Does liquidity risk explain low firm performance following seasoned equity offerings?*

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Abstract

Firms can improve their stock liquidity and lower their costs of capital through seasoned equity offerings (SEO). This paper examines whether SEO firms achieve a liquidity gain and the sources of this gain. It explores the role of liquidity risk in explaining SEO long-run performance. The evidence shows that SEO firms experience significant post-issue improvements in liquidity and reductions in liquidity risk. Size and book-to-market matching fails to control for these liquidity effects, generating the low long-term post-SEO performance documented in the literature. After adjusting for liquidity risk, SEO firms show normal long-term performance.

JEL classification: G1; G2

Keywords: Event studies, seasoned equity offerings, liquidity risk.

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Introduction

Firms care about their stock liquidity because it affects their costs of capital through the premium investors require for holding illiquid or high liquidity-risk stocks.[1] A seasoned equity offering (SEO) can improve liquidity by shifting the firm's shareholder base towards more active traders and by increasing market visibility, where the latter can stimulate trading by lowering the adverse selection costs of trading with a better informed counterparty. Eckbo, Masulis and Norli (2007) confirm that managers consider liquidity improvements when issuing equity.[2]

The purpose of this study is two-fold. First, we investigate whether SEO firms improve their stock liquidity post-issue and where liquidity gains come from. In particular, we examine institutional investor share ownership and analyst coverage, the two factors that previous studies associate with lower adverse selection costs of trading and more frequent trading (Falkenstein, 1996; Irvine, 2003; Roulstone, 2003; Rubin, 2007; Agarwal, 2007). Second, we examine whether liquidity gains and reduced post-SEO liquidity risk explain low long-run post-SEO stock performance.

We examine four measures of liquidity to capture its multiple dimensions. The first two are Hasbrouck's (2009) Gibbs estimate of stock transactions costs, which captures effective spread, and Amihud's (2002) return to volume ratio, which measures the price impact of trade. Goyenko, Holden, and Trzcinka (2009) show that these two liquidity proxies relate closely to realized trade cost and price impact measures estimated from high frequency TAQ and Rule 605 data. The other two measures are stock turnover, which captures the

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[1] A growing literature shows that expected returns are positively related to illiquidity or liquidity risk (e.g., Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Liu, 2006).

[2] As a real-life example, New Oriental Education and Technology Group Inc (NYSE:EDU) justified a new equity issue as follows, "New Oriental Education and Technology Group Inc could embark on a secondary share issue valued at more than 100 mln USD next year to add liquidity to trading in its stock, chief financial officer Louis Hsieh said. The investment banks are asking us to float more shares, so that would be the most likely outcome, he said. Such an issue would help trading volume as well as allow long-term shareholders and venture capital firms to realize returns on their stock, he added." Xinhua Financial Network, 18 October 2006.

ability to trade large quantities of stock, and Liu's (2006) illiquidity measure, which captures multidimensional aspects of liquidity, with an emphasis on trading speed.

We show that SEO firms experience significant improvements in post-issue liquidity. Hasbrouck's (2009) Gibbs estimate falls by 24% over the five years after the issue compared with the five years pre-issue. Liu's (2006) trading discontinuity measure shows a 69% liquidity gain over the same period. Similar comparisons using stock turnover and Amihud's (2002) return to volume ratio indicate liquidity gains of 70% and 56%. We find that SEO firms have significantly higher post-issue liquidity characteristics than size and book-to-market (B/M) matched firms, indicating that size–B/M matching fails to control for SEO firms' liquidity gains.

Examining the sources of post-issue liquidity improvements, SEO firms experience a 22% increase in analyst following over the five years after the issue compared with the five years pre-issue. A higher analyst following improves the amount and quality of information about the firm, lowering the adverse selection costs of trading and increasing market liquidity (Irvine 2003; Roulstone, 2003). The number of institutional investors holding SEO firm stock increases by 39% on average, and their stake increases by 31%. This suggests that SEOs attract institutional investors, who become more dominant after the offering. Increased institutional trading and greater competition between sophisticated investors reduce the adverse selection costs of trading with a better informed party and can explain SEO liquidity gains (Falkenstein, 1996; Rubin, 2007; Agarwal, 2007). We also find that increases in analyst following and institutional investor holdings are larger for Nasdaq than NYSE/AMEX stocks, coinciding with the higher liquidity gains for Nasdaq listed SEOs. Regression analysis confirms that the higher post-issue liquidity of SEO firms is related to changes in analyst coverage and institutional holdings.

Consistent with past evidence, SEOs experience negative buy-and-hold abnormal returns relative to size–B/M matched stocks, and negative alphas in Fama and French (1993) three-factor model (FF3FM) regressions. Post-issue calendar time regressions show that SEO firms load negatively on the liquidity factor of a liquidity-augmented CAPM (LCAPM), with liquidity betas of −0.096 using equal weighting (EW) and −0.066 using value weighting (VW). Given an average monthly liquidity premium over 1970–2009 of 0.615%, these negative loadings lower post-issue SEO expected returns by 0.059% (EW) and 0.041% (VW) per month. The LCAPM alpha with respect to the FF3FM increases to −0.03% from −0.246% per month using EW and to −0.098% from −0.344% per month using VW. This means that after adjusting for liquidity risk, SEO firms show normal long-term performance. Our conclusions remain when we estimate LCAPM regressions for individual SEOs.

A series of robustness checks confirms the liquidity risk explanation of low long-run post-SEO performance. These include examining SEOs by industry, firm age, type of equity issued, hot and cold issue periods, SEO portfolios formed 3- and 6-months after the issue, which allows us to contrast short- and long-term post-issue liquidity gains, and SEOs where the post-issue period includes the liquidity drought during the recent financial crisis. Further analysis shows that size–B/M matched stocks have higher liquidity risk than SEO firms, which explains the significant negative long-run abnormal returns to SEO firms when using these as benchmark stocks. Matching on liquidity after the issue equates SEO and matched stock performance.

This study is not the first to examine the explanatory power of liquidity risk for the long-run performance of SEO firms. Eckbo, Masulis, and Norli (2000), Eckbo and Norli (2005) and Eckbo et al. (2007) also investigate the relation between liquidity and SEO performance. Eckbo et al. (2000) show that SEO stock turnover improves after the issue. Eckbo and Norli (2005) show that a turnover liquidity augmented Carhart (1997) model explains long-term post-IPO performance and, in a robustness test, that this model explains long-term post-SEO returns. Eckbo et al. (2007) report no abnormal performance, using the same model, for industrial, financial, and utility SEOs. This study differs from and complements these earlier studies by providing a detailed and comprehensive description of the liquidity evolution of SEO firms.

First, to capture the multiple dimensions of liquidity, we use four measures to describe SEO liquidity characteristics before and after the issue, and provide a detailed analysis of SEO liquidity dynamics. Second, we show that post-issue liquidity gains are attributable to a reduction in information asymmetry and improved share trading, as analyst coverage of SEO stocks and institutional stock ownership both increase. Third, we show that SEOs experience significant decreases in liquidity risk exposure. Existing studies largely ignore pre- to post-issue changes in liquidity.[3] Fourth, we use a liquidity risk factor based on trading discontinuity that captures multiple dimensions of liquidity. In contrast, Eckbo and Norli's (2005) liquidity risk factor is based on stock turnover. But Lee and Swaminathan (2000) find that high-turnover stocks tend to be small stocks, which questions turnover as a liquidity measure, while Liu (2010) reports an insignificant pre-1963 premium associated with stock turnover. Using all CRSP stocks, we show that the LCAPM describes the cross-section of stock returns based on liquidity sorts over the period 1970–2009, whereas the FF3FM and the FF3FM augmented by a turnover-based factor do not. Fifth, Eckbo and Norli (2005) and Eckbo et al. (2007) include a momentum factor in their analysis, which the literature commonly associates with less-than-rational investor behavior, so their analysis cannot rule out a behavioral explanation of SEO returns. In contrast, our results provide clear and comprehensive evidence of a liquidity-based discount rate explanation of post-SEO returns.

[3] An exception is the independent study of Lin and Wu (2010) who focus on SEO timing and liquidity risk.

The paper continues as follows. Section 2 describes the data and the distribution of new equity issues over the sample period. Section 3 confirms previous findings of low SEO performance using five-year buy-and-hold returns. Section 4 reports the liquidity characteristics of SEO firms before and after the offering, and compared to size–B/M matched stocks. It also explores the relation between post-issue liquidity changes and analyst following and institutional share ownership. Section 5 analyzes SEO performance in calendar and event time. Section 6 presents robustness tests and Section 7 concludes.

2. Data and sample selection criteria

Our sample of seasoned equity offerings is from the SDC New Issues database. The sample period starts in January 1970 and ends in December 2009. To allow for a five-year holding period, the last offering is in December 2004. The sample includes all US domiciled companies listed on NYSE/AMEX/Nasdaq that make SEOs of pure primary shares or combinations of primary and equity sales by a major shareholder (combinations) in the US market. We include industrial, financial, and utility firms but exclude unit offerings and SEOs that simultaneously offer debt, preferred stock, or warrants. The sample also excludes private placements, exchange offers of stock, 144A offers, cancelled offers, and spin-off related issues. These criteria lead to an initial sample of 9,928 issues. From this we exclude equity offerings by the same company occurring during the (five-year) holding period of a previous equity offering, leaving a sample of 6,986 SEOs. This is because Lyon, Barber and Tsai (1999) report severe cross-sectional correlation and misspecified tests when event windows for the same company overlap. Retaining offerings of common stock only (CRSP share codes 10 and 11) with return data available for at least a month after the issue leaves 6,425 SEOs. Data requirements on market and book values of common equity from the Compustat/CRSP merged database leave 4,503 offerings. We find control stocks for 4,446 issues, which form our main sample.

Table 1 describes the sample distribution stratified by exchange, broad industry group (financial, industry, and utility), type of equity issue (pure sales of primary shares and offers accompanied by sales of equity by a major shareholder), membership of nine Fama and French (1993) size–B/M portfolios, issue period, and whether the issue takes place in a hot or cold issue period.[4] Of the 4,446 SEOs, 1,995 are on NYSE/AMEX and 2,451 are on Nasdaq. Industrial firms form the largest new equity issue group with 3,447 SEOs, compared to 482 utility and 517 financial SEOs. Using NYSE breakpoints to split issuers into three portfolios, small (*S*), medium (*Me*), and big (*B*) by market value of common equity and three portfolios, high (*H*), medium (*M*), and low (*L*) by B/M, gives 2,433 small compared to 665 large capitalization stocks and 2,011 low B/M stocks, of which 1,204 are small. This coincides with previous findings that small, low B/M stocks dominate new equity issuers. The number of new equity issues increases over time with 1,809 SEOs in the 1990s. Almost two-thirds of the sample (3,042) occur in hot issue periods with over 56% listed on Nasdaq.

3. The long-run performance of SEOs: event time analysis

Previous studies of post-SEO long-run performance in event time report buy-and-hold returns that are significantly lower, both statistically and economically, than size–B/M matched stocks. To confirm these findings for our sample, we match based on the closest neighbor approach, following Loughran and Ritter (1995). We pair each issuer with non-issuing firms in a 30% bracket of the issuer's equity value at the year-end before the offering, where non-issuers are firms that have not issued equity in the past five years. From this pool we select a control firm with the closest B/M to the issuer's. To avoid hindsight bias we use book value of equity for the fiscal year two years earlier if an issue takes place in the first six

[4] We define an issue month as hot (cold) if the number of SEOs in the month before the issue is above (below) the median monthly number of SEOs in the previous 12 months.

months of a year and book value from the previous fiscal year for issues in the second six months of the year. The definition of B/M follows Fama and French (1992).[5] We include the control for a 5-year holding period and allow each control to pair with one SEO over the holding period. Pairing each control with one SEO over the holding period reduces problems of cross-sectional correlation. If a match delists or issues equity, we choose a new match from the original list of eligible benchmarks. We truncate the SEO and its match return on the date an issuing firm delists. Firm *i*'s t_i-month buy-and-hold return (BHR) is

$$BHR_i = \prod_{\tau=1}^{t_i} \left(1 + R_{i\tau}\right) - 1 \tag{1}$$

where $R_{i\tau}$ is firm *i*'s stock return in month τ. The holding period starts at the beginning of the month following the issue and ends at the earlier of the five-year anniversary or the delisting date. To avoid a delisting bias, we follow Shumway (1997) and Shumway and Warther (1999) and include delisting returns. When a delisting return is missing, we assume a return of −1 for delisting due to liquidation (CRSP codes 400–490), −0.33 for performance related delisting (CRSP codes 500 and 520–584), and zero otherwise. The average holding period return across all sample stocks is $\overline{BHR} = \sum_{i=1}^{N} x_i BHR_i$, where x_i denotes EW or VW. Value weights are based on market value one month before the offer, scaled by the value-weighted NYSE/AMEX/Nasdaq CRSP stock market index to give comparability over time.

