risk of the underlying asset increases, the second term does not change, but the first term declines. The option value becomes less responsive to the value of the underlying asset if the latter is more volatile and its value becomes "less informative".

As idiosyncratic risk increases together with aggregate volatility, option-like firms with high idiosyncratic risk will witness large increases in idiosyncratic risk and the corresponding decline in their betas. Lower betas will, in turn, moderate the increase in future discount rates that happens in volatile periods and the consequent drop in firm value.

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

[4] 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).

[5] A recent analysis by Grullon, Lyandres, and Zhdanov (2012) suggest that changes in idiosyncratic volatility have a substantial effect on the value of real options. In untabulated results, I also confirm that volatility of higher idiosyncratic risk firms responds more to shifts in average idiosyncratic volatility.

Hence, option-like firms with high idiosyncratic risk will again do better than what their CAPM betas imply when aggregate volatility increases.[6]

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 et al. (2006) confirm empirically 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 high turnover variability firms have low expected returns because they have high idiosyncratic risk and are thus a hedge against aggregate volatility risk. The paper adds to the list of the anomalies explained by aggregate volatility risk and strengthens the theory about the relation between idiosyncratic risk and aggregate volatility risk by applying the theory to the anomaly it was not originally designed to explain.

A necessary condition for the aggregate volatility risk explanation of the turnover variability effect (or any other idiosyncratic risk effect) is the existence of systematic component in average idiosyncratic risk that would be correlated with aggregate volatility. The existence of such correlation does not imply that firm-specific shocks have a systematic component, which would contradict the definition of the term "firm-specific". Rather, it is the volatility of these shocks that has a systematic component.

Duarte et al. (2012) and Barinov (2011, 2013) test this hypothesis and arrive at two findings. First, the first principal component in firm-level idiosyncratic volatilities explains 35% of their variance (Duarte et al., 2012). Second, average idiosyncratic volatility and

[6]The formal model that parallels the discussion in the three paragraphs above can be found in the online Theory Appendix at http://people.terry.uga.edu/abarinov/Theory 2014.pdf

average analyst disagreement are strongly related to current values, as well as leads and lags, of such indicators as VIX, realized volatility, expected market volatility, and NBER recession dummy (Barinov, 2011, 2013). For example, in recessions average idiosyncratic risk seems to increase by about 30%, and 1% increase in average idiosyncratic risk causes 0.2-0.4% increase in current and future values of market volatility.

The paper proceeds as follows: Section 2 presents the data sources and defines the main variables. Section 3 starts by showing that firms with high turnover variability are exactly of the type that is, according to my hypothesis and prior research, the best hedge against aggregate volatility risk - high idiosyncratic risk firms. Section 3 also documents that the turnover variability effect weakens by at most 25% after controlling for related anomalies (Ang et al., 2006, Diether et al., 2002) and remains statistically and economically significant. Hence, the turnover variability effect is an independent anomaly that merits a separate explanation.

In Section 4, 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.[7] Section 4 shows that the negative CAPM alphas of high turnover variability firms are explained by their positive FVIX beta (a positive FVIX beta means relatively good performance when VIX increases) both in portfolio sorts and in the cross-sectional regressions with risk-adjusted returns on the left-hand side, as in Brennan et al. (1998).

According to my theory, higher idiosyncratic risk reduces the risk of option-like firms. The natural prediction is that the effect of idiosyncratic risk on expected returns is stronger

[7] 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.

for option-like firms. Section 4 confirms that in the double sorts on turnover variability and measures of equity option-likeness, the turnover 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 turnover variability effect and equity option-likeness is also strong in Fama-MacBeth (1973) regressions.

I also consider alternative explanations of the turnover variability effect. Sections 5.3 and 5.4 look at liquidity/liquidity risk explanations and find that 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 turnover is priced is because it picks up idiosyncratic risk and therefore aggregate volatility risk.

Section 5.1 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 5.1 finds that high turnover variability firms are very illiquid and almost never become more liquid than firms with low variability of turnover.

The strong negative relation between turnover variability and liquidity also sheds light on why firms with high turnover variability have high idiosyncratic risk. 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 5.1 that the frequency of zero returns is 2.5 times higher in the highest turnover variability quintile than in the lowest turnover variability quintile. Liquidity, in turn, is driven by idiosyncratic risk, as much of the microstructure literature suggests. Higher idiosyncratic risk 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 5.5 studies the possibility that the turnover variability effect is mispricing and finds that the turnover variability effect is indeed stronger for firms with higher limits-to-arbitrage. However, this regularity can be explained by the ICAPM with the FVIX factor, which makes the mispricing explanation redundant. I also find that the turnover variability effect is only moderately concentrated at earnings announcements, somewhat inconsistent with the mispricing explanation, and that the stronger turnover variability effect for high limits to arbitrage firms is not concentrated at earnings announcements, which is more consistent with the risk-based explanation.

A paper closest to the current one is Barinov (2014), which argues that turnover is unrelated or even negatively related to liquidity, but positively related to idiosyncratic risk, 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 (2014), are actively traded large firms, firms with high 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 turnover variability effect. I also find, somewhat contrary to Barinov (2014), that while average turnover is unrelated to liquidity, turnover variability is related to variability of liquidity (though variability of liquidity is unrelated to expected returns).

Two more papers, Barinov (2011) and Barinov (2013) explain the idiosyncratic volatility discount and the analyst disagreement effect using the same mechanism this paper uses to explain the turnover variability effect. The analysis in Section 3.1 of this paper shows, however, that the overlap between the turnover variability and these two anomalies is at most 25%, so it is not clear a priori that any factor that explains the turnover variability effect would automatically explain the other two anomalies and vice versa.

## 2 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) and divide NASDAQ turnover by 2.0 prior to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003 to eliminate double-counting. Firms are classified as NASDAQ firms if the exchcd historical listing indicator from the CRSP events file is equal to 3.

The turnover variability is measured using the coefficient of variation: the ratio of the monthly standard deviation to the average during the same period. the latest 36 months (at least 12 valid observations are required).

The proxy for expected aggregate volatility is the old VIX index (current ticker VXO). 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 and rebalanced each month. 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.[8] 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 (from Fama and French, 1997) or the the six size and book-to-market portfolios (from Fama and French, 1993).

The rest of the variables are discussed in detail in online Data Appendix.[9]

# 3 Turnover Variability and Idiosyncratic Risk

## 3.1 Turnover Variability Proxies for Idiosyncratic Risk

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 idiosyncratic risk. Higher idiosyncratic risk, in turn, makes expected returns lower by lowering the risk of option-like equity. Therefore, the first step in testing the hypothesis is to verify that the firms with higher turnover variability have higher idiosyncratic risk.

In untabulated results, I sort firms on turnover variability and look the median values of five idiosyncratic risk measures across the turnover variability quintiles. The five idiosyncratic risk measures are idiosyncratic volatility, analyst disagreement, analyst forecast error, variability of cash flows, and variability of earnings. The detailed definitions of the idiosyncratic risk measures are in online Data Appendix. All the idiosyncratic risk measures suggest that the representative firm with high turnover variability has twice higher idiosyncratic risk than the representative firm with low turnover variability, and

[8] The factor-mimicking regression is performed using all available data, as is customary in the literature since Breeden et al. (1989). The assumption is that investors are more informed than the econometrician and can mimic innovations to aggregate volatility even before VIX is available. However, the results in the paper are robust to using only the information the econometrician has and estimating the factor-mimicking regression using expanding window.

