# The Option Volume to Stock Volume Ratio, Market Efficiency and Future Returns

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**Abstract**

The study of the information value in options has for decades been at the centre of financial research. Recent findings indicate that informed investors prefer to use options to trade on negative information, causing the option volume to stock volume ratio (O/S) to correlate negatively with future returns. Drawing from evidence on mispricing in illiquid markets, this study develops a multimarket model that incorporates price inefficiencies that arise from low levels of liquidity into the O/S framework. In the presence of short sale costs, the model predicts that O/S is more strongly negatively correlated with future returns for firms with low levels of liquidity compared to firms with high levels of liquidity. Using a large sample of cross-sectional and time-series data on US listed stocks and options, this study finds strong empirical support of the model's prediction. We additionally derive a self-financing trading strategy that is based on our empirical results and find that the strategy generates weekly four-factor alphas of 0.53% and CARs of 230.31% during the 2002-2012 period. Thus, we conclude that the linkage between O/S, illiquidity and future stock performance is of high economic significance.

*Keywords:* Return predictability, Option volume, Market efficiency, Informed investors, Liquidity

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# Contents

# 1 Introduction

The question whether options contain information about future movements in the underlying stock and thus aid in the stock price discovery process has extensively been debated within the field of finance. Black & Scholes (1973) argue that options are redundant securities in complete markets as they can easily be replicated by continuous trading in stocks and bonds, implying that signals in the options market cannot lead prices in the stock market. However, the simplified assumptions in the Black-Scholes framework do not necessarily hold in real market settings. In a recent study, Johnson & So (2012),hereafter JS, develop a multimarket asymmetric information model where the prevalence of short sale costs in the stock market induce informed investors to primarily trade options for negative signals. The model implies that option volumes contain information about future stock movements and JS empirically find that the option volume to stock volume ratio (O/S) is indeed negatively correlated with future returns. The result thus provides new evidence in support of the notion that options have a significant role in the stock price discovery process.

In our study, we build on JS's findings by developing a multimarket model that jointly incorporates O/S and price inefficiencies that arise from low levels of liquidity in the stock market. In the presence of short sale costs, our model predicts that O/S is more strongly negatively correlated with future returns for firms with low levels of liquidity compared to firms with high levels of liquidity. The linkage between O/S, liquidity and future returns is derived from research suggesting that informed investors are able to detect and take advantage of price inefficiencies that arise in the stock market [17]. Since price deviations from fundamental values are more prevalent on stocks that are less liquid [11] [28], we assert that the fraction of informed investors trading in a stock and/or its corresponding options will increase in stock illiquidity. Given that informed investors prefer to use options to trade on negative information as suggested by JS, the implication is that O/S will be a stronger negative predictor of future returns for firms with relatively illiquid stocks.

To investigate the outlined prediction of our model, we estimate pooled OLS regressions where weekly return data from a large sample of US stocks is regressed on O/S, liquidity and an interaction variable between O/S and liquidity. We use the quoted spread, Amihud, Zero and market capitalization as liquidity proxies and find empirical support for the theoretical prediction of our multimarket model. Specifically, the result shows that O/S together with low levels of stock liquidity have a statistically significant negative impact on future returns when the quoted spread, Amihud and market capitalization are used as liquidity proxies. The results are also robust across a variety of specifications and after controlling for firm and year fixed effects. We argue that our empirical findings are economically significant by deriving a self-financing trading strategy that successfully exploits the relationship between O/S, liquidity and future returns. Specifically, we construct an equally weighted portfolio that is long stocks in the 1st vigintile and short stocks in the 20th vigintile of an interaction variable that is based on O/S and quoted spread. The trading strategy generates a statistically significant weekly four-factor alpha of 0.533% and yields cumulative abnormal returns that are 61.05 percentage points higher than a similarly constructed strategy solely based on O/S over a ten year period.

This study thus sets out to both extend existing literature on the role of options in the stock price discovery process and to provide novel evidence of the linkage between O/S, liquidity and return predictability. To our knowledge, no existing empirical research has explicitly incorporated the role of price inefficiencies that arise from low levels of liquidity into the O/S framework in order to investigate the trading patterns of informed investors and the implications for subsequent firm performance. The results from this study have two main implications. First, our evidence suggests that informed investors are indeed able to detect and profit from mispricing that arises from stock illiquidity by taking positions in the options market. Second, our findings support the notion that options have a significant role in the stock price discovery process and specifically also highlight how the information content in options depend on levels of stock liquidity.

The remainder of this study is organized as follows. In section 2, we review previous literature regarding the role of options in the stock price discovery process and the relationship between liquidity and market efficiency. In section 3, we synthesize the theoretical foundations into an extended version of JS's multimarket model that serves as a basis for our empirical predictions. We introduce the data in section 4 and describe our empirical measures in section 5. The methodology used in this study is explained in section 6 and the results of the empirical tests and the self-financing trading strategy is presented in section 7. Finally, we discuss the results and implications of our study as well as emphasize potential areas for future research in section 8.

# 2 Previous Literature

Our study is primarily related to two different topics within the field of finance. First, as we examine the information value in relative option trading volumes, our study is connected to previous literature concerning the role of options in the stock price discovery process. Second, research investigating the links between liquidity and market efficiency is highly relevant to our analysis, as an underlying assumption in our theoretical framework is that price inefficiencies are more prevalent on illiquid stocks. We describe key findings in previous literature concerning both topics below.

## 2.1 The Role of Options in the Stock Price Discovery Process

To date, studies investigating the information value of options have primarily used two different approaches. Studies using the first approach focus on examining whether option prices lead stock prices or vice versa. These studies have provided considerable evidence in favor of the notion that options contain significant information. Easley et al (1998) construct a microstructure model where option markets become attractive to informed investors under certain conditions and where option order flows contain information about fundamental value and lead stock prices. Similarly, Pan & Poteshman (2006) demonstrate that the open-buy put-call ratio can predict future stock movements and Anthony (1988) finds that trading in call options lead stock trading by one day. Manaster & Rendleman (1982) reach a similar conclusion as they find that option prices contain information that is not reflected in the underlying for a period up to 24 hours. Chakravarty et al (2004) estimate that 17 percent of the stock price discovery process can be attributable to option markets. However, a few noteworthy studies have reached opposite conclusions. Muravyev et al (2013) argue that options do not aid in the stock price discovery process as they find that option quotes adjust themselves across the stock market and the options market in order to eliminate arbitrage opportunities, whereas stock quotes do not. Their findings are supported by Chan et al (2002) who present evidence that stock net-trade volume can predict option and stock quote revisions as opposed to option net-trade volume.

Studies using the second approach investigate the information content in options indirectly. These studies examine the trading behavior of informed investors and their trading preferences across the options and stock market. The notion is that the trading pattern of informed investors has important implications for the linkage between options and stocks as these investors possess information that may not be fully reflected in stock prices. For instance, options may contain significant information if informed investors have a systematic preference towards trading in the options market rather than in the stock market. Research using this approach has given somewhat mixed results. On the one hand, Back (1992) demonstrates that option markets are attractive due to lower capital requirements and the embedded leverage in options. Biais & Hillion (1994) investigate an introduction of options and argue that option securities increase the profits for informed investors across certain orders of liquidity. Research also suggests that lower transaction costs in the options market and an absence of short sale restrictions can create preferences for trading options[2]. On the

[2] e.g. Diamond & Verrecchia (1987) and Mayhew, Atulya, & Kaldeep (1995)

other hand, Kyle (1985) argues that profit maximizing informed traders try to camouflage their trading activity, implying a preference towards trading in the stock market as stocks generally are more liquid than options [30]. Admati & Pfleiderer (1988) reach a similar conclusion as they find that informed investors attempting to conceal trading activity prefer to trade in more liquid markets.

## 2.2 The Relationship between Liquidity and Market Efficiency

Our analysis also draws from recent studies describing the linkage between liquidity and market efficiency. Chordia et al (2008) use the stock market's capacity to absorb order imbalances as a proxy for market efficiency and examine how this capacity differs across various liquidity regimes. They measure liquidity in terms of bid-ask spreads and find that narrow spreads have a consistent and positive effect on intraday market efficiency as they facilitate arbitrage trading and increase the absorbing capacity of order imbalances in the market. Their findings have been confirmed by Chung & Hrazdil (2010) who use a similar approach with a larger sample of stocks and additionally demonstrate how the impact of liquidity amplifies during periods when new information is released to the market. The existence of a positive relationship between liquidity and market efficiency is also supported by Sadka & Scherbina (2007) who find that less liquid stocks consistently tend to be overpriced in the market. They show that a high degree of analyst dispersion creates information asymmetries in the market and induce market makers to increase trading costs by raising bid-ask spreads, which has an adverse effect on market efficiency and give rise to mispricing. Sadka & Scherbina also conclude that an increase in liquidity narrows no-arbitrage bounds and facilitates the convergence of prices to fundamentals. Importantly for our analysis, findings also indicate that informed investors are able to detect price inefficiencies that arise in the stock market. For instance, Hayunga et al (2012) explore the trading behavior of investors in option markets conditioned on price inefficiencies in the underlying stock. By investigating violations of boundary conditions of American style options and the degree of dispersion between options-implied stock prices and actual prices, they find that informed investors consistently demonstrate an ability to not only detect mispricing in the stock market but also take advantage of it by trading accordingly in the options market.

# 3 A Model of Informed Trading

We present an extension to the model of informed trading in equity and options markets originally developed by JS. Our extension relates to the linkage between liquidity, market efficiency and the presence of traders with private information. As we shall see, the model predicts that this linkage together with O/S can be exploited in order to more accurately predict future returns compared to O/S alone. We will briefly explain the original model and then turn to our extension and its implication for predicting future returns.

## 3.1 The Original Model

In the original model, investors trade sequentially with a risk-neutral market maker and if they want to short sell equity they have to incur a short sale cost, $\rho$. Trades occur at $t = 1$ and are realized at $t = 2$, at which time the value of the stock is

$$\tilde{V} = \mu + \tilde{\epsilon} + \tilde{\eta} \tag{1}$$

where $\mu$ is the exogenous mean equity value, and $\tilde{\epsilon}$ and $\tilde{\eta}$ are normally distributed independent shocks. A fraction of all investors, $\alpha$, are informed and know beforehand the realization of $\tilde{\epsilon}$ and consequently value the stock and options according to the formulas

$$E(\tilde{V}|\tilde{\epsilon} = \epsilon) = \mu + \epsilon \tag{2}$$

$$E(\tilde{C}|\tilde{\epsilon} = \epsilon) = \Phi\left(\frac{\epsilon}{\sigma_\eta}\right)\epsilon + \phi\left(\frac{\epsilon}{\sigma_\eta}\right)\sigma_\eta \tag{3}$$

and

$$E(\tilde{P}|\tilde{\epsilon} = \epsilon) = -\Phi\left(\frac{-\epsilon}{\sigma_\eta}\right)\epsilon + \phi\left(\frac{\epsilon}{\sigma_\eta}\right)\sigma_\eta \tag{4}$$

respectively, where $\tilde{P}$ and $\tilde{C}$ are the put and call values at $t = 2$, $\Phi$ is the standard normal's cumulative distribution function and $\phi$ is the probability distribution function. Investors can only trade in one type of asset and in equilibrium the informed investors have a strict preference between the possible trades. The trading behaviour of informed investors can in equilibrium be described as

$$
f(\epsilon) = \begin{cases} \text{buy puts} & \text{for } \epsilon \leq k_1 \\ \text{sell stock} & \text{for } \epsilon \in (k_1, k_2) \\ \text{sell calls} & \text{for } \epsilon \in (k_2, k_3) \\ \text{make no trade} & \text{for } \epsilon \in (k_3, k_4) \\ \text{sell puts} & \text{for } \epsilon \in (k_4, k_5) \\ \text{buy stock} & \text{for } \epsilon \in (k_5, k_6) \\ \text{buy calls} & \text{for } \epsilon > k_6 \end{cases} \tag{5}
$$

where $k_1 - k_6$ represents distinct cut-off points related to the magnitude of the private information. The fraction of uninformed investors, $(1 - \alpha)$, trade for other reasons, with fractions $q_1$, $q_2$, $q_3$, $q_4$, $q_5$ and $q_6$ choosing to buy stock, sell stock, buy calls, sell calls, buy puts and sell puts, respectively, where $\sum_{i=1}^{6} q_i = 1$.

Given that uniformed investors are equally likely to buy and sell each asset, one of the main empirical predictions of this model is that O/S is negatively correlated with future stock returns. The reason is that informed traders prefer to use the options market as an investment vehicle for trading on negative information due to the prevalence of short sale costs in the stock market.

