Can liquidity risk explain the underperformance following seasoned equity offerings?*

Pawel Bilinski, Manchester Business School

Weimin Liu, Nottingham University Business School

Norman Strong, Manchester Business School

April 2008

Abstract

This paper examines the role of liquidity risk in explaining the long-run performance of seasoned equity offerings (SEOs). We show that size and book-to-market matching does not control for the reduction in liquidity risk of SEO firms. Using Liu's (2006) liquidity augmented CAPM we find that issuers have lower exposure to liquidity risk compared to size and book-to-market matched benchmarks, and that the two-factor model explains the long-term performance of SEO firms in all instances we consider.

JEL classification: G1; G2

Keywords: Event studies, seasoned equity offerings.

* Pawel Bilinski is grateful for funding from the Marie Curie Early Stage Research Training Programme. We thank Michael Brennan and seminar participants at a conference at Manchester Business School for helpful comments. All errors and omissions are our own.

1. Introduction

Stocks are exposed to high liquidity risk if their trading is illiquid. While the literature is still exploring the dynamics of stock liquidity, it is clear that seasoned equity offering (SEO) firms care about the liquidity of their shares since this affects their costs of capital through the premium investors require for holding illiquid or high liquidity-risk stocks.[1] Managers of SEO firms have incentives to promote liquidity to facilitate their SEOs. Corwin (2003) finds that more liquid stocks experience lower new issue underpricing and Butler et al. (2005) report that investment banks charge lower fees to firms with more liquid securities before the offering. Managers of SEO firms also have incentives to promote liquidity to lower their costs of capital. The SEO event itself has the potential to improve liquidity since it is likely to increase the firm's shareholder base and to increase the firm's visibility in the market. Eckbo et al. (2005) confirm that managers consider liquidity improvements when deciding to issue equity.[2]

This paper investigates whether SEO firms improve their liquidity and whether any liquidity gain can explain their documented long-run underperformance.[3] We employ Liu's (2006) liquidity measure, since it captures the multidimensional nature of liquidity, and his liquidity-augmented CAPM, since this model performs well in explaining the cross-section of stock returns and, in particular outperforms the Fama–French three-factor model.[4] We find that SEO firms experience significant improvements in liquidity over the post-offering period relative to pre-offering liquidity levels. In the post-offering period SEO firms also have significantly higher liquidity characteristics than size and book-to-market (B/M) matched benchmarks, indicating that size and B/M matching fails to control for SEO firms' liquidity gains. We also examine whether size and B/M benchmarks provide reasonable matches on liquidity risk. The results indicate that post-offering liquidity risk is significantly lower for SEO firms than for matched counterparts. These results suggest that liquidity or liquidity risk

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

[2] As an example, New Oriental Education and Technology Group Inc (NYSE:EDU) justifies 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

[3] Based on buy-and-hold abnormal returns and a 5–year holding period, Loughran and Ritter (1995) report a 33% underperformance, Jegadeesh (2000) a 34.3% underperformance, Brav et al. (2000) 26.3%, and Eckbo et al. (2000) 23.2%. Jegadeesh (2000), Loughran and Ritter (2000), Bayless and Jay (2003) confirm SEO underperformance using calendar time regressions.

[4] We also use the turnover based liquidity metric of Datar et al. (1998) in parts of the study.

has the potential to explain the long-term underperformance of SEOs. As Liu (2006) shows that liquidity risk matters over and above liquidity as a characteristic, we focus on the liquidity risk explanation of SEO long-term performance. In robustness checks, we form calendar time portfolios based on a decomposed buy-and-hold approach (Liu and Strong 2006). We find that this approach offers higher precision, as standard errors narrow and adjusted R^2s increase compared with the traditional calendar time portfolio approach.

Using calendar time regressions and Liu's liquidity augmented CAPM, we find that SEOs load significantly on the liquidity factor after the offering. Negative sensitivity to liquidity lowers post-offering SEO returns by 0.128% using equal weighting *(EW)* and to 0.103% per month using value weighting *(VW)*. The intercept estimate of abnormal return increases to −0.014% (0.078%) compared with the intercept estimate from the Fama and French three-factor model of −0.307% (−0.231%) using *EW (VW)*. The difference in the liquidity sensitivity of SEOs and of their size and book-to-market matches is 0.225 (0.188) using *EW (VW)*. This confirms that benchmark stocks have higher risk exposures, which results in apparently significant buy-and-hold abnormal returns using size and B/M matched stocks.

Our research is the first to support the liquidity-based discount rate explanation for SEOs returns as opposed to the behavioural hypothesis in Loughran and Ritter (1995). We focus on the dynamics in the evolution of liquidity characteristics in event time and sensitivity to liquidity risk in calendar time.[5] We provide a battery of robustness tests to ensure the main results are not driven by biases in the research design. Our results enrich the limited evidence on the importance of liquidity in explaining long-run SEO returns.

The paper continues as follows. Section 2 describes the data and the frequency of new equity issues over the sample period. We confirm previous findings of SEO underperformance over a three-year holding period in event and calendar time in Section 3. In Section 4 we document the liquidity characteristics gains and lower sensitivity to liquidity risk of issuers after the offering. We find that liquidity risk plays a central role in explaining SEO returns as the liquidity augmented CAPM leaves no SEO underperformance. In Section 5 we show misspecification of the size and book-to-market matching as it does not capture

[5] Eckbo et al. (2000) report a differential average 5-year liquidity characteristic for SEOs and size and book-to-market matches before and after the offering. Eckbo and Norli (2005) show that liquidity enhanced Carhart (1997) model explains SEOs returns in calendar time. Using momentum factor presupposes behavioural explanation for SEOs returns and does not allow to dissect the discount rate from the sentiment explanation for low SEOs returns.

SEO liquidity. Section 6 presents robustness tests, including a new way to form calendar time portfolios based on decomposed buy-and-hold returns. Section 7 concludes.

2. Data and sample selection criteria

We draw our sample of seasoned equity offerings from the SDC New Issues database. The sample period starts in January 1970 and ends in December 2004. To allow for a 3-year holding period, the last offering is in December 2001. We follow the selection criteria of Eckbo et al. (2000) and Brav et al. (2000). We include all companies listed on NYSE/AMEX/NASDAQ that make pure secondary offerings or combinations of secondary and equity sales by a major shareholder (combinations). The offerings are firm commitment, underwritten offers of common stock only (CRSP share codes 10 and 11) by US domiciled companies in the US market. We include industrial, financial and utility firms but exclude closed-end funds, unit investment trusts, real estate investment trusts, American Depository Receipts, unit offerings, and SEOs that simultaneously offer debt, preferred stock, or warrants. In addition we exclude private placements, exchange offers of stock, 144A offers, cancelled offers, and spin-off related issues.

These criteria lead to an initial sample of 7,135 issues. Figure 1 shows their distribution over time. Similar to previous research, we observe offerings clustering during 1971–72, 1975–76, 1978–83, 1985–86, 1991–93 and 1995–97. Moreover, SEO waves mirror market performance measured by S&P500 returns. The correlation between S&P500 returns and the number of SEOs is 0.484. The clustering of SEOs gives rise to two statistical issues in testing for abnormal performance. It induces a bias in cross-sectional standard errors of abnormal performance measures in event time and it induces heteroskedasticity in the residual portfolio variance in event and calendar time.

From the initial sample, we retain offerings that have stock return data available for at least a month after the issue. We collect information on firm characteristics, such as the market and book values of common equity from the Compustat/CRSP merged database. We include a company that issues seasoned equity, at the earliest, three years after its IPO, which ensures that we do not confuse the SEO and IPO puzzles.[6] We exclude equity offerings by the same company that occur during the holding period of the first equity offering. These criteria narrow the sample to 3,741 offerings, giving one of the largest samples of SEOs in

[6] This eliminates 2,616 observations from our sample, which is the main reason for a lower sample size than some previous studies.

the literature.[7] We find control stocks for 3,364 issues, which form the final sample for our analysis.

We use two liquidity measures. One is a turnover rate measure of liquidity in month t, TR, defined as the average number of shares traded over the previous three months divided by month t's number of shares outstanding (Datar et al. 1998) and expressed as a percentage. The turnover rate proxies (inversely) for an investor's expected holding period. The other liquidity measure is Liu's (2006) $LM12$ measure, which is defined as the standardized turnover-adjusted number of zero-trading volume days over the prior 12 months

$$LM12 = \left(\text{number of zero volume days in prior 12 months} + \frac{1/TR12}{Deflator}\right) \times \frac{21 \times 12}{NoTD},$$

where $TR12$ is daily turnover averaged over the prior 12 months, $NoTD$ is the number of exchange trading days over the prior 12 months, and $Deflator$ is set at 11,000 to ensure that $\frac{1/TR12}{Deflator}$ is less than 1. As Liu (2006) explains, $LM12$ captures the multidimensional 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.[8]

In Table 1 we report descriptive statistics for the final sample stratified according to the exchange where the issuer's stock lists, its membership in six Fama and French (1993) size and B/M portfolios, its broad industry group (financial, industry and utility), the type of equity issue (pure secondary issues and offerings accompanied by sales of equity by a major shareholder), and whether the offering takes place in a hot or cold issue period. We define an issue period as hot (cold) if the annual number of SEOs relative to the total annual number of firms listed on CRSP is above (below) the median calculated over the period 1970–2001.

The median capitalization of issuers is \$259m with a median B/M ratio of 0.534. Over 59% of issuers are small firms. Smaller firms find it more difficult to generate the necessary internal cash flow to exploit profitable growth opportunities and experience more constrained access to debt markets.[9] Therefore they are more likely to issue equity to raise finance. Almost 67% of issues occur in hot periods and Figure 1 shows that market

[7] Loughran and Ritter (1995) investigate 3,702 SEOs, Spiess and Affleck-Graves (1995) study 1,247, Lee (1997) 1,513, Jegadeesh (2000) 2,992, Brav et al. (2000) 3,775, Kahle (2000) 1,739, Clark et al. (2001) 3,092 SEOs, and Eckbo et al. (2000) 3,851.

[8] Both liquidity measures impose low data requirements and are correlated with other liquidity measures such as bid–ask spread (Amihud and Mendelson 1986), the liquidity ratio (Hasbruck and Schwartz 1988), the probability of informed trading (Easley et al. 1996), and return reversal (Pastor and Stambaugh 2003).