[9] http://people.terry.uga.edu/abarinov/Data Appendix (Turnover Variability).pdf

the difference is highly statistically significant. I conclude that sorting firms on turnover variability inadvertently creates a strong sort on idiosyncratic risk, which can explain the turnover variability effect.

Panel A of Table I looks at the relation between turnover variability and idiosyncratic risk in multivariate context, regressing turnover variability on the five measures of firm-specific uncertainty and controls[10]. I find that the strong positive relation between turnover variability and idiosyncratic risk remains intact in multivariate regressions. All but one t-statistics of the slopes on the idiosyncratic measures exceed 5.

To sum up, the empirical evidence strongly supports the hypothesis that in asset-pricing tests, turnover variability picks up idiosyncratic risk. I delay the discussion of the economic forces that drive the link between turnover variability and idiosyncratic risk to Section 5.2, which looks at liquidity of the turnover variability quintile portfolios.

## 3.2 Turnover Variability Effect versus Idiosyncratic Risk Effects

The close relation between turnover variability and several measures of idiosyncratic risk established in Table I and the prevalent negative correlation between expected returns and these measures[11] suggest that the turnover variability effect should overlap with the idiosyncratic risk 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 turnover variability effect exists because turnover variability picks

[10] The controls include the well-known determinants of trading activity from Chordia, Huh, and Subrahmanyam (2007): positive/negative return (equal to monthly return if it is positive/negative and zero otherwise), visibility proxies: market-to-book, firm's age, and firm's market cap, liquidity proxies: firm's market cap and price level, risk proxies: market beta and leverage, and number of analysts following the firm as a proxy for information asymmetry.

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

up idiosyncratic risk would lose plausibility. On the other hand, the overlap should be far from complete, because otherwise the turnover variability effect would not merit an independent explanation.

My theory[12] predicts that it is the volatility of fundamentals of the underlying asset behind valuable real options that is related to expected returns. Therefore, all empirical measures of idiosyncratic risk are only proxies for this unobservable parameter. Hence, their impact on returns should overlap, but not necessarily overlap completely.

Panel B of Table I runs Fama-MacBeth regressions of returns on standard asset-pricing controls, lagged turnover variability, and several measures of idiosyncratic risk. The standard controls used in all regressions are market 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 turnover in the previous year. To save space, the coefficients on the controls are not tabulated.

The idiosyncratic risk measures I control for in Panel B are idiosyncratic volatility (motivated by the anomaly in Ang et al., 2006), analyst disagreement (motivated by the anomaly in Diether et al., 2002) and variability of earnings (as far as I know, the negative relation between earnings variability and future returns I find in Panel B of Table I has not been documented in the literature). The two other variables from Panel A were dropped from the analysis: the results with cash flow and earnings variability are very similar, and analyst forecast error is not related to expected returns.

In order to eliminate the impact of skewness and outliers, I transform all independent variables into ranks confined between zero and one. In each month, all firms in my sample are ranked in the ascending order on the variable in question and then I assign to each firm its rank instead of the ranking variable, with zero assigned to the firm with the lowest

[12] See the online Theory Appendix at http://people.terry.uga.edu/abarinov/Theory 2014.pdf.

value of the variable. I then divide the rank by the number of firms with valid observations in each month less one, to ensure the rank is between zero and one. Since the ranks are between zero and one, the coefficients in Panel B can be easily interpreted as the difference in expected returns between the firms with the lowest and highest values of the variable.

Panel B reports that the idiosyncratic risk effects are reduced by 25% controlling for turnover variability, and vice versa. For example, comparing columns one and three I observe that the idiosyncratic volatility discount drops from 1.23% to 1.08% per month after controlling for turnover variability, and comparing columns two and three I observe that the turnover variability effect decreases from 41.4 bp to 32.4 bp per month controlling for idiosyncratic volatility. All effects in Panel B remain statistically significant, with the exception of the last column, in which all effects are controlled for at once, and earnings variability loses significance. Most importantly, the turnover variability effect stays large and significant irrespective of what the controls are. I conclude that the turnover variability effect is not subsumed by either of the idiosyncratic risk measures and thus, merits a separate explanation.

# 4 Explaining the Turnover Variability Effect

## 4.1 FVIX as an Aggregate Volatility Risk Factor

The main prediction of this paper is that the turnover variability effect is explained by aggregate volatility risk, i.e., by the fact that firms with high (low) 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, 2013), 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 online Data Appendix[13] for discussion of the factor-mimicking procedure). FVIX 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.

[13]http://people.terry.uga.edu/abarinov/Data Appendix (Turnover Variability).pdf, page 3.

Third, as Chen (2002) suggests, a valid volatility risk factor should be able to predict future volatility. Barinov (2013) 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.

## 4.2 Turnover Variability and Aggregate Volatility Risk: Portfolio Sorts

Table II looks at the quintile sorts on 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 two rows Panel A consider average raw returns and value-weighted CAPM alphas and confirms that the turnover variability effect is strong and significant at 33-48 bp per month. This is close to the estimates from the cross-sectional regressions in Panel B of Table I despite different sample periods. The effect is more significant in risk-adjusted returns, since high turnover variability firms have high market betas. The third row looks at Fama-French (1993) alphas and brings similar numbers.

The fourth 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 turnover variability. The alpha differential flips the sign, loses significance and is a few bp per month away from zero. Also, all alphas of 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) turnover variability.

The driving force behind the success of the ICAPM with FVIX is revealed in the fifth row, which reports the FVIX betas. FVIX betas of firms with high turnover variability are significantly more positive than FVIX betas of firms with low turnover variability. This pattern in FVIX betas suggest that firms with high (low) 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 turnover variability effect and reveals the ability of stocks with high turnover variability to provide a hedge against aggregate volatility risk.

I conclude from Table II that the turnover variability effect exists not because liquidity variability is negatively related to expected returns (it is not, more on that in Section 5.3 and Table IX), but because turnover variability picks up idiosyncratic risk, which is in turn negatively related to aggregate volatility risk and thus to expected returns, as prior research (Barinov, 2011, 2013) suggests.

## 4.3 Turnover Variability and Aggregate Volatility Risk: Cross-Sectional Regressions

In Table III, I test the ability of aggregate volatility risk to explain the turnover variability effect using cross-sectional regressions. I follow the approach in Brennan, Chordia, and Subrahmanyam (1998) and regress risk-adjusted returns on stock characteristics, transformed into ranks confined between 0 and 1, as described in Section 3.2. The risk-adjustment starts with estimating the factor betas for each firm-month, using firm-level returns in months $t$-1 to $t$-36. The risk-adjusted returns in month $t$ are the raw returns less the sum of the products of these betas with factor returns in month $t$. My hypothesis is that turnover variability will be significant in all regressions, in which the risk-adjustment does not include FVIX, and will lose significance once the risk-adjustment includes FVIX.

In the first column, I report the regression with raw returns on the left-hand side (no risk-adjustment). The regression shows the presence of the well-known anomalies in my sample period (the value effect, momentum, short-term reversal, the turnover effect) and estimates the turnover variability effect at 55.5 bp per month.

In the second column, I perform the CAPM-based risk-adjustment, effectively turning the left-hand side variable into the firm-level CAPM alpha (plus random noise), and observe that all effects, including the turnover variability effect, stay the same after the risk-adjustment.

In the third column, I perform the risk-adjustment based on the Fama-French model. The risk-adjustment expectedly eliminates the value effect and reduces the turnover variability effect from 53.6 bp, t-statistic 3.42, to 39.2 bp per month, t-statistic 2.95.

