Risk and Long-Run IPO Returns

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Abstract

It is well known that, despite having a market beta that is greater than one, the typical IPO stock performs poorly relative to the market during its first years of trading. With a sample exceeding six thousand Nasdaq IPOs, we show that the poor performance reflects risk factor exposures partly related to unique leverage and liquidity characteristics of IPO firms. The average IPO firm has both lower leverage and greater liquidity (turnover) than the typical non-IPO firm matched on size and book-to-market ratio. Our factor model estimation reveals that leverage-related factors such as unexpected inflation and term spreads lowers expected return to IPO stocks relative to the matched, non-IPO firms. Moreover, we introduce a new liquidity factor and show that this factor is significant and reduces expected IPO returns relative to non-IPO stocks. The factor model estimation produces insignificant intercept term and thus "prices" IPO stocks within a rational, multifactor pricing framework. We also show that the frequency of exchange delistings due to either liquidations or takeovers is not greater for IPO stocks than for non-IPO firms. IPO firms do, however, have a somewhat greater probability than non-IPO firms of return realizations in excess of 1,000%, perhaps confirming the notion of IPO stocks as "longshots".

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1 Introduction

Firms moving from the early start-up phase to a successful initial public offering (IPO) have significantly increased their odds in favor of long-run survival. This risk reduction notwithstanding, IPO stocks are commonly viewed as "longshots" when compared to more seasoned, publicly traded equities. As the firm generates earnings and increases its pledgeable asset base in the post-IPO period, it gains access to new funding sources—including public debt markets—which further reinforces its chance of survival. Moreover, the scrutiny that goes with public trading tends to reduce information asymmetry and increases stock liquidity. In fact, there is substantial evidence that underwriter fees and offering price discounts are smaller for seasoned equity offerings (SEOs) than for IPOs, as suggested by the risk-reducing effects of stock exchange seasoning.[1]

It is also well known that despite the deep initial offering price discount, IPO stocks generate low returns over holding periods of two–to–five years following the IPO date. To some researchers, these holding-period returns appear so low as to challenge the fundamental notion of rational and efficient capital market pricing [e.g., Ritter (1991), Loughran and Ritter (1995)], and provide a motivation for the development of behavioral asset pricing models where the marginal investor is slow to assimilate publicly available information [e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)].

This paper addresses the ongoing controversy over the nature and determinants of the generally low long-run IPO stock returns. Existing empirical evidence fails to provide clear answers. Fama and French (1993) document that small growth stocks generally have low returns during the post-1963 period. Moreover, Brav, Geczy, and Gompers (2000) report that the Fama and French (1993) three-factor model prices their portfolio of IPO stocks (in the sense that the three-factor model regressions fail to produce significant intercept terms). This suggests that the low IPO stock returns is in part a manifestation of a more general phenomenon affecting small growth stocks. It does not, however, resolve the issue of what this "general phenomenon" might be (other than lowering book-to-market ratios). Moreover, Loughran and Ritter (2000) and others essentially maintain that risk factors represented by (unconstrained) stock portfolios of the type in Fama and French (1993) lack the power to discriminate between rational and irrational pricing theories. The problem is

[1]See, e.g., Eckbo and Masulis (1995) and Ibbotson and Ritter (1995) for reviews of much of the evidence on direct flotation costs.

that such stock portfolios (and therefore the model expected return) are affected by the market sentiment to the same degree as the underlying securities.

We address the long-run IPO return controversy using the most comprehensive sample to date: in excess of six thousand IPOs that took place on the Nasdaq from its opening in 1973 through year 1998. We focus exclusively on the Nasdaq exchange as more than 90% of all IPOs over this time periods took place in this market. Nasdaq IPO firms are "small" within the NYSE/AMEX stock universe but closer to "average" within the Nasdaq population. Thus, when we draw a control firm matched on equity size, we are drawing a typical-sized Nasdaq firm. We then study how the IPO stock differs from this typical Nasdaq stock, as well as from stocks matched on both size and book-to-market ratio. As it turns out, IPO firms differ in important ways from non-IPO firms matched on size and book-to-market ratio, and they typically have lower average realized returns.

We start by showing that IPO firms on average have lower average debt-to-asset ratio and higher stock liquidity (measured as stock turnover) in at least three of the five years following the IPO. While we do not provide a theory for why IPO firms should have low leverage, it is possible that firms self-select the IPO date in response to private information about favorable future investment opportunities. When this information becomes public (as a result of the IPO event), the resulting market capitalization joins the IPO equity infusion in lowering leverage ratios. In any event, since leverage "turbo-charges" stock returns [Galai and Masulis (1976)], and since greater stock liquidity is a potential risk-reducing factor [e.g., Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998)], it follows that these characteristics support lower *expected* returns to IPO stocks. As explained below, we examine this possibility explicitly in the context of alternative asset pricing models.

Our descriptive analysis also includes new evidence on the nature of IPO stocks as "longshots". Specifically, we show the frequency of extreme events such as delistings due to either liquidations or acquisitions, as well as overall frequency of extreme return realizations (including -100% and greater than 1000%). Perhaps surprisingly, IPO stocks are *not* particularly unusual in terms of the frequency of either liquidations or acquisition events. However, IPO stocks do exhibit a greater frequency than non-IPO stocks of extreme, positive return realizations.

We perform two distinct and separate asset pricing tests. The first exploits our finding that the average IPO stock has greater liquidity (turnover) than non-IPO stocks for most of the five years following the IPO. To directly test the hypothesis that the greater liquidity lowers expected stock return, we add a liquidity risk factor to a model containing the three factors of Fama and French (1993) as well as a momentum factor [Carhart (1997)]. To our knowledge, this is the first empirical asset pricing model containing a pervasive liquidity factor, computed as the return differential between portfolios of low-liquidity and high-liquidity stocks. Interestingly, when sorting the CRSP stock universe into 25 portfolios based on size and book-to-market-ratio, we find that this liquidity factor tend to perform as well as the well-known momentum factor. Moreover, as predicted, the liquidity factor reduces the expected return to our portfolio of IPO stocks relative to the portfolio of non-IPO matched firms.

The second set of asset pricing tests utilizes an empirical factor model in the tradition of the intertemporal asset pricing model of Merton (1973) and the arbitrage pricing theory (APT) of Ross (1976). The macroeconomic risks include real consumption growth, measures of changes in the yield curve slope, and changes in the default spread.[2] In addition to illuminating potential "bad model" problems in the context of long-horizon returns [Fama (1998)], we offer two major reasons for being agnostic when it comes to selecting the empirical asset pricing model. The first is that our evidence of lower leverage in IPO firms leads us to predict a lower IPO-stock exposure to risk factors such as default risk and bond market yields. Our estimates of the factor contributions to expected IPO portfolio excess return supports this prediction.

Our second motivation for exploring a model with macroeconomic risks has to do with statistical power in the presence of market sentiment. A model with macroeconomic risk factors have better power characteristics than the Fama-French model (and our extension of it) under the sentiment hypothesis. The reason is simple: regardless of the conjectured market mispricing, the weights in our APT factor mimicking portfolios are constructed to track the underlying macroeconomic risk. If the macroeconomic target (such as aggregate consumption) is unaffected by market sentiment, then the tracking portfolio is arguably less influenced by market sentiment than an unconstrained factor portfolio of stocks.

The overall conclusion from our factor model estimation is that investing in IPO stocks yields a significant but "normal" risk premium. That is, with holding periods up to five years, IPO

[2] Our choice of risk factors reflects, among others, Chen, Roll, and Ross (1986), Ferson and Harvey (1991), Shanken (1992) Evans (1994), Ferson and Korajczyk (1995), and Ferson and Schadt (1996).

excess returns are positive and reflect risk exposures attenuated by both lower leverage and greater liquidity. The resulting estimates of abnormal returns are not reliably different from zero. The combination of low realized excess return and insignificant abnormal performance further suggests that our evidence of a greater frequency of extreme returns observations (-100% and greater than +1,000%) is best interpreted as firm-specific, non-priced risk. Moreover, given our evidence, it is unlikely that these extreme events reflect differential frequencies of either takeovers or liquidations relative to the average non-IPO matched firm.

The paper is organized as follows. Section 2 contains a description of the data and key sample characteristics, including leverage, liquidity, 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. The factor model with macroeconomic risk factors is presented in Section 3. The factor model estimation is also performed on portfolios of matched firms (matching on size as well as on size and book-to-market ratios), and on a "zero-investment" portfolio long in matched firms and short in the IPO stocks. Since the zero-investment portfolio represents the difference between IPOs and their matches, results based on this portfolio are relatively robust with respect to omitted factor bias. Section 4 presents the general liquidity risk factor and applies it to our IPO portfolio, while Section 5 concludes the paper.

2 Sample Characteristics

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.[3] These sources generate a total sample of 6,379 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)

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

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. This reflects the fact that more than 90% of the IPOs over the 28-year period took place on Nasdaq.

Figure 1 shows the annual distribution of the 6,379 IPOs in our total sample. Compustat provides book-to-market data for 5,456 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.

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 the Nasdaq stock exchange at the end of the year prior to the IPO. 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 are 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 looking maximum three years forward. 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 \$76 mill. with issue proceeds equaling 39% of its equity size. The average book-to-market ratio is 0.32. 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 Buy-and-hold returns

It is common in the long-run performance literature to report the cross-sectional average of compounded (holding period) returns, also referred to as "buy-and-hold average return" ($BHAR$). 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.[4] For a sample of N stocks, $BHAR$ is given by

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

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

$$BHAAR_{IPOs} \equiv BHAR_{IPOs} - BHAR_{matches}. \tag{2}$$

Table 2 shows the values of $BHAR$ and $BHAAR$ using control firms matched on size and both size and book-to-market ratio. Notice first that when using value-weighting, there is no evidence of IPO underperformance. Thus, in the following, we focus on the results for equal-weighted returns.

Panel (A) shows that for the full sample of 6,379 IPOs the equally weighted $BHAR$ for issuers is 40.4%. 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

[4]While not shown here, using shorter holding periods (1-year, 2-year, .. 4-year) does not alter the main conclusions of this paper.

Ritter (1995). The discrepancy between our result and the result of Loughran and Ritter (1995) is due to the extremely low returns earned by companies that went public during the period 1970–1972. The equal-weighted $BHAR$ for size-matched firms is 68.7%, resulting in a relative IPO underperformance of $BHAAR = -28.8\%$, which compares to the $BHAAR$ 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 $BHAR$ between issuers and the size and book-to-market matched firms is now an insignificant 2.2%. Interestingly, this result is sensitive to the selection of Compustat information on book values. The insignificant 2.2% underperformance results when missing Compustat book value information is replaced by bringing back the first future book value observation (maximum of three years out). While this is the standard procedure in the extant literature, it carries with it a survivorship bias. The last panel in Tables 2 computes $BHAR$ and $BHAAR$ free of this survivorship bias. That is, a firm is included only as of the date the book value information is available on Compustat. The value of $BHAAR$ is now -11.7%, which is statistically significant on a 7% level.

