Variation in Liquidity, Costly Arbitrage, and the Cross-Section of Stock Returns

Badrinath Kottimukkalur*

January 2018

Abstract

This paper provides an arbitrage based explanation for the puzzling negative relationship between variation in liquidity and stock returns. A simple model shows that if liquidity varies over time, arbitrageurs will limit their exposure to stocks with high variation in liquidity. These stocks are more likely to be mispriced due to reduced arbitrage activity. Consistent with the model, in empirical tests, mispricing is severe in stocks having high turnover volatility (TURNVOL). Furthermore, the negative relationship between TURNVOL and returns is present only in difficult-to-short stocks. Costly arbitrage due to the variation in liquidity and the arbitrage asymmetry arising due to the short sale constraints together explain the negative TURNVOL-return relationship.

I thank Jeff Busse, Tarun Chordia, Ilia Dichev, Clifton Green, and Narasimhan Jegadeesh and the seminar participants at Emory University for helpful comments.

* George Washington University. Email: badrinath@gwu.edu.

1. Introduction

Chordia, Subrahmanyam, and Anshuman (2001) document that stocks with higher variation in liquidity earn lower returns. This negative relationship is puzzling. As Amihud, Mendelson, and Pedersen (2005) observe, “In addition, 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 should earn higher returns. However, the empirical relationship is negative. Despite the surprising finding, the literature has not explored this relationship thoroughly.

Pereira and Zhang (2010) provide a rational explanation for the puzzling relationship. In their model, the variation in liquidity provides a valuable option as it enables risk-averse investors to time their trades based on the state of liquidity. They assume that the investor is able to observe the level of liquidity in each state before trading. This assumption need not necessarily apply to all subsets of investors. For example, there are reasons to believe that one subset of investors, the arbitrageurs, might be constrained and might not be able to time their trades in the future periods. They might be forced to close their positions irrespective of future state of liquidity if their investors withdraw capital (Shleifer and Vishny, 1997). Coval and Stafford (2007) provide supportive evidence of this by documenting price pressure in stocks held by mutual funds experiencing extreme outflows. In the presence of such constraints, the variation in liquidity can affect a risk-averse arbitrageur’s demand and therefore have an effect on mispricing and returns. This paper explores the relationship between variation in liquidity and stock returns when arbitrageurs are subject to such constraints.

In the model, a risk-averse arbitrageur allocates wealth 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. Larger trade size reduces the profits from the trade as compared to smaller trade size. In addition, the price impact varies over time. This variation introduces an additional risk to the arbitrageurs. The additional risk is due to the uncertainty 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. The model implies that these stocks are more likely to be mispriced due to the reduced arbitrage activity.

There is strong empirical support for the prediction. In empirical tests, variation in turnover, also studied by Chordia, Subrahmanyam, and Anshuman (2001), serves as the proxy for variation in liquidity. 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. 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.

In empirical tests, each month, stocks are first sorted into quintiles based on mispricing scores as of previous month. Then within each mispricing quintile, stocks are further sorted into quintiles based on volatility in turnover (TURNVOL) as of previous month. TURNVOL is computed as the standard deviation of monthly turnover in the previous 60 months. The portfolio returns are value-weighted and Fama and French (2015) five factor model is used for risk-adjustment. In the underpriced (overpriced) quintile, the risk-adjusted returns increase (decrease) with TURNVOL. Furthermore, stocks in the high TURNVOL quintile earn the highest (lowest) risk-adjusted returns among underpriced (overpriced) stocks. This implies that among the underpriced stocks, the high TURNVOL stocks were the most underpriced. TURNVOL computed using monthly data assumes that arbitrageurs have a longer holding horizon. If most arbitrageurs close their positions within a month, then daily turnover volatility (DTURNVOL) will be a more appropriate measure. When the above analysis is repeated using DTURNVOL the results are qualitatively similar. The mispricing is also severe in high DTURNVOL stocks. The results provide compelling evidence of lower arbitrage activity in stocks with high turnover volatility.

