Liquidity risk, leverage and long-run IPO returns*

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Abstract

We examine the risk-return characteristics of a rolling portfolio investment strategy where more than six thousand Nasdaq initial public offering (IPO) stocks are bought and held for up to five years. The average long-run portfolio return is low, but IPO stocks appear as "longshots", as five-year buy-and-hold returns of 1,000 percent or more are somewhat more frequent than for non-issuing Nasdaq firms matched on size and book-to-market ratio. The typical IPO firm is of average Nasdaq market capitalization but has relatively low book-to-market ratio. We also show that IPO firms exhibit relatively high stock turnover and low leverage, which may lower systematic risk exposures. To examine this possibility, we launch an easily constructed "low minus high" (LMH) stock turnover portfolio as a liquidity risk factor. The LMH factor produces significant betas for broad-based stock portfolios, as well as for our IPO portfolio and a comparison portfolio of seasoned equity offerings. The factor-model estimation also includes standard characteristics-based risk factors, and we explore mimicking portfolios for leverage-related macroeconomic risks. Because they track macroeconomic aggregates, these mimicking portfolios are relatively immune to market sentiment effects. Overall, we cannot reject the hypothesis that the realized return on the IPO portfolio is commensurable with the portfolio's risk exposures, as defined here.

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1 Introduction

As shown by Ritter (1991) and Loughran and Ritter (1995), stocks performing either IPOs or seasoned equity offerings (SEOs) generate surprisingly low returns over holding periods of two–to–five years following the issue date. To some researchers, this long-run return evidence challenges the efficient markets hypotheses and motivates the development of behavioral asset pricing models.[1] Responding to this challenge, Brav and Gompers (1997), Brav, Geczy, and Gompers (2000) and Eckbo, Masulis, and Norli (2000) present large-sample evidence that the low post-issue return pattern is consistent with standard multi-factor pricing models, and tend to be concentrated in small growth stocks. Thus, the low post-issue returns may be a manifestation of the more general finding of Fama and French (1992) that small growth stocks tend to exhibit low returns during the post-1963 period.

This paper presents new evidence on potential risk-based explanations for the low IPO returns. Despite the controversy, surprisingly little is known about the true long-run risk-return characteristics of IPO stocks. With a sample exceeding 6,000 Nasdaq IPOs over the 1972-1998 period, we show that IPO stocks exhibit significantly greater stock turnover and are less leveraged when compared to non-IPO firms matched on stock exchange, equity size and book-to-market ratio.[2] The discovery of greater stock turnover is important as it suggests a potential liquidity-based explanation for lower *expected* returns to IPO stocks not previously accounted for. Our finding of lower leverage is consistent with the fact that IPO firms tend to have fewer assets in place and lower current earnings to support extensive borrowing as compared to more seasoned companies. We explore these findings by estimating parameters in empirical factor models where the risk factors have links to stock liquidity and leverage. Our main hypothesis is that IPO stocks have lower expected return due to lower exposures to these and other risk factors.

Starting with our analysis of liquidity, a number of empirical studies suggest that greater stock liquidity reduces risk.[3] To examine this possibility, we expand the Fama and French (1993) model

[1]See, e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999). In behavioral models, the marginal investor is either slow to assimilate publicly available information, or ignores this information altogether.

[2]Over the sample period, more than 95% of all IPOs took place on Nasdaq. While the typical NYSE/Amex IPO remaining in the population is somewhat larger (in terms of market value), including NYSE/Amex IPOs in our sample does not materially affect any of the paper's conclusions. Thus, in the empirical analysis below, both the sample of IPO firms and matched non-IPO companies are Nasdaq firms.

[3]See, e.g., Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and

with momentum and two alternative liquidity risk factor representations. The first liquidity factor is original to this paper. It is generated in a similar manner to the Fama-French size and book-to-market factors, except that we sort first on size and then on percentage stock turnover. The (characteristics-based) liquidity factor is then a portfolio that is long in low-turnover stocks and short in high-turnover stocks, henceforth "low-minus-high" or LMH. For comparison purposes, we also explore the liquidity factor estimated by Pastor and Stambaugh (2003) using order-flow related return reversals. Since the two factors capture different aspects of liquidity, an examination of both enhances our understanding of liquidity pricing effects in the context of new issues.

We apply the factor model with liquidity risk to our portfolio of IPOs. For purposes of comparison, we also apply the model to the portfolio of 1,704 industrial seasoned equity offerings (SEOs) compiled by Eckbo, Masulis, and Norli (2000) over the period 1964–1995. As was shown in the earlier paper, SEO industrial stocks also exhibit high (turnover) liquidity relative to non-issuing firms matched on size and book-to-market. We test directly for differences in expected returns between issuer and matched firms by applying the factor model to a "zero-investment" portfolio that is long in issuers and short in matched firms. Results for the zero-investment portfolios are relatively robust to omitted-factor bias. Our LMH factor and the Pastor-Stambaugh factor both produce significant factor sensitivities (betas) for a number of the twenty-five Fama-French size- and book-to-market sorted stock portfolios. Consistent with a liquidity-risk effect in new-issue stocks, we find significant liquidity-betas for the IPO and SEO portfolios while liquidity betas for the portfolios of non-issuing matched firms are not significantly different from zero. Moreover, there is no evidence of mispricing: our estimates of abnormal returns (Jensen's alpha) are not reliably different from zero.

Having examined liquidity effects, we then turn to the potential for the relatively low leverage to also impact IPO returns. Here our pricing model consists of portfolios that mimic macroeconomic risks based on changes in the term spread, the default spread, and unexpected inflation.[4] There are two main reasons why such a model is of interest in addition to the liquidity risk model. The first is statistical: A model with macroeconomic risks has desirable power characteristics under the

Radcliffe (1998), Chordia, Subrahmanyam, and Anshuman (2001), Eckbo and Norli (2002), Easley, Hvidkjaer, and O'Hara (2002), and Pastor and Stambaugh (2003).

[4]In the absence of a universally accepted empirical asset pricing model, our approach to model selection is agnostic. We choose risk factors based on the works of, e.g., Chen, Roll, and Ross (1986), Ferson and Harvey (1991), Shanken (1992) Evans (1994), Ferson and Korajczyk (1995), and Ferson and Schadt (1996).

alternative hypothesis of market sentiment (or irrationality). This follows because the weights in our factor mimicking portfolios are constructed to track the underlying macroeconomic risks. If the macroeconomic risk (such as aggregate consumption) is itself unaffected by market sentiment, then the tracking portfolio is also less influenced by market sentiment than are unconstrained factor portfolios of stocks, such as those represented by various sorts on size, book-to-market ratio, and liquidity.

The second motivation for examining a model with macroeconomic risks is economic: Factor loadings (betas) estimated using equity returns depend on the firm's leverage ratio (Galai and Masulis (1976), Hecht (2000), Charoenrook (2001)). The leverage effect enters through the product of the firm-value beta and the elasticity of equity price with respect to firm value. Since this elasticity increases with leverage, systematic risk is generally increasing in leverage (and time varying as leverage changes over time). Our test strategy involves comparing factor loadings of IPO stocks with those of non-IPO matched firms, to see if these differ in the direction predicted by the "turbo charging" effect of leverage. The overall conclusion from this part of the paper is that, while the explanatory power of the macro model is lower than the liquidity based model, there is some evidence that IPO stock returns respond to leverage-related risk factors. Moreover, our estimates of alpha conditional on the macro model are again insignificantly different from zero.

The rest of the paper is organized as follows. Section 2 contains a description of the data and key sample characteristics, including leverage, turnover, and frequency plots of extreme events and returns. This section also presents average long-run buy-and-hold returns as well as the return to 5-year rolling portfolios of IPO stocks. Section 3 presents the liquidity risk factor analysis. The pricing model with macroeconomic risk factors is presented in Section 4. Section 5 concludes the paper.

2 Sample selection and descriptive statistics

2.1 Selection of IPOs and control firms

The primary data source for our sample of IPOs is Securities Data Corporation's (SDC's) New Issues database over the 1972 to 1998 period. The sample also includes IPOs from the dataset compiled by Ritter (1991), covering the period 1975–1984, that is not present in the SDC database.[5] These sources generate a total sample of 6,139 IPOs satisfying the following sample restrictions: The issuer is domiciled in the U.S., the IPO is on the Nasdaq Stock Exchange and it involves common stocks only (excludes unit offerings), and the issuer must appear on the CRSP tapes within two years of the offering.

Our sample selection criteria differ somewhat from those used by Loughran and Ritter (1995) and Brav, Geczy, and Gompers (2000). The primary difference is our longer sample period: Loughran and Ritter (1995) draw their sample of 4,753 IPOs from the period 1970–1990, while the total sample of 4,622 IPOs in Brav, Geczy, and Gompers (2000) is from the 1975–1992 period. Moreover, these other studies do not restrict their samples to Nasdaq IPOs. The Nasdaq-only restriction excludes a total of 432 NYSE/AMEX IPOs that satisfy our remaining selection criteria. During our sample period, more than 90% of the IPOs took place on Nasdaq.

Figure 1 shows the annual distribution of the 6,139 IPOs in our total sample. Compustat provides book-to-market data for 5,365 of the sample IPOs, with the missing information for the most part occurring prior to the 1990s. Figure 1 also reveals a clustering of IPOs ("hot issue" period) in the early to mid 1980s. Moreover, the figure shows a steady growth in the number of IPOs from a low in 1990 through a high in 1996, with a subsequent decline towards the end of the sample period.

Figure 2 (A) shows a frequency distribution of the equity size of the IPO firms relative to size-deciles of NYSE and Nasdaq firms. When using NYSE size-breakpoints, it is clear that the IPO stocks are relatively small as they tend to cluster in decile 1 (smallest) and 2. However, when using Nasdaq breakpoints, the IPO sample is concentrated around deciles 6-8. Thus, the typical IPO firm is *not* small relative to seasoned Nasdaq firms. Turning to Figure 2 (B), we see that the IPO sample is concentrated around the lowest book-to-market-ratio deciles whether one uses NYSE or Nasdaq breakpoints. Thus, the typical IPO exhibits low book-to-market regardless of the stock exchange universe.

In order to provide a link to earlier studies, in particular Ritter (1991) and Loughran and Ritter (1995), we systematically compare the returns on IPO stocks to a set of control firms matched on both size and book-to-market ratio. Size-matched firms are selected from all companies listed on

[5] The IPOs compiled by Ritter (1991) is publicly available on the IPO resource page http://www.iporesources.org.

the Nasdaq stock exchange at the end of the year prior to the IPO and that are not in our sample of IPOs for a period of five years prior to the offer date. The size-matched firm is the firm closest in market capitalization to the issuer, where the issuer's market capitalization is the first available market capitalization on the CRSP monthly tapes after the offering date.

When matching on size and book-to-market ratios, we use the same set of Nasdaq firms as above, and select the subset of firms that have equity market values within 30% of the equity market value of the issuer. This subset is ranked according to book-to-market ratios. The size and book-to-market matched firm is the firm with the book-to-market ratio, measured at the end of the year prior to the issue year, that is closest to the issuer's ratio. Matched firms are included for the full five-year holding period or until they are delisted, whichever occurs sooner. If a match delists, a new match is drawn from the *original* list of candidates described above.

If available on COMPUSTAT, the issuer book value of equity is also measured at the end of the year prior to the issue year. If this book value is not available, we use the first available book value on Compustat starting with the issue year and ending with the year following the issue year.[6] Following Fama and French (1993) book value is defined as "the COMPUSTAT book value of stockholders equity, plus balance sheet deferred taxes and investment tax credits (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the value of preferred stock." (Fama and French, 1993, p.8).

Panel A of Table 1 shows several characteristics of the sample IPO firms and the control firms matched on size and book-to-market. The average issuer has a total equity value of $79 mill. with issue proceeds equaling 33% of its equity size. The average book-to-market ratio is 0.38. Matched firms, whether matching on size only or size and book-to-market ratio, have greater leverage and lower monthly turnover rates than issuer firms. We return to this observation below.

2.2 Five-year buy-and-hold returns

Ritter (1991) and Loughran and Ritter (1995) report the cross-sectional average of compounded (holding period) returns, also referred to as "average buy-and-hold return" ($\overline{\text{BHR}}$). In this section, we replicate their measure using our sample. This serves to establish whether their finding of

[6] On average, the first available book value is found 6.1 months after the offer date. Brav and Gompers (1997) look a maximum of 12 months ahead for book values while Brav, Geczy, and Gompers (2000) look a maximum of 18 months ahead.

negative long-run performance continues to hold for the substantially longer sample period used in this paper. Let R_{it} denote the return to stock i over month t, and let ω_i denote stock i's weight in forming the average holding-period return. The holding period for stock i is T_i which is either five years or the time until delisting, whichever comes first.[7] For a sample of N stocks, $\overline{\text{BHR}}$ is given by

$$\overline{\text{BHR}} \equiv \sum_{i=1}^{N} \omega_i \left[\prod_{t=\tau_i}^{T_i} (1 + R_{it}) - 1 \right] \times 100. \tag{1}$$

Furthermore, several event studies use the difference in $\overline{\text{BHR}}$ for the event firms and their matched firms as a definition of event-induced "abnormal" return, $\overline{\text{BHAR}}$. In our context, this is given by

$$\overline{\text{BHAR}}_{\text{IPOs}} \equiv \overline{\text{BHR}}_{\text{IPOs}} - \overline{\text{BHR}}_{\text{Matches}}. \tag{2}$$

Table 2 shows the values of $\overline{\text{BHR}}$ and $\overline{\text{BHAR}}$ using control firms matched on size and both size and book-to-market ratio. Panel (A) shows that for the full sample of 6,139 IPOs the equally weighted $\overline{\text{BHR}}$ for issuers is 36.7%. This average buy-and-hold return is very close to the average return reported by Brav, Geczy, and Gompers (2000), but about twice as high as the return reported by Loughran and Ritter (1995). The discrepancy between our result and the result of Loughran and Ritter (1995) is in part due to the extremely low returns earned by companies that went public during their sample period prior to 1972. The equal-weighted $\overline{\text{BHR}}$ for size-matched firms is 65.4%, resulting in a relative IPO underperformance of $\overline{\text{BHAR}} = -28.8\%$, which compares to the $\overline{\text{BHAR}}$ of -50.7% reported for the IPO sample in Loughran and Ritter (1995).