The fourth column risk-adjusts firm-level returns using the market beta and the FVIX beta from the two-factor ICAPM. Consistent with my hypothesis that aggregate volatility risk is responsible for the turnover variability effect, the slope on turnover variability in the fourth column decreases by a factor of two as compared with the second column and becomes statistically insignificant. I also observe, consistent with Barinov (2011) and Barinov (2014), that the risk-adjustment that uses FVIX eliminates the value effect and the turnover effect.

Overall, the cross-sectional regressions in Table III corroborate the evidence in Table II that FVIX can explain the turnover variability effect.

### 4.4 Turnover Variability, Option-Like Equity, and Aggregate Volatility Risk

Panel A of Table IV looks at the abnormal return differential between low and high turnover 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 idiosyncratic risk, and idiosyncratic risk is more negatively related to returns for growth firms (see, e.g., Barinov, 2011, 2013).

Panel A shows that the turnover variability effect 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 explanation 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 hypothesis that firms with high turnover variability are better hedges against aggregate volatility risk if their equity is option-like.

Panel B of Table IV repeats the analysis of Panel A looking at the other dimension of equity option-likeness - the one that comes from the existence of risky debt. I resort to the three groups (top 30%, middle 40%, bottom 30%) instead of quintiles because the number of rated firms that have enough data to compute 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.

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 turnover variability effect under my hypothesis. 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.

Panel B delivers results similar to Panel A. In CAPM alphas, the turnover variability effect is by about 50 bp per month stronger for bad credit rating firms. The difference is reduced to at most 17 bp by controlling for FVIX. FVIX also explains the turnover variability effect for bad credit rating firms, which are the only group where it is significant in the CAPM alphas. FVIX betas of the low-minus-high turnover variability strategy are also significantly more negative in bad credit rating subsample.

Overall, the evidence in Table IV is consistent the central idea of this paper that turnover variability is negatively related to expected returns because higher turnover variability means higher idiosyncratic risk, and higher idiosyncratic risk means lower exposure of option-like firms to aggregate volatility risk.

### 4.5 Turnover Variability Effect and Equity Option-Likeness in Cross-Sectional Regressions

Table V tests the robustness of the results in the previous subsection by switching from portfolio sorts to cross-sectional regressions and adding more measures of equity option-likeness to the analysis. In addition to market-to-book and credit rating, Table V uses investment growth, sales growth, and O-score.

The first column in Panel A verifies that the turnover variability effect is visible in cross-sectional regressions that use the standard asset-pricing controls (same as in Table I). The slopes on the control variables are not reported to save space. The next columns add the products of option-likeness measures with turnover variability. My hypothesis is that the coefficients on the products will be significantly negative.

The slopes on the products, reported in the bottom row of Panel A, measure the difference in the turnover variability effect between firms with the least and the most option-like equity. According to Panel A, the turnover variability effect is by 49.3-79.6 bp per month stronger for growth firms than for value firms. The interaction effect is large and statistically significant irrespective of whether one measures growth options with market-to-book, investment growth, or sales growth. Likewise, the turnover variability effect is by about 42.3 bp (69.5 bp) per month stronger for high O-score (bad credit rating) firms.

Panel B checks whether the effects of turnover variability and its product with the measures of equity option-likeness on expected returns are mirrored by similar effects on FVIX betas. To that end, Panel B changes the dependent variable from returns to firm-level FVIX betas and re-runs the regressions from Panel A. The control variables (untabulated) stay the same.

The first column finds that higher variability of turnover implies significantly higher FVIX betas. The difference in FVIX betas between firms with the least variable and the most variable turnover is 0.865, close to what Table II finds in portfolio sorts.

The next three columns of Panel B show that FVIX beta of the low-minus-high turnover variability strategy strongly increase in measures of growth options. The product of turnover variability with market-to-book, for example, suggest that the FVIX beta of the low-minus-high turnover variability portfolio changes by 0.9 between the value and growth subsample. Likewise, the last two columns of Panel B confirm that the FVIX beta of the low-minus-high turnover variability portfolio is significantly greater for distressed firms, irrespective of whether distress is measured by credit rating or by O-score.

I conclude from Table V that the link between the 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.

## 4.6 Turnover Variability Effect and the Conditional CAPM

My explanation of the turnover variability effect suggests that one reason why high turnover variability firms are low-risk firms is that their betas drop in recession, when average idiosyncratic risk increases and real options become less sensitive to changes in the value of the underlying assets.

In Table VI, I estimate the Conditional CAPM assuming that the market beta is a linear function of lagged values of default spread, dividend yield, Treasury bill rate, and term spread. In Panel A, the Conditional CAPM is fitted to the returns of the low-minus-high turnover variability portfolio (LMH) and the difference of LMH returns between growth and value (MB) and good and bad credit rating firms (Cred). In Panel B, the Conditional CAPM is fitted to the top turnover variability quintile (High) and its intersection with the top market-to-book quintile (HiGro) and the 30% of firms with the worst credit rating (HiBad).

In the first three columns of Panel A, I observe that, with one exception, all arbitrage portfolios have higher betas in recessions, as my theory predicts. If the low-minus-high turnover varaibility strategy is followed using only option-like firms, the change in betas is usually greater, as predicted. The change in the betas is sizeable: the average value of the five significant betas is 0.316, which is roughly 6 times greater than the similar change in betas for the value-minus-growth strategy, reported in Petkova and Zhang (2005).

The first three columns of Panel B look at the betas of high turnover variability firms and confirm that they indeed decline during recessions. The decline is greater if those firms are also option-like. Since portfolios in Panel B are a part of the arbitrage portfolios in Panel A, comparing the changes in betas in the two panels leads to the conclusion that the change in betas in Panel A is driven primarily by the fact that high turnover variability firms have lower betas in recessions, again consistent with my theory. In the majority of cases, the change in Panel B is at least 75% of the change in Panel A.

In the last three columns, I report the CAPM, ICAPM, and Conditional CAPM alphas of the portfolios in question. The CAPM alphas are almost always large, significant and have the expected sign (positive in Panel A, negative in Panel B). The ICAPM alphas (last column) are small and insignificant (almost always within 15 bp of zero), consistent with previously reported results.

The new result is the Conditional CAPM alphas in column five. The low beta in recessions is not the only reason why high turnover variability firms are low-risk firms. The Conditional CAPM misses out on the fact that these firms have smaller losses in recessions, partly due to the lower betas and partly due to the positive link between option-like firms' values and idiosyncratic risk. Hence, I expect that the Conditional CAPM alphas will fall in between the CAPM and ICAPM alphas and will likely remain relatively large.

This is exactly what I find in the fifth column of both panels. The Conditional CAPM alphas are often marginally significant, but they are still economically sizeable. For example, in Panel A all alphas are above 28 bp per month, even though only one of them is significant at the 5% level. On average, making the beta time-varying reduces the alphas by 10-15 bp per month. I conclude that while the changes in the betas of high turnover variability firms predicted by my theory are large and economically important, the use of the ICAPM is necessary to explain the turnover variability effect.

# 5 Alternative Explanations of the Turnover Variability Effect

## 5.1 Turnover Variability and Variability of Liquidity

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 trade with a lower price impact. Pereira and Zhang (2010) assume that investors in firms with high 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.

One obvious condition for this theory is a relatively high probability that a firm with highly variable turnover will have higher liquidity than a firm with low turnover variability. If firms with high variability of trading activity are, on average, very illiquid, and despite higher variability, their liquidity is very rarely higher than liquidity of firms with low turnover variability, then it is unlikely that investors will be able to wait until that happens.

