Variation in Liquidity and Costly Arbitrage

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Abstract

This paper explores the relationship between the variation in liquidity and arbitrage activity. A model shows that arbitrageurs will limit their exposure to stocks with high variation in liquidity. The model predicts that mispricing will be severe in stocks with high variation in liquidity. I test the predictions by using standard deviation of monthly turnover (TURNVOL) as the measure of variation in liquidity. Consistent with the model, I find that mispricing is severe in high TURNVOL stocks. Furthermore, the negative relationship between variation in liquidity and returns, documented in prior literature, is absent after accounting for the mispricing in high TURNVOL stocks.

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1. Introduction

Arbitrageurs play an important role in the financial markets. In frictionless markets, arbitrageurs help reduce mispricing and therefore make prices more efficient. However, in practice, arbitrageurs do not have unlimited access to capital. They rely on external capital to trade on profitable opportunities. They are also exposed to numerous frictions in the financial markets which limit their effectiveness in correcting mispricing. Literature has documented a variety of factors that hinder arbitrage activity. For example, Shleifer and Vishny (1997) discuss how noise trader sentiment could limit arbitrage. In addition, Pontiff (2006) argues that idiosyncratic volatility is an important holding cost for arbitrageurs. Furthermore, Hong and Stein (2003) and Nagel (2005) highlight how short sale constraints prevent mispricing from being eliminated. Complementing previous studies, this paper explores how one such friction, the variation in liquidity, affects the behavior of arbitrageurs.

When arbitrageurs rely on external capital, variation in liquidity can affect their investment decisions. If arbitrageurs experience outflows, they might be forced to close positions during a bad liquidity state resulting in lower profitability. If the outflows are extreme, they might even incur losses in their positions. Coval and Stafford (2007) provide supportive evidence by documenting price pressure in stocks held by mutual funds experiencing extreme outflows. Therefore, given the reliance on external capital, the variation in liquidity can affect arbitrageur's demand and mispricing in the underlying assets.

In order to understand arbitrageur's behavior, I present a model where a risk-averse arbitrageur allocates capital between a risk-free asset and a risky asset. The profits obtained by trading in the risky asset are affected by the price impact induced by trade size. Due to the price impact, a larger trade size generates smaller profits. I allow for variation in liquidity by making price impact stochastic. This variation introduces an additional risk to the arbitrageurs because they now are uncertain about the state of liquidity in the future. The arbitrageurs are averse to the possibility of liquidating their position in a bad liquidity state. Therefore, they reduce their exposure to stocks with high variation in liquidity. In equilibrium, due to the lower activity by arbitrageurs, mispricing is severe in stocks having high variation in liquidity.

The model predicts that magnitude of mispricing increases with variation in liquidity. I test the prediction using standard deviation of monthly turnover (TURNVOL) as the measure of variation in liquidity. For robustness, I also use three other measures: (a) standard deviation of daily turnover (DTURNVOL), (b) standard deviation of Amihud (2002) illiquidity measure (AMIHUDVOL), and (d) coefficient of variation in turnover (CVTURN). Stambaugh, Yu, and Yuan (2015) mispricing scores identify mispricing in a stock. The mispricing score is computed as the composite score of a stock's ranking in 11 different anomalies. A low (high) mispricing score indicates that the stock is underpriced (overpriced). As the mispricing corrects over time, the stocks that were underpriced (overpriced) in the previous period earn higher (lower) returns.

Each month, I sort stocks independently into quintiles on mispricing scores and TURNVOL as of the previous month. Then, I compute the value-weighted risk-adjusted returns for the quintile portfolios using Fama and French (2015) five-factor model. I find that, in the underpriced (overpriced) quintile, the risk-adjusted returns increase (decrease) with TURNVOL. Then within each TURNVOL quintile, I form long-short mispricing portfolios by buying stocks in underpriced quintile and short selling stocks in the most overpriced quintile. The risk-adjusted returns of long-short mispricing portfolios is the primary measure of mispricing in this paper. The risk-adjusted returns of the long-short mispricing portfolios increase with TURNVOL. The findings are consistent with mispricing increasing in variation in liquidity, thereby supporting the predictions of the model. Then, I explore how the investor sentiment affects this relationship.

When arbitrage is hindered, investor sentiment drives the mispricing (Stambaugh, Yu, and Yuan, 2015). If arbitrage activity is lower in high TURNVOL stocks, then the mispricing should even higher during periods of high investor sentiment. In order to test the hypothesis, I use Baker and Wurgler (BW) (2006) investor sentiment measure. High (low) sentiment months are the months during which the BW investor sentiment is above (below) the median of the whole sample. First, there is evidence of mispricing in high TURNVOL stocks low sentiment periods. Furthermore, in high sentiment periods, the overpricing in high TURNVOL stocks is more severe as compared to low sentiment periods. The findings provide further support for lower arbitrage activity in high TURNVOL stocks.

Next, I study the cross-sectional relationship between variation in liquidity and average returns. Amihud, Mendelson, and Pedersen (2005) observe, "… because liquidity varies over time, risk averse investors may require a compensation for being exposed to liquidity risk". If variation in liquidity is a risk, stocks with higher variation in liquidity should earn higher returns. However, Chordia, Subrahmanyam, and Anshuman (2001) document that stocks with higher variation in liquidity earn lower average returns. This negative relationship is puzzling. Pereira and Zhang (2010) provide a rational explanation for the puzzling relationship.[2] They assume that the investor is able to observe the level of liquidity in each state before trading. In their model, the variation in liquidity provides a valuable option as it enables risk-averse investors to time their trades based on

[2] Barinov (2015) notes exposure to aggregate volatility risk factor can explain the relationship.

the state of liquidity. However, arbitrageurs do not have this option to time their exit, especially when they experience outflows.

I test whether the higher mispricing in stocks with high variation in liquidity can explain the negative cross-sectional relationship between variation in liquidity and average returns using Fama-Macbeth regressions. I find that, when not accounting for the effect of mispricing, the stocks with high variation in liquidity earn lower average returns as documented in the prior studies. However, the relationship disappears after accounting for the mispricing due to limited arbitrage. The findings are consistent with limited arbitrage and arbitrage asymmetry in stocks with high variation in liquidity. Arbitrage asymmetry arises due to the difficulty in short selling stocks as compared to correcting underpricing (Stambaugh, Yu, and Yuan, 2015). In the presence of short-sale constraints, arbitrageurs allocate more capital to correct underpricing because their ability to correct overpricing is affected. Therefore, there is higher overpricing on average leading to the negative relationship between TURNVOL and stock returns.

This paper contributes to the literature on costly arbitrage, and variation in liquidity and stock returns. Prior literature has documented other factors limiting arbitrage. I contribute to the costly arbitrage literature by documenting that variation in liquidity is an additional risk faced by arbitrageurs. Further, this study complements Pereira and Zhang (2010) and contributes to the literature on variation in liquidity and cross-section of asset returns by providing an arbitrage based explanation and empirical support. This study also adds to arbitrage asymmetry literature. For example, Stambaugh, Yu, and Yuan (2015) show that arbitrage asymmetry can explain the negative relationship between idiosyncratic volatility and returns initially found in Ang, Hodrick, Xing, and Zhang (2006).[3] The findings in this paper are consistent with arbitrage asymmetry in stocks with high variation in liquidity.

2. Model

This section presents a simple two-period model. First, I solve for the arbitrageur's demand then I equate asset supply and demand to derive the implications for returns.

2.1 Assumptions

Assets: There are two assets. Risk-free asset and a risky asset. S is the total supply of the risky asset.