Table 2 reports average BHRs for issuers and matches over a five-year holding period; *Diff*, denoting the difference, gives issuers' percentage buy-and-hold abnormal returns (BHARs). Average BHAR is −27.67% using EW and −26.10% using VW. With EW, NYSE/AMEX issuers have less underperformance than Nasdaq stocks (−23.43% vs. −31.12%) and similar levels of underperformance using VW (−26.23% vs. −25.26%).

[5] Book value is the Compustat book value of stockholders' equity plus balance sheet deferred taxes and investment tax credits less the book value of preferred stock. The value of preferred stock is the redemption, liquidation, or par value, in that order depending on availability. Market value of equity is the number of shares outstanding times the end of month closing price.

Skewness-adjusted *t*-statistics recommended by Lyon, Barber and Tsai (1999) show significant SEO underperformance in all specifications at 5%.

Test statistics can be negatively biased due to cross-sectionally correlated abnormal returns. Jegadeesh and Karceski (2009) propose a correlation and heteroskedasticity consistent test that adjusts for cross-sectional correlation. Their test statistic takes the form $t = w'\overline{AR}(H) / w'Vw$, where w is a vector of weights,[6] $\overline{AR}(H)$ is the H-month holding period (60 months in this study) average abnormal return of each monthly cohort of securities experiencing an event in month t and V is the $T\times T$ variance–covariance matrix of $\overline{AR}(H)$, where T is the number of monthly cohorts. Overlapping returns lead to non-zero serial covariances between observations closer than H months apart; all higher order covariances are set to zero. Estimates of V are based on a generalized version of White's (1980) heteroskedasticity-consistent variance estimator. The penultimate column of Table 2 reports the Jegadeesh-Karceski *t*-test, which decreases the magnitude of test statistics on average by over 76 percent. For example, the *t*-statistic moves from −8.345 to −1.801 for the pooled sample using EW. Despite lower *t*-values, however, abnormal returns remain significant at 10%, with the one exception of Nasdaq returns using VW, which are insignificant. We conclude that both economically and statistically the SEO puzzle is evident in our sample.

4. The evolution of SEO liquidity characteristics

Numerous studies find a negative relation between stock liquidity and expected return (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Amihud 2002). Chordia et al. (2000), Lo and Wang (2000), and Hasbrouck and Seppi (2001) find commonalities in liquidity in the cross-section of stocks. Pastor and Stambaugh

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[6] For EW, the i^{th} element is the ratio of the number of events in month t to the total sample size; for VW, the i^{th} element is the ratio of the monthly cohort's market value to the total sample market capitalization.

(2003), Sadka (2006), and Liu (2006) show that market liquidity is a relevant state variable for asset pricing. This section explores the liquidity evolution of SEO firms.

In their horserace of effective spread and price impact proxies, Goyenko et al. (2009, 167) find that "measures intended to capture other features of transaction costs, Amihud, Pastor and Stambaugh, and Amivest, do a poor job estimating effective and realized spreads", which illustrates the need to use multiple measures to capture different liquidity dimensions. We use four liquidity measures, each emphasizing different liquidity dimensions. This offers a more complete description of the evolution of SEO liquidity.

The first measure is Hasbrouck's (2009) Gibbs estimate of stock transactions costs, *c*, based on Roll (1984). Hasbrouck's (2009) horserace of four effective transaction cost measures shows that *c* clearly dominates and, among twelve spread proxies, Goyenko et al. (2009, Table 3) find that *c* has the highest annual cross-sectional correlations with effective and realized spreads calculated from TAQ data. We obtain data on *c* from Joel Hasbrouck's website.

The second liquidity measure is share turnover (*TR*), which represents the trading quantity dimension of liquidity. *TR* is the daily number of shares traded (*volume*) as a percentage of the number of shares outstanding on the day (*shares out*), averaged over the number of trading days (n) in the prior 12 months

$$TR_i = \frac{1}{n}\sum_{t=1}^{n}\frac{volume_{it}}{shares\,out_{it}} \qquad (2)$$

To calculate *TR*, a stock must have daily trading volume data available over the prior 12 months. Datar et al. (1998) report a close link between *TR* and bid-ask spread. Brennan et al. (1998) and Datar et al. (1998) show a negative cross-sectional relation between *TR* and expected returns.

The third (il)liquidity measure is Liu's (2006) *LM*12, defined as the standardized turnover-adjusted number of zero-trading volume days over the prior 12 months

$$LM12_i = \left(\text{number of zero volume days in the prior 12 months}_i + \frac{1/TR12_i}{Deflator} \right) \times \frac{21 \times 12}{NoTD}, \quad (3)$$

where *TR*12 is the sum of daily turnovers (in percentage) over the prior 12 months, *Deflator* = 20,000 to ensure that $(1/TR12)/Deflator < 1$, and *NoTD* is the number of exchange trading days over the prior 12 months; the final term standardizes the number of trading days in a month to 21. Calculating *LM*12 requires daily trading volumes over the prior 12 months. *LM*12 captures multiple features of liquidity such as trading quantity, trading costs, and trading continuity, with particular emphasis on the latter, which is the major generator of the liquidity premium.

The final (il)liquidity measure is Amihud's (2002) return to volume metric, denoted *RtoV*, which measures the price impact of trade. Among different price impact proxies, Goyenko et al. (2009) report that *RtoV* is generally the best candidate. *RtoV* is the daily ratio of absolute daily return, *R*, to the dollar denominated trading volume on the day, *volume* \$, averaged over the prior 12 months,

$$RtoV_i = \frac{1}{n} \sum_{t=1}^{n} \frac{|R_{it}|}{volume\$_{it}}. \quad (4)$$

Constructing *RtoV* requires at least an 80% availability of daily trading volumes in the prior 12 months,[7] and excludes zero trading volume days.

Analyzing liquidity characteristics requires each SEO and control stock to have at least one month with non-missing liquidity characteristics over both the 5-year pre- and post-issue periods. This reduces the sample to 3,587 issues but ensures a consistent comparison of pre- and post-offering liquidity characteristics. We examine all four liquidity measures from January 1965 to December 2009.[8] The sample reduction (from 4,446 to 3,587) is due to more

[7] Amihud (2002) requires at least 200 daily trading volumes in the prior 12 months.
[8] Hasbrouck (2009) estimates *c* at the year-end using daily price data over the prior 12 months. We use this estimate for each of the next twelve months.

frequent missing liquidity characteristics for Nasdaq compared to NYSE/AMEX issuing and control stocks.[9]

4.1 The evolution of SEO and benchmark stock liquidity around equity issues

Figure 1 shows the evolution of the four liquidity measures during the five years before and after the issue for SEO firms and their size–B/M matches. In Figure 1a, the cost of trading SEO stocks, c ($\times 10^2$), increases from 0.82 five years before to 1.063 ten months before the issue. It decreases in the period leading up to an issue, reaching 0.967 one month before. This coincides with the period when the company is planning the issue. Trading costs continue to drift down following the issue, from 0.918 one month after to 0.694 eighteen months after, leveling out at 0.723 over the subsequent period. Matching stocks experience no improvements in trading costs with a mean c of 0.877 before and 0.925 after the issue.

Figure 1b shows a gradual increase in average daily turnover rates. Daily turnover increases from 0.29% five years before to 0.384% twelve months before the issue. *TR* jumps to 0.524% one month before the issue and continues to increase after the issue, from 0.628% one month after to a peak of 0.744% in the eleventh month after. Average *TR* decreases to 0.616% two years after the issue and levels out at around 0.61% over the remaining period. Size–B/M control stocks exhibit little change in *TR* with average *TR* increasing from 0.333% pre-issue to 0.456% post-issue. Figure 1c shows a similar picture for *LM*12. *LM*12 falls sharply in the year before the issue, from 8.021 twelve months before to 5.757 one month before, a fall of 28.2 percent, and decreases further around the issue (from 5.757 one month before to 4.802 one month after, a fall of 16.6 percent). Liquidity continues to improve over the next eleven months, with an average *LM*12 gain of 66.8 percent (from 4.802 one month after the issue to 1.597 twelve months after) and levels out around an average of 2.065 over

[9] Footnote 10 below summarises the results of an analysis of the possible effects of this sample reduction, which suggests that conclusions reached on the smaller sample apply to the main sample.

the remaining period. Mean *LM*12 for matching stocks is 8.412 in the 60 months before the issue and 7.855 in the five-years after.

Figure 1d shows that *RtoV* ($\times 10^6$ from now on) is relatively flat until month 12 before the issue. But it decreases from 2.208 twelve months before the issue to 1.335 one month before. It continues to fall during the twelve months after the issue (from 0.935 one month after to 0.505 twelve months after) and levels out at an average 0.884 over the remaining period with a slight spike in months 38 to 42 after the issue. Control stocks have an average *RtoV* of 1.375 pre-issue, drifting upwards to an average of 2.008 post-issue.

Table 3, Panel A shows the mean liquidity characteristics of SEOs, size–B/M matches, and their differences for the 5-year pre-issue period. SEOs have significantly higher trading costs than benchmark stocks pre-issue with a mean *c* difference between SEOs and control stocks of 0.065. SEOs have lower *LM*12 and higher *TR* (mean differences between SEOs and control stocks of −1.413 and 0.029%) and higher *RtoV* (mean difference of 0.465). Mean differences in liquidity between SEOs and control stocks are highly significant, which suggests that size–B/M matching fails to match on liquidity.

Table 3, Panel B shows the mean liquidity characteristics of SEOs and their size–B/M matches over the 5-year post-issue period. We make two observations. First, SEO liquidity improves relative to benchmark stocks. SEO trading costs fall and the average difference in *c* between SEOs and size–B/M matches falls to −0.191. The mean differences in *LM*12 and *TR* increase in magnitude to −5.653 and 0.182%, 4 and 6.3 times the magnitudes in Panel A. The difference in *RtoV* becomes negative, decreasing from 0.465 in Panel A to −1.153 in Panel B. Second, the increased liquidity mismatch post-issue is due to higher SEO liquidity. Issuers' trading costs fall from 0.962 in Panel A to 0.736 in Panel B, a 23.51% decrease. *LM*12 falls from 7.075 in Panel A to 2.228 in Panel B, a 68.51% decrease, and turnover improves from 0.374% to 0.636%, a 70.22% gain. There is a comparable improvement in SEO return-to-volume, which falls from 1.857 to 0.821, a 55.79% reduction. Nasdaq listed issuers experience the biggest liquidity gains post-issue with *c* falling from 1.595 to 0.984, *LM*12 falling from 12.69 to 3.034, *TR* increasing from 0.592% to 0.923%, and *RtoV* falling from 3.378 to 1.049. The results in Table 3 clearly reveal that SEOs improve their liquidity following the offering and that size–B/M matching does not control for SEO liquidity characteristics.

4.2 SEO return performance relative to liquidity matched control stocks

Our results suggest that the high liquidity of SEO stocks may explain their low performance relative to size–B/M matched stocks. We therefore test whether liquidity matching after the issue equates SEO and control firm returns. Table 4 reports SEO buy-and-hold abnormal returns relative to size–B/M matches and post-issue *LM*12-matched control firms. We match on *LM*12 in months 8, 12, and 18 after the offering to control for the gradual improvement in SEO liquidity evident in Figure 1. Missing liquidity characteristics in the matching month lead to slight sample reductions. Issuing stocks underperform size–B/M control stocks based on skewness adjusted *t*-statistics and Jegadeesh and Karceski's (2009) *t*-test over all three holding periods (at 5%) for all portfolios using EW and the majority of portfolios using VW. *LM*12 matching reduces the BHARs using EW from −35.75% to −17.97% for the match made in month eight, from −28.3% to −13.25% for the match made in month twelve, and from −19.26% to −8.25% for the match made in month eighteen. Corresponding increases in BHARs using VW are from −22.35% to −13.93%, from −17.7% to −10.89%, and from −10.63% to 0.67%. Based on skewness adjusted *t*-statistics and Jegadeesh and Karceski's (2009) *t*-test, SEOs do not underperform liquidity matched benchmarks over any of the holding periods.[10] Matching on *c*, *TR*, or *RtoV* also shows less SEO underperformance than size–B/M matching.