[9] See Himmelberg and Petersen (1994), Gilchrist et al. (1995), Fazzari et al. (1998), and Carpenter and Petersen (2002).

downturns occur shortly after peaks of the issuing wave. The ability to liquidate a position quickly and inexpensively becomes especially valuable during these periods. The "flight to quality" effect described by Pastor and Stambaugh (2003) further increases the value of this option. Before the SEO offering, NYSE/AMEX SEOs have a mean turnover rate of 5.877 and an average number of (turnover-adjusted) zero-trading-volume days of 3.244 over the prior 12 months. The corresponding numbers for NASDAQ SEOs are 17.738 and 9.306. Liu (2006) reports average *TR* and *LM*12 of 0.223 and 10.39 for NYSE/AMEX stocks over the period 1963–2003 and 0.45 and 35.63 for Nasdaq stocks over the period 1983–2003. Therefore, both liquidity measures in Table 1 indicate that SEOs exhibit higher pre-offering average liquidity compared to the CRSP populations.

NYSE/AMEX listed firms comprise over 60% of our sample. Nasdaq offerings tend to occur shortly after IPOs, which eliminates a larger proportion of them from our analysis. Nasdaq firms have lower B/M ratios compared to NYSE/AMEX firms (median of 0.354 vs. 0.684), consistent with their higher growth options. Industrial firms comprise over 66% of issues, followed by utilities, which list mainly on NYSE/AMEX (697 out of 776 utilities). Equity sales by major shareholders accompany 27% of equity sell-offs. Finally, 1,936 issues take place in hot and 1,428 in cold issue periods.

3. The long-run performance of SEOs

Previous evidence on the long-run performance of SEOs indicates their considerable economically and statistically significant underperformance. These findings come primarily from research that uses a control firm approach with size and B/M matching. We replicate matching based on the closest neighbour approach following Ritter (1991). We pair each issuer with non-issuing firms within a 30% calliper of the offering firm's equity market value measured in June before the offer date. For offers in the first half of the year, market value is in June of the previous year; for offers in the second half of the year market value is in June of the offer year. Non-issuers are companies that have not issued new equity for the past three years and we select them at the earliest three years after their Initial Public Offering. From this pool we select a control firm with the closest B/M to that of the issuer. To avoid hindsight bias, for issues taking place in the first six months of a year we choose book value of equity for the fiscal year two years earlier; for offer dates in the second six months of the year, book value is from the previous fiscal year. We define B/M as in Fama and French

(1992).[10] We include the control for a 3-year holding period and allow each control to be paired with only one SEO over the holding period.[11] If a match delists or issues equity, we choose a new match from the original list of eligible benchmarks. If an issuing firm delists, we assume zero returns for the SEO and its match until the end of the holding period.

For each sample firm i we calculate its t-month buy-and-hold return (BHR) as $BHR_i = \prod_{\tau=1}^{t}(1+R_{i\tau})-1$, where $R_{i\tau}$ is the return of stock i in month τ. For issues in the first half of the year the holding period starts at the end of June of that year. For offers in the second half of the year, the holding period starts at the end of December of that year. For some offers there may be a gap of up to six months between the offer date and the start of the holding period. The reason for this is that we use a new method to calculate portfolio returns in calendar time based on decomposed BHRs. To implement this method, we use a gap between the offer date and portfolio formation of up to 6 months. The gap in event time ensures comparability between estimates of abnormal performance in event and calendar time. However, we replicate our event time analysis using a holding period starting at the end of the issue month and all conclusions remain the same.

The average holding period return across all sample stocks is $\overline{BHR} = \sum_{i=1}^{N} x_i BHR_i$, where x_i denotes either *EW* or *VW*. We base value weights on market capitalization one month before the offer and scale these by the value-weighted CRSP stock market index at each point in time. This standardization ensures that early and later observations receive consistent weights.

We report average BHRs for issuers and their matches over a 3-year holding period in Panel A of Table 2. Column *Diff*, denoting the difference between these two figures, gives the buy-and-hold abnormal return (BHAR) of issuers. The average *EW* BHAR is –19.4%, decreasing to –20.3% using *VW*. NASDAQ stocks underperform more than NYSE/AMEX stocks: –26.7% (–42.2%) compared to –19.3% (–17.0%) using *EW* (*VW*).[12] In unreported

---

[10] Fama and French (1992) define book value as the COMPUSTAT book value of stockholders equity plus balance sheet deferred taxes and investment tax credits less the book value of preferred stock. They use the redemption, liquidation, or par value to estimate the value of preferred stock. Market value of equity is the number of shares outstanding times the stock price at the end of June each year.

[11] We replicate the analysis for a 5-year holding period. All conclusions remain the same.

[12] Similar to Eckbo et al. (2000), we include exchange as an additional matching dimension when analysing abnormal performance across exchanges. This reduces the sample size by 37 stocks and means the abnormal performance across exchanges is not equal to the weighted sum of abnormal performances across exchanges.

results, a Wilcoxon signed-rank test indicates a significant median underperformance at 1% for the pooled and individual exchanges.

To adjust for the downward bias in cross-sectional standard errors of BHARs, we next investigate abnormal performance in calendar time as in Lyon et al. (1999). Each calendar month we calculate abnormal return, AR_{it}, for event firms as the difference between the monthly return on sample firm i, R_{it}, and its benchmark stock return, $E(R_{it})$. We calculate the mean abnormal return across firms in the portfolio as $MAR_t = \sum_{i=1}^{n_t} x_{it} AR_{it}$, where n_t is the number of firms in the portfolio in month t and x_{it} is the weight of the security in the portfolio (either *EW* or *VW*). A test of the null hypothesis is based on a grand mean monthly abnormal return $MMAR_T = \frac{1}{T} \sum_{t=1}^{T} MAR_t$ (where *T* is the number of months over the sample period) and a time series standard deviation of MAR_t. Based on *MMAR* and *EW* we find consistent underperformance of SEOs in the full sample and on NYSE/AMEX (Table 2, Panel B).[13] However the difference in performance of new equity issuers and their matches is insignificant when using *VW* for NYSE/AMEX stocks.

To investigate whether a factor model can explain the underperformance following SEOs, we regress issuer portfolio returns on an asset pricing model in calendar time. Fama (1998) and Mitchell and Stafford (2000) advocate the calendar time approach as less susceptible to the bad model problem. The method does not compound spurious abnormal returns, poses fewer statistical problems (less skewness and kurtosis), and adjusts directly for cross-sectional correlation. Barber and Lyon (1997) criticize the approach as it does not correspond to investors' experiences when investing in event firms. Loughran and Ritter (2000) argue that working in calendar time (weighting time periods equally) rather than in event time (weighting stocks equally) has less power to reject the null when there are time varying misvaluations of stocks and firms cluster by taking actions to exploit this mispricing, which is consistent with Figure 1. The intercept of a calendar time regression estimates the mean monthly abnormal return and forms the basis of our tests. The models we discuss

[13] Fama (1998) and Mitchell and Stafford (2000) suggest standardizing monthly portfolio returns by an estimate of their cross-sectional monthly standard deviation. This adjusts for heteroskedasticity and "effectively gives more weight to periods of heavy event activity than periods of low event activity because the portfolio residual variance is decreasing in portfolio size, all else equal" (Mitchell and Stafford 2000, 318). We implement this standardization; however the standard errors are only slightly different and do not change the inferences. Also, as the minimum number of stocks in our portfolios is never less than 19, we have diversified portfolios, which may limit standard error improvements based on this method.

include Fama and French's (1993) three-factor model and Fama and French's (1993) model with *SMB* and *HML* purged of equity issuers as Loughran and Ritter (2000) recommend.[14] We report the intercepts from regressing equal and value weighted portfolios on the factor models in Panel C of Table 2. All *EW* portfolio alphas are significant. When we compare the intercepts with the *MMAR* estimates from Panel B, we find that the degree of underperformance increases for the pooled sample and for *EW* NYSE/AMEX issuers. The performance of *VW* NYSE/AMEX issuers is lower by 6.6 percentage points and the performance of the two Nasdaq portfolios is lower by 8.2 (1.0) percentage points using *EW* (*VW*). We do not find significant underperformance using *VW* portfolios for the pooled sample and NYSE/AMEX issuers.

Panel D indicates that using purged *HML* and *SMB* factors in the Fama and French three-factor model reduces alphas on average by 5.7 (3.73) percentage points for *EW* (*VW*) portfolios. This supports the benchmark contamination hypothesis of Loughran and Ritter (2000). Sensitivity to the purged factors is almost 100% smaller compared to the unpurged factors. As SEOs on average covary positively with *HML* and *SMB*, purging decreases the expected returns on the issuer portfolio.

We conclude that in economic and statistical terms there is evidence of the SEO puzzle in our sample.

4. The importance of liquidity risk in explaining SEO performance

Numerous studies find a negative relation between individual stock liquidity and expected stock returns (Amihud and Mendelson 1986, Brennan and Subrahmanyam 1996, Brennan et al. 1998). Chordia et al. (2000), Lo and Wang (2000), and Hasbrouck and Seppi (2001) find commonalities in liquidity in the cross-section of stocks. Both Pastor and Stambaugh (2003) and Liu (2006) show that market liquidity is a relevant state variable for asset pricing, and Liu's liquidity augmented CAPM provides a good description of cross-sectional stock returns. This section explores the liquidity evolution of SEO firms and examines the power of liquidity risk to explain the post SEO stock price performance.

Figure 2a depicts the evolution of the liquidity measures of Datar et al. (1998), *TR*, and of Liu (2006), *LM*12, from three years before to three years after an SEO. Figure 2a shows that issuers' turnover rates increase in the period leading up to the offering. Average turnover rate increases from 7.154 twelve months before the issue to 10.339 one month

[14] Purged SMB and HML factors do not contain stocks that publicly issued equity for cash during the prior five years, or have been CRSP-listed for less than five years, see Loughran and Ritter (2000).

before the issue, an increase of 44 percent. This coincides with the period when the company is likely to plan the equity issue. The average turnover rate continues to increase around the offering, from 10.339 one month before to 13.274 one month after the issue, a further increase of 28 percent. Average *TR* levels out around 10 over the remainder of the holding period. *LM*12 declines sharply in the year before the issue (from 9.841 twelve months before the offering to 5.7 one month before the issue, a fall of 42 percent) and decreases further around the issue (from 5.7 one month before to 4.627 one month after the issue, a fall of 19 percent). Liquidity continues to improve over the next ten months, with an average gain of 58 percent (from 4.146 two months after the issue to 1.752 eleven months after the offering). It levels out around an average of 2.1 over the remainder of the holding period. This evidence on liquidity dynamics is consistent with Denis and Kadlec (1994) and Eckbo et al. (2000) who report that issuers' liquidity measured by the turnover ratio improves following an SEO.