As shown in the right half of Table 2, the underperformance resulting from size matching disappears when matched firms are selected using both size and book-to-market ratio. The difference in $\overline{\text{BHR}}$ between issuers and the size and book-to-market matched firms is now an insignificant -2.4%. Interestingly, this result is sensitive to the selection of Compustat information on book values. The insignificant -2.4% underperformance results when missing Compustat book value information is replaced by bringing back the first future book value observation (maximum of two years out). While this is the standard procedure in the extant literature, it carries with it a survivorship bias. The second part of Panel (B) Table 2 computes $\overline{\text{BHR}}$ and $\overline{\text{BHAR}}$ free of this survivorship bias.

[7] In an earlier draft, we showed that using shorter holding periods (1-year, 2-year, .. 4-year) does not alter the main conclusions of this paper. These additional results are available upon request.

That is, a firm is included only as of the date the book value information is available on Compustat. The value of $\overline{\text{BHAR}}$ is now -21.0%, which is statistically significant at 1% level.[8]

With the exception of the descriptive analysis above, we choose not to focus on estimates of $\overline{\text{BHAR}}$ in the remainder of the paper. There are three main reasons for this choice. First, our objective is to investigate the risk-return characteristics of issuers. This amounts to implementing a feasible portfolio strategy based on successive return observations in calendar time. The portfolio approach allows us to ask whether a strategy of purchasing and holding successive IPO stocks receives an expected return commensurable with risk (however defined). In contrast, the five-year buy-and-hold return $\overline{\text{BHR}}$ equal-weighs returns in *event* time, and thus does not constitute a realizable portfolio return ex ante. The reason is that investors do not know the future number of IPOs ahead of time, and thus cannot reallocate their investments in IPOs accordingly.

Second, our portfolio approach avoids the selection bias ("pseudo market timing") problem for $\overline{\text{BHAR}}$ identified by Schultz (2003). Suppose that more firms issue equity as stock price increases. For example, the higher stock price may represent the discounted expected cash flow from new and valuable investment projects that will need external financing. Alternatively, the price increase may reflect a reduction in risk and thus in the cost of equity capital, which in turn increases the number of investment projects with positive net present value. Either way, this issue behavior has nothing to do with managers predicting future returns. Schultz (2003) shows that if firms tend to issue after stock price increases (for whatever reason), issues will on average be followed ex post by underperformance. The reason is simple. Suppose expected one-period returns are zero for all periods and all IPOs. Moreover, the return distribution is a bimodal $+10\%$ and -10% in each period. Let there be a single IPO at time zero. If the return in period one is -10%, there will be no new IPOs at time one. Alternatively, suppose the return in period one is $+10\%$ and that there are four IPOs in this period. Now, compute the one-period $\overline{\text{BHAR}}$ for these two equally likely sample paths. It is 2% for the "up" sample and -10% for the "down" sample, with an equal-weighted average of -4%. Schultz (2003) refers to this result as "pseudo market timing" because it may easily be confused by the researcher with real forecasting ability on the part of issuing firms' managers.

[8] Eckbo, Masulis, and Norli (2000) estimate $\overline{\text{BHAR}}$ for their sample of SEOs over the period 1964–95. For industrial issuers, $\overline{\text{BHAR}}$ equals -26.9% relative to non-issuers matched on size only, and -23.2% relative to firms matched on both size and book-to-market ratio. They also report that SEOs have relatively high liquidity. We return to this SEO sample in the section on liquidity risk below.

Third, standard test statistics of long-run return metrics such as $\overline{\text{BHAR}}$ presume cross-sectionally independent observations, which is a problem when observations cluster in event time, as they certainly do for IPOs (see Figure 1). See Kothari and Warner (1997), Barber and Lyon (1997), Lyon, Barber, and Tsai (1999), and Mitchell and Stafford (2000) for detailed analysis of the statistical properties—and suggestions for bias corrections—of average buy-and-hold returns.

2.3 Post-IPO portfolio raw returns

The primary object of analysis in this paper is a 5-year running portfolio of IPO stocks. An IPO stock is first included in this "issuer portfolio" in the month following the IPO date and held for five years or until it delists from the exchange, whichever comes first. The first month of the portfolio is January 1973 and the last month is December 2002. Thus, there are a total of 360 monthly portfolio return observations over the 30-year period.

Returning to Table 1, Panel (B) shows the average monthly compounded return to the issuer and matching firm portfolios using either equal-weights or value-weights. For the full sample of 6,139 IPOs, the average monthly return is 1.18% given equal-weighted portfolio returns. However, a more interesting number is the compound monthly return over the January 1973 through December 2002 sample period. The compound monthly return is the monthly return that allows a $1 investment in January 1973 to grow to $21.57 by December 2002. As shown in Panel (B), the compound monthly return equals 0.86% for the equal-weighted issuer portfolio, 1.04% for the portfolio of size-matched firms, and an intermediate 0.99% for the portfolio of firms matched on both size and book-to-market ratio. The compound monthly return is generally lower when portfolios are value-weighted.

The growth rates of the issuer and matched firm portfolios are shown in Figure 3 for the case of equal-weighted (EW) portfolios. The right side legend indicates the identity of the portfolio, and inside the parentheses are the terminal value of the initial $1 investment and the compound monthly return. Figure 3 also highlights the market-wide poor performance of the early years 1972-74. While not shown here, if the starting point for the portfolio strategy is moved up to January 1975, the implied growth rates increases substantially for all portfolios. As noted by previous authors as well, the effect of value-weighting is to reduce the difference between the average monthly compounded returns of issuers and non-issuer stocks.

Several conclusions emerge. First, regardless of the weighting scheme, the issuer portfolio performs better than the risk-free asset but worse than the Nasdaq market index. As shown below, this underperformance is not driven by a low exposure to market risk: the portfolio market beta is close to one. In Figure 3, the issuer portfolio underperforms the market index by 0.18% per month, or by 11.4% over the five-year holding period. Over the same period, the issuer portfolio underperformed the portfolio of size-matched firms by 11.4% and slightly outperformed the size and book-to-market matched firms. These percentages compare to the underperformance of 28.9% and the underperformance of 2.4% discussed earlier in Panel (B) of Table 2. Thus, while our portfolio metric attenuates the magnitude of the underperformance (perhaps because it gives equal weight to each of the 360 months in the total sample period, while $\overline{\text{BHR}}$ gives equal weight to each IPO *event*), there is nevertheless evidence of significantly lower long-run returns to IPOs than to non-issuing firms matched on size and book-to-market ratio.[9]

2.4 Delistings and extreme returns

The return to the issuer portfolio is affected by delistings over the five-year holding period. Delistings due to bankruptcy and liquidations reduce the realized return to the portfolio while delistings due to premium takeovers increases portfolio return. Thus, the low return realization for the issuer portfolio may reflect a greater probability of negative delisting events than the case is for the portfolio of non-IPO control firms.

Figures 4 and 5 address this possibility. Figure 4 (A) shows the annual frequency of delistings due to liquidations over the sample period for both IPO and non-IPO firms. In each year, the front column shows the percent of the total number of recent IPO firms (i.e., firms that undertook an IPO within the past five years) that delisted that year. The rear column shows the same frequency for non-IPO firms. The frequency is very similar for the two categories of firms and thus provide no basis for arguing that IPO stocks have a greater risk of liquidations. Thus, the liquidation rate is not an explanation for the low IPO return realizations.

Figure 4 (B) plots the frequency of delistings due to merger, takeover, exchange offer or other events where common stockholders were bought out. If IPO stocks provide a better-than-average bet on a future takeover, then it ought to be apparent from this figure. However, the figure provides

[9] As shown in an earlier draft, the effect of value-weighting is to nearly eliminate this underperformance This is not surprising as value-weights favors larger, more successful stocks.

no basis for such an inference: if anything, in most years, the frequency of these takeover events appear somewhat *lower* than for non-IPO stocks.

Figure 5 further indicates the nature of IPO stocks as "longshots." Figure 5 (A) shows the left tail of the frequency distribution of returns, i.e., returns below 500%. The plots are for the IPO stocks as well as for firms matched on size and book-to-market ratio. Inspection of the left boundary (at -100%) shows that IPO stocks do not exhibit an abnormal chance of this extreme negative value. This finding is generally consistent with the evidence in Figure 4.

On the other hand, there is some evidence in Figure 5 (B) that IPO stocks have a greater probability than non-IPO stocks of experiencing extreme return realizations of 1,000% of higher. The right tail of the return distribution is somewhat higher for IPO stocks. Given the evidence on takeover frequencies in Figure 4 (B), the extra probability mass under the 1,000% return outcome is not driven by acquisitions. Rather, it may reflect the probability of the firm "growing into another Microsoft" on its own. Regardless, given the low average return realization of the IPO portfolio, this extra "longshot" probability does not appear to represent priced risk.

2.5 Post-IPO leverage and stock turnover

Table 3 shows average leverage ratios and stock turnover for the issue year and each of the five years following the issue. Panel (A) of Table 3 shows the average annual values of monthly turnover, computed as trading volume divided by the number of shares outstanding. IPO stocks have significantly greater turnover than either size-matched or size/BM-matched firms in each of the five years starting in year 1. Also, IPO stock turnover tends to be greatest in the year of the issue.

Panel (B) documents that IPO stocks have significantly lower leverage than either the size-matched or size/BM-matched firms in year 0 (the year of the IPO) as well as in the two following years. This is true whether we measure leverage as the ratio of long-term debt to total assets, long-term debt to market value of equity, or total debt (current liabilities plus long-term debt) to total assets. We do not have data on actual leverage changes (i.e., equity issues and/or debt repurchases) other than the IPO itself. Of course, the IPO-proceeds itself cause a substantial reduction in leverage. Moreover, since IPO-companies are younger than the matched firms, they tend to have less collateral and may therefore have lower optimal leverage ratios. The lower debt policy may also be reinforced by the significant growth opportunities often found in private companies selecting to go public. As these growth opportunities are exercised and the firm builds collateral, the leverage ratios of IPO firms and the matched companies tend to converge, much as shown in Panel (A) over the five-year post-IPO period.

3 Liquidity risk and expected returns

3.1 What is aggregate liquidity risk?

Liquid assets trade with small direct transaction costs such as commissions and bid-ask spreads, with a minimal time delay in execution, and with little or no price impact of the trade. Consistent with the notion that market liquidity affects *individual* stock prices, there is evidence that publicly listed firms trade at a premium over private companies, and that individual bid-ask spreads affect expected stock returns.[10] However, classical equilibrium asset pricing models provide no guidance as to whether these firm-specific liquidity effects, when aggregated across all firm in the market, form a source of systematic (priced) risk. For example, in the intertemporal model (ICAPM) of Merton (1973), investors continuously and costlessly rebalance their portfolios to maintain optimal hedges against unexpected changes in consumption and investment opportunities. Thus, liquidity risk plays no role. However, as explored by Lo and Wang (2000), with trading frictions, investors' hedging demands give rise to concerns about market liquidity. This provides a powerful motivation for an empirical search for a priced liquidity risk factor.[11]

Brennan and Subrahmanyam (1996), Datar, Naik, and Radcliffe (1998), Brennan, Chordia, and Subrahmanyam (1998), Chordia, Subrahmanyam, and Anshuman (2001) all find that stock expected returns are cross-sectionally related to individual stock liquidity measures. Using daily returns data for a single year, Chordia, Roll, and Subrahmanyam (2000) go on to demonstrate that *market wide* liquidity, measured by averaging individual spreads and volumes, is a significant determinant of the liquidity of individual assets (which they refer to as "commonality in liquidity").[12] With monthly returns over the past four decades, Eckbo and Norli (2002) show that several

[10] See, e.g., Wruck (1989) and Hertzel and Smith (1993) for comparisons of public and private firms, and Stoll and Whaley (1983), Amihud and Mendelson (1986), and Chen and Kan (1996) for the impact of bid-ask spreads.

[11] Theoretical relationships between liquidity and asset prices are also discussed in, e.g., Amihud and Mendelson (1986), Constantinides (1986), Heaton and Lucas (1996), Vayanos (1998), Huang (2001), and Lo, Mamayski, and Wang (2001). Baker and Stein (2001) extend the analysis to a setting with irrational investors.

[12] Huberman and Halka (2001) studies the innovations in aggregate measures of liquidity similar to the aggregate measures used by Chordia, Roll, and Subrahmanyam (2000), and find positive correlations between innovations

measures of aggregate liquidity, including our LMH measure (described below), exhibit such commonality. Also using long time series of monthly returns, Eckbo and Norli (2002) and Pastor and Stambaugh (2003) estimate liquidity betas for large stock portfolios, and find results consistent with the hypothesis that aggregate liquidity risk is priced.