4.3 What explains SEO liquidity gains after the issue?

We explore two explanations for increases in SEO liquidity after the offering. First, an equity offering is likely to increase analyst coverage. Previous studies show that issuing firms actively seek analyst coverage after the issue and analyst coverage can form part of the underwriting agreement (Krigman, Shaw, and Womack, 2001; Cliff and Denis, 2004). Higher analyst following increases market visibility and improves the amount and quality of information about the firm available to investors (Imhoff and Lobo, 1992; Barron et al. 2002; Francis, et al. 2002). This in turn reduces information asymmetry and the cost of trading with better informed investors, leading to higher price informativeness and stock liquidity (Brennan and Subrahmanyam, 1995; Hong, Lim, and Stein, 2000; Irvine, 2003; Roulstone, 2003; Barth and Hutton, 2004; Chang, Dasgupta, and Hilary, 2006).

Second, previous studies report a positive relation between institutional shareholding and stock liquidity (Falkenstein, 1996; Rubin, 2007; Agarwal, 2007). This is because (1) institutional investors trade more often and trade larger share volumes, and (2) an increased presence of institutional investors increases competition among investors, improving market efficiency and reducing the likelihood of trading against a better informed counterparty.

To test these two propositions, we examine changes in analyst following and in institutional holdings for five years before and after the issue for SEOs and size–B/M matches. We calculate the number of analysts following a firm, *#Anal*, as the number of analysts providing earnings forecasts for a firm, over all possible forecast horizons, in the

[10] To check that our analysis of liquidity dynamics on a reduced sample is representative of the full sample, we conduct two additional analyses. First, we examine BHARs for the 3,587 SEOs. Untabulated results show no significant differences from results for the full sample in Table 2. Second, we replicate the calendar time analysis of Section 5 below for the 3,587 SEOs to investigate their liquidity risk dynamics after the issue. The results for the reduced sample are qualitatively similar to the main sample results, corroborating our findings.

past 12 months including the current month. The calculation of *#Anal* is based on the IBES detail files. We exclude stocks not covered by IBES and assume analyst coverage is zero if a stock is listed on IBES but has no analyst following in the past 12 months including the current month.

Institutional holdings data are from the Thomson Reuters 13F Holdings database (formerly the CDA/Spectrum database). The Securities and Exchange Commission requires institutions that manage equity in excess of $100 million to file (quarterly) form 13F, listing holdings larger than 10,000 shares or $200,000 in market value. At the quarter-end, we calculate the total number of institutions holding shares in a firm, *#Inst*, and the total number of shares they hold. To find the proportion of shares held by institutions, *%SharesInst*, we scale total institutional shareholdings by the number of shares outstanding from CRSP at the end of the reporting quarter. Additional data requirements leave 2,172 SEOs over 1985–2009.[11]

4.3.1 The evolution of analyst following and institutional investor holdings around SEOs

Figure 2 examines the evolution of analyst following and institutional investor shareholdings for SEO firms and their size–B/M matches for five years before and after the issue. Subsequently, Table 5 reports the mean analyst following and institutional holdings of SEOs, size–B/M matches, and tests their differences around the offering. The next section presents results of a regression analysis testing whether changes in analyst following and institutional investor holdings explain post-issue liquidity gains of SEO stocks.

Figure 2a shows a pre-issue decline in analyst coverage, with the average number of analysts covering SEO stocks decreasing from 9.27 five years before the issue to 7.65 six months before the issue. However, *#Anal* increases sharply from this latter value to 10 sixteen

[11] IBES and Thomson Reuters 13F Holdings data start in 1980. To avoid data errors, we exclude the first five years of data when calculating analysts following and institutional holdings.

months after the issue, a 30.7% increase. Analyst coverage levels out at 10.44 over the remaining period. Analyst coverage of benchmark stocks decreases from 8.28 over the five-years before the issue to 7.51 over the five-years after the issue. The results in Figure 2a are consistent with our prediction that new equity issues attract increased analyst coverage.

Figure 2b shows that the number of institutional investors holding SEO stock declines before the offering, falling from 85.99 five-years before the issue to 73.16 twelve months before the issue. However, similar to analyst following, *#Inst* increases to 87.28 one month before the issue and reaches a peak of 134.88 five-years after the issue. Mean institutional holdings of size–B/M matches are 87.78 before the issue and 96.09 after the issue. Figure 2c reports the proportion of SEO firm shares held by institutional investors. *%SharesInst* is roughly constant around 40–41% up to twelve months before the issue. Institutional ownership increases from 40.1% twelve months before the issue to 53.6% twelve months after the issue, a 33.6% increase, and levels off at 55.6% over the remaining period. The proportion of shares held by institutional investors in size–B/M matches is 41.8% before the issue and 47.8% after the offering. Together, Figures 2b and 2c suggest that share issues attract institutional investors, who become the dominant shareholders after the offering. The results in Figure 2 are consistent with Gibson et al. (2004), who find an increase in institutional holdings in SEO firms in the four quarters after the SEO, and Lin and Wu (2010), who also report an increase in SEO institutional holdings and analyst coverage after the issue.

Table 5 shows the mean analyst following and institutional holdings of SEOs, size–B/M matches, and their differences around the offering. Panel A shows the results for the 5-year pre-issue period. Compared to size–B/M matches, SEOs have higher analyst following before the issue and a greater percentage of institutional ownership. NYSE/AMEX listed SEOs have higher analyst following and institutional holdings than Nasdaq listed issuers, consistent with Falkenstein's (1996) findings that institutional investors prefer to hold larger and more liquid stocks.

Table 5, Panel B reports mean analyst coverage and institutional investor holdings of SEOs, size–B/M matches, and their differences for the 5-year post-issue period. Analyst coverage of SEO stocks increases from 8.288 before the issue to 10.117 after the issue, and the difference in analyst coverage of SEOs compared to benchmark stocks increases from 0.342 to 2.644. Analyst following of benchmark stocks decreases after the issue. The number of institutional investors holding SEO stock increases from 79.402 before the issue to 110.048 after the issue, a 38.6% gain. The percentage of SEO firm shares held by institutional investors increases from 42.12% before the issue to 55.17% after the issue, a 30.99% increase. Benchmark stocks show only a 14.29% increase in institutional holdings. The difference in institutional investor ownership of SEOs compared to size–B/M matches after the offering increases from 0.62% before the issue to 7.74% after the issue. The increase in SEO analyst coverage and institutional holdings compared to benchmark stocks after the issue mirrors the SEO liquidity gains compared to size–B/M matches in Table 3. Further, Nasdaq issuers experience the largest increase in analyst coverage after the issue (an increase of 60.96%) and institutional holdings (*#Inst* increases by 81.09% and *%SharesInst* shows a 44.12% gain), consistent with the higher liquidity gains for Nasdaq listed SEOs in Table 3.

4.3.2 Liquidity gains and changes in analyst following and institutional investor holdings around SEOs

To test formally whether changes in analyst following and institutional investor holdings explain post-issue liquidity gains of SEO stocks, we estimate the following regression

$$
\begin{aligned}
LiqGain_i = {} & \alpha_0 + \alpha_1 \Delta \#Anal_i + \alpha_2 \Delta \% SharesInst_i + \alpha_3 \Delta \#Inst_i + \alpha_4 \% NewShares_i \\
& + \alpha_5 \, B/M_{\,i} + \alpha_6 \ln MV_i + \alpha_7 Hot_i + \alpha_8 Nasdaq_i + \varepsilon_i
\end{aligned} \tag{5}
$$

where $LiqGain_i$ is the change in one of the four liquidity measures from Table 3 in the 5-year post-issue period for SEO firm *i*. The changes in *c*, *RtoV* and *LM*12 are multiplied by −1 so that positive values of *LiqGain* reflect SEO liquidity increases after the issue. Δ*#Anal*, Δ*%SharesInst* and Δ*#Inst* are the changes, in percentage, in analyst coverage and institutional holdings of SEOs after compared to before the issue, and *%NewShares* is the proportion of (primary and secondary) shares issued relative to the number of shares outstanding one month before the offering. The book-to-market ratio is for the fiscal year two years before the offering if an issue takes place in the first six months of a year, and for the previous fiscal year for issues in the second six months of the year. Market capitalization is measured one month before the offering and scaled by the CRSP stock market index to give comparability over time. *Hot* and *Nasdaq* are indicator variables for hot-issue periods and for SEO listings on Nasdaq. We winsorize all variables at the top and bottom 1% of values.

Table 6 shows the results of estimating model (5). For ease of exposition, the coefficients when *c* is the liquidity measure are multiplied by 10^3. We find a positive association between SEO liquidity gains and changes in analyst following and in the (percentage) institutional investor ownership of SEOs (Δ*%SharesInst*) for the majority of the liquidity measures. The increase in the number of institutional investors holding SEO stock after the offering, Δ*#Inst*, is positively associated with stock turnover. With the exception of stock turnover, larger equity offerings relative to the pre-issue number of shares outstanding increase SEO stock liquidity. Value firms and smaller firms have greater liquidity gains. Nasdaq listed SEOs experience larger gains with respect to −*c* and stock turnover. Overall, the results in Table 6 show that post-issue SEO liquidity gains are associated with increases in analyst coverage and institutional investor holdings.

5. Calendar time analysis

Fama and French (1993, 1995, 1996), Perez-Quiros and Timmermann (2000), and Lettau and Ludvigson (2001) challenge the notion that firm characteristics drive expected stock returns. A calendar time analysis allows us to examine whether a factor model can explain low SEO long-run performance. Fama (1998) and Mitchell and Stafford (2000) advocate the calendar time approach as being less susceptible to bad model problems as it does not compound spurious abnormal returns. It also poses fewer statistical problems (less skewness and kurtosis) and adjusts directly for cross-sectional correlation. The intercept (alpha) of a calendar time regression estimates the mean monthly abnormal return.

We first replicate previous evidence on SEO calendar time performance in FF3FM regressions with a five-year holding period. Table 7 reports alphas and factor loadings from regressing equal and value weighted SEO portfolio excess returns on the three factors, using the main sample of 4,446 SEOs. We require at least 10 stocks in a monthly calendar time portfolio to ensure that a few stocks do not unduly influence the parameter estimates and to limit heteroskedasticity of the portfolio residual variance.[12] This restricts the sample period to April 1970–December 2009.

In general, SEO returns covary positively with each of the three factors, although Nasdaq SEOs load negatively on *HML*. The pooled sample alpha is −0.246% using EW and −0.344% using VW, and Nasdaq SEOs have more negative alphas than NYSE/AMEX SEOs. All alphas using EW are significant at 5% and all alphas using VW are significant at 10%.[13] Overall, the Fama and French (1993) model fails to explain low SEO performance.

[12] The average number of stocks in a calendar time portfolio is 501 per month, which on average produces homoscedastic standard errors. However, we correct test statistics for heteroskedasticity in Tables 7–13 whenever White's (1980) model specification test rejects the null of homoscedasticity.

[13] The pooled sample alpha is a non-linear combination of the exchange regression alphas and includes the diversification effect of pooling stocks across the two exchanges. The pooled sample alpha also adjusts for constraining the factor loadings to average values across the exchanges. For example, the higher pooled alpha adjusts for the *HML* loading in the pooled regression being over three times lower than for NYSE/AMEX issuers.

5.1 Tests based on liquidity augmented asset pricing models

To assess the explanatory power of liquidity risk for post-SEO performance, we initially use Liu's (2006) LCAPM.[14] The LCAPM consists of the market factor and a liquidity risk factor, LIQ

$$E(R_i - R_f) = \beta_{mi} E(R_m - R_f) + \beta_{li} E(LIQ) \quad (6)$$

Liu (2010) shows that *LM*12 captures multiple liquidity dimensions and that it generates a more robust premium than bid-ask spread, Hasbrouck's *c*, the number of zero daily returns, stock turnover, and return-to-volume. We construct *LIQ* based on *LM*12. Specifically, we independently sort NYSE/AMEX/Nasdaq stocks at the end of each month based on *LM*12 and form two portfolios. One is a low liquidity portfolio, *LL*, containing the highest *LM*12 NYSE/AMEX stocks, based on a 15% NYSE breakpoint, and the 35% highest *LM*12 Nasdaq stocks. The other is a high liquidity portfolio, *HL*, containing the lowest *LM*12 NYSE/AMEX stocks, based on a 35% NYSE breakpoint, and the 15% lowest *LM*12 Nasdaq stocks. The two portfolios are equally-weighted and held for six months after portfolio formation. The liquidity risk factor, *LIQ*, is constructed as the monthly profits from buying one dollar of *LL* and selling one dollar of *HL*. Model (6) excludes *SMB* and *HML* because distress risk proxied by these two factors is a source of stock illiquidity. Thus, liquidity risk should capture distress risk more directly. Liu (2006) shows that model (6) not only explains the *TR* and *LM*12 premiums, which the FF3FM model does not, but it also accounts for market anomalies associated with size, book-to-market, cash-flow-to-price, earnings-to-price, dividend yield, and long-term contrarian investment.

