Federal Reserve Bank of New York
Staff Reports

Evaluating the Riskiness of Initial Public Offerings: 1980-2000

Stavros Peristiani

Staff Report no. 167
May 2003

Evaluating the Riskiness of Initial Public Offerings: 1980-2000
Stavros Peristiani
Federal Reserve Bank of New York Staff Reports, no. 167
May 2003
JEL classification: G3, G24

Abstract

In the wake of the dot.com collapse, investor sentiment toward initial public offerings (IPOs) has turned negative. To many investors, IPOs have come to symbolize the insider abuses and stock market excesses of the Internet bubble period; to others, investing in IPOs is inherently fraught with danger. This paper asks the question, Have IPOs indeed become more perilous to the investing public over time?

I employ two approaches to investigate the post-issue riskiness of IPOs for the 1980-2000 period. First, I compare the stock price volatility for issuing and nonissuing firms. Second, I use a qualitative model to estimate the likelihood that new issues will survive in the aftermarket. Both methodologies show that the riskiness of IPO shares relative to the shares of a nonissuing peer group has increased roughly 30 percent in the 1990s.

Although the proliferation of Internet companies in this period helps account for the increased risk, my empirical analysis reveals a more gradual shift in risk that cannot be fully explained by the high-tech bubble. Specifically, I find that companies taken public by top-tier underwriters or funded by venture capital exhibit higher relative volatility and a lower likelihood of survival.

Keywords: initial public offerings (IPOs), relative risk of IPOs, probability of delisting, adverse selection, underwriter-issuer agency conflicts; Internet IPOs.

Research and Market Analysis Group, Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045 (e-mail: steve.peristiani@ny.frb.org). The author thanks Gijoon Hong for valuable research assistance and Charlie Himmelberg, Jim Mahoney, Hamid Mehran, Tony Rodrigues, and Joshua Rosenberg for many useful comments and suggestions. The author is also grateful to Eli Ofek, who provided a list of Internet IPOs.

1. INTRODUCTION

Investors in initial public offerings (IPOs) had a truly bittersweet experience in the last few years. Shareholders of Internet IPOs, in particular, endured the worst disappointment after seeing the value of their investments go through the roof only to cave in a similarly dramatic fashion. In just one year, the Dow Jones Composite Internet Index collapsed from a high of 450 in January 2000 to below 50 by August 2001.

The recent debacle of Internet IPOs has brought to the forefront several issues that have long been debated in the financial literature. As always in the aftermath of any stock market collapse, it is customary to expect the resurgence of financial pundits professing the perils of IPO investing. The poor performance of issuers over the last few years, however, should not have astonished market participants. The long-term performance of new issues has been thoroughly analyzed in the academic literature. Several studies (for example, Ritter (1991) and Loughran and Ritter (1995)) have extensively documented a significant underperformance of IPO shares relative to the shares of broad market indices. Fama and French (1995, 2002) have attributed the poor performance to a group of very small high-growth but less profitable companies. Recent event-time studies, however, find that IPO performance improves significantly when issuers are compared with a similar cohort of publicly traded firms and once all appropriate risk factors are taken into account (Brav and Gompers (1997), Eckbo and Norli (2001), and Ritter (2002)).

This time around, however, market scrutiny seems to have gone beyond the customary process of appraising aftermarket performance. Many investors, entrepreneurs, and analysts today are not only questioning the merits of investing in IPOs, but more importantly, are actually doubting the benefits from the decision to go public. This intense criticism is nowhere more evident than in the financial press. Several stories in business newspapers and other financial publications point to a widening "credibility gap" between investment banks their corporate clients and the investing public.[1]

Loughran and Ritter (2002) attribute this conflict to efforts by underwriters to maximize rent-seeking activities from buy-side trading customers. Spurred by the explosive growth of mutual funds and hedge funds, a large fraction of investment banks' income today is derived from lucrative trading fees and other commissions. Issuers have facilitated this rent-seeking process by accepting greater underpricing in exchange for better aftermarket support and more favorable analyst coverage. Moreover, the authors argue that the decision-making process of IPO insiders (company executives and venture investors) may have been distorted by other pecuniary benefits offered by investment banks (the so-called "corruption hypothesis").

A key prerequisite for the agency conflicts hypothesis is that the issuing company must be willing to leave money on the table (large underpricing), which is then allocated to the preferred customers of the underwriting investment banks. Loughran and Ritter present evidence to support this apparent misalignment in incentives between underwriters, issuing firms and shareholders. In particular, their analysis finds a sharp increase in the IPO underpricing in the

[1] The negative coverage in the financial press is best illustrated by the front-cover headline of the May 14, 2001 issue of *Fortune* that declared "Can we trust Wall Street again?" In the same issue, an article titled "Betrayal on Wall Street" by Shawn Tully, starts with the by-line: "The credibility gap between investment banks and their clients has never been wider: Why? Just look at the IPO con game." For more critical stories of the IPO process, the reader can refer to: "The Ugly Truth About IPOs," *Fortune*, November 23, 1998, reported by Nelson D. Schwartz; "The IPO Market is as Sleazy as Ever," *CBS MarketWatch.com*, September 18, 2002, reported by Mike Tarsala; "NASD Regulation Charges Credit Suisse First Boston with Siphoning Tens of Millions of Dollars of Customers' Profits in Exchange for "Hot" IPO shares," *NASD Regulation News Release*, January 22, 2002 (http:/www.nasdr.com/news/2002/release_02_005.html).

1990s.[2] The average first-day return for IPOs jumped from 7 percent during the 1980s to 15 percent during the period 1990-98. Ljungqvist (2002) examines the relationship between underwriter compensation and underpricing for U.K IPOs. The study affirms the presence of conflicts of interest in IPO managers that have integrated corporate underwriting and brokerage businesses, finding that underpricing is significantly lower for issuers that rely on more specialized corporate finance managers.

This problem with agency conflicts in investment banking has also surfaced in analyst recommendations. A number of papers in the finance literature (Boni and Womack (2002) and Michaely and Womack (1999)) underscore the presence of misaligned incentives among many Wall Street analysts and argue that the recent credibility problems of sell-side analyst were driven by the same desire to boost investment-banking business.

A critical implication of the agency problems between issuing firms and underwriters is that investors may have been increasingly exposed to lower quality riskier IPOs. Perhaps a direct manifestation of these rising risks is the upsurge in the number of shareholder class-action lawsuits in 2001. Many of these lawsuits have been initiated by IPO investors who bought these risky issues that eventually collapsed.[3]

In addition to the agency conflict hypothesis, there are several other compelling explanations for the rising of risk exposure of IPOs. During the 1990s, we witnessed a

---

[2] Fulghieri and Spiegel (1993) present a theoretical model that attempts to explain the apparent underpricing in new issues and the role of the underwriter. In particular, they focus on the dual role of the IPO managers as underwriters and as investment firms with a large group of clients.

[3] See, for example, "Lawsuits Surge on Scrutiny of Analysts' IPO Bonuses," *Investor Relations Business*, September 17, 2001; "IPOs Fuel Upswing in Shareholder Suits," Business Insurance, August 27, 2001, reported by Roberto Ceniceros; "Melvyn Weiss Asks Billions From Wall Street in IPO Civil Suits," *Bloomberg Markets*, November 2001, reported by Edward Robinson.

proliferation of high-tech and Internet IPOs. The timing of these speculative offerings was perhaps fortuitous, decided by a number of economic developments and technological advances coming together in the late 1980s. During the 1990s, we witnessed an unrivaled push to deregulate most industries (especially, telecommunications and financial services), massive capital expenditures by corporations, the development of personal computing with powerful software, and technological innovations in networking. The emergence of the National Association of Securities Dealers Automated Quotation (NASDAQ) system with its computerized market maker infrastructure has made it possible for many small firms to get better coverage, improving liquidity and reducing transaction costs.

A large literature of theoretical models attributes the IPO underpricing to information asymmetries between the issuer and investors (Rock (1986) and Allen and Faulhaber (1989)). For example, Rock (1986) argues that the asymmetry between informed and uninformed investors creates a "lemons problem," in the sense that uninformed investors end up owning the riskier issue. A similar adverse selection friction may also be at work between the underwriter and issuer. A risky firm planning to go public may be more compelled to seek the advice of a larger full-service advisor that has the marketing resources and capacity to support the issue in the aftermarket. This type of issuer-underwriter adverse selection might not make sense in normal economic circumstances where sophisticated and better-informed advisors can easily judge the quality of the firm. In a more speculative or "irrational" market environment, however, such as the Internet bubble period, underwriters and other market participants may genuinely overestimate the true value of firms seeking to go public.

Is there any evidence to support the claims that firms issuing equity have increasingly become more risky over time? In contrast to recent papers examining the rise in IPO underpricing, which is tantamount to a first-day return, this paper investigates the long-term (aftermarket) risk of the IPO. We analyze the post-issue riskiness of IPO firms over a long horizon using two distinct approaches. First, we employ an event-time methodology to compare the stock return volatility of issuers and their nonissuing peers. In many ways, this approach is very similar to long-term performance studies where now the focus is on relative stock price volatility instead of abnormal returns. One apparent weakness of event studies is that performance often depends on the choice of the appropriate benchmark (Fama (1998)). As mentioned previously, there is considerable evidence from event-time studies suggesting that IPOs underperform most broad market indexes (Ritter (1991)). However, the return performance of IPOs improves significantly when the issuing firm is compared to a control firm with similar asset size and book-to-market ratio.

Our second approach avoids benchmarking altogether by examining the long-term viability of IPOs as a going concern. Following an IPO, firms can reach several possible states: (a) continue to operate as an independent firm, (b) merge or be acquired by another firm, (c) convert again into a private company, and (d) fail. Under the first three outcomes, the company is able to survive in some form, meaning that shareholders retain ownership or get repaid for their investment. In contrast, shareholders almost always lose in the event of failure. We use a qualitative model to measure the probability of survival of IPOs in the aftermarket.