The empirical analysis in Jones (2001) and Avramov, Chao, and Chordia (2002) also suggests that accounting for aggregate liquidity risk improves asset pricing. Jones (2001) provides information on quoted spreads and turnover for the 30 Dow Jones Industrial Average stocks for the period 1898-1998. He concludes that spreads and turnover predict monthly stock returns up to one year ahead, suggesting that liquidity is an important determinant of conditional expected returns. Avramov, Chao, and Chordia (2002) show that including either our LMH turnover measure or the Pastor and Stambaugh (2001) measure of liquidity takes the market portfolio closer to multifactor efficiency in the sense of Merton (1973) and Fama (1996). They explain this result by noting that liquidity risk is typically a major concern whenever the market declines and investors are prevented from hedging via short positions.[13]

Overall, this suggests that, since IPO and SEO firms have significantly higher turnover than matched firms (Panel (A) of Table 3), they should command lower expected returns than the matched firms. Of course, given the lack of a theoretical foundation for the existence of priced liquidity risk, our empirical hypothesis is that our liquidity factor proxy is correlated with some true, underlying pervasive risk. This characterization holds for any empirical risk factor that does not have a direct counterpart in theory (such as book-to-market and momentum).

We now turn to an empirical examination of this proposition using the LMH and Pastor-Stambaugh definitions of liquidity risk.

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from independent samples. Using principal component analysis, Hasbrouck and Seppi (2001) also provide evidence consistent with commonality in liquidity. Breen, Hodrick, and Korajczyk (2000) study a liquidity factor using short-horizon, high-frequency (intra-day) data.

[13]Chordia, Subrahmanyam, and Anshuman (2001) include as one of their explanatory variables in cross-sectional (2nd-step Fama-MacBeth) regressions individual firm turnover *volatility.* This volatility variable receives a significantly *negative* coefficient, indicating that average returns are lower the greater "turnover risk". This does not necessarily map into a similar inference about the likely impact of *aggregate* volatility risk. However, it does suggests that future research on liquidity risk ought to explore a proxy for aggregate turnover volatility.

3.2 Constructing aggregate liquidity factors

The LMH factor

We construct the turnover factor LMH using an algorithm similar to the one in Fama and French (1993) for their size (SMB) and book-to-market ratio (HML) factors. To construct LMH, we start in 1972 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks and three portfolios formed using NYSE/AMEX stocks ranked on turnover. Next, six portfolios are constructed from the intersection of the two market value- and the three turnover portfolios. Monthly value-weighted returns on these six portfolios are calculated starting in January 1973. Portfolios are reformed in January every year using firm rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with low turnover and the equal-weighted average return on the two portfolios with high turnover.

The Pastor-Stambaug factor

Pastor and Stambaugh (2003) develops a risk factor based on the idea that a given order flow should be followed by greater return reversal for stocks that are illiquid than for stocks that are liquid. Factor construction starts with the estimation (using OLS) of the coefficient ps_i in the following regression:[14]

$$r_{id+1}^{\mathrm{AR}} = \gamma_0 + \gamma_1 R_{id} + \mathrm{ps}_i \left[\mathrm{sign}(r_{id}^{\mathrm{AR}}) \times \mathrm{vol}_{it}\right] + \epsilon_{it}. \tag{3}$$

where r_{id+1}^{AR} is abnormal return for firm i on day $d+1$, R_{id} is return for firm i on day d, and vol_{it} is volume measured in millions of dollars. The abnormal return is estimated as $R_{id} - R_{md}$, where R_{md} is the return on the CRSP value weighted portfolio of all NYSE, American exchange (AMEX), and Nasdaq firms. Equation (3) is estimated for all firms in a given month using daily data, and repeated for all months. Thus, the maximum number of observations for any given regression is the number of trading dates in a month (between 20 and 22 days). Firm-months with less than 15 daily return observations are not used.

The Pastor and Stambaugh (2003) liquidity risk factor is constructed by forming in each month

[14]The specification in (3) is consistent with the view that inventory control effects on stock prices are inherently transient (Hasbrouck, 1991a,b). It is also consistent with Campbell, Grossman, and Wang (1993), who find that returns accompanied by high volume tend to be reversed more strongly.

the average (across firms) estimate of ps_i (see equation 3). As the authors point out, this average will tend to decrease over time due to a general increase in turnover and dollar volume over the sample period (the larger the dollar value of trading volume in equation. (3), the smaller the estimate of ps_i). Thus, they multiply the average value of ps_i for month t by the factor (m_t/m_1), where m_t is the total dollar value of the firms in the sample at the end of month $t-1$ and m_1 is the dollar value at the start of the estimation period. We follow the same approach, creating a monthly time series for the Pastor-Stambaug liquidity factor, denoted PS.

Table 4 shows the mean, standard deviation and pairwise correlations for the two liquidity factors as well as four additional factors used in the empirical analysis to follow. The additional factors are the excess return on the value-weighted market portfolio (RM), the two Fama-French factors SMB, and HML, and a momentum factor portfolio labeled UMD.[15] This momentum factor is constructed in a slightly different way than in Carhart (1997). In particular, six value-weighted portfolios are constructed as the intersections of two portfolios formed on market value of equity (size) and three portfolios formed on prior twelve month return. Portfolios are formed monthly using the median NYSE value for the size portfolios and the 30th and 70th NYSE percentiles for the prior twelve month returns. The momentum factor, UMD, is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

In Panel (A), notice that the mean return of the liquidity factor LMH is positive. Recall that the factor is a portfolio that is long in low-liquidity stocks and short in high-liquidity stocks. To the extent that illiquid stocks are more "risky" than liquid stocks, they have higher average returns so the factor portfolios have positive returns on average. Interestingly, Panel (A) also shows that the return on LMH is slightly greater than on the SMB factor and has a lower standard deviation.

The average for the PS factor is not measured in returns and is not comparable to the other averages. Specifically, the PS factor is constructed as the factor shocks themselves, which by construction have a mean of zero. The value -0.028 arises because the PS factor is constructed over the period 1963-2002, while reported mean is from the period 1973-2002. Thus, in contrast to the five other risk factors in Panel A, the mean value of the PS factor cannot be interpreted as a risk premium. Pastor and Stambaugh (2003) estimate a positive risk premium for the PS factor.

Panel (B) of Table 4 shows that the HML portfolio is positively related to LMH. This is likely a

[15]We thank Ken French for providing us with the return series on these factors.

reflection of the fact that it is constructed in the same way as HML relative to size sorted portfolios. The momentum portfolio (UMD) generally has a lower correlation with the other characteristic-based factors.

3.3 Liquidity- and momentum factor betas for broad-based portfolios

Table 5 shows the betas for each of the three factors LMH, PS , and UMD, when estimated using the Fama-French 25 size and book-to-market sorted portfolios. The beta of each factor is estimated by adding that factor (only) to the Fama-French three-factor model. This table complements the analysis in Eckbo and Norli (2002). The issue is whether the two liquidity factors have significant betas for large portfolios not sorted ex ante on liquidity. We also show the betas for the momentum factor as this factor has also been suggested as a way to expand the set of pervasive risks already in the Fama-French model.

In panel B of the table, we list several test statistics for the hypothesis that the factor-betas are jointly equal to zero across the 25 portfolios. The test statistics are defined as follows. Suppose returns on N assets are generated by the model

$$r_t = \alpha + \beta F_t + \epsilon_t, \tag{4}$$

where r_t is a vector that stacks N excess returns for period t, α is an N-vector of intercepts, β is an $(N \times K)$ matrix of factor sensitivities, and F_t is a K-vector of factors. With T observations on r_r and F_t, equation (4) can be written as:

$$R = XB + E \tag{5}$$

where R is $(T \times N)$ with typical row r_t', X is $(T \times (K+1))$ with typical row $[1 \quad F_t']$, B is the $((K+1) \times N)$ matrix $[\alpha \quad \beta]'$, and E is $(T \times N)$ with typical row ϵ_t'. Suppose that ϵ_t, conditional on X, is independent and identically distributed (i.i.d) jointly normal with zero mean and variance-covariance matrix Σ. F_1 is an exact test statistic for the hypothesis that the factor sensitivities of the N assets with respect to factor k, β_k, are equal to zero:[16]

$$F_1 = \left(\frac{T-K-N}{NT}\right)(F_k' M F_k)\hat{\beta}_k' \hat{\Sigma}^{-1}\hat{\beta}_k \sim F_{N,T-K-N} \tag{6}$$

where F_k is column k from X, M is an idempotent matrix constructed using the first k columns of X, and $\hat{\Sigma}$ and $\hat{\beta}_k$ are both ordinary least squares (OLS) estimates.

An asymptotically valid test that accounts for conditional heteroskedasticity of the error term ϵ_t is given by

$$J_2 = \hat{\beta}_k' \hat{G}_a^{-1} \hat{\beta}_k \overset{A}{\sim} \chi^2_N, \tag{7}$$

where

$$\hat{G}_a^{-1} = \sum_{t=1}^{T} e'(X'X)^{-1} x_t x_t' (X'X)^{-1} e \ \otimes \hat{\epsilon}_t \hat{\epsilon}_t',$$

and e is a column vector where all elements are zero except for the last element, which is one.[17] To improve on the small sample properties of J_2, we also use

$$F_2 = \left(\frac{T-K-N}{NT}\right) J_2 \sim F_{N,T-K-N} \tag{8}$$

In sum, the test statistics F_1, F_2 and J_2 all test the null hypothesis that assets have zero sensitivity to a given factor k. F_1 provides an exact test of the null when the error terms from (4) are i.i.d. normal. If the error terms are i.i.d. but non-normal, F_1 is valid asymptotically. To account for the possibility of conditional heteroskedasticity, we report F_2 and J_2 which are asymptotically valid in this case. F_2 has been shown to have somewhat better small sample properties than J_2.[18]

Starting with the LMH factor, the hypothesis that the individual portfolio betas are jointly equal to zero is rejected at the 1 percent level or better by all three test statistics. Nineteen of the 25 portfolio receive negative beta estimates. Across five size-quintile divisions, portfolios with both low- and high book-to-market ratios tend to receive a negative betas. Turning to the PS factor, only seven are significant at the 1% level, and the hypothesis that all the betas are jointly equal to zero is rejected at the 3 percent level by the F_1 test, but is not rejected at standard levels of significance

[16] See Anderson (1984) and p. 410 in Seber (1984).
[17] That is, $e'Ae$ picks out the lower right element of the square matrix A.
[18] We thank Raymond Kan for pointing this out to us.

by the two other test, F_2 and J_2. It is also interesting that UMD receives eleven significant beta estimates, and the joint hypothesis is again rejected by only the F_1 test. In sum, Table 5 indicates that the LMH factor is significant across the 25 portfolio universe, while the significance of PS and UMD is generally weaker and depends on the test statistic used.

Table 6 shows the impact on the three Fama-French factor betas of adding our LMH factor. The first three columns of the table shows the Fama-French beta estimates without LMH included in the regression model, while the three last columns show the corresponding beta estimates with LMH included in the model. Despite the sizable univariate correlations between LMH and both HML and SMB reported earlier in Table 4, LMH is jointly orthogonal to the three Fama-French factors. As a result, including LMH does not materially affect the Fama-French factor betas. See Eckbo and Norli (2002) for further evidence on the pricing effects of LMH and other liquidity factors.

3.4 Applying liquidity factors to IPO and SEO portfolios

Next, we apply the new factor model to the portfolio returns of IPOs, SEOs, and non-issuing matched firms. The results are shown in Table 7 for IPOs, and in Table 8 for SEOs. In both tables, we use the Fama-French three-factor model, augmented with the momentum factor UMD and one of our two liquidity factors LMH and PS . The tables report results for equal-weighted portfolios only, as estimates using value-weighted portfolios do not lead to materially different conclusions.[19] We estimate the factor model for three different portfolios. "Issuer" is the equal-weighted portfolio of issuing firms. "Match" is the equal-weighted portfolio of non-issuing firms matched either on size (Panel A) or both size and book-to-market (Panel B).[20] Finally, "Issuer-match" is an equal-weighted, zero-investment portfolio that is long in issuer stocks and short in the matched firms. The latter portfolio is particularly interesting as it implicitly controls for any omitted risk factor with identical factor betas across issuer and matched firms.

We focus first on the constant term alpha for IPOs in Table 7. The alpha is not statistically significant for the issuer portfolio in any of the regressions. For example, the alpha is 0.35% per

[19] Results for value-weighted portfolios were reported in earlier drafts and are available from the authors upon request.

[20] The "Issuer" portfolio is re-estimated in Panel B because the matching procedure in this panel reduces the issuer sample size.

month in the full sample of 6,139 IPOs and when using the LMH liquidity factor. The p-value of this estimate is 0.138. The estimate of alpha increases slightly to 0.40% when restricting the sample of have size and book-to-market matching firms in Panel B. Thus, reducing the IPO sample by 774 issues does not materially impact the constant term in the regression. Notice that the point estimates of alpha are *positive* (although insignificant) across all regressions, which contrasts with the negative estimate reported by Brav, Geczy, and Gompers (2000). They report an alpha of -0.37% when using the Fama-French factors, with a t-value of -1.94. Their sample selection period ends in 1992 (and their return measurement period in 1997), and we replicate their estimate if we likewise restrict our sample selection period and eliminate the momentum and liquidity factors.