When arbitrage is hindered, investor sentiment drives the mispricing (Stambaugh, Yu, and Yuan, 2015). Baker and Wurgler (BW) (2006) provide a measure of investor sentiment. High (low) sentiment months are those where the BW investor sentiment is above (below) the median. During high sentiment periods, overpricing in high TURNVOL stocks is stronger. This provides additional support for reduced arbitrage activity in high TURNVOL stocks.

Next, this study explores whether arbitrage asymmetry can explain the negative relationship between variation in liquidity and stock returns. Stambaugh, Yu, And Yuan (2015) show that in the presence of short-sale constraints, arbitrageurs allocate more capital to correct underpricing because their ability to correct overpricing is affected. This asymmetry in arbitrage can lead to negative relationship between TURNVOL and stock returns. If the arbitrageurs allocate more capital to correct underpricing in high TURNVOL stocks, there would be more overpricing in high TURNVOL stocks on average. Due to more overpricing on average the high TURNVOL stocks earn lower returns.

In arbitrage asymmetry tests, Institutional Ownership (IO) serves as a proxy for the difficulty in shorting a stock. Lower institutional ownership results in lower availability of stocks to borrow in order to short (Nagel, 2005). Each month, stocks are sorted into quintiles based on IO as of the previous month. Within each IO quintile, stocks are then sorted into quintiles on TURNVOL. The negative relationship between variation and liquidity and stock returns is primarily found in stocks with low IO. The results show that the negative relationship is found only in difficult-to-short stocks, providing evidence of arbitrage asymmetry. Further support is found in individual stock Fama-Macbeth regressions. In the Fama-Macbeth regressions, high TURNVOL stocks earn lower average returns as documented in the prior studies. However, the relationship disappears after accounting for the mispricing in high TURNVOL stocks due to limited arbitrage. The findings provide evidence that TURNVOL limiting arbitrage and arbitrage asymmetry together explain the negative TURNVOL-average return relation.

This paper contributes to the literature on costly arbitrage, arbitrage asymmetry, and variation in liquidity and stock returns. Prior literature has documented other factors limiting arbitrage. Shleifer and Vishny (1997) discuss how noise trader sentiment could limit arbitrage. Pontiff (2006) argues that idiosyncratic volatility is an important holding cost for arbitrageurs. Hong and Stein (2003) and Nagel (2005) highlight how short sale constraints prevent mispricing from being eliminated. This paper adds to the costly arbitrage literature by documenting that variation in liquidity is an additional risk faced by arbitrageurs.

Prior literature has explored the effect of arbitrage asymmetry on stock returns. 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). 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. This paper shows that arbitrage asymmetry can also explain the negative relationship between variation in liquidity and stock returns. Thus, this study contributes to the literature on volatility of liquidity and asset returns by providing an arbitrage based explanation and empirical support.

2. Model

This section presents a simple two period model. This partial equilibrium model derives the exposure of an arbitrageur to a risky asset in the presence of variation in liquidity.

2.1 Assumptions

Assets: There are two assets. Risk-free asset and a risky asset.

Periods: In period 0, the arbitrageur chooses the amount of wealth to be allocated to risky asset. In period 1, the arbitrageur closes the position by selling the risky asset. Pereira and Zhang (2010) solve a multi-period problem where the investor can observe the state of liquidity in each period before trading. In the model here, the investor closes the positions in period 1. This is more appropriate for an arbitrageur who relies on external funds. The potential outflows from investors constrains the arbitrageur from timing the state of liquidity. Outflows are not assumed to be stochastic for simplicity of exposition.

Payoffs: The risk-free returns are assumed to be 0. $r_f = 0$. 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 wealth W_0 in the risky asset. The purchase (sale) of X shares results in price increase (decrease) of $\psi(X)$. 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 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 and allocates a portion X of initial wealth W_0 between a risk free asset and risky asset at period 0. The arbitrageur sells the positon X in period 1.

Profits: The profits in period 1 by trading X in 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. The second term accounts for round trip price impact costs. 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 decreases the payoff in period 1 if the investor buys the risky asset in period 0. However, it increases the outflow in period 1 if the investors shorts the risky asset in period 1.