This paper is structured as follows. Section 2 re-examines briefly the return performance of IPOs. This section documents the underperformance of IPOs, which was thoroughly examined in the literature. Consistent with other event-time studies, we find that this long-term return anomaly tends to disappear once we control for asset size and book-to-market differences. In section 3, we turn our attention to examining the long-term market volatility of firms that went public during 1980-2000. We use a simple log volatility ratio to calibrate the relative riskiness of the issuer compared to a size and book-to-market nonissuing control firm. Our event-time analysis shows that in the 1990s shareholders of IPOs faced greater risk than during the decade of the 1980s. On a scale of zero to one, we estimate that the relative market risk of the average IPO rose from around 0.50 in the 1980s to 0.63 in the 1990s, roughly a 26 percent increase. As expected, speculative high-tech and Internet companies have greatly contributed to higher volatility during the 1990s. We also find that shareholders of firms that were advised by top-tier underwriters or received venture capital funding were exposed to greater aftermarket risk.

In Section 4, we explore an alternative measure of IPO risk. Using a logit regression model, we estimate the probability of survival of issuers and nonissuing firms. The logit analysis reaffirms evidence showing a rise in relative market volatility in the 1990s. In fact, the results are qualitatively and quantitatively very similar. We find that the odds of an IPO firm not surviving (that is, delisting) compared to the odds of a nonIPO firm delisting increase from around 0.91 in the 1980s to 1.29 in the 1990s, approximately a 30 percent increase in default risk. Moreover, the likelihood of survival during 1990-2000 is lower for IPOs managed by large underwriters or issuers backed by venture capital.

Both empirical approaches confirm that high-growth Internet companies have greatly increased the risk of IPOs in the late 1990s. Amazingly, the odds of delisting for an Internet IPO are nearly five times higher than the odds of delisting by a non-Internet issuing firm. These results indeed reinforce the view that a broad shift in the composition of companies going public toward lower quality and riskier high-tech Internet firms has heightened aftermarket risk. The empirical evidence does not appear to support the adverse selection premise that riskier issuers favored the services of large and more reputable lead managers or were sought after by these top-tier advisors. Regression analysis shows that Internet IPOs (in effect the riskier issuers) were broadly distributed across small and large underwriters. Our empirical results are somewhat consistent with the agency conflicts view that large underwriters used IPOs to enhance synergies with other investment-banking businesses.

2. A RE-EXAMINATION OF THE LONG-TERM PERFORMANCE OF IPOs

A. *A Brief Review of the Literature*

A full assessment of the risk-return profile of issuing firms can not be achieved without first discussing and evaluating their long-term return performance. The long-run performance of IPOs has been thoroughly investigated in the academic literature. Ritter (1991) was the first to document the negative aftermarket performance of stocks that went public for a large sample of new issues. Using a variety of benchmarks, Ritter shows that IPOs severely underperform over a 3-year period. For instance, when compared to a sample of listed firms matched by industry and size, the cumulative adjusted return of new issues during 1975-84 was roughly –30 percent.[4]

The long-run underperformance of IPOs documented by Ritter (1991) and other subsequent studies is an anomaly that has attracted a lot of attention in the corporate finance literature. The discussion on the performance of IPOs centers mostly on two methodological facets. Brav and Gompers (1997) argue that the performance IPOs improves substantially once a proper peer group is used as a benchmark, especially in size and book-to-market comparisons. In a more recent paper, Ritter (2002) also documents the difference between relative and absolute performance. He shows that new issues trail a benchmark of similarly sized nonissuing firms

[4] It is almost impossible to summarize the voluminous literature on IPO performance in this section. The reader can refer to several papers that review the literature at a length. In particular, Ritter (2002) and Ritter and Welch (2002) provide an extensive review of several articles analyzing the long-run return of firms going public as well as firms issuing seasoned equity.

after five years by roughly 3.4 percent per year. Compared to a similar-sized and book-to-market control, however, IPOs appear to outperform their peers by 0.2 percent per year.

Another dispute in the literature of long-term event studies is model specification. Several recent papers (e.g., Barber and Lyon (1997) and Kothari and Warner (1997)) argue that tests for abnormal returns based on reference portfolios are misspecified. Barber and Lyon present evidence that a buy-and-hold abnormal return (BHAR) comparison with a control group matched by size and book-to-market ratio, or some other firm characteristic, ameliorates these biases. Mitchell and Stafford (2000), however, cast some doubt on the statistical reliability of the BHAR methodology, arguing that abnormal returns are cross-correlated.

B. *Selection of IPO Sample*

The sample of IPOs was compiled from Thompson Financial's *Securities Data Corporation* (SDC) new issues databases. To analyze stock performance, we matched the SDC list of new issues with the University of Chicago's Center of Research in Securities Prices (CRSP) database using the 6-digit CUSIP code. As seen from Table 1, about 11 percent of the IPOs were left out because they could not be matched exactly with the CRSP database or, when there was a match, the issuing firm was not immediately included in CRSP.[5] Consistent with other studies analyzing IPOs, we deleted from the sample all closed-end funds, real estate investment trusts (REITS), American depository receipts (ADRs), unit trusts, and finally all

[5]Approximately 700 of the firms from the SDC new issues list could not be matched with CRSP based on their 6-digit cusip information. The remaining 300 or so issuing firms were excluded because they did not have pricing information within 30 days of their offering, although most of them did eventually appeared in the CRSP database. The long-term performance analysis of IPOs is based only on the sample of firms that have complete price information from the onset of the IPO. The performance results were very similar if the IPOs with incomplete information were kept in the sample. By eliminating these firms, however, we were able to maintain a more stable sample size for the post-IPO performance comparisons.

firms with an offer price below \$5 per share. Section A.1 in the Appendix as well as notes in the tables discuss in greater detail how the sample was constructed.

The final sample consists of 6,974 firms that went public from 1980 to 2000. As expected, this sample of IPOs mirrors quite accurately the distribution of firms across all industrial classifications. More important for our study, the final sample of issuing firms is a fairly good representation of issuance across the 1980s and 1990s (Figure 1). At times, our empirical analysis will be based on this full sample of IPOs. Invariably, some firms will drop out of the analysis, as some issuers are not included in the COMPUSTAT database or have missing information on other explanatory variables.

C. *IPO Performance During 1980-2000*

Consistent with the literature, we let $\mathrm{R_{ti}}$ represent the monthly simple return of stock (i) at month (t), and $\mathrm{E(R_{ti})}$ denote the expected (benchmark) return for the sample firm. The abnormal return is simply defined by $\mathrm{AR_{ti} = R_{ti} - E(R_{ti})}$. From the abnormal return measures, we can calculate yearly buy-and-hold abnormal returns (BHAR) for each firm:

$$BHAR_{\tau i} = \prod_{t=1}^{\tau}[1 + R_{ti}] - \prod_{t=1}^{\tau}[1 + E(R_{ti})]. \tag{1}$$

The cumulative adjusted return (CAR) is defined by:

$$CAR_{i\tau} = \sum_{t=1}^{\tau} AR_{ti}. \tag{2}$$

Studies analyzing the long-run performance of IPOs have considered a wide variety of benchmarks. In this paper, we compute a firm's abnormal return performance based on three benchmarks that were widely applied in the literature. First, we calculate CARs and BHARs for a five-year monthly horizon $(\tau = 1, \ldots, 60)$ using the CRSP NYSE/AMEX/NASDAQ value-weighted market index. In contrast to the value-weighted CRSP index, which comprises a large portfolio of stocks, the second benchmark for the IPO firm corresponds to a one-to-one comparison with a size-matched firm that has not issued equity over the five years prior to the offering. Similarly, the third benchmark compares an issuing firm to a size- and book-to-market matched control firm (often referred to as *style matching*).[6]

Figure 2 illustrates in a nutshell many of the conclusions of the empirical literature analyzing the post-issue long-run performance of IPOs. The top panel in the figure presents BHARs for the period 1980-2000, while the middle and bottom panels summarize return performance over the 1980s and 1990s, respectively. The top panel affirms Ritter's initial findings for the period 1980-2000, showing that BHARs become increasingly more negative and statistically different from zero after a year or so. The underperformance is quite severe in the long run, accruing to roughly 33 percent after five years. This strikingly poor performance relative to the value-weighted CRSP index is also observed in the 1980s and 1990s. The performance of offering firms is much improved relative to a size-matched nonissuing firm, although BHARs in the 1980s are still negative and statistically significant from zero. When compared against a style-matched nonissuing cohort, IPOs actually achieve positive abnormal returns, although in most cases we cannot reject the hypothesis that they outperform their control.[7] A recent study by Eckbo and Norli (2000) uses a factor model approach to evaluate the return performance of IPO firms. The authors find that the abnormal return of a zero-investment

---

[6] Section 2 in the Appendix describes in greater detail how the different benchmarks were constructed.

[7] In part, this insignificance stems from the fact that the variance of the benchmark return is larger for size- and style-matched comparisons because, after all, $E(R_{ti})$ is measured by the return of a single control firm. In contrast, in a value-weighted market index comparison, $E(R_{ti})$ is an average return with a much lower standard deviation.

portfolio, consisting of a long position in the matched firm and a short position in the IPO firm, is not significantly different from zero. They also attribute the apparent underperformance relative to a size-matched peer to the fact that IPO companies are less risky in terms of factors related to leverage and liquidity.