Participants: There are three participants: index funds, noise traders, and one arbitrageur. Index funds hold a fraction k of the total supply of assets S. The noise trader demand is given by Z. Z is exogenous. There is one arbitrageur who is active in the market. This arbitrageur has W_0 in total assets under management, raised from external investor and allocates a fraction (w) of that to the risky asset. The arbitrageur's demand for risky-asset is thus $X = w\ W_0$.

Periods: In period 0, the arbitrageur chooses X to be allocated to risky asset. In period 1, the arbitrageur closes the position by selling the risky asset. In the model in Pereira and Zhang (2010) an investor can time the trades, by choosing to trade in good liquidity state and refraining from trading in a bad liquidity state. In the model here, the outflows constrains the arbitrageur from timing the state of liquidity. I assume the arbitrageur experiences outflows with probability 1. Therefore, the arbitrageur has to close the position in period 1. Outflows are not assumed to be stochastic for simplicity of exposition.

[3] Diether, Malloy, Scherbina (2002) and Stambaugh, Yu, and Yuan (2012) provide support to Miller (1977) by showing that in the presence of short sale constraints, stocks with higher difference of opinion earn lower returns

Payoffs: The risk-free return is $r_f = 0$. The price of the risky asset is assumed to be \$1 at time 0. $S_0 = 1$. S_1 is the price in period 1. The excess returns of the risky asset is given by $S_1 - 1 = \tilde{r} \sim N(\mu_r, \sigma_r^2)$.

Stochastic price impact: Let the arbitrageur allocate X of initial assets W_0 in the risky asset. The purchase (sale) of X shares results in price increase (decrease) of ψX. ψ is the coefficient of price impact in the risky asset and is normally distributed. $\psi \sim N(\mu_\psi, \sigma_\psi^2)$. ψ is assumed to be independent of $\tilde{r}$. Stochastic price impact captures the variability in liquidity. Pereira and Zhang (2010) also model variation in liquidity by making price impact stochastic. The price impact coefficient (ψ_0)at initiation of the trade is known. However the price impact in period 1 (ψ_1) when the position has to be closed is uncertain.

The assumptions on risk-free rate, stock price, and timing of incurring price impact are for simplicity of exposition. Relaxing those assumptions make the model more involved without affecting the implication.

Utility: The arbitrageur has CARA (exponential) utility on total assets under management in the next period 1.

Profits: The profit in period 1 by trading X in the risky asset is given by

$$P = X\,\tilde{r} - q(\psi_1 X + \psi_0 X)$$

where q denotes the direction of trade in period 0. q=1 if the arbitrageur buys the risky asset in period 0 and sells it period 1. q=-1 if the arbitrageur short sells the risky asset in period 0 and buys back in period 1. Short-sale costs are assumed to be zero. ψ_1 is the price impact coefficient at exit and ψ_0 is the price impact coefficient at the initiation of trade. The second term accounts for round trip price impact costs. If the investor buys the risky asset in period 0, the second term decreases the inflows in period 1. However, if the investors shorts the risky asset in period 0, it increases the outflows in period 1 thereby reducing profits from the trade.

2.2 Arbitrageurs Demand

The maximization problem is given by

$$\max_X V(X) = E\,[-\exp(-\gamma\,\{W_0 + X\,\tilde{r} - \ q(\psi_1 X + \psi_0 X)\}\,)]$$

where $\gamma > 0$ is the arbitrageur's risk aversion coefficient.

Given the assumptions the assets under management in period 1 is normally distributed. As Campbell (2017) notes, this is equivalent to

$$\max_X \gamma\left(W_0 + X\big(\mu_r - q(\mu_\psi + \ \psi_0)\big)\right) - \frac{1}{2}\ \gamma^2 X^2(\sigma_r^2 + \ \sigma_\psi^2)$$

Arbitrageurs demand is given by

$$X = \frac{\mu_r - q(\mu_\psi + \ \psi_0)}{\gamma(\sigma_r^2 + \ \sigma_\psi^2)} \qquad (1)$$

We can see the following implications.

(i) If the stock is perfectly liquid ($\psi = 0$), X equals the demand for an investor with CARA utility in the absence of frictions.

(ii) If the price impact is constant ($\mu_\psi = \ \psi_0 \ = \psi$), X equals the demand when the CARA investor faces a transaction cost of ψ.

(iii) When the price impact is stochastic, the arbitrageur's demand (X) is decreasing in the volatility of the price impact (σ_ψ^2).

The model suggests that the variation in liquidity reduces arbitrage activity. This occurs as the arbitragers worry about the uncertainty in state of liquidity next period. Because they face outflows, they might have to liquidate their positions in a bad liquidity state reducing gains from trade. They are averse to this possibility. Therefore, they reduce their exposure to stocks with high variation in liquidity.

2.3 Expected Returns

S is the total supply of asset. k denotes the fraction of asset held by index funds and Z represents the noise trader demand. Net demand for the asset must equal supply

$$X + Z + k\,S = S$$

$$X = (1 - k)\,S - Z$$

Substituting the expression of X from (1) we get

$$\mu_r = \gamma\left(\sigma_r^2 + \sigma_\psi^2\right)\{(1 - k)\,S - Z\} + q(\mu_\psi + \psi_0)$$

$$\mu_r = \gamma\left(\sigma_r^2 + \sigma_\psi^2\right)Y + q(\mu_\psi + \psi_0) \qquad (2)$$

Where $Y = (1 - k)\,S - Z$ denotes the excess noise trader demand for the asset. If $Y > 0$ ($Y < 0$) then the asset is underpriced (overpriced). From (2) we find that the relationship between excess returns μ_r and variation in liquidity σ_ψ^2 is positive (negative) for underpriced (overpriced) assets.

Let us assume there are two assets with the only difference being the noise trader demand and hence the returns. Also, assume asset 1 is underpriced with $Y_1 > 0$, and asset 2 is overpriced with $Y_2 < 0$. If we construct a long-short portfolio of purchasing asset 1 and short selling asset 2, the net expected return of the long-short mispricing portfolio is given by

$$\mu_{r1} - \mu_{r2} = \gamma\left(\sigma_r^2 + \sigma_\psi^2\right)(Y_1 - Y_2) + 2(\mu_\psi + \psi_0) \qquad (2)$$

Because $(Y_1 - Y_2) > 0$, the expected returns on the mispricing portfolio is positive and increases with variation in liquidity σ_ψ^2. Therefore, the model implies that the mispricing is increasing with variation in liquidity. The rest of the paper empirically tests the model's implications.

3. Data

Returns, trading volume, total shares outstanding, and stock price are from CRSP and book value is from COMPUSTAT. Stambaugh, Yu, and Yuan (2015) mispricing scores are from Yu Yuan's website, Fama and French (2015) factor returns are from Kenneth French's website and Baker and Wurgler (2006) investment sentiment series is from Jeffrey Wurgler's website. The sample period used in this paper is from January 1966 to December 2016.

Only stocks listed on NYSE/AMEX and NASDAQ are considered. NASDAQ volume is not comparable to NYSE. To make them comparable, the volume adjustment proposed by Gao and Ritter (2010) is followed.

3.1 Variables

The following variables are used in the empirical analysis in the paper.

SIZE: Market capitalization of a stock as of the previous month.

BM: Book-to-market for stocks from July of year t to June of year t+1 is the book value for the fiscal reported in calendar year t-1 divided by market capitalization of stock as of year-end t-1. This follows Fama and French (1992). BM values are winsorized at 1% and 99% levels.