The maximization problem is given by

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

where γ is the arbitrageur's risk aversion. As Campbell (2017) notes, this is equivalent to

$$\min\ log\ E\ [\exp\big(-\gamma\ (W_0 + X\ \tilde{r} -\ q(\psi_1(X) + \psi_0(X)))\big)]$$

Given our assumptions the wealth in period 1 is log normally distributed. Therefore this reduces to

$$\min\ log\ E\ \big[\exp\big(-\gamma\ (W_0 + X\ \tilde{r} -\ q(\psi_1(X) + \psi_0(X)))\big)\big]$$

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

This is again equivalent to

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

Arbitrageurs demand is given by

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

We can see the following implications.

(i) If the stock is perfectly liquid ($\psi = 0$) this reduces to the demand for CARA utility.

(ii) If the price impact function is a constant ($\mu_\psi =\ \psi_0\ = \psi$) the demand is equivalent to the demand when there is transaction cost is ψ.

(iii) The important implication of the model is that the demand of the arbitrageur is decreasing in the volatility of the price impact coefficient σ_ψ^2.

The model suggests that the variation in liquidity reduces arbitrage activity. This occurs as arbitragers worry about the uncertainty in state of liquidity next period. If 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. These stocks are more likely to be mispriced due to the reduced arbitrage activity. The model implies that the mispricing will be higher in stocks having high 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.

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, stocks are sorted into quintiles on the mispricing score 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. Then, within each mispricing quintile stocks are in turn sorted into quintiles on TURNVOL. Table 1, Panel A presents the average market capitalization of the stocks in each group. Underpriced stocks are relatively larger and overpriced stocks are relatively smaller in size. This is due to the difficulty in shorting small stocks (D'avolio, 2002). Within each mispricing quintile, the high TURNVOL stocks are smaller in size than the low TURNVOL stocks since large stocks have relatively stable turnover compared to small stocks. Table 1, Panel B presents the average standard deviation of monthly turnover in each group. Turnover volatility is high in overpriced stocks compared to underpriced stocks. Table 2 presents the correlations.

4.1 Turnover Volatility and Mispricing

Table 3 presents the risk adjusted returns of the value weighted portfolios formed by sorting first on mispricing and then on TURNVOL. The risk-adjusted returns are computed using the Fama and French (2015) five factor model with investment and profitability as new factors in addition to market, size and value factors. 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 final 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 61 basis points a month and is statistically significant.

Among the most 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 -70 basis points and is statistically significant. The last two rows report the difference between alphas and respective t-statistics of the most underpriced stocks and the most overpriced stocks within each TURNVOL quintile. This is a measure of mispricing. The magnitude of mispricing increases with TURNVOL. The results are consistent with arbitrage activity being limited in high TURNVOL stocks.

4.2 Other measures of turnover volatility

Previous tests used monthly turnover volatility measure 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 TURNVOL 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. To test if the choice of holding period affects the results Table 4 studies the relationship between the risk-adjusted returns and a measure of turnover volatility computed from daily turnover (DTURNVOL). The results are qualitatively similar to previous tests. Among underpriced stocks the Fama and French 5-factor alpha increases with DTURNVOL and among overpriced stocks the alpha decreases with turnover but is not monotonic. Long-short DTURNVOL portfolio has positive and significant alpha in underpriced stocks and negative and significant alpha in overpriced stocks. The findings provide evidence that results are not sensitive to the period used to compute turnover volatility.[2]

4.3 Sentiment and Mispricing

This section investigates how the relationship between TURNVOL and mispricing is affected by investor sentiment using Baker and Wurgler (BW) (2006) sentiment (BW). In the presence of arbitrage costs, as arbitrageurs are unable to eliminate mispricing, sentiment will drive the mispricing (Stambaugh, Yu and Yuan, 2015). When sentiment is high overpricing will be larger. Because high TURNVOL stocks is where arbitrageurs will be hindered the most, we should see high TURNVOL stocks in the most overpriced quintile having lower returns following high sentiment periods. Similarly the most underpriced stocks with high TURNVOL should earn higher returns following low sentiment periods.