Turning to the "Issuer-match" portfolios, the alpha estimates are generally small (ranging from -0.11 to 0.09) and statistically insignificant in all of the regressions. These regressions reflect the *differential* exposure of issuer and matched firms to the risk factors. To illustrate, suppose the true set of risk factors is given by the vector F, and that a subset F_1 of this vector is included in the regression model, with the complement vector F_2 omitted. Let "I" denote issuer and "M" matched firm. The "Issuer-match" regression is then

$$r_I - r_M = (\alpha_I - \alpha_M) + (\beta_{1I} - \beta_{1M})F_1 + \epsilon, \tag{9}$$

where $\epsilon = (\beta_{2I} - \beta_{2M})F_2 + u$, where u is a white noise error term. The definition of a "good match" is that β_I is close to β_M. Thus, if the size- and book-to-market matching used in the literature in fact produces a good match, then you expect the "Issuer-match" regression to have both a small alpha and values of beta close to zero. While the alpha-estimates are indeed small, the estimated betas for HML and liquidity are not.

For example, when using LMH as a liquidity risk factor, the estimated beta for HML is -0.12 (p-value 0.019) when matching on size- and book-to-market (Panel B, third regression). Under the hypothesis that HML is a true risk factor, this means that the size- and book-to-market matching technique advocated by Loughran and Ritter (1995) and Loughran and Ritter (2000) is insufficient to control for even the type of risk that emanates from book-to-market.

Turning to the liquidity risk factors, the "Issuer-match" regressions yield significant liquidity betas in all four regressions (the highest p-value is 0.08 for LMH in Panel B). Moreover, the sign of beta is negative, which in the case of LMH means a reduction in the portfolio's expected return since this factor has a positive risk premium estimate (Table 4). In the case of the PS factor, the contribution to expected portfolio return is also negative given the positive risk premium estimate for PS reported by Pastor and Stambaugh (2003).

Focusing on LMH, in Panel B of Table 7, the estimated beta for LMH is -0.13 with a p-value of 0.08. The product of this estimate and the average return on the LMH portfolio over the sample period equals -0.023% per month. This reduction in expected return is over and beyond the effect of LMH on the expected return of the matched firms. Similarly, the residual HML-type of risk in the "Issuer-match" portfolio reduces the expected return to the issuer portfolio by 0.058% per month.[21]

Finally, Eckbo, Masulis, and Norli (2000) report that firms undertaking seasoned equity offerings over the period 1964–1995, also have higher liquidity (measured as turnover) than matched firms. However, they do not test for the risk reducing effects of liquidity on the performance of their sample SEOs. We perform this analysis in Table 8, using both LMH and PS as liquidity risk factors. When applying the above factor model to their sample of 1,704 SEOs by industrial firms, we find that the liquidity factor is again statistically significant. Focusing on the "Issuer-match" portfolio regressions, the estimated beta for the LMH factor is -0.34% per month when matching on both size- and book-to-market (Panel B). Applying the same factor risk premium as in the previous paragraph, this implies a reduction in the expected return of issuing firms by 0.06% per month over and beyond the effect of LMH on the matching firms. In sum, it appears that the net effect of the liquidity factor is to reduce the expected return to both IPO and SEO stocks.[22]

We now turn to an examination of the impact of leverage-differences between IPO firms and their non-issuing matched firms.

[21] In this computation, a factor's risk premium is calculated as the average monthly factor (portfolio) return. When the factor is not a portfolio, which is the case for the Pastor-Stambaugh liquidity risk measure PS , this approach to measuring the risk premium obviously does not work. For example, as indicated earlier, PS has a mean of zero by construction and cannot be interpreted as a return. Eckbo and Norli (2002) provides estimates of risk premia across alternative liquidity factor definitions.

[22] It is also interesting to note that, in both Table 7 and Table 8, the marginal reduction in expected return on the "Issuer-match" portfolio is greater for the liquidity factor LMH than for the momentum factor UMD. The empirical relationship between UMD and LMH is explored further in Eckbo and Norli (2002).

4 Leverage and expected returns

In this section we estimate a factor model where we replace the Fama-French factors SMB and HML, and the momentum factor UMD, with leverage-related risk factors. The motivation for this exercise is twofold. First, as mentioned in the introduction, leverage "turbo charges" equity returns.[23] In a multifactor setting, this return effect of leverage appears in the factor loading of *each* risk factor. Thus, it is possible that the lower leverage of IPO firms documented earlier in Table 3, reduces the factor loadings of IPO firms relative to non-issuing matched firms. We examine this possibility by estimating factor betas for a set of leverage-related risk factors.

Second, a model with macroeconomic risks have desirable power characteristics if the market exhibits sentiment (or irrationality). As shown below, the weights in our factor mimicking portfolios are constructed to track the underlying macroeconomic risks. If the macroeconomic risk (such as aggregate consumption) is itself unaffected by market sentiment, then the tracking portfolio is also less influenced by market sentiment than are unconstrained factor portfolios of stocks, such as those represented by various sorts on size and book-to-market ratio, and liquidity. We continue to include our liquidity factor LMH, however, as this allows us to further investigate the performance of this new factor in the presence of macroeconomic risks.

4.1 Factor mimicking procedure

As listed in Panel (A) of Table 9, the model contains a total of seven factors: the market (RM), the liquidity factor LMH, and five macroeconomic risks. They are the seasonally adjusted percent change in real per capita consumption of nondurable goods (RPC), the difference in the monthly yield change on BAA-rated and AAA-rated corporate bonds (BAA−AAA), unexpected inflation (UI), the return spread between Treasury bonds with 20-year and one-year maturities (20y−1y), and the return spread between 90-day and 30-day Treasury bills (TBILLspr). These are the same factors that are used in Eckbo, Masulis, and Norli (2000) in their study of the performance after seasoned security offerings, and similar factors also appear in, Ferson and Harvey (1991), Evans

[23] Galai and Masulis (1976) illustrate this effect using the standard Capital Asset Pricing Model (CAPM) and the Black-Scholes option pricing model. Let $\eta_s = (\partial s/\partial v)/(s/v)$ denote the elasticity of the stock price s with respect to total firm value v, The market beta estimated using equity returns can be written as $\beta_s = N(d_1)(v/s)\beta_v = \eta_s\beta_v$ where $N(d_1)$ is the cumulative Normal probability at d_1 as defined in the Black-Scholes model, and β_v is the market beta estimated using total firm returns.

(1994), Ferson and Korajczyk (1995), and Ferson and Schadt (1996).[24]

Of the seven factors, four are themselves security portfolios, which do not require factor mimicking. We create factor-mimicking portfolios for the remaining three, RPC, BAA−AAA, and UI as follows: We start by regressing the return of each of the 25 size and book-to-market sorted portfolios of Fama and French on the set of seven factors. These 25 time-series regressions produce a (25×7) matrix B of betas for the seven factors. Let V denote the (25×25) covariance matrix of the error terms from these regressions (assumed to be diagonal). Then then the weights used to construct mimicking portfolios from the 25 Fama-French portfolios are formed as

$$w = (B'V^{-1}B)^{-1}B'V^{-1}. \tag{10}$$

For each factor k, the return in month t on the corresponding mimicking portfolio is determined by multiplying the kth row of factor weights with the vector of month t returns for the 25 Fama-French portfolios. Mimicking portfolios are distinguished from the underlying macro factors ΔRPC, BAA−AAA, and UI using the notation $\widehat{\Delta\mathrm{RPC}}$, $\mathrm{BA}\widehat{\mathrm{A}-\mathrm{A}}\mathrm{AA}$, and $\widehat{\mathrm{UI}}$.

As shown in Panel (B) of Table 9, the factor-mimicking portfolios are reasonable: they have significant pairwise correlation with the raw factors they mimic, and they are uncorrelated with the other mimicking portfolios and the other raw factors. Moreover, Panel (C) of Table 9 shows that when we regress the mimicking portfolios on the set of six raw factors, it is only the own-factor slope coefficient that is significant.[25] Turning to Panel (D) of Table 9, the pairwise correlation coefficient between the six macroeconomic factors ranges from a minimum of −0.298 between ΔRPC and UI, and a maximum of 0.395 between TBILLspr and 20y−1y.

[24]The returns on T-bills, and T-bonds as well as the consumer price index used to compute unexpected inflation are from the CRSP bond file. Consumption data are from the U.S. Department of Commerce, Bureau of Economic Analysis (FRED database). Corporate bond yields are from Moody's Bond Record. Expected inflation is modeled by running a regression of real T-bill returns (returns on 30-day Treasury bills less inflation) on a constant and 12 of its lagged values.

[25]Let b_k be the kth row of B. The weighted least squares estimators in (10) are equivalent to choosing the 25 portfolio weights w_k for the kth mimicked factor in w so that they minimize $w_k' V w_k$ subject to $w_k b_i = 0$, $\forall k \neq i$, and $w_k' b_k = 1$, and then normalizing the weights so that they sum to one. Lehmann and Modest (1988) review alternative factor mimicking procedures. As they point out, the normalization of the weights will generally produce own-factor loadings, as those listed in Panel (C) of Table 9, that differ from one.

4.2 Model estimates

Table 10 reports estimates of alpha and factor loadings (betas) for our three equal-weighted portfolios, "Issuer", "Match" and "Issuer-match". The regression R^2 is of a similar magnitude to the R^2 reported in Table 7 for the characteristics-based factor model. For example, the regression for the "Issuer" portfolio in Panel A produces an R^2 of 0.85 in Table 7 and 0.80 in Table 10. Thus, there is little evidence that one particular model produces a superior goodness-of-fit. This is perhaps not surprising, as the factors in both types of models are represented by large stock portfolios. As the true factor structure is unknown—and unidentified even in theory—a consistent interpretation is that all of these factor portfolios are correlated with the true underlying factor structure.

None of the alpha estimates in Table 10 are significantly different from zero. Thus, we reach the same overall conclusion as we did with the characteristic-based model regressions in Table 7: We cannot reject the hypothesis that the expected return to IPO stocks is commensurable with their risk exposures.

Turning to the individual factor loadings reported in Table 10, the market beta of the "Issuer" portfolio in Panel A is 0.83, which is lower than the beta of 0.93 for the corresponding regression in Table 7. A market beta less than one in part explains why the portfolio *raw* return shown earlier in Figure 3 grows at a slower rate than the equal-weighted Nasdaq market itself. Second, the "Issuer" portfolio receives a large and significant liquidity beta of -1.34, down from -0.39 in Table 7. The liquidity beta of the "Issuer-match" portfolio is a significant -0.48, which is the strongest evidence yet that greater liquidity reduces the exposure of IPO stocks to liquidity risk, relative to non-issuing firms matched on size- and book-to-market.

Turning to the impact of macroeconomic risks on the "Issuer" portfolio, four of the five included factors are significantly different from zero with p-values of 0.017 or lower. When matching on size and book-to-market ratio (Panel B), the "Issuer-match" portfolio receives a significant beta for the percent change in real per capita consumption of non-durable goods (ΔRPC) and for the credit spread (BAA–AAA). Each of these factor betas are negative, indicating that a given factor shock reduces the realized return on issuer stock more than the return on the non-issuing matched firms. The significantly negative beta for the credit spread (BAA–AAA) is consistent with the hypothesis that the lower leverage of IPO firms in the post-issue period tend to reduce these firms' exposure to leverage-related risk. This lower exposure produces a lower expected return relative to non-issuing firms matched on size and book-to-market.[26]

5 Conclusion

We examine the risk-return characteristics of a rolling portfolio investment strategy where more than six thousand Nasdaq IPO stocks are bought and held for up to five years, 1973-2002. The analysis provides new evidence on the risk-return characteristics of this investment strategy. The risk factors that we consider are in part motivated by our finding that IPO stocks have significantly greater liquidity (turnover) and lower leverage ratios than seasoned firms matched on size and book-to-market. We examine the risk-reducing effects of greater liquidity through the lens of a factor model based on the Fama and French (1993) three-factor model augmented with a momentum factor and an easily constructed liquidity risk factor introduced here. This liquidity factor is a portfolio that are long in low-turnover stocks short in high-turnover stocks ("low-minus-high", LMH). For comparison purposes, we also provide estimates based on the liquidity factor proposed by Pastor and Stambaugh (2003) which explores the delayed price response to order flow.

We show that the LMH factor produces factor betas of a magnitude and significance comparable to that produced by the momentum factor. When applied to the IPO portfolio, the LMH liquidity factor reduces expected portfolio return, as predicted. Moreover, the model produces a statistically insignificant intercept term (Jensen's alpha). Thus, we cannot reject the hypothesis that the IPO portfolio receives an expected return commensurable with its risk. A similar conclusion emerges

[26]The above estimation of the macrofactor model assumes that the factor loadings (β) are constant through time. Following Ferson and Schadt (1996), we re-estimated Jensen's alpha in a conditional factor model framework assuming that the factor loadings are linearly related to a set of L known information variables Z_{t-1}:

$$\beta_{1pt-1} = b_{p0} + B_{p1} Z_{t-1}.$$

Here, b_{p0} is a K-vector of "average" factor loadings that are time-invariant, B_{p1} is a $(K \times L)$ coefficient matrix, and Z_{t-1} is an L-vector of information variables (observables) at time $t-1$. The product $B_{p1} Z_{t-1}$ captures the predictable time variation in the factor loadings. Thus, the return-generating process becomes

$$r_{pt} = b'_{p0} r_{Ft} + b'_{p1}(Z_{t-1} \otimes r_{Ft}) + e_{pt},$$

where the KL-vector b_{p1} is vec(B_{p1}) and the symbol $\otimes$ denotes the Kronecker product. (The operator vec$(\cdot)$ vectorizes the matrix argument by stacking each column starting with the first column of the matrix.) As information variables, Z_{t-1}, we used the lagged dividend yield on the CRSP value-weighted market index, the lagged 30-day Treasury bill rate, and the lagged values of the credit and yield curve spreads, BAA$-$AAA and TBILLspr, respectively. The resulting estimates of Jensen's alpha support the overall conclusion of zero abnormal IPO stock performance. The estimates are available upon request.

when we apply the same factor model to the portfolio of seasoned equity offerings (SEOs) in Eckbo, Masulis, and Norli (2000). The liquidity-based factor model prices both the IPO and the SEO portfolios in the sense of producing insignificant intercept terms (Jensen's alpha).