TURN: Monthly turnover of a stock as of previous month. Turnover is defined as the trading volume in a stock divided by total shares outstanding.

TURNVOL: Standard deviation of monthly turnover computed using the previous 60 months of turnover. A stock should have at least 18 months of turnover data in the previous 60 months.

DTURNVOL: Standard deviation of daily turnover computed using previous 3 months of daily turnover. A stock should have at least 18 days of daily turnover data in the previous 3 months.

AMIHUD: Amihud (2002) illiquidity measure as of the previous month computed using daily return and volume data in the month. AMIHUD illiquidity for the month t for stock i is calculated as

$$AMIHUD_{it} = \frac{1}{T}\sum_{d=1}^{T}\frac{|R_{id}|}{DVOL_{id}}$$

where $|R_{id}|$ is the absolute return of the stock i on day d of the month t. DVOL is the dollar volume in the stock for that day.

AMIHUDVOL: Volatility in AMIHUD illiquidity measure computed using the previous 60 months of data. A stock should have a minimum of 18 months of AMIHUD illiquidity data in the previous 60 months.

CVTURN: Ratio of TURNVOL and TURN. Prior studies use average TURN in the previous 60 months in computing CVTURN. I use the TURN in the denominator because it contains the latest information about turnover.

1/PRICE: Reciprocal of the price of a stock as of previous month.

IVOL: Standard deviation of residuals obtained by regressing daily returns each month on Fama and French 3 factors. This methodology follows Stambaugh, Yu, and Yuan (2015). IVOL is computed only for stocks with at least 18 return observations in a month.

MISPRICING: Stambaugh, Yu and Yuan (2015) construct a measure of mispricing based on a stock's composite ranking in the following 11 anomalies.

(a) Net stock issues
(b) Composite equity issues
(c) Accruals
(d) Net Operating Assets
(e) Asset Growth
(f) Investment-to-Assets
(g) Distress
(h) O-score
(i) Momentum
(j) Gross Profitability Premium
(k) Return on Assets

RET23: For the month t, RET23 is the cumulative return in the months t-2 and t-3.

RET46: For the month t, RET46 is the cumulative return in the months from t-4 to t-6.

RET712: RET712 is the cumulative return in the months from t-7 to t-12.

SENTIMENT: Baker and Wurgler (2006) sentiment measure is the first principal component of the following five measures. Their latest measure does not include NYSE share turnover.

(a) Closed-end fund discount

(b) No of IPOs

(c) IPO first-day returns

(d) Equity share in total new issues

(e) Dividend premium

The data for Baker and Wurgler (2006) investor sentiment measure is only available till Sep 2015. Therefore for the tests involving investor sentiment the data the sample size ends Sep 2015.

4. Results

Each month, I sort stocks independently into quintiles based on the mispricing score and measures of variation in liquidity as of the previous month. The stocks in the quintile with lowest mispricing score are the most underpriced stocks and stocks in the highest mispricing score quintile are the most overpriced stocks. Table 1 presents the average market capitalization, number of stocks, and the variation in liquidity in each group. Underpriced stocks are relatively larger and overpriced stocks are relatively smaller in size. This is consistent with the difficulty in shorting small stocks (D'avolio, 2002). Within each mispricing quintile, the high variation in liquidity stocks are smaller in size compared to the stocks in low variation in liquidity group. The liquidity is stable in large stocks as compared to small stocks. This is more pronounced in Panel C and Panel D when AMIHUDVOL and CVTURN are the measures of variation in liquidity. Table 2 presents the correlations.

4.1 Variation in Liquidity and Mispricing

Table 3 presents the risk-adjusted returns of the portfolios sorted on mispricing and variation in liquidity. The value-weighted risk-adjusted returns are computed using the Fama and French (2015) five-factor model. Panel A presents the results for portfolios sorted on TURNVOL which is the main measure of variation in liquidity in this paper. The first row reports the risk-adjusted returns of the stocks in the most underpriced group. The most underpriced stocks earn higher returns as the underpricing in the previous period is corrected. Among the underpriced stocks the returns increase with TURNVOL. This suggests that the underpricing in the previous period is positively related to TURNVOL. Among the underpriced stocks, the stocks in the high TURNVOL quintile earn the highest returns consistent with them being most underpriced. The last column reports the risk-adjusted returns of long-short portfolios formed by buying high TURNVOL stocks and shorting low TURNVOL stocks within each mispricing group. The difference is 53 basis points a month and is statistically significant.

Overpriced stocks are the stocks in the highest mispricing quintile. Among overpriced stocks, the risk-adjusted returns decrease with TURNVOL. The high TURNVOL stocks earn the lowest returns consistent with them being the most overpriced. In most overpriced quintile, the long-short TURNVOL portfolio alpha is -79 basis points and is statistically significant.

The last two rows report the risk-adjusted returns of long-short mispricing portfolios formed by buying stocks in underpriced quintile and short selling stocks in the most overpriced quintile. The risk-adjusted returns of these long-short mispricing portfolios is the primary measure of mispricing in this paper. The risk-adjusted returns increase with TURNVOL. The relationship between mispricing and TURNVOL is positive, consistent with lower arbitrage activity in high TURNVOL stocks. [4]

TURNVOL is computed using monthly data following Chordia, Subrahmanyam and Anshuman (2001) who use monthly variation in trading volume to study the relationship between variation in trading volume and the cross-section of returns. For the purpose of this study, it is important that the period used to compute variation in liquidity that is comparable to the arbitrageurs holding period. Active mutual funds turnover their holdings about once a year. But some hedge funds can flip holdings faster. In order to understand if relatively higher frequency in variation in liquidity affects arbitrage activity I study DTURNVOL which is computed from daily turnover data. Panel B, presents the results. The results are qualitatively similar to Panel A. Among underpriced stocks the risk-adjusted returns increase with DTURNVOL and among overpriced stocks the alpha decreases with DTURNVOL. Long-short DTURNVOL portfolio has positive alpha in underpriced stocks and negative alpha in overpriced stocks. Finally, the long-short mispricing portfolio returns increase monotonically with DTURNVOL.

Panel C and Panel D report the results for AMIHUDVOL and CVTURN. The results are qualitatively similar to the results when using TURNVOL and DTURNVOL. Among underpriced (overpriced) stocks, underpricing (overpricing) increases with both AMIHUDVOL and CVTURN. The relationship is not monotonic in underpriced stocks in Panel D for CVTURN because the increase in underpricing is only evident until quintile 4 and there is a dip in underpricing in quintile 5. From the last row of both panels we find that the risk-adjusted returns of long-short mispricing portfolios increase monotonically with both AMIHUDVOL and CVTURN. The results show that

[4] Internet Appendix IA.1 presents the results of equal weighted returns. The inference is similar to value weighted returns.

mispricing is increasing in variation in liquidity. This is consistent with lower arbitrage activity in stocks with high variation in liquidity consistent with predictions of the model.

4.2 Sentiment and Mispricing

This section investigates how the relationship between variation in liquidity and mispricing is affected by investor sentiment. In the presence of arbitrage costs, as arbitrageurs are unable to eliminate mispricing, sentiment will drive the mispricing (Stambaugh, Yu and Yuan, 2015). Therefore, there would be higher mispricing driven by overpricing in high sentiment periods as compared to low sentiment periods. To test the hypothesis, I use Baker and Wurgler (BW) (2006) measure of investor sentiment. I classify months as high and low sentiment depending on whether BW sentiment measure was higher or lower than median respectively.

