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A Comprehensive Study of Liquidity before and after SEOs and SEO Underpricing

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A Comprehensive Study of Liquidity before and after SEOs and SEO Underpricing*

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Abstract

We comprehensively study various measures of liquidity of stock trading around SEOs and SEO underpricing, using a sample of 3,811 SEOs made from 1997 to 2012 and a matched non-SEO sample. We find that all measures of liquidity reduce significantly for the SEO firms after SEOs. Furthermore the magnitudes of reductions in transaction cost measures of liquidity are significantly associated with offer size, the change in stock price, and the change in volatility with expected signs. Most importantly, the magnitude of SEO underpricing is significantly and negatively related to the reductions in transaction cost measures of liquidity.

JEL Classification: G10

Keywords: Seasoned equity offerings (SEOs); SEO underpricing; Information asymmetry; Liquidity; Transaction cost

1. Introduction

Seasoned equity offerings (SEOs) are a popular approach for firms to raise additional equity capital.[1] The existing literature on SEOs has mainly explored three issues: (1) price phenomena around SEOs, (2) post-SEO underperformance, and (3) post-SEO risk reduction. The first issue includes two price phenomena around an SEO event. One phenomenon is the negative stock price response; that is, the stock prices of SEO firms tend to drop on the announcement day.[2] The other phenomenon is the underpricing; that is, SEO firms tend to price their new shares on the offer day below the closing price on the day before.[3]

The second issue is that SEO firms tend to underperform in the long run after the offer day.[4] Two major theories have emerged to explain the post-issue underperformance.[5] The first one is the market-timing theory, which refers to the practice of some firms of issuing shares when they are overvalued and repurchasing them when they are undervalued. According to Loughran and Ritter (1995), firms tend to issue equities when they are substantially overvalued, leading to poor long-run performance after SEOs. An extension

[1] Gao and Ritter (2010) categorize SEOs into fully marketed offers, accelerated offers, and rights offers. Fully marketed offers are traditional bookbuilt offers. Accelerated offers, including bought deals and accelerated bookbuilt offers, are usually shelf-registered offers. In rights offers, rights are issued to existing stockholders so that they can purchase additional shares. Before the late 1990s, the US equity market was dominated by fully marketed SEOs, while many Asian, European, and Australian SEOs were rights offers. Since the late 1990s, however, accelerated offers have gained popularity. In 2004, approximately half of the SEOs in the U.S. and more than a third of the SEOs in the rest of the world were accelerated SEOs.

[2] See, for example, Asquith and Mullins (1986), Masulis and Korwar (1986), Korajczyk, Lucas, and McDonald (1991), Lang and Lundholm (2000), and Lee and Masulis (2009).

[3] See, for example, Corwin (2003), Altinkilic and Hansen (2003), and Lee and Masulis (2009).

[4] See, for example, Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Loughran and Ritter (1997), Loughran and Ritter (2000), and Baker and Wurgler (2000).

[5] Other than the major theories, model misspecification may also help explain the underperformance. According to Brav, Geczy, and Gompers (2000), SEO returns underperform various characteristic-based benchmarks in event-time performance tests. However, the time-series factor models, which can price SEO portfolio returns, show that SEO returns covary with the returns of non-issuing firms.

of the market-timing theory, called the earnings management theory, can also explain the underperformance. The practice of earnings management inflates stock prices temporarily, causing overvaluation before SEOs and underperformance afterwards. Rangan (1998) and Teoh, Welch, and Wong (1998) document a negative relation between pre-offering abnormal accruals and post-offering abnormal stock returns. Jo and Kim (2007) find that firms with extensive disclosure are likely to engage in less earnings management and give better post-SEO performance.

The second major theory for long-term underperformance is the behavioral under- and over-reaction theory. Daniel, Hirshleifer, and Subrahmanyam (1998) argue that since investors are in general overconfident, they tend to overreact to private information signals and underreact to public information signals. Since SEOs are often initiated when stocks are overvalued by the market, they are associated with initial negative announcement date returns. Due to investor underreaction to public information, SEOs are normally followed by long-run post-announcement underperformance. Lee (1997) reports that growth firms experience significant deterioration in earnings performance after SEOs, but mature firms do not. The finding is consistent with the overvaluation hypothesis that managers issue equity securities when they expect significant decreases in the growth of their firms while investors are still optimistic about their growth potential.

The third issue explored in the SEO literature is that post-SEO risk reduction is largely consistent with post-SEO underperformance; that is, lower post-SEO stock returns (versus pre-SEO stock returns) are related to lower post-SEO risk (versus pre-SEO risk). Several types of risks have been examined: valuation uncertainty risk, systematic risk, investment risk, unexpected inflation and default risks, leverage risk, and liquidity risk. Carlson, Fisher, and Giammarino (2006) point out that equity issuance is associated with firm expansion. As firms grow, they issue new equity and then invest the proceeds in real assets. That is, they convert real options into assets in place. Since the new assets in place have less valuation uncertainty than the real options they replace, SEO firms' risks are reduced. Carlson, Fisher, and Giammarino (2010) further report that systematic risk (measured by beta) increases before SEOs and decreases gradually thereafter, which is in line with real options theory.

Lyandres, Sun, and Zhang (2008) argue that in the post-SEO period, SEO issuers invest more and face less investment risk than non-issuers. Therefore SEO firms earn lower returns. Eckbo, Masulis, and Norli (2000) observe that as equity issuers lower their leverage after SEOs, they become less exposed to unexpected inflation and default risks. Elliott, Prevost, and Rao (2009) find that bondholders make significant positive returns upon the announcement of an SEO, supporting the leverage risk reduction hypothesis. Eberhart and Siddique (2002) examine the long-term performance of bonds and stocks following their SEOs, and document higher bond returns than stock returns. They note that SEOs reduce default risk, and thus transfer wealth from shareholders to bondholders. Eckbo and Norli (2005) present evidence that SEO firms have significantly higher turnovers than their matched non-SEO firms; that is, they face lower liquidity risk after SEOs. Ginglinger, Matsoukis, and Riva (2013) investigate the impact of market liquidity on the choice of SEO flotation methods (public offerings vs. rights issues) in France. They find that market liquidity improves after SEOs, and it increases more after public offerings compared to rights offerings. Bilinski, Liu, and Strong (2012) examine U.S. firms during 1970-2009, and show that SEO firms experience significant post-issue improvements in liquidity and reductions in liquidity risk. After adjusting for liquidity risk, SEO firms show normal long-term performance.

Following the third strand of literature (i.e., the one on post-SEO risk reduction), this paper conducts a comprehensive investigation of the changes in information asymmetry, liquidity, and transaction costs around SEOs. It is a worthwhile endeavor since information asymmetry risk is associated with stock returns and the cost of capital (e.g., Easley, Hvidkjaer, and O'Hara (2002); Easley and O'Hara (2004)). In addition, recent studies have employed the theory of information asymmetry to analyze a number of SEO-related issues, including management guidance on earnings, management compensation, management quality, underwriters, dual-class firms, and dividend-paying firms.[6] Finally, it is well documented that liquidity and transaction costs are also associated with the cost of

[6] More specifically, Li and Zhuang (2012) show that management guidance on firms' future earnings and other financial information (i.e., voluntary disclosure) serves to alleviate information asymmetry around SEOs, thus reducing the magnitude of SEO underpricing. Datta, Iskandar-Datta, and Raman (2005) report a negative relation between the stock market's response to SEO announcements and the equity-based compensation of issuing firm managers. The market believes that managers with higher equity-based compensation tend to issue more overvalued equity, benefiting existing shareholders and exacerbating the adverse selection problem for potential shareholders. Chemmanur, Paeglis, and Simonyan (2010) report that higher quality managers are more credible to equity market investors, thereby reducing the information asymmetry between insiders and outsiders. SEO firms with higher management quality tend to have more reputable underwriters, smaller underwriting spreads, and lower SEO discounts. Luo, Rao, and Yue (2010) find that firms with a low degree of information risk tend to hire prestigious underwriters, based on SEOs in China. Chaudhuri and Seo (2012) demonstrate that returns around SEO announcement dates and long-run stock performance following SEOs are significantly related to measures of divergence between insiders' voting and cash flow rights, based on U.S. dual-class companies. This is because the misalignment of interests between insiders and outside shareholders can create incentives for managers to undertake value-destroying investments. Booth and Chang (2011) document that since the mid-1980s the difference in the level of information asymmetry between dividend- and non-dividend-paying firms has increased sharply, and the market has reacted less negatively to SEO announcements by dividend-paying firms.

capital and stock returns (e.g., Amihud and Mendelson (1986), Datar, Naik, and Radcliffe (1998), Pástor and Stambaugh (2003), and Acharya and Pedersen (2005)).