Table VII shows that this is exactly the case. Panel A sorts firms into quintiles based on their turnover variability and reports median values of several liquidity characteristics in each of these quintiles. Panels A finds that firms with the highest turnover variability have 2 to 4 times higher effective bd-ask spread, 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, proxied by the frequency of zero returns as suggested by Lesmond et al. (1999).

Panel B tabulates the probability that the liquidity of firms with highest turnover variability, as measured by the liquidity measure in the respective column, will beat the liquidity of firms with lowest turnover variability. The first row shows that the probability of the median firm with high turnover variability being more liquid than the median firm with low turnover variability 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 turnover variability quintile to the cut-off of the least liquid 25% in the lowest 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 turnover variability quintile. Then, conditional on the fact that A fell in the bottom liquidity quartile among low turnover variability firms and B fell in the top liquidity quartile among high turnover variability firms (which is itself an event with probability 6.25%), the probability of B being more liquid than A is about 40%.[14] 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 turnover variability becomes more liquid than a firm with low turnover variability.

In untabulated results, I hypothesize and confirm that the negative relation between variability of the Amihud measure and future returns documented in Pereira and Zhang (2010) is due to the mechanically positive correlation between turnover variability and variability of the Amihud measure (both turnover and the Amihud measure are ratios that include trading volume). In portfolio sorts, I find that the negative relation between the Amihud measure and future alphas is marginally significant at about 20 bp per month and dissipates completely after controlling for FVIX. I also find that firms with higher variability of the Amihud measure have significantly more positive FVIX betas.

## 5.2 Why Do Firms with High Turnover Variability Have Higher Idiosyncratic Risk?

Panel A of Table VII also sheds light on the driving force behind the relation between turnover variability and idiosyncratic risk. Panel A suggests that firms with high 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 suggests that a representative firm with low (high) turnover variability is not traded on 10% (23%) of trading days. It appears that the infrequent trading is the force that creates the high turnover variability: if instead of moving smoothly, trading volume jumps between zero and a multi-period volume that includes the pent-up demand from the prior no-trade periods, trading activity will naturally be more volatile.

Infrequent trading of high turnover variability firms is, in turn, caused by their high

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

trading costs, and the high trading costs are a consequence of high idiosyncratic risk. Hence, the mechanism linking turnover variability and idiosyncratic risk works as follows: higher idiosyncratic risk results in higher trading costs, higher trading costs bring about infrequent trading, and infrequent trading makes turnover more variable by introducing jumps from zero to multi-day trading volume.

Table VIII presents univariate regressions that establish the existence of the links discussed above in my sample. I perform the regressions for all firms (top row) and then separately for each size decile. Running the regressions separately in each size decile is equivalent to a non-parametric control for size.

In the first column, I regress log of turnover variability (CVTurn) on log of idiosyncratic volatility (IVol). The regressions are performed cross-sectionally a-la Fama-MacBeth. The first column confirms the result in Panel A of Table 1 that CVTurn is positively correlated with IVol. The results using other measures of idiosyncratic risk (untabulated) are similar.

The second column of Table VIII confirms my first hypothesis that infrequent trading creates turnover variability. I regress log CVTurn on log of Zero, the fraction of zero-return days, and observe a strong and significant positive relation.

The next three columns of Table VIII test my second hypothesis that trading frequency is inversely related to trading costs. I regress log of Zero on three effective bid-ask spread measures - the Roll (JF 1984) measure, the Spread measure of Corwin and Schultz (JF 2012), and the effective tick measure of Holden (JFM 2009) - and find, for all measures and all size deciles, that higher spreads mean more no-trade days.[15]

According to the microstructure literature, higher idiosyncratic risk results in higher bid-ask spread both through the inventory and asymmetric information channel. In the

[15] The general positive link between the fraction of no-trade days and trading costs was first reported by Lesmond et al. (1999).

rightmost three columns of Table VIII, I test whether spreads are indeed positively related to idiosyncratic risk. I use IVol as a measure of idiosyncratic risk (using other variables like cash flow variability or analyst disagreement yields similar results). Again, for all spread measures and all size deciles, I find that higher IVol means higher trading costs.

Overall, the table confirms my story about how the positive relation between turnover variability and idiosyncratic risk (column one) comes into place. Higher idiosyncratic risk means higher trading costs (columns six to eight), higher trading costs imply more no-trade days (columns three to five), and more no-trade days imply higher turnover variability (column two).[16]

A referee suggested that one cannot exclude the reverse causality here: variable trading activity may increase the chance of no-trade days, and no-trade days may cause higher idiosyncratic volatility, because the return following a no-trade day will jump from zero to the two-day return. However, my explanation of the turnover variability effect only needs a strong association between turnover variability and idiosyncratic volatility, established in Panel A of Table I and then again in column one of Table VIII, and does not depend on which way the causality goes.

The fact that the explanation of the link between turnover variability and idiosyncratic risk works through liquidity does not imply that controlling for liquidity will eliminate the turnover variability effect. Firms with high turnover variability have low liquidity, which should be compensated for by high expected returns if liquidity is priced, but the turnover variability effect implies that firms with high turnover variability have lower, not higher

[16] In untabulated results, I control for size by adding it to the regressions in Table VIII as the second independent variable, and confirm that the results are the same. I have also experimented with controlling for the determinants of trading activity from Panel A of Table 1, with similar results. I suspect though that such experiments are "over-controlling" to an extent, because the question I am trying is "why does turnover variability pick up idiosyncratic risk?" - in single sorts, not multiple regressions.

expected returns. Thus, controlling for liquidity will only make the turnover variability effect stronger.

A referee suggested that if the link between turnover variability and idiosyncratic risk works through infrequent trading, then the turnover variability effect should be significantly stronger for small firms and illiquid firms. In untabulated results, I confirm that this is the case. I perform conditional double sorts first on size/frequency of zero returns and then on turnover variability. I find that the turnover variability effect varies from about 40 bp per month for smaller stocks and stocks with the highest frequency of zero returns to 20 bp (5 bp) per month for large (most frequently traded) stocks.

### 5.3 Liquidity Variability and Expected Returns

Panel A of Table IX tests whether higher variability of trading activity is indeed related to variability of liquidity and performs quintile sorts on turnover variability and reports median coefficient of variation of several liquidity measures across the quintiles.

Expectedly, Table IX finds that firms with more variable 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 turnover variability firms. The increase in the variability of spread measures from low to high turnover variability firms is between one-third and one-half (with the exception of the Roll measure, which yields a smaller, 10-15%, increase).

Panel B of Table IX considers the relation between expected returns and the variability of the six measures of liquidity from Panel A. Panel B of Table IX performs firm-level Fama-MacBeth regressions of returns on the liquidity variability measures lagged by two months and the standard controls from Table I (untabulated to save space). Also, the untabulated controls include of the level of the liquidity variable, the variability of which is used in the regression. When Panel B performs the horse race between variability of liquidity and variability of turnover, the controls also include average value of turnover in the past year. All independent variables, except for market beta, are ranks confined between 0 and 1.

The first row of Panel B 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 B 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.

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

## 5.4 Variability of Trading Activity and Liquidity Risk

Chordia et al. (2001) suggest that low returns to high turnover variability firms are puzzling because such firms have a higher chance of experiencing low turnover and hence higher trading costs. That should 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 turnover variability are related to market-wide illiquidity. If firms with high 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.

In this subsection, I check whether higher variability of trading activity implies higher or lower liquidity risk. Following Acharya and Pedersen (2005), I define liquidity risk in three ways: as the tendency to experience low returns in response to increases in market illiquidity, as the tendency to experience high trading costs during market declines, and as the tendency to experience high trading costs in an illiquid market.