Figure 2b depicts the evolution of average loading on liquidity risk *LIQ*, which is the difference in average returns between portfolios of low and high liquidity stocks based on the *LM*12 measure. We base the results on an event time, rolling window regression, using Liu's (2006) liquidity-augmented CAPM with two years of return data for each of the 3,364 SEOs. Sensitivity to liquidity risk remains stable from −36 to −12 months before the issue, with an average coefficient of 0.189. The loading decreases from 0.17 twelve months before the issue to 0.099 one month before. Liquidity risk exposure falls by 122.63% by 2 years after the issue (from 0.075 to −0.226) and it levels off thereafter with an average coefficient of −0.229. Sensitivity to the market premium increases from 1.036 thirty-six months before the offering to 1.182 one month before and decreases to 0.91 thirty-six months after.[15]

In Panel A of Table 3 we form two calendar time portfolios, where the first includes SEOs for three years before the issue and the second for three years after.[16] We regress both portfolios on the liquidity augmented CAPM. Regression 1 gives results for the pre-issue period, regression 2 for the post-issue period. The coefficient on the liquidity factor decreases for *EW* (*VW*) portfolios from an insignificant 0.01 (−0.037) pre-issue to a significant −0.209 (−0.169) with a t-statistic of −4.57 (−3.9) post-issue. The pre-SEO intercept is significantly positive, indicating monthly abnormal returns of 1.761% (1.291%)

[15] Prior to issue investors face uncertainty of offering withdrawal, which may explain the increased market beta. As the uncertainty resolves at the issue, market beta decreases.

[16] The sample period in Panel A and B of Table 3 starts in 1971 to allow for 3-year holding period before the SEO.

using *EW* (*VW*). This is consistent with Loughran and Ritter's (1995) prediction that overvalued stocks are more likely to issue new equity to take advantage of their misvaluation. Following the issue, we find no SEO abnormal performance. We reject the hypothesis of intercept equality at less than 1% (Panel B). Table 3 also shows a significant difference in the market betas of the two portfolios, but even combined with *SMB* and *HML*, the market premium is unable to explain SEO performance as Table 2 shows.

Panel C of Table 3 reports the intercepts and factor sensitivities directly comparable with the results from Table 2. SEOs load negatively on *LIQ* for the pooled sample and when we stratify issuers according to exchange. The pooled portfolio and Nasdaq issuers load negatively and significantly on *LIQ*, which lowers their expected returns by –0.128% (–0.103%) per month for the former and by –0.301% (–0.382%) per month for the latter using *EW* (*VW*).[17] NYSE/AMEX issuers do not bear any liquidity risk, which means that issuers bear less liquidity risk than the average stock, which has a significant positive loading on *LIQ* (Liu, 2008, Table 7). *VW* portfolios load more negatively on *LIQ* as larger stocks are on average more liquid. None of the intercepts is distinguishable from zero and they increase in value from –0.307% (–0.231%) using the Fama and French three-factor model in Table 2 to –0.014% (0.078%) for the pooled *EW* (*VW*) sample. Overall, the estimates of Liu's two-factor model show that issuers' lower exposure to liquidity risk explains their post-issue performance.

5. Misspecification of the method of matching

The method of matching assumes that the benchmark mimics the risk exposure of the event stock. We investigate next if size and book-to-market matching captures the liquidity feature of SEOs. Table 4 reports the differences in size, *B/M*, and liquidity characteristics between SEOs and their size and *B/M* matched benchmarks over the two years before and the three years after the issue. The results show that size and book-to-market matching is successful on the *MV* characteristic but not on *B/M* over the 3-year post-SEO period. SEOs increase their book values, which increases the average *B/M* difference to a significant 0.202 over the three years after the issue. More important, size and book-to-market matching fails to capture the liquidity characteristics of SEO firms over either the pre- or post-issue periods.

[17] We obtain these numbers by multiplying the average liquidity premium over the sample period 1970–2004 by the liquidity factor coefficient, e.g. the coefficient on *LIQ* for the *EW* pooled portfolio is −0.179 and the average monthly liquidity premium over 1970–2004 equals 0.713%, which lowers SEOs expected returns by –0.128%=–0.179 *0.713% .

Specifically, SEOs exhibit significantly greater liquidity than their *MV* and *B/M* matches. For example, the difference in *LM*12 between SEOs and their *MV* and *B/M* matches is, on average, –1.137 over the pre-issue period, and this difference increases further (in absolute term) to –5.087 over the post-issue period.

Figures 3a and 3b depict the evolution of average *TR* and *LM*12 from 24 months before to 36 months after the offer for issuers and their matches. Both figures confirm that *MV* and *B/M* matches mismatch on liquidity at the time of offering and over the holding period. The mismatch is due to the liquidity improvements of SEOs, as matches exhibit little variation in their liquidity levels.

Fama and French (1993, 1995, 1996), Perez-Quiros and Timmermann (2000), and LeHau and Ludvigson (2001) challenge the notion that firm characteristics drive expected stock returns. Working in calendar time allows us to investigate whether two-dimensional characteristics matching is sufficient to capture the covariance structure of event returns. We therefore repeat our analysis using factor regressions and a calendar time rolling portfolio of issuers and matches to verify if size and book-to-market matching captures the covariance of SEO returns. Figures 3c and 3d show the sensitivity of SEOs and their benchmarks to *LIQ* and *MKT* using a liquidity-augmented CAPM. We find that size and book-to-market matches mimic SEO liquidity risk exposure before the issue. However, following the issue, we observe strong decreases in *LIQ* loading for SEOs not matched by *MV* and *B/M* benchmark stocks, which persists throughout the holding period. A similar pattern applies to the market premium. We also run a regression of return differences between SEOs and their *MV* and *B/M* benchmarks on the two Liu factors. We find a significant coefficients on *LIQ* of –0.225 (–0.188) and on *MKT* of –0.107 (–0.130) using *EW* (*VW*), which indicates higher risk exposures of the benchmark stocks.[18]

In sum, the method of *MV* and *B/M* matching compares returns of high-liquidity issuer stocks with returns of low-liquidity benchmark stocks, leading to measurement bias. Moreover, *MV* and *B/M* characteristics matching does not guarantee that the risk sensitivity of the benchmark captures the covariance structure of SEO returns. Stocks with large differences in liquidity characteristics also tend to have large differences in sensitivities to *LIQ*, which further magnifies the measurement bias. As buy-and-hold returns compound any risk mismatch over the holding period, the measurement bias can easily be misinterpreted as SEO underperformance.

[18] The significance is at less than 1%. In all instances, the intercept term is indistinguishable from zero.

6. Robustness tests

Above results may be driven by faults in the research design. Averaging of SEOs returns for the pooled and exchange stratified samples can dilute the underperformance effect if it is confined to a particular stock grouping. Monthly rebalancing of calendar time portfolio involves prohibitive transaction costs and does not correspond to investor's experience when investing into event firms. To address these concerns, we run a number of robustness tests.

6.1 SEOs underperformance: subsample results

In Table 5 we analyse performance of SEOs across a number of sub-portfolios that include: three industry groups, types of equity issued (secondary offerings and combinations of secondary and equity sale by major shareholder), Fama and French size and B/M based portfolios, hot vs. cold periods, and offerings occurring from January 1970 to December 1986 and from January 1987 to December 2001. We also investigate 12 and 24 month holding periods to verify that abnormal performance is not confined to a shorter horizon. The liquidity-augmented CAPM captures the performance of SEOs across the majority of sub-portfolios. Only the *VW* portfolio of offers accompanied by equity sell-off by major shareholders exhibits significant underperformance. The negative intercept of −0.469% results from overweighting returns on three large capitalization stocks in portfolio return as we use beginning of the holding period market values. Black & Decker Manufacturing Corp., Hospital Corp. of America and Caesars World Inc experienced average BHARs of −100% and excluding them eliminates the underperformance.

6.1 Conditional heteroskedasticity

Fama (1998) points out that a changing number of event stocks in calendar time portfolios leads to heteroskedasticity. He proposes weighting observations by the monthly estimate of the portfolio's standard deviation. Mitchell and Stafford (2000) show that using weighted least squares with the number of stocks in a portfolio as weights assumes independence of observations, which cross-sectional correlation violates. They support Fama's (1998) weighting scheme. In practice, most studies use White's (1980) consistent variance estimator, which allows for various heteroskedasticity structures. MacKinnon and White (1985) argue, however, that this estimator is valid only in large samples and propose alternative variance estimators. Long and Ervin (2000) find that White's test for heteroskedasticity often fails to detect its presence in small samples and suggest using a heteroskedasticity consistent estimator whenever the researcher suspects its presence. White's (1980) adjustment assumes independence of heteroskedastic error terms.

Engle (1982) proposes the ARCH model to describe the behaviour of the variance term in time series. The model is particularly useful in the case of volatility clustering, which the rebalanced calendar time portfolios exhibit. However, using the ARCH error term presupposes that it captures the true form of heteroskedasticity and that it does not impose unwarranted assumptions that improve power yet lead to test misspecification. We test for the presence of ARCH effects using Engle LM and Portmanteau Q (McLeod and Li 1983) tests. We find pervasive autocorrelation in the residuals across all series for the liquidity-augmented CAPM with the one exception of the *VW* Nasdaq portfolio.

To adjust for conditional heteroskedasticity we use the generalized ARCH (GARCH) model (Bollerslev 1986, Taylor 1986). The conditional variance in the GARCH (1, 1) case that we consider takes the form $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2$, where σ_t^2 is the conditional variance term, α_0 is the mean long-term variance, and α_1 and γ_1 are the coefficients on volatility in the previous period, u_{t-1}^2, and on the lagged conditional variance σ_{t-1}^2.[19] A large value of the previous residual and conditional variance maps into more extreme conditional variance in the current period.

We report regression results based on maximum likelihood estimation and the liquidity-augmented CAPM in Table 6. A general observation is that the coefficients on all three conditional variance terms are statistically significant in the majority of specifications. Using *EW* (*VW*), the alpha terms decrease from −0.014% (0.078%) to −0.086% (0.043%) for the pooled sample, from −0.130% (0.024%) to −0.162% (0.018%) for NYSE/AMEX issuers and from 0.053% to −0.033% for Nasdaq issuers. Our results indicate that White's (1980) covariance estimator is sufficient to capture the underlying heteroskedasticity in the calendar time series.