Unlike previous studies which focus on one or two aspects of liquidity, in this paper we comprehensively examine various measures of liquidity before and after SEOs, including the adverse selection measure of Lin, Sanger, and Booth (1995), the order imbalance measures, the illiquidity measure of Amihud (2002), the quoted and effective bid-ask spreads, and the effective cost and price impact measures of Hasbrouck (2009). As the existing literature has demonstrated, SEO events lead to increases in stock shares outstanding, equity amount, and asset size, and decreases in various types of financial risks (valuation uncertainty risk, systematic risk, investment risk, unexpected inflation and default risks, leverage risk, and liquidity risk). Hence, we hypothesize that the stock trading of SEO firms would become less risky in the post-offer period, and therefore the information asymmetry, liquidity, and transaction costs would all reduce following SEO events. Most importantly, in line with the expected reductions in liquidity after SEOs, we also examine the association between changes in liquidity and SEO underpricing, which has never been examined before.[7]

Our empirical study employs a sample of 3,811 SEOs made from 1997 to 2012 and a matched sample of non-SEO firms in the same period. For both SEO firms and non-SEO

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[7] Corwin (2003) finds that the magnitude of underpricing (measured as a positive spread) is positively related to offer size, and negatively related to firm size. Chemmanur, He, and Hu (2009) demonstrate that more pre-offer institutional net buying and larger institutional SEO allocations are associated with a smaller SEO discount. Lee and Masulis (2009) report that poor accounting information quality is associated with a larger offer price discount. Intintoli and Kahle (2010) find that higher insider ownership reduces float, thereby increasing price pressure and SEO price discount. Autore (2011) argues that the recent temporal increase in SEO price discounting is due to a greater prevalence of overnight shelf offers. Huang and Zhang (2011) reveal the negative relation between the number of managing underwriters for an SEO and offer price discount. Dai (2012) shows the positive association between market volatility and the magnitude of underpricing even after controlling for other factors.

firms, we compare the levels of information asymmetry, liquidity, and transaction cost measures during the pre-announcement period (about 60 trading days) with those during the post-offer period (about 60 trading days also). Moreover, we examine the effects of some firm characteristics on the magnitude of transaction cost reductions, and the impact of transaction cost reductions on the SEO underpricing. Our results show that the information asymmetry, liquidity, and transaction cost measures of SEO firms are all significantly higher in the pre-announcement period than in the post-offer period. In contrast, the information asymmetry, liquidity, and transaction cost measures of non-SEO firms differ very little between the two periods. In addition, the magnitudes of the reductions in transaction costs are significantly related to offer size, the change in stock price, and the change in volatility with expected signs. Most importantly, we also find that the greater the reduction in transaction costs, the smaller is the magnitude of SEO underpricing even after controlling for other firm characteristics, which is new to the literature.

The remainder of this paper is organized as follows. Section 2 describes various measures of liquidity. Section 3 discusses the sample selection and the matched sample. Section 4 reports the empirical results. Section 5 concludes the paper.

2. Measures of Liquidity

We investigate various measures of information asymmetry, liquidity, and transaction costs. The information asymmetry measures include the adverse selection component of effective spreads (λ), the absolute daily order imbalance in terms of trades divided by the sum of buy and sell trades (OI_n), and the absolute daily order imbalance in terms of shares divided by the sum of buy and sell shares (OI_v). The liquidity measures include the illiquidity (*ILL*) and the trading frequencies (Buy_n, $Sell_n$, Buy_v, and $Sell_v$). The transaction cost measures include the quoted bid-ask spreads (*Q-spread* and *Q-spread* (*bp*)), the effective bid-ask spreads (*E-spread* and *E-spread* (*bp*)), the effective cost (C^{TAQ}), and the price impact (PI^{TAQ}). Please see Table 1 for the detailed definitions of variables. In the following subsections, we discuss these measures in detail.

[Insert Table 1 Here]

2.1. Information asymmetry measures

According to Lin, Sanger, and Booth (1995), the adverse selection component of effective spreads is the slope coefficient (λ) estimated from the following regression model:

$$\Delta Q_{t+1} = \lambda Z_t + \varepsilon_{t+1}, \tag{1}$$

where $\Delta Q_{t+1} = Q_{t+1} - Q_t$, and $Z_t = P_t - Q_t$. Here Q_t denotes the natural logarithm of the quote midpoint (*Mid-quote*) at time *t*, P_t represents the natural logarithm of the trade price at time *t*, and Z_t stands for the effective bid-ask spread at time *t*. All trades except for opening transactions on each day are included in the empirical analysis. A higher value of λ indicates that the adverse selection component of effective spreads is more severe.

The daily order imbalance in terms of trades (OI_n) is calculated as the absolute difference between the number of trades initiated by buy orders and the number of trades initiated by sell orders divided by the total number of trades (i.e., $Buy_n + Sell_n$) in a day. The daily order imbalance in terms of shares (OI_v) is calculated as the absolute difference between the share volume initiated by buy orders and the share volume initiated by sell orders divided by the total share volume (i.e., $Buy_v + Sell_v$) in a day.

Our hypothesis is that the information asymmetry cost would decrease after SEOs. Thus, we expect that the adverse selection component of effective spreads (λ), the normalized absolute order imbalance in terms of trades (OI_n), and the normalized absolute order imbalance in terms of shares (OI_v) would all reduce in the post-SEO period.

2.2. Liquidity measures

Following Amihud (2002), the illiquidity measure (*ILL*) for each stock is calculated based on the following equation:

$$ILL = \frac{10^8}{D} \sum_{d=1}^{D} \frac{|R_d|}{VOL_d}, \tag{2}$$

where $|R_d|$ is the absolute value of stock return on day d, VOL_d is the daily volume in dollars on day d, and D is the number of trading days in a period (such as three months before the SEO). This ratio of absolute daily return to daily dollar volume represents the absolute percentage price change per dollar of daily trading volume, or the daily price impact of the order flow.

As for trading frequencies, Buy_n ($Sell_n$) is the number of transactions (i.e., trades) initiated by buy orders (sell orders) in a day. Buy_v ($Sell_v$) is the trading volume in thousands of shares initiated by buy orders (sell orders) in a day. Since firms tend to have more shares outstanding, higher turnovers, and lower illiquidity costs after SEOs, our hypothesis is that the illiquidity (*ILL*) would reduce and the trading frequencies (Buy_n, $Sell_n$, Buy_v, and $Sell_v$) would increase in the post-SEO period.

2.3. Transaction cost measures

The quoted bid-ask spread measures include the quoted bid-ask spread (i.e., the ask price minus the bid price) in dollars (*Q-spread*) and the quoted bid-ask spread in the hundredth percentage (*Q-spread* (*bp*)), which is defined as *Q-spread*/*Mid-quote*. The effective bid-ask spread measures include the effective bid-ask spread in dollars (*E-spread*) and the effective bid-ask spread in the hundredth percentage (*E-spread* (*bp*)). *E-spread* is calculated as 2×|*Trade price – Mid-quote*|, while *E-spread* (*bp*) is *E-spread/Mid-quote*.

Based on Hasbrouck (2009), the effective cost of a single trade is defined as the absolute difference between the natural logarithm of the transaction price and the natural logarithm of the prevailing quote midpoint (*Mid-quote*). The effective cost of trading a firm's stock (C^{TAQ}) during a period is estimated as the average effective cost over all trades during the period, weighted by the dollar value of the trade. Besides the effective cost, the price impact of a trade can also contribute to the transaction cost when an order is executed in multiple trades. According to Hasbrouck (2009), the price impact coefficient (PI^{TAQ}) is the slope coefficient estimated from the following regression:

$$\Delta P_\tau = PI^{TAQ}\left(Signed\sqrt{Dollar\ Volume}\right)_\tau + \varepsilon_\tau, \tag{3}$$

where ΔP_τ is the change in the natural logarithm of stock prices between time $\tau - 1$ and τ. $Signed\sqrt{Dollar\ volume}$ is the aggregated signed dollar volume for each five-minute interval indexed by τ and is defined as sign(*Dollar volume*)×sqrt(|*Dollar volume*|). If the trade is initiated by buy (sell) orders, then *Dollar volume* is positive (negative). We follow Lee and Ready (1991) method to identify a buy or sell order (to be discussed in details in

Section 3). This price impact measure is also used by Hasbrouck (2009) and Goyenko, Holden, and Trzcinka (2009). Eq. (3) is estimated during the 3-month period either before the SEO announcement or after the SEO issue.

Our hypothesis is that the bid-ask spread measures, the effective cost, and the price impact would all reduce after SEO events, in line with the hypothesized reductions in information asymmetry and liquidity costs.

3. Data Description and the Matched Sample

We obtain data on SEOs from the Investment Dealers' Digest Directory of Corporate Financing over the period 1997–2012. An SEO is included in our sample if it meets the following criteria: (1) the issue is a primary seasoned offering; (2) the issue involves only common stocks; (3) the company is not a regulated utility; (4) data for the company are available in the Trade and Quote (TAQ) database and the Center for Research in Security Prices (CRSP) daily database; and (5) the company has at least 60 days of intraday tick information in the TAQ database in the four months before the announcement and the four months after the issue. Overall, our sample contains 3,811 SEOs in the sample period. The common stocks of the SEOs in our sample are traded on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), or NASDAQ.