Turning to Panel (C) of Table 2, we see that IPO underperformance measured using $BHAAR$ is greater during the "hot issue" period 1980–1984: -33.4% using size and book-to-market matching without survivorship bias. Greater underperformance following periods with greater issue activity is consistent with the "window-of-opportunity" hypothesis which holds that some issuers successfully time the IPO to periods where the market is more likely to overprice new issues (Ritter, 1991; Loughran and Ritter, 1995, 2000). Panel (C) shows that this IPO underperformance is *not* eliminated by matching on book-to-market ratio. A similar finding is reported in Loughran and Ritter (2000).

2.3 Post-IPO portfolio 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, whatever comes first. The first month of the portfolio is January 1973 and the last month is December 2000. Thus, there are a total of 336 monthly portfolio return observations over the 28-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 6,379 IPOs, the average monthly return is 1.14% given equal-weighted portfolio returns. However, a more interesting number is the monthly growth rate R implied by a \$1 initial investment in January 1973 growing to become \$X=16.88 by December 2000. This growth rate is given by

$$R = e^{\ln(X)/T} - 1 \tag{3}$$

where "ln" denotes the natural logarithm and T is the number of months in the estimation (=336). As shown in Panel (B), R equals 0.84% per month for the equal-weighted issuer portfolio, 1.14% for the portfolio of size-matched firms, and an intermediate 1.05% for the portfolio of firms matched on both size and book-to-market ratio. R is generally lower when portfolios are value-weighted.

The different growth rates of the issuer and matched firm portfolios are illustrated in Figure 2 - Figure 4. In each figure, the right side legend indicates the identity of the portfolio and its weighting scheme (EW=equal-weighting; VW=value-weighting). Moreover, the terminal value of the initial \$1 investment, as well as the implied growth rate R, are given in parentheses. Figure 2 shows equal-weighted portfolios over the total sample period, and highlights the market-wide poor performance of the early years 1972-74. In fact, as shown in Figure 3, if the starting point for the portfolio strategy is moved up to January 1975, the implied growth rates increases substantially for all portfolios. Finally, Figure 4 shows the effect of value-weighting, again using the full sample period 1973-2000.

Several conclusions emerge. First, regardless of the weighting scheme, the issuer portfolio performs better than the risk-free asset but substantially worse than the Nasdaq market index. In Figure 2, the issuer portfolio underperforms the market index by 0.26% per month, or by 15.6% over the five-year holding period. Over the same period, the issuer portfolio underperformed the portfolio of size-matched firms by 18.0% and the size and book-to-market matched firms by 12.6%. These percentages compare to the underperformance of 26.6% and the overperformance of 2.2% 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 338 months in the total sample period, while $BHAR$ gives equal weight to each IPO *event*), there is nevertheless evidence of significantly lower long-run returns to IPOs than to control firms matched on size and book-to-market ratio.[5]

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.

Figure 5 – Figure 8 address this possibility. Figure 5 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) than are 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 6 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 Figure 6. However, the figure provides no basis for such an inference: if anything, in most years, the frequency of these takeover events appear *lower* than for non-IPO stocks.

Figure 7 and Figure 8 further indicate the nature of IPO stocks as "longshots". Figure 7 show 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 either size-matched firms or firms matched on both 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 is true for both populations of matched firms, and it is consistent with the evidence in Figure 5.

On the other hand, there is some evidence in Figure 8 that IPO stocks have a greater probability

[5] Again, the effect of value-weighting is to nearly eliminate this underperformance (Figure 4). This is not surprising as value-weights favors larger, more successful stocks.

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 6, 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 liquidity

Table 3 shows average leverage ratios and measures of stock liquidity for the issue year and each of the five years following the issue. Panel (A) 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 firm-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.

Panel (B) of Table 3 shows the average annual values of our measure of liquidity: monthly turnover computed as trading volume divided by the number of shares outstanding. With this measure, IPO stocks are significantly more liquid than either size-matched or size/BM-matched firms in each of the five years starting in year 1. Also, IPO stock liquidity tends to be greatest in the year of the issue.

3 Leverage and expected returns

In this section we report abnormal returns to portfolios of issuing and matched firms defined using a factor model with leverage-related risk factors. The regression results help answer the question of whether the relatively low returns to IPO stocks shown earlier is consistent with standard risk arguments. The most powerful answer to this questions comes from examining the abnormal return to a zero-investment portfolio strategy where one shorts the IPO stock and goes long in the matched firm, with a holding period of five years.

3.1 Model specification and factor mimicking

Let r_{pt} denote the return on portfolio p in excess of the risk-free rate, and assume that expected excess returns are generated by a K-factor model,

$$E(r_{pt}) = \beta_p' \lambda, \tag{4}$$

where β_p is a K-vector of risk factor sensitivities (systematic risks) and λ is a K-vector of expected risk premiums. This model is consistent with the APT model of Ross (1976) and Chamberlain (1988) as well as with the intertemporal (multifactor) asset pricing model of Merton (1973).[6] The excess-return generating process can be written as

$$r_{pt} = E(r_{pt}) + \beta_p' f_t + e_{pt}, \tag{5}$$

where f_t is a K-vector of risk factor shocks and e_{pt} is the portfolio's idiosyncratic risk with expectation zero. The factor shocks are deviations of the factor realizations from their expected values, i.e., $f_t \equiv F_t - E(F_t)$, where F_t is a K-vector of factor realizations and $E(F_t)$ is a K-vector of factor expected returns.

Regression equation (5) requires specification of $E(F_t)$, which is generally unobservable. However, consider the excess return r_{kt} on a "factor-mimicking" portfolio that has unit factor sensitivity to the kth factor and zero sensitivity to the remaining $K-1$ factors. Since this portfolio must also satisfy equation (4), it follows that $E(r_{kt}) = \lambda_k$. Thus, when substituting a K-vector r_{Ft} of

[6] Connor and Korajczyk (1995) provide a review of APT models.

the returns on factor-mimicking portfolios for the raw factors F, equations (4) and (5) imply the following regression equation in terms of observables:

$$r_{pt} = \beta_p' r_{Ft} + e_{pt}. \tag{6}$$

Equation (6) generates stock p's returns. Thus, inserting a constant term α_p into a regression estimate of equation (6) yields an unbiased estimate of abnormal return. We employ monthly returns, so this "Jensen's alpha," first introduced by Jensen (1968), measures the average monthly abnormal return to a portfolio over the estimation period.

As listed in Panel (a) of Table 4, the model contains a total of six factors: the value-weighted CRSP market index (RM), 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 (1994), Ferson and Korajczyk (1995), and Ferson and Schadt (1996).[7]

Of the six factors, three are themselves security returns, and we create factor-mimicking portfolios for the remaining three, RPC, BAA$-$AAA, and UI. Factor-mimicking portfolio are constructed by first regressing the return of each of the 25 size and book-to-market sorted portfolios of Fama and French on the set of six factors. These 25 time-series regressions produce a (25×6) matrix B of slope coefficients against the six factors. If V is the (25×25) covariance matrix of error terms for these regressions (assumed to be diagonal), then the weights used to construct mimicking portfolios from the 25 Fama-French portfolios are formed as

$$w = (B'V^{-1}B)^{-1}B'V^{-1}. \tag{7}$$

[7]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.

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 $\widehat{\Delta \text{RPC}}$, $\text{BA}\widehat{\text{A} - \text{A}}\text{AA}$, and $\widehat{\text{UI}}$.

As shown in Panel (B) of Table 4, 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 4 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.[8] Turning to Panel (D) of Table 4, 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.

We now turn to the estimation of this macro-factor model using portfolios of IPO stocks and their control firms.

3.2 Performance estimates

We estimate the parameters in the following macro-factor model:

$$r_{pt} = \alpha_p + \beta_1 \text{RM}_t + \beta_2 \widehat{\Delta \text{RPC}}_t + \beta_3 (\text{BA}\widehat{\text{A} - \text{A}}\text{AA})_t + \beta_4 \widehat{\text{UI}}_t + \beta_5 (20\text{y} - 1\text{y})_t + \beta_6 \text{TBILLspr}_t + e_t, \tag{8}$$

where e_t is a mean zero error term in month t, and the constant term (Jensen's alpha) is the average monthly abnormal return to portfolio p. The model is estimated using OLS with standard errors computed using the heteroscedasticity-consistent estimator of White (1980).

Table 5 reports total sample estimates of Jensen's alpha and factor loadings for six portfolios: equal-weighted (EW) and value-weighted (VW) portfolios consisting of IPO-stocks only ("Issuer"), size-matched firms only ("Match"), and the zero investment portfolio short in IPO stocks and long in the matched firms ("Zero"). Thus, for IPO stocks to underperform the matched firms

[8] Let b_k be the kth row of B. The weighted least squares estimators in (7) 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 4, that differ from one.

(which would be consistent with the evidence presented earlier), the estimate of alpha for the zero investment portfolio must be positive.

Notice first that nine of the twelve alpha estimates in Table 5 are negative and all are insignificant. The overall conclusion is that the monthly abnormal performance of IPO stocks is statistically indistinguishable from the average monthly abnormal performance of the corresponding portfolio of matched firms. In other words, the apparent underperformance of IPO stocks generated by the matched firm technique is eliminated once we take into account the differential exposures (factor loadings) of IPO stocks and matched firms to the macroeconomic risk factors in our regression model.

Turning to the individual factor loadings reported in Table 5, IPO stocks have a significantly greater exposure than matched firms to the market factor (RM). The market beta for IPO stocks is 1.38-1.43 for the equal-weighted portfolio and 1.58-1.62 for the value weighted portfolio (Panels A and B). The corresponding beta ranges from 0.97-1.26 for the equal-weighted portfolios of matched firms and from 1.07-1.33 for value-weighted matched firms. In other words, this risk factor *reduces* the expected return to our zero-investment portfolio (since this portfolio is short in issuer stocks). Thus, the contribution of the market risk factor itself is to make the evidence of low IPO long-run returns even more puzzling. For this underperformance to be explained in terms of compensation for differential risk exposure, there must exist other, non-market risk factors that reduces the expected return to IPO stocks relative to size-matched firms.

Table 5 shows that, of the other non-market risk factors, the percent change in real per capita consumption of non-durable goods (ΔRPC) is statistically significant and positive for each of the issuer- and match portfolios. Thus, expected portfolio returns are increasing in this factor. However, since the factor loadings are almost identical across the two portfolios (with a value of 0.06 for EW-Issuer and 0.05 for EW-Match), this particular risk factor does not contribute to our understanding of the *differential* risk exposure of IPO stocks versus size-matched firms.