Table 5 reports the risk-adjusted alpha for high and low sentiment months. Months are classified as high and low sentiment depending on whether BW sentiment measure was higher or lower than median respectively. Following low sentiment months, high TURNVOL stocks in the most underpriced quintile earn higher returns. Following high sentiment months high TURNVOL stocks in the most overpriced quintile earn lower returns. This provides additional support that TURNVOL hinders arbitrage and hence sentiment drives mispricing in high TURNVOL stocks.

4.4 Arbitrage Asymmetry and negative TURNVOL-return relation

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

[2] Internet Appendix IA.1 reports the results when repeating the analysis using volatility in Amihud (2002) measure. The results are qualitatively similar.

arbitrage capital will be deployed to correct underpricing. It is easier to correct underpricing as there are no constraints on the long side. As a result overpricing will continue to exist in stocks with short-sale constraints. The negative relationship between TURNVOL and returns could arise due to arbitrage asymmetry. This section explores how short sale constraints affect the relationship between TURNVOL and returns.

Institutional ownership (IO) serves as a measure of short sale constraints (Nagel, 2005). Institutional Ownership is computed as the percent of institutional stock holding in a stock. The data is from Thomson Reuters. Sample period is from 1980 to 2016 due to data availability. First, stocks are sorted into quintiles based on IO as of the previous month. Then within each IO quintile they are in turn sorted into quintiles based on TURNVOL. Table 6 presents the results. In the lowest IO group, the group with highest short sale constraints, stocks with high TURNVOL earn negative risk-adjusted returns. In TURNVOL quintiles 3 and 4 the negative risk-adjusted return are very significant. This is not monotonic since the highest TURNVOL quintile in the lowest IO group earns less negative return compared to group 4. From the last column, the long-short TURNVOL portfolio is negative and significant at 10% level for the one tailed test. The test is one tailed as arbitrage asymmetry implies that the negative relationship will be found in the lowest IO group (difficult-to-short stocks). In unreported tests, the significance improves if other factor models are used for risk adjustment. The stocks in other IO groups do not show the negative-return relation. In the last row and last column of the table, the difference in returns is negative and significant for the long-short portfolio IO portfolios formed by buying high TURNVOL stocks and selling low TURNVOL stocks. The results show that the negative TURNVOL-return relationship is primarily found in stocks with short sale constraints providing support for arbitrage asymmetry. Next section provides additional support to this using Fama-Macbeth analysis.

4.5 Individual stocks Fama-Macbeth analysis

Table 7 reports the results of the Fama-Macbeth regression of individual stock excess returns on characteristics. Individual stocks risk adjusted returns are computed following Brennan, Chordia and Subrahmanyam (1998). The characteristics considered are SIZE, BM, 1/PRICE, RET23, RET46, RET712, Mispricing and Mispricing interacted with TURNVOL. Natural logarithm of all variables is used to control for skewness with the exception of mispricing and other return based variables. MISPRICING is a continuous variable with high value suggesting overpricing.

In the first column of Table 7, TURNVOL has a negative coefficient. This is 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, mispricing and the interaction of mispricing and TURNVOL are added. The coefficient on TURNVOL now becomes positive and significant which should be the case if it is a risk. The coefficient on the interaction term is negative and significant. This suggests that it is the high TURNVOL stocks that are overpriced that earn negative returns. This provides additional support to the arbitrage asymmetry discussed in the previous section. TURNVOL as a limiting factor to arbitrage and arbitrage asymmetry together explain the negative TURNVOL-average return relation.

4.6 TURNVOL vs IVOL

Pontiff (2006) argues that idiosyncratic volatility (IVOL) is an important holding cost incurred by the arbitrageurs. For turnover volatility to be an additional factor limiting arbitrage it must explain the mispricing after controlling for IVOL. From Table 2 the correlation between

IVOL and TURNVOL is low suggesting that TURNVOL is an additional factor affecting arbitrage. This is formally tested in this section. Each month stocks are sorted into three groups on mispricing scores. Then within each mispricing tercile, stocks are sorted into three groups on IVOL. Then within each mispricing-IVOL group, stocks are sorted into three groups based on TURNVOL.