In addition to the test sample of SEOs, we also form a control sample of matched non-SEO firms. The SEO firms and non-SEO firms are matched based on stock price, trading volume, and industry.[8] More specifically, we use sequential matching to find the appropriate non-SEO firms. For each SEO firm in the sample, we first pick out from the databases those non-SEO candidate firms that are from the same industry. We then cross out the ones that are not covered by both the TAQ and CRSP databases. Finally, among those qualified firms, we choose the one with the closest average trading volume and average stock price during the six months before the SEO as the matched non-SEO firm to the SEO firm.[9]

To investigate whether a firm's SEO affects its various liquidity measures of stock trading, we use the TAQ information for the 60 days before the announcement and the 60 days after the issue to estimate all the variables specified in Table 1. We exclude all trades and quotes that occurred before the open and at the open, as well as those occurring at the close and after the close. In other words, all trades that occurred during the opening and closing auctions were omitted. Furthermore, we exclude all trades with non-typical settlement conditions. We also exclude all quotes with zero bid or ask prices, quotes with higher bid prices than ask prices, quotes for which the bid-ask spread is greater than 50% of the price, and trades with zero prices to eliminate possible data errors.

Two main adjustments are made to the data during our data processing. First, trades occurring within five seconds of each other at the same price and with no intervening quote

[8] Easley, Kiefer, O'Hara, and Paperman (1996) show that the trading frequency affects the level of asymmetric information. Since the results for firms matched based on other firm characteristics (e.g., size, B/M, industry, etc.) are very similar, to save space, we will only report the results for firms matched based on stock price, trading volume, and industry. The results for firms matched by other criteria are available from the authors upon request.

[9] We choose the firm that minimizes the sum of $\left|\frac{AvgPrice_{non-SEO} - AvgPrice_{SEO}}{AvgPrice_{SEO}}\right|$ and $\left|\frac{AvgVolume_{non-SEo} - AvgVolume_{SEO}}{AvgVolume_{SEO}}\right|$ as the matched non-SEO firm.

revisions are collapsed into one trade. Second, trades are classified into buys and sells using the technique developed by Lee and Ready (1991). That is, trades at prices above the midpoint of the bid and ask prices are defined as buys, and those below the midpoint are sells. Trades occurring precisely at the midpoint of the bid and ask prices are classified using the tick test. A trade executed at a price higher than the previous trade is defined as a buy, whereas one executed at a lower price is a sell. If the trade occurred at the midpoint and at the same price as the last trade, its price is compared with the next most recent trade. This process continues until the trade is classified.

4. Empirical Results

4.1. Summary statistics for SEOs

Table 2 presents the distribution of seasoned common stock offerings by year and by exchange. The entire sample contains a total of 2,942 unique firms and a total of 3,811 SEOs. The majority of the SEO firms made only one SEO during the entire sample period (1997–2012). The number of offerings each year ranges from 49 to 339. The average offer price is $26.25, the average of aggregate gross proceeds is $193.13 million, and the average relative offer size is 23.28% of pre-SEO market capitalization.[10]

[Insert Table 2 Here]

[10] The relative offer size is defined as the offering gross proceeds divided by the pre-offering market value of the issuer's common stocks (Eckbo, Masulis, and Norli, 2000).

4.2. Liquidity around SEOs

Table 3 reports summary statistics for various measures of liquidity for SEO firms in Panel A and for the matched non-SEO firms in Panel B, and summary statistics for the differences in these measures between the two sets of firms in Panel C. Results in Panel A indicate that various measures of information asymmetry, illiquidity, and trading costs tend to decline following SEO events. First, the information asymmetry measures, including the adverse selection component of effective spread (λ), the normalized absolute order imbalance in terms of trades (OI_n), and the normalized absolute order imbalance in terms of shares (OI_v), all reduce significantly at the 1% level after SEOs. Second, after SEOs, the level of the Amihud illiquidity measure (*ILL*) reduces significantly at the 1% level, while the trading frequencies (Buy_n, $Sell_n$, Buy_v, and $Sell_v$) increase significantly at the 1% level. These results suggest that the stocks of SEO firms tend to have lower liquidity costs or become more liquid after the issue. Third, the quoted and effective bid-ask spreads in dollars (*Q-spread* and *E-spread*) and in the hundredth percentage (*Q-spread* (*bp*) and *E-spread* (*bp*)), and the effective cost (C^{TAQ}) and the price impact (PI^{TAQ}) suggested by Hasbrouck (2009), all decrease significantly at the 1% level, implying lower transaction costs after SEOs. The reductions in bid-ask spreads are in line with the reductions in information asymmetry and liquidity costs in the post-SEO period, since information asymmetry and liquidity costs are components of bid-ask spreads.

Panel B of Table 3 shows that most *t*-statistics for the changes in the information asymmetry, illiquidity, and transaction cost measures are insignificant for the matched non-SEO firms. Hence, unlike for the SEO firms, information asymmetry, illiquidity, and transaction costs tend to remain the same in the post-SEO period for the matched non-SEO firms.

Panel C of Table 3 presents differences in various measures of information asymmetry, illiquidity, and transaction costs between the SEO and matched non-SEO firms. We note that the changes in the differences are significant at the 1% level for most of the measures, confirming the results in Panel A of Table 3. Therefore, for the SEO firms, the changes in trading activities (including the decreases in the adverse selection component of effective spread and the order imbalance measures, the decrease in illiquidity, the increases in trading frequencies, the decreases in quoted and effective bid-ask spreads, and the decreases in effective cost and price impact) can all be ascribed to the SEO event, and they reflect a reduction in information asymmetry, illiquidity, and transaction costs. In contrast, previous literature has shown that share repurchases, which involve a process that is the reverse of an SEO, exert the opposite effects on bid-ask spreads and information asymmetry. For example, Brockman and Chung (2001) document that bid-ask spreads widen during repurchase periods.[11] In addition, by decomposing bid-ask spreads into different cost components, they show that adverse selection costs increase substantially after share repurchases.

[Insert Table 3 Here]

Since the various measures of liquidity may be serially correlated and may exhibit a declining trend over time due to increased arbitrage activities (Chordia, Subrahmanyam, and Tong, 2011), to further explore the changes in these measures around SEO events, we

[11] The authorized repurchase period is one year after the passage of the resolution of a buyback plan.

regress each measure against a constant, a time trend, a post-SEO dummy, and a set of control variables. The cross-sectional regression model is:

$$Var = c + \alpha_0 Trend + \alpha_1 PostSEO + \beta CONTROL + \varepsilon, \tag{4}$$

where *Var* is any one of the various measures of liquidity, including λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread (bp)*, C^{TAQ}, and PI^{TAQ}.[12] *Trend* is the time trend variable, calculated as the number of quarters between the SEO issue quarter and the first quarter of our sample period (i.e., the 4th quarter of 1996). Since arbitrage activities have gradually increased and financial markets have also gradually become more efficient over time (Chordia, Subrahmanyam, and Tong, 2011), the levels of information asymmetry, illiquidity, and transaction costs may also have reduced steadily. To exclude the possibility that our results are driven by the time trend, we include this time trend dummy variable (*Trend*) into the regression model. *PostSEO* is a dummy variable, which equals 1 for the period after the SEO issue and 0 for the period before the SEO announcement.

CONTROL represents a vector of control variables (firm size, stock price, trading volume, volatility, and industry), and β represents a vector of coefficients for the control variables. More specifically, firm size is the logarithm of market capitalization before announcement or after issuing; stock price is the average close price of the firm during the three months period before the announcement or after issuing. Trading volume is the average trading volume during the three months period either before the announcement or after issuing. Volatility is the return volatility during the three months period either before the announcement or after issuing. Finally, industry is the four-digit SIC code of the firm.

[12] We do not include the liquidity measures of Buy_n, $Sell_n$, Buy_v, and $Sell_v$ in our regression analyses, since the increases in these liquidity measures may be simply attributed to the increases in the number of shares outstanding after SEOs.

Chordia, Roll, and Subrahmanyam (2000) have found that these variables are important determinants of liquidity in the cross-section. The *t*-statistics are adjusted by the Newey-West (1987) method. If the dependent variable (*Var*) reduces considerably after SEOs, the regression coefficient α_1 should be negative and significant.