Admittedly, much of the improved performance in IPOs in the 1990s may be due to the Internet bubble period. The vast improvement in BHARs relative to style benchmark also underscores the difference between using reference portfolios and individual control firms. Buy-and-hold geometric return measures tend to magnify underperformance (or overperformance) because they compound monthly returns. The geometric compounding of abnormal returns may be more problematic in size or style matching comparisons because returns of the control firm are also more variable. Figure 3 presents an alternative comparison by computing the CARs over the same period. Overall, the CAR analysis reveals similar patterns in the performance of issuing firms, albeit the magnitude of the excess performance is more confined. Consistent with previous findings, IPOs trail the value-weighted CRSP index by roughly 14 percent after five years. However, offering firms catch up and sometimes surpass the style-matched control, although the CAR differential between the two groups is now considerably smaller and statistically insignificant.

In summary, our analysis of a fairly large sample of IPOs over the last two decades highlights the conflicting findings of the large literature on the long-run performance of IPOs. The extent of the underperformance depends critically on the methodology of measuring abnormal returns. Generally, IPOs are found to underperform broad market indices or portfolios such as the CRSP value-weighted index or the S&P500 Index. However, the performance of issuers is much improved in a one-to-one comparison with nonissuing firms having similar financial attributes. A recent paper by Gompers and Lerner (2002) also illustrates the importance of methodology. The authors are the first to investigate the performance of IPOs during the pre-NASDAQ period (1935-1972). The study shows again that IPOs underperform vis-à-vis a value-weighted index. More important, the authors demonstrate that IPOs do as well when they are compared to an equal-weighted index or when the calendar-time approach is utilized.

How investors should view these different return comparisons depends of course on their ultimate goals and appetite for risk. On one hand, individual investors that mindlessly put their 401(k) savings in indexed funds, instead of pursuing less diversified or complex investment strategies, may be more whetted to making broad value-weighted comparisons. On the other hand, a manager of a mutual fund that specializes in IPO investing may prefer a narrow comparison similar to a style-matched index. As we shift our focus to comparing risk, what we should take away from these long-term return comparisons is that overall IPOs appear to perform as well as nonissuing firms in a one-to-one style-matched comparison.

3. MEASURING THE RISKINESS OF IPOs FROM STOCK PRICES

To get a more complete picture of the risk-return tradeoff of IPOs, the remaining sections of the paper focus on analyzing risk. The scope of the analysis is not necessarily to find whether issuing firms are more or less risky than their nonissuing peers. Firms that go public are probably riskier than more established enterprises after all. Investors are expected to demand a higher return from IPOs to compensate for the bigger risk exposure. This greater exposure to risk is also evident from the higher volatility of IPO stock returns. Our aim instead is to determine if the risk characteristics of issuers have changed over time. Does the average IPO firm in the 1980s have the same risk profile as a firm that went public in the 1990s? And if indeed, as many have argued, IPO investing has become more perilous in the 1990s, what are some of the contributing factors?

In many ways, these questions are difficult to resolve because the pool of issuers is very different across the two decades. In the 1990s, we witnessed a proliferation in chancy technology and Internet firms. To properly determine the riskiness of an IPO over time, we need to control for the underlying shifts in the make-up of issuing firms and their nonissuing peers.

We employ two distinct measures of uncertainty to assess the relative riskiness of IPOs. First, we analyze a traditional market-based measure of risk derived from the volatility of returns. The second approach is broader because it assesses the viability of the firm as a going concern. Although the survival of a publicly traded company is less trivial to measure, this approach offers a more complete gauge of firm uncertainty. As expected, these two methods overlap in the sense that the likelihood of default of a firm is positively correlated with stock volatility. Shareholders hold a call option on the firm's assets therefore a rise in equity volatility enhances the value of their claims. However, volatility is harmful to bondholders because it increases the probability of default.

A. A *Relative Measure of the Stock Volatility of IPOs*

To calculate the long-run volatility of the firm, we use daily stock returns from the CRSP tapes. We estimate the volatility of firm (i) at month (t) based on the sample standard deviation of daily stock returns $(\hat{\sigma}_{ti})$.[8] To obtain a relative measure of excess volatility, we compare the sample volatility of the issuer with a suitably matched firm. In long-run return performance

[8] We can also derive a more idiosyncratic measure of stock return volatility from excess stock returns by subtracting the market return. This step is somewhat redundant in our case because ultimately we end up constructing a normalized measure of risk. Nevertheless, we also computed log volatility ratios based on the excess returns of the offering firm and its matched peer. Overall, our findings were quite similar.

comparisons, we had the flexibility to compare an IPO with (a) a broad portfolio of stocks, and (b) a single matched firm. The first comparison, however, is inappropriate in the present context because the issuing firm and its reference portfolio of stocks have very different sampling distributions. The more reasonable approach in the current framework would be a direct comparison of the issuing firm to a size-matched or style-matched nonissuing firm (for simplicity, referred to as the peer). The relative riskiness of an IPO can be measured by the log volatility ratio:

$$\sigma - RATIO_{ti} = \log\left(\frac{\hat{\sigma}_{IPO,\,ti}}{\hat{\sigma}_{PEER,\,ti}}\right). \tag{3}$$

Under the null hypothesis, the mean σ-RATIO is expected to be zero, meaning that the issuing firm would have the same level of risk as its peer.

Table 2 reports descriptive statistics for the log volatility ratio in the 1980s and 1990s. The top panel of the table summarizes the information for the style-matched cohort (that is, a size- and book-to-market match). The lower panel presents the size-matched results. The columns in the table report the post-issue risk performance of issuing firms for the first five years after the IPO. The summary statistics in the table are not cumulative instead each column represents the average performance in that year. Looking at the style-matched comparison, we observe that IPOs are relatively more risky (that is, σ-RATIO is positive and statistically significant from zero) than their matched peers. The mean and median log volatility ratios for offering firms are significantly higher in the 1990s. The widening gap in risk performance in the 1990s is evident in most yearly comparisons, pointing to a gradual increase in risk. The jump in risk is also validated by t-test statistics at the bottom of Panel A, showing that the mean log volatility ratios in the 1990s are significantly higher than in the 1980s. The results for the size-matched cohort are fairly similar (Panel B), although the difference in the log volatility ratio is now wider because matching by size alone is less accurate.

One attractive feature of the BHAR and CAR measures is that they offer a fairly discernible way of quantifying the relative return performance of offering firms over the long run. For example, we have shown that in the 1990s IPOs trailed the value-weight CRSP index by about 33 percent. However, the task of quantifying in a meaningful way the apparent discrepancies in σ-RATIO is less trivial. In this section, we propose a simple approach to illustrate the shift in the magnitude of risk across the two decades that is based on a nonparametric (kernel) density estimation method. This nonparametric technique makes it possible to estimate the distribution of the log volatility ratios for the two subperiods.[9] Figure 4 plots the empirical density for the style-matched yearly volatility ratios separately for the 1980s and 1990s. The empirical density of the volatility ratio during the 1980s is fairly symmetric and centered just above zero, revealing again that new issues were slightly more risky than nonissuers in this period. The figure also clearly reveals a significant shift to the right in the distribution of the log volatility ratio during the 1990s, which is now centered at around 0.23.

To better understand the dynamics in the increase of market risk during the 1990s, we have also estimated the empirical density for the subperiods 1990-1995 and 1996-2000. In light of the enormous rise in the stock prices of Internet and information technology companies in the late 1990s, one would expect the upsurge in market volatility to be concentrated in the latter half of the decade. Indeed, we find that the log volatility densities are centered on around 0.17 and

[9] The nonparametric method of estimation derives an empirical probability density function from observed data. Simply put, a known density function, often referred to as the *kernel*, is averaged across ranges of the observed data to derive a smooth approximation of the empirical density (for a detailed discussion, see Silverman (1986)).

0.35 during 1990-1995 and 1996-2000, respectively. Investors during the Internet bubble period were therefore exposed to greater uncertainty. At the same time, however, the nonparametric analysis reveals a more gradual rise in IPO market risk that crept in long before the dot.com mania.

By definition, the log volatility ratio is positive when IPOs are riskier. We can use this feature of the log volatility ratio to calibrate the observed rise in market risk during the 1990s. The total market risk of an IPO is measured by the probability that its log volatility ratio is greater than zero or $\mathrm{P}(\sigma\text{-RATIO}_{ti} > 0)$. Thus, the increase in risk in the two decades is defined as:

$$\Delta\mathrm{Risk} = \mathrm{P}_{90s}(\sigma\text{-RATIO}_{ti} > 0) - \mathrm{P}_{80s}(\sigma\text{-RATIO}_{ti} > 0).$$

Using the empirical CDFs of the log volatility ratios, we can compute the two components of $\Delta Risk$. From the empirical CDFs, we find that $\mathrm{P}_{90s}(\sigma\text{-RATIO}_{ti} > 0)=0.6375$ and $\mathrm{P}_{80s}(\sigma\text{-RATIO}_{ti} > 0)=0.5046$, meaning that relative market risk for IPOs rose by 13.29 percent in the 1990s. The crosshatched area in Figure 4 indicates the actual shift in market volatility risk.

B. *Why Are IPOs Riskier in the 1990s?*

We have documented a significant rise in the relative market risk of IPOs during the 1990s. While a lot of the increase in risk can be traced to more speculative Internet and technology issues, the upsurge in market volatility was widespread in all industries. Furthermore, the evidence suggests that the increase in IPO risk was more gradual and was discernible as far back as the early 1990s. On the surface, the rising market uncertainty in the 1990s may not be a total surprise. A paper by Campbell et al. (2001) documents that idiosyncratic firm-level volatility has almost doubled between 1962 and 1997. The firm-specific idiosyncratic risk examined in this paper is an absolute measure of uncertainty. Presumably, the same positive trend in firm-level volatility should also be present in the matched sample of nonissuing firms. Our findings, showing a significant rise in the relative log volatility ratio, suggest that the growth in market volatility risk was higher for IPOs.