To explore the source of SEO firms' negative FF3FM alphas in Table 7 and whether liquidity risk can explain SEO performance, as a first step, Table 8 examines whether alternative asset pricing models explain the returns to liquidity-sorted portfolios. We classify

[14] Section 6.3 reports robustness tests using other liquidity risk model specifications.

stocks into *LM*12 deciles at the end of each year from 1969 to 2008 and calculate decomposed portfolio buy-and-hold returns for the next twelve months using EW (Liu and Strong, 2008).[15]

The first row of Table 8 shows the mean value of *LM*12 for each portfolio, from the lowest liquidity portfolio, *LL*, to the highest liquidity portfolio, *HL*. The second row reports the proportion of firms within each liquidity decile that make an SEO in the following twelve months. This proportion increases almost monotonically from portfolio *LL* to portfolio *HL*, with the proportion within the two highest liquidity deciles being 9.5%, compared with 0.7% for the two lowest liquidity deciles. The fact that this proportion is far from uniform across the deciles indicates the potential relevance of liquidity.

The next four rows of Table 8 report the alphas and associated *p*-values from FF3FM and LCAPM regressions of the monthly decile portfolio returns. The FF3FM alpha is large and negative for the most liquid decile, *HL,* which contains the highest proportion of SEOs, suggesting the reason for the negative SEO FF3FM alphas in Table 7. In contrast, the LCAPM alphas are insignificant across all liquidity deciles.

We also estimate Eckbo and Norli's (2005) model, minus the momentum factor, and report alphas for this model and associated *p*-values in the last two rows of Table 8.[16] This four factor model eliminates the negative performance of the most liquid decile, *HL*, but, similar to the FF3FM, it underprices the low liquidity deciles *LL*, *L*2, and *L*3.

The results in Table 8 confirm that the LCAPM can explain cross-sectional variation in returns to liquidity-sorted portfolios. In contrast, the FF3FM overprices the most liquid

[15] We discuss the decomposed buy-and-hold returns method of Liu and Strong (2008) in detail in Section 6.2. Our conclusions are qualitatively the same using traditional calendar time portfolio analysis.

[16] To create their liquidity factor, *LMH,* we follow Eckbo and Norli (2005) and sort all NYSE/AMEX stocks into two portfolios based on market value of equity and three portfolios based on stock turnover at each year-end, and calculate monthly portfolio returns using VW for the next twelve months. *LMH* is the difference in equally weighted returns on the two low turnover portfolios (*L*) and the two high turnover portfolios (*H*). Portfolios are rebalanced in December each year. Over January 1970–December 2009, *LMH* has a mean value of 0.284% and a correlation of 0.662 with *LIQ*.

stocks, offering a potential explanation for previous findings of low SEO performance using a FF3FM benchmark. The FF3FM augmented by Eckbo and Norli's (2005) liquidity factor fails to price low liquidity portfolios.

5.2 Liquidity risk as an explanation for low SEO performance after the issue and relative to size and book-to-market stocks

To examine whether liquidity risk can explain post-SEO stock price performance, Table 9, Panel A reports intercepts and factor loadings of LCAPM calendar time portfolio regressions using the same SEO portfolio returns as in Table 7. None of the intercepts is distinguishable from zero. The coefficient on *LIQ* for all issuers is −0.096 using EW and −0.066 using VW, with Nasdaq issuers driving these loadings. Given an average monthly liquidity premium over 1970–2009 of 0.615%, these liquidity loadings lower the pooled and Nasdaq SEO expected returns by −0.059% and −0.126% per month using EW and by −0.041% and −0.274% per month using VW. NYSE/AMEX issuers have less liquidity risk than the average CRSP stock, which has a loading of 0.299 on *LIQ* over our sample period, 1/1970–12/2009 (results untabulated).

Table 9, Panel B tests the significance of the differences in SEO factor loadings before and after the offering using Lagrange Multiplier (*LM*) tests from seemingly unrelated regressions. The *LIQ* loading before the offering is from LCAPM regressions over five years before the issue. The columns headed *Difference: after − before* gives the difference in factor loadings. Post-issue *LIQ* loadings are significantly lower for all SEO samples except for the NYSE/AMEX portfolio using VW. This confirms a reduction in SEO liquidity risk exposure after the issue and complements the results on the evolution of liquidity characteristics in Figure 1 and Table 3. Differences in SEO market sensitivities are significant for all SEO samples using EW and Nasdaq issuers using VW. Lower *MKT* betas after the issue are consistent with Carlson, Fisher and Giammarino (2010), who argue that exercising growth options reduces SEO market risk. However, the post-issue market risk reduction is too small to fully explain low long-run SEO performance. For example, for the pooled sample using EW, lower market risk reduces post-issue monthly expected returns by 0.037% (−0.086 × 0.429%) compared to a 0.131% reduction attributable to lower liquidity risk. Overall, the LCAPM estimates show that lower liquidity risk exposures explain issuers' post-issue performance.

A diversification effect in calendar time portfolios may explain the zero LCAPM alphas in Table 9. To test if our method of applying the calendar time analysis affects our inferences, we estimate the LCAPM for individual SEO stocks. Following Lin and Wu (2010) we estimate the following regression model

$$R_{it} - R_{ft} = \alpha_{i,0} + \alpha_{i,1} \times D_{SEO} + (\beta_{mi,0} + \beta_{mi,1} \times D_{SEO})(R_{mt} - R_{ft}) + (\beta_{li,0} + \beta_{li,1} \times D_{SEO})LIQ_t + \varepsilon_{it} \quad (7)$$

where the 0 and 1 subscripts indicate estimates for the pre- and post-issue periods, and D_{SEO} equals 1 for the post-issue period and 0 otherwise. If the LCAPM explains SEO post-issue performance, $a_{i,0} + a_{i,1}$ should be zero. Lower post-offering sensitivity to liquidity risk implies $\beta_{li,1} < 0$. The regression spans the period five years before and after the equity issue and we require at least six observations before and after the issue for each SEO to estimate the model, which eliminates two SEOs from the sample.[17]

Table 10, Panel A shows average estimates for model (7) across 4,444 SEOs. Consistent with previous evidence (Bayless and Jay, 2003), we find strong pre-issue SEO abnormal performance of 1.657% using EW and 0.850% using VW. But we find no evidence of post-issue negative abnormal performance based on the LCAPM, with $\alpha_0 + \alpha_1$ being insignificantly different from zero for SEO portfolios using both EW and VW. Further, *LIQ* factor loadings are lower after the issue, with reductions across all SEOs of −0.287 using EW

[17] The results are robust to using a minimum of 18 observations before and after the issue for each SEO.

and −0.068 using VW. The post-issue fall in liquidity risk is higher for Nasdaq than for NYSE/AMEX stocks. Controlling for lower liquidity risk, the regression results also show a reduction in market risk post-SEO. Our conclusions remain qualitatively the same when we adjust *p*-values for SEO clustering in event time.

Table 10, Panel B repeats the regressions using the FF3FM. This model fails to explain post-issue SEO returns and produces negative average values for $\alpha_0 + \alpha_1$ for SEO portfolios using both EW and VW. Consistent with Table 7, the magnitude of SEO underperformance is higher for Nasdaq than for NYSE/AMEX listed equity issuers (−0.224% vs. −0.102% using EW and −0.220% vs. −0.091% using VW). Table 10, Panel C summarizes the results on SEO abnormal performance and risk changes from Panels A and B and provides further details of their cross-section distribution. Overall, the results in Table 10 reinforce the liquidity risk explanation of the low SEO return performance after the offering.

Finally, we examine whether size–B/M matching captures the liquidity features of SEOs. We calculate returns for a zero-investment portfolio long in issuers and short in benchmark stocks, and regress these on the LCAPM. Untabulated results show that the zero-investment portfolio has a significantly negative *LIQ* loading for all portfolios using EW and for the portfolio of Nasdaq issuers using VW. Further, the liquidity risk mismatch is higher for Nasdaq than for NYSE/AMEX listed SEOs. This evidence indicates that two-dimensional matching on size–B/M does not guarantee that the benchmark's risk sensitivity captures the covariance structure of SEO returns. Stocks with large differences in liquidity characteristics also tend to have large differences in *LIQ* sensitivities.

In summary, SEOs improve their liquidity following the offering, which reduces their exposure to liquidity risk and explains their post-offering performance. Size–B/M matching compares returns of high-liquidity issuers with returns of low-liquidity benchmark stocks, leading to benchmark bias. As buy-and-hold returns compound any risk mismatch over the holding period, it is easy to misinterpret the bias as SEO underperformance.

6. Robustness tests

Particular research design choices may drive our previous results. Averaging SEO returns across samples can dilute the underperformance effect if it is confined to a particular stock grouping. Monthly rebalancing of calendar time portfolios involves excessive transaction costs and does not correspond to an investor's experience when investing in event firms. Finally, our results could be due to our particular choice of liquidity augmented asset pricing model. To address these concerns, we run several robustness tests.

6.1 SEO long-run performance: subsample results

Table 11, Panels A–C analyse the performance of SEOs across several sub-portfolios: three industry groups, two types of equity issued (primary shares and combinations of secondary and equity sale by a major shareholder), and nine Fama and French size and B/M portfolios. Panel C examines hot vs. cold periods, as Loughran and Ritter (2000) report greater SEO underperformance during hot issue periods, and interpret this as evidence of time-varying misvaluation. Panel D examines SEOs within and outside a five-year period after an IPO in order to gauge the sensitivity of our results to low post-IPO performance. Panel E investigates 12- 24-, 36-, and 48-month holding periods to verify that abnormal performance is not confined to a shorter horizon, while Panel F examines equity issues during 1970–2001 and 2002–2004 to test if poor stock return performance during the financial crisis 2007–2009 affects our results. Table 11 shows that regression alphas are insignificant in every single case, showing that the LCAPM captures the performance of SEOs across all sub-portfolios.

Table 11, Panel H shows LCAPM estimates for SEO portfolios formed three and six months after the issue. This serves to distinguish between short- and long-term SEO liquidity improvements after the offering. For example, (short-term) underwriter price-stabilization activity after the issue may temporarily increase SEO stock liquidity, but the increased stock liquidity may disappear once price support is withdrawn (Benveniste et al., 1996, 1998).[18] We find that SEO portfolios formed three and six months after the offering load negatively on the *LIQ* factor, which suggests that post-SEO liquidity gains extend beyond the immediate period after the SEO.

6.2 Decomposed buy-and-hold returns

Liu and Strong (2008) criticize portfolios formed with the frequent rebalancing implicit in standard calendar time portfolios and point out that monthly rebalancing is inconsistent with a multi-month holding period strategy and involves prohibitive transaction costs. We apply their technique to decompose long-term SEO portfolio buy-and-hold returns to a monthly frequency.[19] This method transfers the integrity of a buy-and-hold investment strategy to calendar time and directly adjusts for cross-sectional correlation. An investor incurs transaction costs only twice, at the beginning and end of the five-year holding period, compared with the monthly transaction costs implicit in the standard calendar time approach.

We apply the decomposed buy-and-hold return approach as follows. Every six months we form a portfolio of all stocks issuing equity in the previous six months and calculate BHRs for this portfolio over the five-year event window as the weighted sum of individual

[18] Previous studies show that stock flipping (selling allocated shares shortly after an IPO) explains a substantial proportion of share trading after the issue. Using sales of 10,000 shares or more to approximate seller-initiated block trades, Krigman et al. (1999) find that flipping explains 45% of trading volume on the first post-IPO trading day for cold issues and 22% for hot issues. Using detailed data on stock flipping around IPOs, Aggarwal (2003) reports that 19% of trading volume within two days of the IPO is due to stock flipping, with institutional investors flipping more than retail customers. However, Chemmanur et al. (2009) find that institutional investors sell only 3.2% of the SEO stock allocated to them in the first two days after the issue and conclude that stock flipping is rare after SEOs.

[19] Gao and Liu (2008) use this technique to examine long-term post-acquisition performance.

BHRs. We obtain decomposed buy-and-hold monthly portfolio returns using equation (3) of Liu and Strong (2008)

$$R_{pt} = \sum_{i=1}^{n} \frac{x_i \prod_{\tau=1}^{t-1} \left(1 + R_{i\tau}\right)}{\sum_{j=1}^{n} x_j \prod_{\tau=1}^{t-1} \left(1 + R_{j\tau}\right)} R_{it} \text{ for } t = 2, \ldots, m \tag{8}$$

where R_{pt} is the month *t* return on a portfolio of n stocks with monthly returns on individual stocks of $R_{i\tau}$, m is the number of holding period months, and x_i is stock *i*'s portfolio weight. For $t = 1$, $R_{p1} = \sum_{i=1}^{n} x_i R_{i1}$. This approach imposes no portfolio rebalancing over the five-year holding period. Given a time series of decomposed BHRs, the grand calendar time portfolio return is $R_{kt} = w_t \sum_{p=1}^{k_t} R_{pt}$, where w_t denotes either EW or VW (see Figure 3). EW uses the inverse of the number of decomposed BHR portfolios. VW uses portfolio market values at the start of the holding period. With a five-year holding period there is a minimum of one and maximum of ten overlapping portfolios.