6.2. Decomposed buy-and-hold returns

Liu and Strong (2006) criticize portfolios formed with frequent rebalancing, which is implicit in standard calendar time portfolios. They point out that monthly rebalancing is inconsistent with a multi-month holding period strategy and involves prohibitive transaction

[19] Hou et al. (2001, 14) expand the conditional variance term to include a number of event firms parameter, $\gamma_2 n_t$, which allows the "number of firms in the portfolio to (nonlinearly) affect the point estimates obtained in the (asset pricing) equation". We test this specification, but find γ_2 is indistinguishable from zero.

costs. To address this criticism, we propose a new technique based on decomposed buy-and-hold returns. This method transfers the soundness of the buy-and-hold investment strategy into calendar time and directly adjusts for cross-sectional correlation. We show that it improves the precision of regression estimates as, on average, standard errors narrow and adjusted R^2 s increase. Below we discuss the decomposed BHR portfolio formation.

Every six months we form a portfolio of all stocks that issued equity in the previous six months. We calculate BHRs for this portfolio over the 3-year event window as the weighted sum of individual BHRs. We obtain the decomposed buy-and-hold monthly portfolio returns using equation (3) from Liu and Strong (2006)

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

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 the portfolio weight for stock i. For $t = 1$, $r_{p1} = \sum_{i=1}^{n} x_i r_{i1}$. Given a time series of decomposed BHRs, we construct a grand calendar time portfolio return as $R_{pt} = \sum_{p=1}^{w_t} r_{pt} \Big/ w_t$ where w_t is the number of overlapping decomposed buy-and-hold portfolios in month t (see Figure 4). With a three-year holding period there is a minimum of one and maximum of six overlapping portfolios.

Liu and Strong (2006) 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.[20] They report a positive bias for small, low-price and loser stocks and a negative bias in large and high-price stocks. Our SEO portfolios represent a mix of both type of stocks, hence there is no statistical difference between average monthly returns on both series. Neither the traditional rebalanced calendar time nor the decomposed BHR portfolio exhibits excessive skewness or kurtosis, which allows for simple *t*-statistics.

We replicate the analysis for the decomposed BHR portfolio and liquidity augmented CAPM in Table 7. Panel A shows the results for the pooled sample and exchanges, while

[20] The negative autocorrelation is due to nonsynchronous trading, transactions costs and bid-ask spreads (Fisher 1966, Roll 1984, Jegadeesh and Titman 1995). Positive portfolio autocorrelation results from delays in price adjustment (Lo and Mackinlay 1990, Mech 1993).

Panels B to G replicate the analysis for the subportfolios we analyse in Table 5. None of the alphas indicate SEO underperformance and the *VW* underperformance of offers accompanied by equity sell-off by major shareholders becomes indistinguishable from zero. In the decomposed method, period *t* portfolio returns are value weighted by *t-1* market values, which adjusts for the decreasing contribution of loser stocks to portfolio returns. The traditional calendar time approach from Table 5 does not account for the fact that the three stocks that contribute to the significantly negative intercept lose on average 41.3% of their value over the three-year following the offering.

In Table 5, the rebalanced portfolio of SEOs for the sub-period January 1970 to December 1985 exhibits marginally significant underperformance (p = 0.053). However, we find no underperformance for the decomposed BHR portfolio over this period in Table 7. The marginally significant intercept for 1970–1985 may result from a negative bias of the rebalanced portfolio compared to the decomposed BHR, which may be greater over this sample period. Positive autocovariance in portfolio returns leads to lower returns on the rebalanced vs. the decomposed portfolio (0.863% vs. 0.953%), which the negative intercept adjusts for. Fama (1998) points out that most financial puzzles are stronger in the early period of CRSP returns and disappear in the later period, consistent with a higher impact of microstructure biases on return estimates. The decomposed buy-and-hold approach, to some extent, mitigates biases due to microstructure effects, yet does not produce materially different conclusions from the traditional calendar time portfolio approach in the case of SEO. Liu and Strong (2006) conclude that the magnitude of bias depends on the event under consideration and the sample structure. SEOs include liquid stocks from all size-based portfolios and are unlikely to suffer from the market microstructure biases that the decomposed method adjusts for.

9. Conclusions

This study examines the SEO long-term underperformance puzzle taking into account liquidity risk. We find that size and book-to-market based benchmarks do not capture the liquidity risk evolution of SEO firms. Our analysis shows that issuers are significantly more liquid and bear less liquidity risk than their size and book-to-market matched counterparts. The liquidity-augmented CAPM captures the performance of SEOs in all portfolios we consider.

In comparison to the size and book-to-market matching approach, using factor model regressions better captures the dynamics of risk sensitivities. We propose a new method to form calendar time portfolios based on decomposed buy-and-hold returns. The decomposed BHR portfolio transfers the soundness of the buy-and-hold investment strategy to calendar time, directly adjusts for cross-sectional correlation, and avoids biases due to market microstructure common to the rebalanced calendar time method. We show that Liu's (2006) liquidity augmented CAPM also captures the returns of SEOs in this case.

Our study supports the liquidity-based low discount rate explanation for SEOs returns. We find no evidence of long-run underreaction to the issue signal advocated by Loughran and Ritter (1995). The results enhance the evidence on SEOs liquidity risk exposure from Eckbo and Norli (2005) who conjoin it with the behavioural explanation.

References:

Acharya, V., Pedersen, L.H, 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375–410.

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

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223–249.

Barber, B., Lyon, J., 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. Journal of Financial Economics 43, 341–372.

Blume, M., Stambaugh, R., 1983. Biases in computed returns: an application to the size effect. Journal of Financial Economics 12, 387–404.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307–328.

Brav, A., Geczy, C., Gompers, P.A., 2000. Is the abnormal return following equity issuances anomalous? Journal of Financial Economics 56, 209–249.

Brennan, M., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specification, security characteristics, and the cross-section of expected stock return. Journal of Financial Economics 49, 345–373.

Brennan, M., Subrahmanyam, A., 1996. Market microstructure and asset pricing. Journal of F Financial Economics 41, 441–464.

Butler, A.W., Grullon, G., Weston, J.P., 2004. Stock market liquidity and the cost of issuing equity. Journal of Financial and Quantitative Analysis 40, 331–348

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Carpenter, R.R., Petersen, B.C., 2002. Is the growth of small firms constrained by internal finance? Review of Economics and Statistics, 84, 298–309.

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. Journal of Financial Economics 56, 3–28.

Clarke, J., Dunbar, C., Kahle, K.M., 2001. Long-run performance and insider trading in completed and cancelled seasoned equity offerings. Journal of Financial and Quantitative Analysis 36, 415–430.

Conrad, J., Kaul, G., 1988. Time-variation in expected returns. Journal of Business 61, 409–425.

Corwin, S., 2003. The determinants of underpricing for seasoned equity offers. Journal of Finance 58, 2249–2279.

Datar, V.T., Naik, N.Y., Radcliffe, R., 1998. Liquidity and stock returns: an alternative test. Journal of Financial Markets 1, 203–219.

Denis, D., Kadlec, G., 1994. Corporate events, trading activity, and the estimation of systematic risk: evidence from equity offerings and share repurchases. Journal of Finance 49, 1787–1811.

Easley, D., Kiefer, N., O'Hara, M., Paperman, J., 1996. Liquidity, information and infrequently traded stocks. Journal of Finance, 51, 1405–1436.

Eckbo, B.E., Masulis, R.W., Norli, Ø., 2000. Seasoned public offerings: Resolution of the 'new issues puzzle'. Journal of Financial Economics 56, 251–291.

Eckbo, B.E., Masulis, R.W., Norli, Ø., 2005. Security Offerings: A Survey. In: Eckbo, B.E., ed. Handbook of Corporate Finance: Empirical Corporate Finance. Elsevier/North-Holland.

Eckbo, B.E., Norli, Ø., 2005. Liquidity risk, leverage and long-run IPO returns. Journal of Corporate Finance 11, 1–35.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987–1006.

Fama, E.,1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283–306.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47,427–465.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. Journal of Finance 50, 131–155.

Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

Fazzari, S., Hubbard, G., Petersen, B.C., 1988. Financing Constraints and Corporate Investment. Brookings Papers on Economic Activity, 19, 141–195.

Fisher, L., 1966. Some new stock market indices. Journal of Business 29, 191–225.

Gilchrist, S., Himmelberg, Ch.P., 1995. Evidence on the role of cash flow for investment. Journal of Monetary Economics, 36, 541–572.

Hasbrouck, J., Schwartz, R., 1988. Liquidity and execution costs in equity markets. Journal of Portfolio Management, 7–16.

Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows, and liquidity. Journal of Financial Economics 59, 383–411.

Himmelberg, Ch.P., Petersen, B.C.,1994. R&D and internal finance: A panel study of small firms in high-tech industries. Review of Economics and Statistics, 56, 38–51.

Hou, K, Olsson, P, Robinson, D, 2001. Does takeover increase stockholder value? Working paper, Duke University.

Jaffe, J.F., 1974. Special information and insider trading. Journal of Business 47, 410–428.

Jegadeesh, N., 2000. Long-term performance of seasoned equity offerings: Benchmark errors and biases in expectations. Financial Management 29, 5–30.

Jegadeesh, N., Titman, S., 1995. Short horizon return reversals and the bid-ask spread. Journal of Financial Intermediation 4, 116–132.

Kahle, K.M., 2000. Insider trading and the long-run performance of new security issues. Journal of Corporate Finance 6, 25–53.

Lee, I., 1997. Do firms knowingly sell overvalued equity? Journal of Finance 52, 1439–1466.

Lettau, M., Ludvigson, S., 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. Journal of Political Economy 109, 1238–1287.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. Journal of Financial Economics 82, 631–671.

Liu, W., 2008. The liquidity-augmented CAPM over 1926 to 1963. Working paper, University of Nottingham.

Liu, W., Strong, N., 2006. Biases in decomposing holding period portfolio returns. Review of Financial Studies, forthcoming.

Lo, A.W., Mackinlay, A.C., 1990. When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175–205.

Lo, A.W., Wang, J., 2000. Trading volume: definitions, data analysis, and implications of portfolio theory. Review of Financial Studies 13, 257–300.