## 3.2 Extension to the Model

In our extension to the model we emphasize the circumstances under which informed investors are able to take advantage of their ability to detect mispricing in the stock market. We model the fraction of informed investors trading in a stock and/or its corresponding option as

$$
\alpha = \nu + \omega * \mathit{Quoted\ Spread} \tag{6}
$$

where $\nu$ is the fraction of informed investors trading in a stock and/or an option with a quoted spread of zero, *Quoted Spread* is a proxy for stock liquidity and $\omega$ is a positive variable describing the relationship between the presence of informed investors and the quoted spread. Notice that the model is not restricted to using the quoted spread as a proxy for liquidity and we will incorporate a variety of proxies in our empirical testing of the model's predictions. The intuition behind the extension is related to evidence suggesting that price inefficiencies are more prevalent on illiquid stocks [11] [28] and that informed investors are able to detect and profit from these price inefficiencies [17]. Specifically, since there is more mispricing for informed investors to detect and take advantage of on stocks that are illiquid, the fraction of informed investors trading in a stock and/or an option will increase in illiquidity.

**Empirical predictions:**
Thus, given that uninformed investors are equally likely to buy and sell each asset and that informed investors have a preference for trading on negative information in the options market, and that $\omega > 0$, then

1. *O/S will be negatively correlated with future returns (from the original model)*
2. *The fraction of informed investors trading in a stock and/or its corresponding option will increase if the stock is illiquid*
3. *The predictive power of O/S will be increasing in stock illiquidity*

In other words, a high O/S combined with a high level of stock illiquidity will correlate more negatively with future returns than O/S alone.

## 3.3 Derivation of Empirical Predictions

In order to show that an increase in the fraction of informed investors, $\alpha$, trading in a stock and/or option causes O/S to correlate more negatively with future returns in the presence of short sale costs we first define $\overline{V_S} = E(\tilde{V} - \mu | stock\ trade)$, $\overline{V_O} = E(\tilde{V} - \mu | option\ trade)$ and $D \equiv \overline{V_S} - \overline{V_O}$. Differentiating $D$ with regard to $\rho$, we get

$$\frac{\partial D}{\partial \rho} = \frac{\overline{V_S}}{\partial \rho} - \frac{\overline{V_O}}{\partial \rho} = \sum_{i=1}^{6} \left( \frac{\overline{V_S}}{\partial k_i} - \frac{\overline{V_O}}{\partial k_i} \right) \frac{\partial k_i}{\partial \rho}. \tag{7}$$

From JS we additionally have that

$$\frac{\partial \overline{V_S}}{\partial k_1} = \alpha \frac{\phi(k_1)}{p_s} (\overline{V_S} - k_1) > 0 \tag{8}$$

$$\frac{\partial \overline{V_S}}{\partial k_2} = \alpha \frac{\phi(k_2)}{p_s} (k_2 - \overline{V_S}) < 0 \tag{9}$$

$$\frac{\partial \overline{V_O}}{\partial k_1} = \alpha \frac{\phi(k_1)}{p_o} (k_1 - \overline{V_O}) < 0 \tag{10}$$

and

$$\frac{\partial \overline{V_O}}{\partial k_2} = \alpha \frac{\phi(k_2)}{p_o} (\overline{V_O} - k_2) > 0 \tag{11}$$

where $p_s$ and $p_o$ are the unconditional probabilities of a stock trade and an option trade occurring, respectively. Given the inequality signs in (8) through (11), we thus have that

$$\frac{\partial D}{\partial \rho} = \left(\frac{\partial \overline{V_S}}{\partial k_1} - \frac{\partial \overline{V_O}}{\partial k_1}\right)\frac{\partial k_1}{\partial \rho} + \left(\frac{\partial \overline{V_S}}{\partial k_2} - \frac{\partial \overline{V_O}}{\partial k_2}\right)\frac{\partial k_2}{\partial \rho} \rightarrow \frac{\partial D}{\partial \rho} > 0 \tag{12}$$

since $\partial k_1/\partial\rho > 0$, $\partial k_2/\partial\rho < 0$, and $\rho$ is not included in $k_3$-$k_6$.

Now consider the effect on (12) that an increase in $\alpha$ will have. In the components of (12) where $\alpha$ is present, i.e. (8) through (11), it shows up both directly and indirectly through $p_s$, $p_o$, $\overline{V_S}$ and $\overline{V_O}$.

First, if we solely focus on $p_s$[3] and $p_o$[4], notice that an increase in $\alpha$ can either increase or decrease $p_s$ and $p_o$. However, note that the net change in $\alpha/p_s$ and $\alpha/p_o$ as a result of an increase in $\alpha$ will always be positive. The effect is thus that (8) and (11) becomes more positive, and (9) and (10) becomes more negative, implying that the inequality in (12) will be greater the higher the $\alpha$.

Second, consider how $\alpha$ affects (12) through $\overline{V_S}$[5] and $\overline{V_O}$[6]. Notice that the positive net change in $\alpha/p_s$ and $\alpha/p_o$ as a result of an increase in $\alpha$ implies that both $\overline{V_S}$ and $\overline{V_O}$ are increasing in $\alpha$. However, the increases in $\overline{V_S}$ and $\overline{V_O}$ have zero net effect on (12). Specifically, note that an increase in $\overline{V_S}$ will make (8) less positive, and (9) more negative. An increase in $\overline{V_O}$ will similarly make (10) more negative, and (11) less positive. These effects will cancel each other out in (12), thus leaving the inequality unchanged.

As a result, we have that

$$\frac{\partial D^*}{\partial \rho} > \frac{\partial D}{\partial \rho} > 0 \tag{13}$$

since

$$\left(\frac{\partial \overline{V_S}}{\partial k_1} - \frac{\partial \overline{V_O}}{\partial k_1}\right)\frac{\partial k_1}{\partial \rho} < \left(\frac{\partial \overline{V_S}^*}{\partial k_1} - \frac{\partial \overline{V_O}^*}{\partial k_1}\right)\frac{\partial k_1}{\partial \rho} \tag{14}$$

and

$$\left(\frac{\partial \overline{V_S}}{\partial k_2} - \frac{\partial \overline{V_O}}{\partial k_2}\right)\frac{\partial k_2}{\partial \rho} < \left(\frac{\partial \overline{V_S}^*}{\partial k_2} - \frac{\partial \overline{V_O}^*}{\partial k_2}\right)\frac{\partial k_2}{\partial \rho} \tag{15}$$

where the updated PDEs with a higher $\alpha$, $\alpha^*$, has been denoted with a star. This means that, since there is no net effect of changes in $\alpha$ through $\overline{V_S}$ and $\overline{V_O}$ on $\partial D/\partial\rho^*$, we have that an increase in $\alpha/p_s$ and $\alpha/p_s$ as a result of an increase in $\alpha$ will increase $\partial D/\partial\rho^*$.

This implies that $D \equiv E(\tilde{V}|\textit{stock trade}) - E(\tilde{V}|\textit{option trade})$ is increasing in short sale cost more sharply the higher the fraction of informed investors, and that the inequality

[3] $p_s = (1-\alpha)(q_1+q_2) + \alpha(\Phi(k_2) - \Phi(k_1) + \Phi(k_6) - \Phi(k5))$

[4] $p_o = (1-\alpha)(q_3+q_4+q_5+q_6) + \alpha(\Phi(k_1) + \Phi(k_3) - \Phi(k_2) + \Phi(k_5) - \Phi(k_4) + 1 - \Phi(k_6))$

[5] $\overline{V_S} = (\alpha/p_s)(\phi(k_1) - \phi(k_2) + \phi(k_5) - \phi(k_6))$

[6] $\overline{V_O} = (\alpha/p_o)(-\phi(k_1) + \phi(k_2) - \phi(k_3) + \phi(k_4) - \phi(k_5) + \phi(k_6))$

$E(\tilde{V}|option\ trade) \leq E(\tilde{V}|stock\ trade)$ is greater the higher the fraction of informed investors. The implication is that, given that the fraction of informed investors trading in a stock and/or its corresponding option is higher if the stock is illiquid as described in section 3.2, the predictive power of O/S with regard to future returns is increasing in stock illiquidity (and in short sale cost). In other words, the model predicts that O/S is more strongly negatively correlated with future returns the more illiquid the stock.

# 4 Data

Our option data come from the Ivy DB OptionMetrics LLC database, which contains information on all US listed equity and index options. The data include the daily number of traded put and call contracts as well as strike prices and times to expiration. We focus on common stocks in our study and exclude indices, closed-end funds, exchange-traded funds, Real Estate Investment Trusts and American Depositary Receipts. Our sample period covers all available data in OptionMetrics, spanning from June 1996 to August 2013. As JS, we exclude firms with less than 25 call and 25 put contracts traded during a week in order to lessen the impact of measurement issues related to option markets that suffer from low liquidity. We do not distinguish options based on moneyness in our analysis. In order to lower the impact of long-horizon hedgers and mechanical option trading related to rolling forward contracts to the next maturity date, we also exclude options that matures within five days of the trade or more than thirty days after the trade[7].

Our stock data come from the Center for Research in Security Prices (CRSP), which cover all common stocks listed on NYSE, AMEX and Nasdaq. The CRSP data consist of daily prices, bid and ask prices, number of shares outstanding, and number of shares traded. The data also contain stock returns, which have been adjusted for stock splits and dividends are assumed to be reinvested on the ex-distribution date. Fama-French-Carhart factors are taken from Kenneth French's web site at Dartmouth. Our final dataset, consisting of the intersection of the OptionMetrics and CRSP data, includes a total amount of 802,103 firm-weeks. The average number of unique firms per year is 2,041 and the total number of unique firms is 5,473.

[7]See Johnson & So (2012)

# 5 Variable Selection and Descriptions

Next, we present and define the key measures used in our empirical tests. We introduce the O/S measure and describe the underlying theory of the liquidity proxies used in this study: quoted bid-ask spread, Zero, Amihud and market capitalization. We also examine the advantages and drawbacks of each proxy before proceeding with the analysis.

## 5.1 Option Volume to Stock Volume Ratio

The O/S measure is the ratio between option volume and stock volume for a given firm. We calculate O/S for every firm-week in our sample as

$$O/S_t^i = \frac{Option\ Volume_t^i}{Stock\ Volume_t^i} \tag{16}$$

where $Option\ Volume_t^i$ is the sum of all daily traded put and call contracts that matures between five and thirty days after the trade date for firm $i$ in business week $t$ and $Stock\ Volume_t^i$ is the total number of shares traded for firm $i$ in business week $t$.

## 5.2 Liquidity Measures

The concept of market liquidity and its underpinnings is rather elusive and arguably impossible to capture in one single measure. Generally, liquidity measures are supposed to capture one or more of the following characteristics of market liquidity [29]: i) tightness (transaction costs), ii) immediacy (speed of execution), iii) depth (prevalence of abundant orders), iv) breadth (volume size and price impact of orders) and v) resiliency (speed of correcting order imbalances). In our study, we use quoted bid-ask spread, Zero, Amihud and market capitalization as proxies for stock liquidity.

### 5.2.1 Quoted Bid-Ask Spread

The quoted spread is a common proxy for liquidity and it has been used widely in previous studies[8]. The quoted spread captures transaction costs and is thus primarily a measure of market tightness. A common rationale for using the quoted spread as a proxy for liquidity is that it captures both explicit and implicit transaction costs [29]. Specifically, the quoted spread reflects transaction costs related to i) order processing ii) asymmetric information,

[8]See Sarr & Lybek (2002), Sadka & Scherbina (2007), & Chordia, Roll & Subrahmanyam (2008)

iii) carrying inventory and iv) oligopolistic market structures. The quoted spread is defined:

$$Quoted\ Spread_t^i = \frac{1}{n}\sum_{j=1}^{n}\frac{askhi_{j,t}^i - bidlo_{j,t}^i}{askhi_{j,t}^i} \tag{17}$$

where $Quoted\ Spread_t^i$ is the spread for firm $i$ during week $t$, $n$ ranges from 4 to 6 depending on the number of trading days in a week, $askhi_{j,t}^i$ is the highest ask price during day $j$ in week $t$ for stock $i$ and $bidlow_{j,t}^i$ is the lowest bid price for stock $i$ on day $j$ in week $t$. We use the quoted spread as a proxy for liquidity in our main regression specifications.