Liu and Strong (2008) show that negative serial correlation in individual stock returns leads to higher returns, while positive autocovariances in portfolio returns lead to lower returns on rebalanced portfolios compared with the decomposed portfolio. They report a positive bias for small, low-price and loser stocks and a negative bias for large and high-price stocks. Our SEO portfolios comprise a mix of both stock types and there is no statistical difference between average monthly returns of both series.

Table 12 reports results using decomposed portfolio BHRs in LCAPM calendar time regressions. For comparison, we report results from a standard calendar time approach. None of the alphas indicate SEO underperformance. The decomposed buy-and-hold approach does not produce materially different conclusions from the standard calendar time approach. This is not surprising as SEOs include liquid stocks from all size-based portfolios and are less likely to suffer from the microstructure biases that the decomposed method adjusts for.

6.3 Alternative specifications of the liquidity factor

Finally, we test the robustness of our results on the lower post-issue SEO liquidity risk exposure to alternative specifications of the liquidity factor. We use the FF3FM augmented by Eckbo and Norli's (2005) *LMH* factor, and by the residuals (*LIQ_res*) from regressing *LIQ* on *SMB* and *HML* (without a constant) to test if *LIQ* captures a liquidity effect controlling for size and book-to-market effects. Table 13 shows that *LMH* and *LIQ_res* are significant, controlling for the Fama–French factors. The significant loading on *LIQ_res* indicates the incremental power of liquidity risk over the Fama–French size and *B/M* factors to explain the cross-section of returns.[20, 21]

7. Conclusions

Using four measures that each emphasize a different dimension of liquidity, we find that SEO firms are significantly more liquid after the issue and relative to size–B/M matched stocks. Examining the potential causes of post-issue liquidity changes, we show that SEO firms experience an increase in analyst following and in institutional holdings of their stock over the five years after the issue compared with the five years pre-issue. Higher analyst following improves the amount and quality of information about the firm, which lowers adverse selection costs of trading and improves stock liquidity. Increased trading by institutional investors reduces the adverse selection costs of trading with a better informed party, further explaining SEO liquidity gains after the issue.

[20] We also regress SEO EW and VW pooled portfolio returns on the FF3FM augmented by Pastor and Stambaugh's (2003) traded liquidity factor (*PS_VW*). Untabulated results show significant *PS_VW* loadings for the VW portfolio only.
[21] As *LIQ*_res is a non-traded factor, the intercepts from *LIQ*_res augmented FF3FM regressions do not have the standard interpretation as tests for abnormal stock performance

Estimates from pricing models show that SEOs bear less liquidity risk after the offering and that size-B/M benchmarks are unable to capture the dynamics of SEO firms' liquidity risk. In contrast, the liquidity augmented CAPM captures the performance of SEOs. Our study supports a liquidity-based, low discount rate explanation for SEO returns.

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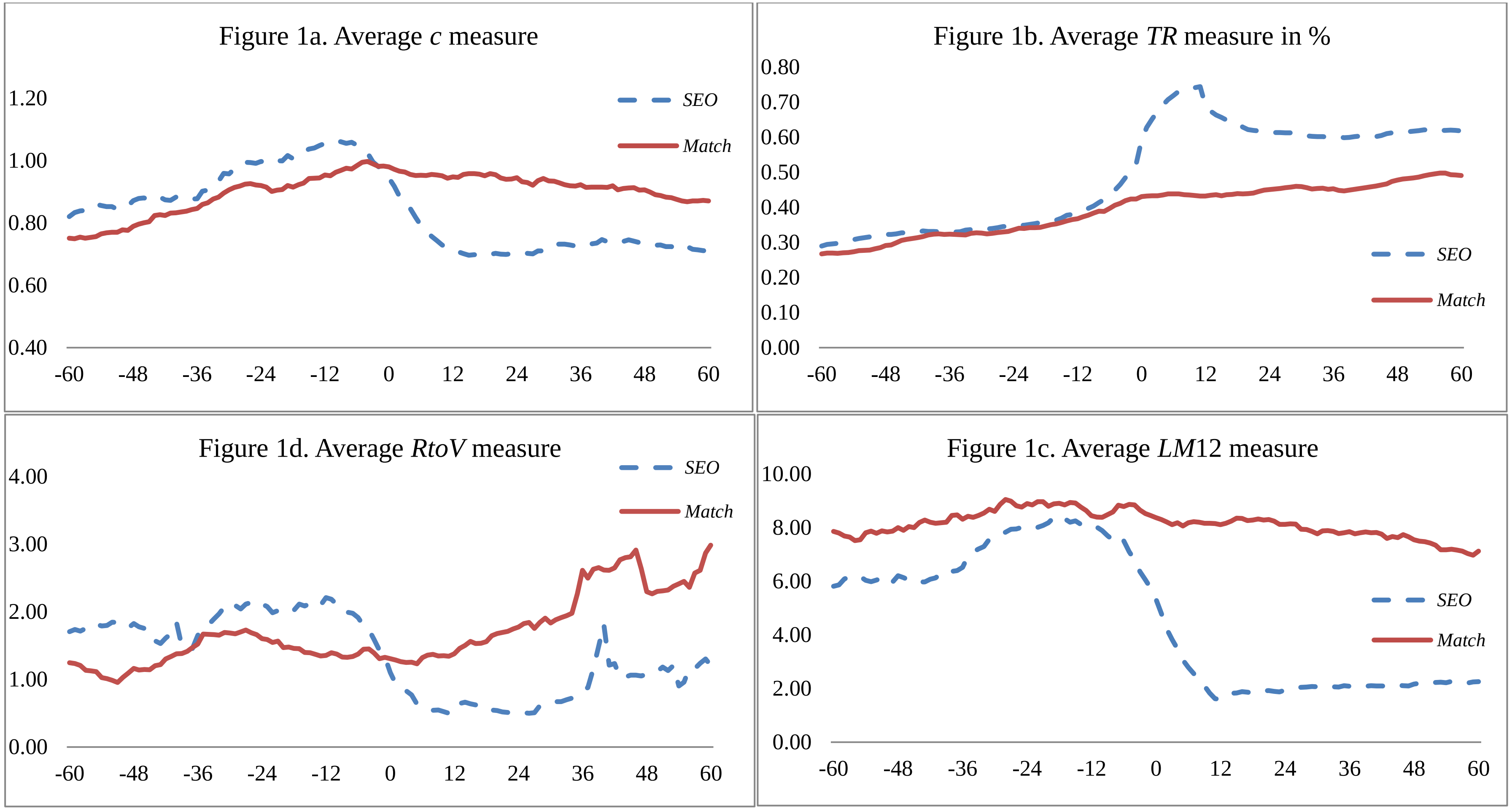
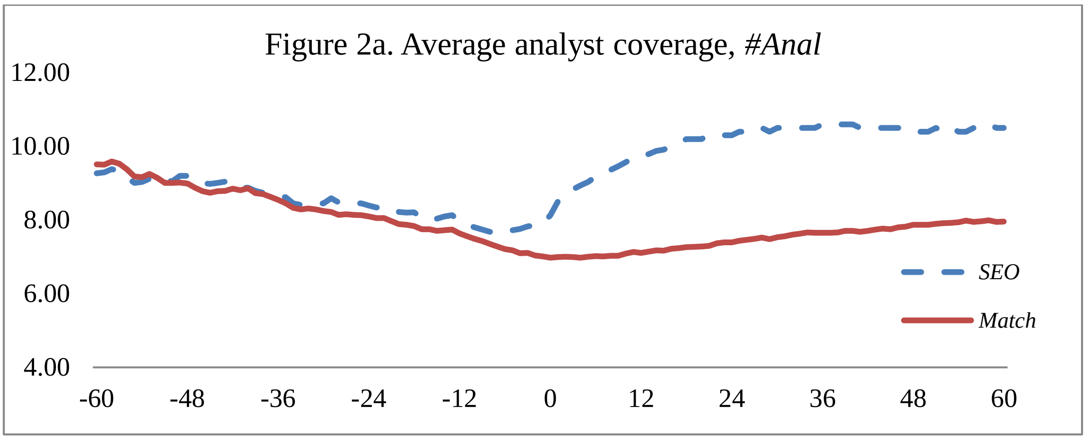
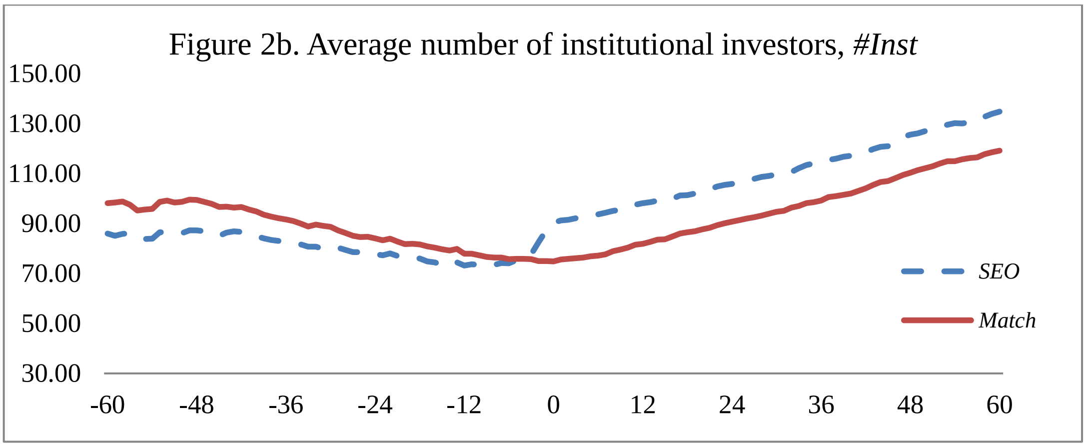


Figure 1. Evolution of four liquidity measures for a sample of SEOs and their size–B/M matched control stocks.

Figure 1a shows the average cost of share trading, c ($\times 10^2$). Figure 1b shows the average daily turnover rate, *TR* (in %). Figure 1c shows the average liquidity measure of Liu (2006), *LM*12. Figure 1d shows Amihud's (2002) return to volume measure, *RtoV* ($\times 10^6$). The effective cost of trading, *c*, is Hasbrouck's (2009) annual Gibbs estimate of transactions cost. *TR* is the daily number of shares traded divided by the number of shares outstanding on the day averaged over the prior 12 months. *RtoV* is the absolute daily return divided by the dollar denominated trading volume on the day averaged over the prior 12 months. The figures report the end of month liquidity characteristics for the sample of 3,587 SEOs (*SEO*) and their size–B/M matched control stocks (*Match*) for the 5-year periods before and after the issue.





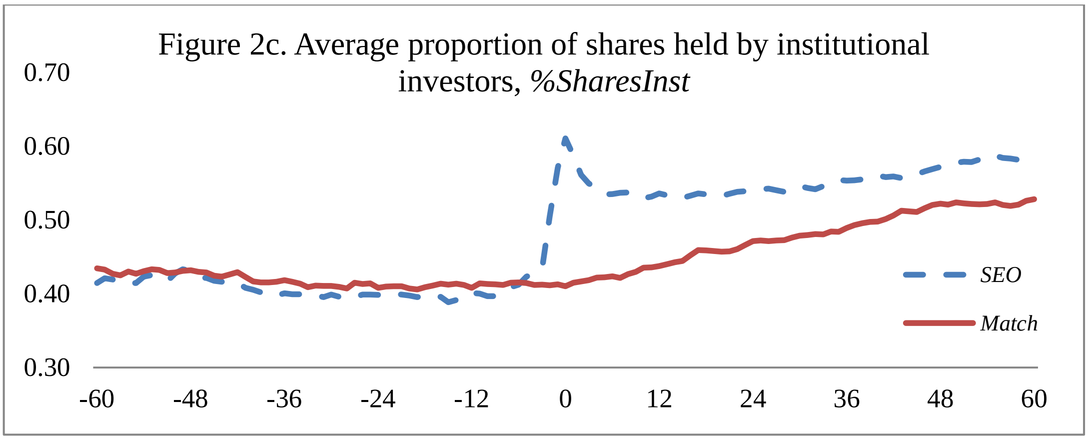


Figure 2. Evolution of analyst coverage and institutional shareholding for a sample of SEOs and their size–B/M matched control stocks.

Figure 2a shows the average number of analysts following a firm, *#Anal*. Figure 2b shows the average number of institutional investors holding SEO stock, *#Inst*. Figure 2c shows the average proportion of common shares held by institutional investors, *%SharesInst*. The figures report the end of month characteristics for a sample of 2,172 SEOs (*SEO*) and their size–B/M matched control stocks (*Match*) for the 5-year periods before and after the issue.