Long, J.S., Ervin, L.H., 2000. Using heteroscedasticity consistent standard errors in the linear regression model. The American Statistician 54, 217–224.

Loughran, T., Ritter, J., 1995. The new issues puzzle. Journal of Finance 50, 23–51.

Loughran, T., Ritter, J., 2000. Uniformly least powerful tests of market efficiency. Journal of Financial Economics 55, 361–389.

Lyon, J., Barber, B., Tsai, C., 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 54, 165–201.

MacKinnon, J.G., White, H., 1985. Some heteroskedasticity consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics 29, 53–57.

Mandelker, G., 1974. Risk and return: The case of merging firms. Journal of Financial Economics 1, 303–335.

McLeod, A.I., Li., W.K., 1983. Diagnostic checking ARMA time series models using squared-residual autocorrelations. Journal of Time Series Analysis 4, 269–273.

Mech, T.S., 1993. Portfolio return autocorrelation. Journal of Financial Economics 34, 307–344.

Mitchell, M., Stafford, E., 2000. Managerial decisions and long-term stock price performance. Journal of Business 73, 287–329.

Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Perez-Quiros, G., Timmermann, A., 2000. Firm size and cyclical variations in stock returns. Journal of Finance 55, 1229–1262.

Ritter, J.R., 1991. The long-run performance of initial public offerings. Journal of Finance 47, 3–27.

Roll, R., 1983. On computing mean returns and the small firm premium. Journal of Financial Economics 12, 371–386.

Roll, R., 1984. A simple implicit measure of the effect bid-ask spread in an Efficient Market. Journal of Finance 39, 1127–1139.

Spiess, K., Affleck-Graves, J., 1995. Underperformance in long-run stock returns following seasoned equity offerings. Journal of Financial Economics 38, 243–268.

Taylor, S., 1986. Modelling financial time series. John Wiley & Sons Ltd, New York.

White, H.,1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.

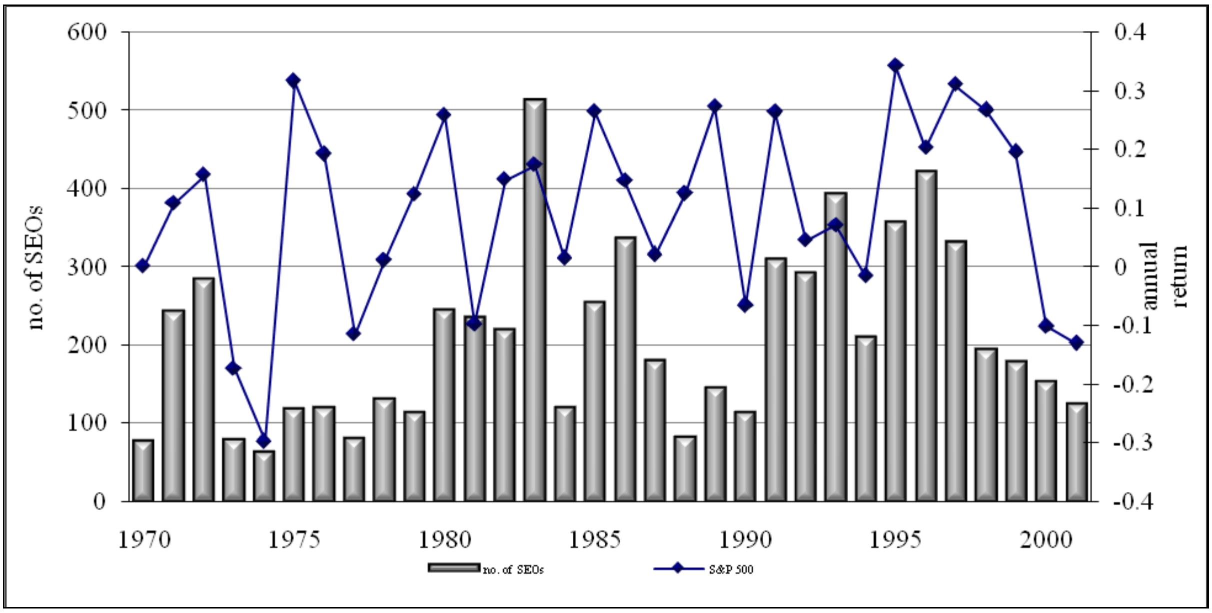
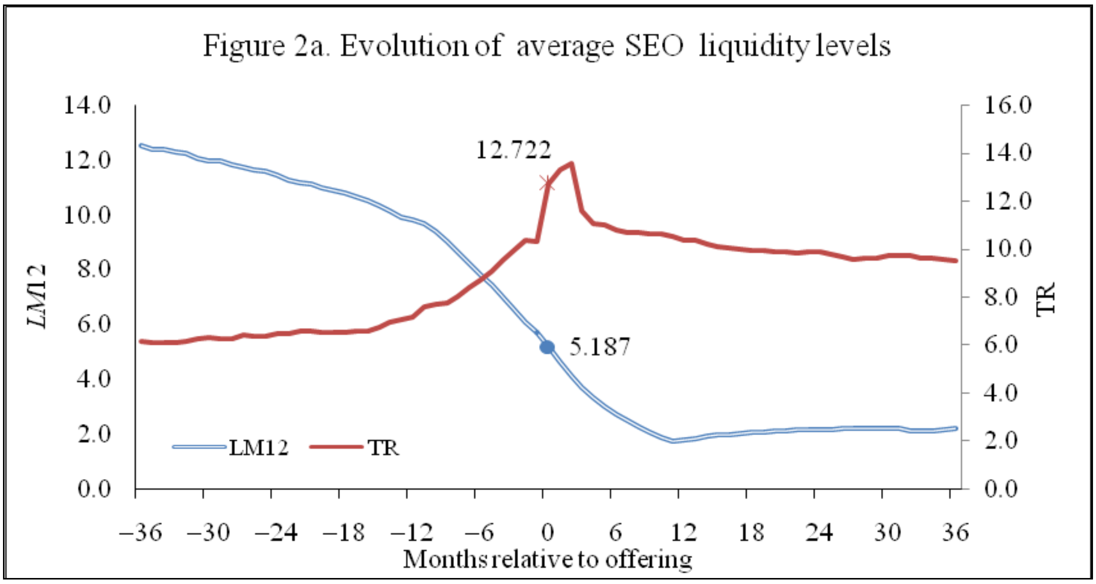


Figure 1. Annual distribution of seasoned equity offerings and S&P 500 returns over the period 1970–2001.

There are 7,135 offers from the SDC Platinum database that meet the sample eligibility criteria of Eckbo et al. (2000) and Brav et al. (2000) that we use in the study. The figure shows their annual distribution over 1970–2001 together with annual returns on the S&P500 index. We obtain data on the S&P500 index from Global Financial Data.



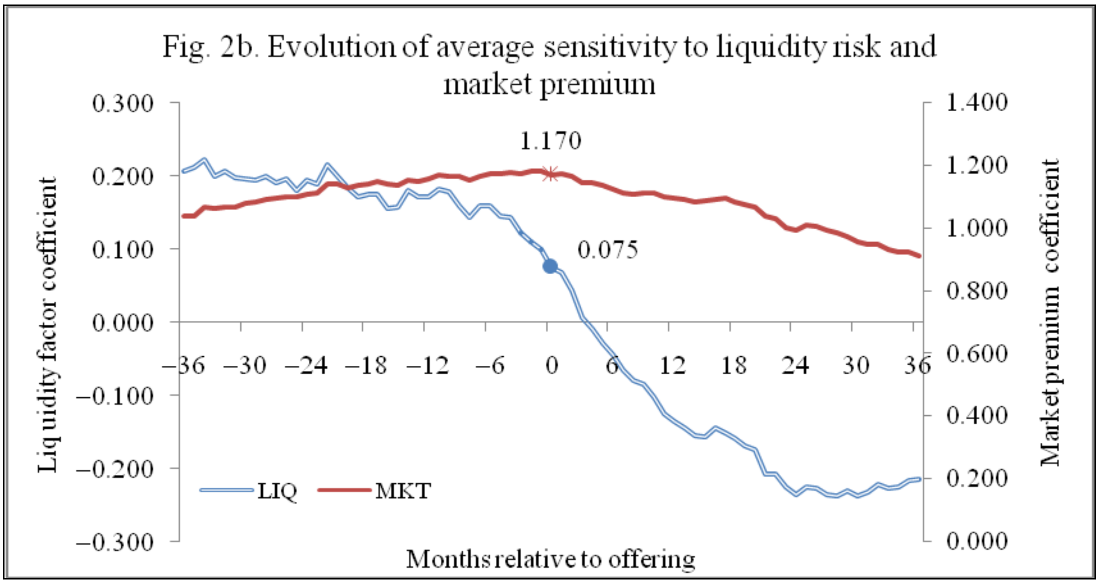


Figure 2. Evolution of two liquidity measures and sensitivities to liquidity risk and market premium for a sample of SEOs.

Figure 2a shows the evolution of average liquidity measures of Datar et al. (1998), *TR*, and of Liu (2006), *LM*12, for the sample of SEOs. Figure 2b shows the evolution of average sensitivity to the liquidity factor, *LIQ*, and the market premium, *MKT*. We measure liquidity levels in Figure 2a at the end of each month for 3 years before and after the issue. The factor loadings are from event time rolling window regressions with two years of return data for each of the 3364 SEOs. We use the liquidity augmented CAPM as the asset pricing model.