The third risk factor in Table 5, the credit spread (BAA–AAA) is also statistically significant. However, in light of the estimated factor loadings, this factor also does not contribute much to explain the differential return on the issuer- and matched-firm stocks. Interestingly, the remaining three risk factors combine to more than offset the strong impact of the market index on issuer expected returns. First, while unexpected inflation (UI) increases the expected return to the equal-weighted portfolio of issuers, it does so only marginally and by a smaller amount than the matched firms (the factor loadings are .05 and .04 for EW-issuer and EW-Match, respectively). Overall, although the magnitude is small, there is a tendency for shocks to unexpected inflation to lower issuer returns relative to matched-firm returns.

Most of the offsetting effect comes from the long-term spread (20y–1y) and the short T-bill spread (TBILLspr). Both factors produce relatively large factor loadings and they reduce the expected return to issuer firms. Equal-weighted portfolios have significant loadings on the term spread factor, while the factor loadings on the T-bill-spread factor are insignificant. Overall, the evidence in Table 5 indicate that while issuing firms have higher exposure to market risk, the effect of the market factor is more than offset by lower post-issue exposure to unanticipated inflation and the spreads at both the short- and the long ends of the term structure.

A consistent explanation is that, since the IPO lowers leverage, issuers' exposures to unexpected inflation and term premium risks decrease, thus decreasing their stocks' expected returns relative to matched firms. The result is a value of Jensen's alpha for the zero-investment portfolio that is insignificantly different from zero.[9]

4 Liquidity and expected returns

4.1 Liquidity factor construction

Brennan and Subrahmanyam (1996), Datar, Naik, and Radcliffe (1998), and Brennan, Chordia,

[9]The above estimation of model (8) 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. After substituting this equation back into Eq. (6), the return-generating process becomes

$$r_{pt} = b_{p0}' r_{Ft} + b_{p1}' (Z_{t-1} \otimes r_{Ft}) + e_{pt}, \tag{9}$$

where the KL-vector b_{p1} is $\mathrm{vec}(B_{p1})$ and the symbol $\otimes$ denotes the Kronecker product. (The operator $\mathrm{vec}(\cdot)$ 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.

and Subrahmanyam (1998) find that stock expected returns are cross-sectionally related to stock liquidity measures. In particular, share turnover appears to be a priced asset characteristic that lowers a stock's expected return. This suggests that, since IPO firms have significantly higher liquidity than matched firms (Table 3), they are also less risky and should command lower expected returns than the matched firms over the post-issue period.

We examine this proposition using a factor model that includes liquidity as a risk factor. This serves to link our IPO performance analysis to the asset pricing literature more generally, and it provides new information on the role of liquidity as a determinant of expected returns. Absent a theoretically "best" definition of liquidity, our approach is agnostic, and we use monthly turnover, defined as the number of shares traded over the month divided by number of shares outstanding, to construct the liquidity factor.

We construct the liquidity factor, named TO, using an algorithm similar to the one used by Fama and French (1993) when constructing their size (SMB) and book-to-market ratio (HML) factors. To construct TO, we start in June of year t, use all NYSE, AMEX, and Nasdaq listed common stocks, and form two portfolios based on a ranking of the end-of-month market value of equity and three portfolios formed using stocks ranked on turnover. The portfolio breakpoints are based on NYSE listed stocks only.

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 July year t and ending in June the following year. The TO factor 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.[10] When Fama and French constructed their SMB and HML factors, the idea was to "mimic the underlying risk factors in returns related to size and book-to-market equity." Their procedure tries to accomplish this goal by making sure that the average size for the firms in the three book-to-market portfolios is the same, while also maintaining the same average book-to-market ratio for the two size portfolios. The idea behind TO is similar, but we try to capture the risk factor in return related to liquidity.

Having constructed the liquidity factor, we place this factor in a five-factor model that in

[10] Comparing this procedure with the one used by Fama and French to create SMB and HML, TO "plays the role" of the book-to-market factor.

addition includes the three Fama-French factors (the market index RM, SMB, and HML), as well as a momentum mimicking portfolio labeled UMD.[11] The momentum factor is constructed in a similar way as the momentum factor used by Carhart (1997). Six value-weight portfolios are formed as the intersections of two portfolios formed on market value of equity (size) and three portfolios formed on prior twelve month return. The monthly size breakpoint is the median NYSE market value of equity. The breakpoints for the prior twelve month returns are the 30th and 70th NYSE percentiles. 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.

Table 6 shows the mean, standard deviation and pairwise correlations for the five risk factors. In Panel A, notice that the mean return the liquidity factor is positive. Recall that the factor is a portfolio long in low-liquidity stocks and short in high-liquidity stocks. Thus, to the extent that illiquid stocks are more "risky" than liquid stocks, they have higher average returns and thus the factor portfolios have positive returns on average. Panel B of Table 6 shows that the HML portfolio is positively related to TO. This is likely a reflection of the fact that it is constructed in the same way as HML relative to size sorted portfolios. The momentum mimicking portfolio (UMD) does not show any strong correlation with the other characteristic-based mimicking factors, suggesting that these portfolios mimic underlying risk factors not captured by the other factor portfolios.

4.2 Model estimates

Table 7 shows estimates of the five-factor model for each of the Fama-French 25 size and book-to-market sorted portfolios. The table shows that adding the UMD factor and the TO factor to the three-factor model of Fama and French (1993) improves the general model fit for most portfolios. Interestingly, the liquidity risk factor TO appears to add at least as much explanatory power as the momentum factor UMD.

Next, we apply the new factor model to the portfolio returns of IPOs and matched firms. The results are shown in Table 8. Starting with the original Fama-French model in the top half of panel (A), there is little evidence of significant IPO underpricing. Jensen's alpha for the equal-weighted zero-investment portfolio is an insignificant -0.12% (p-value of 0.313), while value-weighting produces a Jensen's alpha of 0.095, also statistically insignificant. Moreover, moving to the expanded

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

model in the second half of panel (A), the alphas of the zero-investment portfolios are again uniformly insignificantly different from zero. A very similar conclusion holds for Panel (B) where the control firms are matched on size and book-to-market ratio.

As seen in Table 8, adding the momentum and liquidity factors only slightly improves the fit of the original Fama-French regression. For example, for the equal-weighted, zero-investment portfolio in Panel (A), the R^2 increases from 0.531 in the Fama-French model to 0.543 in our expanded model. With value-weighted portfolios, the increase in R^2 is from 0.503 to 0.550. Notice also that for value-weighted portfolios, adding the three factors appears to reduce the significance of the original book-to-market (HML) factor.

The momentum factor UMD is generally insignificant a 5% level, with the single exception of the value-weighted matched firm portfolio in Panel (B). In contrast, the liquidity factors receives a significant factor loading in several of the portfolios, including all of the zero-investment portfolios. The factor loading on TO is generally negative, as expected. Greater liquidity lowers expected return, and the reduction is greater for issuer stocks than for the matched firms in Table 8.

Finally, we also apply the extended Fama-French model to a portfolio of *seasoned* equity offerings (SEOs). The sample is compiled by Eckbo, Masulis, and Norli (2000) and contains a total of 3,315 SEOs from the period 1964–1997 (see the original paper for sample characteristics). While Eckbo, Masulis, and Norli (2000) find that SEO firms have higher liquidity than the (size-based) matched firms, they do not explicitly test for the risk reducing effects of liquidity. Thus, the SEO portfolio provides both an independent portfolio test of the impact of our TO factor and an opportunity to confirm the conjecture of Eckbo, Masulis, and Norli (2000) that the greater liquidity of SEO stocks reduces SEO stock expected return relative to matched firms.

The results are shown in Table 9. The matched firms are identified by the earlier paper and matches on equity size only. The conclusion is similar to that for IPO stocks: The liquidity factor is statistically significant and contributes to a greater extent than the momentum factor to the expected returns of issuers. Specifically, judging from the zero-investment portfolio, the net effect of the liquidity factor is to reduce the expected return to SEO stocks.

5 Conclusion

This paper addresses the controversy over the nature and determinants of the generally low long-run IPO stock returns. With a sample of 6,000+ Nasdaq IPOs from 01/73–12/98, we report several findings that help understand the economic source of the low IPO return realizations. Although IPO stocks tend to be among the class of small growth stocks, the low returns are not fully explained by the returns on non-IPO stocks matched on size and book-to-market ratio. Rather, there is a tendency for IPO stocks to underperform these matched firms as well.

We investigate the risk-return relationship for IPO stocks within a rational, multifactor asset pricing framework. The choice of factors is in part suggested by our finding that IPO stocks have significantly lower leverage ratios and exhibit greater liquidity than other small growth stocks. Since leverage "turbo charges" stock returns, reducing leverage also reduces the stock's exposure to leverage-related risk factors. We find that this is the case in a factor model with macroeconomic risks such as the default spread, the term spread and unexpected inflation. This factor model also prices the IPO portfolio in the sense of producing a statistically insignificant intercept term (Jensen's alpha).

Moreover, 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 a new liquidity risk factor introduced here. The liquidity factor is constructed as the return differential between a portfolio of low-liquidity stocks and a portfolio of high-liquidity stocks. There is theoretical reason to suspect that such a factor is priced, and we show that the factor indeed produces factor loadings of a magnitude and significance comparable to that produced by the momentum factor. When applied to the IPO portfolio, the liquidity factor reduces expected portfolio return, as predicted. A similar conclusion emerges when applying the same factor model to the portfolio of seasoned equity offerings studied in Eckbo, Masulis, and Norli (2000). The factor model prices both the IPO and the SEO portfolios in the sense of producing insignificant intercept terms.

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 little evidence that IPO stocks exhibit a chance of delisting that differs from the typical non-IPO stock. 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. 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. On the other hand, the extra probability mass fits with the popular notion of IPO stocks as "longshot" bets on large, future returns.

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Figure 1
Annual distribution of the sample of 6,379 Nasdaq-IPOs with offer dates between 1972–1998.