Turning to the leverage characteristic, since leverage "turbo charges" equity returns by increasing factor loadings, reducing leverage also reduces the stock's exposure to leverage-related risk factors. Using a factor model with macroeconomic risks, we find that IPO stocks have somewhat lower exposures than matched firms to a leverage-related factor such as the default spread. In the macroeconomic risk model, the IPO portfolio continues to receive a significantly negative liquidity beta. Thus, our evidence is consistent with the hypothesis that the lower liquidity and the lower leverage both contribute to a lower expected return on IPO shares.

Overall, we cannot reject the hypothesis that the expected return on IPO stocks is commensurable with it's portfolio risk, as defined here. The evidence of zero abnormal portfolio return emerges even before taking into account transaction costs of the monthly portfolio rebalancing implied by the investment strategy.

We also investigate the nature of the return distribution of IPO stocks by quantifying the frequency of extreme events, including delistings due to liquidations and takeovers, as well as extreme return observations. Interestingly, there is no evidence that IPO firms exhibit a chance of delisting that differs from the typical non-IPO Nasdaq-listed company. Moreover, the frequency of -100% return realizations is no greater for IPO stocks than for non-IPO firms matched on either size and size and book-to-market ratio. This may in part reflect the fact that the typical IPO firm is of average equity size (but below average book-to-market) when compared to the population of Nasdaq companies. However, there is a somewhat greater chance that an IPO stock will experience a return realization of 1,000% or more. The low expected return to IPO stocks suggests that this extra probability mass represents non-priced risk, consistent with the popular notion of IPO stocks as "longshot" bets on large, future returns.

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Figure 1
Annual Distribution of 6,139 Nasdaq IPOs with offer dates between 1972–1998.

The column heights represent the number of Nasdaq IPOs in the sample for a given year.

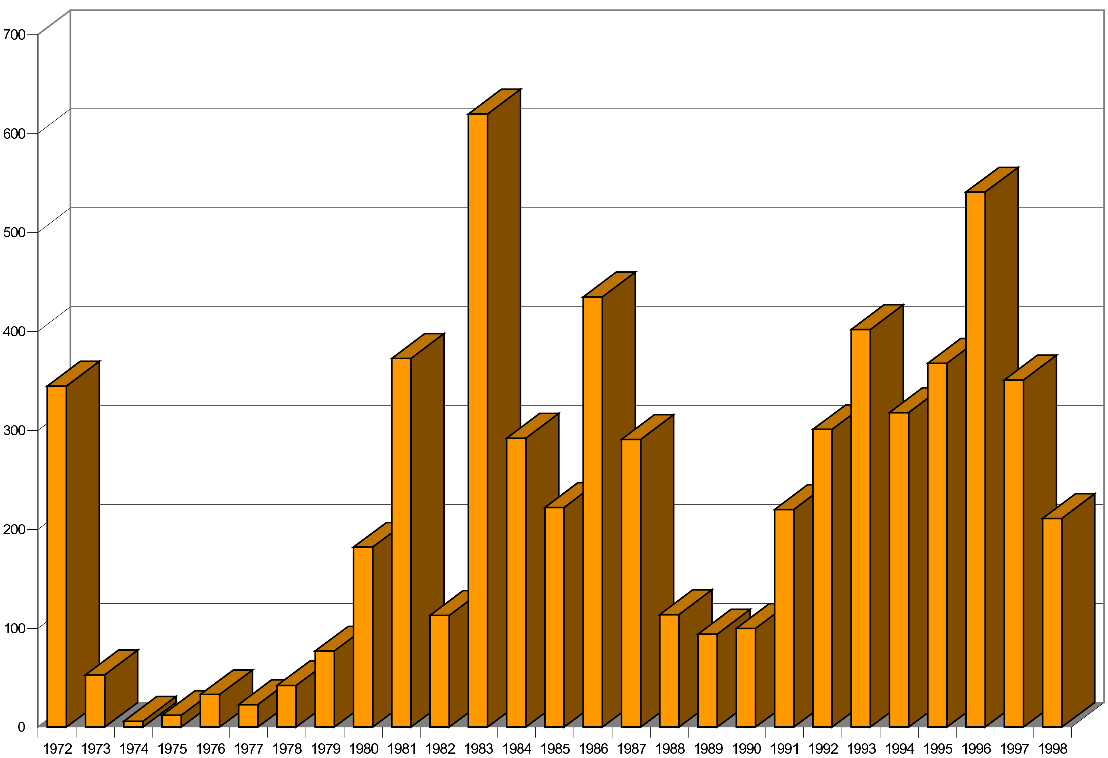
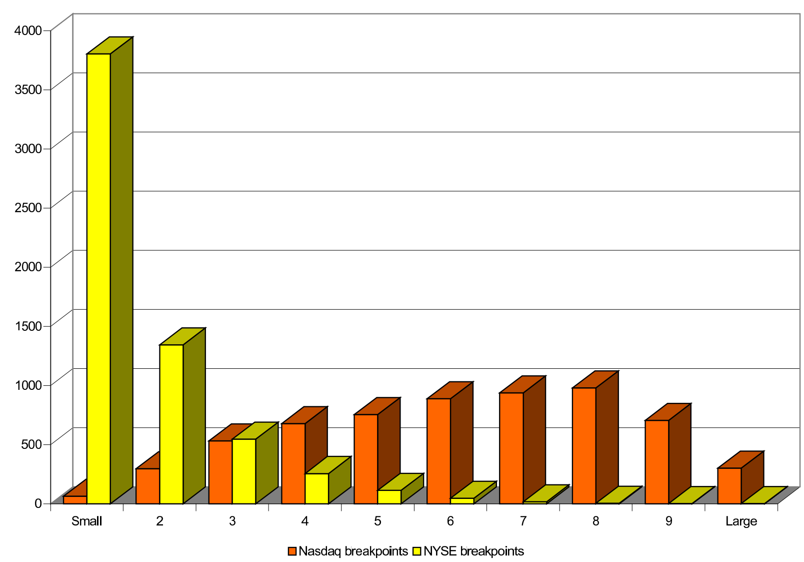


Figure 2
IPO size and book-to-market ratio distributions, for the total sample of 6,139 Nasdaq IPOs, 1973-2002.

In Panel A, each IPO are placed in a size decile using either NYSE size breakpoints or Nasdaq size breakpoints. In panel B, each IPO are placed in a book-to-market ratio decile using either NYSE book-to-market breakpoints or Nasdaq book-to-market breakpoints. The column heights represent the number of IPOs in each decile.

(A) IPO size distribution



(B) IPO book-to-market ratio distribution

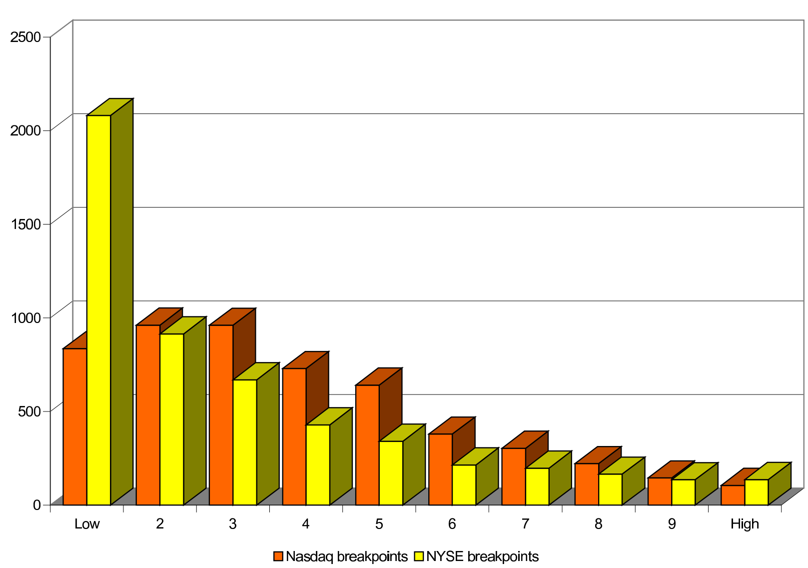


Figure 3
Compounded returns on equally weighted portfolios, 1973–2002.

The graphs depicts how the value of a $1 investment evolves over the sample period January 1973 to December 2002. The portfolios are the EW CRSP Nasdaq index, an EW portfolio of Nasdaq-IPOs, an EW portfolio of size-matched firms, an EW portfolio of size-book-to-market ratio matched firms, and 30-day Treasury bills. The total sample is 6,139 IPOs, 1973–2002.

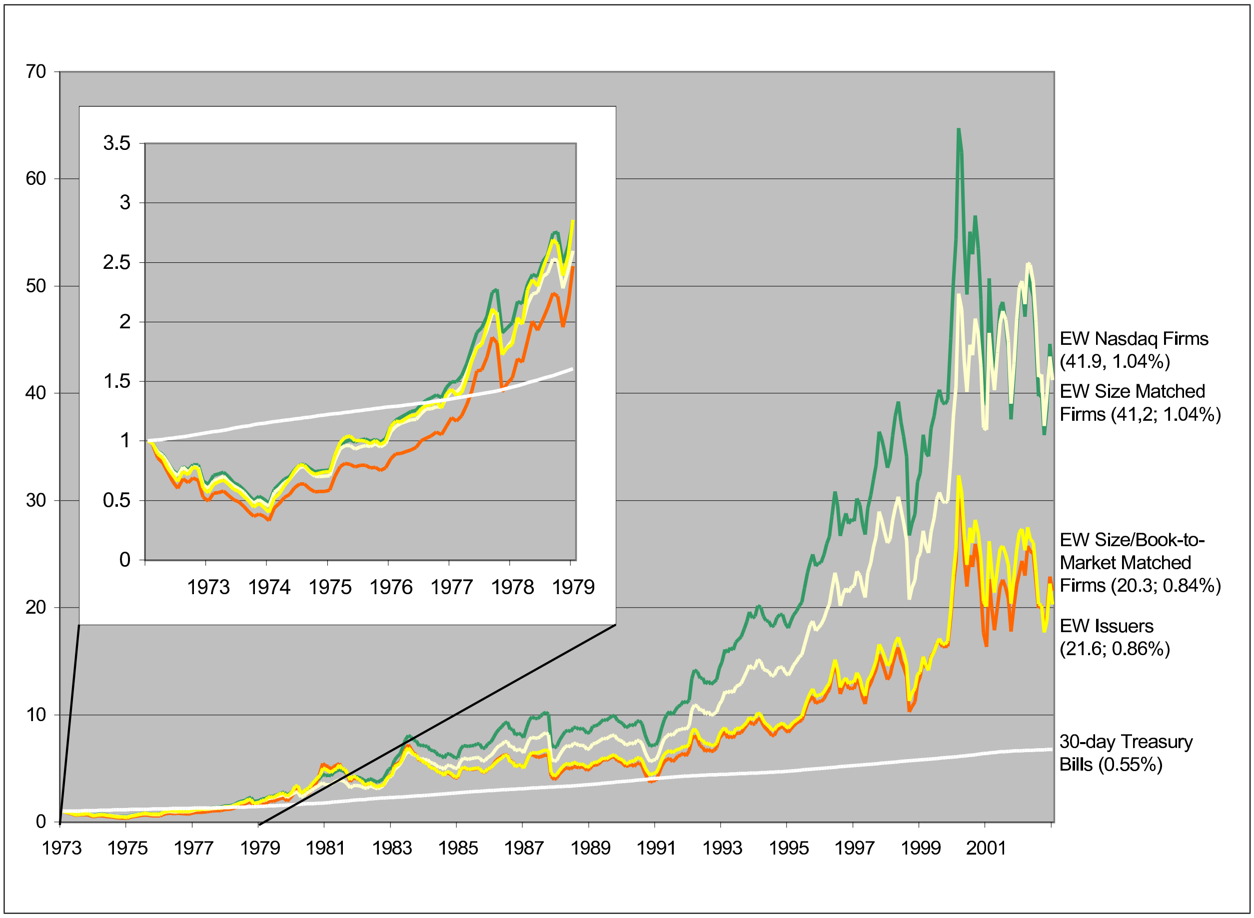
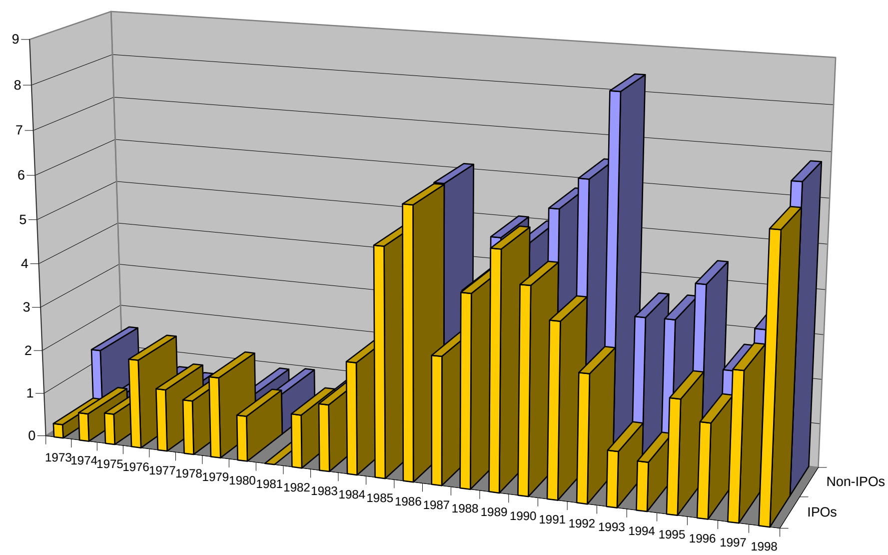


Figure 4
Delistings due to liquidation, mergers or takeovers.