Table 4 reports the risk-adjusted returns for high and low sentiment months. Panel A presents the results for TURNVOL. Following low sentiment months, high TURNVOL stocks in the most underpriced quintile earn higher returns. From the last row, I find that the risk-adjusted returns of long-short mispricing portfolio increases with TURNVOL following low sentiment periods.

Table 4 also presents the difference in risk-adjusted returns between high and low sentiment months for quintile portfolios. In the overpriced quintile, the long-short TURNVOL portfolio earns more negative returns in high sentiment months as compared to low sentiment months. This is consistent with higher sentiment driving more overpricing in high TURNVOL stocks when arbitrage is limited. From the last row, I find that the mispricing is even higher in high TURNVOL stocks in high sentiment mont hs as compared to low sentiment months. Panel B, Panel C, and Panel D report the results for DTURNVOL, AMIHUDVOL, and CVTURN respectively. The results are qualitatively similar to Panel A. The findings are consistent with sentiment driving mispricing when arbitrage is limited in stocks with high variation in liquidity.

4.3 Arbitrage and negative TURNVOL-return relation

Chordia, Subrahmanyam, and Anshuman (2001) document that stocks with higher variation in liquidity earn lower average returns in the cross-section. This negative relationship is puzzling because if variation in liquidity is a risk they must earn higher returns. I investigate whether limited arbitrage can explain this relationship using Fama-Macbeth regression of individual stock excess returns on characteristics.

I compute individual stocks risk-adjusted returns following Brennan, Chordia and Subrahmanyam (1998). The characteristics include ln(SIZE), ln(BM), 1/PRICE, RET23, RET46, RET712, IVOL, ln(TURN), ln(TURNVOL), MISPRICING and MISPRICING interacted with ln(TURNVOL). Table 5 presents the results.

In the first column of Table 5, ln(TURNVOL) has a negative coefficient, consistent with the findings in Chordia, Subrahmanyam, and Anshuman (2001). This is the negative TURNVOL-return relation puzzle. High TURNVOL stocks earn lower risk adjusted returns. In the second column, I add mispricing and the interaction of mispricing and ln(TURNVOL) to the specification. The coefficient on mispricing is negative because stocks with higher mispricing scores are overpriced and earn subsequently lower returns. The coefficient on the interaction term is negative and significant suggesting that it is the high TURNVOL stocks that are overpriced that earn negative returns. The coefficient on ln(TURNVOL) now becomes insignificant. The negative relationship between variation in liquidity and returns documented in the prior literature is absent after accounting for the higher mispricing due to lower arbitrage activity in high variation in liquidity stocks. The other columns of the table report the results when using other measures of variation in liquidity. The results when using other measures are qualitatively similar. The negative relationship disappears after accounting for higher mispricing in stocks with high variation in liquidity.

The findings are consistent with arbitrage asymmetry in stocks with high TURNVOL stocks. Arbitrage asymmetry is the difficulty in correcting overpricing due to short-sale constraints. Stambaugh, Yu, and Yuan (2015) note that due to the arbitrage asymmetry, more arbitrage capital will be deployed to correct underpricing. It is easier to correct underpricing because there are no constraints on the long side. As a result overpricing will continue to exist in stocks with short-sale constraints. [5]

4.4 Variation in liquidity vs Other Arbitrage Limiting factors

In this section, I test whether variation in liquidity is an addition limiting factor to arbitrage after accounting for the level of liquidity and idiosyncratic volatility (IVOL). The model suggests that arbitrageur demand is decreasing in level of trading costs. In addition, Pontiff (2006) argues that idiosyncratic volatility (IVOL) is an important holding cost incurred by the arbitrageurs. For variation in turnover to be an additional factor limiting arbitrage it must explain the mispricing after controlling for TURN and IVOL.

To test whether variation in liquidity is an additional factor, I sort stocks into terciles (3 x 3 x 3) sequentially on TURN/IVOL, mispricing, and variation in liquidity. Internet Appendix

[5] Another implication of arbitrage asymmetry is that the risk-adjusted returns of long-short TURNVOL portfolios will be negative overall. Further, we would expect the magnitude of overpricing to be significantly higher than magnitude of underpricing. While this relationship is not obvious in the last column of Table 3 Panel A when using value-weighted returns, it is clearly visible in the last column of Internet Appendix IA.1 Panel A when the returns are equal weighted. The equal-weighted returns of long-short TURNVOL portfolios is clearly decreasing in level of mispricing and the relationship is monotonic.

Tables IA.2 and IA.3 report the results after controlling for TURN and IVOL respectively. Panel A of both tables report the results for TURNVOL. The last row of Panel A, reports the risk-adjusted returns of long-short portfolios formed by purchasing stocks in most underpriced terciles and short selling stocks in most overpriced terciles. The long short mispricing portfolio returns increase with TURNVOL in low TURN, high TURN, low IVOL, and high IVOL terciles. The results are consistent with TURNVOL affecting arbitrage activity in addition to turnover and idiosyncratic volatility.

5. Conclusion:

This study highlights an important holding cost faced by the arbitrageurs: variation in liquidity. When liquidity varies, a stock's liquidity in the future is unknown to the arbitrageur while initiating a position. Arbitragers worry about the uncertainty in the state of liquidity in the future. If they face outflows, they might have to liquidate their positions in a bad liquidity state reducing gains from trade. As they are averse to this possibility, arbitrageurs reduce their exposures to stocks having high variation in liquidity. Due to reduced arbitrage activity, there is more mispricing in these stocks. Consistent with the claim, in empirical tests, mispricing is severe in high variation in liquidity stocks. Among overpriced stocks, stocks with high variation in liquidity are more overpriced and earn lower returns subsequently. Also, in high variation in liquidity stocks, overpricing is severe during periods of high investor sentiment.

Prior literature has documented a negative relationship between variation in liquidity and average returns. This study provides an arbitrage based explanation for the puzzling negative relationship. The negative TURNVOL – return relationship is absent after accounting for mispricing in stocks with high variation in liquidity. The findings are consistent with arbitrage asymmetry in stocks with high variation in liquidity.

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Table 1: Average Size and Variation in Liquidity of Portfolios sorted on Mispricing and Variation in Liquidity Measures

The table presents the average market capitalization (in $ Millions), number of stocks, and variation in liquidity of portfolios formed by sorting stocks into quintiles on the mispricing and measures of variation in liquidity. At the beginning of each month, stocks are sorted independently into quintiles based on their mispricing scores and measures of variation in liquidity as of the previous month. Four different measures of variation in liquidity are used in this paper. TURNVOL is the standard deviation of monthly turnover in the previous 60 months, DTURNVOL is the standard deviation of daily turnover in the previous 60 days, AMIHUDVOL is the standard deviation of Amihud (2002) illiquidity measure in the previous 60 months, and CVTURN is the ratio of TURNVOL and the turnover (TURN) at the end of previous month. Panel A, Panel B, Panel C, and Panel D present the statistics for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016.