Table 8 presents the results. In the most underpriced group, the alphas increase with TURNVOL across all IVOL groups. In the most overpriced group, the alphas decrease with TURNVOL across all IVOL groups. Across all stocks, after controlling for IVOL, the long-short TURNVOL portfolios earn positive and significant returns in the underpriced group and negative and significant returns in the overpriced group respectively. The evidence provided in this section suggests that TURNVOL limits arbitrage over and above IVOL.

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 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 an increased likelihood of mispricing in these stocks. Consistent with the claim, mispricing is severe in high TURNVOL stocks. Among overpriced stocks, high TURNVOL stocks are more overpriced and earn lower returns subsequently. Also, in high TURNVOL 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 found only in stocks with short sale constraints. This is the result of asymmetry in arbitrage arising due to the difficulty in eliminating overpricing in the presence of short sale constraints. Therefore, more arbitrage capital flows to correct underpricing. Consequently, the high TURNVOL stocks are overpriced on average and therefore earn low returns.

References:

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2005). Liquidity and asset prices. *Foundations and Trends® in Finance*, 1(4), 269-364.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259-299.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645-1680.

Brennan, M. J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, *49*(3), 345-373.

Campbell, J. Y. (2017). *Financial Decisions and Markets: a Course in Asset Pricing*. Princeton University Press.

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics*, 59(1), 3-32.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479-512.

D'avolio, G. (2002). The market for borrowing stock. *Journal of Financial Economics*, 66(2), 271-306.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5), 2113-2141.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427-465.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Gao, X., & Ritter, J. R. (2010). The marketing of seasoned equity offerings. *Journal of Financial Economics*, *97*(1), 33-52.

Hong, H., & Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies*, 16(2), 487-525.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, 32(4), 1151-1168.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics*, 78(2), 277-309.

Pereira, J. P., & Zhang, H. H. (2010). Stock returns and the volatility of liquidity. *Journal of Financial and Quantitative Analysis*, *45*(4), 1077-1110.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, 42(1), 35-52.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1), 35-55.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2), 288-302.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, *70*(5), 1903-1948.

Table 1: Average Size and Turnover Volatility of Stocks sorted on Mispricing and Turnover Volatility

The table presents the average market capitalization (in $ Millions) and standard deviation of monthly turnover (TURNVOL) of stocks in the mispricing and turnover volatility quintiles. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of monthly turnover as of the previous month. Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. Standard deviation is computed using previous 60 months of turnover data. Sample period is from January 1966 to December 2016.

	Lowest TURNVOL	2	3	4	Highest TURNVOL
		Panel A : Market Cap (in $ Millions)			
Most Underpriced	9,094	6,509	3,937	2,434	2,089
2	3,565	3,870	2,868	2,226	1,953
3	1,504	2,534	2,067	1,818	1,644
4	1,293	1,853	1,592	1,338	1,297
Most Overpriced	1,009	1,435	1,085	1,006	1,014
		Panel B : Standard Deviation of Monthly Turnover			
Most Underpriced	0.011	0.021	0.032	0.049	0.111
2	0.010	0.021	0.032	0.050	0.116
3	0.008	0.020	0.033	0.052	0.126
4	0.009	0.021	0.036	0.056	0.140
Most Overpriced	0.012	0.028	0.045	0.070	0.174

Table 2: Correlations

The table reports the correlation between the variables used in the paper. TURNVOL is the standard deviation of monthly turnover computed using the turnover from previous 60 months. DTURNVOL is the standard deviation of daily turnover computed using previous 3 months of daily data. AMIHUD is the monthly Amihud (2002) illiquidity measure. AMIHUDVOL is the volatility in AMIHUD Illiquidity measure computed using the monthly AMIHUD measure from previous 60 months. 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 individual stock correlations. Sample period is from January 1966 to December 2016.

	TURNVOL	DTURNVOL	IVOL	TURN	SIZE
TURNVOL	1.00	0.35	0.04	0.33	0.18
DTURNVOL	0.35	1.00	0.13	0.65	0.19
IVOL	0.04	0.13	1.00	0.26	-0.19
TURN	0.33	0.65	0.26	1.00	0.25
SIZE	0.18	0.19	-0.19	0.25	1.00

Table 3: Risk-Adjusted Returns of Portfolios sorted on Mispricing and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and TURNVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of *monthly turnover* as of the previous month(TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. 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).