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

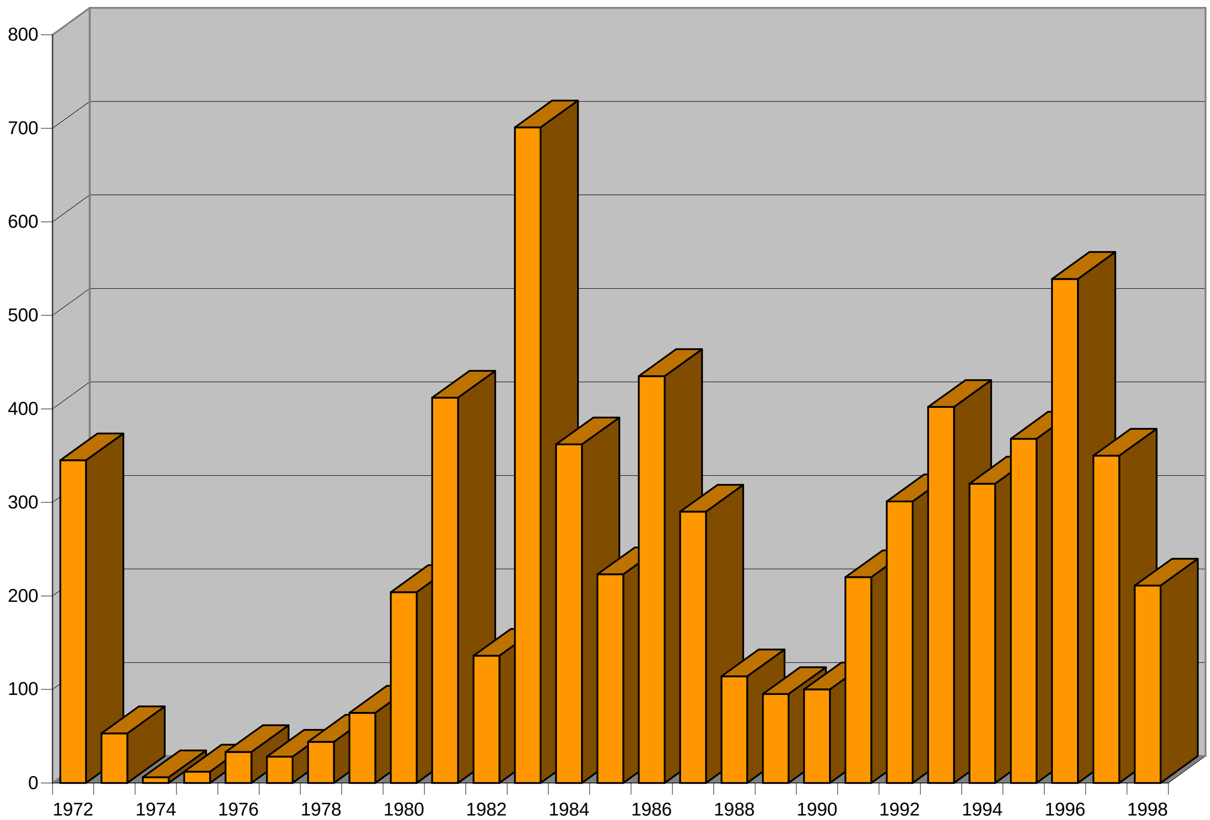

Figure 2
Compounded returns on the equal-weighted (EW) CRSP Nasdaq index, an EW portfolio of 6,379 Nasdaq-IPOs, an EW portfolio of matching firms, and 30-day Treasury bills, 1973–2000.

The graphs depicts how the value of a $1 investment evolves over the sample period January 1973 to December 2000. The terminal value of the $1 investment and the implied average monthly growth rate are shown in parentheses.

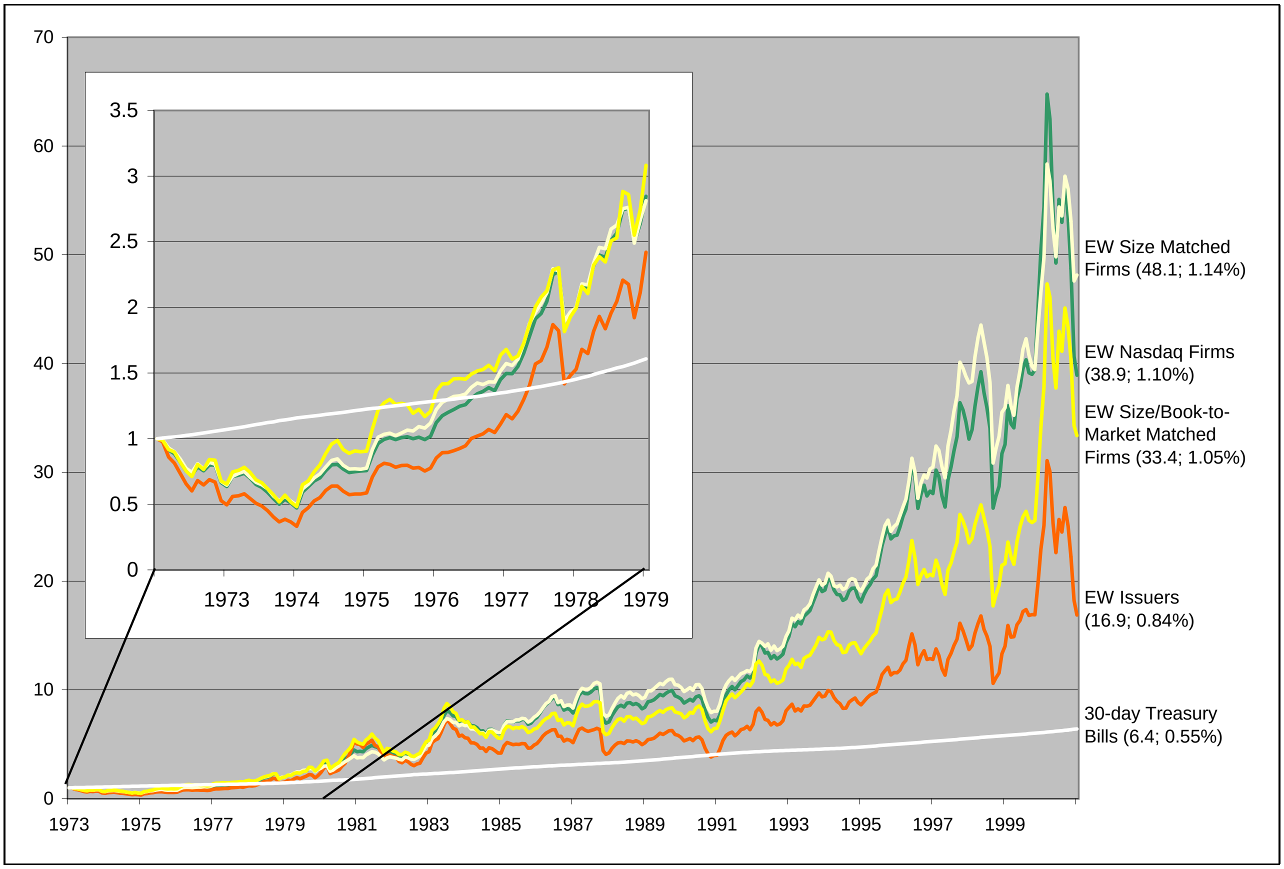

Figure 3
Compounded returns on the EW CRSP Nasdaq index, an EW portfolio of Nasdaq-IPOs, an EW portfolio of matching firms, and 30-day Treasury bills, 1975–2000.

The graphs depicts how the value of a $1 investment evolves over the sample period January 1975 to December 2000. The terminal value of the $1 investment and the implied average monthly growth rate are shown in parentheses.

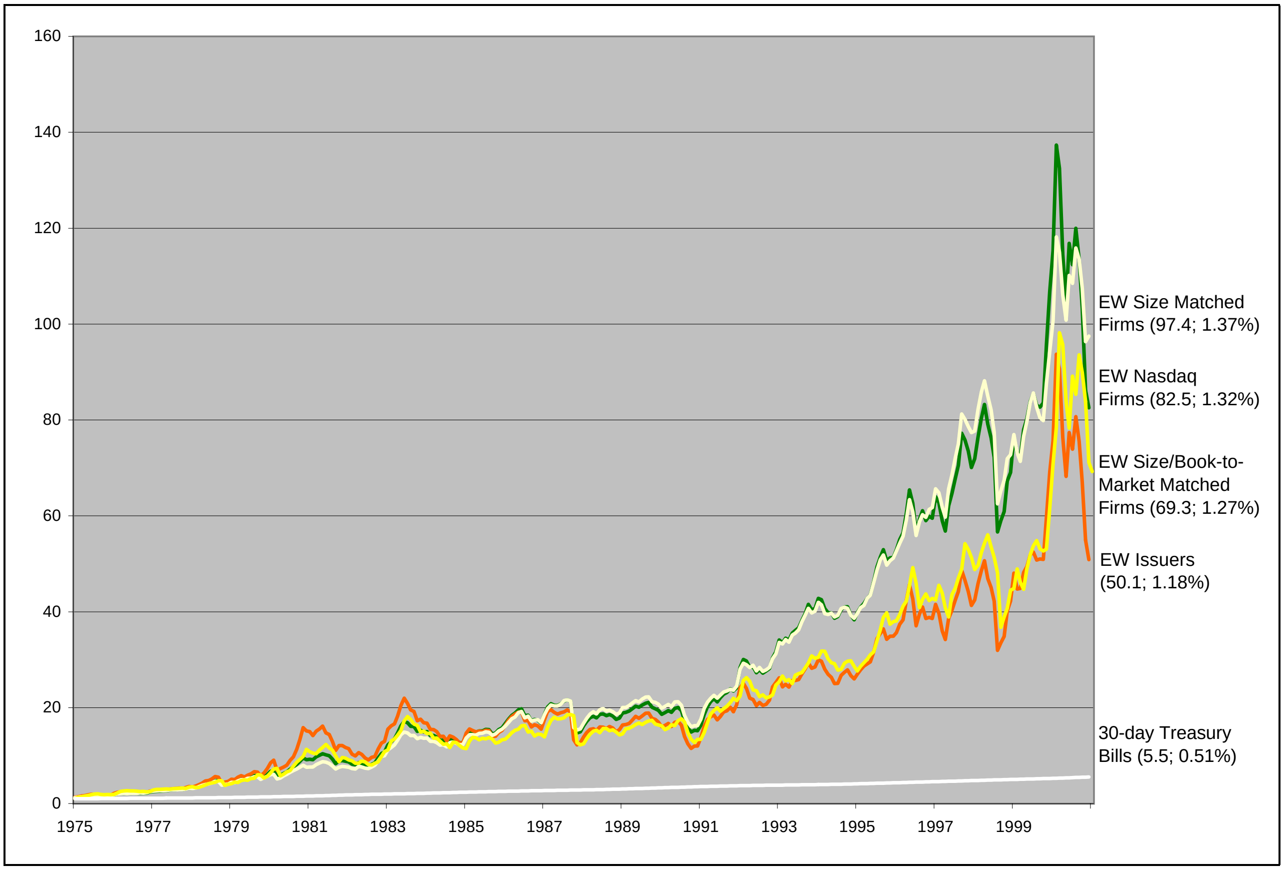

Figure 4
Compounded returns on the value-weighted (VW) CRSP Nasdaq index, a VW portfolio of Nasdaq-IPOs, a VW portfolio of matching firms, and 30-day Treasury bills, 1973–2000.

The graphs depicts how the value of a $1 investment evolves over the sample period January 1973 to December 2000. The terminal value of the $1 investment and the implied average monthly growth rate are shown in parentheses.