Panel A: TURNVOL

	Market Capitalization					No of Stocks					TURNVOL				
	Variation in Liquidity					Variation in Liquidity					Variation in Liquidity				
Mispricing	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Low	8,105	6,185	3,238	1,919	1,936	109	126	113	99	80	0.010	0.020	0.032	0.051	0.115
2	3,312	3,385	2,508	1,800	1,880	112	118	112	100	86	0.009	0.020	0.032	0.051	0.118
3	1,575	2,234	1,832	1,653	1,513	117	107	107	103	95	0.009	0.020	0.032	0.051	0.123
4	1,264	1,676	1,493	1,262	1,189	110	97	102	108	111	0.009	0.020	0.032	0.051	0.127
High	792	1,318	1,214	1,013	957	79	80	94	119	156	0.009	0.020	0.032	0.051	0.133

Panel B: DTURNVOL

	Market Capitalization					No of Stocks					DTURNVOL				
	Variation in Liquidity					Variation in Liquidity					Variation in Liquidity				
Mispricing	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Low	8,934	5,632	3,608	2,187	1,462	105	117	112	104	90	0.001	0.001	0.002	0.004	0.009
2	3,841	3,234	2,450	1,963	1,369	110	114	110	102	92	0.001	0.001	0.002	0.004	0.009
3	1,844	2,214	1,921	1,592	1,139	116	108	104	102	98	0.001	0.001	0.002	0.004	0.010
4	1,309	1,740	1,534	1,312	945	109	100	102	106	110	0.001	0.001	0.002	0.004	0.010
High	907	1,321	1,213	1,034	804	87	88	99	115	138	0.001	0.001	0.002	0.004	0.010

(Table 1 continued)

Panel C: AMIHUDVOL

	Market Capitalization					No of Stocks					AMIHUDVOL				
	Variation in Liquidity					Variation in Liquidity					Variation in Liquidity				
Mispricing	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Low	12,326	1,044	438	191	74	146	106	97	90	89	0.27	0.43	0.62	0.96	3.07
2	9,216	1,085	434	200	72	127	108	100	98	95	0.27	0.43	0.62	0.96	3.37
3	7,574	1,071	446	201	71	105	108	104	105	107	0.27	0.43	0.62	0.96	3.61
4	6,703	1,090	439	205	76	87	107	110	112	112	0.27	0.43	0.62	0.96	3.41
High	6,201	1,045	462	227	107	63	100	117	123	125	0.27	0.43	0.62	0.97	3.14

Panel D: CVTURN

	Market Capitalization					No of Stocks					CVTURN				
	Variation in Liquidity					Variation in Liquidity					Variation in Liquidity				
Mispricing	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Low	7,947	4,927	3,179	1,877	970	129	114	103	95	86	0.01	0.06	0.26	1.1	18.9
2	4,986	3,121	2,082	1,612	809	115	110	105	99	99	0.01	0.06	0.26	1.1	19.2
3	3,389	2,221	1,501	1,074	664	104	105	104	105	109	0.01	0.06	0.26	1.1	18.8
4	2,754	1,820	1,164	787	516	98	103	106	109	111	0.01	0.06	0.26	1.09	18.6
High	1,903	1,500	1,002	695	450	81	96	109	119	122	0.01	0.06	0.26	1.1	21

Table 2: Correlations

The table reports the correlation between the variables used in the paper. TURNVOL is the standard deviation of monthly turnover in the previous 60 months, DTURNVOL is the standard deviation of daily turnover in the previous 60 days, AMIHUDVOL is the standard deviation of Amihud (2002) illiquidity measure in the previous 60 months, and CVTURN is the ratio of TURNVOL and the turnover (TURN) at the end of previous month. IVOL is the standard deviation of return residuals from Fama and French 3 factor model computed using daily returns in the previous month. TURN is the ratio of trading volume in the previous month and total shares outstanding. SIZE is the market capitalization of the stock as of the previous month. Reported numbers are cross sectional averages of times series correlations of individual stocks. Sample period is from January 1966 to December 2016.

Variables	IVOL	AMIHUDVOL	CVTURN	DTURNVOL	SIZE	TURN	TURNVOL
IVOL	1.00	0.07	-0.23	0.18	-0.12	0.34	0.05
AMIHUDVOL	0.07	1.00	0.04	-0.04	-0.22	-0.08	-0.10
CVTURN	-0.23	0.04	1.00	-0.35	-0.17	-0.61	0.08
DTURNVOL	0.18	-0.04	-0.35	1.00	0.19	0.65	0.36
SIZE	-0.12	-0.22	-0.17	0.19	1.00	0.25	0.17
TURN	0.34	-0.08	-0.61	0.65	0.25	1.00	0.34
TURNVOL	0.05	-0.10	0.08	0.36	0.17	0.34	1.00

Table 3: Risk-Adjusted Returns of Portfolios sorted on Mispricing and Variation in Liquidity Measures

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and measures of variation in liquidity. At the beginning of each month, stocks are sorted independently into quintiles based on their mispricing scores and measures of variation in liquidity as of the previous month. Portfolios returns are *value-weighted*. Panel A, Panel B, Panel C, and Panel D present the alphas for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

Panel A: TURNVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	-0.04%	-0.01%	0.43%	0.39%	0.50%	0.53%
	(-0.49)	(-0.15)	(4.98)	(3.37)	(2.96)	(2.87)
2	-0.12%	-0.09%	-0.02%	0.30%	0.53%	0.65%
	(-1.43)	(-1.29)	(-0.26)	(2.87)	(3.02)	(3.41)
3	-0.19%	-0.02%	-0.12%	0.04%	0.36%	0.55%
	(-1.80)	(-0.22)	(-1.45)	(0.38)	(2.57)	(2.80)
4	-0.17%	-0.28%	-0.10%	-0.21%	0.02%	0.19%
	(-1.51)	(-2.82)	(-0.99)	(-1.88)	(0.14)	(0.99)
High	-0.21%	-0.21%	-0.42%	-0.58%	-1.00%	-0.79%
	(-1.63)	(-1.52)	(-3.56)	(-4.98)	(-7.36)	(-4.20)
Low - High	0.17%	0.19%	0.85%	0.97%	1.49%	1.32%
	(1.20)	(1.11)	(5.53)	(5.37)	(6.82)	(5.15)

Panel B: DTURNVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	-0.04%	0.04%	0.17%	0.42%	0.54%	0.59%
	(-0.55)	(0.46)	(2.02)	(4.09)	(3.77)	(3.40)
2	-0.02%	-0.01%	0.02%	0.11%	0.34%	0.37%
	(-0.25)	(-0.10)	(0.25)	(1.14)	(2.25)	(2.25)
3	-0.25%	-0.11%	0.05%	-0.02%	0.22%	0.48%
	(-2.70)	(-1.40)	(0.51)	(-0.19)	(1.73)	(2.74)
4	-0.18%	-0.18%	-0.17%	-0.04%	-0.18%	0.00%
	(-1.70)	(-1.95)	(-1.82)	(-0.37)	(-1.39)	(0.03)
High	-0.42%	-0.39%	-0.53%	-0.41%	-0.75%	-0.34%
	(-3.33)	(-3.16)	(-4.48)	(-3.59)	(-5.51)	(-1.84)
Low - High	0.37%	0.43%	0.71%	0.83%	1.29%	0.92%
	(2.53)	(2.68)	(4.32)	(5.16)	(6.53)	(3.92)

(Table 3 continued)

Panel C: AMIHUDVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	0.10%	0.18%	0.36%	0.31%	0.63%	0.52%
	(2.08)	(2.33)	(3.94)	(3.42)	(5.13)	(4.08)
2	0.01%	0.20%	0.18%	0.27%	0.37%	0.36%
	(0.20)	(2.04)	(2.41)	(3.13)	(2.61)	(2.45)
3	-0.05%	0.18%	0.28%	0.24%	0.03%	0.08%
	(-0.93)	(1.61)	(2.95)	(2.26)	(0.26)	(0.64)
4	-0.20%	0.04%	0.10%	0.00%	0.00%	0.20%
	(-2.84)	(0.47)	(1.24)	(0.03)	(-0.02)	(1.25)
High	-0.46%	-0.42%	-0.46%	-0.54%	-0.82%	-0.35%
	(-3.89)	(-3.75)	(-4.54)	(-5.85)	(-5.98)	(-1.96)
Low - High	0.56%	0.60%	0.82%	0.86%	1.44%	0.88%
	(3.78)	(4.07)	(5.51)	(6.34)	(8.77)	(4.11)