	Lowest TURNVOL	2	3	4	Highest TURNVOL	Highest - Lowest TURNVOL
Most Underpriced	-0.04%	-0.01%	0.24%	0.42%	0.57%	0.61%
	(-0.52)	(-0.12)	(2.76)	(3.91)	(3.86)	(3.59)
2	-0.08%	-0.09%	-0.03%	0.21%	0.41%	0.49%
	(-0.95)	(-1.23)	(-0.43)	(2.09)	(2.69)	(2.85)
3	-0.17%	-0.04%	-0.18%	0.02%	0.31%	0.48%
	(-1.55)	(-0.47)	(-2.18)	(0.25)	(2.23)	(2.43)
4	-0.13%	-0.27%	-0.09%	-0.26%	0.07%	0.19%
	(-1.09)	(-2.61)	(-0.99)	(-2.32)	(0.46)	(0.97)
Most Overpriced	-0.23%	-0.18%	-0.54%	-0.82%	-0.93%	-0.70%
	(-1.97)	(-1.39)	(-4.25)	(-6.28)	(-5.71)	(-3.70)
Most Underpriced - Most Overpriced	0.19%	0.17%	0.78%	1.24%	1.49%	1.30%
	(1.32)	(1.01)	(4.63)	(6.94)	(6.98)	(5.62)

Table 4: Risk-Adjusted Returns of Portfolios sorted on Mispricing and DTURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and DTURNVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of daily turnover as of the previous month(DTURNVOL). Daily Turnover is defined as the ratio of daily trading volume and total shares outstanding in a stock. DTURNVOL is computed from 3 months of prior daily turnover data. 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).

	Lowest DTURNVOL	2	3	4	Highest DTURNVOL	Highest - Lowest DTURNVOL
Most Underpriced	-0.07%	0.05%	0.26%	0.35%	0.59%	0.66%
	(-0.89)	(0.57)	(2.94)	(3.64)	(4.25)	(3.94)
2	-0.01%	-0.03%	-0.02%	0.15%	0.21%	0.22%
	(-0.12)	(-0.33)	(-0.29)	(1.56)	(1.45)	(1.35)
3	-0.28%	-0.13%	0.00%	0.04%	0.23%	0.50%
	(-2.67)	(-1.52)	(-0.03)	(0.36)	(1.83)	(2.96)
4	-0.13%	-0.20%	-0.14%	-0.06%	-0.23%	-0.10%
	(-1.18)	(-2.08)	(-1.61)	(-0.60)	(-1.77)	(-0.54)
Most Overpriced	-0.39%	-0.42%	-0.54%	-0.45%	-0.80%	-0.41%
	(-3.37)	(-3.33)	(-4.56)	(-3.60)	(-5.19)	(-2.21)
Most Underpriced - Most Overpriced	0.32%	0.47%	0.80%	0.80%	1.39%	1.07%
	(2.25)	(2.82)	(4.76)	(4.89)	(6.93)	(4.73)

Table 5: Risk Adjusted Returns of portfolios sorted on Mispricing and TURNVOL in High-Sentiment and Low-Sentiment Periods.

The table presents the Fama French three factor alpha of portfolios ranked on mispricing and TURNVOL for High Sentiment and Low Sentiment months. Each month, stocks are sorted into quintiles based on their mispricing scores as of previous month. Within each mispricing quintile, they are sorted in turn into quintiles on the standard deviation of monthly turnover (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock and is computed using 60 months of previous turnover data. Sample period is from January 1966 to December 2016. Reported numbers are a_H and a_L 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 and $d_{L,t}$ is the dummy variable that takes value of 1 if the sentiment in the previous month was below median . Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