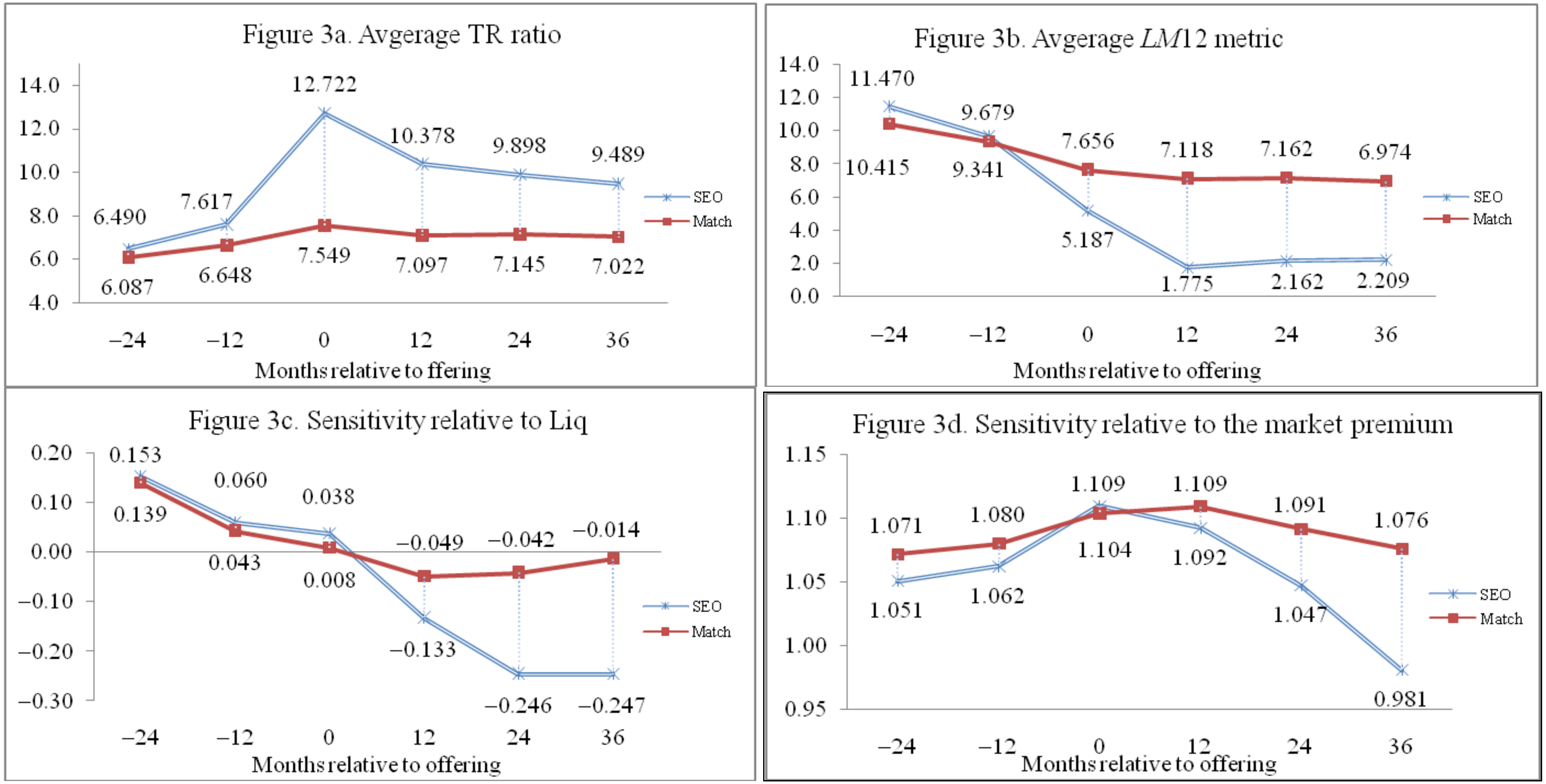


Figure 3. Evolution of two liquidity measures and sensitivities to liquidity risk and market premium for a sample of SEOs and their control firms.

Figure 3a and 3b show the evolution of liquidity levels, *TR* and *LM*12, for the sample of SEOs and their size and B/M matches from two years before the issue to three years after. We measure each characteristic at the year end. Figure 3c and 3d show the sensitivity to the liquidity factor and the market premium. For the latter, we form calendar time portfolios of issuers and matches and include each stock from t to t + 24 months after the issue (where t = –48, –36, –24, –12, 0, 12).

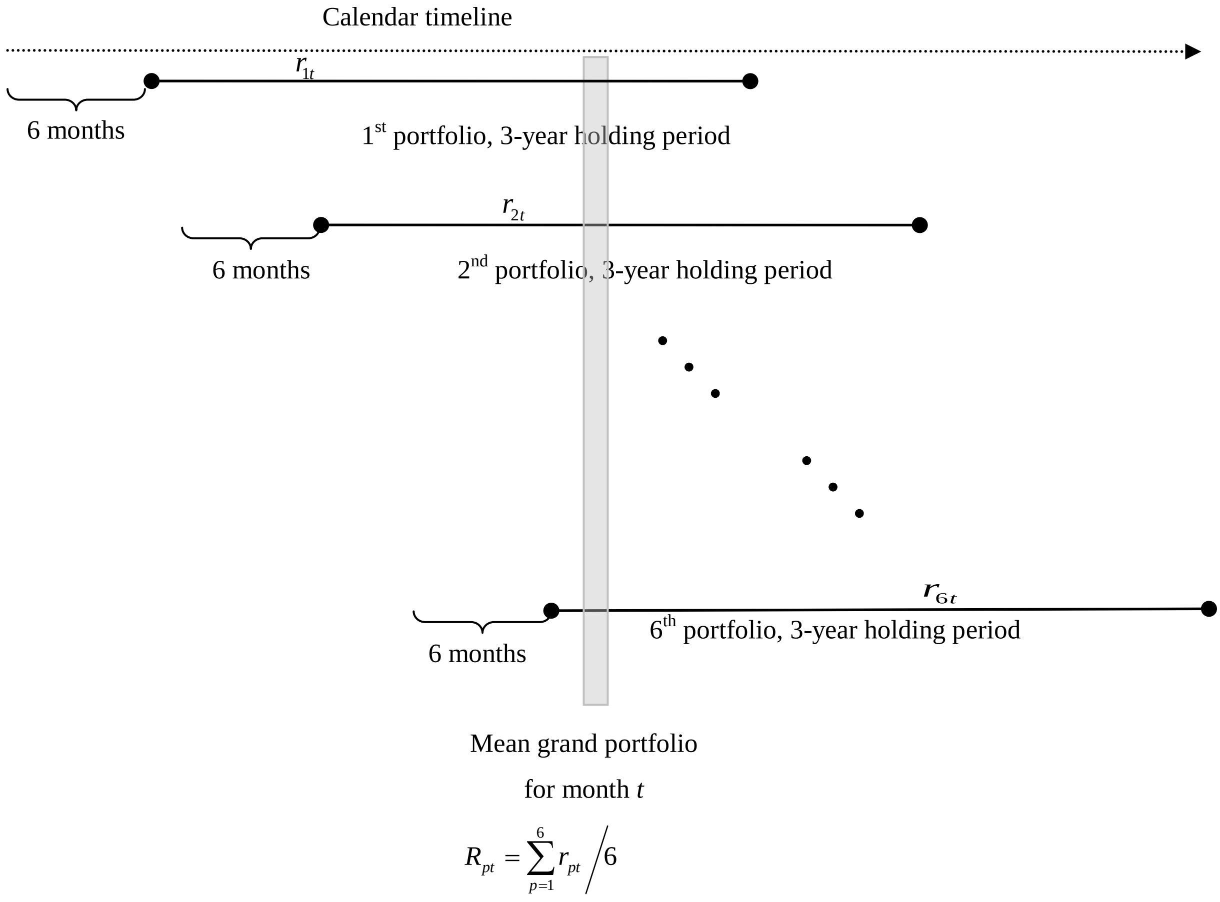


Figure 4. Schematic for the construction of the decomposed BHR portfolio.

Every six months we form a portfolio of all stocks that issued equity in the previous six months. We calculate buy-and-hold returns, r_{pt}, for this portfolio over the 3-year event window as the weighted sum of individual BHRs. We decompose the portfolio BHRs into monthly portfolio returns using a formulae from Liu and Strong (2006). Having a time series of decomposed BHRs, we construct a grand calendar time portfolio return as $R_{pt} = \sum_{p=1}^{w_t} r_{pt} \Big/ w_t$ where w_t is the number of decomposed BHR portfolios in month *t*.

Table 1. Descriptive statistics for the SEO sample.

Part I of the table reports descriptive statistics for 3,364 SEOs over the period 1970–2001 on NYSE/AMEX/NASDAQ. *N* is the number of public offerings of seasoned equity. *MV* is the total market value of common equity (in $m) in June of the year before the equity offering. *B*/*M* is the book-to-market ratio measured in December before the offering. *TR* is the turnover rate liquidity measure of Datar et al. (1998), expressed as a percentage. *LM*12 is Liu's (2006) liquidity measure. We standardize market capitalization by the *VW* CRSP stock market index to ensure comparability over time. Part II of the table shows the distribution across six Fama and French size and book-to-market portfolios, where *S* stands for small, *B* for big, *L* for low, *M* for medium, and *H* for high. Part III of the table shows the number of offerings made by financial (*Fin*), industrial (*Ind*), and utility (*Util*) firms, the type of offering (*Sec* for secondary equity offering and *Com* for a mix of secondary and major shareholder equity sale) and the offering period (*Hot* for offerings made in 1971–72, 1975–76, 1978–83, 1985–86, 1991–93 and 1995–97 and *Cold* for all other years.

	I			II						III						
				Fama and French portfolios						Industry Group			Type of issue		Issue period	
Variable	Mean	Median	Std Dev.	*SL*	*SM*	*SH*	*BL*	*BM*	*BH*	*Fin*	*Ind*	*Util*	*Com*	*Sec*	*Hot*	*Cold*
All exchanges (N = 3364)																
N				1108	626	251	613	470	296	356	2232	776	889	2475	2252	1112
MV	851570	258743	4139094	189570	176666	131951	2329905	1602466	1113288	1772299	641952	1032095	399809	1013838	690046	1178684
B/*M*	0.735	0.534	1.820	0.303	0.736	2.164	0.360	0.939	1.596	1.367	0.467	1.219	0.469	0.831	0.774	0.657
TR	10.499	5.895	14.811	15.627	8.320	6.542	12.139	5.616	3.625	7.642	13.607	2.871	14.067	9.217	8.961	13.613
*LM*12	5.533	0.000	18.042	5.894	12.433	15.280	0.403	0.446	0.020	12.742	5.363	2.712	8.152	4.592	5.719	5.156
NYSE/AMEX (N = 2032)																
N				418	315	167	433	416	283	181	1154	697	380	1652	1467	565
MV	1093162	349008	5125172	169647	189809	138215	2447536	1671149	1104382	2821861	804525	1122134	458750	1239093	890755	1618705
B/*M*	0.922	0.684	2.302	0.374	0.801	2.573	0.414	0.966	1.603	1.928	0.560	1.259	0.586	0.999	0.933	0.893
TR	5.877	3.949	6.490	8.543	5.222	4.414	6.937	4.890	3.362	6.668	7.697	2.658	7.511	5.501	5.608	6.577
*LM*12	3.244	0.000	12.253	5.105	7.929	10.196	0.417	0.172	0.021	7.616	3.716	1.327	6.876	2.409	3.320	3.048
NASDAQ (N = 1295)																
N				675	317	82	166	47	8	173	1053	69	505	790	754	541
MV	483632	162800	1756494	201941	167212	113173	2182491	1117180	1613147	692139	469656	174137	350304	568860	303978	734017
B/*M*	0.445	0.354	0.372	0.260	0.670	1.353	0.221	0.685	1.146	0.784	0.366	0.808	0.385	0.484	0.473	0.407
TR	17.738	12.667	20.379	20.079	11.494	10.886	25.511	11.527	13.041	8.385	20.107	5.040	18.921	16.982	15.357	21.057
*LM*12	9.306	0.000	24.239	6.514	16.829	26.067	0.267	2.938	0.000	18.282	7.324	17.051	9.273	9.328	10.654	7.429

Table 2. The long-run performance of SEOs.