The first definition of liquidity risk suggests that liquidity risk can be measured by return loadings on traditional liquidity risk factors. In Panel A of Table X, I use several risk factors - the Pastor and Stambaugh (2003) factor, the Sadka (2006) factor, and the Amihud (2002) factor - and find that firms with higher variability of trading activity have slightly lower, not higher liquidity risk. However, the impact of controlling for liquidity risk on the alpha of the low-minus-high turnover variability portfolio is economically small. The turnover variability effect remains statistically significant at at least 40 bp per month controlling for liquidity risk.

Panel B of Table X reports the slopes from firm-level regressions of changes in the liquidity measures from Table VII on the market return. The slopes are the type-two liquidity risk betas from Acharya and Pedersen (2005). I find that the spread in the trading costs sensitivity between firms with low and high turnover variability takes different signs depending on the liquidity measure. On the balance, the spreads in liquidity risk that suggest higher liquidity risk for high turnover variability firms are more common and statistically significant.

Lastly, in untabulated results I regress changes in the liquidity measures on the liquidity risk factors. Again, I do not observe a clear pattern that would link turnover variability to liquidity risk. Often, a regression of the change in the same liquidity measure on different liquidity risk factors brings opposite conclusions about whether firms with high turnover variability have higher liquidity risk. Most importantly, the regressions of changes in the liquidity measures on the liquidity risk factors produce the differences in slopes between high and low turnover variability firms that are economically small.

To sum up, I do not find a clear relation between turnover variability and liquidity risk. I conclude that liquidity risk does not help significantly to explain the turnover variability effect of Chordia et al. (2001), but is also unlikely to make it more puzzling.[17]

## 5.5 Can the Turnover Variability Effect Be Mispricing?

One possible explanation of the turnover variability effect is that it is mispricing. George and Hwang (2009) suggest that betting against it implies trading in firms with

[17] The lack of a strong relation between turnover variability and liquidity risk does not necessarily contradict the evidence in Table VII that high turnover variability firms are significantly more illiquid. Liquidity and liquidity risk are two different concepts: the former is a firm characteristic, i.e., cost of trading, the latter refers to covariances described in the beginning of this subsection. Untabulated results also show that direct sorts on the liquidity measures from Table VII do not always produce strong sorts on liquidity risk. For example, the Amihud betas are related in cross-section to effective tick, Amihud measure, and the frequency of zero returns, but unrelated to Roll and Gibbs measures and the effective bid-ask spread measure of Corwin and Schultz (2012).

information asymmetry and use analyst coverage as a proxy, finding that the turnover variability effect is significantly stronger for firms with low analyst coverage.

Panel A of Table XI confirms that in the CAPM alphas (first row), the turnover variability effect is indeed stronger when analyst coverage is low. However, when one controls for FVIX (second row), the relation between the turnover variability effect and analyst coverage disappears, and the stronger turnover variability effect for firms with low analyst coverage is reduced to almost zero. The third row shows that these changes are accompanied by more negative FVIX betas of the low-minus-high turnover variability strategy in the low analyst coverage subsample.

I hypothesize and confirm in untabulated results that firms with lower analyst following have much higher turnover variability, and sorting on turnover variability in low analyst following subsample therefore produces a larger spread in turnover variability, expected returns, and aggregate volatility risk.

Another mispricing explanation for the turnover variability effect is 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. The higher is the disagreement between pessimists and optimists, the larger is the mispricing caused by keeping the pessimists out and the lower are the future returns. The empirical hypothesis from the Miller theory is that, since turnover variability is related to analyst disagreement, the turnover variability effect will be stronger if short sale constraints are stronger.

Panels B and C of Table XI report the turnover variability effect across institutional ownership and relative short interest quintiles, which proxy for supply of shares for shorting and shorting demand, respectively. Hence, the Miller theory predicts that the turnover effect will be stronger for firms with low institutional ownership or high relative short interest. 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). Relative short interest is defined as the percentage of shares outstanding that have been shorted.

The first rows of Panels B and C show that the turnover variability effect is indeed stronger for short sale constrained firms. However, controlling for FVIX largely eliminates the turnover variability effect in all short sale constraints quintiles and makes it similar across the quintiles. The changes in the alphas are mirrored by similar patterns in FVIX betas.

In untabulated results, I hypothesize and find that the link between short sale constraints and the turnover variability effect is largely mechanical and stems from the fact that firms with low institutional ownership and/or higher relative short interest have, on average, higher turnover variability.

Lastly, in Panel D of Table XI, I follow the approach first used by La Porta et al. (1997) and look at the announcement returns to the low-minus-high turnover variability strategy across the limits to arbitrage quintiles in Panels A-C, as well as the announcement returns of the turnover variability quintiles (top row). The announcement returns are cumulated in the three days around the announcement day and are size and market-to-book adjusted.

If the turnover variability effect is risk, at most 5-10% of it should be concentrated around earnings announcements,[18] whereas if the turnover variability effect is mispricing, we will observe that its significant concentration at earnings announcements, when the new information hits the market and the mispricing is partially corrected.

The first row of Panel D finds that the difference in CARs between top and bottom turnover variability quintiles is marginally significant at 27 bp. Prior analysis estimates the turnover variability effect at about 50 bp per month or 150 bp per quarter. Hence,

[18]Four three-day announcement windows make up less than 5% of roughly 250 trading days in a year.

at most 20% of the turnover variability effect is concentrated at earnings announcements, which is not too far from the 5-10% we expect if the turnover variability effect is risk.

The next three rows look at the CAR differential between the extreme turnover variability quintiles across the limits to arbitrage quintiles. Inconsistent with the mispricing explanation, I observe no discernible increase in the concentration of the turnover variability effect at earnings announcements as I move from low to high limits to arbitrage firms. The announcement effects are non-monotonically related to limits to arbitrage and the difference in them between high and low limits to arbitrage firms is economically small and statistically insignificant.

To sum up, the evidence in Table XI is largely consistent with the hypothesis that the turnover variability effect is risk, since neither the ICAPM alphas across the limits to arbitrage quintiles, not earnings announcement returns can reject this hypothesis.

# 6 Conclusion

The turnover variability effect of Chordia et al. (2001) creates the impression that liquidity variability bears a negative risk premium. The paper disputes this conclusion and shows that the turnover variability effect can be explained by the fact that variability of trading activity is positively correlated with idiosyncratic risk, and higher idiosyncratic risk means lower aggregate volatility risk. The paper also shows that variability of other liquidity measures is unrelated to expected returns.

Higher idiosyncratic risk lowers the systematic risk of option-like (distressed or growth) firms by making them less responsive to the changes in the value of the underlying assets. This property becomes particularly useful in recessions, when idiosyncratic risk 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 idiosyncratic risk at the level of the underlying asset increases during recessions, and this effect is naturally stronger for high idiosyncratic risk firms.

The paper starts by showing that variability of trading activity is strongly and positively related to several measures of idiosyncratic risk. Further tests show that idiosyncratic risk is linked to turnover variability through liquidity. High idiosyncratic risk implies lower liquidity, lower liquidity brings about infrequent trading, and infrequent trading makes volume and turnover more volatile. Firms with high variability of turnover are indeed several times less liquid and witness no-trade days several times more often than firms with low variability of turnover.

The turnover variability effect disappears in the ICAPM with the market factor and the aggregate volatility risk factor. Consistent with my hypothesis that higher turnover variability implies higher idiosyncratic risk, and higher idiosyncratic risk lowers the risk of option-like equity, I find that the turnover variability effect is significantly stronger for growth firms and distressed firms. I also find that FVIX explains this pattern, lending further support to the hypothesis that turnover variability is related to idiosyncratic risk and therefore to aggregate volatility risk.