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

	Low Sentiment months			High Sentiment months		
	Lowest TURNVOL	Highest TURNVOL	Highest – Lowest	Lowest TURNVOL	Highest TURNVOL	Highest - Lowest
Most Underpriced	-0.14%	0.48%	0.61%	0.17%	0.22%	0.04%
	(-1.49)	(2.43)	(2.79)	(1.15)	(0.85)	(0.14)
2	-0.02%	0.49%	0.51%	-0.13%	-0.11%	0.02%
	(-0.22)	(2.28)	(2.14)	(-0.83)	(-0.42)	(0.07)
3	-0.05%	0.37%	0.42%	-0.29%	-0.14%	0.15%
	(-0.30)	(1.97)	(1.54)	(-1.45)	(-0.55)	(0.44)
4	-0.24%	0.12%	0.35%	0.25%	-0.15%	-0.40%
	(-1.50)	(0.63)	(1.31)	(1.12)	(-0.56)	(-1.05)
Most Overpriced	-0.38%	-0.60%	-0.21%	0.33%	-0.64%	-0.97%
	(-2.47)	(-2.83)	(-0.82)	(1.51)	(-2.18)	(-2.68)
Most Underpriced - Most Overpriced	0.25%	1.07%	0.83%	-0.15%	0.86%	1.01%
	(1.31)	(4.09)	(2.78)	(-0.56)	(2.19)	(2.29)

Table 6: Risk-Adjusted Returns of Portfolios sorted on Institutional Ownership and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on Institutional Ownership (IO) and TURNVOL. At the beginning of each month, stocks are sorted into quintiles based on institutional ownership as of the previous month. Within each short interest quintile, the stocks are in turn sorted into quintiles on the standard deviation of *monthly turnover* as of the previous month (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. Sample period is from January 1980 to December 2016. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Lowest TURNVOL	2	3	4	Highest TURNVOL	Highest - Lowest TURNVOL
Lowest IO	0.02%	0.41%	-0.40%	-0.54%	-0.45%	-0.47%
	(0.12)	(1.45)	(-1.71)	(-2.63)	(-1.49)	(-1.32)
2	0.14%	-0.08%	0.01%	-0.03%	0.25%	0.12%
	(0.82)	(-0.51)	(0.04)	(-0.14)	(0.91)	(0.34)
3	0.15%	0.15%	0.18%	0.18%	0.35%	0.20%
	(0.95)	(0.80)	(0.98)	(1.04)	(1.47)	(0.74)
4	-0.12%	-0.01%	0.46%	0.13%	0.33%	0.44%
	(-1.35)	(-0.11)	(3.40)	(0.95)	(1.76)	(1.99)
Highest IO	-0.23%	-0.30%	-0.11%	0.17%	0.02%	0.25%
	(-2.18)	(-2.74)	(-1.08)	(1.24)	(0.10)	(1.30)
Lowest IO – Highest IO	0.26%	0.70%	-0.29%	-0.70%	-0.47%	-0.73%
	(1.31)	(2.35)	(-1.11)	(-2.75)	(-1.44)	(-1.92)

Table 7: 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. Natural logarithm of all variables is used with the exception of mispricing, RET23, RET46, RET712. SIZE refers to market capitalization, BM refers to the book to market, 1/PRICE is the reciprocal of price, and TURNVOL is the standard deviation of turnover as of previous month computed from monthly turnover data in the prior 60 months. Mispricing is the Stambaugh, Yu, and Yuan(2015) mispricing score. RET23 refers to the return in the second and third month previous to current month. RET46 is the buy and hold return of the stocks from six month to four months before the current month. RET712 refers to the buy and hold return of the stock from twelve month to seven month before the current month. Sample period is from Jan 1966 to Dec 2016. Fama-Macbeth t-statistics in parenthesis.

Variable	Coefficient	Coefficient
Constant	1.308	3.680
	(3.52)	(9.36)
SIZE	-0.060	-0.049
	(-2.97)	(-2.57)
BM	0.151	0.080
	(4.16)	(2.25)
1/PRICE	0.062	0.190
	(0.95)	(3.40)
RET23	0.455	0.302
	(1.93)	(1.23)
RET46	0.533	0.216
	(2.80)	(1.14)
RET712	0.422	0.236
	(3.00)	(1.63)
TURNVOL	-0.172	0.137
	(-5.16)	(2.00)
Mispricing		-0.040
		(-7.49)
Mispricing * TURNVOL		-0.005
		(-3.93)

Table 8: Risk-Adjusted Returns of Portfolios sorted on Mispricing , IVOL and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing, IVOL and TURNVOL. At the beginning of each month, stocks are sorted into three groups based on their mispricing scores as of the previous month. Within each mispricing groups, the stocks are in turn sorted into terciles on the idiosyncratic volatility (IVOL) as of the previous month. Within each mispricing and IVOL groups, the stocks are in turn sorted into terciles on the standard deviation of *monthly turnover* as of the previous month (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. In the table TURNVOL is reported as TVOL. 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).