### 5.2.2 Zero

The quoted bid and ask prices are not necessarily the prices at which trades occur. Trades can occur within quoted spreads and Huang & Stoll (1996) argue that quoted spreads are merely a starting point for negotiations. Petersen & Fialkowski (1994) demonstrate that actual spreads paid by investors average only half the quoted spread on the NYSE. The effective spread may be a more suitable proxy for liquidity in such a scenario, as it is based on actual trading costs paid by a trader. Specifically, the effective spread is defined as

$$Effective\ Spread_t^i = 2 * |ln(P_t^i) - ln(M_t^i)| \tag{18}$$

where $P_t^i$ is the actual execution price for a trade at time $t$ and $M_t^i$ is the quoted midpoint prevailing at the time of execution for stock $i$. Goyenko et al (2009), hereafter GHT, run horseraces between various common proxies for the effective spread and conclude that the Zero measure developed by Lesmond et al (1999) has a relatively high correlation with the effective spread. The Zero measure is defined as

$$Zero_t^i = \frac{No.\ of\ days\ with\ zero\ returns}{Trading\ days\ in\ week} \tag{19}$$

where $Zero_t^i$ is firm $i$'s effective spread during week $t$. Thus, Zero is the proportion of days with zero returns and has the advantage of only requiring time-series of daily stock returns in order to be calculated. More specifically, Zero is an estimate of the effective transaction costs for a marginal investor. The marginal investor will choose not to trade if he faces transaction costs that are greater than the expected value from a trade, which in turn will cause a return of zero. Thus, the logic behind the Zero measure is that the price of an illiquid stock with higher transaction costs will move less frequently on average and have more days of zero returns compared to more liquid stocks with lower transaction costs. We use Zero as a second proxy for liquidity in our robustness specifications.

### 5.2.3 Amihud

Another widely used proxy for liquidity is the Amihud measure developed by Amihud (2002). The measure effectively captures liquidity aspects related to price impact and is thus primarily a measure of market breadth[9]. Specifically, price impact refers to the stock price decrease that follows a trader-initiated sell or the stock price increase that follows a trader-initiated buy [6]. The degree of price movements depends on the market's assessment of the information value of the trade. The Amihud measure is defined as

$$Amihud_t^i = \frac{1}{n}\sum_{j=1}^{n}\frac{1,000,000 * |R_{j,t}^i|}{Closing\ Price_{j,t}^i * Volume_{j,t}^i} \tag{20}$$

where $R_{j,t}^i$ is firm $i$'s stock return on day $j$ in week $t$ and $Closing\ Price_{j,t}^i * Volume_{j,t}^i$ is the dollar volume on day $j$ in week $t$ for firm $i$. Thus, Amihud can be interpreted as the stock price impact per dollar of trading volume. The logic behind the measure stems from Amihud & Mendelson (1986) who find that less liquid stocks on average carries an illiquidity premium in terms of excess spread-adjusted returns. Thus, Amihud exploits the positive relationship between return and illiquidity: a high return per dollar of trading volume is an indicator of stock illiquidity and vice versa. We use Amihud as a third proxy for liquidity in our robustness specifications.

### 5.2.4 Market Capitalization

Market capitalization has also been used as a proxy for liquidity in previous literature. Amihud (2002) argues that firm size and liquidity are positively related since price impacts and quoted spreads are smaller for stocks with a large market capitalization. Banz (1981), Reinganum (1981) and Fama & French (1992) also find that expected stock returns on average are lower for larger sized firms. This evidence supports the notion that firm size and liquidity are positively related, as the returns-illiquidity relationship is positive[10]. Market capitalization is primarily as measure of depth and breadth and is calculated as

$$Market\ Capitalization_t^i = \frac{1}{n}\sum_{i=1}^{n} Stock\ Volume_{j,t}^i * Closing\ Price_{j,t}^i \tag{21}$$

where $n$ is the number of trading days during a week. We use market capitalization as a fourth proxy for liquidity in our robustness specifications.

[9] See Goyenko, Holden & Trzcinka (2009)

[10] See section 5.2.4

## 5.3 Potential Measure Issues

Considering the elusiveness and complexity of liquidity, a word of caution concerning our liquidity measures is necessary at this point. As previously stated, no single measure will be able to capture all the underpinnings of liquidity and every measure carries certain pros and cons. The quoted spread is appealing in the sense that it is easy to calculate and in theory is supposed to capture several types of transaction costs. As described in section 5.2.2, however, trades do regularly occur within the quoted spread. A potential issue is therefore that the quoted spread will be a biased proxy for liquidity, as it will consistently understate the level of liquidity in the market. In this regard, Zero is is a more suitable proxy for liquidity, as it is supposed to capture the effective spread.

Zero is also appealing for its simplicity and accuracy; GHT find that the average monthly time-series correlation based on an equally weighted portfolio over 156 months between Zero and the effective spread is 0.874. Similar studies have shown that Zero is a more accurate measure compared to peer proxies for liquidity [21]. However, GHT also find that Zero performs somewhat worse compared to other liquidity proxies in the cross-section; they estimate the average cross-sectional correlation based on individual firms between Zero and the effective spread to be 0.427. Furthermore, the sample period in GHT stretches from 1993-2005 and it is therefore unclear whether the high correlation exists today. Another potential issue with Zero that is specifically related to our analysis is that we are more likely to observe nonzero returns for all days in our estimation periods, as our analysis is based on firm-weeks rather than firm-months and firm-years as in Lesmond, Ogden & Trzcinka (1999). This may result in a relatively low variable variation which in turn could cause more unreliable regression estimates.

Amihud has the advantage of being a widely recognized and credible proxy for price impact. However, research indicates that Amihud has more merit over longer time horizons. For instance, GHT show that monthly cross-sectional correlation between Amihud and a 5-minute price impact benchmark is only 0.516 (although the correlation is still higher than all other measures tested against this benchmark). Finally, although firm size does have some theoretical merit as a proxy for liquidity, it is arguably a very rough proxy that fails to capture several important aspects of liquidity.

# 6 Methodology

In this section, we describe the methodology used in our empirical tests. We begin by describing the regression specifications used to confirm the O/S results in JS and the then turn to our primary tests where we incorporate the quoted spread into our specifications. Next, we present our robustness tests where we include Zero, Amihud and market capitalization as alternative proxies for liquidity. Finally, we introduce the methodology used to construct our trading strategy, with the purpose of quantifying the economic significance of our findings.

## 6.1 Verification of the O/S and Future Returns Relationship

We begin by verifying the negative relationship between O/S and future returns. The verification serves the purpose of being a natural benchmark in our further empirical analysis. Additionally, it is of interest to examine whether the return predictability has decreased since JS's findings, following a general increase in market efficiency. Similarly to JS, we transform O/S into deciles and estimate the following regression for decile 1 and 10:

$$r^p_{t+1} - r^f_{t+1} = \alpha^p_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} + \epsilon_{t+1} \quad (22)$$

where $r^p_{t+1}$ is the next week return of an equally weighted portfolio of stocks for each of the respective O/S deciles. The risk free rate for the corresponding week is denoted $r^f_{t+1}$ and the market return is denoted $r^{mkt}_{t+1}$. We additionally control for the Fama-French-Carhart factors, where $HML_{t+1}$, $SMB_{t+1}$ and $UMD_{t+1}$ corresponds to the weekly returns of high [book-to-market-ratio] minus low, small [market capitalization] minus big, and high [momentum] minus low strategy portfolios, respectively.

We additionally estimate a version of (22) where we include O/S Decile as an explanatory variable rather than estimating four-factor alphas for O/S Decile 1 and 10 separately. Thus we regress

$$r^i_{t+1} - r^f_{t+1} = \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} + O/S\ Decile^i_t + \epsilon_{t+1} \quad (23)$$

where $O/S\ Decile^i_t$ is the decile transformed counterpart to $O/S^i_t$, and the remaining variables are defined as in (22).

We also include a specification that is similar to (23), but where we use O/S rather than O/S Decile as one of the explanatory variables. As theory suggests a negative relationship between O/S and future returns, we expect O/S to have a negative and significant sign. Similarly, we also expect the O/S Decile coefficient estimate in (23) to be negative, and the four-factor alpha of O/S Decile 10 to be smaller than the corresponding alpha of O/S Decile 1 in (22).

## 6.2 Main Tests

Next we turn to our main test, investigating the relationship between O/S, liquidity and return predictability. We use the quoted spread as a proxy for liquidity in our main tests and estimate a pooled OLS regression where we include an interaction term between the quoted spread and O/S. Specifically, we estimate the following regression specification:

$$\begin{aligned} r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\ &+ \beta_5 Quoted\ Spread^i_t + \beta_6 O/S^i_t + \beta_7 O/S * Quoted\ Spread^i_t + \epsilon_{t+1} \end{aligned} \tag{24}$$

where $Quoted\ Spread^i_t$ is the average quoted spread for stock $i$ during week $t$, $O/S^i_t$ is the option to stock volume ratio for stock $i$ during week $t$, and $O/S * Quoted\ Spread^i_t$ is the interaction between $O/S^i_t$ and $Quoted\ Spread^i_t$. Remaining variables are defined as in (23). We choose to make use of an interaction term to test our hypothesis as the interaction term will be able to capture how the predictive power of O/S is dependent on stock liquidity. As the predictions of our model suggest that O/S is more strongly negatively correlated with future returns when stock liquidity levels are low, we expect that the coefficient estimate of the interaction term will be negative and significant. To see this, note that the quoted spread and stock liquidity is negatively related, meaning that a large quoted spread is an indicator of low stock liquidity. For interpretation purposes and as a check for robustness, we have also included a specification with decile transformed variables:

$$\begin{aligned} r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\ &+ \beta_5 Quoted\ Spread\ Decile^i_t + \beta_6 O/S\ Decile^i_t \\ &+ \beta_7 O/S\ Decile * Quoted\ Spread\ Decile^i_t + \epsilon_{t+1} \end{aligned} \tag{25}$$

where $Quoted\ Spread\ Decile^i_t$ is the decile transformed quoted spread for stock $i$ during week $t$, $O/S\ Decile^i_t$ is the decile transformed O/S ratio for stock $i$ during week $t$, and $O/S\ Decile * Quoted\ Spread\ Decile^i_t$ is interaction between the decile transformed $O/S^i_t$ and $Quoted\ Spread^i_t$ variables. Again, remaining variables are defined as in (23) and we expect the coefficient estimate of the interaction term to be negative and significant.

We additionally estimate one regression setup where the interaction term has been replaced by a dummy variable that indicates in which quoted spread decile and O/S decile the stock is during any given week. This, again, makes the interpretation somewhat easier and also serves as a robustness check of the previous regressions. The regression specification with the dummy variable is

$$\begin{aligned} r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\ &+ \beta_5 Quoted\ Spread\ Decile^i_t + \beta_6 O/S\ Decile^i_t + \beta_7 Dummy\ 1^i_t + \epsilon_{t+1} \end{aligned} \tag{26}$$

where the dummy variable is defined as

$$Dummy\ 1 = \begin{cases} 1 & \text{if } O/S\ Decile{=}10 \text{ and } Quoted\ Spread\ Decile{=}10 \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

Thus, the dummy variable captures the combination of a high O/S ratio and low stock liquidity, meaning that its coefficient estimate should be negative and significant if the prediction of our model holds true. Finally, we estimated variants of specification (24) through (26) where we additionally control for firm and year fixed effects. The fixed effect variant of (24) is specified as

$$\begin{aligned} r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\ &+ \beta_5 Quoted\ Spread^i_t + \beta_6 O/S^i_t + \beta_7 O/S * Quoted\ Spread^i_t + Y_t + X_i + \epsilon_{t+1} \end{aligned} \tag{28}$$

where $Y_t$ captures the year fixed effects, and $X_i$ captures the firm fixed effects. The fixed effects versions of (25) and (26) are similarly defined. By utilizing the fixed effects technique, we are able to control for practically every firm and year characteristic. This gets us closer to the statistical certainty of randomized experiments, and we are more likely to be able to make a causal inference with regards to the effect of liquidity and O/S on future returns.

## 6.3 Robustness Tests

In this section, we describe the part of our analysis that includes Zero, Amihud and market capitalization as alternative proxies for stock liquidity. This analysis is an integral part of our study for two reasons. First, as these measures capture different characteristics of liquidity, we find it interesting to investigate whether stock return predictability differs depending on the underlying measure. Second, the alternative measures serve as robustness checks and ensures the validity of our findings. As additional tests for robustness, we include separate specifications where year and firm fixed effects are controlled for.

First, we use Zero as a proxy for liquidity and estimate the corresponding regression to (24):

$$
\begin{aligned}
r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} + \beta_5 Zero^i_t \\
&+ \beta_6 O/S^i_t + \beta_7 O/S * Zero^i_t + \epsilon_{t+1}
\end{aligned}
\tag{29}
$$

where $Zero^i_t$ is defined as in (19), $O/S * Zero^i_t$ is the interaction between $O/S^i_t$ and $Zero^i_t$, and the remaining variables are defined as in (24).