Panel A covers delistings due to liquidations. Panel B covers number of delistings due to merger, takeover, exchange offers, or other events where common shareholders are bought out. In both panels, front columns are delistings by recent IPO firms (IPO less than five years before delisting date) divided by number of recent IPO firms. Back columns are delistings by Non-IPO firms (IPO more than five years ago) divided by number of non-IPO firms. Total sample of 6,139 IPOs from 1972-1998.

(A) Delistings due to liquidation



(B) Delistings due to merger or takeover

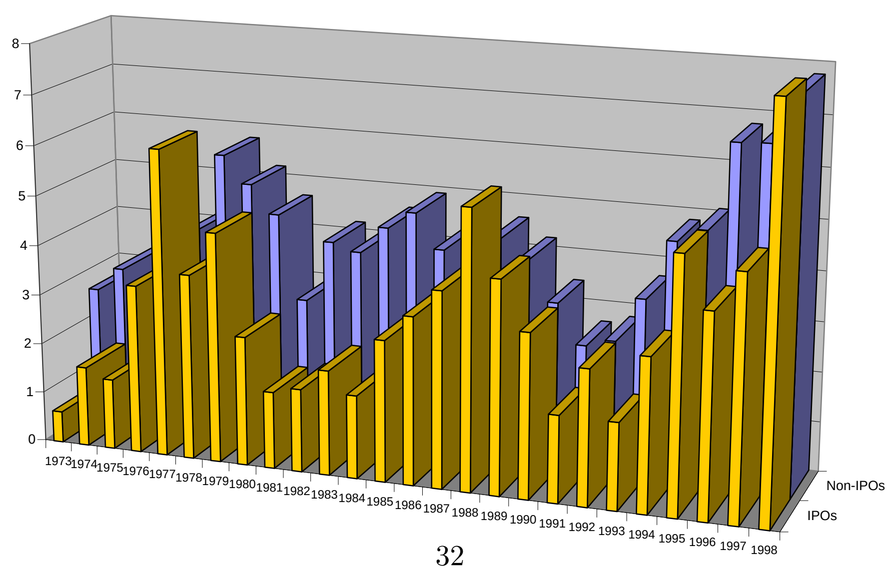
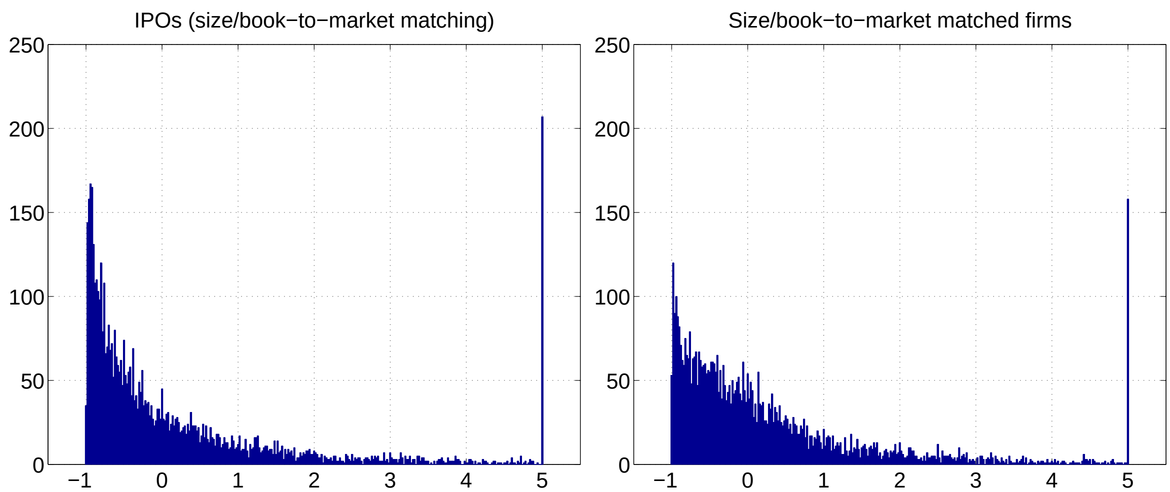


Figure 5
Histogram of five-year holding period returns between −100% and 1000% for issuers and size/book-to-market matched control firms.

Each bar in the histogram represent a 2 percentage point interval, and the height of the bar shows how many firms had a five-year holding period return within this 2 percentage point interval.

(A) Histogram of five-year holding period returns between −100% and 500%



(B) Histogram of five-year holding period returns between 100% and 1000%

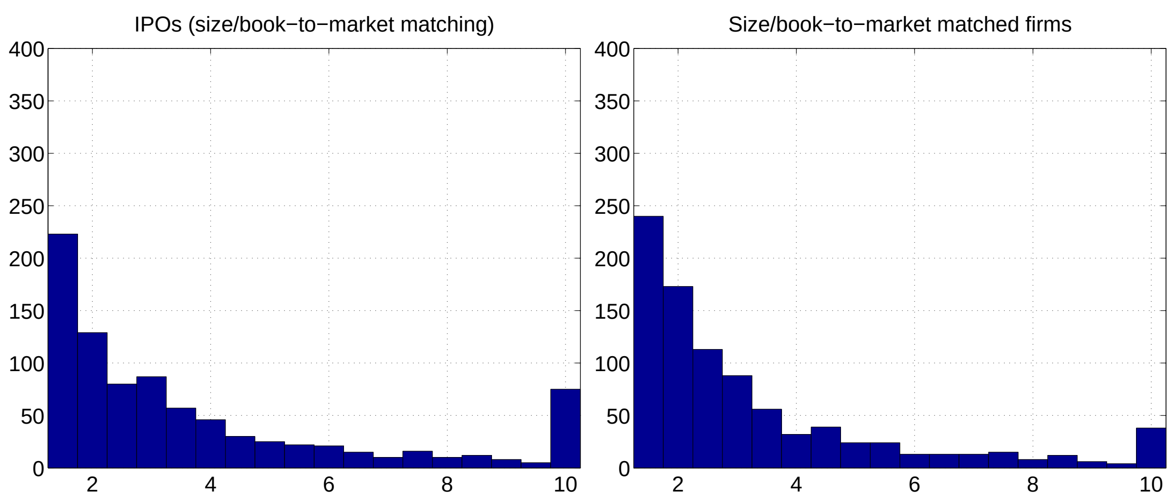


Table 1
Firm characteristics and portfolio characteristics for 6,139 firms going public between 1972 and 1998, and their non-issuing control firms matched on size and size/book-to-market ratio.

The number of observations used to compute the numbers in panel A vary by the variables. The number of observations range between 4,832 and 6,139. The equal weighted and value weighted issuer and match portfolios are constructed using monthly returns between January 1973 and December 2002, which gives 360 monthly returns for each portfolio. All issuers and matching firms are listed on Nasdaq.

	Size matching		Size/Book-to-market matching	
	Issuer	Match	Issuer	Match
(A) Average issuers and matching firms characteristics				
Size (market capitalization)	79.23	79.18	85.62	85.67
Book value of equity	—	—	27.01	27.22
Book-to-market ratio	—	—	0.384	0.385
Issue proceeds/size	0.333	—	0.317	—
Long-term debt/Total assets	0.102	0.150	0.102	0.147
Total debt/Total assets	0.155	0.211	0.154	0.208
Long-term debt/Market value	0.148	0.457	0.147	0.249
Average monthly turnover	0.121	0.071	0.120	0.102
(B) Monthly issuer and matching firm portfolio returns				
Equal weighted portfolios				
Mean percent return	1.18	1.23	1.22	1.27
Median percent return	1.40	1.36	1.57	1.52
Standard deviation of returns	8.08	6.10	8.24	7.49
End-value of a $1 investment	21.57	41.22	24.00	34.92
Compound monthly return 1973-2002	0.86	1.04	0.88	0.99
Value weighted portfolios				
Mean percent return	0.86	0.97	0.98	0.92
Median percent return	1.09	1.67	0.89	1.29
Standard deviation of returns	8.88	6.55	9.05	7.75
End-value of a $1 investment	5.10	15.01	6.97	9.00
Compound monthly return 1973-2000	0.45	0.76	0.54	0.61
Equal and value weighted portfolios				
Number of issuers and matches	6,139	6,139	5,365	5,365
Minimum number of firms in portfolios	79	79	67	67
Maximum number of firms in portfolios	1,722	1,722	1,708	1,708
Average number of firms in portfolios	823	823	738	738

Table 2
Five-year buy-and-hold stock percent returns ($\overline{\mathrm{BHR}}$) for a total of 6,139 firms going public between 1972 and 1998 and their matched control firms

Buy-and-hold percent returns are defined as:

$$\overline{\mathrm{BHR}} \equiv \omega_i \sum_{i=1}^{N} \left[\prod_{t=\tau_i}^{T_i} (1 + R_{it}) - 1 \right] \times 100.$$

When equal-weighting (EW), $\omega_i \equiv 1/N$, and when value-weighting (VW), $\omega_i = MV_i/MV$, where MV_i is the issuer's common stock market value (in 1999 dollars) at the start of the holding period and $MV = \sum_i MV_i$. The abnormal buy-and-hold returns shown in the column marked "Diff" represent the difference between the $\overline{\mathrm{BHR}}$ in the "Issuer" and "Match" columns. The rows marked "N" contain number of issues. The p-values for equal-weighted abnormal returns are p-values of the t-statistic using a two-sided test of no difference in average five-year buy-and-hold returns for issuer and matching firms. The p-values for the value-weighted abnormal returns are computed using $U \equiv \omega' x/(\sigma\sqrt{\omega'\omega})$, where ω is a vector of value weights and x is the corresponding vector of differences in buy-and-hold returns for issuer and match. Assuming that x is distributed normal $N(\mu, \sigma^2)$ and that σ^2 can be consistently estimated using $\sum_i \omega_i (x_i - \bar{x})^2$, where $\bar{x} = \sum_i \omega_i x_i$, U is distributed $N(0,1)$. All issuers and matching firms are listed on Nasdaq.

	Size matching					Size/book-to-market matching				
	N	Issuer	Match	Diff	$p(t)$	N	Issuer	Match	Diff	$p(t)$
(A) Total sample										
EW	6139	36.7	65.4	−28.8	0.000					
VW	6139	53.7	72.8	−19.1	0.028					
(B) Require sample firms to have book values on Compustat										
Holding period starts the month after the IPO date (looking ahead for the first book value on Compustat)										
EW	5365	39.8	68.7	−28.9	0.000	5365	39.8	42.2	−2.4	0.692
VW	5365	57.9	76.8	−18.8	0.054	5365	57.9	57.6	0.3	0.971
Holding period starts the month after first post-IPO book value on Compustat										
EW	5289	40.9	70.3	−29.3	0.000	5289	40.9	62.0	−21.0	0.002
VW	5289	105.4	76.6	28.9	0.187	5289	105.4	90.9	14.5	0.537

Table 3
Average annual leverage ratios and turnover for firms going public between 1972 and 1998 and their non-issuing control firms.

In Panel A, turnover is volume divided by number of shares outstanding. The reported turnovers are average monthly turnover for each year zero to five in the holding period. In Panel B, leverage is computed using long-term debt, total debt (long-term debt plus debt in current liabilities), and total assets at the end of the fiscal year (as reported by COMPUSTAT). Market values are measured at the end of the calendar year. Observations with negative book equity value and observations with a long-term debt to market value ratio that exceeds 10,000 are excluded. All issuers and matching firms are listed on Nasdaq.