The table reports the performance of SEOs over a three-year period following an SEO. Panel A shows the percentage *EW* and *VW* average three-year *BHR*s for equity issuers (*Issuer*) and their matched control firms (*Match*) using size and book-to-market matching. *Diff* gives the difference between these figures in percentage. *SE* reports their standard errors, *t* a two-sided *t*-statistic testing the hypothesis of no difference between average long-run performance of issuers and their matches, and *N* the number of offerings for which we calculate *BHR*s. Panel B reports results using mean monthly abnormal returns (*MMAR*s). *T* denotes the length of the time series in months for *MMAR*s and calendar time regressions. Panel C reports intercepts (α) in percentage from a calendar time regression of SEO returns on the Fama and French (1993) three-factor model. Panel D replicates the analysis using *HML* and *SMB* factors purged of new equity issuers, which we download from Jay Ritter's webpage. The factors are available for 01.1983–12.2003, which slightly shortens our time series. Heteroskedasticity consistent standard errors, *t*-statistics and *p*-values are in columns *SE*, *t* and *p*. R^2 is the R-square.

Weight	Portfolio	*N*/*T*	*Issuer*	*Match*	*Diff (%)*	*SE*	*t*	*p*
Panel A. 3-year BHARs								
EW	All exchanges	3364	0.283	0.477	–19.35	0.028	–7.020	0.000
VW			0.327	0.530	–20.27	0.019	–10.820	0.000
EW	NYSE/AMEX	2032	0.349	0.542	–19.33	0.029	–6.670	0.000
VW			0.335	0.505	–17.01	0.019	–8.860	0.000
EW	NASDAQ	1295	0.165	0.432	–26.70	0.059	–4.550	0.000
VW			0.180	0.602	–42.20	0.073	–5.790	0.000
Panel B. MMAR, 3-year holding period, time series 1970.07–2004.12, N = 557								
EW	All exchanges	414	0.782	1.100	–0.349	0.001	–3.860	0.000
VW			0.838	1.201	–0.275	0.001	–2.180	0.030
EW	NYSE/AMEX	414	0.854	1.203	–0.336	0.001	–3.400	0.001
VW			0.844	1.190	–0.164	0.002	–1.030	0.302
EW	NASDAQ	264	0.653	1.051	–0.388	0.001	–2.650	0.009
VW			0.663	1.138	–0.485	0.002	–2.410	0.017

Weight	Portfolio	*T*	α (%)	*SE*	*t*	*p*	R^2
Panel C. Calendar time regressions with Fama and French (1993) model							
EW	All exchanges	414	–0.307	0.001	–2.740	0.006	0.851
VW			–0.231	0.001	–1.680	0.094	0.851
EW	NYSE/AMEX	414	–0.332	0.001	–2.970	0.003	0.824
VW			–0.230	0.001	–1.540	0.124	0.717
EW	NASDAQ	264	–0.470	0.002	–2.980	0.003	0.869
VW			–0.497	0.002	–2.570	0.011	0.831
Panel D. Calendar time regressions with purged HML and SMB factors							
EW	All exchanges	372	–0.327	0.001	–2.780	0.006	0.861
VW			–0.250	0.001	–1.700	0.090	0.768
EW	NYSE/AMEX	372	–0.362	0.001	–3.110	0.002	0.832
VW			–0.217	0.002	–1.370	0.173	0.715
EW	NASDAQ	252	–0.591	0.002	–3.390	0.001	0.854
VW			–0.603	0.002	–2.980	0.003	0.829

Table 3. Liquidity risk and the long-run performance of SEOs.

Panel A presents results from calendar time liquidity-augmented CAPM regressions, where we include SEOs for three years before (regression 1) and three years after the issue (regression 2). The intercept estimates (α) are in %. *MKT* is a market excess return, *LIQ* is the liquidity factor and is the difference in average returns between portfolios of low and high liquidity stocks based on the *LM*12 measure. *SE* denotes standard errors computed using White's (1980) heteroskedasticity consistent estimator, *t* is the *t*-statistic, *p* is the corresponding *p*-value, *Adj* R^2 is the adjusted R-square. We estimate the equations using OLS. In Panel B we test the hypothesis of coefficient equality between equation 1 and 2. Panel C reports the results for a traditional calendar time regression where we form the SEO portfolio as described in Section 2. The length of the time series in Panels A and B is 402 months and is 414 months in Panel C.

Panel A. Regressions of SEO portfolios created before and after the offering on the liquidity augmented CAPM (pooled sample)

Regression	Weight	Parameter	*Estimate*	*SE*	*t*	*p*	*Adj* R^2	Weight	Parameter	*Estimate*	*SE*	*t*	*p*	*Adj* R^2
1	*EW*	α	1.761	0.002	10.010	0.000	0.782	*VW*	α	1.291	0.001	8.910	0.000	0.775
		MKT	1.130	0.043	21.460	0.000			*MKT*	0.971	0.034	22.960	0.000	
		LIQ	0.010	0.053	0.190	0.849			*LIQ*	–0.037	0.042	–0.660	0.509	
2	*EW*	α	0.041	0.001	0.270	0.785	0.739	*VW*	α	0.069	0.001	0.480	0.634	0.780
		MKT	0.976	0.037	16.090	0.000			*MKT*	0.918	0.035	16.850	0.000	
		LIQ	–0.209	0.046	–2.860	0.005			*LIQ*	–0.169	0.043	–2.670	0.008	

Panel B. Testing the hypotheses of coefficient equality among the system of equations in Panel A

Test	Weight	*t*	*P*	Weight	*t*	*p*
$\alpha_1 = \alpha_2$	*EW*	7.720	0.000	*VW*	6.370	0.000
$MKT_1 = MKT_2$		2.570	0.010		0.990	0.324
$LIQ_1 = LIQ_2$		3.110	0.002		2.160	0.031

Table 3 (*continued*)

Panel C. Calendar time liquidity augmented CAPM regression for the pooled sample and stratified according to exchange

Weight	*Portfolio*	*Variable*	*Estimate*	*SE*	*t*	*p*	R^2	*Weight*	*Variable*	*Estimate*	*SE*	*t*	*p*	R^2
EW	*All exchanges*	α	–0.014	0.002	–0.090	0.925	0.769	*VW*	α	0.078	0.001	0.530	0.598	0.753
		LIQ	–0.179	0.072	–2.480	0.013			*LIQ*	–0.145	0.063	–2.290	0.022	
		MKT	0.970	0.059	16.520	0.000			*MKT*	0.915	0.053	17.130	0.000	
EW	*NYSE/AMEX*	α	–0.130	0.001	–0.950	0.344	0.753	*VW*	α	0.024	0.002	0.150	0.884	0.673
		LIQ	0.049	0.061	0.800	0.424			*LIQ*	–0.019	0.068	–0.270	0.784	
		MKT	0.975	0.055	17.860	0.000			*MKT*	0.921	0.055	16.900	0.000	
EW	*Nasdaq*	α	0.053	0.003	0.200	0.840	0.727	*VW*	α	0.138	0.002	0.570	0.570	0.801
		LIQ	–0.422	0.104	–4.050	0.000			*LIQ*	–0.536	0.089	–6.010	0.000	
		MKT	0.959	0.079	12.080	0.000			*MKT*	0.995	0.072	13.760	0.000	

Table 4. Average quality of matching over two years before and three years after the issue.

The table gives the average difference in characteristics of SEOs and their size and B/M benchmarks. *Mean diff* gives the mean difference in market capitalization (in \$000s), B/M, and the liquidity measures *TR* and *LM*12. *SE* gives standard errors, and *t* and *p* give the corresponding *t*-statistics and *p*-values. We report the median difference as *Median diff* and the *p*-value from a test of the hypothesis that the median difference is zero as Wilcoxon *p*. *Period* specifies the time relative to the beginning of the holding period when we measure the characteristics. Pre-offering characteristics are measured in December over 2-years before the beginning of the holding period. Post-offering characteristics are averages measured in December over 3-years following the offering.

Variable	*Period*	*Mean diff*	*SE*	*t*	*p*	*Median diff*	Wilcoxon *p*
Panel A. Average quality of matching two years before the beginning of the holding period							
MV		−10562	10505	−1.010	0.315	−2810	0.000
B/M		0.015	0.026	0.560	0.572	0.007	0.000
TR	Pre-offering	1.831	0.211	8.670	0.000	0.769	0.000
*LM*12		−1.137	0.494	−2.300	0.021	0.000	0.043
Panel B. Average quality of matching three years after the beginning of the holding period							
MV		13589	41643	0.330	0.744	4135	0.015
B/M	Post-offering	0.202	0.094	2.160	0.031	0.087	0.000
TR		2.579	0.216	11.940	0.000	1.077	0.000
*LM*12		−5.087	0.368	−13.830	0.000	0.000	0.000

Table 5. Calendar time robustness checks.

The table presents the OLS intercepts (α) for a sample of SEOs from calendar time liquidity-augmented CAPM regressions. *SE* denotes heteroskedasticity consistent standard errors, *t* is the *t*-statistic, *p* the corresponding *p*-value, *T* is the length of the portfolio time series, and R^2 is the R-square. Panel A classifies issuers according to industry group: Finance, Industry, and Utility. Panel B shows the distribution of SEOs across type of equity issue: *Combin* and *Sec*. Panel C stratifies issuers across six Fama and French portfolios where *S* denotes small, *B* big, *L* low, *M* medium and *H* high. Panel D groups issues occurring during hot periods (1971–72, 1975–76, 1978–83, 1985–86, 1991–93, 1995–97) and cold periods (all other years). Panel E divides the sample into sub-periods: January 1970–December 1986 and January 1987–December 2001. Panel F shows results for event horizons of 12 and 24 months.