We additionally estimate regression specifications with Zero that corresponds to (25) and (26) where $Zero^i_t$ and $O/S^i_t$ have been replaced by their decile transformed counterparts. Thus, we include the interaction term $O/S\ Decile^i_t * Zero\ Decile^i_t$, and a dummy variable that indicates whether or not a stock is in both the 10th O/S decile and the 10th Zero decile during any given week. As both a high quoted spread and a high Zero are indicators of stock illiquidity, we expect that the interaction terms and the dummy variable will be negative and significant, just as in specification (24) through (26).

Second, we use Amihud as a proxy for liquidity and estimate the corresponding regression to (24):

$$
\begin{aligned}
r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} + \beta_5 Amihud^i_t \\
&+ \beta_6 O/S^i_t + \beta_7 O/S * Amihud^i_t + \epsilon_{t+1}
\end{aligned}
\tag{30}
$$

where $Amihud^i_t$ is defined as in (20), $O/S * Amihud^i_t$ is the interaction between $O/S^i_t$ and $Amihud^i_t$, and the remaining variables are defined as in (24). As with Zero, we also include the Amihud counterpart to specification (25) and (26), where $Amihud^i_t$ and $O/S^i_t$ have been decile transformed. Thus, we include a specification based on the interaction between the decile transformed variables and a specification including a dummy variable that equals 1 if the stock is in both the 10th O/S decile and the 10th Amihud decile. Amihud has a similar interpretation as the quoted spread and Zero, meaning that we expect the coefficient estimates of the interaction terms and the dummy variable to be negative and significant.

Third, we use market capitalization as a proxy for liquidity and estimate a regression specification that is similar to (25):

$$
\begin{aligned}
r^i_{t+1} - r^f_{t+1} =& \alpha^i_{t+1} + \beta_1(r^{mkt}_{t+1} - r^f_{t+1}) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\
&+ \beta_5 Inv.\ Market\ Cap.\ Quartile^i_t + \beta_6 O/S\ Decile^i_t \\
&+ \beta_7 O/S\ Decile * Inv.\ Market\ Cap.\ Quartile^i_t + \epsilon_{t+1}
\end{aligned}
\tag{31}
$$

where $Inv.\ Market\ Cap.\ Quartile_t^i$ is the inverse of the quartile transformed market capitalization for firm i during week t, $O/S * Inv.\ Market\ Cap.\ Quartile_t^i$ is the interaction term that is supposed to capture the way in which $O/S_t^i$'s predictive power is dependent on liquidity. Market capitalization is defined as in (21) and remaining variables are defined as in (25). We also estimate a regression where the interaction term has been substituted for a dummy that is defined correspondingly to (27). Notice that the market capitalization quartiles have been inversed, so that firms in the higher quartiles are less liquid as they have a lower market capitalization and vice versa. In other words, the interpretation of the interaction term and the dummy variable is consistent with previous specifications and we thus expect the coefficient estimates to be negative and significant.

Finally, we also estimate fixed effects variants of most of our regression specifications where Amihud and market capitalization are used as proxies for liquidity. Due to the low variation in Zero[11], we have chosen not to include it in the fixed effects regressions as the within firm Zero variation would become even lower, resulting in unreliable estimates. The fixed effects specifications are defined correspondingly to (28).

## 6.4 Trading Strategy

We additionally investigate whether our empirical findings can be used to construct a self-financing trading strategy that is able to generate abnormal returns by exploiting the relationship between O/S, stock liquidity and future returns. This investigation includes a comparison to a trading strategy solely based on O/S (hereafter O/S strategy) and serves two main purposes. First, it provides evidence on the economic significance of our empirical results, which is especially important considering that the coefficient estimates of the interaction terms and dummy variables in our regression specifications cannot be naturally interpreted. Second, a comparison to the O/S strategy emphasizes the incremental return predictability attributable to stock liquidity and thus highlights the relevance of our empirical findings in relation to those in JS. Our trading strategy (hereafter liquidity strategy) is based on the interaction term

$$O/S_t^i * Quoted\ Spread_t^i \tag{32}$$

and the portfolio is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile. This equally weighted portfolio

[11] See section 5.4

is rebalanced weekly and generates weekly returns of

$$r_t^{Liq.} = \frac{1}{n_1}\sum_{i=1}^{n_1} r_{i,t}^1 - \frac{1}{n_{20}}\sum_{j=1}^{n_{20}} r_{j,t}^{20} \tag{33}$$

where $n_1$ and $n_{20}$ are the number of stocks in vigintile 1 and vigintile 20, respectively, $r_{i,t}^1$ is the weekly return on each of the $i$ stocks in vigintile 1 during week $t$, and $r_{j,t}^{20}$ is the return during week t for each of the $j$ stocks in vigintile 20.

We regress the weekly returns minus the risk free rate of our portfolio on the market risk premium during the corresponding week in order to capture weekly portfolio alphas. We also run a second regression where controls for Fama-French-Carhart factors are included. Thus, the regression specifications are

$$r_{t+1}^{Liq.} - r_{t+1}^f = \alpha_{t+1}^{Liq.} + \beta_1(r_{t+1}^{mkt} - r_{t+1}^f) + \epsilon_{t+1} \tag{34}$$

and

$$r_{t+1}^{Liq.} - r_{t+1}^f = \alpha_{t+1}^{Liq.} + \beta_1(r_{t+1}^{mkt} - r_{t+1}^f) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} + \epsilon_{t+1} \tag{35}$$

where $r_t^{Liq.} - r_t^f$ is the weekly portfolio return over the risk free rate, $(r_t^{mkt} - r_t^f)$ is the weekly market risk premium, and $HML_t$, $SMB_t$ and $UMD_t$ are the Fama-French-Carhart factors high-minus-low, small-minus-big, and momentum.

Next, we compare the portfolio returns from the liquidity strategy to the returns from an O/S strategy that is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of O/S. Thus, we estimate the corresponding regressions to (34) and (35) with O/S strategy returns as the dependent variable and compare the alpha of both portfolios. As an alternative comparison test, we estimate a variant of regression (35) where we include a fifth factor that controls for the excess returns from the O/S strategy:

$$\begin{aligned} r_{t+1}^{Liq.} - r_{t+1}^f = & \alpha_{t+1}^{Liq.} + \beta_1(r_{t+1}^{mkt} - r_{t+1}^f) + \beta_2 HML_{t+1} + \beta_3 SMB_{t+1} + \beta_4 UMD_{t+1} \\ & + \beta_5(R_{t+1}^{O/S} - r_{t+1}^f) + \epsilon_{t+1} \end{aligned} \tag{36}$$

where $R_{t+1}^{O/S} - r_{t+1}^f$ is the excess return of the O/S strategy during week t+1, and the remaining variable are defined as in (35). If the liquidity strategy is superior to the O/S strategy in terms of generating abnormal returns, the constant (alpha) should be positive and significant.

Finally, we test the persistence of the liquidity strategy by regressing weekly returns up to 12 weeks after the observation of O/S and quoted spread on the market risk premium and Fama-French-Carhart factors. In this way, we obtain weekly strategy alphas on the 12 weeks following each O/S and quoted spread observation. We expect that the information content in O/S will be incorporated relatively quickly into stock prices and similarly that informed investors will quickly eliminate arbitrage opportunities related to mispricing, causing the strategy's persistence to be short lived.

# 7 Empirical Results

The following section describes the results of the empirical tests concerning the linkage between O/S, liquidity and stock return predictability. We begin by showing descriptive statistics of the main variables used in our empirical tests. Next, we turn to the empirical results of our main tests and of our robustness specifications as outlined is section 6. Finally, we present the results of our trading strategy and illustrate the economic significance of our empirical results.

## 7.1 Descriptive Statistics

Table 1 presents time-series averages of the cross-sectional statistics for the main variables in our final dataset. The average O/S ratio is about 4.9%, implying that stock trading volume is about 20 times larger than option trading volume in our sample. Calls are generally more liquid than puts and call volume comprises roughly 62% of total option volume in our dataset. Weekly stock trading volume varies considerably among firms, with a mean of approximately 15.1 million traded stocks and with a minimum and maximum of 0 and 6,550 million, respectively. The average quoted spread is 4.2% and the average Zero is 1.6%. Finally, the data consist of both small and large firms in terms of market capitalization, with an average market cap of roughly USD 12 million and a minimum and maximum market cap of USD 3 million and USD 657 billion, respectively.

Table 2 shows yearly mean statistics for our key variables. Both stock and option trading volume increased considerably in 1996-2009, but have decreased in the wake of the most recent financial crisis. The average O/S ratio has increased slightly in recent years, peaking in 2013 at 6.25%. Table 2 also shows that the average quoted spread, Zero and Amihud overall increased considerably during 1996-2013, indicating a gradual increase in stock liquidity and market efficiency. Also note that quoted spreads, Zero and Amihud are fairly volatile across the years. The average quoted spread reached a low of 2.9% in 2013 and peaked at a high of 7.1% following the tech bubble burst in 2000. Amihud correlates to a large extent with the quoted spread, peaking in times of financial instability (2000, 2008) and when stock trading in terms of volume is relatively low (1996-1999). Interestingly, the relationship between Zero and the quoted spread appears to be negative, as average Zero was at a high (1.3%) in 2013 and at a low (0.73%) during the crisis in 2008.

Panel A in Table 3 summarizes O/S as well as average liquidity and return characteristics for each O/S decile in our sample. First, notice that O/S has a wide dispersion, ranging from an average of roughly 0.28% in the lowest decile to 22.7% in the highest decile. Second, high O/S firms tend to both have a higher market capitalization and higher weekly option volume compared to low O/S firms. The average market capitalization of firms in O/S decile 10 is approximately 2.5 times larger compared to O/S decile 1. Mean option volume has a high dispersion, ranging from a low of 390 in decile 1 to a high of 37,316 in decile 10. Third, mean weekly stock volume has a fairly low dispersion across the O/S deciles, ranging from roughly 11.4 million in decile 2 to 19.6 million in decile 9. Forth, the liquidity proxies do not seem to correlate across the O/S deciles. The average quoted spread is fairly constant across all O/S deciles, while Zero is highest in the lowest decile and consistently diminishes up to the highest decile. In contrast, Amihud is lowest in the lowest O/S decile and gradually increases up to the highest decile. Finally, notice that average next week returns are lower for firms in the high O/S deciles compared to firms in the low O/S deciles. The average return in decile 10 is roughly 8 basis points, while the average return in decile 1 is 41 bp. This is consistent with the results in JS and the theoretical model presented in section 3.1, as a high O/S ratio is an indicator of negative private information and therefore should correlate negatively with future returns.

Panel B, C, D and E in Table 3 present next week return characteristics for the following four interaction term deciles: $O/S*Quoted\ Spread$, $O/S*Amihud$, $O/S*Inv.\ Market\ Cap.$ and $O/S*Zero$. As the quoted spread is our primary proxy for liquidity and the trading strategy is based on deciles of $O/S*Quoted\ Spread$, Panel B is of particular interest. As predicted by our model in section 3.2, Panel B indicates that future returns correlate negatively with $O/S*Quoted\ Spread$. Next week returns for firms in the lowest $O/S*Quoted\ Spread$ decile are roughly 26 bp on average, while they are only 6 bp on average for firms in the highest decile. Somewhat similar patterns can be observed in panel C and D. Firms in the lowest $O/S*Amihud$ decile earn an average next week return of approximately 19 bp, while the corresponding return for firms in the highest decile is 6 bp. Next week returns for firms in the lowest $O/S*Inv.\ Market\ Cap.$ decile is 23 bp on average and -3.5 bp in the highest decile. Notice, however, that the pattern in panel C and D is not as evident as in panel B. For instance, firms in $O/S*Amihud$ decile 9 on average experience returns that are 12 bp larger than firms in decile 1 and firms in $O/S*Inv.\ Market\ Cap.$ decile 8 earn average returns that are 13 bp larger than firms in decile 1. Finally, notice in Panel E that the variation in $O/S * Zero$ across firms in our sample is so small that only two deciles can be constructed. This potential issue with Zero was highlighted in section 5.4 and Table 4 additionally shows that the percentage of firms with a Zero of 0 is 92.74% and the cumulative percentage of firms with a Zero of $\leq 0.5$ is 99.94%. In contrast to our prediction and the statistics in Panel B-D, Panel E also reports that average returns for firms in the lowest $O/S * Zero$ decile on average are lower than firms in the highest decile. Firms in the lowest decile on average experience next week returns of 23 bp, compared to 35 bp for firms in the highest decile.