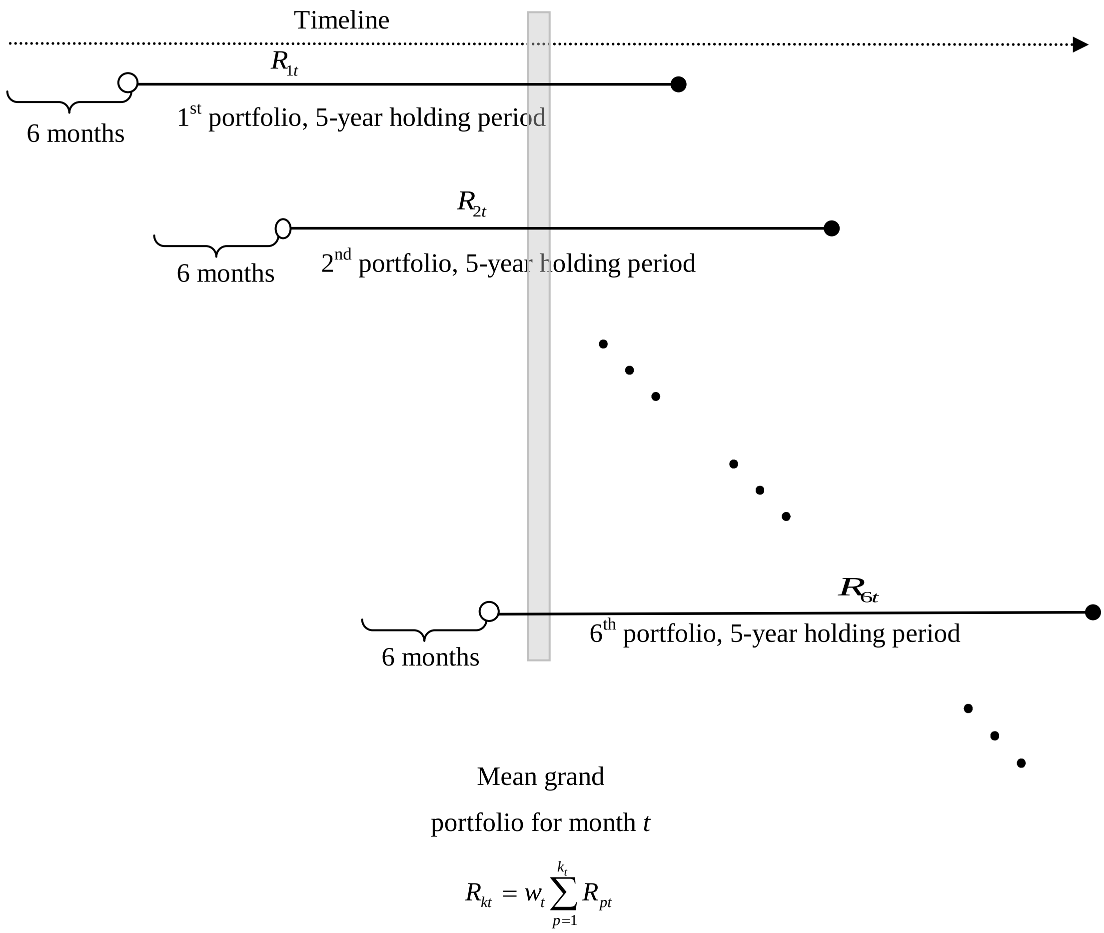


Figure 3. Schematic for the construction of decomposed BHR portfolio returns in calendar time.

Every six months we form a portfolio of all stocks issuing equity in the previous six months. We calculate buy-and-hold returns, R_{pt}, for this portfolio over the 5-year event window as the weighted sum of individual BHRs and decompose portfolio BHRs into monthly portfolio returns (Liu and Strong 2008). The grand calendar time portfolio return is $R_{kt} = w_t \sum_{p=1}^{k_t} R_{pt}$ where w_t denotes equal weighting (EW) or value weighting (VW). EW uses the inverse of the number of decomposed BHR portfolios in month t. VW uses market capitalization at portfolio formation as weights.

Table 1. SEO sample distribution, 1970–2004.

The table describes the distribution of SEOs for the pooled sample and NYSE/AMEX and Nasdaq stocks over 1970–2004, stratified by financial (*Financial*), industrial (*Industrial*), and utility (*Utility*) firms, type of offering (*Primary* for secondary offerings of primary shares and *Combination* for a mix of primary and major shareholder equity sale), nine Fama and French size (Small, *S*, Medium, *Me*, Big, *B*) and book-to-market (High, *H*, Medium, *M*, Low, *L*) portfolios, the offering decade (1970s, 1980s, 1990s, 2000s), and the offering period (*Hot* for months where the number of SEOs in the month before the issue exceeds the median over the previous 12 months, *Cold* for other months).

	Pooled sample	NYSE/AMEX	Nasdaq
Total	4446	1995	2451
Financial	517	242	275
Industrial	3447	1339	2108
Utility	482	414	68
Combination	1481	409	1072
Primary	2965	1586	1379
FF *S–L*	1204	198	1006
FF *S–M*	694	218	476
FF *S–H*	535	205	330
FF *Me–L*	585	250	335
FF *Me–M*	487	325	162
FF *Me–H*	276	197	79
FF *B–L*	222	181	41
FF *B–M*	265	252	13
FF *B–H*	178	169	9
1970s	566	439	127
1980s	1343	626	717
1990s	1809	646	1163
2000s	728	284	444
Hot	3042	1341	1701
Cold	1404	654	750

Table 2. The long-run performance of SEOs.

The table reports the average percentage five-year BHRs of equity issuers (*Issuer*) and control firms (*Match*) matched on size and book-to-market for a sample of 4,446 SEOs using equal weighting (EW) and value weighting (VW). *Diff* is the difference between these figures, *t* a two-sided skewness-adjusted *t*-statistic testing the hypothesis of no difference between the average long-run performance of issuers and matches, and *p* its *p*-value. *t-JK* is the (skewness-adjusted) test statistic for Jegadeesh and Karceski's (2009) heteroskedasticity and correlation consistent *t*-test, with *p-JK* its corresponding *p*-value. *N* is the number of offerings. Value weights standardize market capitalization by the value-weighted CRSP stock market index to ensure comparability over time.

Weight	Portfolio	*N*	*Issuer (%)*	*Match (%)*	*Diff (%)*	*t*	*P*	*t-JK*	*p-JK*
EW	All exchanges	4446	46.12%	73.79%	−27.67%	−8.345	0.000	−1.801	0.072
VW			55.87%	81.97%	−26.10%	−15.026	0.000	−1.947	0.052
EW	NYSE/AMEX	1995	62.22%	85.65%	−23.43%	−5.209	0.000	−1.773	0.076
VW			57.43%	83.66%	−26.23%	−9.031	0.000	−1.828	0.068
EW	Nasdaq	2451	33.02%	64.14%	−31.12%	−6.170	0.000	−1.696	0.090
VW			45.27%	70.53%	−25.26%	−5.995	0.000	−1.601	0.110

Table 3. Liquidity characteristics of SEOs and their matches before and after the issue.

The table reports the average effective cost of trading, *c* ($\times 10^2$), Liu's (2006) liquidity measure, *LM*12, daily share turnover rate, *TR*, and Amihud's (2002) return to volume measure, *RtoV* ($\times 10^6$). The effective cost of trading, *c*, is Hasbrouck's (2009) annual Gibbs estimate of stock transactions costs. *TR* is the daily number of shares traded divided by the number of shares outstanding on the day averaged over the prior 12 months, as a percentage. *RtoV* is the absolute daily return divided by the dollar denominated trading volume on the day averaged over the prior 12 months. The table gives the liquidity characteristics of SEOs (*Issuer*) and their size–B/M benchmarks (*Match*). *Diff* is the mean difference between these values and *p* the corresponding *p*-value. *N* is the number of observations. Panel A shows results for the 5-year period before the offering, Panel B for the 5-year post-offering period.

	Portfolio	*N*	*Issuer*	*Match*	*Diff*	*p*
Panel A. 5-year liquidity characteristics before the offering						
c	All exchanges	3587	0.962	0.898	0.065	0.000
*LM*12			7.075	8.487	−1.413	0.000
TR (%)			0.374	0.345	0.029	0.000
RtoV			1.857	1.391	0.465	0.000
c	NYSE/AMEX	1869	0.590	0.631	−0.041	0.000
*LM*12			3.771	5.063	−1.291	0.000
TR (%)			0.245	0.289	−0.043	0.000
RtoV			0.962	0.643	0.319	0.000
c	Nasdaq	1718	1.595	1.351	0.244	0.000
*LM*12			12.690	14.309	−1.619	0.000
TR (%)			0.592	0.441	0.151	0.000
RtoV			3.378	2.663	0.715	0.000
Panel B. 5-year liquidity characteristics after the offering						
c	All exchanges	3587	0.736	0.927	−0.191	0.000
*LM*12			2.228	7.881	−5.653	0.000
TR (%)			0.636	0.455	0.182	0.000
RtoV			0.821	1.974	−1.153	0.000
c	NYSE/AMEX	1869	0.517	0.672	−0.156	0.000
*LM*12			1.514	5.239	−3.725	0.000
TR (%)			0.383	0.362	0.020	0.000
RtoV			0.619	0.975	−0.356	0.000
c	Nasdaq	1718	0.984	1.215	−0.231	0.000
*LM*12			3.034	10.864	−7.830	0.000
TR (%)			0.923	0.559	0.364	0.000
RtoV			1.049	3.101	−2.052	0.000

Table 4. The long-run performance of SEOs: liquidity matching.

The table reports the average five-year BHRs of equity issuers (*Issuer*) and control firms (*Match*) matched on size and book-to-market (*size–B/M matching*) and post-issue *LM*12 (*LM*12 *matching*) using equal weighting (EW) and value weighting (VW). *Diff* is the difference between these figures. *Holding period* shows the holding period start and end month. *t* is a two-sided skewness-adjusted *t*-statistic testing the hypothesis of no difference between the average long-run performance of issuers and their matches, *p* its *p*-value, *t-JK* the (skewness-adjusted) test statistic for Jegadeesh and Karceski's (2009) heteroskedasticity and correlation consistent *t*-test, with *p-JK* its corresponding *p*-value. *N* is the number of offerings. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time.

	Matching	*Holding period*	*N*	*Issuer (%)*	*Match (%)*	*Diff (%)*	*t*	*p*	*t-JK*	*p-JK*
EW	*size–B/M matching*	8–60	4007	38.40%	74.14%	−35.75%	−10.598	0.000	−1.959	0.050
VW				43.89%	66.24%	−22.35%	−12.874	0.000	−2.425	0.015
EW	*LM*12 *matching*			38.40%	56.37%	−17.97%	−5.469	0.000	−1.334	0.182
VW				43.89%	57.82%	−13.93%	−6.509	0.000	−1.136	0.256
EW	*size–B/M matching*	12–60	4006	38.47%	66.77%	−28.30%	−8.701	0.000	−1.957	0.050
VW				40.45%	58.14%	−17.70%	−10.731	0.000	−2.301	0.021
EW	*LM*12 *matching*			38.47%	51.71%	−13.25%	−4.040	0.000	−1.231	0.218
VW				40.45%	51.33%	−10.89%	−5.740	0.000	−1.031	0.303
EW	*size–B/M matching*	18–60	3911	36.92%	56.19%	−19.26%	−6.288	0.000	−1.988	0.047
VW				40.60%	51.23%	−10.63%	−6.408	0.000	−1.621	0.105
EW	*LM*12 *matching*			36.92%	45.17%	−8.25%	−2.794	0.025	−1.308	0.191
VW				40.60%	39.93%	0.67%	0.314	0.185	0.040	0.968

Table 5. Analyst coverage and institutional holdings of SEOs and their matches before and after the issue.

The table reports the mean analyst following and institutional investor stockholdings of SEOs (*Issuer*) and their size–B/M benchmarks (*Match*) over 1985–2009. *#Anal* is the number of analysts providing earnings forecasts for a firm, over all possible forecast horizons, in the past 12 months including the current month. *#Inst* is the total number of institutions holding stock in a firm. *%SharesInst* is the percentage of shares held by institutional investors. *Diff* is the mean difference between these values and *p* the corresponding *p*-value. *N* is the number of observations. Panel A shows the results for the 5-year period before the offering, Panel B for the 5-year post-offering period.