Why has the relative risk of IPOs gone up in the 1990s? The most direct interpretation is to attribute higher risk to an overall deterioration in the make-up of companies going public during this period. Ritter (1991) documents a significant positive relationship between the age of the issuer and long-run relative return performance. As noted in the introduction, increased competition and agency conflicts may have led to looser underwriting standards. Indeed, companies in the late 1990s went public at an earlier stage of their life cycle than at any other time period. The median age of firms at the time they went public (year firm went public minus year founded) in the period 1998-2000 was roughly 4 years. Remarkably, the mean age during 1980-1989 and 1990-1997 remained stable around 7 years.

In Table 3, we evaluate the relationship between the relative volatility of an IPO and different measures of firm quality. In addition to firm age, the table looks at several other characteristics that proxy for the quality of the issuer. A number of papers have investigated the effect of underwriter reputation on the initial (first day) and long-run performance of IPOs (Carter and Manaster (1990) and Carter, Dark and Singh (1996)). These studies find that companies taken public by top-tier underwriters turn in on average stronger long-run stock return performances. Carter and Manaster (1990) have derived a measure for identifying the more reputable underwriters from the relative position of the participants on the tombstone announcement of the offering (CM_RATING). A simple alternative to the Carter-Manaster rankings is the market share of underwriters (MANAGER_SHARE). As expected, these two alternative measures are closely correlated.

Another simple indicator of firm quality is given by the relative size of the firm at the time of issuance (SIZE), defined as gross proceeds divided by total market capitalization at the time of issuance. In addition to these quantitative factors, we also consider several qualitative IPO characteristics. Brav and Gompers (1997) find that venture-backed IPOs outperform other start-up firms not funded by venture capital. Venture capital firms are in the business of finding successful start-up companies. By providing seed money to these companies, venture capital firms help certify to other investors a firm's potential for success. Finally, we also analyze the log volatility ratio of issuers in the high-technology (HIGHTECH) and Internet (INTERNET) sectors.

Table 3 summarizes the average quality of the issuer based on the quartile categories of the log volatility ratio. Offering firms in the bottom quartile category (those below the 25th percentile) are significantly less risky than IPO firms in the top quartile (those above the 75th percentile). This simple analysis reveals a strong inverse relationship between the age of the firm and relative volatility. Given that the average age of issuers has dropped in the late 1990s, the negative relationship between age and firm-risk indicates at least one possible culprit for the observed rise in the relative risk of IPOs. The remaining firm attributes appear to be also related with market risk. In particular, the σ-RATIO jumps up significantly for Internet and high-tech IPOs, especially during the 1990s, and increases for higher values of lead manager share.

To better ascertain the relationship between firm age and relative risk, we estimate a simple cross sectional regression model. The dependent variable in the regression model is the average σ-RATIO of the issuing company for the first five years after going public (or up to the last month of available information for firms that were delisted or merged). The regression estimates, reported in Table 4, reveal a strong relationship between the relative market risk and several of the IPO attributes, especially for the period 1990-2000. Older and more established companies exhibit lower relative risk. We also find that σ-RATIO is positively related with the offering size (PROCEEDS). As expected, INTERNET dummy coefficient is positive and significant in all specifications, indicating greater price uncertainty in this sector.

Our regression estimates also reveal that issuers taken public by top-tier underwriters or funded by venture capital exposed investors to greater aftermarket risk. As seen from the various regression specifications in Panel B of Table 4, the coefficients on MANAGER_SHARE, CM_RATING, TOPMANAGER, and VENTURE are positive and statistically significant. This outcome is somewhat surprising considering that several studies document superior long-term performance and greater underpricing for issuers taken public by large more reputable managers or those funded by venture capital (see, for example, Ritter (1991), Muscarella and Vetsuypens (1989), and Carter, Dark, and Singh (1997)). The regression results are consistent with the agency conflicts thesis, asserting that investment banks sought to integrate corporate finance services and brokerage trading in the 1990s (Loughran and Ritter (2002)). As shown by Loughran and Ritter, these conflicts of interests may have contributed to the huge increase of the IPO underpricing in the latter half of the 1990s. The upsurge in the aftermarket volatility of IPOs advised by large lead managers is another manifestation of these agency problems. The misaligned incentives between underwriters and issuers not only have promoted a greater underpricing of IPOs but also may have actually encouraged less qualified and riskier firms to go public.

Most of the large equity underwriters in our sample earn their income from investment-banking fees (M&A advisory services and corporate bond underwriting) and from brokerage commissions. The disparity in the sources of revenue is evident from the reported commissions and fees earned by a select group of top-tier underwriters. Excluding IPO fees, these financial firms earned close to $230 billion in commissions and fees from securities brokerage transactions and other investment banking activities from 1997 to 2000. In comparison, their revenue from IPO underwriting fees during the same period amounted to a mere $10 billion.[10] Usually, the top corporate finance underwriters also rank very high in most other investment-banking activities. Equity underwriting measures, like the Carter-Manaster rankings, are therefore useful proxies for the potential benefits from integrating investment-banking businesses. However, there are also several notable exceptions among top-tier equity underwriters that do not maintain a strong presence across all traditional investment-banking lines (for an example, see footnote (13)).

To better gauge the synergies of corporate finance and trading, we construct a composite measure of investment banking activities. Let I_{uj} represent a binary index of participation (1=yes, 0=no) of underwriter (u) in the three possible investment-banking activities: IPO underwriting $(j = 1)$, bond underwriting $(j = 2)$, and M&A advising $(j = 3)$.[11] In theory, an investment bank firm can participate in any one of these three activities, meaning that there are 8 possible

---

[10] The group of large underwriters consists of Goldman Sachs, Merrill Lynch, Citigroup, Morgan Stanley, Lehman Brothers, JP Morgan Chase, BankAmerica-Nationsbank, Bankers Trust (BT Alex Brown)-Deutsche Bank, Fleet Financial Group, Bear Stearns, and DLJ. With the exception of Credit Suisse-First Boston Corp, this list represents the largest equity underwriters during the period 1997-2000. Investment banks report revenues from commissions and fees in their annual 10-K reports. For financial holding companies, like Citigroup, this revenue component was estimated from the *Consolidated Financial Statement for Bank Holding Companies* (FRY-9C Report).

[11] An important component missing from this list of investment-banking sources of income is brokerage services. Brokerage commissions and fees are a significant generator of revenue for most investment banks. Unfortunately, this information is not available for the vast majority of nonpublic underwriters. Moreover, publicly traded investment banks, which are required to report this information, lump commissions and fees from trading with other investment banking and management fees.

outcomes of participation. We use a *multivariate entropy* measure to aggregate the degree of participation in investment banking:

$$IB\_SHARE_u = -\sum_{k=0,1} P(I_{u1}=k)P(I_{u2}=k)P(I_{u3}=k)\,\log\left[P(I_{u1}=k)P(I_{u2}=k)P(I_{u3}=k)\right]. \quad (4)$$

The entropy is a widely accepted measure of uncertainty in statistics. A simple estimate for $P(I_{uj}=1)$, the probability that underwriter u participates in activity j, is provided by the market share S_{uj} of the firm (and similarly for $P(I_{uj}=0)$ by $(1-S_{uj})$). We use again the firm's simple market share S_{u1} to measure participation in equity underwriting. The share of corporate bond underwriting S_{u2} is estimated from the SDC league tables of U.S. domestic straight corporate debt. Similarly, we use the SDC league financial advisor tables to shares of merger-related services.[12] In the current framework, the entropy statistic indicates the concentration in investment banking activities. A high IB_SHARE score represents a firm with strong presence in all three investment-banking lines and, thus, greater incentives to integrate all these activities.[13] The coefficient on IB_SHARE is positive and significant (last column in Table 4). IPOs that were advised by lead underwriters with more integrated investment banking activities

---

[12] The domestic debt rankings were based on the value of proceeds. M&A rankings were on the basis of the net debt of the target firm and included only completed deals.

[13] The multivariate entropy measure is undefined for any firm with a zero market share, that is, $P(I_{uj}=1)=0$. To avoid this problem, we set $P(I_{uj}=1)$ equal to a very small value (for example, 10^{-8}). A higher entropy value signifies a firm with a larger and more integrated investment banking activities. For example, CS-First Boston Corp, with a fairly high market share of 5 percent in IPO underwriting share in the 1990s and a strong presence in both corporate bond underwriting and M&A advising, had an entropy score of 0.72. Although Alex Brown maintained a higher market share in IPO underwriting during the same period (close to 8 percent), it was assigned a lower entropy score (just over 0.25) because of its negligible debt and M&A businesses.

experienced higher stock market volatility in the 1990s. The coefficient estimate on IB_SHARE is slightly more significant compared to the MANAGER_SHARE coefficient, perhaps signifying that this entropy-based measure is more representative of the overall scope of the underwriter's activities. This result reinforces the presence of agency conflicts that can distort the relationships between investment bankers, issuers, and investing clients.

4. THE RISK OF DELISTING AFTER GOING PUBLIC

In the previous section, we presented evidence documenting a significant rise in the market risk of IPOs relative to their style- or size-matched benchmarks. In a perfect market efficiency framework, stock price volatility is simply the outcome of unanticipated or random information about the firm. The log volatility ratio compares the uncertainty embedded in the stock performance of an IPO and its control firm. The implicit assumption in this relative risk comparison is that the issuer and its style-matched peer have a similar risk profile and financial characteristics. Under this assumption, the rise in the log volatility ratio observed during the 1990s may be interpreted as evidence that the market perceived IPOs as more risky. These style- or size-based benchmark comparisons cannot always guarantee that the issuing firm is properly matched with a control firm. If the mismatches occur in an arbitrary manner, the errors should on average cancel out in a large sample

In this section, we use an alternative methodology to evaluate post-issue risk by examining the survival of IPOs. In many ways, a firm's likelihood of survival (or inversely default) and stock return volatility are closely related. A firm with a high probability of failure is a poor performer with uncertain cash flows, resulting in an unsteady stock price. Survival analysis, however, offers also two distinct methodological improvements. First, this approach does not require the construction of a benchmark because failed firms are inherently compared to surviving ones. Second, a qualitative model of survival offers a much easier way to develop a structural model to control for differences in the financial and operating performance of firms.