## 7.2 O/S and Future Returns

The descriptive statistics in Table 3 largely indicate that there is a negative relationship between O/S and future returns. We verify the relationship by running the pooled OLS regressions outlined in section 6.1. The results are reported in Table 5. Column 1 and 2 show results for the subsample including firms in O/S decile 1 and 10, respectively. First notice how the factor loadings on Fama-French-Carhart factors vary between O/S decile 1 and 10. Decile 1 has a statistically significant negative loading on the UMD factor, while decile 10 has an UMD factor loading that is not statistically different from zero. Decile 10 has negative and significant loading on the HML factor, while decile 1 have not. Both decilies have a positive and significant exposure to the SMB factor. Also, decile 1 seems to have a somewhat smaller market exposure compared to decile 10, as the average slope coefficient of the market risk factor for decile 1 and 10 is 1.147 and 1.290, respectively.

Second, we see that the constant (alpha) for firms in O/S decile 1 is positive (0.00205) and statistically significant (t-stat 6.06). The interpretation is that next week returns for firms in the lowest decile have a Fama-French-Carhart adjusted alpha of 20.5 bp on average, supporting JS conclusion that a O/S is negatively correlated to future returns. Third, notice that the constant for firms in O/S decile 10 has the opposite sign (-0.00174) and is statistically significant at the 0.1% level. Thus, firms in the highest O/S decile on average earn next week alphas of -17.4 bp. This is also consistent with the results in JS, as a high O/S is an indicator of negative private information. Finally, the effects in column 1 and 2 are also economically significant; a weekly alpha of 20.5 bp and -17.4 bp corresponds to an annual alpha of 11.24% and -8.66%, assuming annual compounding and 52 trading weeks.

Column 3 presents the result across all O/S deciles. As expected, the coefficient estimate for O/S decile is negative (0.000311) and statistically significant at the 0.1% level. The interpretation is that an increase by one O/S decile on average lowers next week return with

3.11 bp, corresponding to an annual rate of -1.62%. The result is thus consistent with the ones obtained in column 1 and 2 and is also arguably economically significant. Column 4 reports the result of the test where O/S is used as an explanatory variable. Again, the coefficient estimate is negative (-0.00660) and significant at all conventional levels. Note that the interpretation of O/S is somewhat different, as it is expressed as a percentage rather than divided into deciles. For instance, a ten percentage point increase in O/S corresponds to an average next week return of -6.6 bp, or -3.43% on an annual basis. Additionally, the results are qualitatively unchanged if we restrict the sample to only include later observations than those included in JS's empirical tests. We conclude that the results in JS are verified as all specifications in Table 5 support the negative relationship between O/S and future returns.

### 7.3 Main Results

Having confirmed the previously established linkage between O/S and future returns, we now turn to investigate return predictability conditioned on O/S and the quoted spread. An overview of the results is presented in Table 6, where we also have included the O/S decile result from column 3 in Table 5 as a benchmark. Column 2 shows the result of specification (24), where the interaction term is defined as $O/S * Quoted\ Spread$ and the control variables are O/S, Quoted Spread and Fama-French-Carhart factors. First, notice that the sign of the interaction term is negative (-0.464) and statistically significant at the 0.1% level. This result supports the prediction of our theoretical model that a high O/S combined with a low level of stock liquidity is a greater predictor of future returns than O/S alone. As previously mentioned, the coefficient estimate of the interaction term does not have a natural interpretation, but its negative sign indicates that informed investors indeed are able to detect and take advantage of the higher frequency of mispricing on illiquid stocks. Also note that the interpretation of O/S is different compared to previous specifications as it is both included as a control variable and as a part of the interaction term. This explains why O/S has become positive in column 2. In fact, we find that an increase in O/S is correlated with a net decrease in future returns for illiquidity levels around, or higher than, the mean. However, as quoted spread approaches zero, the negative relationship between O/S and future returns diminishes which is consistent with our model predictions.

Column 3 presents the result from specification (25), where we have divided O/S and Quoted Spread into deciles and the interaction term is defined as $O/S\ Decile{*}Quoted\ Spread\ Decile$. Notice that the interaction term is negative (-0.000122) and significant with a t-stat of (-8.52). Additionally, column 4 shows the result of the regression setup in (26), where we have included a dummy variable that equals 1 if O/S decile=10 and Quoted Spread decile=10, and zero otherwise. The coefficient estimate of the dummy variable is negative (-0.00758) and significant at the 0.1% level. Both results in column 3 and 4 are therefore consistent with the predications of our model. Also notice that interaction term in all three specifications is negative and significant at the 0.1% level.

The result of the regression estimates where we have included additional controls for firm and year fixed effects is reported in Table 7. Overall, the results are qualitatively unchanged. The interaction term $O/S * Quoted\ Spread$ in column 1 is still significant at the 0.1% level and the coefficient estimate is even more negative (-0.616). Likewise, the coefficient of the interaction term $O/S\ Decile{*}Quoted\ Spread\ Decile$ in column 2 is more negative (-0.000159) and significant at the 0.1% level. The coefficient of the dummy variable is marginally smaller with firm and year fixed effects (-0.00733) but still significant at the 0.1% level.

## 7.4 Robustness Results

In this subsection, we present the results of our robustness tests where Zero, Amihud and market capitalization have been used as proxies for liquidity.

### 7.4.1 Zero

The results obtained from the regressions where Zero has been used as a proxy for liquidity is presented in Table 8. Notice that all three interaction terms in column 2-4 have negative coefficient estimates, but only the decile based interaction $Zero\ Decile{*}O/S\ Decile$ reported in column 3 is significant at the 10% level. In column 2, where $Zero * O/S$ has been used as an interaction term, the coefficient estimate is -0.0290 but not significant at any conventional levels (t-stat -1.25). Finally, column 4 shows the result of including the dummy variable that equals 1 if Zero Decile=10 and O/S Decile=10, and zero otherwise. We see that the negative coefficient estimate (-0.000860) of the dummy variable is not statistically significant (t-stat -0.48). Thus, the Zero results are somewhat mixed. Although the interaction terms and the dummy variable have the negative sign that our model predicts, only the decile based interaction term is statistically significant. The mixed results should be thought of in the context of the potential issues with Zero as described in section 5.4 and again highlighted in section 7.1 and Table 4.

### 7.4.2 Amihud

Next, we present the empirical results from the specifications where Amihud has been used as a proxy for liquidity. Column 2 in Table 9 shows the result from the specification in (30), where the relationship between O/S and stock liquidity is captured by the interaction term $O/S * Amihud$. Notice that the coefficient estimate of the interaction term is negative (-0.335) and statistically significant at the 1% level. The coefficient from the regression with decile transformed variables in column 3 where $O/S\ Decile * Amihud\ Decile$ has been used as an interaction term is also negative (-0.000147) and significant at the 0.1% level. Column 4 presents the result of the regression including a dummy variable and we see that the coefficient estimate is negative and significant at all conventional levels. Overall, the results of using Amihud as a proxy for liquidity are largely similar to those obtained when using the quoted spread, and in line with the predictions of our model. This holds true even after controlling for firm and year fixed effects, as is shown in column 1 and 2 in Table 11. The coefficient of the interaction term $O/S * Amihud$ in column 1 is more negative (-1.245) when controlling for fixed effects and significant at the 0.1% level. The coefficient of $O/S\ Decile * Amihud\ Decile$ is nearly identical (-0.000145) and significant at the 0.1% level.

### 7.4.3 Market Capitalization

The empirical results from including market capitalization as a proxy for liquidity is reported in Table 10. Column 2 presents the result from (31), where we have included the interaction term $Inv.\ Market\ Cap.\ Quartile * O/S\ Decile$. Remember that the market capitalization variable is inversed so that a high value is supposed to capture a low level of stock liquidity and vice versa. The coefficient estimate of the interaction term is negative (-0.000395) and significant at the 0.1% level. Similar results are obtained in column 3, where a dummy variable that equals 1 if Inv. Market Cap. Quartile=4 and O/S Decile=10, and zero otherwise, is included. The coefficient estimate of the dummy variable is -0.00628 and significant at the 0.1% level. The results are qualitatively unchanged if additional controls for firm and year fixed effects are included, as can be seen in column 3 and 4 in Table 11. Indeed, the results obtained from using market capitalization as a proxy for liquidity is similar to those obtained with the quoted spread and Amihud.

## 7.5 Trading Strategy

Having found statistically significant evidence that is consistent with the predictions of our theoretical model, we next turn to the argument that our empirical findings are of economic significance. Table 12 reports the results of our liquidity strategy that is based on the interaction term $O/S * Quoted\ Spread$ as well as the benchmarking O/S strategy. Column (1) and (2) show the O/S strategy's weekly alphas and exposures to the market and Fama-Franch-Carhart factors, respectively. In both columns, we notice a slight negative exposure to the market that is significant at the 10% level and 5% level, respectively. The O/S strategy has a negative loading of -0.129 on the small-minus-big portfolio that is significant at the 10% level, as well as a highly statistically significant negative exposure to the momentum portfolio with a coefficient estimate of -0.37. It has a positive exposure to the high-minus-low factor of 0.463 and this coefficient estimate is also significant at all conventional levels. With regards to the constant, which can be interpreted as the average weekly portfolio alpha, we notice an average weekly CAPM alpha of 0.484% and a four-factor alpha of 0.499% that are both statistically significant. Thus, we conclude that the O/S strategy generates abnormal returns that are both economic and statistically significant, which is consistent we the results obtained in Table 5.

In column (3) and (4) we present the corresponding results of the liquidity strategy. Notice that the strategy has a significantly more negative market exposure compared to the O/S strategy, with a CAPM beta of -0.703 and a four-factor market beta of -0.538. Additionally, we see in column (4) that the liquidity strategy has a more negative loading on the small-minus-big factor, and a more positive loading on the high-minus-low factor. It has has no statistically significant exposure to the momentum factor. Overall, the factor loadings imply that the liquidity strategy is on average long large value stocks and short smaller growth stocks. Also, the relatively large negative market exposure suggests that the liquidity strategy is more volatile compared to the O/S strategy. More importantly, the constants in column (3) and (4) indicate that the average weekly alpha generated by the liquidity strategy is higher than the corresponding alphas for the O/S strategy. The CAPM alpha and the four-factor alpha are 0.633% and 0.533%, respectively, and thus higher than the alphas of 0.484% and 0.499% in column (1) and (2). Column (5) presents the results of specification (36), where a fifth factor that controls for the excess returns generated by the O/S strategy is included. Interestingly, we see that the liquidity strategy generates an average weekly alpha of 0.184% that is significant at the 5% level even after controlling for this additional factor. The result thus indicates that there is in fact a significant difference between the alphas generated by the O/S based and liquidity based portfolios.

Figure 1 plots yearly liquidity strategy returns alongside the strategy's four-factor expected returns. Note that actual strategy returns are higher than the expected returns in every year except 2008, and on average the difference between actual- and expected returns is 22.41% per year. The figure clearly demonstrates the economic significance of our trading strategy and the strong predictability of the interaction term $O/S * Quoted\ Spread$. Figure 2 presents cumulative abnormal returns (CARs) of the liquidity strategy and the O/S strategy over a 10 year period stretching from 2002 to 2012. Both strategies generate substantial CARs over the ten year period, but we also notice that the liquidity strategy's CAR

(230.31%) exceeds the O/S strategy's CAR (169.61%) by approximately 61.05 percentage points at the end of the period. Notice that we have not accounted for trading costs in these calculations. However, this should not have a significant impact on the two strategies' relative CARs since both strategies are equally trading intensive.

Finally, we examine the longevity of the interaction term $O/S * Quoted\ Spread$'s predictive power. Figure 3 shows weekly four-factor alphas, including 95% confidence intervals, from the first 12 weeks following each O/S and quoted spread observation from week 0. Interestingly, we find that the interaction term is a relatively long term predictor of future returns, with statistically significant positive alphas at the 5% level for week 1, 2, 3 and 5. The weekly alpha for the 4th week is statistically positive at the 10% level. Furthermore, the alpha during the first week (0.533%) is considerably higher than the alphas in week 2 through 5, which average roughly 0.25%. In week 6 through 12 following the O/S and quoted spread observation, the strategy does not generate alphas that are statistically different from zero. Table 13 also reports the persistence of weekly four-factor alphas by each year in our sample. Notice that the predictive power has been rather consistent throughout the years, with a majority of positive four-factor alphas in week 1 through 5. Interestingly, the table also shows that four-factor alphas on average have been relatively large following the financial crisis in 2008.