	Portfolio	*N*	*Issuer*	*Match*	*Diff*	*p*
Panel A. 5-year analyst coverage and institutional investor holdings before the offering						
#Anal			8.288	7.946	0.342	0.000
%SharesInst	All exchanges	2172	42.12%	41.50%	0.62%	0.000
#Inst			79.402	83.931	−4.529	0.000
#Anal			11.941	11.350	0.591	0.000
%SharesInst	NYSE/AMEX	848	49.23%	48.02%	1.21%	0.000
#Inst			123.814	127.215	−3.401	0.000
#Anal			5.017	4.899	0.119	0.000
%SharesInst	Nasdaq	1324	35.75%	35.66%	0.09%	0.635
#Inst			39.645	45.184	−5.539	0.000
Panel B. 5-year analyst coverage and institutional investor holdings after the offering						
#Anal			10.117	7.473	2.644	0.000
%SharesInst	All exchanges	2172	55.17%	47.43%	7.74%	0.000
#Inst			110.048	94.737	15.311	0.000
#Anal			13.103	10.387	2.715	0.000
%SharesInst	NYSE/AMEX	848	60.50%	54.32%	6.19%	0.000
#Inst			166.004	144.457	21.547	0.000
#Anal			8.076	5.481	2.595	0.000
%SharesInst	Nasdaq	1324	51.52%	42.72%	8.80%	0.000
#Inst			71.793	60.746	11.047	0.000

Table 6. Regression analysis of post-issue SEO liquidity gains.

The table reports estimates (*Estimate*) from regressions of post-issue SEO liquidity gains, measured as the change in each of four liquidity characteristics in the 5-year post- vs. pre-issue period. The liquidity characteristics are the effective cost of trading (*c*), share turnover (*TR*), which is the daily number of shares traded divided by the number of shares outstanding on the day averaged over the prior 12 months, Liu's (2006) liquidity measure (*LM*12), and return-to-volume (*RtoV*), which is the absolute daily return divided by the dollar denominated trading volume on the day averaged over the prior 12 months. Δ#*Anal* is the change in the number of analysts providing earnings forecasts for a firm in the 5-year post- vs. pre-issue period. Δ#*Inst* is the change in the total number of institutions holding stock in a firm in the 5-year post- vs. pre-issue period. Δ*%SharesInst* is the change in the proportion of stock held by institutional investors in the 5-year post- vs. pre-issue period. %*NewShares* is the proportion of (primary and secondary) shares issued by the firm relative to the total number of shares outstanding one month before the offering. *B/M* is the book-to-market ratio and *MV* is market capitalization. *Hot* and *Nasdaq* are indicator variables for hot-issue periods and for an SEO listing on Nasdaq. All variables are measured over 1985–2009. *N* is the number of observations, *p* the associated *p*-value, and *Adj* R^2 is the adjusted *R*-squared.

	−*c*		*TR*		−*LM*12		−*RtoV*	
	Estimate	*P*	*Estimate*	*p*	*Estimate*	*p*	*Estimate*	*p*
Intercept	6.405	0.000	0.081	0.191	17.168	0.000	2.648	0.000
Δ#*Anal*	0.202	0.000	0.023	0.000	0.172	0.043	0.063	0.002
Δ*%SharesInst*	7.789	0.000	0.611	0.000	0.263	0.893	1.029	0.027
Δ#*Inst*	−0.005	0.258	0.001	0.000	−0.006	0.491	−0.002	0.361
%NewShares	2.258	0.027	0.066	0.314	8.389	0.000	2.091	0.000
B/M	0.502	0.045	−0.044	0.007	3.110	0.000	0.395	0.003
ln *MV*	−1.123	0.000	−0.008	0.433	−2.971	0.000	−0.493	0.000
Hot	−0.159	0.584	0.019	0.303	−1.098	0.089	−0.141	0.358
Nasdaq	2.304	0.000	0.102	0.000	0.663	0.361	−0.048	0.782
N	2172		2172		2172		2172	
p-value	0.000		0.000		0.000		0.000	
Adj. R^2	0.206		0.218		0.142		0.092	

Table 7. Calendar time regressions of SEO returns on the Fama–French three-factors.

The table reports estimates (*Estimate*) from calendar time regressions of SEO returns on the Fama and French (1993) three factors from April 1970 to December 2009. *MKT* is the market excess return, *SMB* is the average return on a portfolio long in small (*S*) and short in big (*B*) stocks controlling for book-to-market. *HML* is the average return on a portfolio long in high (*H*) and short in low (*L*) book-to-market stocks controlling for size. *T* is the length of the time series in months, *p* denotes *p*-values, and *Adj* R^2 is the adjusted *R*-squared. EW denotes equal weighting and VW value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time.

				EW			VW	
Portfolio	*T*	*Parameter*	*Estimate*	*p*	*Adj.* R^2	*Estimate*	*p*	*Adj.* R^2
All exchanges	477	α	−0.246%	0.007	0.912	−0.344%	0.001	0.847
		MKT	1.126	0.000		1.128	0.000	
		SMB	0.736	0.000		0.097	0.003	
		HML	0.129	0.000		0.347	0.000	
NYSE/AMEX	476	α	−0.297%	0.001	0.882	−0.399%	0.000	0.832
		MKT	1.102	0.000		1.106	0.000	
		SMB	0.470	0.000		−0.024	0.538	
		HML	0.441	0.000		0.490	0.000	
Nasdaq	412	α	−0.312%	0.010	0.896	−0.305%	0.072	0.814
		MKT	1.206	0.000		1.311	0.000	
		SMB	0.965	0.000		0.656	0.000	
		HML	−0.095	0.023		−0.175	0.003	

Table 8. Regressing liquidity portfolio returns on alternative asset pricing models.

The table reports intercepts from calendar time regressions of equally weighted returns to ten liquidity portfolios on Liu's (2006) LCAPM (*LCAPM* α), the Fama and French (1993) model (*FF3FM* α), and the FF3FM with an *LMH* liquidity factor (FF3FM+*LMH* α) from January 1970 to December 2009. The liquidity deciles are sorted from lowest (*LL*) to highest (*HL*) liquidity. Specifically, at year-end, we sort all CRSP stocks into deciles on *LM*12 and calculate equally weighted portfolio returns for the next twelve months using Liu and Strong's (2008) decomposed buy-and-hold returns method. Portfolio returns are adjusted for delisting returns. The liquidity factor in Liu (2006) is the difference in average returns between portfolios of low and high liquidity stocks based on *LM*12. *LMH* is the turnover-based liquidity factor of Eckbo and Norli (2005) and is the average return difference between a portfolio long in low turnover stocks and short in high turnover stocks controlling for firm size. Size quintiles are from smallest (*Small*) to biggest (*Big*) capitalization stocks and book-to-market quintiles are ordered from low (*Low B/M*) to high (*High B/M*). *Mean LM*12 is the mean value of *LM*12 for the portfolio. *SEOs as % of portfolio* is the percentage of portfolio constituents that make an SEO in the following twelve months. *p* denotes *p*-values.

	LL	*L2*	*L3*	*L4*	*L5*	*L6*	*L7*	*L8*	*L9*	*HL*
*Mean LM*12	111.774	47.590	21.552	9.242	3.475	0.974	0.124	0.000	0.000	0.000
SEOs as % of portfolio	0.20%	0.52%	0.88%	1.61%	2.39%	2.58%	2.48%	2.85%	3.90%	5.57%
LCAPM α	0.038%	0.059%	0.049%	0.020%	−0.091%	−0.002%	0.158%	0.183%	0.107%	−0.110%
p	0.797	0.724	0.782	0.903	0.503	0.990	0.158	0.262	0.602	0.629
FF3FM α	0.416%	0.322%	0.236%	0.085%	−0.121%	−0.110%	0.015%	−0.011%	−0.143%	−0.479%
p	0.003	0.010	0.044	0.383	0.228	0.196	0.836	0.901	0.211	0.000
FF3FM+LMH α	0.372%	0.343%	0.224%	0.073%	−0.165%	−0.094%	0.095%	0.126%	0.090%	−0.101%
p	0.008	0.008	0.064	0.468	0.125	0.283	0.288	0.140	0.532	0.373

Table 9. Liquidity risk and the long-run performance of SEOs: calendar time analysis.

Panel A reports coefficients (*Estimate*) from calendar time LCAPM regressions for SEOs for five years after the issue. *MKT* is the market excess return; *LIQ* is the difference in average returns between portfolios of low and high liquidity stocks based on *LM*12. *p* denotes *p*-values, *Adj.*R^2 is the adjusted *R*-squared, and *T* is the length of the time series in months. Panel B tests the hypothesis of coefficient equality in LCAPM regressions for SEOs five years before and after the issue from seemingly unrelated regressions using a Lagrange Multiplier (*LM*) test with a heteroskedasticity consistent covariance matrix. Factor loadings before the issue are from calendar time LCAPM regressions for SEOs for five years before the issue. *Difference: after − before* is the difference in factor loadings after compared to before the issue. EW stands for equal weighting and VW for value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time.

Portfolio	*T*	*Parameter*	EW *Estimate*	EW *p*	EW *Adj.* R^2	VW *Estimate*	VW *p*	VW *Adj.* R^2
Panel A. Regression of SEO portfolios on the LCAPM								
All exchanges	477	α	−0.030%	0.834	0.794	−0.098%	0.388	0.816
		MKT	1.195	0.000		1.035	0.000	
		LIQ	−0.096	0.043		−0.066	0.080	
NYSE/AMEX	476	α	−0.099%	0.435	0.791	−0.209%	0.143	0.816
		MKT	1.139	0.000		1.029	0.000	
		LIQ	0.085	0.044		0.076	0.207	
Nasdaq	412	α	0.001%	0.998	0.735	0.144%	0.527	0.762
		MKT	1.271	0.000		1.203	0.000	
		LIQ	−0.204	0.023		−0.446	0.000	

Portfolio	*Test*	EW *Difference: after − before*	EW *LM*	EW *p*	VW *Difference: after − before*	VW *LM*	VW *p*
Panel B. Testing the hypothesis of coefficient equality between SEO portfolios created before and after the offering regressed on the LCAPM							
All exchanges	*MKT* (before the offering) = *MKT* (after the offering)	−0.086	16.090	0.000	−0.025	0.900	0.344
	LIQ (before the offering) = *LIQ* (after the offering)	−0.212	65.060	0.000	−0.100	9.200	0.002
NYSE/AMEX	*MKT* (before the offering) = *MKT* (after the offering)	−0.063	6.590	0.010	−0.011	0.140	0.705
	LIQ (before the offering) = *LIQ* (after the offering)	−0.181	35.810	0.000	−0.065	3.530	0.060
Nasdaq	*MKT* (before the offering) = *MKT* (after the offering)	−0.084	5.790	0.016	−0.117	3.560	0.059
	LIQ (before the offering) = *LIQ* (after the offering)	−0.184	21.000	0.000	−0.073	1.040	0.308

Table 10. Liquidity risk and the long-run performance of SEOs: firm-specific regressions

Panel A reports average parameter estimates (*Estimate*) from individual SEO regressions for five years before and after the issue. The regression model takes the form

$$R_{it} - R_{ft} = \alpha_{i,0} + \alpha_{i,1} \times D_{SEO} + (\beta_{mi,0} + \beta_{mi,1} \times D_{SEO})(R_{mt} - R_{ft}) + (\beta_{li,0} + \beta_{li,1} \times D_{SEO})LIQ_t + \varepsilon_{it}\,,$$

where the 0 and 1 subscripts indicate estimates for the pre- and post-issue periods and D_{SEO} is an indicator variable for the post-issue period. *MKT* is the market excess return and *LIQ* is the difference in average returns between portfolios of low and high liquidity stocks based on *LM*12. *p* denotes average *p*-values, $Adj.R^2$ is the average adjusted *R*-squared, and *N* is the number of SEOs. Panel B repeats the analysis for the FF3FM (Fama and French 1993). Panel C presents the cross-section distribution of post-issue SEO abnormal performance, $\alpha_0 + \alpha_1$, and changes in risk exposure from the liquidity augmented CAPM (LCAPM) and FF3FM regressions. EW denotes equal weighting and VW value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to ensure comparability over time. *Mean* and *Median* stand for mean and median values, *SE* denotes the standard error, *Q1* and *Q3* stand for the upper and the lower quartile.