A. *Equity Delisting by Exchanges*

Equity delistings are a frequent event in all major stock exchanges. Securities may cease trading or delist from the exchange because of a number of routine reasons: Merger, exchange offer, liquidation, and a voluntary move to another exchange. To protect investors, the Securities Exchange Act of 1934 also authorizes national securities exchanges to drop registered securities that fail specified criteria. For example, a listed company can be dropped because it has insufficient capital, its stock price falls below a minimum level, or the security has an insufficient number of market makers. In some cases (e.g., financial regulated firms such as banks and insurance companies), delistings are often closely associated with regulatory actions that result in a terminal outcome such as a formal closure or failure of the institution. Firms that get delisted by the three major national exchanges (NYSE, NASDAQ, and AMEX) end up trading on the over-the-counter NASDAQ market or the bulletin board (pink sheets). Once moved to a secondary exchange, companies are highly unlikely to relist on a national exchange. A negative performance delisting is usually the first step leading to the eventual financial collapse of the firm

B. *Constructing a Sample of Delisted Securities*

Our analysis focuses on *negative* performance delistings. It is safe to assume that companies that are denied a national listing face severe financial problems. Often a firm is dropped from the exchange after filing for bankruptcy or is close to default, events that result in significant investor losses. Inevitably, firms that move to a secondary exchange often delist again or languish trading as penny stocks. CRSP identifies most performance-related delistings by a range of unique codes (500, 520-591). Shumway and Warther (1999) document a delisting bias stemming from missing returns for stocks dropped from 1962 to 1993. Another possible source of bias encountered in the CRSP tapes is that sometimes a security is dropped although its stock price is fairly high. One possible reason for this inconsistency is that delistings are sometimes unanticipated, as a result most of the sell-off in the stock takes place after it starts trading on the secondary exchange. Sometimes these discrepancies in the CRSP delisting code exist because the company has actually been acquired rather than failed. We correct these inconsistencies using information from Bloomberg Financial. At the same, we use Bloomberg information to verify the final status of every delisted firm. Simply put, a dropped security is considered a failure and kept in the delisting sample only if it has resulted in a significant loss to shareholders.[14]

The baseline for the sample of delisted firms is all active firms trading on the NYSE/AMEX or NASDAQ (those with a delisting code of 100).[15] The sample excludes firms that merged or were acquired (codes 200-290), exchanged stock or liquidated (400-490), and became a foreign security (900-903). In summary, the final sample consists of all active listed

[14] As a result of these corrections, roughly 200 of so-defined negative performance delistings were excluded from the final sample. Using Bloomberg Financial, we were also able to splice together the complete price history for nearly all delisted firms. Most delisted securities resulted in a total loss to shareholders (the median last quoted price for a delisted firm was less than 1 cent per share). A small fraction of negative delistings were excluded from our analysis because (a) they were able to relist again; or (b) managed to recover and were actively traded in secondary markets. Furthermore, we were unable to determine from Bloomberg or other sources the final resolution for a handful of delistings that occurred in the early 1980s. To eliminate possible nonevents (acquisitions and mergers) from these earlier issues, a delisted firm was assumed to be a failure if its last quoted price in the CRSP tapes was less than one-fourth of the IPO price, otherwise the firm was deleted from the sample.

[15] In some instances, a company maintains an active status for a long time even though it has actually filed for Chapter 11 bankruptcy reorganization. For example, K-Mart Corporation filed for bankruptcy on March 12, 2002 but has continued to trade on the NYSE. As long as the NYSE has not delisted the company, our analysis will treat such a case as a nonevent.

firms in the CRSP tapes and firms that were dropped because of negative performance reason from 1980 to 2000.

C. Modeling the Likelihood of a Firm Delisting

A performance-related delisting is a pivotal event often related to a formal filing for bankruptcy. The terminal nature of this event is even more profound in our sample of CRSP delistings that is confined to include only adverse outcomes to investors. Because in our framework a delisting is tantamount to failure, we can model such discrete event in the same way as a corporate bankruptcy.[16] Altman (1968) proposes a formal qualitative statistical model for evaluating corporate performance. In his work, Altman advocates a shift away from simple analytical techniques, such as financial and accounting ratios, to formal statistical methods like discriminant analysis. A large body of work has extended Altman's methodology using other qualitative statistical models of bankruptcy (see for example, Altman, Haldeman and Narayman (1977), Aharony, Jones, and Swary (1980), and Ohlson (1980)).

In a recent paper, Shumway (2001) proposes a dynamic (cross-sectional time-series) hazard model for estimating conditional bankruptcy. Survival models offer a convenient framework for investigating the aftermarket life cycle of IPOs because these firms have a well-defined point of origin. However, this duration approach is blurry for nonissuing firms because they are frequently left-censored.[17] A simple way to circumvent this problem is to use a discrete-

[16] In fact, Chapter 11 corporate reorganizations are not always detrimental to shareholders. Several studies (see, for example, Weiss (1990) and Morse and Shaw (1988)) have shown that the majority of companies that filed for Chapter 11 managed to reemerge under reorganization plans. In contrast, a negative delisting in our study is equivalent to a total failure, which results in a substantial loss to shareholders.

[17] Left censoring corresponds to the case where the time of origin is unknown. A large number of companies listed on the major stock exchanges are left-censored. Although the CRSP tapes provide an origination date, this simply represents the time at which the company was listed on a

choice model like logit or probit. In discrete-choice models, there is no need to focus on the length of the transition from listing on an exchange to delisting, therefore, there is no need to know the actual offering date of the security. The logistic regression model is given by:

$$d_{ti}^{*} = x_{ti\bullet}\gamma + \upsilon_{ti}. \tag{5}$$

The latent variable d_{ti}^{*} is defined by:

$$\begin{aligned} d_{ti} &= 1 \quad \textit{if} \quad d_{ti}^{*} \le 0 \quad \textit{(firm delisted in year t)}, \\ d_{ti} &= 0 \quad \textit{if} \quad d_{ti}^{*} > 0 \quad \textit{(otherwise)}. \end{aligned} \tag{6}$$

The vector $(x_{ti\bullet})$ controls for the firm's financial condition in year $(t-1)$. In addition, the regression includes a number of market-driven explanatory variables and fixed- or time-effects controls. In a way, we can view the dependent variable d_{ti}^{*} as a latent score of firm solvency determined by a vector of financial attributes $(x_{ti\bullet})$. An in-sample measure of the probability of a delisting can be computed from:

$$\hat{p}_{ti} = F(x_{ti\bullet}\hat{\gamma}), \tag{7}$$

where $F(\bullet)$ represents the logistic cumulative distribution.

To gauge a firm's financial or operating performance, we use a number of accounting ratios computed from the COMPUSTAT database. Although we considered several accounting variables proposed in the bankruptcy literature, in the end we decided to focus on three commonly used financial ratios: The ratio of working capital to total assets (WCAP), sales to total assets (SALES), and after-tax rate of return divided by total assets (ROA). In addition, the

major exchange with a unique CRSP perm number. In light of the fact that corporations undergo several structural changes, this origination date does not necessarily correspond with the actual IPO date.

logit specification includes two useful ratios aimed at capturing a firm's intangible value and growth potential. The Q-ratio, defined by market capitalization plus liabilities divided by total assets minus goodwill (QRATIO), has been used in the literature as a measure of franchise value. Finally, per share R&D expenditures are a good proxy of the future growth of the firm.

Shumway (2001) illustrates that a number of market-derived measures of firm performance are also good predictors of bankruptcy. Not surprising, firm size (SIZE) measured by the log market capitalization (in real dollars) is strongly related with failure. Another useful regressor proposed by Shumway is a measure of the firm's abnormal return from the market-weighted CRSP index, which is a good proxy of idiosyncratic risk (EXCESS_RETURN). Riskier firms that are closer to getting delisted and filing for bankruptcy are also more likely to exhibit greater market volatility. We measure a firm's market volatility (VOLATILITY) by averaging monthly standard deviations of daily CRSP returns in year $(t-1)$.

Listing and delisting rules vary across national exchanges. Some exchanges have stricter requirements for maintaining a listing and therefore companies trading on those exchanges have inherently a higher likelihood of delisting. To control for these differences, we added dummy indicators for the major exchanges (NYSE, AMEX, or NASDAQ). We also use dummy variables to highlight the performance of high-growth technology (HIGHTECH) and Internet firms (INTERNET). Finally, although these coefficient estimates are not reported for the sake of brevity, all regression specifications include yearly time-effects.

A small number of studies in the IPO literature analyze more closely the aftermarket transition of issuing firms (Jain and Kini (1999) and Hensler et al. (1997)). In contrast to articles of bankruptcy that stress financial performance, these studies investigate primarily the importance of offering characteristics at the time of the issuance (size of IPO issue, pre-IPO profitability, insider ownership prior to offering, age of the firm at offering, IPO premium, and industry structure). We also analyze the effect of firm-specific IPO measures of the quality of the issuer. This regression specification controls for the age of the firm after the offering (YEARS_LISTED) as well as includes dummy indicator for venture capital funding (VENTURE) and spin-offs (SPINOFF). More important, we use again the market share (MANAGER_SHARE), the Carter-Manaster lead underwriter rankings (CM_RATING), and the entropy measure (IB_SHARE) to control for the presence of agency conflicts. Because these offering attributes are not observed for nonissuing firms, the regression sample in now confined only to the IPOs.