# 8 Conclusion

This study sets out to investigate the dependency of O/S' relationship to future returns on stock illiquidity. Building on previous research on mispricing and liquidity, we extend the multimarket asymmetric information model originally developed by JS in order to explicitly account for the relationship between the presence of informed investors and stock liquidity. In doing so, we find an equilibrium in which O/S is negatively correlated with future returns, and where the predictive power of O/S is increasing in stock illiquidity. We provide empirical evidence that the predictions of our extended model hold true, as we find that the negative correlation between O/S and next week returns is heavily dependent on stock illiquidity. Specifically, the net effect on future returns of a change in O/S is more negative when a stock is illiquid. The results are highly significant when quoted spread, Amihud and market capitalization are used as proxies for stock liquidity, although Zero gives somewhat mixed results. The findings are robust across a variety of regression specifications and also after controlling for firm and year fixed effects.

We additionally construct a trading strategy based on our empirical results in order to quantify the economic significance of our findings. The strategy, which is based on O/S and stock liquidity, generates a weekly four-factor alpha of 0.533%, as well as cumulative abnormal returns that exceed those of a corresponding strategy based solely on O/S by 61.05 percentage points over a 10 year period stretching from 2002-2012. This suggests that the ability of informed investors to detect mispricing arising from low levels of liquidity in the stock market is of such magnitude that a combined measure of O/S and stock liquidity functions as a highly economically significant predictor of future returns. Additionally, we find that the return predictability is relatively long-lived with statistically significant alphas in the first five weeks after each O/S and liquidity observation, which implies that there is inertia with regard to the time it takes for the market to incorporate the information embedded in O/S and liquidity measures.

The findings in this study provide important insights to existing literature related to the O/S framework. The results in JS suggest that informed investors are able to profit on their private information and that they have a preference for trading on negative information in the options market, causing O/S to correlate negatively with future returns. We demonstrate that this ability is increasing when considering stocks that are less liquid and thus priced less efficiently, causing the stock return predictability of O/S to increase significantly in stock illiquidity. Hence, our results provide evidence of the underpinnings of the O/S framework and its critical linkage to stock liquidity. Our findings also contribute to the rather limited existing literature concerning the trading behavior of informed investors, as our results indicate that these investors are able to detect mispricing that arises from low levels of liquidity in the stock market and profit on the mispricing by taking positions in the options market. Finally, our findings support the notion that options have a significant role in the stock price discovery process. We are able to confirm the result in JS, suggesting that O/S is a strong predictor of future movements in the underlying stock. More importantly, our study highlights the benefits of incorporating signals from both the options market and the stock market when investigating the informational content in options. By explicitly integrating stock liquidity into the O/S framework, we demonstrate that option volumes contain even stronger signals about future stock prices compared to findings in previous literature.

We also want to emphasize the limitations of our findings and highlight interest areas for further research. First, as the data in OptionMetrics and CRSP solely covers US options and stocks, the study considers the US market in isolation. In order to provide further insights of the O/S framework and to validate the findings in our study, it would be of interest to investigate if our results are applicable in a setting where international markets are considered. Second, our empirical analysis covers a small sample of low-frequency liquidity proxies developed in previous academic literature. Hence, research integrating a wider variety and more sophisticated proxies into the O/S framework is necessary in order to further confirm the robustness of the O/S-liquidity relationship as well as draw additional conclusions about the relationship's underpinnings. For instance, research incorporating refined liquidity measures based on high-frequency intraday data from Rule 605 or TAQ may provide fruitful insights and also establish whether the return predictability of O/S and stock liquidity is prevalent over shorter horizons. Finally and more broadly, it would be of interest to investigate whether measures of stock liquidity could be successfully incorporated into other frameworks concerning the linkage between the trading patterns of informed investors and stock return predictability. As for the investigation in this paper, we conclude that the results indeed suggest that there is a significant relationship between O/S, liquidity and stock return predictability.

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# A Appendix

Table 1: Descriptive Statistics of Main Variables

Table 1 provides descriptive statistics of the main variables in our empirical tests. The sample consists of 802,103 firm-weeks and the estimation period spans from 1996 through 2013. Firms with less than 25 call and 25 put contracts traded during a week are excluded, as well as options that matures within five days of the trade date or more than thirty days after the trade date. In order to make put and call volume comparable to stock volume, puts and calls have been adjusted for that they are traded in units of 100 shares. Put volume, call volume, option volume and stock volume have also been scaled with a factor of 1,000. Market capitalization is reported in USD million.

| | count | mean | min | max | sd | skewness |
|---|---|---|---|---|---|---|
| $Put\ Volume_t^i$ | 802,103 | 311.4 | 2.500 | 189,414.8 | 1,523.0 | 28.64 |
| $Call\ Volume_t^i$ | 802,103 | 499.0 | 2.500 | 447,955.3 | 3,011.0 | 47.06 |
| $Option\ Volume_t^i$ | 802,103 | 810.4 | 5 | 462,348.1 | 4,136.5 | 31.70 |
| $Stock\ Volume_t^i$ | 802,103 | 15,095.2 | 0 | 6,549,953.5 | 51,762.2 | 39.70 |
| $Market\ Cap._t^i$ | 802,083 | 12,011.1 | 3.347 | 656,669 | 30,519.1 | 6.763 |
| $O/S_t^i$ | 802,083 | 0.0485 | 0.0000290 | 91.68 | 0.145 | 327.3 |
| $Quoted\ Spread_t^i$ | 802,083 | 0.0417 | 0.000310 | 0.509 | 0.0271 | 2.214 |
| $Zero_t^i$ | 802,103 | 0.0163 | 0 | 1 | 0.0609 | 4.131 |
| $Amihud_t^i$ | 802,082 | 0.00276 | 0 | 23.72 | 0.0365 | 493.8 |
| $O/S * Liquidity$ | 802,083 | 0.00193 | 0.000000386 | 3.471 | 0.00548 | 323.2 |
| $Zero * O/S$ | 802,083 | 0.000659 | 0 | 1.085 | 0.00552 | 49.09 |
| $Amihud * O/S$ | 802,082 | 0.000154 | 0 | 11.79 | 0.0134 | 852.3 |
| $Ret_t^i$ | 801,815 | 0.00272 | -0.985 | 11 | 0.0898 | 3.812 |
| $r_t^f$ | 802,103 | 0.000462 | 0 | 0.00132 | 0.000414 | 0.281 |
| $R_t^{Mkt}$ | 802,103 | 0.00127 | -0.151 | 0.152 | 0.0277 | -0.313 |
| $SMB_t$ | 802,103 | 0.000498 | -0.0913 | 0.0647 | 0.0140 | -0.408 |
| $HML_t$ | 802,103 | 0.000781 | -0.0688 | 0.115 | 0.0155 | 0.786 |
| $UMD_t$ | 802,103 | 0.000967 | -0.156 | 0.0838 | 0.0259 | -1.163 |
| $N$ | 802,103 | | | | | |

Table 2: Descriptive Statistics by Year

Table 2 reports yearly mean statistics of the main variables in our empirical tests. The sample consists of 802,103 firm-weeks and the estimation period spans from 1996 through 2013. Firms with less than 25 call and 25 put contracts traded during a week are excluded, as well as options that matures within five days of the trade date or more than thirty days after the trade date. In order to make put and call volume comparable to stock volume, puts and calls have been adjusted for that they are traded in units of 100 shares. Put volume, call volume, option volume and stock volume have also been scaled with a factor of 1,000. Market capitalization is reported in USD million.

| | Put Volume | Call Volume | Option Volume | Stock Volume | Market Cap. | O/S | Quoted Spread | Zero | Amihud |
|---|---|---|---|---|---|---|---|---|---|
| 1996 | 80.41 | 159.4 | 239.8 | 4,409.5 | 7,746.6 | 0.0490 | 0.0422 | 0.0778 | 0.00469 |
| 1997 | 100.4 | 194.0 | 294.4 | 5,016.0 | 9,096.1 | 0.0486 | 0.0421 | 0.0551 | 0.00453 |
| 1998 | 104.2 | 209.2 | 313.3 | 6,120.7 | 11,137.5 | 0.0433 | 0.0481 | 0.0370 | 0.00492 |
| 1999 | 116.7 | 263.3 | 380.0 | 7,783.7 | 14,106.1 | 0.0401 | 0.0531 | 0.0334 | 0.00443 |
| 2000 | 157.2 | 314.6 | 471.8 | 10,537.1 | 14,366.6 | 0.0370 | 0.0709 | 0.0248 | 0.00441 |
| 2001 | 205.7 | 306.3 | 512.0 | 14,768.2 | 13,430.3 | 0.0311 | 0.0591 | 0.0118 | 0.00391 |
| 2002 | 203.9 | 270.9 | 474.8 | 15,216.5 | 11,650.9 | 0.0297 | 0.0501 | 0.00849 | 0.00300 |
| 2003 | 195.7 | 328.1 | 523.8 | 13,818.4 | 11,549.5 | 0.0368 | 0.0353 | 0.0111 | 0.00226 |
| 2004 | 220.3 | 363.4 | 583.8 | 12,553.9 | 12,043.7 | 0.0445 | 0.0318 | 0.0115 | 0.00166 |
| 2005 | 230.1 | 401.7 | 631.8 | 12,229.0 | 12,494.2 | 0.0495 | 0.0287 | 0.0121 | 0.00143 |
| 2006 | 282.0 | 463.9 | 746.0 | 12,699.6 | 12,046.1 | 0.0564 | 0.0301 | 0.0109 | 0.00148 |
| 2007 | 354.4 | 523.1 | 877.5 | 14,582.6 | 12,616.2 | 0.0558 | 0.0324 | 0.00994 | 0.00193 |
| 2008 | 527.1 | 641.1 | 1,168.2 | 20,581.5 | 10,396.2 | 0.0502 | 0.0582 | 0.00731 | 0.00330 |
| 2009 | 530.2 | 814.8 | 1,345.0 | 24,554.1 | 8,919.0 | 0.0510 | 0.0469 | 0.00948 | 0.00280 |
| 2010 | 403.9 | 747.5 | 1,151.4 | 22,398.4 | 11,220.3 | 0.0527 | 0.0332 | 0.0112 | 0.00176 |
| 2011 | 428.1 | 728.5 | 1,156.6 | 19,209.0 | 12,074.8 | 0.0557 | 0.0367 | 0.00982 | 0.00258 |
| 2012 | 445.4 | 723.1 | 1,168.5 | 17,597.5 | 13,720.9 | 0.0589 | 0.0314 | 0.0119 | 0.00240 |
| 2013 | 444.7 | 706.5 | 1,151.2 | 15,918.4 | 15,327.7 | 0.0625 | 0.0286 | 0.0132 | 0.00190 |
| Total | 311.4 | 499.0 | 810.4 | 15,095.2 | 12,011.1 | 0.0485 | 0.0417 | 0.0163 | 0.00276 |
| $N$ | 802103 | | | | | | | | |

## Table 3: Descriptive Statistics by O/S and Interaction Deciles

Panel A in Table 3 reports mean statistics for our main variables by each O/S decile. Option volume has been adjusted for that puts and calls are traded in units of 100 shares. Option volume and stock volume have also been scaled with a factor of 1,000. Market capitalization is reported in USD million. Panel B, C and D present mean next week returns by each decile of the interaction variables ($O/S * Quoted\ Spread$), ($O/S * Amihud$) and (O/$S * Inv.\ Market\ Cap$), respectively. Panel E reports mean next week returns for decile 1 and decile 10 of the interaction variable (O/S*Zero).