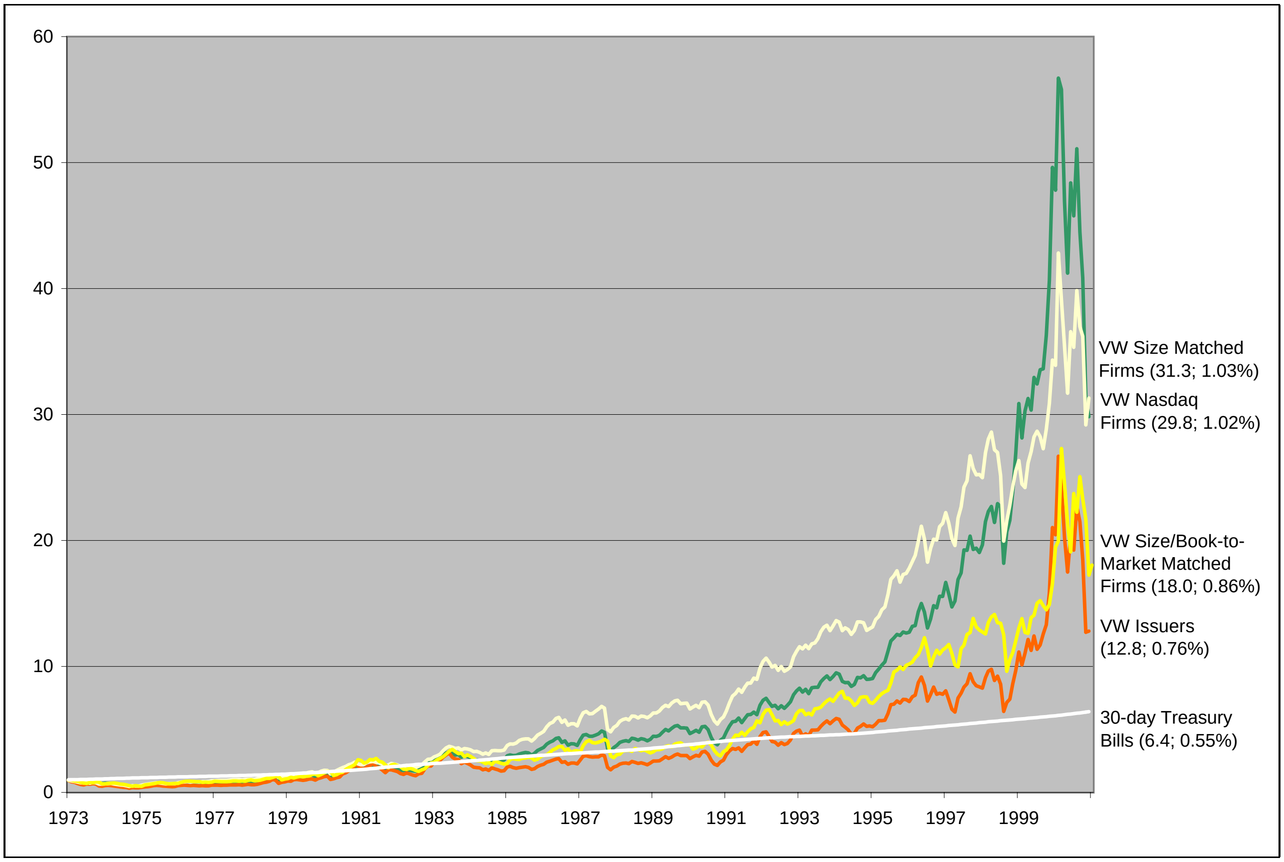

Figure 5
Annual frequency of delistings of IPO and non-IPO stocks due to liquidation, 1973–1998

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.

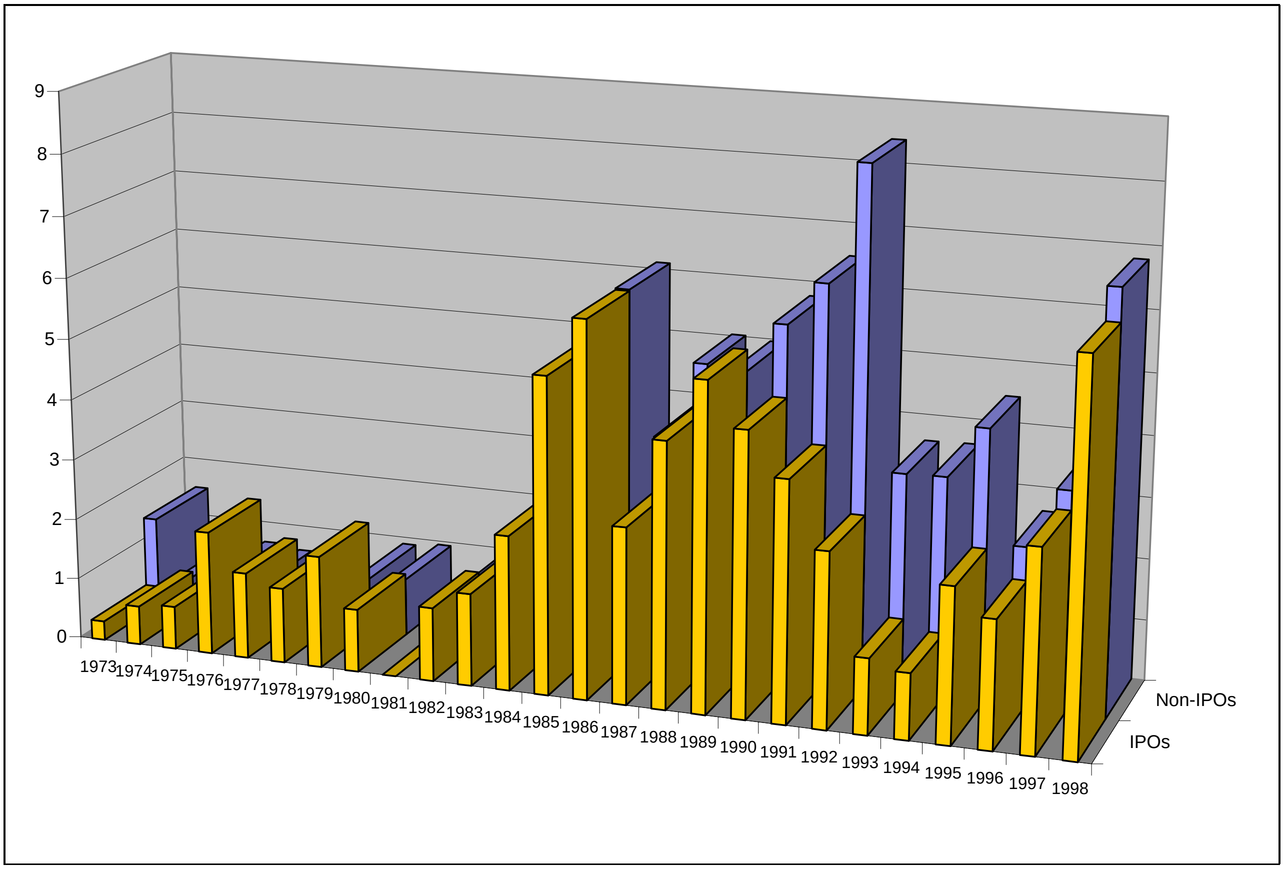

Figure 6
Annual frequency of delistings of IPO and non-IPO stocks due to merger or takeover, 1973–1998

Number of delistings due to merger, takeover, exchange offers, or other events where common shareholders are bought out. 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.

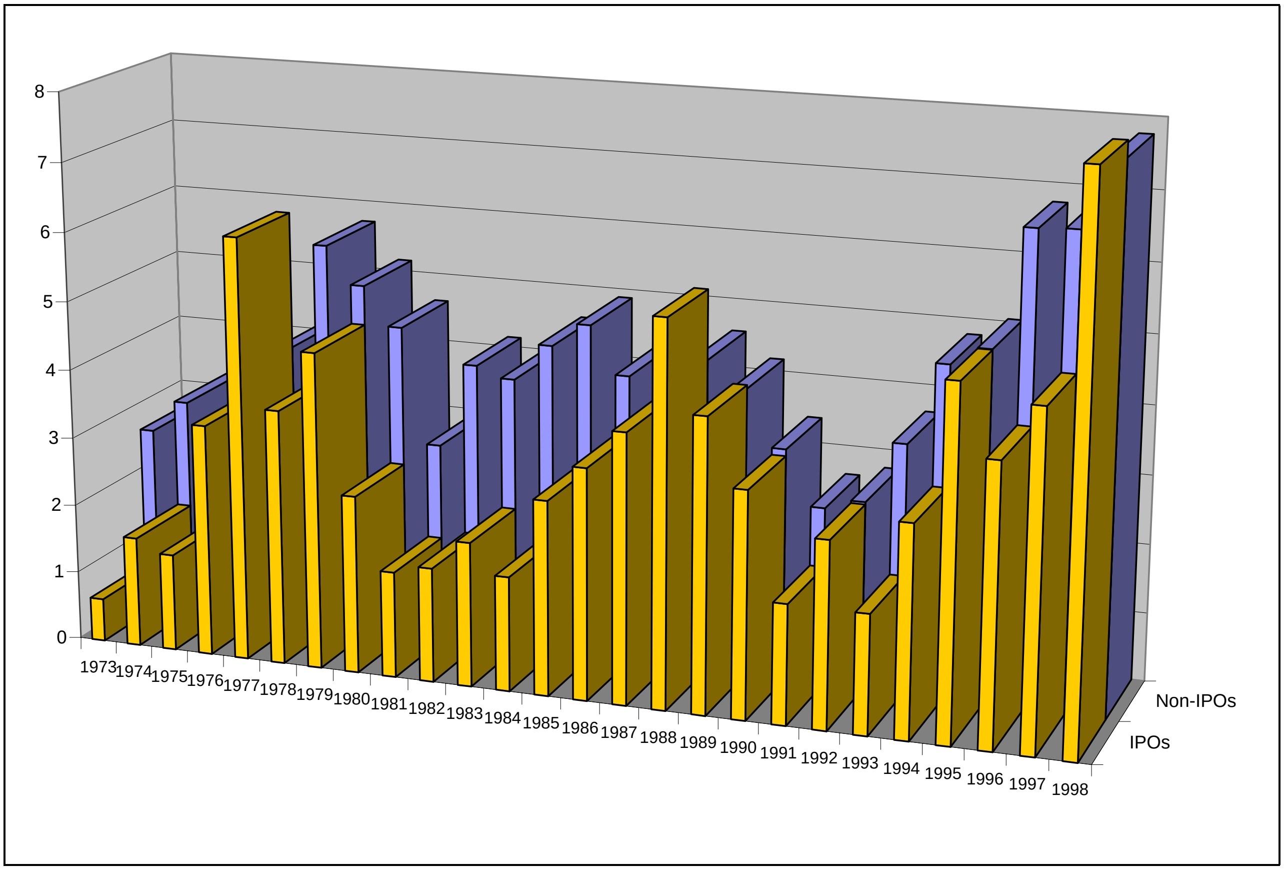

Figure 7
Histogram of five-year holding period returns between −100% and 500% for IPO stocks and matched control firms, 1973–1998

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 whithin this 2 percentage point interval.