D. *Logit Estimates*

Table 5A reports the maximum likelihood estimates of the logistic regression for two different specifications. The first panel in the table presents the logit estimates for the entire population of issuing and nonissuing firms available in COMPUTSTAT from 1980 to 2000 as well as the two subperiods 1980-1989 and 1990-2000. The scope of the analysis in Table 5B is narrower because the regression sample is limited only to IPOs. This specification, however, makes it possible to investigate the relationship between IPO attributes and survival.

At the bottom of the table, we report the likelihood ratio χ^2 statistics and pseudo R^2 for each logit regression specification. The strong significant values of the likelihood ratio statistics indicate that the logit specification fits the data very well. The efficacy of the model is also evident from the predictive accuracy of the logistic regressions, as the concordant ratios are well over 90 percent for all specifications.

As expected, the explanatory variable the log market capitalization of the firm in real dollars (SIZE) has the strongest impact on the probability of delisting. Market participants therefore appear to discipline faltering companies that are close to bankruptcy or delisting. The parameter estimates on the remaining market-derived explanatory variables are mostly significant with the expected sign. Market volatility (VOLATILITY) is positively correlated with the probability of delisting. Better performing firms with higher excess returns (EXCESS_RETURN) are less likely to be dropped by the exchanges.

Consistent with the bankruptcy literature, we find that accounting variables measuring profitability and capitalization are also strong determinants of firm survival. The large negative effect of ROA confirms that more profitable companies are less likely to be delisted. Our empirical results also reveal that higher franchise value (QRATIO) and larger R&D expenditures (R&D) lower the probability of delisting. Since adequate capitalization is an explicit requirement in maintaining an exchange listing, it is not surprising that firms operating with insufficient working capital ratios (WCAP) are in greater danger of losing their exchange listing. Similarly, companies listed on the NYSE face stricter rules are more likely to be dropped from the Big Board when they falter.

More important, the logit analysis shows that IPO firms have on average a higher chance of failure in the 1990s. In contrast, the parameter estimate on the IPO dummy variable in the 1980-1989 regression is insignificant and negative. A simple way to quantify this added risk on issuers is by computing the odds ratios of the IPO responses (Table 6). The odds ratio simply compares the probability of delisting for firms that went public to those that did not.[18] The estimate for the odds ratio during the 1990-2000 period is about 1.293, meaning that the odds of a delisting for IPO companies is about 30 percent greater than the odds of a delisting by a

[18] Algebraically, the odds ratio for IPOs is defined as $\frac{P(issuing\ \ firms\ delists / IPO = 1)}{P(nonissuing\ firm\, delists / IPO = 0)}$.

nonissuing firm. In contrast, the odds ratio for IPO in the 1980s is 0.911 and not significantly different than 1. In a recent study, Fama and French (2002) also document that new listed companies have a lower likelihood of survival compared to seasoned firms.

Admittedly, the coefficient estimates for high-tech offerings do not fully capture the dramatic unraveling in the dot.com sector because these companies span a broad class of industries (see Section A.3 in Appendix for a more detailed of the Internet classification). The collapse of the Internet sector is depicted more accurately by the logit regression reported in the third column of Table 5A, which controls directly for the impact of Internet IPOs. The coefficient on the INTERNET dummy is strongly significant, affirming that these "new economy" companies are responsible for a lot of the deterioration in IPO performance in the late 1990s. More striking, the INTERNET odds ratio estimate implies that the likelihood of an Internet IPO losing its exchange listing is 7.74 times greater than the likelihood of delisting by a nonissuer.

Table 5B investigates the relationship between offering characteristics and survival. The analysis of the IPO sample provide further evidence that the aftermarket survival of the issuers is dominated by company-specific or market performance measures such as profitability, capitalization, and firm market risk. However, the results also establish that offering characteristics can predict the post-issue performance of the firm.

The coefficient on venture explanatory dummy variable (VENTURE) is negative and insignificant in the 1980s. In contrast, investors in venture-backed IPOs faced greater default risk during the 1990s. The odds of delisting for venture-funded firms are around 1.47 higher than the odds of non-venture firms (Table 6). This result seems to contradict perceptions that venture-backed firms are better performers. The prevalent view in corporate finance is that companies seeking venture capital are lesser-known corporations with a greater risk of adverse selection. A venture capital firm acts as a financial intermediary with strong monitoring incentives to reduce moral hazard. However, this monitoring role may be more ambiguous after the offering, as many venture capital investors elect to cash out their gains not long after the firm goes public. Moreover, given the right incentives, venture capitalist along with managers and other insiders may be prematurely lured to the market by investment bankers, seeking to boost the volume of their IPO business. A somewhat surprising finding is that spin-off IPOs have a greater probability of delisting. The prevailing view on corporate spin-offs is that they should enhance value because they improve informational asymmetries.

The logit analysis confirms again that the likelihood of survival decreases for firms taken public by large lead underwriters (measured by MANAGER_SHARE, CM_RATING, and the entropy IB_SHARE), even after controlling for company-specific performance and other important structural factors. The odds of delisting for a firm taken public by a top-tier lead managers during the 1990s (represented in the last row of Table 6 by the dummy variable TOPMANAGER) were 1.98 higher than the odds of delisting by a firm underwritten by smaller and more specialized manager. These results appear to be consistent with the agency conflict thesis that large IPO underwriters had strong incentives to integrate corporate underwriting and trading businesses.

The logit specifications in Table 5C explore the adverse selection hypothesis. The premise here is whether the character of technology or Internet IPOs (the risky firms) differs across large investment banks and their smaller competitors. Internet issuers are more speculative start-ups with bigger information asymmetries. According to the adverse selection hypothesis, these opaque firms would opt for a full-service advisor that has the resources to successfully sell their offering and provide logistical support in the aftermarket. As a result, the testable hypothesis is that risky Internet firms would congregate to the large lead managers. The coefficient on the interaction variable INTERNET×TOPMANAGER is positive but highly insignificant. This outcome suggests that Internet firms that were advised by the top-tier underwriters had the same probability of delisting as those advised by small underwriters. The risk among Internet firms appears to be broadly distributed across all underwriters.

A casual examination of the SIC codes of IPOs also does not reveal any visible "adverse selection" tendencies among issuers. The pattern of the distribution of SIC codes of IPOs is very similar among large and small underwriters. In the past, it was quite unusual for reputable investment banks to advise unprofitable firms. In fact, the gap in pre-issue financial performance (such as profitability and capitalization) between companies advised by top-tier underwriters and those advised by smaller underwriters is very wide in the 1980s. This performance gap has vanished in late 1990s, as a wave of unprofitable issuers cluttered the public equity market.

E. *Estimating the Incremental Effect on Delisting Risk from the Survival Function*

The logit odds ratios presented in Table 6 depict how each factor individually contributes to the probability of delisting. As noted previously, survival models offer another convenient framework for investigating the aftermarket riskiness of firms, especially if we focus exclusively on issuing companies, which have a well-defined point of origin. The hazard approach is very useful in highlighting the marginal effect on survival. The aftermarket experience of the issuing firm is characterized by the hazard rate, the rate at which the life cycle of the firm is completed (that is, the firm is delisted) after (τ) periods, given that it has survived up that time point.[19]

[19] To formally describe the proportional hazard model, let the random variable (τ) represent the life (in months) of the firm after going public. The hazard rate at time (τ) is defined by $h(\tau \mid x_{ti\bullet}\beta) = h(\tau)\exp(x_{ti\bullet}\beta)$. Consistent with equation (6), the vector $(x_{ti\bullet})$ represents again the

Figure 5 plots the estimated survival function of firms that went public between 1990 and 2000. The top solid line in the figure represents the baseline survival (that is, the survival of the average firm). Here, a baseline IPO is a non-Internet firm that has not been advised by a top-tier underwriter, has not received venture capital funding, and is not a spin-off. The figure illustrates that the Internet factor has by far the greatest effect, decreasing the aftermarket survival of issuers after 6 years from 0.99 to 0.91. To be sure, IPOs advised by large underwriter experience a further decline in survival. However, our graphical analysis clearly demonstrates that the most important reason for the increased riskiness of IPOs in the late 1990s is a structural change in the type and quality of firms that chose to go public. Agency conflicts between underwriters, venture capital investors, and issuers have contributed to the poor performance but to a much lesser extent.

5. CONCLUSION

This paper examines the aftermarket riskiness of companies that went public between 1980 and 1990. We have used two different approaches to evaluate a firm's risk profile over these two decades. First, we compared the return volatility of an IPO firm with a comparable nonissuing firm. Second, we employed a logit model to evaluate the likelihood of survival of IPOs. Both methodologies point to similar conclusions. We find that IPO investors were exposed to increased risk during the 1990s. In particular, issuers in this decade exhibited higher return volatility and had a smaller probability of survival than in the 1980s.

---

explanatory variables. The function $h(\tau)$ is commonly referred to as the baseline hazard function. We use the partial maximum likelihood method to estimate β. The survival function of an issuing firm is estimated by $\widehat{S} = [S_0(\tau)]^{\exp(x_{ti} \bullet \widehat{\beta})}$, where $S_0(\tau)$ is a nonparametric estimate of the baseline survival function.