Panel D: CVTURN

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	0.09%	0.14%	0.25%	0.28%	-0.01%	-0.10%
	(1.46)	(1.79)	(2.21)	(2.69)	(-0.07)	(-0.79)
2	-0.09%	0.18%	0.09%	0.01%	0.16%	0.25%
	(-1.44)	(2.30)	(0.99)	(0.10)	(1.32)	(1.75)
3	-0.07%	0.03%	0.03%	-0.17%	0.33%	0.41%
	(-0.98)	(0.41)	(0.32)	(-1.58)	(1.54)	(1.71)
4	-0.13%	-0.24%	-0.03%	-0.18%	-0.11%	0.02%
	(-1.41)	(-2.76)	(-0.30)	(-1.30)	(-0.84)	(0.15)
High	-0.17%	-0.48%	-0.44%	-0.73%	-1.23%	-1.07%
	(-1.29)	(-4.15)	(-3.51)	(-5.69)	(-8.48)	(-6.77)
Low - High	0.26%	0.62%	0.69%	1.01%	1.23%	0.97%
	(1.65)	(4.05)	(3.49)	(5.78)	(7.30)	(5.18)

Table 4: Risk-Adjusted Returns of portfolios sorted on Mispricing and Variation in Liquidity Measures in High-Sentiment and Low-Sentiment Periods.

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and measures of variation in liquidity in High Sentiment and Low Sentiment months. At the beginning of each month, stocks are sorted independently into quintiles based on their mispricing scores and measures of variation in liquidity as of the previous month. Portfolios returns are *value-weighted*. Panel A, Panel B, Panel C, and Panel D present the alphas for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016. Reported numbers are a_L and a_H in the regression below. $d_{H,t}$ is a dummy variable that takes value of 1 if the Baker and Wurgler (2006) investment sentiment measure was above median previous month. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

$$R_{i,t} = a_L + a_H\, d_{H,t} + b\, MKT_t + c\, SMB_t + d\, HML_t + e\, CMA_t + f\, RMW_t + \epsilon_{i,t}$$

Panel A: TURNVOL

	Low Sentiment Months			High - Low Sentiment Months		
	Variation in Liquidity			Variation in Liquidity		
Mispricing	Low	High	High - Low	Low	High	High - Low
Low	-0.08%	0.40%	0.48%	0.07%	0.23%	0.17%
	(-0.91)	(1.92)	(2.08)	(0.46)	(0.78)	(0.48)
High	-0.39%	-0.79%	-0.40%	0.39%	-0.38%	-0.76%
	(-2.25)	(-4.31)	(-1.54)	(1.58)	(-1.51)	(-2.10)
Low - High	0.31%	1.19%	0.88%	-0.32%	0.61%	0.93%
	(1.53)	(4.44)	(2.73)	(-1.16)	(1.53)	(1.95)

Panel B: DTURNVOL

	Low Sentiment Months			High - Low Sentiment Months		
	Variation in Liquidity			Variation in Liquidity		
Mispricing	Low	High	High - Low	Low	High	High - Low
Low	-0.02%	0.32%	0.34%	-0.07%	0.46%	0.53%
	(-0.16)	(1.81)	(1.60)	(-0.42)	(1.70)	(1.57)
High	-0.61%	-0.54%	0.07%	0.40%	-0.42%	-0.82%
	(-3.52)	(-2.91)	(0.26)	(1.69)	(-1.75)	(-2.35)
Low - High	0.59%	0.86%	0.27%	-0.47%	0.88%	1.35%
	(2.91)	(3.53)	(0.89)	(-1.65)	(2.50)	(3.10)

(Table 4 continued)

Panel C: AMIHUDVOL

	Low Sentiment Months			High - Low Sentiment Months		
	Variation in Liquidity			Variation in Liquidity		
Mispricing	Low	High	High - Low	Low	High	High - Low
Low	0.05%	0.50%	0.45%	0.10%	0.31%	0.21%
	(0.82)	(3.10)	(2.65)	(1.01)	(1.34)	(0.89)
High	-0.39%	-0.75%	-0.36%	-0.08%	-0.11%	-0.04%
	(-2.58)	(-4.20)	(-1.58)	(-0.40)	(-0.48)	(-0.11)
Low - High	0.45%	1.26%	0.81%	0.17%	0.42%	0.25%
	(2.31)	(5.83)	(2.98)	(0.68)	(1.39)	(0.64)

Panel D: CVTURN

	Low Sentiment Months			High - Low Sentiment Months		
	Variation in Liquidity			Variation in Liquidity		
Mispricing	Low	High	High - Low	Low	High	High - Low
Low	0.07%	-0.03%	-0.10%	0.02%	0.09%	0.07%
	(0.90)	(-0.22)	(-0.67)	(0.16)	(0.43)	(0.28)
High	-0.23%	-0.86%	-0.63%	0.13%	-0.75%	-0.88%
	(-1.44)	(-4.66)	(-2.91)	(0.62)	(-2.63)	(-2.83)
Low - High	0.31%	0.84%	0.53%	-0.11%	0.83%	0.95%
	(1.51)	(3.74)	(2.02)	(-0.42)	(2.60)	(2.62)

Table 5: Fama-Macbeth Regression of Individual Risk Adjusted Returns on Characteristics

The table reports the Fama Macbeth Regression coefficients of individual risk adjusted stock return on Characteristics using the methodology in Brennan, Chordia and Subrahmanyam (1998). Individual stock excess return is risk adjusted using Fama- French five factors. Factor loadings are allowed to vary over time and are computed from previous 60 months of returns. TURNVOL is the standard deviation of monthly turnover in the previous 60 months, DTURNVOL is the standard deviation of daily turnover in the previous 60 days, AMIHUDVOL is the standard deviation of Amihud (2002) illiquidity measure in the previous 60 months, and CVTURN is the ratio of TURNVOL and the turnover (TURN) at the end of previous month. Mispricing (MISP) is the Stambaugh, Yu, and Yuan(2015) mispricing score. Controls in include ln(SIZE), ln(BM), ln(TURN), RET23, RET46, RET712, 1/PRICE, and IVOL. Sample period is from Jan 1966 to Dec 2016. Fama-Macbeth t-statistics in parenthesis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MISP		-0.030***		-0.031***		-0.036***		-0.017***
		(0.006)		(0.009)		(0.007)		(0.002)
ln(TURNVOL)	-0.300***	-0.098						
	(0.039)	(0.072)						
MISP x ln(TURNVOL)		-0.004**						
		(0.001)						
ln(DTURNVOL)			-0.237***	-0.105				
			(0.033)	(0.070)				
MISP x ln(DTURNVOL)				-0.002*				
				(0.001)				
ln(AMIHUDVOL)					-0.033	0.058*		
					(0.025)	(0.033)		
MISP x ln(AMIHUDVOL)						-0.001**		
						(0.000)		
ln(CVTURN)							-0.300***	-0.129*
							(0.039)	(0.070)
MISP x ln(CVTURN)								-0.003**
								(0.001)
No. of obs	1,235,091	1,235,091	1,235,091	1,235,091	1,235,091	1,235,091	1,235,091	1,235,091