Table 4 presents the regression estimates for SEO firms in Panel A, for non-SEO firms in Panel B, and for their differences in Panel C. To save space, we only report the coefficients for the intercept, the time trend, and the post-SEO dummy, but not the coefficients for the control variables (firm size, stock price, trading volume, volatility, and industry). As Panel A shows, the *PostSEO* dummy is negative and significant at the 1% level for each of the measures (λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread* (*bp*), C^{TAQ}, and PI^{TAQ}), even after controlling for the time trend as well as the control variables known to be associated with liquidity in the cross-section. That is, the stock trading of SEO firms tends to have significantly reduced information asymmetry, illiquidity, and transaction costs shortly after their respective SEOs, and the reductions are not driven by the time trend or firm characteristics. In Panel B, however, the *PostSEO* dummy is insignificantly different from zero, after controlling for the time trend and the control variables for non-SEO firms. In other words, the matched non-SEO firms do not experience any significant changes in information asymmetry, illiquidity, and transaction costs around the SEO events of their respectively matched SEO firms. In Panel C, the *PostSEO* dummy is negative and significant for the difference in each of the measures between SEO firms and non-SEO firms, even after controlling the time trend and the control variables. Hence, the post-SEO differences in information asymmetry, illiquidity, and transaction costs between

SEO and non-SEO firms are significantly lower than the pre-SEO differences. Overall, the results in Table 4 confirm those in Table 3.

[Insert Table 4 Here]

As shown above, various measures of liquidity all reduce significantly after SEOs. The remaining issues to be examined include: (1) the magnitude of the reductions in various measures of liquidity in relation to firm characteristics, and (2) the magnitude of the SEO underpricing in relation to changes in various measures of liquidity well as firm characteristics.

Table 5 provides a correlation matrix for the changes in information asymmetry, illiquidity, and transaction costs ($\Delta\lambda$, ΔOI_n, ΔOI_v, ΔILL, *ΔQ-spread* (*bp*), *ΔE-spread* (*bp*), ΔC^{TAQ}, and ΔPI^{TAQ}), the changes in firm characteristics (*ΔFS*, *ΔPrice*, *ΔVOLA*, and *ΔTV*), offer size (*OS*), and SEO underpricing (*UP*). Most of the correlations are low. A few high correlation cases all are coming from the same categories. For example, the change in the quoted bid-ask spread (Δ*Q-spread* (*bp*)) is highly correlated with the change in the effective bid-ask spread (Δ*E-spread* (*bp*)); and the change in the effective cost (ΔC^{TAQ}) is highly correlated with the change in the quoted bid-ask spread (Δ*Q-spread* (*bp*)) as well as the change in the effective bid-ask spread (Δ*E-spread* (*bp*)). In addition, the change in firm size ((*ΔFS*) is highly correlated with the change in price (*ΔPrice*). More importantly, there is a significantly negative correlation between underpricing and each of the four transaction cost measures, namely the quoted spread (*ΔQ-spread* (*bp*)), effective spread (*ΔE-spread* (*bp*)), effective transaction cost (ΔC^{TAQ}), and price impact (ΔPI^{TAQ}). This preliminary correlation analysis appears to suggest that the smaller magnitude of SEO underpricing is positively associated with the perceived greater reductions in transaction cost measures after SEOs.

[Insert Table 5 Here]

4.3. Determinants of changes in liquidity measures

To investigate the magnitude of the reductions in various measures of liquidity in relation to firm characteristics, we conduct a panel regression of the change in each of the measures against five determinants, according to the following equation:

$$\Delta Var = \alpha_0 + \alpha_1 \Delta FS + \alpha_2 OS + \alpha_3 \Delta Price + \alpha_4 \Delta VOLA + \alpha_5 \Delta TV + \varepsilon, \quad (5)$$

where ΔVar is the difference in a variable (*Var*) between the post-issue and pre-announcement periods (i.e., $Var_{Afert\_SEO} - Var_{Before\_SEO}$). *Var* is λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread* (*bp*), C^{TAQ}, or PI^{TAQ}. ΔFS is the difference in the market capitalization between the post-issue and pre-announcement periods of an SEO, divided by the pre-announcement market capitalization. *OS* is the offer size of the SEO in dollars divided by the market capitalization.[13] The risk reduction theory predicts that the larger the offer size, the greater the improvement in liquidity or information asymmetry; as a result, the coefficient on *OS* is expected to be negative. $\Delta Price$ is the difference in the average close price between the post-issue and pre-announcement periods of an SEO. We expect the coefficient on $\Delta Price$ to be negative, suggesting that a smaller decrease in stock price is associated with greater improvement in liquidity or information asymmetry. $\Delta VOLA$ is the difference in return volatility between the post-issue and pre-announcement periods of an

[13] *OS* can also be defined as the number of shares offered divided by the number of shares outstanding. These two definitions produce the same results.

SEO. The risk reduction explanation predicts a positive coefficient on Δ*VOLA*, suggesting that a greater reduction in volatility is expected to be associated with a greater improvement in liquidity or information asymmetry. Δ*TV* is the difference in the average trading volume between the post-issue and pre-announcement periods of an SEO. Since we pool time-series and cross-sectional data together in the regression tests, the *t*-statistics are adjusted for the clustering effects of firms and SEO years.

Table 6 presents regression estimates for determinants of the changes in information asymmetry, illiquidity, and transaction cost measures. The results from SEO firms are reported in Panel A, where Δ represents the difference in a variable between the post-issue and pre-announcement periods of an SEO. The results from the differences in variables between SEO and non-SEO firms are presented in Panel B, where the differences are calculated as SEOs' differences minus matched non-SEOs' differences.

[Insert Table 6 Here]

In both Panels A and B of Table 6, we note that some of the five determinants (Δ*FS*, *OS*, Δ*Price*, Δ*VOLA*, and Δ*TV*) have significant and consistent effects on some of the changes in liquidity measures. First, offer size (*OS*) has a significant (at the 5% or 1% level) and negative effect on Δ*ILL*, Δ*Q-spread* (*bp*), Δ*E-spread* (*bp*), and ΔC^{TAQ}, and these negative effects hold true for both SEO firms as well as the differences between SEO and non-SEO firms. The results indicate that the larger the offer size, the greater the reduction in illiquidity and transaction cost measures, which is consistent with the prediction of the risk reduction theory. Second, the change in price (Δ*Price*) has a significant (at the 1% level) and negative relation with Δ*Q-spread* (*bp*), Δ*E-spread* (*bp*), and ΔC^{TAQ}. In addition, these negative relations hold true for both SEO firms as well as the differences between SEO and non-SEO firms. The results suggest that a smaller reduction (or a larger increase) in price is associated with a larger reduction in transaction cost measures, which is largely consistent with the investor expectation argument. Third, the change in stock return volatility ($\Delta VOLA$) has a significant (at the 1% level) and positive effect on Δ*Q-spread* (*bp*) and ΔPI^{TAQ} for both SEO firms as well as the differences between SEO and non-SEO firms. In other words, a larger reduction in volatility is related to a larger reduction in quoted spreads and price impacts, which is also in line with the risk reduction explanation.

Overall, the results in Table 6 show that reductions in illiquidity and transaction cost measures are in general significantly associated with offer size, the change in stock price, or the change in return volatility after SEOs, and the associations are consistent with the predictions of the existing theories. More importantly, the finding that the larger the offer size (*OS*), the greater the reduction in the illiquidity or transaction cost measures (including ΔILL, Δ*Q-spread* (*bp*), Δ*E-spread* (*bp*), and ΔC^{TAQ}) appears to survive from the inclusions of other control variables known to be important determinants of liquidity in the cross-section analysis (Chordia, Roll, and Subrahmanyam, 2000).

4.4. SEO underpricing and changes in liquidity measures

It is also important to investigate whether investors *ex ante* price in the magnitude of the underpricing of SEOs which reflects the expected reductions in our various measures of liquidity. To examine the relation between the changes in various measures of liquidity and SEO underpricing, we conduct a panel regression of SEO underpricing (*UP*) against the changes in various measures of liquidity controlling for other firm characteristics, according to the following equation:

$$UP = \alpha_0 + \alpha_1 \Delta Var + \beta CONTROL + \varepsilon, \tag{6}$$

where Δ*Var* is as defined in Eq. (5). SEO underpricing (*UP*) is calculated as 100×(*Offer price – Pre-offer price*)/*Pre-offer price*. By this definition, *UP* is in general negative and the more negative it is, the greater the underpricing. The economic intuition suggests that if investors *ex ante* perceive greater reductions in information asymmetry, illiquidity, or transaction costs, the underpricing should be smaller. That is, the regression coefficient on Δ*Var* is expected to be negative.