	Most Underpriced								Most Overpriced			
	Low TVOL	2	High TVOL	High -Low TVOL	Low TVOL	2	High TVOL	High -Low TVOL	Low TVOL	2	High TVOL	High -Low TVOL
Low IVOL	-0.09%	-0.04%	0.31%	0.40%	-0.04%	-0.14%	-0.03%	0.01%	-0.15%	-0.19%	-0.55%	-0.41%
	(-1.42)	(-0.54)	(3.54)	(3.55)	(-0.42)	(-1.64)	(-0.32)	(0.05)	(-1.31)	(-1.86)	(-4.99)	(-2.76)
2	-0.03%	0.24%	0.42%	0.45%	-0.28%	-0.05%	0.30%	0.58%	-0.17%	-0.41%	-0.54%	-0.37%
	(-0.31)	(2.58)	(3.45)	(2.92)	(-2.20)	(-0.52)	(2.60)	(3.23)	(-1.24)	(-3.01)	(-4.04)	(-2.28)
High IVOL	0.05%	0.41%	0.47%	0.42%	-0.14%	-0.01%	-0.08%	0.06%	-0.55%	-0.88%	-1.14%	-0.59%
	(0.48)	(3.08)	(2.74)	(2.26)	(-1.00)	(-0.06)	(-0.48)	(0.29)	(-3.60)	(-6.11)	(-5.87)	(-2.68)
High - Low IVOL	0.15%	0.45%	0.16%		-0.10%	0.13%	-0.05%		-0.41%	-0.69%	-0.59%	
	(1.06)	(2.91)	(0.89)		(-0.60)	(0.74)	(-0.24)		(-2.27)	(-4.08)	(-2.93)	
All Stocks	-0.07%	0.09%	0.43%	0.49%	-0.13%	-0.06%	0.16%	0.29%	-0.16%	-0.29%	-0.57%	-0.41%
	(-1.25)	(1.42)	(4.43)	(4.24)	(-1.72)	(-0.93)	(1.95)	(2.25)	(-1.57)	(-3.32)	(-5.28)	(-2.92)

Internet Appendix

Table IA.1: Risk-Adjusted Returns of Portfolios sorted on Mispricing and AMIHUDVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and AMIHUDVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of monthly Amihud(2002) Illiquidity measure(AMIHUDVOL). AMIHUDVOL is computed from previous 60 months of AMIHUD measure. 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).

	Lowest AMIHUDVOL	2	3	4	Highest AMIHUDVOL	Highest - Lowest AMIHUDVOL
Most Underpriced	0.10%	0.20%	0.35%	0.35%	0.57%	0.47%
	(1.99)	(2.78)	(4.77)	(3.73)	(5.39)	(4.23)
2	0.02%	0.11%	0.22%	0.26%	0.34%	0.33%
	(0.36)	(1.32)	(2.52)	(3.00)	(2.72)	(2.43)
3	-0.06%	0.23%	0.27%	0.23%	0.11%	0.16%
	(-1.01)	(2.01)	(2.80)	(2.38)	(0.95)	(1.25)
4	-0.18%	0.03%	0.03%	-0.09%	0.09%	0.27%
	(-2.69)	(0.32)	(0.38)	(-0.87)	(0.61)	(1.58)
Most Overpriced	-0.45%	-0.45%	-0.50%	-0.65%	-0.69%	-0.24%
	(-4.10)	(-3.69)	(-5.58)	(-5.64)	(-4.95)	(-1.34)
Most Underpriced - Most Overpriced	-0.55%	-0.65%	-0.85%	-1.00%	-1.26%	-0.71%
	(-3.88)	(-4.18)	(-6.94)	(-6.37)	(-7.66)	(-3.47)