INTERNET APPENDIX

Table IA.1: Risk-Adjusted Returns of Portfolios sorted on Mispricing and Variation in Liquidity Measures

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and measures of variation in liquidity. At the beginning of each month, stocks are sorted independently into quintiles based on their mispricing scores and measures of variation in liquidity as of the previous month. Portfolios returns are *equal-weighted*. Panel A, Panel B, Panel C, and Panel D present the alphas for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

Panel A: TURNVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High – Low
Low	0.26%	0.31%	0.44%	0.44%	0.52%	0.25%
	(4.68)	(5.94)	(7.88)	(6.18)	(5.22)	(2.06)
2	0.13%	0.10%	0.18%	0.25%	0.19%	0.07%
	(2.13)	(1.71)	(3.37)	(3.93)	(2.21)	(0.59)
3	0.16%	0.03%	0.01%	0.07%	0.08%	-0.08%
	(2.40)	(0.45)	(0.15)	(1.20)	(1.02)	(-0.68)
4	0.00%	-0.15%	-0.09%	-0.15%	-0.13%	-0.13%
	(-0.05)	(-2.07)	(-1.41)	(-2.27)	(-1.51)	(-1.04)
High	-0.25%	-0.35%	-0.61%	-0.77%	-0.95%	-0.70%
	(-2.62)	(-3.72)	(-7.46)	(-8.89)	(-8.18)	(-4.99)
Low - High	0.51%	0.67%	1.04%	1.21%	1.46%	0.95%
	(5.48)	(7.09)	(11.33)	(10.92)	(9.40)	(5.65)

Panel B: DTURNVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High – Low
Low	0.27%	0.27%	0.32%	0.55%	0.57%	0.31%
	(4.94)	(4.76)	(5.87)	(8.35)	(5.57)	(2.46)
2	0.11%	0.15%	0.16%	0.19%	0.23%	0.12%
	(1.75)	(2.59)	(2.75)	(3.35)	(2.68)	(0.98)
3	-0.03%	0.08%	0.10%	0.00%	0.19%	0.22%
	(-0.50)	(1.32)	(1.63)	(0.04)	(2.14)	(1.70)
4	-0.20%	-0.13%	-0.13%	0.00%	-0.07%	0.14%
	(-2.60)	(-1.85)	(-1.89)	(0.06)	(-0.78)	(1.03)
High	-0.60%	-0.51%	-0.59%	-0.71%	-0.77%	-0.17%
	(-6.34)	(-4.79)	(-6.18)	(-7.69)	(-7.36)	(-1.28)
Low - High	0.87%	0.77%	0.91%	1.26%	1.34%	0.48%
	(9.56)	(7.85)	(8.87)	(10.53)	(8.82)	(3.08)

(Table IA.1 continued)

Panel C: AMIHUDVOL

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	0.13%	0.22%	0.40%	0.43%	0.82%	0.69%
	(2.81)	(3.69)	(6.61)	(6.60)	(9.08)	(6.73)
2	-0.04%	0.10%	0.22%	0.21%	0.34%	0.37%
	(-0.73)	(1.91)	(4.00)	(3.06)	(3.37)	(3.42)
3	-0.07%	0.04%	0.15%	0.02%	0.19%	0.26%
	(-1.14)	(0.64)	(2.73)	(0.38)	(1.88)	(2.19)
4	-0.25%	-0.11%	-0.02%	-0.09%	-0.09%	0.15%
	(-3.07)	(-1.61)	(-0.23)	(-1.36)	(-0.87)	(1.23)
High	-0.55%	-0.62%	-0.63%	-0.63%	-0.73%	-0.19%
	(-4.33)	(-5.08)	(-6.70)	(-7.33)	(-6.72)	(-1.30)
Low - High	0.68%	0.84%	1.03%	1.06%	1.55%	0.88%
	(5.00)	(6.36)	(8.57)	(9.60)	(14.61)	(6.03)

Panel D: CVTURN

	Variation in Liquidity					
Mispricing	Low	2	3	4	High	High - Low
Low	0.45%	0.36%	0.39%	0.37%	0.29%	-0.17%
	(7.29)	(6.11)	(6.69)	(5.63)	(3.89)	(-1.67)
2	0.18%	0.22%	0.16%	0.11%	0.10%	-0.08%
	(3.09)	(4.15)	(2.89)	(1.70)	(1.18)	(-0.72)
3	0.25%	0.13%	0.06%	-0.04%	-0.11%	-0.36%
	(3.87)	(2.34)	(1.21)	(-0.56)	(-1.29)	(-3.06)
4	0.11%	0.04%	-0.06%	-0.26%	-0.37%	-0.48%
	(1.43)	(0.62)	(-0.95)	(-3.31)	(-3.96)	(-3.60)
High	-0.20%	-0.41%	-0.51%	-0.70%	-1.14%	-0.94%
	(-1.94)	(-4.47)	(-5.12)	(-7.16)	(-9.87)	(-6.72)
Low - High	0.66%	0.77%	0.90%	1.07%	1.43%	0.77%
	(5.31)	(6.43)	(7.83)	(9.62)	(14.43)	(6.15)

Table IA.2: Risk-Adjusted Returns of Portfolios Sorted on TURN, Mispricing, and Variation in Liquidity

The table presents the Fama and French five factor alpha of portfolios sorted *sequentially* into terciles on TURN, Mispricing, and variation in liquidity. At the beginning of each month, stocks are sorted into three groups based on their turnover (TURN) as of previous month. Within each TURN group, the stocks are then sorted into terciles mispricing scores as of the previous month. Within each TURN and mispricing group, the stocks are sorted into terciles on measures of variation in liquidity. Portfolios returns are *value-weighted*. Panel A, Panel B, Panel C, and Panel D present the alphas for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

Panel A : TURNVOL

	Low TURN				High TURN			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.13%	-0.13%	0.03%	0.16%	0.13%	0.27%	0.53%	0.40%
	(-1.39)	(-1.40)	(0.30)	(1.21)	(1.51)	(2.24)	(3.31)	(2.59)
2	0.10%	-0.17%	-0.14%	-0.23%	-0.05%	0.24%	0.30%	0.35%
	(0.77)	(-1.83)	(-1.34)	(-1.52)	(-0.56)	(2.00)	(1.93)	(2.04)
High	-0.22%	-0.38%	-0.81%	-0.59%	-0.35%	-0.61%	-0.73%	-0.38%
	(-1.76)	(-3.49)	(-6.86)	(-3.84)	(-3.18)	(-4.81)	(-4.61)	(-2.36)
Low - High	0.09%	0.25%	0.84%	0.75%	0.48%	0.88%	1.26%	0.78%
	(0.58)	(1.88)	(5.65)	(3.66)	(3.67)	(5.35)	(6.05)	(4.00)

Panel B : DTURNVOL

	Low TURN				High TURN			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.13%	-0.04%	0.02%	0.15%	0.18%	0.29%	0.48%	0.30%
	(-1.49)	(-0.46)	(0.19)	(1.21)	(2.03)	(2.44)	(3.08)	(2.06)
2	-0.01%	-0.10%	-0.08%	-0.07%	0.05%	0.27%	0.17%	0.12%
	(-0.10)	(-1.09)	(-0.88)	(-0.48)	(0.55)	(2.34)	(1.12)	(0.69)
High	-0.31%	-0.41%	-0.43%	-0.12%	-0.46%	-0.57%	-0.69%	-0.23%
	(-2.47)	(-4.14)	(-3.89)	(-0.89)	(-4.12)	(-4.74)	(-4.30)	(-1.38)
Low - High	0.18%	0.36%	0.45%	0.27%	0.64%	0.86%	1.17%	0.52%
	(1.20)	(2.95)	(3.53)	(1.55)	(4.61)	(5.31)	(5.45)	(2.63)