Since it is very difficult to establish the causality between underpricing and the reductions in information asymmetry, illiquidity, or transaction costs, we also control for other potential explanations of underpricing. Our controls (*CONTROL*) include *FS*, *OS*, *IO*, *VOLA*, *Sentiment*, *M/B*, and *Leverage*. *FS* is the logarithm of market capitalization before the announcement of the SEO. The economic intuition suggests that since asymmetric information risk is smaller for large firms, they should have a smaller magnitude of underpricing; that is, the coefficient on *FS* is expected to be positive. Previous studies (e.g., Corwin (2003)) have also confirmed the prediction. *OS* is the relative offer size and is defined as the offer size of the SEO in dollars divided by the market capitalization. Previous studies find that offer size is positively associated with the magnitude of SEO underpricing (e.g., Corwin (2003)), which suggests that the coefficient on *OS* is expected to be negative.[14]

IO is the institutional ownership before the announcement of the SEO. High institutional ownership should reduce asymmetry information, which leads to a smaller magnitude of underpricing, suggesting a positive coefficient on *IO*. *VOLA* is return volatility calculated from the past-12-month returns ending three months before the announcement of the SEO. High volatility indicates higher asymmetry information, which leads to a lager magnitude of underpricing (e.g., Corwin (2003)), suggesting a negative coefficient on *VOLA*. *Sentiment* is the Baker-Wurgler (2006) sentiment index before the announcement of the SEO, which measures investor sentiment.[15] *M/B* is the market-to-book ratio before the SEO announcement. Both investor sentiment and *M/B* measure the degrees of overvaluation in the aggregate market and the individual firm, respectively. Overvalued firms are expected to offer larger discounts for their SEOs, suggesting a negative coefficient on either *Sentiment* or *M/B*. *Leverage* is the debt-to-equity ratio. High leverage firms should improve their financial risk much more than low leverage firms after SEOs, suggesting a positive coefficient on *Leverage*.

Table 7 presents the results of regressions of SEO underpricing against changes in information asymmetry, illiquidity, and transaction cost measures, controlling for *FS*, *OS*, *IO*, *VOLA*, *Sentiment*, *M/B*, and *Leverage*. Among the control variables, we note that

[14] However, in our sample, we find that relative offer size (*OS*) is highly and negatively correlated with firm size (*FS*), which may generate the collinearity problem.
[15] We retrieved the investor sentiment data from Wurgler's website. However, this sentiment index is only available until the end of 2010. We also use the consumer sentiment index from University of Michigan (which is available for our entire sample period) to replace the Baker-Wurgler sentiment index and find similar results.

underpricing is in general not associated with institutional ownership (*IO*), return volatility (*VOLA*), or leverage (*Leverage*). In contrast, underpricing is in general positively and significantly related to firm size (*FS*) and relative offer size (*OS*), and negatively and significantly related to the sentiment index (*Sentiment*) and the market-to-book ratio (*M/B*). The results suggest that larger firms, firms with smaller relative offer size, higher investor sentiment, or a higher market-to-book ratio before SEOs tend to experience a larger magnitude of SEO underpricing. The results for *FS*, *Sentiment*, and *M/B* are consistent with our prediction. The result for *FS* is also consistent previous findings (e.g., Corwin (2003)). However, the result for relative offer size (*OS*) is inconsistent with those from previous studies (e.g., Corwin (2003)). A possible explanation is that smaller offer size (in percentage) may indicate smaller commissions for investment banks and thus a need for a bigger offer discount.

[Insert Table 7 Here]

After controlling for those firm characteristics that might have potential to explain the degree of SEO underpricing, we still observe that SEO underpricing is significantly affected by some of our liquidity measures. Most importantly, underpricing is negatively and significantly related to the changes in quoted spread (*ΔQ-spread* (*bp*)), effective spread (*ΔE-spread* (*bp*)), effective transaction cost (ΔC^{TAQ}), and price impact (ΔPI^{TAQ}) at the 1% or 5% level. The results suggest that when investors perceive a larger reduction in transaction costs, the magnitude of underpricing is smaller. This is consistent with our expectation. For other measures of liquidity or information asymmetry, we find that although they are positively associated with *UP*, none of them are significant at any conventional level.

Overall, the results in Table 7 show that the magnitude of SEO underpricing is indeed negatively associated with investors' perceived reductions in transaction cost measures of liquidity. That is, when investors expect a greater reduction in the transaction cost measures of liquidity, SEO discounts are smaller. This is the first finding in the SEO literature.

5. Conclusions

In this paper, we conduct a comprehensive investigation of the changes in various measures of liquidity around SEO events. We document significant reductions in the adverse selection component of effective spread (λ), the normalized absolute order imbalance in terms of trades (OI_n), the normalized absolute order imbalance in terms of shares (OI_v), the Amihud's illiquidity (*ILL*), the quoted bid-ask spread (*Q-spread* (*bp*)), the effective bid-ask spread (*E-spread* (*bp*)), the effective transaction cost (C^{TAQ}), and the price impact (PI^{TAQ}) during the three months after an SEO (versus during the three months before an SEO announcement). In addition, the magnitudes of the reductions in the transaction cost measures of liquidity are significantly related to offer size, change in price, and change in volatility. More importantly, the magnitude of SEO underpricing is significantly and negatively associated with the degree of reductions in transaction cost measures of liquidity even after controlling for other firm characteristics known to be determinants of SEO underpricing.

Our findings from the post-SEO reductions in information asymmetry, illiquidity, and transaction costs are in line with existing empirical results for other types of risk. That is, after SEOs, firms are apt to experience reductions in valuation uncertainty risk, systematic risk, investment risk, unexpected inflation and default risks, leverage risk, and liquidity risk. Our finding that the greater the reductions in the transaction cost measures of liquidity, the smaller the magnitude of SEO underpricing is new to the literature and offers an addition channel for understanding the determinations of SEO underpricing.

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Table 1. Definitions of liquidity measures

λ	The adverse selection measure of Lin, Sanger, and Booth (1995). It is the slope coefficient estimated from the regression $\Delta Q_{t+1} = \lambda Z_t + e_{t+1}$, where $\Delta Q_{t+1} = Q_{t+1} - Q_t$, and $Z_t = P_t - Q_t$; Q_t is the natural logarithm of the quote midpoint (*Mid-quote*) at time *t*, and P_t is the natural logarithm of the trade price at time *t*. The regression is estimated for each firm during the 3-month period around the SEO announcement/issue using the high-frequency (TAQ) data.
Buy_n	Daily number of transactions (in terms of trades) initiated by buy orders. Transaction types are classified using the Ready and Lee (1991) method.
$Sell_n$	Daily number of transactions (in terms of trades) initiated by sell orders. Transaction types are classified using the Ready and Lee (1991) method.
Buy_v	Daily trading volume (in terms of thousand shares) initiated by buy orders. Transaction types are classified using the Ready and Lee (1991) method.
$Sell_v$	Daily trading volume (in terms of thousand shares) initiated by sell orders. Transaction types are classified using the Ready and Lee (1991) method.
OI_n	Daily absolute order imbalance in terms of trades, divided by the sum of buy and sell trades; that is, $\|Buy_n\text{-}Sell_n\|/(Buy_n+Sell_n)$.
OI_v	Daily absolute order imbalance in terms of share volume, divided by the sum of buy and sell volume; that is, $\|Buy_v\text{-}Sell_v\|/(Buy_v+Sell_v)$.
ILL	The Amihud (2002) illiquidity measure, calculated as $\|Daily\ return\|/Daily\ dollar\ volume$, averaged over all days with nonzero volume. It is calculated for each firm during the 3-month period around the SEO announcement/issue.
Q-spread	Daily quoted spread in dollars, calculated as *Ask price – Bid price*. Quotations with a size or price of zero are ignored.
Q-spread (*bp*)	Daily quoted spread in the hundredth percentage, calculated as *Q-spread/Mid-quote*. Quotations with a size or price of zero are ignored.
E-spread	Daily effective spread in dollars, calculated as |*Trade price – Mid-quote*| × 2.
E-spread (*bp*)	Daily effective spread in the hundredth percentage, calculated as *E-spread/Mid-quote*.
C^{TAQ}	Effective cost. For a given trade, the effective cost is the difference between the natural logarithm of the transaction price (*Trade price*) and the natural logarithm of the prevailing quote midpoint (*Mid-quote*). It is estimated for each firm during the 3-month period around the SEO announcement/issue using the high-frequency (TAQ) data. C^{TAQ} is the average over all trades during the 3-month period, weighted by the dollar value of the trade.
PI^{TAQ}	Price impact coefficient. It is the slope coefficient estimated from the regression $\Delta P_\tau = PI^{TAQ}\left(Signed\sqrt{Dollar\ volume}\right)_\tau + \varepsilon_\tau$, where ΔP_τ is the change in the natural logarithm of stock prices between τ-1 and τ and $Signed\sqrt{Dollar\ volume}$ = sign(*Dollar volume*)×sqrt(|*Dollar volume*|) is the aggregated signed dollar volumes for each five-minute interval indexed by τ. If the trade is initiated by buy (sell) orders, then *Dollar volume* is positive (negative). The slope coefficient is estimated for each firm during the 3-month period around the SEO announcement /issue using the high-frequency (TAQ) data.