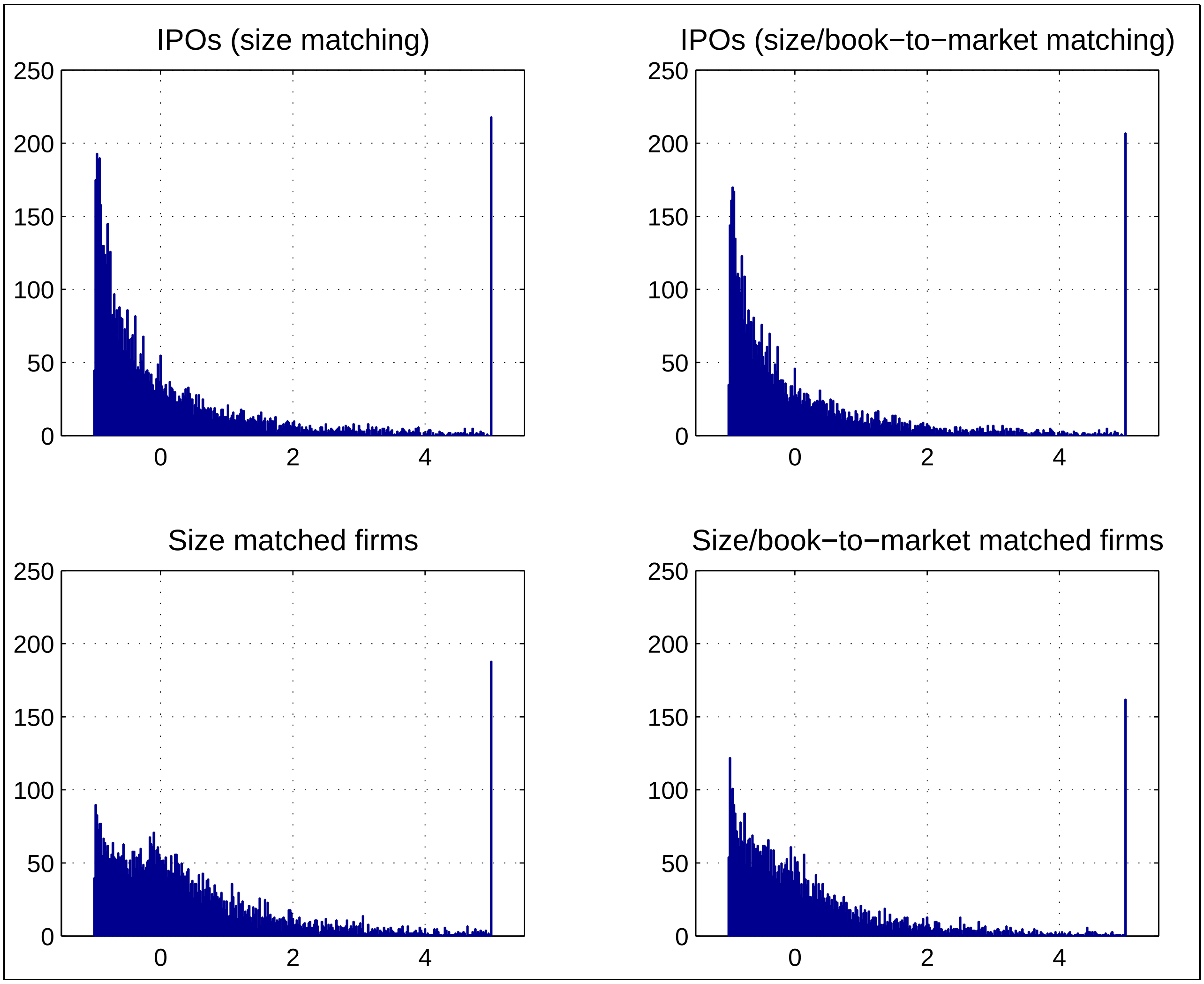

Figure 8
Histogram of five-year holding period returns between 100% and 1000% for IPO stocks and matched control firms, 1973–1998

Each bar in the histogram represent a 50 percentage point interval, and the height of the bar shows how many firms had a five-year holding period return within this 50 percentage point interval.

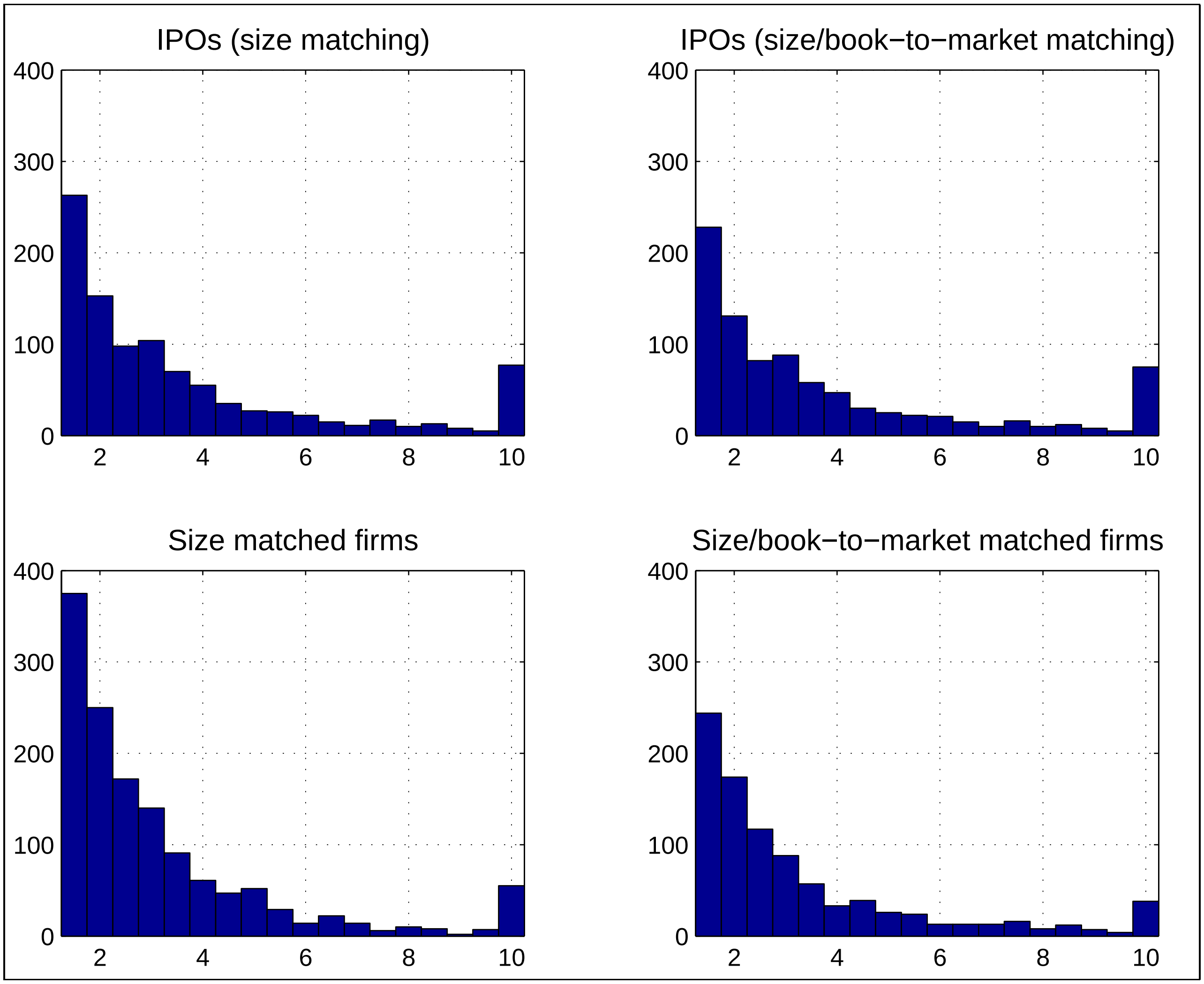

Table 1
Firm portfolio characteristics for IPOs between 1972 and 1998 and the non-IPO control firms matched on size and size/book-to-market ratio. All issuers and matching firms are listed on Nasdaq.

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 6,379. The equal weighted and value weighted issuer and match portfolios are constructed using monthly returns between January 1973 and December 2000, which gives 336 monthly returns for each portfolio.

	Size matching		Size/Book-to-market matching	
	Issuer	Match	Issuer	Match
(A) Average issuers and matching firms characteristics				
Size (market capitalization)	76.41	76.37	82.89	83.17
Book value of equity	—	—	26.49	26.80
Book-to-market ratio	—	—	0.385	0.386
Issue proceeds/size	0.391	—	0.322	—
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	1.14	1.31	1.20	1.30
Median percent return	1.54	1.54	1.44	1.44
Standard deviation of returns	7.70	5.38	7.90	7.00
End-value of a $1 investment	16.88	48.14	19.47	33.37
Implied average return to compound	0.84	1.14	0.89	1.05
Value weighted portfolios				
Mean percent return	1.12	1.19	1.23	1.11
Median percent return	1.21	1.76	1.28	1.47
Standard deviation of returns	8.45	5.59	8.62	7.02
End-value of a $1 investment	12.80	31.31	17.63	18.04
Implied average return to compound	0.76	1.03	0.86	0.86
Equal and value weighted portfolios				
Number of issuers and matches	6,379	6,379	5,456	5,456
Minimum number of firms in portfolios	86	86	71	71
Maximum number of firms in portfolios	1,722	1,722	1,678	1,678
Average number of firms in portfolios	888	888	776	776

Table 2
Five-year buy-and-hold stock percent returns (BHAR) to firms going public between 1972 and 1998 and their matched control firms, classified by type of matching procedure (size/size-and-book-to-market), sample period, and portfolio weights (equal-/value-weighted). All issuers and matching firms are listed on Nasdaq.

Buy-and-hold percent returns are defined as:

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

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 average 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 $N(0,1)$.