(A) Turnover

	Issuers and size matched firms				Issuers and size-book-to-market matched firms			
Year	N	Issuer	Match	p-diff	N	Issuer	Match	p-diff
0	5195	0.126	0.074	0.000	4501	0.128	0.113	0.008
1	5536	0.111	0.074	0.000	4792	0.117	0.111	0.039
2	5314	0.120	0.077	0.000	4668	0.127	0.111	0.000
3	4601	0.120	0.079	0.000	4196	0.129	0.110	0.000
4	3823	0.119	0.077	0.000	3679	0.129	0.112	0.000
5	3165	0.106	0.071	0.000	3180	0.119	0.105	0.000

(B) Leverage

		Long-term debt divided by total assets			Long-term debt divided by market value of equity			Total debt divided by total assets		
Year	N	Issuer	Match	p-diff	Issuer	Match	p-diff	Issuer	Match	p-diff
Issuers and size matched firms										
0	4005	0.101	0.137	0.000	0.155	0.383	0.000	0.151	0.191	0.000
1	3879	0.124	0.143	0.000	0.289	0.467	0.000	0.183	0.200	0.000
2	3516	0.139	0.144	0.259	0.400	0.463	0.029	0.198	0.200	0.633
3	3079	0.147	0.145	0.710	0.443	0.525	0.014	0.207	0.199	0.096
4	2491	0.147	0.140	0.100	0.609	0.481	0.045	0.208	0.197	0.042
5	2082	0.150	0.145	0.252	0.685	0.532	0.033	0.209	0.203	0.296
Issuers and size/book-to-market matched firms										
0	4661	0.103	0.133	0.000	0.164	0.244	0.000	0.155	0.189	0.000
1	4408	0.125	0.139	0.000	0.293	0.315	0.224	0.185	0.196	0.005
2	3910	0.138	0.140	0.662	0.386	0.357	0.279	0.197	0.195	0.705
3	3362	0.145	0.146	0.881	0.443	0.402	0.143	0.207	0.201	0.269
4	2725	0.145	0.146	0.837	0.550	0.406	0.000	0.206	0.204	0.652
5	2274	0.151	0.149	0.624	0.621	0.480	0.017	0.211	0.210	0.828

Table 4
Descriptive statistics for characteristic based risk factors, January 1973 to December 2002 sample period.

The size factor (SMB) is the return on a portfolio of small firms minus the return on a portfolio of large firms (See Fama and French, 1993). The momentum factor (UMD) is constructed using a procedure similar to Carhart (1997): It is the return on a portfolio of the one-third of the CRSP stocks with the highest buy-and-hold return over the previous 12 months minus the return on a portfolio of the one-third of the CRSP stocks with the lowest buy-and-hold return over the previous 12 months. The SMB, HML, and UMD factors are constructed by Ken French and are downloaded from his web-page. The liquidity factor LMH is constructed using an algorithm similar to the one used by Fama and French (1993) when constructing the SMB and HML factors. To construct LMH, we start in 1972 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks and three portfolios formed using NYSE/AMEX stocks ranked on turnover. Next, six portfolios are constructed from the intersection of the two market value and the three turnover portfolios. Monthly value-weighted returns on these six portfolios are calculated starting in January 1973. Portfolios are reformed in January every year using firm rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with low turnover and the equal-weighted average return on the two portfolios with high turnover. The PS factor is constructed as in Pastor and Stambaugh (2003) using order-flow related return reversals.

(A) Characteristic based factors

	N	Mean	Std Dev
Excess return on the value-weighted market portfolio (RM)	360	0.400	4.760
Difference in returns between small firms and big firms (SMB)	360	0.164	3.378
Difference in return between firms with high and low book-to-market (HML)	360	0.491	3.233
Difference in return between winners and losers (UMD)	360	0.986	4.334
Difference in return between firms with high and low turnover (LMH)	360	0.175	2.851
Pastor-Stambaugh liquidity factor (PS)[1]	360	-0.028	0.087

(B) Correlation between characteristic based factors

	RM	SMB	HML	UMD	LMH	PS
RM	1.000					
SMB	0.257	1.000				
HML	-0.473	-0.312	1.000			
UMD	0.093	0.101	-0.314	1.000		
LMH	-0.673	-0.544	0.522	-0.098	1.000	
PS	0.278	0.064	-0.151	-0.024	-0.147	1.000

[1] Note that, in contrast to the five other risk factors in Panel A, the mean value of the PS factor cannot be interpreted as a risk premium. See the text for details.

Table 5
Factor betas for factors added to the Fama-French three factor model using 25 size and book-to-market ratio sorted portfolios as test assets, 1973–2002

The model is:

$$R = XB + E$$

where R is $(T \times N)$ with typical row r_t', X is $(T \times (K+1))$ with typical row $[1 \;\; F_t']$, B is the $((K+1) \times N)$ matrix $[\alpha \;\; \beta]'$, and E is $(T \times N)$ with typical row ϵ_t'. The table reports test statistics F_1, J_2, and F_2 for the null hypothesis that the factor sensitivities of the N assets with respect to each factor, when added to the Fama-French three factor model, is equal to zero. The test statistics are as reported in equations (6), (7), and (8). The "Small" and "Big" portfolios contain the smallest and biggest firms on NYSE/AMEX/Nasdaq using NYSE breakpoints. The "Low" and "High" portfolios contain the firms NYSE/AMEX/Nasdaq with the lowest and highest book-to-market ratios using NYSE breakpoints. The parentheses contain p-values.

Portfolio	LMH	PS	UMD
A. Liquidity betas when a liquidity factor is added to the Fama-French model			
Small-Low	−0.249 (0.00)	−0.065 (0.01)	−0.018 (0.54)
Small-2	−0.038 (0.48)	−0.051 (0.01)	0.004 (0.85)
Small-3	0.047 (0.26)	0.011 (0.47)	0.029 (0.09)
Small-4	0.067 (0.12)	0.017 (0.26)	0.010 (0.54)
Small-High	0.010 (0.82)	0.004 (0.78)	−0.041 (0.03)
P2-1	−0.294 (0.00)	−0.034 (0.06)	−0.064 (0.00)
P2-2	0.023 (0.62)	0.024 (0.14)	−0.047 (0.01)
P2-3	−0.017 (0.68)	0.026 (0.07)	−0.034 (0.04)
P2-4	0.121 (0.00)	0.014 (0.31)	−0.021 (0.20)
P2-5	−0.136 (0.00)	−0.007 (0.62)	−0.018 (0.26)
P3-1	−0.203 (0.00)	−0.025 (0.15)	−0.056 (0.00)
P3-2	−0.207 (0.00)	0.044 (0.02)	−0.042 (0.05)
P3-3	−0.109 (0.02)	0.033 (0.05)	−0.043 (0.03)
P3-4	0.027 (0.58)	0.013 (0.44)	−0.031 (0.11)
P3-5	−0.192 (0.00)	0.005 (0.81)	−0.079 (0.00)
P4-1	−0.242 (0.00)	0.004 (0.82)	0.002 (0.92)
P4-2	−0.214 (0.00)	0.052 (0.01)	−0.046 (0.04)
P4-3	−0.225 (0.00)	0.041 (0.03)	−0.062 (0.00)
P4-4	−0.042 (0.40)	−0.019 (0.27)	−0.060 (0.00)
P4-5	−0.216 (0.00)	0.030 (0.16)	−0.056 (0.02)
Big-Low	0.170 (0.00)	−0.002 (0.89)	−0.023 (0.14)
Big-2	−0.100 (0.04)	0.038 (0.02)	−0.002 (0.93)
Big-3	−0.141 (0.01)	−0.003 (0.87)	0.019 (0.40)
Big-4	−0.072 (0.14)	−0.036 (0.03)	−0.038 (0.05)
Big-High	−0.182 (0.01)	−0.029 (0.24)	−0.045 (0.11)
B. Test statistics under the null of jointly zero betas			
$F1_{(25,331)}$	7.16 (0.000)	1.57 (0.043)	2.69 (0.000)
$J2_{(25)}$	58.90 (0.000)	18.36 (0.827)	37.24 (0.055)
$F2_{(25,331)}$	2.17 (0.001)	0.68 (0.881)	1.37 (0.114)

Table 6
Factor betas for the Fama-French three factor model with and without the LMH liquidity, 1973–2002

The model is:

$$R = XB + E$$

where R is $(T \times N)$ with typical row r_t', X is $(T \times (K+1))$ with typical row $[1 \;\; F_t']$, B is the $((K+1) \times N)$ matrix $[\alpha \;\; \beta]'$, and E is $(T \times N)$ with typical row ϵ_t'. The test assets are the Fama-French 25 size and book-to-market ratio sorted portfolios. The "Small" and "Big" portfolios contain the smallest and biggest firms on NYSE/AMEX/Nasdaq using NYSE breakpoints. The "Low" and "High" portfolios contain the firms NYSE/AMEX/Nasdaq with the lowest and highest book-to-market ratios using NYSE breakpoints. The parentheses contain p-values.

	Fama-French without LMH			Fama-French with LMH		
Portfolio	Mkt	SMB	HML	Mkt	SMB	HML
Small-Low	1.06 (0.00)	1.33 (0.00)	−0.35 (0.00)	0.98 (0.00)	1.25 (0.00)	−0.32 (0.00)
Small-2	0.96 (0.00)	1.30 (0.00)	0.05 (0.16)	0.94 (0.00)	1.29 (0.00)	0.05 (0.13)
Small-3	0.91 (0.00)	1.08 (0.00)	0.27 (0.00)	0.93 (0.00)	1.09 (0.00)	0.27 (0.00)
Small-4	0.89 (0.00)	0.99 (0.00)	0.44 (0.00)	0.91 (0.00)	1.02 (0.00)	0.44 (0.00)
Small-High	0.99 (0.00)	1.06 (0.00)	0.67 (0.00)	0.99 (0.00)	1.06 (0.00)	0.67 (0.00)
P2-1	1.12 (0.00)	1.00 (0.00)	−0.39 (0.00)	1.03 (0.00)	0.90 (0.00)	−0.35 (0.00)
P2-2	1.04 (0.00)	0.89 (0.00)	0.21 (0.00)	1.05 (0.00)	0.89 (0.00)	0.20 (0.00)
P2-3	1.00 (0.00)	0.74 (0.00)	0.46 (0.00)	0.99 (0.00)	0.74 (0.00)	0.46 (0.00)
P2-4	0.98 (0.00)	0.72 (0.00)	0.60 (0.00)	1.01 (0.00)	0.75 (0.00)	0.58 (0.00)
P2-5	1.10 (0.00)	0.86 (0.00)	0.80 (0.00)	1.06 (0.00)	0.81 (0.00)	0.82 (0.00)
P3-1	1.07 (0.00)	0.74 (0.00)	−0.45 (0.00)	1.01 (0.00)	0.68 (0.00)	−0.42 (0.00)
P3-2	1.08 (0.00)	0.52 (0.00)	0.28 (0.00)	1.02 (0.00)	0.45 (0.00)	0.31 (0.00)
P3-3	1.03 (0.00)	0.43 (0.00)	0.56 (0.00)	1.00 (0.00)	0.40 (0.00)	0.57 (0.00)
P3-4	1.01 (0.00)	0.38 (0.00)	0.70 (0.00)	1.02 (0.00)	0.39 (0.00)	0.69 (0.00)
P3-5	1.12 (0.00)	0.51 (0.00)	0.85 (0.00)	1.06 (0.00)	0.45 (0.00)	0.88 (0.00)
P4-1	1.06 (0.00)	0.42 (0.00)	−0.43 (0.00)	0.99 (0.00)	0.34 (0.00)	−0.40 (0.00)
P4-2	1.12 (0.00)	0.22 (0.00)	0.30 (0.00)	1.05 (0.00)	0.16 (0.00)	0.33 (0.00)
P4-3	1.11 (0.00)	0.18 (0.00)	0.57 (0.00)	1.04 (0.00)	0.11 (0.00)	0.60 (0.00)
P4-4	1.05 (0.00)	0.19 (0.00)	0.64 (0.00)	1.03 (0.00)	0.17 (0.00)	0.65 (0.00)
P4-5	1.17 (0.00)	0.19 (0.00)	0.82 (0.00)	1.10 (0.00)	0.12 (0.00)	0.85 (0.00)
Big-Low	0.96 (0.00)	−0.29 (0.00)	−0.38 (0.00)	1.01 (0.00)	−0.23 (0.00)	−0.40 (0.00)
Big-2	1.05 (0.00)	−0.23 (0.00)	0.15 (0.00)	1.02 (0.00)	−0.26 (0.00)	0.16 (0.00)
Big-3	1.00 (0.00)	−0.23 (0.00)	0.29 (0.00)	0.95 (0.00)	−0.28 (0.00)	0.31 (0.00)
Big-4	1.01 (0.00)	−0.19 (0.00)	0.66 (0.00)	0.99 (0.00)	−0.22 (0.00)	0.67 (0.00)
Big-High	1.03 (0.00)	−0.16 (0.00)	0.81 (0.00)	0.98 (0.00)	−0.21 (0.00)	0.83 (0.00)

Table 7
Jensen's alphas and factor loadings for characteristic based factors for stock portfolios of a total of 6,139 firms going public (IPOs) on Nasdaq and their non-issuing control firms, 1973–2002.