Table 2. Distribution of seasoned common stock offerings (SEOs) by year and by exchange

This table presents the distribution of seasoned common stock offerings by year and by exchange. The sample period is from 1997 to 2012. Relative offer size is calculated as the gross proceeds divided by the pre-offering market value of the issuer's common stocks.

	All offers					NYSE/Amex offers				Nasdaq offers			
Year	No. of Firms	No. of offerings	Offer price	Aggregate gross proceeds ($M)	Relative offer size (%)	No. of offerings	Offer price	Aggregate gross proceeds ($M)	Relative offer size (%)	No. of offerings	Offer price	Aggregate gross proceeds ($M)	Relative offer size (%)
1997	49	49	27.25	104.87	22.69	36	29.03	118.04	21.31	13	22.31	68.41	26.51
1998	307	314	28.65	132.39	29.32	130	31.62	200.43	30.68	184	26.55	84.32	28.35
1999	325	333	41.31	219.48	28.35	94	36.35	312.43	23.96	239	43.26	182.92	30.10
2000	298	304	49.40	248.19	18.31	69	44.24	362.08	20.96	235	50.92	214.75	17.54
2001	261	270	25.96	181.18	36.67	137	28.78	240.67	50.96	133	23.04	119.90	21.96
2002	231	241	23.28	176.36	21.59	142	24.94	243.72	21.09	99	20.89	79.76	22.31
2003	294	307	21.84	149.99	27.88	157	24.76	197.11	32.24	150	18.78	100.68	23.30
2004	288	295	25.40	169.37	26.00	153	28.30	240.28	28.87	142	22.27	92.97	22.91
2005	150	152	26.42	243.02	28.58	69	26.89	361.40	31.84	83	26.02	144.60	25.84
2006	220	238	26.09	191.48	14.01	99	31.20	292.11	13.83	139	22.45	119.81	14.10
2007	204	214	24.34	197.53	15.39	83	28.43	318.75	15.12	131	21.75	120.72	15.55
2008	100	105	24.37	347.94	12.41	61	27.09	535.47	12.56	44	20.60	87.97	12.20
2009	319	339	14.22	202.96	17.01	140	18.73	370.81	15.02	199	11.05	84.87	18.36
2010	247	271	14.55	168.89	28.37	112	20.51	314.57	18.08	159	10.36	66.27	34.75
2011	195	205	19.76	203.30	17.06	87	25.73	342.51	17.52	118	15.36	100.66	16.80
2012	160	174	19.18	205.63	16.26	81	23.04	321.81	13.69	93	15.81	104.43	18.08
All	2,942	3,811	26.25	193.13	23.28	1,650	27.46	288.44	24.40	2,161	25.34	120.36	22.34

Table 3. Summary statistics for various measures of liquidity

This table reports summary statistics for various measures of liquidity for SEO firms in Panel A and for the matched non-SEO firms in Panel B, and summary statistics for the differences in these measures between SEO and non-SEO firms in Panel C. λ is the adverse selection measure of Lin, Sanger, and Booth (1995). OI_n (OI_v) is the daily absolute order imbalance in terms of trades (shares), divided by the sum of buy and sell trades (shares). *ILL* is the Amihud (2002) illiquidity measure. Buy_n ($Sell_n$) is the number of trades initiated by buy (sell) orders. Buy_v ($Sell_v$) is the number of shares initiated by buy (sell) orders. *Q-spread* (*Q-spread* (*bp*)) is the quoted bid-ask spread in dollars (in the hundredth percentage). *E-spread* (*E-spread* (*bp*)) is the effective bid-ask spread in dollars (in the hundredth percentage). C^{TAQ} is the effective cost, while PI^{TAQ} is the price impact coefficient. Full definitions of variables are given in Table 1. Diff is the difference in the estimate concerned between the after-issue and before-announcement periods. The *t*-statistic is used to test the null hypothesis that Diff = 0. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Before announcement (1)		After issue (2)		Diff=(2)-(1)		
	Mean	Median	Mean	Median	Mean	Median	t-stat
Panel A: Summary statistics for SEO firms							
λ	0.497	0.488	0.426	0.417	-0.064	-0.061	-11.83***
OI_n	12.984	9.171	12.131	8.507	-0.986	-0.982	-3.16***
OI_v	14.752	8.884	13.356	8.550	-1.368	-0.811	-3.08***
ILL	1.072	0.786	0.387	0.372	-0.685	-0.397	-5.16***
Buy_n	231.163	195.304	310.325	252.969	80.789	74.354	15.43***
$Sell_n$	273.716	221.350	363.885	380.433	93.715	89.660	15.87***
Buy_v	146.448	155.745	214.606	195.006	69.492	66.810	11.44***
$Sell_v$	177.251	163.930	251.516	204.009	77.028	77.322	11.43***
Q-spread	0.260	0.220	0.227	0.192	-0.030	-0.020	-11.83***
Q-spread (*bp*)	114.238	100.681	94.029	81.352	-20.455	-18.961	-27.39***
E-spread	0.149	0.114	0.127	0.097	-0.021	-0.011	-12.10***
E-spread (*bp*)	67.248	54.645	53.546	44.467	-14.185	-8.209	-21.81***
C^{TAQ}	0.314	0.264	0.255	0.222	-0.059	-0.036	-22.57***
PI^{TAQ}	2.375	1.719	1.454	1.479	-0.875	-0.867	-5.32***
Panel B: Summary statistics for non-SEO firms							
λ	0.512	0.512	0.519	0.534	0.003	0.006	0.34
OI_n	13.655	10.001	14.491	10.458	0.486	0.303	1.55
OI_v	14.828	10.058	15.856	10.771	0.702	1.489	1.10
ILL	1.149	0.974	1.078	0.909	-0.087	-0.063	-0.33
Buy_n	197.381	180.138	198.885	182.016	2.934	2.115	0.95
$Sell_n$	230.237	187.538	236.619	192.640	6.778	5.224	1.90*
Buy_v	149.198	154.272	150.931	148.891	-2.527	-2.315	-0.68
$Sell_v$	174.334	157.572	187.293	163.655	3.620	3.263	0.99
Q-spread	0.231	0.192	0.227	0.181	-0.001	-0.002	-0.54
Q-spread (*bp*)	111.242	95.957	111.571	93.615	-1.644	-1.546	-0.33
E-spread	0.128	0.097	0.126	0.094	-0.001	-0.001	-0.36
E-spread (*bp*)	65.172	48.678	66.157	49.091	-0.591	-0.825	-0.96
C^{TAQ}	0.309	0.244	0.304	0.240	-0.003	-0.003	-1.11
PI^{TAQ}	2.011	1.836	2.105	2.372	0.051	0.035	0.25

Table 3 continued.

	Before announcement (1)		After issue (2)		Diff=(2)-(1)		
	Mean	Median	Mean	Median	Mean	Median	t-stat
Panel C: Summary statistics for the differences between SEO and non-SEO firms							
$\Delta\lambda$	0.003	-0.001	-0.089	-0.071	-0.092	-0.074	-4.57***
ΔOI_n	-0.439	-0.299	-2.359	-1.958	-1.691	-1.861	-3.92***
ΔOI_v	-0.514	-0.756	-2.479	-2.178	-1.897	-1.825	-2.05**
ΔILL	-0.073	0.111	-0.690	-0.637	-0.605	-0.633	-2.47***
ΔBuy_n	36.305	22.323	111.440	81.708	77.817	70.337	12.70***
$\Delta Sell_n$	46.487	35.810	127.266	140.197	86.305	84.591	12.32***
ΔBuy_v	-2.389	-1.492	64.307	48.677	75.249	68.440	10.48***
$\Delta Sell_v$	3.080	4.205	64.902	49.328	76.122	68.368	9.76***
Δ*Q-spread*	0.028	0.021	0.000	0.004	-0.028	-0.019	-8.16***
Δ*Q-spread* (*bp*)	1.632	2.613	-17.542	-11.804	-18.695	-16.372	-19.01***
Δ*E-spread*	0.021	0.013	0.000	0.004	-0.020	-0.010	-8.32***
Δ*E-spread* (*bp*)	1.195	2.490	-12.611	-5.084	-13.561	-8.454	-15.50***
ΔC^{TAQ}	0.005	0.008	-0.051	-0.020	-0.056	-0.037	-13.57***
ΔPI^{TAQ}	0.364	0.472	-0.651	-0.381	-0.824	-0.692	-2.33**