			EW			VW		
Portfolio	*N*	*Parameter*	*Estimate*	*p*	*Adj. R^2*	*Estimate*	*p*	*Adj. R^2*
Panel A. Regression of individual SEO returns on the liquidity augmented CAPM								
All exchanges	4444	α_0	1.657%	0.000	0.225	0.850%	0.000	0.321
		α_1	−1.629%	0.000		−0.844%	0.000	
		$\alpha_0 + \alpha_1$	0.027%	0.588		0.006%	0.830	
		MKT	1.268	0.000		1.011	0.000	
		$MKT \times D_{SEO}$	−0.190	0.000		−0.069	0.000	
		LIQ	0.130	0.000		0.053	0.000	
		$LIQ \times D_{SEO}$	−0.287	0.000		−0.068	0.000	
NYSE/AMEX	1995	α_0	0.874%	0.000	0.254	0.559%	0.000	0.328
		α_1	−0.840%	0.000		−0.570%	0.000	
		$\alpha_0 + \alpha_1$	0.034%	0.498		−0.011%	0.697	
		MKT	1.172	0.000		0.967	0.000	
		$MKT \times D_{SEO}$	−0.128	0.000		−0.048	0.001	
		LIQ	0.260	0.000		0.094	0.000	
		$LIQ \times D_{SEO}$	−0.236	0.000		−0.054	0.003	
Nasdaq	2449	α_0	2.294%	0.000	0.201	2.897%	0.000	0.271
		α_1	−2.272%	0.000		−2.770%	0.000	
		$\alpha_0 + \alpha_1$	0.022%	0.791		0.127%	0.129	
		MKT	1.346	0.000		1.318	0.000	
		$MKT \times D_{SEO}$	−0.241	0.000		−0.217	0.000	
		LIQ	0.024	0.553		−0.229	0.000	
		$LIQ \times D_{SEO}$	−0.329	0.000		−0.170	0.000	

Table 10, cont.

Portfolio	*N*	*Parameter*	EW *Estimate*	*p*	*Adj. R^2*	VW *Estimate*	*p*	*Adj. R^2*
Panel B. Regression of individual SEO returns on the FF3FM								
All exchanges	4444	α_0	1.531%	0.000	0.287	0.713%	0.000	0.385
		α_1	−1.700%	0.000		−0.820%	0.000	
		$\alpha_0+\alpha_1$	−0.169%	0.000		−0.107%	0.000	
		MKT	1.134	0.000		1.023	0.000	
		$MKT\times D_{SEO}$	−0.007	0.718		−0.026	0.015	
		SMB	0.965	0.000		0.129	0.000	
		$SMB\times D_{SEO}$	−0.151	0.000		−0.064	0.000	
		HML	0.051	0.063		0.153	0.000	
		$HML\times D_{SEO}$	0.032	0.323		0.058	0.000	
NYSE/AMEX	1995	α_0	0.768%	0.000	0.319	0.452%	0.000	0.393
		α_1	−0.870%	0.000		−0.543%	0.000	
		$\alpha_0+\alpha_1$	−0.102%	0.034		−0.091%	0.000	
		MKT	1.050	0.000		0.985	0.000	
		$MKT\times D_{SEO}$	0.013	0.477		−0.022	0.068	
		SMB	0.654	0.000		0.023	0.117	
		$SMB\times D_{SEO}$	−0.109	0.000		−0.042	0.015	
		HML	0.284	0.000		0.227	0.000	
		$HML\times D_{SEO}$	0.032	0.321		0.051	0.007	
Nasdaq	2449	α_0	2.152%	0.000	0.261	2.548%	0.000	0.326
		α_1	−2.376%	0.000		−2.767%	0.000	
		$\alpha_0+\alpha_1$	−0.224%	0.002		−0.220%	0.006	
		MKT	1.202	0.000		1.293	0.000	
		$MKT\times D_{SEO}$	−0.024	0.473		−0.052	0.068	
		SMB	1.219	0.000		0.880	0.000	
		$SMB\times D_{SEO}$	−0.185	0.000		−0.216	0.000	
		HML	−0.139	0.002		−0.368	0.000	
		$HML\times D_{SEO}$	0.032	0.540		0.101	0.018	

Model	*Weight*	*N*	*Mean*	*SE*	*Median*	*Q1*	*Q3*
Panel C. The cross-section distribution of post-issue SEO abnormal performance, $\alpha_0+\alpha_1$, and risk changes							
LCAPM	EW	$\alpha_0+\alpha_1$	0.027%	0.001	0.091%	−1.105%	1.286%
		$MKT\times D_{SEO}$	−0.190	0.026	−0.127	−0.822	0.463
		$LIQ\times D_{SEO}$	−0.287	0.030	−0.184	−1.107	0.565
	VW	$\alpha_0+\alpha_1$	0.006%	0.000	−0.034%	−0.602%	0.502%
		$MKT\times D_{SEO}$	−0.069	0.012	−0.061	−0.358	0.309
		$LIQ\times D_{SEO}$	−0.068	0.015	−0.084	−0.447	0.494
FF3FM	EW	$\alpha_0+\alpha_1$	−0.169%	0.000	−0.060%	−1.133%	0.992%
		$MKT\times D_{SEO}$	−0.007	0.021	0.014	−0.505	0.525
		$SMB\times D_{SEO}$	−0.151	0.029	−0.115	−0.889	0.592
		$HML\times D_{SEO}$	0.032	0.032	0.016	−0.821	0.885
	VW	$\alpha_0+\alpha_1$	−0.107%	0.000	−0.142%	−0.570%	0.392%
		$MKT\times D_{SEO}$	−0.026	0.011	−0.026	−0.394	0.316
		$SMB\times D_{SEO}$	−0.064	0.015	−0.006	−0.500	0.353
		$HML\times D_{SEO}$	0.058	0.016	0.040	−0.380	0.460

Table 11. Calendar time robustness checks: subsample analysis.

The table reports coefficients (*Estimate*) from calendar time LCAPM regressions for subsamples of SEOs. *T* is the length of the portfolio time series, *p* denotes *p*-values, and *Adj.* R^2 the adjusted *R*-squared. Panel A classifies issuers according to industry group: *Industry*, *Finance* and *Utility*. Panel B shows the distribution of SEOs across equity issue type: *Combination* and *Primary*. Panel C stratifies issuers across nine Fama and French portfolios formed on size (Small, *S*, Medium, *Me*, Big, *B*) and book-to-market (High, *H*, Medium, *M*, Low, *L*). Panel D groups issues in *Hot* and *Cold* periods (*Hot* for months where the number of SEOs in the month before the issue exceeds the median over the previous 12 months, *Cold* for other months). Panel E groups issues occurring within five years of the IPO date (Age < 5 years) and five years after the IPO (Age ≥ 5 years). Panel F shows results for event horizons of 12, 24, 36, and 48 months. Panel G groups equity issues over 1970–2001 and 2002–2004. Panel H shows LCAPM estimates for SEO portfolios formed three and six months after the issue. EW denotes equal weighting and VW value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time.

			EW			VW		
Group	*T*	*Parameter*	*Estimate*	*p*	*Adj.* R^2	*Estimate*	*P*	*Adj.* R^2
Panel A. Industry classification of SEOs								
Industry	475	α	−0.063%	0.722	0.766	−0.037%	0.770	0.837
Finance	373	α	−0.334%	0.102	0.654	−0.354%	0.236	0.552
Utility	466	α	0.183%	0.248	0.466	0.082%	0.650	0.365
Panel B. Type of equity offering.								
Combination	465	α	−0.146%	0.439	0.748	−0.114%	0.473	0.803
Primary	476	α	0.051%	0.717	0.776	−0.097%	0.417	0.790
Panel C. Fama and French size and book-to-market portfolios.								
FF *S–L*	457	α	−0.143%	0.588	0.638	−0.017%	0.950	0.648
FF *S–M*	458	α	−0.153%	0.486	0.669	−0.080%	0.718	0.688
FF *S–H*	436	α	0.050%	0.818	0.607	0.148%	0.498	0.630
FF *Me–L*	452	α	0.061%	0.728	0.766	0.034%	0.854	0.755
FF *Me–M*	457	α	0.042%	0.781	0.737	−0.083%	0.623	0.692
FF *Me–H*	382	α	−0.009%	0.960	0.723	−0.079%	0.692	0.701
FF *B–L*	433	α	0.097%	0.474	0.823	0.021%	0.873	0.793
FF *B–M*	445	α	0.004%	0.983	0.645	−0.049%	0.780	0.617
FF *B–H*	378	α	−0.099%	0.635	0.525	−0.119%	0.584	0.406
Panel D. Hot vs cold issuing period								
Hot	477	α	−0.046%	0.773	0.766	−0.065%	0.586	0.807
Cold	464	α	−0.016%	0.913	0.776	−0.147%	0.369	0.716
Panel E. Age of the issuer								
Age < 5 *years*	463	α	−0.093%	0.637	0.747	0.113%	0.605	0.747
Age ≥ 5 years	477	α	−0.008%	0.952	0.803	−0.110%	0.353	0.787
Panel F. 12-, 24-, 36-, *and* 42-*month holding period*								
12 *months*	430	α	0.169%	0.348	0.777	0.116%	0.321	0.828
24 *months*	442	α	−0.085%	0.579	0.801	−0.110%	0.279	0.853
36 *months*	454	α	−0.112%	0.438	0.803	−0.095%	0.312	0.863
48 *months*	466	α	−0.092%	0.527	0.802	−0.058%	0.636	0.833
Panel G. SEOs issued over 1970–2001 and 2002–2004								
SEOs 2002–2004	94	α	0.097%	0.775	0.809	−0.297%	0.449	0.745
SEOs 1970–2001	441	α	−0.025%	0.872	0.786	−0.036%	0.704	0.854
Panel H. SEO portfolios formed three and six months after the issue								
		α	−0.086%	0.550	0.787	−0.115%	0.326	0.808
3-*months*	475	*MKT*	1.190	0.000		1.037	0.000	
		LIQ	−0.099	0.039		−0.060	0.119	
		α	−0.085%	0.562	0.779	−0.118%	0.329	0.794
6-*months*	472	*MKT*	1.188	0.000		1.032	0.000	
		LIQ	−0.086	0.077		−0.054	0.179	

Table 12. Decomposed buy-and-hold returns.

The table reports the intercepts (α) for a sample of SEOs from calendar time regressions on the LCAPM using rebalanced portfolio returns (*Reb*) and decomposed buy-and-hold returns (*DBHR*). The sample period is July 1970–December 2009. T is the length of the portfolio time series in months, p denotes p-values, and *Adj.* R^2 is the adjusted R-squared. The table reports results for the pooled sample and for issuers stratified according to the exchange where the firm lists. EW denotes equal weighting and VW value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time.

			EW			VW		
Portfolio	Method	T	α	p	*Adj.* R^2	α	p	*Adj.* R^2
All exchanges	*Reb*	474	−0.062%	0.664	0.789	−0.126%	0.278	0.805
	DBHR		−0.056%	0.661	0.830	−0.047%	0.733	0.794
NYSE/AMEX	*Reb*	474	−0.105%	0.403	0.787	−0.187%	0.144	0.747
	DBHR		−0.067%	0.572	0.802	−0.077%	0.552	0.786
Nasdaq	*Reb*	414	−0.049%	0.814	0.730	0.020%	0.928	0.763
	DBHR		−0.127%	0.462	0.762	−0.081%	0.707	0.721

Table 13. FF3FM with alternative liquidity factors.

The table reports coefficients (*Estimate*) from calendar time regressions for SEOs for five years after the issue on the FF3FM with alternative liquidity factors. The sample period is April 1970–December 2009. *MKT* is the market excess return, *SMB* is the difference in average returns on a portfolio of small (*S*) and big (*B*) stocks controlling for book-to-market. *HML* is the average return difference between a portfolio long in high (*H*) and short in low (*L*) book-to-market stocks controlling for size. *LMH* is the turnover-based liquidity factor of Eckbo and Norli (2005) and is the average return difference between a portfolio long in low turnover stocks (*L*) and short in high (*H*) turnover stocks controlling for firm size. *LIQ_res* are the residuals from regressing Liu's (2006) liquidity factor, *LIQ*, on *SMB* and *HML* without a constant. *LIQ* is the difference in average returns between portfolios of low and high liquidity stocks based on *LM*12. EW denotes equal weighting and VW value weighting. Value weights standardize market capitalization by the value-weighted CRSP stock market index to give comparability over time. *T* is the length of the time series in months, *p* denotes *p*-values, and $Adj.R^2$ is the adjusted *R*-squared.

			EW			VW		
Factor base	*T*	*Parameter*	*Estimate*	*p*	*Adj.* R^2	*Estimate*	*p*	*Adj.* R^2
TR	477	α	−0.078%	0.371	0.924	−0.225%	0.027	0.855
		MKT	0.977	0.000		1.022	0.000	
		SMB	0.611	0.000		0.008	0.827	
		HML	0.145	0.000		0.359	0.000	
		LMH	−0.332	0.000		−0.236	0.000	
LIQ	477	α	−0.140%	0.123	0.917	−0.186%	0.107	0.862
		MKT	1.050	0.000		1.014	0.000	
		SMB	0.757	0.000		0.129	0.000	
		HML	0.093	0.003		0.293	0.000	
		LIQ_res	−0.177	0.000		−0.265	0.000	