Panel A: Summary Statistics by O/S Decile

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock Volume | 16,270.5 | 11,369.8 | 11,607.3 | 12,043.5 | 13,315.8 | 14,878.7 | 16,727.2 | 18,623.4 | 19,590.9 | 16,527.1 | 802,083 |
| Option Volume | 39.02 | 70.40 | 115.2 | 174.4 | 269.6 | 413.3 | 643.9 | 1,015.1 | 1,631.3 | 3,731.6 | 802,083 |
| O/S | 0.00275 | 0.00620 | 0.00992 | 0.0144 | 0.0202 | 0.0277 | 0.0383 | 0.0544 | 0.0836 | 0.227 | 802,083 |
| Quoted Spread | 0.0405 | 0.0412 | 0.0420 | 0.0425 | 0.0428 | 0.0427 | 0.0426 | 0.0419 | 0.0411 | 0.0392 | 802,083 |
| Amihud | 0.00185 | 0.00262 | 0.00271 | 0.00292 | 0.00296 | 0.00294 | 0.00283 | 0.00297 | 0.00263 | 0.00317 | 802,082 |
| Zero | 0.0184 | 0.0180 | 0.0177 | 0.0177 | 0.0170 | 0.0167 | 0.0160 | 0.0150 | 0.0138 | 0.0123 | 802,083 |
| Market Cap. | 7,510.6 | 7,218.6 | 7,860.8 | 8,730.4 | 10,005.0 | 11,794.4 | 14,110.0 | 16,615.1 | 18,105.5 | 18,158.1 | 802,083 |
| $Ret^i_{t+1}$ | 0.00413 | 0.00371 | 0.00312 | 0.00266 | 0.00225 | 0.00199 | 0.00133 | 0.00241 | 0.00208 | 0.000756 | 620,031 |

Panel B: Future Returns by $O/S * Quoted\ Spread\ Decile$

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Ret^i_{t+1}$ | 0.00259 | 0.00309 | 0.00322 | 0.00364 | 0.00271 | 0.00271 | 0.00211 | 0.00166 | 0.00162 | 0.000648 | 620,031 |

Panel C: Future Returns by $O/S * Amihud\ Decile$

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Ret^i_{t+1}$ | 0.00186 | 0.00209 | 0.00195 | 0.00260 | 0.00218 | 0.00277 | 0.00308 | 0.00285 | 0.00312 | 0.000645 | 620,030 |

Panel D: Future Returns by $O/S * Inv.\ Market\ Cap.\ Decile$

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Ret^i_{t+1}$ | 0.00229 | 0.00344 | 0.00214 | 0.00302 | 0.00170 | 0.00238 | 0.00262 | 0.00361 | 0.00229 | -0.000350 | 620,031 |

Panel E: Future Returns by $O/S * Zero\ Decile$

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| mean | 0.00225 | . | . | . | . | . | . | . | . | 0.0035 | 620,031 |

Table 4: Distribution of the Zero Variable

Table 4 shows the distribution of the liquidity proxy Zero.The sample consists of 802,103 firm-weeks and the estimation period spans from 1996 through 2013. Zero is defined as the proportion of days with zero returns in each firm-week. Shown are frequencies, percentages and cumulative percentages.

| Zero | Frequency | Percentage | Cumulative Percentage |
|---|---|---|---|
| 0 | 743,838 | 92.74 | 92.74 |
| 0.167 | 370 | 0.0461 | 92.78 |
| 0.200 | 47,026 | 5.863 | 98.64 |
| 0.250 | 6,098 | 0.760 | 99.41 |
| 0.333 | 77 | 0.00960 | 99.41 |
| 0.400 | 3,848 | 0.480 | 99.89 |
| 0.500 | 352 | 0.0439 | 99.94 |
| 0.600 | 417 | 0.0520 | 99.99 |
| 0.667 | 4 | 0.000499 | 99.99 |
| 0.750 | 34 | 0.00424 | 100.00 |
| 0.800 | 32 | 0.00399 | 100.00 |
| 1.000 | 7 | 0.000873 | 100 |
| Total | 802,103 | 100 | |
| $N$ | 802,103 | | |

Table 5: Regression Analysis - O/S Confirmation

Table 5 presents regression results for O/S. Column (1) and (2) show results for the subsample including firms in O/S decile 1 and O/S decile 10, respectively. Deciles are constructed at the end of each week and firms with the highest O/S are located in decile 10 and firms with the lowest O/S are located in decile 1. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.147*** | 1.290*** | 1.293*** | 1.293*** |
| | (67.29) | (83.47) | (262.86) | (262.85) |
| $SMB_{t+1}$ | 0.517*** | 0.489*** | 0.555*** | 0.555*** |
| | (15.84) | (16.49) | (59.00) | (59.03) |
| $HML_{t+1}$ | 0.0136 | -0.250*** | -0.271*** | -0.271*** |
| | (0.40) | (-8.72) | (-30.67) | (-30.69) |
| $UMD_{t+1}$ | -0.324*** | -0.0227 | -0.152*** | -0.152*** |
| | (-15.37) | (-1.35) | (-27.67) | (-27.66) |
| $O/S\ Decile_t^i$ | | | -0.000311*** | |
| | | | (-9.28) | |
| $O/S_t^i$ | | | | -0.00660*** |
| | | | | (-6.36) |
| Constant | 0.00205*** | -0.00174*** | 0.00212*** | 0.000653*** |
| | (6.06) | (-5.95) | (9.79) | (5.99) |
| Observations | 48,187 | 73,122 | 620,027 | 620,027 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Regression Analysis - Main Tests

Table 6 reports regression results for the specifications including O/S and Quoted Spread. Column (1) is identical to column (3) in Table 5 and serves as a benchmark. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.293*** | 1.293*** | 1.292*** | 1.293*** |
| | (262.86) | (262.45) | (262.44) | (262.46) |
| $SMB_{t+1}$ | 0.555*** | 0.555*** | 0.555*** | 0.555*** |
| | (59.00) | (59.00) | (59.07) | (59.02) |
| $HML_{t+1}$ | -0.271*** | -0.271*** | -0.272*** | -0.272*** |
| | (-30.67) | (-30.61) | (-30.74) | (-30.74) |
| $UMD_{t+1}$ | -0.152*** | -0.151*** | -0.152*** | -0.153*** |
| | (-27.67) | (-27.57) | (-27.70) | (-27.74) |
| $O/S\ Decile_t^i$ | -0.000311*** | | 0.000335*** | -0.000281*** |
| | (-9.28) | | (5.79) | (-8.51) |
| $Quoted\ Spread_t^i$ | | 0.0492*** | | |
| | | (5.54) | | |
| $O/S_t^i$ | | 0.00747** | | |
| | | (2.99) | | |
| $(O/S * Quoted\ Spread)_t^i$ | | -0.464*** | | |
| | | (-4.62) | | |
| $Quoted\ Spread\ Decile_t^i$ | | | 0.000701*** | 0.0000368 |
| | | | (7.64) | (0.93) |
| $(O/S\ Decile * Quoted\ Spread\ Decile)_t^i$ | | | -0.000122*** | |
| | | | (-8.52) | |
| $Dummy\ 1_t^i$ | | | | -0.00758*** |
| | | | | (-3.63) |
| Constant | 0.00212*** | -0.00114*** | -0.00157*** | 0.00180*** |
| | (9.79) | (-3.83) | (-4.37) | (7.62) |
| Observations | 620,027 | 620,027 | 620,027 | 620,027 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Firm and Year Fixed Effects Regressions - Quoted Spread

Table 7 presents results for the fixed effect regressions including O/S and Quoted Spread. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) |
|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.293*** | 1.293*** | 1.293*** |
| | (118.55) | (118.49) | (118.54) |
| $SMB_{t+1}$ | 0.559*** | 0.555*** | 0.554*** |
| | (31.37) | (31.21) | (31.16) |
| $HML_{t+1}$ | -0.257*** | -0.265*** | -0.265*** |
| | (-10.39) | (-10.73) | (-10.74) |
| $UMD_{t+1}$ | -0.145*** | -0.150*** | -0.150*** |
| | (-15.32) | (-15.68) | (-15.71) |
| $Quoted\ Spread_t^i$ | 0.124*** | | |
| | (11.74) | | |
| $O/S_t^i$ | 0.00663* | | |
| | (2.38) | | |
| $(O/S * Quoted\ Spread)_t^i$ | -0.616*** | | |
| | (-5.15) | | |
| $Quoted\ Spread\ Decile_t^i$ | | 0.00118*** | 0.000297*** |
| | | (11.91) | (6.00) |
| $(O/S\ Decile * Quoted\ Spread\ Decile)_t^i$ | | -0.000159*** | |
| | | (-10.56) | |
| $Dummy\ 1_t^i$ | | | -0.00733*** |
| | | | (-3.31) |
| Observations | 620,027 | 620,027 | 620,027 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Robustness Tests - Alternative Liquidity Measures, pt. 1

Table 8 reports regression results for the specifications including O/S and Zero. Column (1) is identical to column (3) in Table 5 and serves as a benchmark. Zero is defined as the proportion of days with zero returns in each firm-week. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.293*** | 1.293*** | 1.293*** | 1.293*** |
| | (262.86) | (262.87) | (262.87) | (262.87) |
| $SMB_{t+1}$ | 0.555*** | 0.555*** | 0.555*** | 0.555*** |
| | (59.00) | (59.05) | (59.01) | (59.01) |
| $HML_{t+1}$ | -0.271*** | -0.272*** | -0.271*** | -0.271*** |
| | (-30.67) | (-30.70) | (-30.68) | (-30.68) |
| $UMD_{t+1}$ | -0.152*** | -0.153*** | -0.152*** | -0.152*** |
| | (-27.67) | (-27.68) | (-27.68) | (-27.68) |
| $O/S\ Decile^i_t$ | -0.000311*** | | -0.000260*** | -0.000306*** |
| | (-9.28) | | (-6.23) | (-9.10) |
| $Zero^i_t$ | | 0.00683** | | |
| | | (3.10) | | |
| $O/S^i_t$ | | -0.00628*** | | |
| | | (-5.95) | | |
| $(Zero * O/S)^i_t$ | | -0.0290 | | |
| | | (-1.25) | | |
| $Zero\ Decile^i_t$ | | | 0.000256* | 0.0000952 |
| | | | (2.40) | (1.91) |
| $(Zero\ Decile * O/S\ Decile)^i_t$ | | | -0.0000307 | |
| | | | (-1.72) | |
| $Dummy\ 2^i_t$ | | | | -0.000860 |
| | | | | (-0.48) |
| Constant | 0.00212*** | 0.000558*** | 0.00170*** | 0.00194*** |
| | (9.79) | (4.99) | (6.35) | (8.40) |
| Observations | 620,027 | 620,027 | 620,027 | 620,027 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Robustness Tests - Alternative Liquidity Measures, pt. 2

Table 9 presents regression results for the specifications including O/S and Amihud. Column (1) is identical to column (3) in Table 5 and serves as a benchmark. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.294*** | 1.293*** | 1.293*** | 1.294*** |
| | (262.84) | (262.90) | (262.93) | (262.89) |
| $SMB_{t+1}$ | 0.554*** | 0.555*** | 0.555*** | 0.555*** |
| | (58.96) | (59.03) | (58.99) | (58.97) |
| $HML_{t+1}$ | -0.271*** | -0.270*** | -0.270*** | -0.271*** |
| | (-30.62) | (-30.59) | (-30.59) | (-30.62) |
| $UMD_{t+1}$ | -0.152*** | -0.151*** | -0.151*** | -0.152*** |
| | (-27.56) | (-27.50) | (-27.47) | (-27.55) |
| $O/S\ Decile_t^i$ | -0.000309*** | | 0.000417*** | -0.000264*** |
| | (-9.22) | | (7.07) | (-7.92) |
| $Amihud_t^i$ | | 0.181** | | |
| | | (2.96) | | |
| $O/S_t^i$ | | -0.00619*** | | |
| | | (-5.97) | | |
| $(Amihud * O/S)_t^i$ | | -0.335** | | |
| | | (-2.71) | | |
| $Amihud\ Decile_t^i$ | | | 0.000987*** | 0.000133*** |
| | | | (9.87) | (3.30) |
| $(Amihud\ Decile * O/S\ Decile)_t^i$ | | | -0.000147*** | |
| | | | (-9.84) | |
| $Dummy\ 3_t^i$ | | | | -0.00830*** |
| | | | | (-4.58) |
| Constant | 0.00213*** | 0.000368** | -0.00286*** | 0.00126*** |
| | (9.84) | (2.71) | (-7.07) | (4.85) |
| Observations | 620,027 | 620,026 | 620,026 | 620,026 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Robustness Tests - Alternative Liquidity Measures, pt. 3

Table 10 reports regression results for the specifications including O/S and market capitalization. Column (1) is identical to column (3) in Table 5 and serves as a benchmark. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) |
|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.293*** | 1.293*** | 1.293*** |
| | (262.86) | (262.94) | (262.91) |
| $SMB_{t+1}$ | 0.555*** | 0.555*** | 0.555*** |
| | (59.00) | (59.00) | (59.00) |
| $HML_{t+1}$ | -0.271*** | -0.271*** | -0.271*** |
| | (-30.67) | (-30.64) | (-30.67) |
| $UMD_{t+1}$ | -0.152*** | -0.152*** | -0.152*** |
| | (-27.67) | (-27.58) | (-27.65) |
| $O/S\ Decile^i_t$ | -0.000311*** | 0.000605*** | -0.000225*** |
| | (-9.28) | (8.71) | (-6.84) |
| $(Inv.\ Market\ Cap.\ Quartile^i_t$ | | 0.00256*** | 0.000399*** |
| | | (10.84) | (4.03) |
| $(Inv.\ Market\ Cap.\ Quartile * O/S\ Decile)^i_t$ | | -0.000395*** | |
| | | (-11.05) | |
| $Dummy\ 4^i_t$ | | | -0.00628*** |
| | | | (-6.53) |
| Constant | 0.00212*** | -0.00385*** | 0.000837** |
| | (9.79) | (-8.39) | (3.06) |
| Observations | 620,027 | 620,027 | 620,027 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Firm and Year Fixed Effects - Alternative Specifications