Several factors have contributed to the deteriorating quality of the issuers. In the 1990s, we witnessed the proliferation of many chancy high-growth technology and Internet issuers. In particular, the Internet high-tech dummy explanatory variable in the logit regressions is strongly correlated with the probability of failure. Although Internet companies have elevated the level of risk in the late 1990s, our findings also reveals a more gradual rise in riskiness throughout the decade. Our regression analysis shows that IPOs managed by large underwriters or funded by venture capital have experienced greater aftermarket risk and a lower probability of survival. A closer investigation of the regression findings does not provide any support to the adverse selection viewpoint that riskier issuers sought the services of large underwriters. The empirical evidence, however, appears to be consistent with the agency problems hypothesis proposed in the recent academic literature, emphasizing conflicts of interest among issuers, underwriters, and their investing clients.

In the last two decades, the U.S. has managed to transform from a sluggish industrial and manufacturing economy into a highly dynamic information- and innovation-driven economy. U.S. public equity markets have been a key catalyst of economic growth during this period. In addition to providing direct financing, equity offerings indirectly promote private funding for small start-up entrepreneurs by enabling venture investors to harvest their investment in the public markets. The observed rise in IPO risk in the 1990s has therefore the potential to adversely affect both private and public capital formation.

It remains to be seen what will be the consequences of the structural deterioration and the apparent conflicts of interest in the new issues market. Historically, the IPO market has always shown the resiliency to rebound after a "cold issue" period. In contrast to previous problems, however, the new issues market today may not fully recover unless a serious process of reform is set in place to make corporate financing more efficient and eliminate all agency problems between market participants.

APPENDIX

A.1 *IPO sample*

The sample was assembled together by combining the list of IPOs provided by SDC with information from the CRSP tapes. We used the 6-digit CUSIP to match firms in the two databases. The final sample of IPOs excludes (a) all IPOs with a CRSP starting date that is more than 30 days later than the SDC IPO date, and (b) IPOs with an offering price less than $5. In addition, we eliminated from the sample all closed-end funds, REITs, ADRs, and Unit Trusts.

A.2 *Constructing Benchmarks*

To analyze the relative performance of IPOs, we calculate the buy-and-hold abnormal returns (BHARs) and cumulative abnormal returns (CARs) for three different benchmarks: (a) the CRSP value-weighted index, (b) a size-matched comparison, and (3) a style-matched control. For the value-weighted comparisons, the adjusted return is given by the difference between the return of the IPO firm at month (t) and the value-weighted return of the CRSP index in the same month. For size-matched comparisons, the adjusted return is again the difference between the return of the IPO firm at month (t) and the return of its size-matched firm. To choose a proper size match for the issuer, we compared its initial market capitalization in the first month after going public with all other firms that existed for at least 5 years prior to the date of the IPO. The firm with the closest market capitalization was selected to be the control. If the stock price information of the matching firm was unavailable for the entire historical period, the algorithm selected the company with the next closest market capitalization. This process was continued until we spliced together a complete history of the adjusted returns for each IPO.

For style-matched comparisons, we compared the IPO firm with a cohort firm according to size and market-to-book value. The market-to-book ratio was computed from COMPUSTAT. To choose a size and market-to-book nonissuing peer, we first ranked the IPO firms into ten size groups based on their initial monthly market capitalization. Subsequently, the market-to-book ratio was compared with the rest of the nonissuing firms within the same decile group. All control firms existed for at least 5 years prior to that particular IPO date. A firm with the closest market-to-book ratio was selected to be the control. Consistent with the size-matching procedure, this selection process was continued until the full history of the IPO firm was completely filled.

A.3 *Description of Selected Explanatory Variables*

The Carter-Manaster lead underwriter rankings (CM_RATING) were obtained from Jay Ritter's website. Appendix 3 in Loughran and Ritter (2002) provides a detailed discussion of how the prestige rankings database was put together. We also ranked underwriters according to their market share in each decade (MANAGER_SHARE). The market share was computed on the basis of gross proceeds. Because several large investment banks were acquired or merged with other financial institutions, we first calculated the market shares of each underwriter by year and subsequently averaged these yearly values to come up with an overall rank over the decade. The market share rankings are highly correlated with the Carter-Manaster ratings. The variable TOPMANAGER is a binary indicator for the large prestigious underwriters in each decade. With the exception of a couple of minor subjective corrections, the market share and the Carter-Manaster rank determined the top underwriter groups in each decade. The top-tier underwriters in the 1990s are: Goldman Sachs, Merrill Lynch, Morgan Stanley, Deutsche Bank-BT-Alex Brown, Credit Suisse First Boston, Smith Barney, First Boston Corporation, Lehman Brothers, Salomon Brothers-Salomon Smith Barney, Donalson Lufkin Jenrette, Lehman Brothers, Chase-HQ, and JP Morgan Securities. Sometimes the corporate status of the investment bank changes over time (for instance, Smith Barney evolved from Smith Barney-Harris Upham to Smith Barney-Shearson to Smith Barney Inc. before was finally acquired by Salomon Brothers). In the 1980s, the top lead advisors are: Merrill Lynch, Shearson Loeb Rhoades, Goldman Sachs, Alex Brown, Paine Webber, Morgan Stanley, Kidder Peabody, E. F. Hutton, L.F. Rothchild, Prudential Bache, Lehman Brothers, Salomon Brothers, First Boston, and Drexel Burham Lambert.

The issuer's founding date was compiled from SDC, Dunn and Bradstreet and an online list available at Jay Ritter's website. In many ways, the process of identifying a firm's establishment date is somewhat judgmental. For instance, sometimes in spin-offs the "founding date" is listed as the year before the IPO (or even coincides with the issue year), although the firm may have existed as a subsidiary for several years prior to the offering. To avoid these discrepancies, the founding date of each IPO was determined on a case-by-case basis. Through this subjective process, we were able to identify the establishment date for about 4,500 issuers in our sample.

The classification of technology firms is based on the following SIC codes (2836, 3570-3579, 3660-3679, 3840-3845, 4810-4819, 5045, 5734, 5961, 7370-7379). The process of identifying Internet IPOs was more judgmental because these firms are dispersed across a variety of sectors. First, we constructed a preliminary file from Ivo Welch's list of Internet IPOs (available at http://www.iporesources.org/internetmadness.html) and from a list provided to us by Eli Ofek (see Ofek and Rirchardson (2002)). We supplemented this list by adding suitable firms from several Internet indexes (Bloomberg US Internet Index, CBOE Internet Index, DJ Internet Commerce Index, DJ Internet Service Index, Goldman-Sachs Internet Index, Fortune E-50 Index, Isdex Internet Stock Index, Street.com Net Index, and Standard 100 Inet Index). Finally, we used the company profile description from Bloomberg Financial to verify the preliminary list and see if any other excluded firm that went public after 1994 had an Internet-related business. The final sample of Internet IPOs includes 529 firms.

REFERENCES

Aharony, Joseph, Charles P. Jones, and Itzhak Swary. “An Analysis of Risk and Return Characteristics of Corporate Bankruptcy Using Capital Market Data,” *Journal of Finance* 35 (September 1980), 1001-16.

Allen, Franklin and G. Faulhaber. “Signalling by Underpricing in the IPO Market,” *Journal of Financial Economics* 23 (1989), 303-323.

Altman, Edward I. “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy,” *Journal of Finance* 23 (September 1968), 589-609.

Altman, Edward I., R. G. Halderman, and P. Narayaman. “ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations,” *Journal of Banking and Finance* 1 (June 1977).

Barber, Brad M, and John D. Lyon. “Detecting Long-Run Abnormal Stock Returns,” *Journal of Financial Economics* 43 (December 1997), 341-372

Brav, Alon and Paul Compers. “Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Nonventure Capital-Backed Companies,” *Journal of Finance* 52 (December 1997), 1791-1821.

Boni, Leslie, and Kent L. Womack. “Wall Street’s Creditbility Problem: Misaligned Incentives and Dubious Fixes?” Working Paper 02-04, Financial Institutions Center, Wharton School University of Pennsylvania (February 2002).

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu. “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk,” *Journal of Finance* 56(February 2001), 1-43.

Carter, Richard, Frederick Dark, and Ajai Singh. “Underwriter Reputation, Initial Returns and Long-Run Performance of IPO Stocks,” *Journal of Finance* 53 (December 1998), 285-311.

Carter, Richard and Steven Manaster. “Initial Public Offerings and Underwriter Reputation,” *Journal of Finance* 45 (December 1990), 1045-1068.

Eckbo, B. Espen , and Oyvind Norli. “Leverage, Liquidity, and Long-Run IPO Returns,” Amos Tuck School of Business, Dartmouth College, Unpublished Paper (February 2000).

Estrella, Arturo. “A New Measure of Fit for Equations with Dichotomous Dependent Variables,” Journal of Business and Economics Statistics 16, (April 1998), 198-205.

Fama, Eugene F. “Market Efficiency, Long-Term Returns, and Behavioral Finance,” *Journal of Financial Economics* 49 (December 1998), 283-306.

Fama, Eugene F., and Kenneth R. French. “Size and Book-to-Market Factors in Earnings and Returns,” *Journal of Finance* 50 (March 1995), 131-155.

Fama, Eugene F., and Kenneth R. French. “New Lists and Seasoned Firms: Fundamentals and Survival Rates,” Unpublished Paper, July 2002.

Fulghieri, Paolo, and Matthew Spiegel. “A Theory of the Distribution of Underpriced Initial Public Offers by Investment Banks,” *Journal of Economics and Management Strategy* 4 (Winter 1993), 509-530.

Gompers, Paul, and Joshua Lerner. “The Really Long-Term Performance of Initial Public Offerings: The pre-Nasdaq Evidence,” National Bureau of Economic Research, Working Paper 8505.

Hensler, Douglas A., Ronald C. Rutherford, and Thomas M. Springer. “The Survival of Initial Public Offerings in the Aftermarket,” *Journal of Financial Research* 20 (Spring 1997). 93-100.