	Size matching					Size/book-to-market matching				
	N	Issuer	Match	Diff	$p(t)$	N	Issuer	Match	Diff	$p(t)$
(A) Total sample										
EW	6379	40.4	69.1	−28.8	0.000					
VW	6379	68.7	78.6	−10.0	0.302					
(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	5456	45.2	71.8	−26.6	0.000	5456	45.2	42.9	2.2	0.711
VW	5456	75.2	80.4	−5.2	0.624	5456	74.3	58.9	15.4	0.136
Holding period starts the month after first post-IPO book value on Compustat										
EW	5311	46.9	73.6	−26.6	0.000	5311	46.9	58.6	−11.7	0.071
VW	5311	75.2	81.1	−5.9	0.578	5311	126.3	89.3	36.9	0.094
(C) "Hot issue" period 1980–1984										
Holding period starts the month after the IPO date (looking ahead for the first book value on Compustat)										
EW	1815	6.0	75.5	−69.5	0.000	1464	2.3	25.8	−23.5	0.000
VW	1815	4.9	96.2	−91.3	0.000	1464	2.2	38.4	−36.2	0.000
Holding period starts the month after first post-IPO book value on Compustat										
EW						1397	3.7	37.1	−33.4	0.000
VW						1397	25.0	61.9	−37.0	0.009

Table 3

Average annual leverage ratios and liquidity for firms going public between 1972 and 1998, and their non-issuing control firms matched on size and size/book-to-market ratio. All issuers and matching firms are listed on Nasdaq.

The leverage variables are 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. 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.

(A) 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	4042	0.100	0.145	0.000	0.153	0.438	0.000	0.152	0.202	0.000
1	3959	0.124	0.149	0.000	0.290	0.483	0.000	0.184	0.205	0.000
2	3444	0.139	0.147	0.057	0.372	0.459	0.001	0.199	0.203	0.337
3	2849	0.151	0.149	0.771	0.433	0.509	0.025	0.212	0.206	0.231
4	2170	0.150	0.146	0.465	0.572	0.488	0.202	0.213	0.206	0.278
5	1869	0.153	0.152	0.802	0.659	0.511	0.042	0.213	0.213	0.952
Issuers and size/book-to-market matched firms										
0	4654	0.102	0.144	0.000	0.161	0.255	0.000	0.154	0.203	0.000
1	4421	0.125	0.150	0.000	0.291	0.337	0.012	0.185	0.211	0.000
2	3751	0.139	0.150	0.010	0.379	0.350	0.248	0.199	0.209	0.031
3	3088	0.147	0.153	0.206	0.448	0.409	0.297	0.209	0.213	0.496
4	2346	0.146	0.152	0.246	0.524	0.417	0.062	0.209	0.216	0.270
5	1986	0.156	0.158	0.692	0.608	0.483	0.031	0.217	0.225	0.229

(B) Liquidity measured as monthly average turnover

		Issuers and size matched firms			Issuers and size-book-to-market matched firms		
Year	N	Issuer	Match	p-diff	Issuer	Match	p-diff
0	5195	0.126	0.074	0.000	0.125	0.105	0.000
1	5536	0.111	0.074	0.000	0.114	0.098	0.000
2	5314	0.120	0.077	0.000	0.126	0.097	0.000
3	4601	0.120	0.079	0.000	0.125	0.100	0.000
4	3823	0.119	0.077	0.000	0.124	0.102	0.000
5	3165	0.106	0.071	0.000	0.113	0.090	0.000

Table 4
Factor mimicking portfolios and macroeconomic variables used as risk factors, January 1973 to December 2000.

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)	336	0.539	4.649
Change in real per capita consumption of nondurable goods (ΔRPC)[a]	336	0.053	0.686
Difference in BAA and AAA yield change (BAA−AAA)	336	-0.012	1.138
Unanticipated inflation (UI)[b]	336	-0.024	0.253
Return difference on Treasury bonds (20y−1y)[c]	336	0.109	2.649
Return difference on Treasury bills (TBILLspr)[d]	336	0.052	0.115

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

Mimicking factor	ΔRPC	BAA−AAA	UI
$\widehat{\Delta\text{RPC}}$	0.265 (0.000)	0.011 (0.836)	−0.046 (0.401)
$\widehat{\text{BAA}-\text{AAA}}$	0.004 (0.935)	0.265 (0.000)	−0.026 (0.631)
$\widehat{\text{UI}}$	0.001 (0.991)	−0.031 (0.575)	0.287 (0.000)

(C) Correlation between macroeconomic factors

	RM	$\widehat{\Delta\text{RPC}}$	$\widehat{\text{BAA}-\text{AAA}}$	$\widehat{\text{UI}}$	20y−1y	TBILLspr
RM	1.000					
$\widehat{\Delta\text{RPC}}$	-0.008	1.000				
$\widehat{\text{BAA}-\text{AAA}}$	0.013	-0.099	1.000			
$\widehat{\text{UI}}$	0.020	-0.298	0.266	1.000		
20y−1y	0.314	-0.004	0.080	-0.067	1.000	
TBILLspr	0.115	0.028	0.066	-0.062	0.395	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 5

Jensen's alphas and constant factor loadings for stock portfolios of firms going public on Nasdaq and non-issuing Nasdaq firms matched on size and size/book-to-market ratio, classified by portfolio weights. Portfolios are first formed in January 1973 and held until December 2000.

The model is:

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

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long the stock of the matching firm and short the stock of the issuer, 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. 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 heteroscedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=336, N=888, I=6,379)						
Portfolio	$\hat{\alpha}$	RM	$\widehat{\Delta \mathrm{RPC}}$	$\widehat{\mathrm{BAA} - \mathrm{AAA}}$	$\widehat{\mathrm{UI}}$	20y−1y	TBILLspr	Rsq
(A) Issuers and size matched control firms								
EW-issuer	−0.17 (.510)	1.38 (.000)	0.06 (.000)	−0.03 (.000)	0.05 (.000)	−0.42 (.000)	−0.46 (.845)	0.704
EW-match	0.10 (.566)	0.97 (.000)	0.05 (.000)	−0.01 (.000)	0.04 (.000)	−0.26 (.000)	1.76 (.218)	0.736
EW-zero	−0.27 (.102)	0.41 (.000)	0.01 (.104)	−0.01 (.000)	0.01 (.212)	−0.16 (.027)	−2.22 (.178)	0.364
VW-issuer	−0.12 (.651)	1.58 (.000)	0.03 (.023)	−0.02 (.016)	−0.02 (.360)	−0.29 (.012)	−2.37 (.305)	0.731
VW-match	−0.02 (.903)	1.07 (.000)	0.03 (.012)	−0.01 (.095)	0.00 (.691)	−0.14 (.023)	1.54 (.316)	0.780
VW-zero	−0.10 (.635)	0.51 (.000)	0.00 (.583)	−0.01 (.117)	−0.02 (.093)	−0.14 (.129)	−3.92 (.034)	0.309
(B) Issuers and size/book-to-market matched control firms								
EW-issuer	−0.09 (.741)	1.43 (.000)	0.06 (.000)	−0.03 (.000)	0.05 (.000)	−0.46 (.000)	−1.36 (.573)	0.712
EW-match	−0.01 (.965)	1.26 (.000)	0.06 (.000)	−0.02 (.000)	0.05 (.000)	−0.38 (.000)	0.67 (.751)	0.726
EW-zero	−0.08 (.570)	0.17 (.000)	−0.00 (.294)	−0.00 (.183)	0.00 (.535)	−0.08 (.126)	−2.03 (.121)	0.126
VW-issuer	0.01 (.973)	1.62 (.000)	0.03 (.023)	−0.02 (.017)	−0.02 (.310)	−0.32 (.006)	−2.92 (.231)	0.729
VW-match	−0.15 (.473)	1.33 (.000)	0.04 (.010)	−0.01 (.031)	0.00 (.909)	−0.20 (.010)	−0.04 (.981)	0.764
VW-zero	0.15 (.397)	0.29 (.000)	−0.01 (.256)	−0.00 (.351)	−0.02 (.056)	−0.12 (.133)	−2.88 (.113)	0.159

Table 6
Descriptive statistics for characteristic based risk factors, January 1973 to December 2000 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)]FamaFren93. 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 liquidity factor TO is constructed using an algorithm similar to the one used by Fama and French (1993) when constructing the SMB and HML factors. To construct TO, we start in September 1972 and form two portfolios based on a ranking of the end-of-month market value of equity and three portfolios formed using stocks ranked on TO. 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 October 1972. Portfolios are reformed in January, April, July, and October, using firm rankings from the previous month. The TO 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.

(A) Characteristic based factors

	N	Mean	Std Dev
Difference in returns between small firms and big firms (SMB)	336	0.099	3.346
Difference in return between firms with high and low book-to-market (HML)	336	0.453	3.120
Difference in return between winners and losers (UMD)	336	1.010	3.814
Difference in return between firms with high and low turnover (TO)	336	0.045	3.649

(B) Correlation between characteristic based factors

	RM	SMB	HML	UMD	TO
RM	1.000				
SMB	0.257	1.000			
HML	-0.473	-0.312	1.000		
UMD	0.093	0.101	-0.314	1.000	
TO	-0.634	-0.594	0.741	-0.324	1.000

Table 7
Factor-betas and t-values for the extended Fama-French model using 25 size and book-to-market sorted portfolios as test assets

The model is:

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

where r_{pt} is excess return on the 25 Fama and French (1993) size and book-to-market ratio sorted portfolios. 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. TO (monthly volume divided by number of shares outstanding) is a liquidity factor that is constructed using the same algorithm used to construct HML. Thus, TO is the difference between the equal-weighted average return on two size sorted portfolios with low turnover and the equal-weighted average return on two size sorted portfolios with high turnover. The coefficients are estimated using OLS. Standard errors are computed using the heteroscedasticity consistent estimator of White (1980). The model is estimated using monthly data over the sample period July 1963 through December 1999, giving 438 observations. The numbers in parentheses are t-values. The first five portfolios, in row P11 to P15, contain small firms with book-to-market ratios ranging from low (P11) to high (P15). The second group of five portfolios, in row P21 to P25, contain the second smallest firms with book-to-market ratios ranging from low (P11) to high (P15). The remaining groups follow the same pattern. Parentheses contain t-values.