Table 11 presents results for the fixed effect regressions including O/S, Amihud and market capitalization. All specifications are regressed on the market risk premium as well as the Fama-French-Carhart factors SMB, HML and UMD. The sample period stretches from 1996 through 2013 and includes 620,027 observations.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_{M,t+1} - r_{f,t+1}$ | 1.293*** | 1.292*** | 1.292*** | 1.293*** |
| | (118.69) | (118.60) | (118.78) | (118.79) |
| $SMB_{t+1}$ | 0.554*** | 0.557*** | 0.555*** | 0.554*** |
| | (31.07) | (31.26) | (31.15) | (31.15) |
| $HML_{t+1}$ | -0.264*** | -0.257*** | -0.261*** | -0.262*** |
| | (-10.75) | (-10.45) | (-10.69) | (-10.71) |
| $UMD_{t+1}$ | -0.148*** | -0.145*** | -0.147*** | -0.147*** |
| | (-15.57) | (-15.25) | (-15.49) | (-15.53) |
| $Amihud_t^i$ | 0.635*** | | | |
| | (6.31) | | | |
| $O/S_t^i$ | -0.00899*** | | | |
| | (-6.86) | | | |
| $(Amihud * O/S)_t^i$ | -1.245*** | | | |
| | (-6.15) | | | |
| $Amihud\ Decile_t^i$ | | 0.00312*** | | |
| | | (25.75) | | |
| $O/S\ Decile_t^i$ | | 0.000309*** | 0.000643*** | -0.000353*** |
| | | (4.37) | (7.50) | (-8.62) |
| $(Amihud\ Decile * O/S\ Decile)_t^i$ | | -0.000145*** | | |
| | | (-8.43) | | |
| $(Inv.\ Market\ Cap.\ Quartile_t^i$ | | | 0.00903*** | 0.00662*** |
| | | | (28.36) | (29.48) |
| $(Inv.\ Market\ Cap.\ Quartile$ $*O/S\ Decile)_t^i$ | | | -0.000456*** | |
| | | | (-10.66) | |
| $Dummy\ 4_t^i$ | | | | -0.00614*** |
| | | | | (-5.44) |
| Observations | 620,026 | 620,026 | 620,027 | 620,027 |

$t$ statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 12: Trading Strategy - Weekly alphas

Table 12 reports weekly alphas for the liquidity strategy and the O/S strategy.The liquidity strategy is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of the interaction variable ($O/S *$ *Quoted Spread*). The O/S strategy is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of O/S. Column (1) and (2) shows weekly O/S strategy alphas and exposures to the market and Fama-Franch-Carhart factors, respectively. Column (3) and (4) present the corresponding results for the liquidity strategy. Column (5) shows weekly alpha for the liquidity strategy after controlling for excess returns generated by the O/S strategy.

| | $R^{O/S}_{t+1} - r^f_{t+1}$ | | $R^{Liquidity}_{t+1} - r^f_{t+1}$ | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $R_{M,t+1} - r_{f,t+1}$ | -0.0787 | -0.0848* | -0.703*** | -0.538*** | -0.479*** |
| | (-1.90) | (-2.15) | (-14.60) | (-12.40) | (-14.24) |
| $SMB_{t+1}$ | | -0.129 | | -0.790*** | -0.699*** |
| | | (-1.78) | | (-9.89) | (-11.31) |
| $HML_{t+1}$ | | 0.463*** | | 0.927*** | 0.603*** |
| | | (6.70) | | (12.18) | (9.99) |
| $UMD_{t+1}$ | | -0.370*** | | 0.0492 | 0.308*** |
| | | (-8.72) | | (1.05) | (8.17) |
| $R^{O/S}_{t+1} - r^f_{t+1}$ | | | | | 0.699*** |
| | | | | | (23.65) |
| Constant | 0.00484*** | 0.00499*** | 0.00633*** | 0.00533*** | 0.00184* |
| | (4.43) | (5.02) | (5.00) | (4.88) | (2.15) |
| Observations | 832 | 832 | 832 | 832 | 832 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Table 13: Weekly four-factor alphas

Table 13 reports the persistence of the liquidity strategy that is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of the interaction variable ($O/S * Quoted\ Spread$). Shown in Panel A are weekly four-factor alphas from the first 12 weeks following each O/S and quoted spread observation from week 0. The corresponding four-factor alphas are reported by year in Panel B. The sample period stretches from 1996 through 2013 and the weekly four-factor alphas are shown in percent.

Panel A: Weekly alpha relative to O/S and quoted spread observation

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 8 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weekly alpha | 0.533 | 0.325 | 0.286 | 0.217 | 0.286 | -0.0978 | -0.0738 | -0.0406 | 0.0767 | -0.174 | -0.0865 | -0.0622 |

Panel B: Weekly alpha relative to O/S and quoted spread observation per year

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1996 | -0.389 | -0.279 | -0.123 | -0.363 | -0.784 | -1.679 | -1.481 | -0.944 | -1.588 | -1.752 | -1.028 | -1.299 |
| 1997 | 0.696 | 0.432 | -0.228 | 0.276 | -0.541 | -0.603 | -1.235 | -1.143 | 0.287 | -1.734 | 0.0663 | 0.141 |
| 1998 | 0.753 | -0.239 | 0.313 | -0.0765 | 0.720 | -0.513 | -0.593 | -1.419 | -0.520 | 1.158 | -1.094 | 0.507 |
| 1999 | 1.290 | 0.812 | 1.068 | 0.651 | 1.253 | 0.619 | 0.224 | -0.317 | 0.0167 | 0.842 | -0.454 | -0.960 |
| 2000 | 0.172 | 0.605 | 0.981 | -1.019 | 0.466 | -1.196 | -0.601 | 0.626 | 1.004 | 0.0647 | -0.311 | -1.268 |
| 2001 | 0.443 | 0.378 | 0.285 | 2.277 | 0.424 | 0.0511 | 0.857 | -0.0606 | 0.467 | -1.168 | -0.0562 | -0.356 |
| 2002 | 0.472 | 0.125 | 0.396 | 0.512 | 0.00365 | -1.133 | -0.819 | -0.828 | -0.337 | -0.360 | -0.196 | -0.158 |
| 2003 | -0.0929 | 0.207 | -0.0306 | 0.156 | 0.333 | -0.00785 | -0.976 | -0.771 | -1.426 | -0.935 | -0.307 | -0.0597 |
| 2004 | 0.325 | -0.338 | -0.0973 | -0.566 | 0.692 | -0.630 | -0.524 | -0.285 | -0.0530 | 0.157 | 0.110 | -0.274 |
| 2005 | 0.509 | 0.544 | 0.160 | 0.325 | 0.284 | 0.696 | 0.0134 | 0.300 | -0.00791 | -0.0563 | -0.217 | 0.141 |
| 2006 | 0.328 | 0.257 | 0.479 | 0.127 | -0.102 | -0.0373 | -0.427 | -0.349 | -0.278 | -0.386 | -0.0535 | 0.285 |
| 2007 | 0.299 | 0.387 | 0.190 | -0.174 | 0.125 | -0.328 | -0.310 | -0.0134 | -0.327 | -0.187 | -0.248 | -0.0542 |
| 2008 | 0.0384 | -0.0148 | -0.149 | -0.528 | -0.113 | -0.0291 | 0.841 | 0.478 | 0.656 | 0.00951 | 0.0187 | -0.147 |
| 2009 | 0.583 | 0.345 | 0.329 | 0.406 | 0.512 | -0.133 | 0.267 | 0.780 | -0.0160 | 0.0584 | -0.259 | -0.00444 |
| 2010 | 0.840 | 0.701 | 0.315 | 0.303 | -0.186 | 0.223 | -0.0883 | 0.231 | -0.0737 | -0.0296 | 0.599 | -0.166 |
| 2011 | 0.873 | 0.693 | 0.547 | 0.588 | 0.411 | 0.457 | 0.387 | 0.488 | 0.405 | 0.231 | 0.549 | 0.897 |
| 2012 | 0.172 | 0.279 | 0.180 | 0.269 | 0.179 | 0.198 | 0.0572 | 0.269 | 0.148 | 0.0683 | 0.428 | 0.0689 |
| 2013 | 0.504 | 0.738 | 0.549 | 0.246 | 0.395 | 0.357 | 0.437 | 0.388 | 0.132 | 0.175 | -0.106 | -0.773 |
| $N$ | 865 | | | | | | | | | | | |

Figure 1: Yearly Strategy Returns and Expected Strategy Returns

Figure 1 illustrates yearly returns of the liquidity strategy as well as the strategy's four-factor expected returns. The strategy is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of the interaction variable ($O/S * Quoted\ Spread$). Returns are calculated as weekly compounded returns and shown in percent. The comparison period stretches from 1997 through 2012.

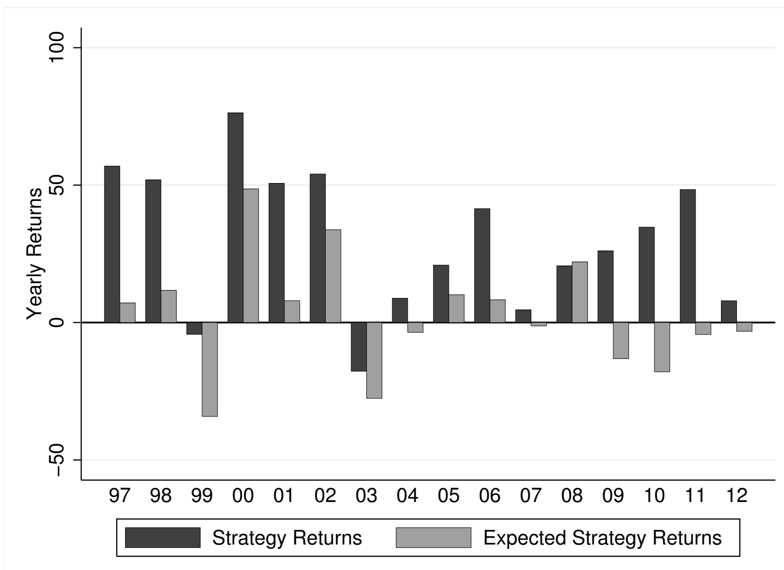

Figure 2: Cumulative Abnormal Returns for the Liqudity- and O/S Strategy

Figure 2 plots cumulative abnormal returns (CARs) for the liquidity strategy and for the O/S strategy. The liquidity strategy is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of the interaction variable ($O/S * Quoted\ Spread$). The O/S strategy is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of O/S. CAR is calculated as the sum of weekly abnormal returns and shown in percent. The comparison period stretches from 2002 through 2012.

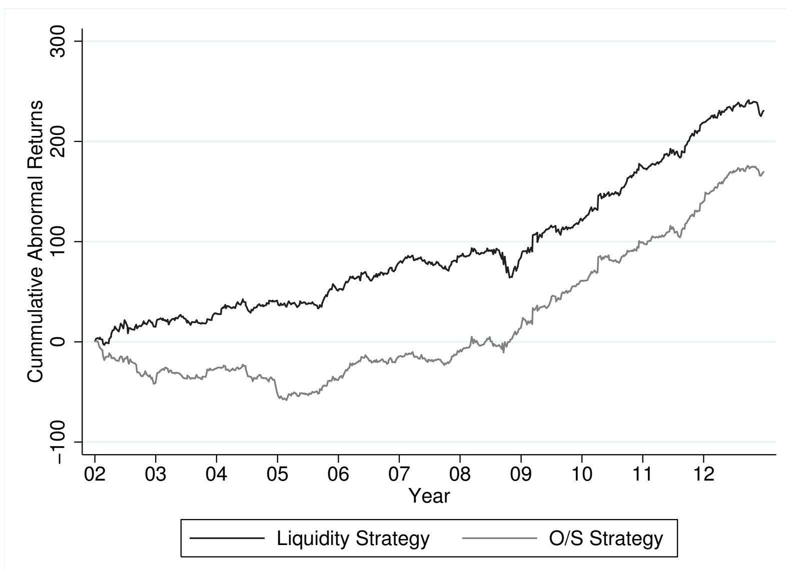

Figure 3: Weekly four-factor alphas

Figure 3 plots the persistence of the liquidity strategy that is long an equally weighted number of stocks in the 1st vigintile and short an equally weighted number of stocks in the 20th vigintile of the interaction variable ($O/S * Quoted\ Spread$). Shown are weekly four-factor alphas, including 95% confidence intervals, from the first 12 weeks following each O/S and quoted spread observation from week 0. Weekly four-factor alphas are shown in percent and the sample period stretches from 1996 through 2013.