Weight	Group	*T*	α	*SE*	*t*	*p*	R^2	Weight	α	*SE*	*t*	*p*	R^2
Panel A. Industry classification of SEOs													
EW	Finance	258	–0.384%	0.003	–1.340	0.181	0.578	*VW*	–0.184%	0.004	–0.500	0.616	0.562
EW	Industrial	408	–0.063%	0.002	–0.350	0.725	0.778	*VW*	0.078%	0.002	0.480	0.631	0.821
EW	Utility	384	–0.037%	0.002	–0.210	0.834	0.349	*VW*	–0.248%	0.003	–0.880	0.381	0.228
Panel B. Type of equity offering													
EW	Combin	396	–0.269%	0.002	–1.310	0.191	0.739	*VW*	–0.469%	0.002	–2.400	0.017	0.742
EW	Sec	414	0.060%	0.002	0.390	0.694	0.745	*VW*	0.129%	0.002	0.810	0.418	0.716
Panel C. Fama and French size and book-to-market portfolios													
EW	*SL*	378	–0.182%	0.003	–0.690	0.488	0.688	*VW*	–0.034%	0.003	–0.130	0.900	0.691
EW	*SM*	384	–0.210%	0.002	–1.150	0.252	0.599	*VW*	–0.269%	0.002	–1.420	0.155	0.597
EW	*SH*	336	–0.114%	0.002	–0.550	0.584	0.512	*VW*	0.017%	0.002	0.070	0.942	0.408
EW	*BL*	390	0.210%	0.002	1.220	0.223	0.838	*VW*	0.066%	0.002	0.400	0.691	0.791
EW	*BM*	402	–0.053%	0.002	–0.310	0.754	0.603	*VW*	0.002%	0.003	0.010	0.992	0.506
EW	*BH*	300	0.039%	0.002	0.190	0.849	0.444	*VW*	0.125%	0.002	0.600	0.547	0.420
Panel D. Hot vs. cold issuing period													
EW	Hot	306	–0.250%	0.002	–1.430	0.154	0.758	*VW*	–0.060%	0.001	–0.430	0.666	0.798
EW	Cold	342	0.118%	0.002	0.660	0.512	0.720	*VW*	0.220%	0.002	1.180	0.240	0.680
Panel E. Sample sub-periods: January 1970–December 1986 and January 1987–December 2001													
EW	Jan 1970–Dec 1986	234	–0.296%	0.002	–1.950	0.053	0.810	*VW*	–0.126%	0.002	–0.780	0.436	0.771
EW	Jan 1987–Dec 2001	210	0.164%	0.003	0.620	0.537	0.767	*VW*	0.182%	0.002	0.790	0.428	0.774
Panel F 12 and 24 months holding period													
EW	12 months	390	–0.064%	0.002	–0.360	0.723	0.742	*VW*	–0.113%	0.002	–0.570	0.568	0.702
EW	24 months	402	–0.073%	0.001	–0.490	0.771	0.771	*VW*	–0.093%	0.002	–0.580	0.560	0.716

Table 6. Factor regressions with GARCH(1,1) error term.

The table reports intercept and coefficients estimates (*Estimate*) from calendar time regressions for equal and value weighted portfolios of SEOs with a GARCH (1,1) error term. *SE* denotes standard error, and *t* and *p* the *t*-statistic and its *p*-value. R^2 is the R-square. The model used is the liquidity augmented CAPM (Liu 2006). ARCH0 denotes the estimate of ω, ARCH1 of α_1 and GARCH1 of γ_1.

Weight	Variable	*Estimate*	*SE*	*t*	*p*	R^2	Weight	Variable	*Estimate*	*SE*	*t*	*p*	R^2
All exchanges													
EW	α	–0.086%	0.001	–0.790	0.431	0.768	*VW*	α	0.043%	0.001	0.420	0.672	0.752
	MKT	0.978	0.025	38.820	0.000			*MKT*	0.913	0.022	42.120	0.000	
	LIQ	–0.144	0.034	–4.230	0.000			*LIQ*	–0.105	0.034	–3.060	0.002	
	ARCH0	0.000	0.000	2.930	0.003			*ARCH0*	0.000	0.000	2.880	0.004	
	ARCH1	0.177	0.045	3.970	0.000			*ARCH1*	0.215	0.047	4.590	0.000	
	GARCH1	0.785	0.048	16.530	0.000			*GARCH1*	0.773	0.048	16.180	0.000	
NYSE/AMEX													
EW	α	–0.162%	0.001	–1.550	0.121	0.752	*VW*	α	0.018%	0.001	0.160	0.875	0.673
	MKT	0.981	0.023	43.330	0.000			*MKT*	0.903	0.023	38.830	0.000	
	LIQ	0.004	0.034	0.110	0.914			*LIQ*	–0.024	0.034	–0.710	0.479	
	ARCH0	0.000	0.000	2.350	0.019			*ARCH0*	0.000	0.000	3.110	0.002	
	ARCH1	0.137	0.035	3.950	0.000			*ARCH1*	0.206	0.038	5.500	0.000	
	GARCH1	0.834	0.040	20.920	0.000			*GARCH1*	0.780	0.038	20.430	0.000	
Nasdaq													
EW	α	–0.033%	0.002	–0.140	0.890	0.727	*VW*	α	0.138%	0.002	0.680	0.496	0.801
	MKT	0.962	0.071	13.650	0.000			*MKT*	0.995	0.060	16.570	0.000	
	LIQ	–0.419	0.063	–6.620	0.000			*LIQ*	–0.536	0.056	–9.630	0.000	
	ARCH0	0.001	0.000	9.720	0.000								
	ARCH1	0.154	0.080	1.940	0.052								
	GARCH1	0.000	0.000	0.000	1.000								

Table 7. Decomposed buy-and-hold returns.

The table reports the intercepts (α) for a sample of SEOs from calendar time OLS regressions of the liquidity-augmented CAPM using the decomposed BHR approach. *SE* denotes robust standard errors, *t* and *p* the *t*-statistic and its *p*-value, *T* is the length of the portfolio time series, and R^2 is the R-square. Panel A shows results for the pooled sample and for issuers stratified according to the exchange where the firm lists its stocks. Panel B classifies issuers according to industry group: Finance, Industry, and Utility. Panel C shows the distribution of SEOs across the equity issue type: *Combin* and *Sec*. Panel D stratifies issuers across six Fama and French portfolios where *S* denotes small, *B* big, *L* low, *M* medium, and *H* high. Panel E groups issues occurring during hot periods (1971–72, 1975–76, 1978–83, 1985–86, 1991–93, 1995–97) and cold periods (all other years). Panel F divides the sample into sub-periods: January 1970–December 1986 and January 1987–December 2001. Panel G shows results for event horizons of 12 and 24 months.

Weight	Portfolio	*T*	α	*SE*	*t*	*p*	R^2	Weight	α	*SE*	*t*	*p*	R^2
Panel A. Pooled/exchanges stratified sample													
EW	All exchanges	414	–0.007%	0.001	–0.050	0.962	0.767	VW	0.017%	0.001	0.140	0.892	0.787
EW	NYSE/AMEX	414	–0.099%	0.001	–0.760	0.450	0.740	VW	–0.082%	0.001	–0.590	0.555	0.714
EW	Nasdaq	264	-0.058%	0.003	–0.230	0.820	0.721	VW	0.038%	0.002	0.160	0.872	0.777
Panel B.	*Industry classification of SEOs*												
EW	Finance	258	–0.331%	0.003	–1.110	0.268	0.566	VW	–0.135%	0.003	–0.390	0.699	0.512
EW	Industrial	408	0.023%	0.002	0.130	0.898	0.772	VW	0.050%	0.001	0.360	0.718	0.829
EW	Utility	384	0.032%	0.002	0.170	0.864	0.339	VW	–0.088%	0.002	–0.400	0.689	0.316
Panel C.	*Type of equity offering*												
EW	Combin	396	–0.034%	0.002	–0.170	0.865	0.741	VW	–0.144%	0.002	–0.780	0.436	0.765
EW	Sec	414	0.046%	0.001	0.310	0.759	0.732	VW	0.084%	0.001	0.640	0.521	0.758
Panel D.	*Fama and French size and book-to-market portfolios*												
EW	*SL*	378	0.104%	0.003	0.350	0.730	0.650	VW	0.186%	0.003	0.590	0.556	0.645
EW	*SM*	384	–0.016%	0.002	–0.090	0.925	0.584	VW	–0.093%	0.002	–0.530	0.594	0.575
EW	*SH*	336	–0.150%	0.002	–0.660	0.508	0.471	VW	–0.011%	0.002	–0.050	0.961	0.421
EW	*BL*	390	–0.015%	0.001	–0.100	0.921	0.821	VW	–0.091%	0.001	–0.610	0.544	0.810
EW	*BM*	402	–0.031%	0.002	–0.200	0.845	0.601	VW	–0.032%	0.002	–0.190	0.846	0.582
EW	*BH*	300	–0.050%	0.002	–0.240	0.813	0.425	VW	–0.001%	0.002	0.000	0.998	0.398
Panel E. Hot vs. cold issuing period													
EW	Hot	306	0.009%	0.002	0.040	0.969	0.706	VW	0.036%	0.001	0.240	0.812	0.791
EW	Cold	342	0.024%	0.002	0.150	0.885	0.728	VW	0.089%	0.002	0.550	0.585	0.719
Panel F. Sample sub-periods: January 1970–December 1986 and January 1987–December 2001													
EW	Jan 1970- Dec 1986	234	–0.126%	0.001	–0.910	0.366	0.830	VW	–0.104%	0.002	–0.680	0.498	0.780
EW	Jan 1987-Dec 2001	210	0.017%	0.003	0.060	0.951	0.740	VW	0.038%	0.002	0.210	0.837	0.825
Panel G. 12 and 24 months holding period													
EW	12 months	390	–0.103%	0.002	–0.540	0.589	0.711	VW	–0.079%	0.002	–0.480	0.631	0.739
EW	24 months	402	–0.061%	0.001	–0.430	0.668	0.768	VW	–0.110%	0.001	–0.820	0.415	0.771