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

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

I entertain the possibility that the turnover variability effect may be mispricing. I find that the turnover variability effect is stronger for the firms with higher limits to arbitrage, but the aggregate volatility risk factor explains this relation. I also find that the turnover variability effect is not concentrated at earnings announcements, and its relation to limits to arbitrage is not driven by earnings announcement returns either, inconsistent with the mispricing explanation.

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## Table I. Variability of Trading Activity, Idiosyncratic Risk, and Expected Returns

Panel A presents the slopes from cross-sectional firm-level regressions of turnover variability (CVTurn) on different measures of idiosyncratic risk. The regressions include controls (see Section 3.1) and consider each idiosyncratic risk measure separately. All explanatory variables are ranks between 0 and 1. Panel B 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 (MB), size, cumulative return between month t-2 and t-12 (MOM), return in the past month (REV), and turnover (Turn). Detailed definitions of all variables are in online 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 and Idiosyncratic Risk

$$\gamma\text{s from } \boldsymbol{CVTurn_t = \gamma \cdot IdioRisk_t + X'\beta}$$

| | **IVol** | **Disp** | **Error** | **CVCFO** | **CVEarn** |
|---|---|---|---|---|---|
| **CVTurn** | 0.089 | 0.032 | 0.019 | 0.054 | 0.038 |
| **t-stat** | *11.8* | *9.10* | *5.85* | *2.51* | *8.35* |

### Panel B. Turnover Variability, Uncertainty Measures, and Expected Returns

| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| **CVTurn** | | -0.414 | -0.324 | | -0.330 | -0.293 | | -0.437 | -0.415 | -0.250 |
| **t-stat** | | *-4.34* | *-3.84* | | *-2.58* | *-2.37* | | *-3.70* | *-3.54* | *-2.06* |
| **IVol** | -1.227 | | -1.076 | | | | | | | -0.784 |
| **t-stat** | *-5.09* | | *-5.41* | | | | | | | *-3.49* |
| **Disp** | | | | -0.473 | | -0.347 | | | | -0.307 |
| **t-stat** | | | | *-2.35* | | *-1.87* | | | | *-1.81* |
| **CVEarn** | | | | | | | -0.326 | | -0.247 | 0.069 |
| **t-stat** | | | | | | | *-2.42* | | *-2.34* | *0.62* |

## Table II. 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. Detailed definitions of turnover variability are in online 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 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**

| | Low | CV2 | CV3 | CV4 | High | L-H |
|---|---|---|---|---|---|---|
| **Raw** | 0.977 | 0.892 | 0.881 | 0.731 | 0.649 | 0.328 |
| **t-stat** | *3.81* | *3.14* | *2.83* | *2.10* | *1.63* | *1.46* |
| $\boldsymbol{\alpha}_{CAPM}$ | 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* |
| $\boldsymbol{\alpha}_{FF}$ | 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* |
| $\boldsymbol{\alpha}_{ICAPM}$ | -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* |
| $\boldsymbol{\beta}_{FVIX}$ | -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 B. Equal-Weighted Returns**

| | Low | CV2 | CV3 | CV4 | High | L-H |
|---|---|---|---|---|---|---|
| **Raw** | 1.164 | 1.092 | 1.016 | 0.938 | 0.780 | 0.383 |
| **t-stat** | *4.07* | *3.56* | *3.09* | *2.71* | *2.32* | *2.33* |
| $\boldsymbol{\alpha}_{CAPM}$ | 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* |

## Table III. Variability of Trading Activity and Aggregate Volatility Risk in Cross-Sectional Regressions

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is indicated in the header of each column. The alphas ($\overline{\alpha}$) are firm-level risk-adjusted returns estimated as in Brennan et al. (1998) (the details on risk-adjustment are in online Data Appendix). All independent variables are ranks between 0 and 1. The controls are market-to-book (MB), size, cumulative return between month t-2 and t-12 (MOM), return in the past month (REV), and turnover (Turn). Detailed definitions of all variables are in online 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.

| | **Raw** | $\overline{\boldsymbol{\alpha}}_{CAPM}$ | $\overline{\boldsymbol{\alpha}}_{FF}$ | $\overline{\boldsymbol{\alpha}}_{ICAPM}$ |
|---|---|---|---|---|
| **Size** | -0.158 | -0.175 | -0.087 | -0.964 |
| **t-stat** | *-0.43* | *-0.52* | *-0.36* | *-2.66* |
| **MB** | -0.859 | -0.795 | -0.281 | -0.232 |
| **t-stat** | *-2.56* | *-2.60* | *-1.25* | *-0.74* |
| **Mom** | 1.300 | 1.011 | 0.785 | 1.041 |
| **t-stat** | *3.32* | *2.66* | *2.12* | *2.28* |
| **Rev** | -0.408 | -0.407 | -0.660 | -0.612 |
| **t-stat** | *-2.00* | *-2.06* | *-3.10* | *-2.19* |
| **Turn** | -0.549 | -1.056 | -0.883 | -0.383 |
| **t-stat** | *-1.67* | *-3.80* | *-4.58* | *-1.35* |
| **CVTurn** | -0.555 | -0.536 | -0.392 | -0.250 |
| **t-stat** | *-5.46* | *-3.42* | *-2.95* | *-1.54* |

## Table IV. Variability of Trading Activity, Equity Option-Likeness, and Aggregate Volatility Risk

The table reports the CAPM and ICAPM alphas and the FVIX betas for the turnover variability arbitrage portfolio formed separately within each market-to-book quintile (Panel A) or credit rating tercile (Panel B). The arbitrage portfolio buys firms in the lowest and short firms in the highest turnover variability quintile. All quintiles use NYSE (exchcd=1) breakpoints. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. Detailed definitions of all variables are in online 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 priced 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** |
| $\boldsymbol{\alpha}_{CAPM}$ | 0.013 | 0.084 | 0.611 | 0.654 | 0.354 | 0.341 | $\boldsymbol{\alpha}_{CAPM}$ | -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* |
| $\boldsymbol{\alpha}_{ICAPM}$ | -0.133 | -0.227 | 0.303 | 0.229 | -0.185 | -0.052 | $\boldsymbol{\alpha}_{ICAPM}$ | -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* |
| $\boldsymbol{\beta}_{FVIX}$ | -0.351 | -0.648 | -0.637 | -0.941 | -1.169 | -0.818 | $\boldsymbol{\beta}_{FVIX}$ | -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. 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* |

## Table V. Variability of Trading Activity and Option-Like Equity

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return in Panel A and firm-level FVIX beta in Panel B. The first line of each panel reports the slopes on CVTurn, the second line reports the slope on its product with the column header - MB (market-to-book), IG (investment growth), SG (sales growth), Cred (credit rating), and O-score. 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), and return in the past month (REV). Detailed definitions of all variables are in online 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 Trading Activity, Option-Like Equity, and Expected Returns

| | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| **CVTurn** | -0.555 | -0.197 | -1.557 | -0.351 | -0.164 | 1.612 |
| **t-stat** | *-5.46* | *-1.16* | *-4.55* | *-2.31* | *-1.33* | *2.33* |
| | | **MB** | **IG** | **SG** | **Cred** | **O-Score** |
| **CVTurn×Var** | | -0.796 | -0.712 | -0.493 | -0.695 | -0.423 |
| **t-stat** | | *-2.68* | *-4.80* | *-2.98* | *-2.42* | *-1.68* |