The model is:

$$r_{pt} = \alpha_p + \beta_1 \mathrm{RM}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{UMD}_t + \beta_5 \mathrm{Liquidity}_t + e_t$$

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long issuers and short in matching firms. Portfolios are first formed in January 1973 and held until December 2002. RM is the excess return on a value weighted market index, SMB and HML are the Fama and French (1993) size and book-to-market factors, UMD is a momentum factor and is constructed as the return difference between the one-third highest and one-third lowest CRSP performers over the past 12 months. The SMB, HML, and UMD factors are constructed by Ken French and are downloaded from his web-page. The liquidity factor LMH is constructed using an algorithm similar to the one used by Fama and French (1993) when constructing the SMB and HML factors. To construct LMH, we start in 1972 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks and three portfolios formed using NYSE/AMEX stocks ranked on turnover. Next, six portfolios are constructed from the intersection of the two market value and the three turnover portfolios. Monthly value-weighted returns on these six portfolios are calculated starting in January 1973. Portfolios are reformed in January every year using firm rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with low turnover and the equal-weighted average return on the two portfolios with high turnover. The PS factor is constructed as in Pastor and Stambaugh (2003) using order-flow related return reversals. In the panel headings, T is the number of months in the time series regression, N is the average number of firms in the portfolio, and I is the number of issues used to construct the portfolio. The coefficients are estimated using OLS. Standard errors are computed using the heteroskedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=360, N=823)					
Portfolio	$\hat{\alpha}$	RM	SMB	HML	UMD	Liquidity	A-Rsq
(A) Issuers and size matched control firms (I=6,139)							
Liquidity measured using turnover (LMH)							
Issuer	0.35 (0.138)	0.93 (0.000)	1.06 (0.000)	−0.11 (0.182)	−0.13 (0.133)	−0.39 (0.016)	0.850
Match	0.26 (0.069)	0.86 (0.000)	0.95 (0.000)	0.14 (0.004)	−0.13 (0.007)	−0.09 (0.325)	0.907
Issuer−match	0.09 (0.501)	0.07 (0.103)	0.11 (0.048)	−0.26 (0.000)	−0.00 (0.967)	−0.29 (0.001)	0.435
Liquidity measured as delayed price response to order flow (Pastor and Stambaugh, 2003, PS *)*							
Issuer	0.25 (0.261)	1.08 (0.000)	1.19 (0.000)	−0.16 (0.052)	−0.15 (0.103)	−0.08 (0.137)	0.846
Match	0.24 (0.068)	0.90 (0.000)	0.99 (0.000)	0.13 (0.007)	−0.14 (0.009)	−0.02 (0.582)	0.906
Issuer−match	0.01 (0.959)	0.19 (0.000)	0.21 (0.000)	−0.29 (0.000)	−0.02 (0.734)	−0.06 (0.033)	0.416
(B) Issuers and size/book-to-market matched control firms (I=5,365)							
Liquidity measured using turnover (LMH)							
Issuer	0.40 (0.099)	0.95 (0.000)	1.06 (0.000)	−0.14 (0.114)	−0.12 (0.183)	−0.40 (0.014)	0.849
Match	0.37 (0.027)	0.95 (0.000)	1.05 (0.000)	−0.03 (0.648)	−0.13 (0.025)	−0.27 (0.025)	0.883
Issuer−match	0.02 (0.849)	0.00 (1.000)	0.01 (0.683)	−0.12 (0.019)	0.01 (0.898)	−0.13 (0.082)	0.098
Liquidity measured as delayed price response to order flow (Pastor and Stambaugh, 2003, PS *)*							
Issuer	0.28 (0.198)	1.11 (0.000)	1.20 (0.000)	−0.20 (0.029)	−0.14 (0.140)	−0.08 (0.141)	0.844
Match	0.30 (0.060)	1.05 (0.000)	1.14 (0.000)	−0.06 (0.296)	−0.14 (0.019)	−0.05 (0.193)	0.881
Issuer−match	−0.01 (0.900)	0.05 (0.048)	0.06 (0.116)	−0.13 (0.007)	−0.00 (0.970)	−0.03 (0.208)	0.092

Table 8
Jensen's alphas and factor loadings for characteristic based factors for stock portfolio stock portfolios of firms undertaking seasoned equity offerings (SEOs) and their matched control firms, 1964–1997

The model is:

$$r_{pt} = \alpha_p + \beta_1 \mathrm{RM}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{UMD}_t + \beta_5 \mathrm{Liquidity}_t + e_t$$

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long issuers and short in matching firms. Portfolios are first formed in March 1964 and held until December 1997. Sample source: Eckbo, Masulis, and Norli (2000). RM is the excess return on a value weighted market index, SMB and HML are the Fama and French (1993) size and book-to-market factors, UMD is a momentum factor and is constructed as the return difference between the one-third highest and one-third lowest CRSP performers over the past 12 months. The factor is constructed by Ken French and is downloaded from his web-page. LMH (monthly volume divided by number of shares outstanding) is a liquidity factor that is constructed using the same algorithm used to construct HML. To construct LMH, we start in 1972 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks and three portfolios formed using NYSE/AMEX stocks ranked on turnover. Next, six portfolios are constructed from the intersection of the two market value and the three turnover portfolios. Monthly value-weighted returns on these six portfolios are calculated starting in January 1973. Portfolios are reformed in January every year using firm rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with low turnover and the equal-weighted average return on the two portfolios with high turnover. The PS factor is constructed as in Pastor and Stambaugh (2003) using order-flow related return reversals. In the panel headings, T is the number of months in the time series regression, N is the average number of firms in the portfolio, and I is the number of issues used to construct the portfolio. The coefficients are estimated using OLS. Standard errors are computed using the heteroskedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=406, N=361)					
Portfolio	$\hat{\alpha}$	RM	SMB	HML	UMD	Liquidity	A-Rsq
(A) Industrial issuers and size matched control firms (I=1,704)							
Liquidity measured using turnover (LMH)							
Issuer	−0.03 (0.745)	1.08 (0.000)	0.74 (0.000)	−0.02 (0.684)	−0.11 (0.000)	−0.32 (0.000)	0.939
Match	−0.15 (0.070)	0.98 (0.000)	0.82 (0.000)	0.33 (0.000)	−0.09 (0.001)	−0.08 (0.107)	0.925
Issuer−match	0.12 (0.333)	0.10 (0.001)	−0.08 (0.075)	−0.34 (0.000)	−0.02 (0.487)	−0.24 (0.000)	0.280
Liquidity measured as delayed price response to order flow (Pastor and Stambaugh, 2003, PS *)*							
Issuer	−0.16 (0.070)	1.20 (0.000)	0.91 (0.000)	−0.07 (0.065)	−0.08 (0.003)	−0.06 (0.002)	0.934
Match	−0.19 (0.020)	1.02 (0.000)	0.86 (0.000)	0.31 (0.000)	−0.08 (0.002)	−0.04 (0.035)	0.925
Issuer−match	0.03 (0.837)	0.18 (0.000)	0.04 (0.293)	−0.38 (0.000)	−0.00 (0.903)	−0.02 (0.501)	0.259
(B) Industrial issuers and size/book-to-market matched control firms (I=1,485)							
Liquidity measured using turnover (LMH)							
Issuer	0.13 (0.223)	1.06 (0.000)	0.53 (0.000)	0.07 (0.071)	−0.14 (0.000)	−0.37 (0.000)	0.905
Match	0.03 (0.718)	1.06 (0.000)	0.61 (0.000)	0.17 (0.000)	−0.14 (0.000)	−0.03 (0.607)	0.914
Issuer−match	0.10 (0.450)	0.00 (1.000)	−0.08 (0.079)	−0.10 (0.040)	0.00 (0.949)	−0.34 (0.000)	0.113
Liquidity measured as delayed price response to order flow (Pastor and Stambaugh, 2003, PS *)*							
Issuer	−0.03 (0.812)	1.19 (0.000)	0.73 (0.000)	0.01 (0.744)	−0.11 (0.000)	−0.07 (0.000)	0.897
Match	0.01 (0.932)	1.08 (0.000)	0.63 (0.000)	0.16 (0.000)	−0.13 (0.000)	−0.04 (0.055)	0.914
Issuer−match	−0.03 (0.803)	0.11 (0.001)	0.09 (0.047)	−0.15 (0.003)	0.03 (0.474)	−0.04 (0.157)	0.071

Table 9
Factor mimicking portfolios and macroeconomic variables used as risk factors, January 1973 to December 2002.

A factor mimicking portfolio is constructed by first regressing the returns on each of the 25 size and book-to-market sorted portfolios of Fama and French (1993) on the total set of six factors, i.e., 25 time-series regressions producing a (25×6) matrix B of slope coefficients against the factors. If V is the (25×25) covariance matrix of the error terms in these regressions (assumed to be diagonal), then the weights on the mimicking portfolios are: $w = (B'V^{-1}B)^{-1}B'V^{-1}$ (see Lehmann and Modest (1988)). For each factor k, the return in month t for the corresponding mimicking portfolio is calculated from the cross-product of row k in w and the vector of month t returns on the 25 Fama-French portfolios.

(A) Raw macroeconomic variables

	N	Mean	Std Dev
Excess return on the market index (RM)	360	0.400	4.760
Difference in return between firms with high and low turnover (LMH)	360	0.175	2.851
Change in real per capita consumption of nondurable goods (ΔRPC)[a]	360	0.041	0.697
Difference in BAA and AAA yield change (BAA−AAA)	360	0.010	1.167
Unanticipated inflation (UI)[b]	360	-0.020	0.254
Return difference on Treasury bonds (20y−1y)[c]	360	0.131	2.652
Return difference on Treasury bills (TBILLspr)[d]	360	0.051	0.112

(B) Correlation between raw macroeconomic factor and the factor mimicking portfolio

Mimicking factor	ΔRPC	BAA−AAA	UI
$\widehat{\Delta \text{RPC}}$	0.208 (0.000)	0.026 (0.622)	−0.061 (0.250)
$\widehat{\text{BAA} - \text{AAA}}$	0.018 (0.733)	0.159 (0.002)	−0.031 (0.559)
$\widehat{\text{UI}}$	−0.003 (0.949)	−0.033 (0.529)	0.183 (0.001)

(C) Correlation between macroeconomic factors

	RM	LMH	$\widehat{\Delta \text{RPC}}$	$\widehat{\text{BAA} - \text{AAA}}$	$\widehat{\text{UI}}$	20y−1y	TBILLspr
RM	1.000						
LMH	-0.679	1.000					
$\widehat{\Delta \text{RPC}}$	0.070	-0.024	1.000				
$\widehat{\text{BAA} - \text{AAA}}$	0.032	-0.085	-0.180	1.000			
$\widehat{\text{UI}}$	-0.055	0.016	-0.566	0.492	1.000		
20y−1y	0.233	-0.014	0.034	0.035	-0.059	1.000	
TBILLspr	0.111	0.003	0.031	0.045	-0.052	0.374	1.000

[a]Seasonally adjusted real per capita consumption of nondurable goods are from the FRED database.
[b]Unanticipated inflation (UI) is generated using a model for expected inflation that involves running a regression of real returns (returns on 30-day Treasury bills less inflation) on a constant and 12 of it's lagged values.
[c]This is the return spread between Treasury bonds with 20-year and 1-year maturities.
[d]The short end of the term structure (TBILLspr) is measured as the return difference between 90-day and 30-day Treasury bills.

Table 10

Jensen's alphas and macro-factor loadings for stock portfolios of a total of 6,139 firms going public (IPOs) on Nasdaq and their non-issuing control firms, 1973–2002.

The model is:

$$r_{pt} = \alpha_p + \beta_1 \mathrm{RM}_t + \beta_2 \mathrm{LMH}_t + \beta_3 \widehat{\Delta\mathrm{RPC}}_t + \beta_4 (\widehat{\mathrm{BAA}-\mathrm{AAA}})_t + \beta_5 \widehat{\mathrm{UI}}_t + \beta_6 (20\mathrm{y}-1\mathrm{y})_t + \beta_7 \mathrm{TBILLspr}_t + e_t$$

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long issuers and short in matching firms. Portfolios are first formed in January 1973 and held until December 2002. RM is the excess return on the market index, RPC is the percent change in the real per capita consumption of nondurable goods, BAA−AAA is the difference in the monthly yield changes on bonds rated BAA and AAA by Moody's, UI is unanticipated inflation, 20y−1y is the return difference between Treasury bonds with 20 years to maturity and 1 year to maturity, and TBILLspr is the return difference between 90-day and 30-day Treasury bills. The factors $\widehat{\Delta\mathrm{RPC}}$, $\widehat{\mathrm{BAA}-\mathrm{AAA}}$, and $\widehat{\mathrm{UI}}$ are mimicking portfolios for the corresponding raw factors. T is the number of months in the time series regression, N is the average number of firms in the portfolio, and I is the number of issues used to construct the portfolio. The coefficients are estimated using OLS. Standard errors are computed using the heteroskedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=360, N=823)							
Portfolio	$\hat{\alpha}$	RM	LMH	$\widehat{\Delta\mathrm{RPC}}$	$\widehat{\mathrm{BAA}-\mathrm{AAA}}$	$\widehat{\mathrm{UI}}$	20y−1y	TBILLspr	Rsq
(A) Issuers and size matched control firms (I=6,139)									
Issuer	0.10 (0.673)	0.83 (0.000)	−1.34 (0.000)	0.02 (0.000)	−0.02 (0.000)	0.20 (0.000)	−0.19 (0.017)	1.82 (0.354)	0.802
Match	0.07 (0.661)	0.71 (0.000)	−0.85 (0.000)	0.02 (0.000)	−0.01 (0.000)	0.18 (0.000)	−0.15 (0.013)	3.43 (0.017)	0.827
Issuer−Match	0.02 (0.864)	0.12 (0.008)	−0.48 (0.000)	−0.00 (0.447)	−0.01 (0.000)	0.02 (0.061)	−0.04 (0.493)	−1.61 (0.272)	0.412
(B) Issuers and size/book-to-market matched control firms (I=5,365)									
Issuer	0.18 (0.442)	0.86 (0.000)	−1.36 (0.000)	0.02 (0.000)	−0.02 (0.000)	0.20 (0.000)	−0.21 (0.011)	1.02 (0.616)	0.803
Match	0.21 (0.312)	0.83 (0.000)	−1.16 (0.000)	0.02 (0.000)	−0.02 (0.000)	0.19 (0.000)	−0.20 (0.009)	1.70 (0.275)	0.819
Issuer−match	−0.02 (0.843)	0.03 (0.450)	−0.19 (0.007)	−0.00 (0.091)	−0.01 (0.013)	0.01 (0.392)	−0.02 (0.668)	−0.69 (0.566)	0.116