Table 4. Tests of various measures of liquidity for SEO and non-SEO firms

This table presents the regression estimates for SEO firms in Panel A, non-SEO firms in Panel B, and the differences between SEO and non-SEO firms in Panel C. The cross-sectional regression model is

$$Var = c + \alpha_0 Trend + \alpha_1 PostSEO + \beta CONTROL + \varepsilon,$$

where *Var* is any one of the following liquidity measures: λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread* (*bp*), C^{TAQ}, and PI^{TAQ}. λ is the adverse selection measure of Lin, Sanger, and Booth (1995). OI_n (OI_v) is the daily absolute order imbalance in terms of trades (shares), divided by the sum of buy and sell trades (shares). *ILL* is the Amihud (2002) illiquidity measure. *Q-spread* (*bp*) is the quoted bid-ask spread in the hundredth percentage. *E-spread* (*bp*) is the effective bid-ask spread in the hundredth percentage. C^{TAQ} is the effective cost, while PI^{TAQ} is the price impact coefficient. Full definitions of variables are given in Table 1. *Trend* is the time trend variable, calculated as the number of quarters between the SEO issue quarter and the first quarter of our sample period (i.e. the 4th quarter of 1996). *PostSEO* is the dummy variable, which equals 1 for the period after the SEO issue, and 0 for the period before the SEO announcement. *CONTROL* represents a vector of control variables (firm size, price, trading volume, volatility, and industry), and β represents a vector of coefficients. In specific, firm size is the logarithm of market capitalization before announcement or after issuing; price is the average close price of the firm during the three months period before the announcement or after issuing; trading volume is the average trading volume during the three months period either before the announcement or after issuing; volatility is the return volatility during the three months period either before the announcement or after issuing; and industry is the four-digit SIC code of the firm. For simplicity, we do not report the coefficients for the control variables in the table. The numbers in parentheses are *t*-statistics adjusted by the Newey-West (1987) method. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Var	*Intercept*	*t-statistic*	*Trend*	*t-statistic*	*PostSEO*	*t-statistic*
Panel A: SEO firms						
λ	0.538***	(39.79)	0.003***	(12.15)	-0.076***	(-13.14)
OI_n	0.118***	(15.98)	0.001***	(6.93)	-0.008***	(-2.88)
OI_v	0.101***	(12.95)	0.002***	(10.32)	-0.003***	(-3.13)
ILL	0.159***	(7.32)	0.001	(0.52)	-0.068***	(-5.29)
Q-spread (*bp*)	1.539***	(39.89)	-0.003***	(-4.34)	-0.215***	(-24.61)
E-spread (*bp*)	0.876***	(28.79)	-0.003***	(-5.68)	-0.147***	(-20.73)
C^{TAQ}	0.359***	(32.47)	-0.002	(-1.45)	-0.059***	(-21.58)
PI^{TAQ}	-1.947***	(-10.87)	0.044***	(15.48)	-0.866***	(-14.27)
Panel B: Non-SEO firms						
λ	0.338***	(2.93)	0.006***	(3.25)	0.049	(0.95)
OI_n	0.128***	(14.23)	0.002***	(8.71)	0.007**	(2.05)
OI_v	0.107***	(11.48)	0.003***	(14.19)	0.010*	(1.80)
ILL	0.268***	(7.53)	-0.001	(-0.40)	-0.008	(-0.48)
Q-spread (*bp*)	1.738***	(38.60)	-0.009***	(-12.88)	-0.020	(-1.09)
E-spread (*bp*)	0.916***	(24.14)	-0.004***	(-7.48)	-0.010	(-1.22)
C^{TAQ}	0.004***	(25.18)	-0.007***	(-3.36)	-0.000	(-1.01)
PI^{TAQ}	-0.450***	(-3.07)	0.012***	(5.58)	-0.119	(-0.98)

Table 4 continued.

Var	*Intercept*	*t-statistic*	*Trend*	*t-statistic*	*PostSEO*	*t-statistic*
Panel C: Differences between SEO and non-SEO firms						
$\Delta\lambda$	0.123	(1.07)	-0.002	(-1.14)	-0.027***	(-3.53)
ΔOI_n	-0.004	(-0.36)	0.000	(0.60)	-0.015***	(-3.35)
ΔOI_v	0.005	(0.44)	-0.001	(-1.32)	-0.006**	(-2.11)
ΔILL	-0.046	(-1.48)	0.002	(1.53)	-0.037**	(-2.18)
ΔQ-spread (*bp*)	-0.230***	(-6.69)	0.009***	(13.67)	-0.189***	(-15.33)
ΔE-spread (*bp*)	-0.129***	(-5.09)	0.004***	(6.91)	-0.130***	(-12.42)
ΔC^{TAQ}	-0.001***	(-4.79)	0.001***	(7.30)	-0.005***	(-12.87)
ΔPI^{TAQ}	-0.259***	(-13.58)	0.044***	(11.68)	-0.985***	(-10.20)

Table 5. Correlation matrix

This table reports a correlation matrix for the changes in various measures of liquidity (*Δλ*, ΔOI_n, ΔOI_v, *ΔILL*, *ΔQ-spread* (*bp*), *ΔE-spread* (*bp*), ΔC^{TAQ}, and ΔPI^{TAQ}), the firm features (*ΔFS*, *OS*, *ΔPrice*, *ΔVOLA*, and *ΔTV*), and SEO underpricing (*UP*). λ is the adverse selection measure of Lin, Sanger, and Booth (1995). OI_n (OI_v) is the daily absolute order imbalance in terms of trades (shares), divided by the sum of buy and sell trades (shares). *ILL* is the Amihud (2002) illiquidity measure. *Q-spread* (*bp*) is the quoted bid-ask spread in the hundredth percentage. *E-spread* (*bp*) is the effective bid-ask spread in the hundredth percentage. C^{TAQ} is the effective cost, while PI^{TAQ} is the price impact coefficient. Full definitions of variables are given in Table 1. Δ*FS* is the difference in the market capitalization between the post-issue and pre-announcement periods of an SEO, divided by the pre-announcement market capitalization. *OS* is the offer size of the SEO in dollars divided by the market capitalization. Δ*Price* is the difference in the average close price between the post-issue and pre-announcement periods of an SEO. Δ*VOLA* is the difference in return volatility between the post-issue and pre-announcement periods of an SEO. Δ*TV* is the difference in the average trading volume between the post-issue and pre-announcement periods of an SEO. *UP* is the SEO underpricing, calculated as 100×(*Offer price–Pre-offer price*)/*Pre-offer price*.

	ΔOI_n	ΔOI_v	*ΔILL*	*ΔQ-spread(bp)*	*ΔE-spread(bp)*	ΔC^{TAQ}	ΔPI^{TAQ}	*ΔFS*	*OS*	*ΔPrice*	*ΔVOLA*	*ΔTV*	*UP*
Δλ	0.068	0.051	-0.038	-0.008	-0.038	-0.046	-0.092	-0.020	0.038	-0.017	0.053	0.006	-0.012
ΔOI_n		0.424	0.003	0.072	0.173	0.069	0.060	-0.046	0.009	0.002	0.034	-0.034	0.020
ΔOI_v			0.048	0.027	0.057	0.004	0.061	0.003	0.005	0.022	0.012	-0.024	-0.002
ΔILL				0.138	0.153	0.114	-0.019	-0.028	-0.117	0.000	-0.014	0.028	0.009
ΔQ-spread (bp)					0.752	0.660	-0.121	-0.260	-0.265	-0.155	0.089	0.047	-0.136
ΔE-spread(bp)						0.771	-0.103	-0.224	-0.237	-0.121	0.084	0.046	-0.112
ΔC^{TAQ}							-0.111	-0.182	-0.228	-0.116	0.062	0.057	-0.107
ΔPI^{TAQ}								0.123	0.065	0.070	-0.127	-0.047	-0.067
ΔFS									0.363	0.775	-0.044	0.365	0.320
OS										0.083	-0.010	-0.040	0.205
ΔPrice											0.046	-0.080	0.379
ΔVOLA												0.126	0.010
ΔTV													-0.001

Table 6. Determinants of changes in liquidity measures around SEOs

This table presents regression estimates for determinants of the changes in various measures of liquidity. Results of SEO firms are reported in Panel A, and *Δ* represents the difference in a variable between the post-issue and pre-announcement periods of an SEO. Results of the differences between SEO and non-SEO firms are presented in Panel B, and the differences are calculated as SEOs' differences minus matched non-SEOs' differences. The panel regression model is:

$$\Delta Var = \alpha_0 + \alpha_1 \Delta FS + \alpha_2 OS + \alpha_3 \Delta Price + \alpha_4 \Delta VOLA + \alpha_5 \Delta TV + \varepsilon,$$

where ΔVar is the difference in a variable (*Var*) between the post-issue and pre-announcement periods of an SEO. The variable (*Var*) is λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread* (*bp*), C^{TAQ}, or PI^{TAQ}. λ is the adverse selection measure of Lin, Sanger, and Booth (1995). OI_n (OI_v) is the daily absolute order imbalance in terms of trades (shares), divided by the sum of buy and sell trades (shares). *ILL* is the Amihud (2002) illiquidity measure. *Q-spread* (*bp*) is the quoted bid-ask spread in the hundredth percentage. *E-spread* (*bp*) is the effective bid-ask spread in the hundredth percentage. C^{TAQ} is the effective cost, while PI^{TAQ} is the price impact coefficient. Full definitions of variables are given in Table 1. ΔFS is the difference in the market capitalization between the post-issue and pre-announcement periods of an SEO, divided by the pre-announcement market capitalization. *OS* is the offer size of the SEO in dollars divided by the market capitalization. $\Delta Price$ is the difference in the average close price between the post-issue and pre-announcement periods of an SEO. $\Delta VOLA$ is the difference in return volatility between the post-issue and pre-announcement periods of an SEO. ΔTV is the difference in the average trading volume between the post-issue and pre-announcement periods of an SEO. The *t*-statistics adjusted for the clustering effects of firms and SEO years are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: SEO firms