### Panel B. Variability of Trading Activity, Option-Like Equity, and FVIX Betas

| | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| **CVTurn** | 0.865 | 1.109 | 0.575 | 0.308 | 0.827 | -1.562 |
| **t-stat** | *6.80* | *6.19* | *3.36* | *2.39* | *5.74* | *-6.38* |
| | | **MB** | **IG** | **SG** | **Cred** | **O-Score** |
| **CVTurn×Var** | | 0.902 | 2.290 | 0.292 | 1.008 | 0.558 |
| **t-stat** | | *4.66* | *7.24* | *2.12* | *7.79* | *3.43* |

# Table VI. Turnover Variability Effect and Conditional CAPM

The table reports Conditional CAPM betas across different states of the world, as well as the alphas from the CAPM, the Conditional CAPM, and the ICAPM with FVIX. LMH is the portfolio long in low and short in high turnover variability stocks. MB (Cred) is the return differential between the LMH portfolio formed in the highest market-to-book (worst credit rating) quintile and the LMH portfolio formed in the lowest market-to-book (best credit rating) quintile. High is the top turnover variability quintile. HiGro (HiBad) is the intersection of High and top market-to-book quintile (30% of firms with worst credit rating). Recession (Expansion) is the period when the expected market risk premium is higher (lower) than its in-sample median. The expected risk premiums and the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. The $t$-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

## Panel A. Turnover Variability Effect

### Value-Weighted Returns

| | $\beta_{Rec}$ | $\beta_{Exp}$ | $\Delta\beta$ | $\alpha_{CAPM}$ | $\alpha_{CCAPM}$ | $\alpha_{ICAPM}$ |
|---|---|---|---|---|---|---|
| **LMH** | -0.060 | -0.336 | 0.276 | 0.476 | 0.306 | -0.043 |
| **t-stat** | *-1.77* | *-6.20* | *4.33* | *2.46* | *1.70* | *-0.19* |
| **MB** | -0.260 | -0.131 | -0.129 | 0.341 | 0.475 | -0.052 |
| **t-stat** | *-6.67* | *-1.56* | *-1.41* | *0.92* | *1.06* | *-0.14* |
| **Cred** | 0.110 | -0.509 | 0.619 | 0.532 | 0.360 | 0.171 |
| **t-stat** | *2.98* | *-8.64* | *8.15* | *2.27* | *1.47* | *0.68* |

### Equal-Weighted Returns

| | $\beta_{Rec}$ | $\beta_{Exp}$ | $\Delta\beta$ | $\alpha_{CAPM}$ | $\alpha_{CCAPM}$ | $\alpha_{ICAPM}$ |
|---|---|---|---|---|---|---|
| **LMH** | 0.101 | -0.056 | 0.157 | 0.363 | 0.287 | -0.063 |
| **t-stat** | *5.72* | *-2.39* | *5.33* | *2.11* | *1.66* | *-0.29* |
| **MB** | -0.331 | -0.604 | 0.273 | 0.733 | 0.616 | 0.318 |
| **t-stat** | *-11.5* | *-13.5* | *4.95* | *3.25* | *2.84* | *1.16* |
| **Cred** | 0.088 | -0.167 | 0.255 | 0.444 | 0.361 | 0.144 |
| **t-stat** | *5.00* | *-4.09* | *5.63* | *1.87* | *1.62* | *0.68* |

## Panel B. High Turnover Variability Firms

### Value-Weighted Returns

| | $\beta_{Rec}$ | $\beta_{Exp}$ | $\Delta\beta$ | $\alpha_{CAPM}$ | $\alpha_{CCAPM}$ | $\alpha_{ICAPM}$ |
|---|---|---|---|---|---|---|
| **High** | 1.012 | 1.223 | -0.211 | -0.352 | -0.217 | -0.039 |
| **t-stat** | *37.4* | *27.1* | *-4.00* | *-2.33* | *-1.50* | *-0.23* |
| **HiGro** | 1.184 | 1.480 | -0.296 | -0.310 | -0.174 | 0.044 |
| **t-stat** | *48.7* | *36.0* | *-5.93* | *-1.63* | *-0.96* | *0.22* |
| **HiBad** | 1.233 | 1.709 | -0.476 | -0.583 | -0.326 | -0.035 |
| **t-stat** | *39.8* | *36.9* | *-7.89* | *-2.21* | *-1.34* | *-0.13* |

### Equal-Weighted Returns

| | $\beta_{Rec}$ | $\beta_{Exp}$ | $\Delta\beta$ | $\alpha_{CAPM}$ | $\alpha_{CCAPM}$ | $\alpha_{ICAPM}$ |
|---|---|---|---|---|---|---|
| **High** | 1.068 | 1.122 | -0.054 | -0.091 | -0.076 | 0.217 |
| **t-stat** | *54.4* | *56.8* | *-2.00* | *-0.52* | *-0.42* | *1.06* |
| **HiGro** | 1.297 | 1.623 | -0.326 | -0.732 | -0.582 | -0.104 |
| **t-stat** | *48.4* | *36.1* | *-5.96* | *-2.84* | *-2.30* | *-0.34* |
| **HiBad** | 1.236 | 1.448 | -0.212 | -0.466 | -0.336 | -0.016 |
| **t-stat** | *82.8* | *52.8* | *-6.51* | *-2.08* | *-1.46* | *-0.06* |

## Table VII. Variability of Trading Activity and Liquidity

Panel A presents the median values of several liquidity measures across turnover 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 online Data Appendix.

Panel B presents the estimated frequency of the median liquidity of the highest turnover variability quintile being better than the median liquidity of the lowest turnover variability quintile (50vs50) and the estimated frequency of the 25th liquidity percentile in the highest turnover variability quintile being better than the the 75th liquidity percentile in the lowest turnover 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. 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% |

## Table VIII. Variability of Trading Activity and Idiosyncratic Volatility

The table presents univariate cross-sectional regressions described by the equations below (the model number corresponds to the column number). The regressions are performed a-la Fama-MacBeth first in the full sample (first row) and then separately in each size decile. The size deciles use market cap from December of the previous year and NYSE breakpoints.

$$
\begin{aligned}
&(1) \quad Model\ 1 : log(CVTurn_i) = a + b \cdot log(IVol_i)\\
&(2) \quad Model\ 2 : log(CVTurn_i) = a + b \cdot log(Zero_i)\\
&(3) \quad Model\ 3 : log(Zero_i) = a + b \cdot log(Roll_i)\\
&(4) \quad Model\ 4 : log(Zero_i) = a + b \cdot log(Spread_i)\\
&(5) \quad Model\ 5 : log(Zero_i) = a + b \cdot log(EffTick_i)\\
&(6) \quad Model\ 6 : log(Roll_i) = a + b \cdot log(IVol_i)\\
&(7) \quad Model\ 7 : log(Spread_i) = a + b \cdot log(IVol_i)\\
&(8) \quad Model\ 8 : log(EffTick_i) = a + b \cdot log(IVol_i)
\end{aligned}
$$

| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
|---|---|---|---|---|---|---|---|---|
| **All Firms** | 0.197 | 1.350 | 1.880 | 2.997 | 1.073 | 0.507 | 0.368 | 0.562 |
| **t-stat** | *15.2* | *11.7* | *14.9* | *13.8* | *24.7* | *19.3* | *8.40* | *12.4* |
| **Small** | 0.033 | 0.557 | 0.409 | 2.755 | 1.446 | 0.386 | 0.233 | 0.218 |
| **t-stat** | *5.26* | *7.26* | *3.05* | *13.6* | *15.5* | *29.9* | *5.68* | *13.5* |
| **Decile2** | 0.070 | 0.137 | 1.030 | 3.148 | 1.156 | 0.414 | 0.435 | 0.306 |
| **t-stat** | *10.7* | *2.01* | *8.16* | *8.22* | *12.0* | *30.4* | *9.11* | *21.8* |
| **Decile3** | 0.077 | 0.148 | 1.141 | 3.577 | 1.366 | 0.407 | 0.427 | 0.305 |
| **t-stat** | *11.1* | *2.79* | *10.1* | *7.46* | *13.4* | *33.8* | *9.11* | *23.6* |
| **Decile4** | 0.080 | 0.286 | 1.438 | 3.264 | 1.869 | 0.406 | 0.424 | 0.285 |
| **t-stat** | *11.2* | *3.47* | *9.63* | *5.88* | *15.3* | *33.5* | *10.1* | *22.2* |
| **Decile5** | 0.075 | 0.304 | 1.995 | 3.486 | 2.119 | 0.434 | 0.457 | 0.290 |
| **t-stat** | *9.39* | *2.96* | *12.3* | *6.49* | *15.4* | *29.7* | *12.4* | *19.7* |
| **Decile6** | 0.083 | 0.400 | 2.208 | 3.650 | 2.824 | 0.456 | 0.471 | 0.277 |
| **t-stat** | *9.49* | *5.14* | *11.1* | *6.17* | *17.8* | *33.6* | *17.7* | *18.8* |
| **Decile7** | 0.052 | 0.401 | 2.421 | 4.672 | 3.249 | 0.445 | 0.475 | 0.247 |
| **t-stat** | *5.67* | *4.62* | *11.1* | *6.87* | *23.1* | *31.5* | *26.2* | *18.3* |
| **Decile8** | 0.068 | 0.449 | 2.331 | 5.192 | 4.063 | 0.435 | 0.425 | 0.205 |
| **t-stat** | *6.37* | *3.36* | *8.45* | *6.53* | *25.4* | *26.9* | *29.1* | *14.4* |
| **Decile9** | 0.058 | 0.492 | 3.064 | 5.913 | 5.344 | 0.434 | 0.391 | 0.167 |
| **t-stat** | *5.06* | *3.52* | *9.02* | *6.98* | *21.8* | *24.8* | *32.1* | *13.5* |
| **Large** | 0.116 | 0.288 | 2.586 | 6.709 | 6.173 | 0.413 | 0.360 | 0.263 |
| **t-stat** | *8.83* | *2.17* | *7.23* | *6.62* | *19.9* | *28.9* | *32.8* | *16.7* |

## Table IX. Variability of Trading Activity and Variability of Liquidity

Panel A presents the median variability of several liquidity measures across turnover variability quintiles. The quintiles are rebalanced monthly and use NYSE (exchcd=1) breakpoints. Panel B presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. All independent variables, except for market beta, are ranks between 0 and 1. The top row reports the slopes on liquidity variability, used one at a time. The next pair of rows adds turnover variability to the controls. The controls (not tabulated) are the market beta, size, market-to-book, cumulative return in the past 12 months, and turnover. Detailed definitions of all variables are in online 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 priced 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. Variability of Liquidity and Expected Returns**

**B1: $\gamma$s 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* |

**B2: $\gamma$s 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* |

# Table X. Variability of Trading Activity and Liquidity Risk

Panel A presents the alphas from the Fama-French (FF) model ($\alpha_{FF}$) and the alphas from the FF model augmented by a liquidity risk factor (for example, $\alpha_{Sad}$ is the alpha from the FF model with the Sadka factor added), as well as the liquidity betas from the augmented FF models, across the quintile sorts on volume/turnover variability. Panel B 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. 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.

| | **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* |
| $\boldsymbol{\alpha_{PS}}$ | 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* |
| $\boldsymbol{\beta_{PS}}$ | 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* |
| $\boldsymbol{\alpha_{Sad}}$ | 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* |
| $\boldsymbol{\beta_{Sad}}$ | 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* |
| $\boldsymbol{\alpha_{Ami}}$ | 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* |
| $\boldsymbol{\beta_{Ami}}$ | 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* |

| | **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* |

## Table XI. Turnover Variability Effect, Limits to Arbitrage, and Expected Returns

Panels A to C reports the CAPM and ICAPM alphas and the FVIX betas for the turnover variability arbitrage portfolio formed separately in each limits-to-arbitrage quintile. The turnover variability arbitrage portfolio is long in the lowest turnover variability quintile and short in the highest turnover variability quintile. The limits to arbitrage measures are number of analysts following the firm (Panel A), residual institutional ownership (Panel B), and relative short interest (Panel C). Panel D reports size and market-to-book adjusted announcement returns of the turnover variability quintiles (first row) and the turnover variability arbitrage portfolio across limits-to-arbitrage quintiles (next rows). 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. Turnover Variability Effect and the Number of Analysts Following the Firm

| | **Low** | **# An2** | **# An3** | **# An4** | **High** | **L-H** |
|---|---|---|---|---|---|---|
| $\boldsymbol{\alpha}_{CAPM}$ | 0.423 | 0.440 | 0.363 | 0.327 | 0.152 | 0.271 |
| **t-stat** | *2.18* | *2.34* | *2.15* | *2.02* | *0.84* | *1.78* |
| $\boldsymbol{\alpha}_{ICAPM}$ | -0.017 | 0.080 | -0.043 | 0.092 | -0.033 | 0.016 |
| **t-stat** | *-0.09* | *0.44* | *-0.22* | *0.58* | *-0.20* | *0.11* |
| $\boldsymbol{\beta}_{FVIX}$ | -0.977 | -0.776 | -0.874 | -0.503 | -0.429 | -0.548 |
| **t-stat** | *-2.52* | *-2.11* | *-2.64* | *-1.98* | *-1.55* | *-2.50* |

### Panel B. Turnover Variability Effect and Residual Institutional Ownership

| | **Low** | **RI 2** | **RI 3** | **RI 4** | **High** | **L-H** |
|---|---|---|---|---|---|---|
| $\boldsymbol{\alpha}_{ICAPM}$ | 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 C. Turnover Variability Effect and Relative Short Interest**

| | 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 D. Earnings Announcements Effects and Limits to Arbitrage**

| | Low | CV2 | CV3 | CV4 | High | L-H |
|---|---|---|---|---|---|---|
| **CAR** | 0.176 | 0.127 | 0.084 | 0.076 | -0.096 | 0.272 |
| **t-stat** | *3.46* | *1.83* | *1.08* | *1.12* | *-0.70* | *1.75* |
| | **Low** | **# An2** | **# An3** | **# An4** | **High** | **L-H** |
| **L-H CAR** | 0.215 | -0.012 | 0.109 | 0.192 | 0.061 | 0.154 |
| **t-stat** | *1.37* | *-0.05* | *0.60* | *1.06* | *0.24* | *0.53* |
| | **Low** | **RI 2** | **RI 3** | **RI 4** | **High** | **L-H** |
| **L-H CAR** | 0.105 | 0.360 | -0.160 | 0.224 | 0.232 | -0.127 |
| **t-stat** | *0.64* | *1.45* | *-0.71* | *1.22* | *0.83* | *-0.40* |
| | **Low** | **RSI2** | **RSI3** | **RSI4** | **High** | **H-L** |
| **L-H CAR** | -0.017 | 0.394 | 0.095 | -0.158 | 0.227 | 0.244 |
| **t-stat** | *-0.08* | *1.68* | *0.33* | *-0.64* | *0.86* | *0.74* |