(Table IA.2 continued)

Panel C : AMIHUDVOL

	Low TURN				High TURN			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.13%	0.04%	0.33%	0.46%	0.23%	0.37%	0.42%	0.19%
	(-1.61)	(0.58)	(3.53)	(4.18)	(2.47)	(3.33)	(3.20)	(1.42)
2	-0.04%	-0.08%	0.09%	0.13%	0.05%	0.36%	0.45%	0.40%
	(-0.37)	(-0.94)	(0.93)	(0.92)	(0.59)	(2.52)	(3.50)	(2.51)
High	-0.27%	-0.57%	-0.47%	-0.19%	-0.62%	-0.29%	-0.51%	0.11%
	(-2.54)	(-5.82)	(-4.24)	(-1.39)	(-5.34)	(-2.62)	(-3.98)	(0.63)
Low - High	0.15%	0.62%	0.80%	0.65%	0.84%	0.67%	0.92%	0.08%
	(1.17)	(6.04)	(6.86)	(4.02)	(6.00)	(4.54)	(5.99)	(0.44)

Panel D : CVTURN

	Low TURN				High TURN			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.11%	-0.11%	0.01%	0.12%	0.02%	0.42%	0.43%	0.40%
	(-1.31)	(-1.13)	(0.09)	(0.96)	(0.25)	(3.77)	(3.32)	(2.91)
2	-0.04%	-0.15%	-0.10%	-0.06%	0.01%	0.12%	0.30%	0.29%
	(-0.36)	(-1.47)	(-0.97)	(-0.40)	(0.08)	(1.13)	(2.21)	(1.88)
High	-0.19%	-0.49%	-0.82%	-0.63%	-0.42%	-0.56%	-0.70%	-0.28%
	(-1.64)	(-4.62)	(-6.23)	(-4.20)	(-3.32)	(-4.47)	(-4.82)	(-1.73)
Low - High	0.08%	0.38%	0.83%	0.75%	0.45%	0.98%	1.13%	0.68%
	(0.58)	(2.98)	(5.75)	(4.20)	(2.90)	(5.84)	(5.50)	(3.25)

Table IA.3: Risk-Adjusted Returns of Portfolios Sorted on IVOL, Mispricing, and Variation in Liquidity

The table presents the Fama and French five factor alpha of portfolios sorted *sequentially* into terciles on IVOL, Mispricing, and variation in liquidity. At the beginning of each month, stocks are sorted into three groups based on their idiosyncratic volatility (IVOL) as of previous month. Within each IVOL group, the stocks are then sorted into terciles mispricing scores as of the previous month. Within each IVOL and mispricing group, the stocks are sorted into terciles on measures of variation in liquidity. Portfolios returns are *value-weighted*. Panel A, Panel B, Panel C, and Panel D present the alphas for TURNVOL, DTURNVOL, AMIHUDVOL, and CVTURN respectively. Sample period is from January 1966 to December 2016. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

Panel A : TURNVOL

	Low IVOL				High IVOL			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.08%	0.01%	0.36%	0.44%	0.08%	0.45%	0.20%	0.12%
	(-1.28)	(0.08)	(3.49)	(3.56)	(0.67)	(3.41)	(1.15)	(0.64)
2	-0.04%	-0.07%	0.05%	0.09%	-0.20%	-0.25%	-0.08%	0.12%
	(-0.46)	(-0.91)	(0.50)	(0.64)	(-1.51)	(-1.81)	(-0.49)	(0.55)
High	-0.09%	-0.19%	-0.29%	-0.20%	-0.53%	-1.01%	-1.12%	-0.59%
	(-0.80)	(-2.00)	(-2.99)	(-1.36)	(-3.51)	(-6.75)	(-6.19)	(-2.90)
Low - High	0.01%	0.20%	0.65%	0.64%	0.61%	1.46%	1.32%	0.71%
	(0.06)	(1.45)	(4.44)	(3.64)	(3.07)	(7.03)	(5.68)	(2.91)

Panel B : DTURNVOL

	Low IVOL				High IVOL			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.08%	0.05%	0.15%	0.23%	0.20%	0.23%	0.26%	0.06%
	(-1.25)	(0.66)	(1.58)	(2.07)	(1.35)	(1.87)	(1.54)	(0.29)
2	-0.03%	-0.08%	-0.04%	-0.01%	-0.45%	-0.08%	-0.13%	0.32%
	(-0.32)	(-0.96)	(-0.44)	(-0.09)	(-3.62)	(-0.53)	(-0.87)	(1.57)
High	-0.13%	-0.22%	-0.30%	-0.16%	-0.91%	-0.76%	-1.10%	-0.20%
	(-1.30)	(-2.33)	(-3.37)	(-1.40)	(-5.75)	(-5.22)	(-6.74)	(-1.05)
Low - High	0.05%	0.26%	0.45%	0.40%	1.10%	0.98%	1.36%	0.26%
	(0.43)	(2.13)	(3.33)	(2.58)	(5.24)	(5.23)	(5.96)	(1.00)

(Table IA.3 continued)

Panel C : AMIHUDVOL

	Low IVOL				High IVOL			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	0.00%	0.04%	0.24%	0.24%	0.21%	0.27%	0.40%	0.19%
	(-0.05)	(0.57)	(3.24)	(2.73)	(1.77)	(2.21)	(3.11)	(1.11)
2	-0.03%	0.02%	0.05%	0.09%	-0.26%	0.08%	0.27%	0.53%
	(-0.55)	(0.24)	(0.70)	(0.87)	(-2.16)	(0.55)	(1.59)	(2.87)
High	-0.20%	-0.18%	-0.05%	0.15%	-0.95%	-0.66%	-0.88%	0.07%
	(-2.59)	(-2.12)	(-0.56)	(1.49)	(-6.18)	(-5.74)	(-5.48)	(0.33)
Low - High	0.20%	0.21%	0.29%	0.09%	1.16%	0.93%	1.28%	0.12%
	(1.95)	(2.37)	(2.91)	(0.77)	(6.22)	(5.74)	(6.97)	(0.50)

Panel D : CVTURN

	Low IVOL				High IVOL			
	Variation in Liquidity				Variation in Liquidity			
Mispricing	Low	2	High	High - Low	Low	2	High	High - Low
Low	-0.02%	0.12%	0.18%	0.20%	0.25%	0.31%	-0.09%	-0.34%
	(-0.42)	(1.40)	(1.81)	(1.77)	(1.90)	(2.31)	(-0.72)	(-1.86)
2	-0.03%	-0.07%	-0.06%	-0.03%	-0.20%	0.10%	-0.51%	-0.31%
	(-0.44)	(-0.80)	(-0.55)	(-0.22)	(-1.52)	(0.71)	(-3.73)	(-1.71)
High	-0.06%	-0.36%	-0.34%	-0.28%	-0.77%	-0.92%	-1.45%	-0.68%
	(-0.67)	(-3.99)	(-3.26)	(-2.09)	(-5.13)	(-5.79)	(-8.38)	(-3.79)
Low - High	0.04%	0.48%	0.52%	0.48%	1.02%	1.23%	1.36%	0.34%
	(0.33)	(3.64)	(3.64)	(2.94)	(5.44)	(5.67)	(6.95)	(1.47)