ΔVar	Intercept	*ΔFS*	*OS*	*ΔPrice*	*ΔVOLA*	*ΔTV*	Adj. R^2
$\Delta\lambda$	0.056***	-0.007	7.433**	-0.023	0.124***	0.111	0.052
	(6.13)	(-1.20)	(2.01)	(-0.56)	(3.07)	(0.28)	
ΔOI_n	-0.005	-0.001	1.466	0.030	0.036	-0.304	0.053
	(-1.26)	(-1.15)	(0.92)	(1.63)	(1.56)	(-1.25)	
ΔOI_v	0.001	-0.001	0.165	0.029*	0.012	-0.253	0.013
	(0.23)	(-0.47)	(0.12)	(1.74)	(0.58)	(-1.11)	
ΔILL	0.009	0.023	-40.571***	0.067*	0.101***	1.399***	0.149
	(0.70)	(0.35)	(-4.18)	(1.80)	(2.72)	(4.20)	
ΔQ-spread(bp)	-0.096***	-0.023	-42.772***	-0.309***	0.247***	0.766	0.095
	(-8.98)	(-1.62)	(-8.60)	(-4.27)	(4.68)	(1.42)	
ΔE-spread(bp)	-0.061***	0.021	-32.544***	-0.152***	0.192***	0.806*	0.078
	(-6.72)	(1.45)	(-7.70)	(-3.13)	(3.67)	(1.94)	
ΔC^{TAQ}	-0.030***	0.003	-12.932***	-0.071***	0.053***	0.342**	0.069
	(-9.31)	(1.06)	(-8.27)	(-3.66)	(2.90)	(2.08)	
ΔPI^{TAQ}	-0.060***	0.015	-6.309*	-0.108*	0.308***	0.866**	0.028
	(-6.96)	(1.62)	(-1.68)	(-1.86)	(4.90)	(2.23)	

Table 6 continued.

Panel B: Differences between SEO and non-SEO firms

ΔVar	Intercept	*ΔFS*	*OS*	*ΔPrice*	*ΔVOLA*	*ΔTV*	Adj. R^2
$\Delta\lambda$	-0.014 (-0.24)	0.013 (0.80)	12.195 (0.52)	-0.132 (-0.91)	0.459 (1.11)	-0.970 (-0.54)	0.016
ΔOI_n	-0.007 (-1.04)	-0.004 (-0.60)	-3.191 (-1.07)	0.037 (1.07)	0.034 (1.38)	-0.223 (-0.68)	0.035
ΔOI_v	-0.008 (-1.33)	-0.003 (-0.99)	1.051 (0.05)	0.044 (1.64)	0.017 (0.69)	-0.023 (-0.07)	0.012
ΔILL	0.011 (0.59)	-0.007 (-1.61)	-27.021** (-2.18)	0.086 (1.11)	-0.061 (-1.14)	0.633 (1.62)	0.050
ΔQ-spread(bp)	-0.066*** (-4.49)	-0.023* (-1.88)	-43.228*** (-6.97)	-0.366*** (-4.57)	0.155*** (2.62)	-0.984 (-1.54)	0.067
ΔE-spread(bp)	-0.056*** (-4.22)	-0.017* (-1.81)	-30.475*** (-5.40)	-0.273*** (-4.43)	0.082 (1.56)	-0.370 (-0.69)	0.045
ΔC^{TAQ}	-0.026*** (-4.93)	-0.036 (-0.96)	-10.810*** (-5.39)	-0.109*** (-4.15)	0.012 (0.55)	-0.219 (-0.77)	0.034
ΔPI^{TAQ}	0.069*** (5.10)	-0.013 (-0.21)	-11.280** (-2.05)	-0.053*** (-2.82)	0.219*** (3.35)	-1.017*** (-2.56)	0.015

Table 7. Determinants of SEO Underpricing: the role of perceived improvement in liquidity

This table presents regression estimates for the underpricing of the SEOs. The panel regression model is:

$$UP = \alpha_0 + \alpha_1 \Delta Var + \beta CONTROL + \varepsilon,$$

where *UP* is the SEO underpricing, calculated as 100×(*Offer price–Pre-offer price*)/*Pre-offer price*. ΔVar is the difference in a variable (*Var*) between the post-issue and pre-announcement periods of an SEO. The variable (*Var*) is λ, OI_n, OI_v, *ILL*, *Q-spread* (*bp*), *E-spread* (*bp*), C^{TAQ}, or PI^{TAQ}. λ is the adverse selection measure of Lin, Sanger, and Booth (1995). OI_n (OI_v) is the daily absolute order imbalance in terms of trades (shares), divided by the sum of buy and sell trades (shares). *ILL* is the Amihud (2002) illiquidity measure. *Q-spread* (*bp*) is the quoted bid-ask spread in the hundredth percentage. *E-spread* (*bp*) is the effective bid-ask spread in the hundredth percentage. C^{TAQ} is the effective cost, while PI^{TAQ} is the price impact coefficient. Full definitions of variables are given in Table 1. *CONTROL* represents a vector of control variables (*OS*, *IO*, *VOLA*, *Sentiment*, and *M/B*), and β represents a vector of coefficients. In specific, *FS* is the logarithm of market capitalization before the announcement of the SEO. *OS* is the offer size of the SEO in dollars divided by the market capitalization. *IO* is the institutional ownership before the announcement of the SEO. *VOLA* is volatility of the past-12-month returns ending three months before the announcement of the SEO. *Sentiment* is the Baker-Wurgler (2006) sentiment index before the announcement of the SEO. *M/B* is the market-to-book ratio before the SEO announcement. *Leverage* is the debt-to-equity ratio. The *t*-statistics adjusted for the clustering effects of firms and SEO years are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Intercept	ΔVar	*FS*	*OS*	*IO*	*VOLA*	*Sentiment*	*M/B*	*Leverage*	Adj. R^2
Var=λ	-0.055*	0.023	0.507	6.773***	-1.858	-0.126***	-0.312***	-0.128**	0.478	0.348
	(-2.08)	(1.40)	(1.48)	(3.18)	(-0.02)	(-4.03)	(-5.33)	(-2.49)	(0.38)	
Var=OI_n	-0.116***	0.044	1.196***	12.815***	-1.015	0.019	-0.312***	-0.099**	0.324	0.319
	(-4.42)	(1.11)	(3.51)	(5.87)	(-1.02)	(0.58)	(-5.47)	(-1.96)	(0.26)	
Var=OI_v	-0.115***	0.013	1.193***	12.883***	-0.990	0.019	-0.315***	-0.100**	0.328	0.314
	(-4.39)	(0.34)	(3.49)	(5.88)	(-0.99)	(0.59)	(-5.52)	(-1.98)	(0.27)	
Var=*ILL*	-0.109***	0.013	1.108***	13.078***	-1.119	0.019	-0.314***	-0.108**	0.185	0.321
	(-4.10)	(0.90)	(3.20)	(5.92)	(-1.12)	(0.59)	(-5.49)	(-2.11)	(0.15)	
Var=*Q-spread(bp)*	-0.152***	-0.071***	1.659***	10.737***	-1.060	0.002	-0.326***	-0.115**	0.448	0.492
	(-5.73)	(-6.44)	(4.81)	(4.91)	(-1.07)	(0.06)	(-5.78)	(-2.29)	(0.37)	
Var=*E-spread(bp)*	-0.149***	-0.076***	1.642***	11.370***	-1.035	0.006	-0.331***	-0.114**	0.188	0.427
	(-5.56)	(-5.11)	(4.69)	(5.19)***	(-1.04)	(0.18)	(-5.84)	(-2.26)	(0.15)	
Var=C^{TAQ}	-0.154***	-0.216***	1.666***	11.544***	-1.140	0.015	-0.322***	-0.113**	0.244	0.334
	(-5.70)	(-5.51)	(4.75)	(5.28)	(-1.15)	(0.47)	(-5.68)	(-2.25)	(0.20)	
Var=PI^{TAQ}	-0.122***	-0.270**	1.280***	12.945***	-1.059	0.004	-0.300***	-0.103**	0.306	0.446
	(-4.60)	(-2.11)	(3.72)	(5.92)	(-1.06)	(0.13)	(-5.22)	(-2.03)	(0.25)	