	Intercept	RM	SMB	HML	UMD	TO	ARsq
P11	−0.46 (−4.67)	1.00 (35.85)	1.33 (28.96)	−0.19 (−4.25)	0.03 (0.91)	−0.16 (−2.89)	0.93
P12	−0.01 (−0.08)	0.97 (39.52)	1.24 (32.96)	0.11 (2.61)	−0.01 (−0.23)	−0.04 (−0.67)	0.94
P13	0.01 (0.12)	0.96 (50.97)	1.12 (41.95)	0.24 (8.24)	−0.03 (−1.41)	0.04 (1.16)	0.96
P14	0.14 (2.26)	0.93 (49.91)	1.09 (41.32)	0.40 (13.16)	−0.02 (−0.74)	0.08 (2.22)	0.96
P15	0.11 (1.66)	0.99 (48.63)	1.18 (35.63)	0.62 (18.02)	0.01 (0.61)	0.09 (2.05)	0.95
P21	−0.11 (−1.39)	1.01 (44.29)	0.87 (24.31)	−0.33 (−9.02)	−0.06 (−2.00)	−0.33 (−6.65)	0.96
P22	−0.02 (−0.27)	1.01 (45.62)	0.91 (29.66)	0.06 (1.98)	−0.08 (−3.54)	−0.03 (−0.73)	0.96
P23	0.13 (2.20)	0.99 (52.82)	0.81 (30.78)	0.28 (9.11)	−0.04 (−2.14)	0.04 (1.06)	0.95
P24	0.07 (1.19)	1.01 (52.69)	0.75 (28.62)	0.49 (16.05)	−0.01 (−0.50)	0.08 (2.41)	0.95
P25	0.00 (0.02)	1.07 (55.58)	0.86 (32.66)	0.74 (23.63)	0.02 (1.12)	0.01 (0.22)	0.95
P31	0.00 (0.06)	1.02 (40.77)	0.60 (16.71)	−0.33 (−8.92)	−0.07 (−2.76)	−0.26 (−5.91)	0.95
P32	0.07 (0.94)	1.01 (41.73)	0.60 (18.25)	0.09 (2.37)	−0.04 (−1.52)	−0.04 (−0.92)	0.93
P33	−0.01 (−0.12)	1.00 (41.77)	0.53 (16.02)	0.35 (9.72)	−0.07 (−2.97)	0.03 (0.65)	0.92
P34	0.04 (0.58)	1.00 (48.82)	0.47 (16.77)	0.53 (16.71)	−0.03 (−1.29)	0.05 (1.09)	0.93
P35	0.05 (0.66)	1.03 (44.28)	0.56 (15.88)	0.79 (21.77)	−0.02 (−0.68)	−0.12 (−2.64)	0.92
P41	0.14 (1.82)	0.99 (41.77)	0.25 (7.36)	−0.37 (−11.21)	−0.03 (−1.03)	−0.21 (−3.95)	0.94
P42	−0.11 (−1.27)	1.08 (36.15)	0.25 (6.47)	0.09 (2.13)	−0.10 (−3.37)	−0.01 (−0.18)	0.91
P43	0.04 (0.49)	1.04 (44.80)	0.20 (5.15)	0.38 (9.54)	−0.06 (−2.39)	−0.07 (−1.27)	0.91
P44	0.11 (1.39)	1.00 (33.70)	0.17 (4.69)	0.56 (14.92)	−0.07 (−2.38)	−0.08 (−1.56)	0.90
P45	0.06 (0.61)	1.06 (34.90)	0.22 (4.88)	0.88 (20.06)	−0.06 (−1.94)	−0.30 (−5.31)	0.88
P51	0.21 (3.24)	0.97 (46.80)	−0.20 (−7.33)	−0.44 (−12.50)	−0.01 (−0.48)	0.06 (1.74)	0.93
P52	−0.03 (−0.36)	1.05 (46.64)	−0.20 (−6.07)	0.01 (0.27)	−0.02 (−0.89)	0.06 (1.41)	0.91
P53	−0.11 (−1.40)	1.01 (37.88)	−0.22 (−5.53)	0.20 (4.53)	0.04 (1.19)	0.08 (1.52)	0.85
P54	−0.04 (−0.56)	0.99 (39.77)	−0.24 (−7.01)	0.60 (18.06)	−0.07 (−3.04)	−0.09 (−2.09)	0.89
P55	−0.12 (−1.20)	0.95 (29.95)	−0.19 (−3.79)	0.93 (15.53)	−0.03 (−0.99)	−0.29 (−5.23)	0.82

Table 8

Jensen's alphas, Fama and French (1993) factor loadings, and factor loadings for momentum and liquidity factors for stock portfolios of firms going public on Nasdaq and non-issuing Nasdaq firms matched on size and size/book-to-market, classified by portfolio weights. Portfolios are first formed in January 1973 and held until December 2000.

The model is:

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

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long the stock of the matching firm and short the stock of the issuer. 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. TO (monthly volume divided by number of shares outstanding) is a liquidity factor that is constructed using the same algorithm used to construct HML. Thus, TO is the difference between the equal-weighted average return on two size sorted portfolios with low turnover and the equal-weighted average return on two size sorted portfolios with high turnover. 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 heteroscedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=336, N=888, I=6,379)					
Portfolio	$\hat{\alpha}$	RM	SMB	HML	UMD	TO	A-Rsq
(A) Issuers and size matched control firms							
EW-issuer	−0.06 (0.709)	1.06 (0.000)	1.18 (0.000)	−0.09 (0.329)			0.861
EW-match	0.06 (0.464)	0.86 (0.000)	0.91 (0.000)	0.30 (0.000)			0.915
EW-zero	−0.12 (0.313)	0.20 (0.000)	0.27 (0.000)	−0.38 (0.000)			0.531
VW-issuer	0.20 (0.179)	1.13 (0.000)	0.90 (0.000)	−0.72 (0.000)			0.901
VW-match	0.11 (0.235)	0.90 (0.000)	0.70 (0.000)	−0.06 (0.238)			0.917
VW-zero	0.09 (0.604)	0.23 (0.000)	0.20 (0.018)	−0.66 (0.000)			0.503
EW-issuer	0.01 (0.967)	1.02 (0.000)	1.12 (0.000)	−0.03 (0.770)	−0.06 (0.383)	−0.14 (0.166)	0.861
EW-match	0.13 (0.145)	0.87 (0.000)	0.94 (0.000)	0.23 (0.000)	−0.05 (0.062)	0.07 (0.180)	0.917
EW-zero	−0.13 (0.268)	0.14 (0.001)	0.19 (0.003)	−0.26 (0.000)	−0.00 (0.934)	−0.22 (0.003)	0.543
VW-issuer	0.14 (0.306)	0.96 (0.000)	0.64 (0.000)	−0.34 (0.000)	0.03 (0.544)	−0.66 (0.000)	0.920
VW-match	0.02 (0.801)	0.87 (0.000)	0.66 (0.000)	0.03 (0.640)	0.07 (0.068)	−0.11 (0.120)	0.920
VW-zero	0.11 (0.474)	0.09 (0.098)	−0.02 (0.826)	−0.37 (0.000)	−0.04 (0.535)	−0.55 (0.000)	0.550
(B) Issuers and size/book-to-market matched control firms							
EW-issuer	0.00 (0.983)	1.08 (0.000)	1.19 (0.000)	−0.13 (0.172)			0.859
EW-match	0.04 (0.737)	1.01 (0.000)	1.13 (0.000)	0.09 (0.214)			0.878
EW-zero	−0.04 (0.717)	0.07 (0.016)	0.05 (0.215)	−0.22 (0.000)			0.183
VW-issuer	0.32 (0.039)	1.14 (0.000)	0.90 (0.000)	−0.76 (0.000)			0.896
VW-match	0.08 (0.476)	1.01 (0.000)	0.90 (0.000)	−0.35 (0.000)			0.932
VW-zero	0.24 (0.168)	0.13 (0.013)	−0.00 (0.982)	−0.41 (0.000)			0.236
EW-issuer	0.06 (0.695)	1.04 (0.000)	1.13 (0.000)	−0.07 (0.491)	−0.05 (0.458)	−0.13 (0.195)	0.860
EW-match	0.13 (0.317)	1.00 (0.000)	1.13 (0.000)	0.06 (0.394)	−0.07 (0.134)	−0.01 (0.919)	0.879
EW-zero	−0.07 (0.511)	0.04 (0.207)	0.00 (0.957)	−0.14 (0.041)	0.02 (0.562)	−0.13 (0.055)	0.192
VW-issuer	0.25 (0.063)	0.97 (0.000)	0.62 (0.000)	−0.35 (0.000)	0.03 (0.530)	−0.71 (0.000)	0.917
VW-match	−0.04 (0.688)	0.97 (0.000)	0.83 (0.000)	−0.21 (0.000)	0.09 (0.015)	−0.18 (0.011)	0.937
VW-zero	0.30 (0.048)	−0.00 (0.970)	−0.21 (0.028)	−0.14 (0.062)	−0.06 (0.311)	−0.52 (0.000)	0.304

Table 9

Jensen's alphas, Fama and French (1993) factor loadings, and factor loadings for momentum and liquidity factors for stock portfolios of SEO firms and their size-matched control firms. Sample of seasoned equity offerings in Eckbo, Masulis, and Norli (2000). Portfolios are first formed in March 1964 and held until December 1997.

The model is:

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

where r_{pt} is either a portfolio excess return or a return on a zero investment portfolio that is long the stock of the matching firm and short the stock of the issuer. 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. TO (monthly volume divided by number of shares outstanding) is a liquidity factor that is constructed using the same algorithm used to construct HML. Thus, TO is the difference between the equal-weighted average return on two size sorted portfolios with low turnover and the equal-weighted average return on two size sorted portfolios with high turnover. 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 heteroscedasticity consistent estimator of White (1980). The numbers in parentheses are p-values.

		Factor betas (T=406, N=361, I=3315)					
Portfolio	$\hat{\alpha}$	RM	SMB	HML	UMD	TO	A-Rsq
EW-issuer	−0.23 (0.011)	1.18 (0.000)	0.91 (0.000)	−0.04 (0.290)			0.931
EW-match	−0.26 (0.001)	1.00 (0.000)	0.86 (0.000)	0.34 (0.000)			0.922
EW-zero	0.03 (0.802)	0.17 (0.000)	0.04 (0.310)	−0.38 (0.000)			0.262
VW-issuer	−0.16 (0.117)	1.08 (0.000)	0.10 (0.018)	−0.09 (0.045)			0.865
VW-match	−0.01 (0.924)	0.97 (0.000)	0.05 (0.185)	0.01 (0.792)			0.822
VW-zero	−0.15 (0.339)	0.11 (0.003)	0.05 (0.380)	−0.10 (0.076)			0.043
EW-issuer	−0.05 (0.572)	1.09 (0.000)	0.75 (0.000)	0.05 (0.268)	−0.12 (0.000)	−0.31 (0.000)	0.938
EW-match	−0.17 (0.042)	0.99 (0.000)	0.83 (0.000)	0.34 (0.000)	−0.09 (0.001)	−0.04 (0.345)	0.924
EW-zero	0.12 (0.348)	0.10 (0.001)	−0.08 (0.073)	−0.29 (0.000)	−0.04 (0.201)	−0.26 (0.000)	0.284
VW-issuer	0.01 (0.934)	1.01 (0.000)	−0.03 (0.546)	−0.03 (0.513)	−0.12 (0.000)	−0.24 (0.000)	0.873
VW-match	−0.04 (0.743)	0.98 (0.000)	0.07 (0.080)	0.00 (0.934)	0.02 (0.455)	0.03 (0.650)	0.821
VW-zero	0.05 (0.770)	0.03 (0.466)	−0.09 (0.099)	−0.04 (0.602)	−0.15 (0.001)	−0.27 (0.003)	0.076