Kothari, S. P, and Jerold B. Warner. “Measuring Long-Horizon Security Price Performance,” *Journal of Financial Economics* 60 (December 1997).

Ljungqvist (2002). “Conflicts of Interest and Efficient Contracting in IPOs,” New York University-Stern School of Business, Unpublished Paper (September 2002).

Loughran, Tim, and Jay R. Ritter. “The New Issues Puzzle,” *Journal of Finance* 50 (December 1995), 23-51.

Loughran, Tim, and Jay R. Ritter. “Why Don’t Issuers Get Upset About Leaving Money on the Table in IPOs,” *Review of Financial Studies* (2002), 413-440.

Loughran, Tim, and Jay R. Ritter. “Why Has IPO Underpricing Increased Over Time,” Unpublished Paper, University of Notre Dame and University of Florida (August 2002).

Lyon, John D., and Brad M. Barber, and C. L. Tsai. “Improved Methods for Tests of Long-Run Abnormal Stock Returns,” *Journal of Finance* 54, (December 1999), 165-201.

Megginson, William L., and Kathleen A. Weiss. “Venture Capitalist Certification in Initial Public Offerings,” *Journal of Finance* 46 (July 1991), 879-903.

Michaely, Roni, and Kent L. Womack. “Conflict of Interest and the Credibility of Underwriter Analyst Recommendations,” *Review of Financial Studies* 12 (1999), 653-686.

Mitchell, Mark L., and Erik Stafford. “Managerial Decisions and Long Term Stock Price Performance,” *Journal of Business* 73 (December 1996), 287-329.

Morse, Dale, and Wayne Shaw. " Investing in Bankrupt Firms," *Journal of Finance* 43 (December 1988), 1193-1206.

Muscarella, Chris J., Michael R.Vetsuypens. "A Simple Test of Baron's Model of IPO Underpricing," *Journal of Financial Economics* 24(September 1989), 125-35.

Jain, Bharat A., and Omesh Kini. "The Life Cycle of Initial Public Offering Firms," *Journal of Business Finance and Accounting* 26 (November/December 1999), 1281-1307.

Ofek, Eli, and Matthew Richardson, "DotCom Mania: The Rise and Fall of Internet Stock Prices," Unpublished Paper, Stern School of Business, New York University, 2002.

Ohlson, James A. "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research* 18 (Spring 1980), 109-31.

Ritter, Jay R. "The Long Run Performance of Initial Public Offerings," *Journal of Finance* 46 (March 1991), 3-27.

Ritter, Jay R. "Investment Banking and Securities Issuance," in *Handbook of the Economics of Finance*, edited by George Constantinides and Rene Stulz, 2002.

Ritter, Jay R, and Ivo Welch. "A Review of IPO Activity, Pricing and Allocations," Yale ICF Working Paper no. 02-01, February 2002.

Rock, K. "Why New Issues are Underpriced," *Journal of Financial Economics* 15 (1986), 187-212.

Silverman B.W. *Density Estimation for Statistics and Data Analysis*. London: Chapman Hall, 1988

Shumway, Tyler. "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business* 74 (January 2001).

Shumway, Tyler, and Vincent A.Warther. "The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect," *Journal of Finance* 54(December 1999), 2361-79.

Weiss, Lawrence A. "Priority of Claims and Ex-Post Re-contracting in Bankruptcy," *Journal of Financial Economics* 27 (1990), 285-314.

TABLE 1. IPO Sample Selection Criteria and Descriptive Statistics

This table describes the sample selection criteria for the IPO sample used in the analysis (for a more detailed description, see Section A.1 in the Appendix). The IPO sample was compiled from the Thompson Financial *Securities Data Corporation* (SDC) new issues databases. Moreover, we matched the SDC list of new issues with the University of Chicago's Center of Research in Securities Prices (CRSP) database using the 6-digit CUSIP code. We also eliminated from the sample all fund offerings and small firms. Note that numbers in the eliminated IPO categories do not sum up exactly to the total number excluded because of double counting.

SAMPLE CONSTRUCTION		
Total IPOs from SDC (1980-2000)		9,890
Total CRSP-matched IPOs		8,848
Categories of IPOs excluded		
Closed-end funds		534
REITs		168
ADRs		260
Unit Trusts		74
IPOs with Offer price < \$5		845
	Total Excluded	1,874
Final number of IPOs in the Sample		6,974
Sample IPO Characteristics		Mean
Offering price (in dollars)		10.5
Gross proceeds (\$ millions)		49.8
Age since establishment date (in years)		10.9
Percent with venture capital funding		32.1
Percent spin-offs		10.7

TABLE 2. Summary Statistics for the Log Volatility Ratio (σ-RATIO)

The (σ-RATIO) is defined by:

$$\sigma - RATIO_{ti} = \log\left(\frac{\hat{\sigma}_{IPO,\,ti}}{\hat{\sigma}_{PEER,\,ti}}\right),$$

where ($\hat{\sigma}_{IPO,ti}$) represents the monthly return volatility of the IPO firm and ($\hat{\sigma}_{PEER,ti}$) is the monthly return volatility of the matched firm. Columns summarize the monthly ratio for the first five years after the offering.

Period	Year 1	Year 2	Year 3	Year 4	Year 5
		A. Style-matched			
1980s					
Mean	-0.11***	0.03***	0.06***	0.06***	0.07***
Median	-0.10***	0.03***	0.04***	0.04***	0.04***
Maximum	5.02	4.24	4.55	4.67	4.27
Minimum	-4.48	-3.83	-3.72	-3.59	-4.11
1990s					
Mean	0.27***	0.26***	0.25***	0.22***	0.21***
Median	0.27***	0.25***	0.24***	0.22***	0.21***
Maximum	4.61	4.62	4.28	4.09	4.22
Minimum	-3.30	-3.51	-3.70	-3.72	-3.56
t-test for equality in means across decades	45.3***	26.7***	20.4***	16.5***	12.4***
		B. Size-matched			
1980s					
Mean	0.13***	0.24***	0.27***	0.29***	0.30***
Median	0.14***	0.23***	0.26***	0.29***	0.30***
Maximum	4.43	4.50	4.70	5.99	4.28
Minimum	-4.39	-4.83	-3.77	-4.32	-3.54
1990s					
Mean	0.38***	0.39***	0.40***	0.41***	0.41***
Median	0.38***	0.38***	0.39***	0.40***	0.41***
Maximum	4.69	5.06	5.09	4.30	4.77
Minimum	-3.57	-3.52	-3.49	-4.10	-4.14
t-test for equality in means across decades	40.6***	22.3***	18.9***	15.7***	11.9***

TABLE 3. The Relationship Between the Log Volatility Ratio (σ-RATIO) and IPO Characteristics

The (σ-RATIO) is defined by:

$$\sigma - RATIO_{ti} = \log\left(\frac{\hat{\sigma}_{IPO,\,ti}}{\hat{\sigma}_{PEER,\,ti}}\right),$$

where ($\hat{\sigma}_{IPO,ti}$) represents the monthly return volatility of the IPO firm and ($\hat{\sigma}_{PEER,ti}$) is the monthly return volatility of the matched firm. When σ-RATIO is equal to zero the IPO firm has exactly the same market risk as its peer. A positive σ-RATIO indicates that the IPO firm is riskier than its control. The variable AGE is the age of the IPO firm from the date it was founded (in years); PROCEEDS represents gross IPO proceeds divided total market capitalization (decimal); TOPMANAGER is a dummy indicator for the top lead managers (see Section A.3 in the Appendix); VENTURE is binary indicator for venture funding; MANAGER_SHARE represents the market share of the lead manager of the offering in each decade; CM_RATING is the Carter-Manaster lead manager reputation rankings. Finally, INTERNET and HIGHTECH represent dummy variables for Internet and high technology firms, respectively. Values in the table are averages for each quartile category.

Quartile Categories of σ-RATIO	σ-RATIO	AGE	PROCEEDS	VENTURE	MANAGER_ SHARE	CM_ RATING	TOPMANAGER	INTERNET	HIGHTECH
Panel A: 1980-1989									
0-25th Percentile	-0.650	14.8	0.002	0.233	2.275	6.422	0.164		0.108
25th-50th Percentile	-0.180	13.0	0.004	0.273	2.605	6.734	0.214		0.111
50th-75th Percentile	0.137	12.6	0.005	0.401	2.904	7.016	0.262		0.121
75th-100th Percentile	0.681	10.3	0.006	0.402	3.164	7.030	0.256		0.146
Panel B: 1990-2000									
0-25th Percentile	-0.349	12.2	0.003	0.303	3.113	6.769	0.272	0.026	0.106
25th-50th Percentile	0.148	11.6	0.004	0.378	3.769	7.087	0.352	0.061	0.169
50th-75th Percentile	0.488	9.7	0.004	0.483	4.073	7.517	0.391	0.135	0.226
75th-100th Percentile	1.024	6.8	0.006	0.594	4.847	7.790	0.451	0.273	0.311

TABLE 4. Cross Sectional Regressions of Log Volatility Ratio on IPO characteristics

The linear regression model is defined as:

$$\sigma-RATIO_i = \beta_0 + \beta_1 AGE_i + \beta_2 PROCEEDS_i + \beta_3 VENTURE_i + \beta_4 MANAGER\_SHARE_i + \beta_5 INTERNET_i + \beta_6 HIGHTECH_i + \varepsilon_i.$$

See Table 3 for definition of variables. IB_SHARE measures the overall investment-banking share of the lead manager (IPO underwriting services, domestic corporate debt, M&A advising). The dependent variable σ-RATIO$_i$ is the average relative volatility over T months, $(T \le 60\ months)$. The symbols (*), (**), and (***) indicate statistical significance at the 10-, 5- and 1-percent level.

	A. Period: 1980-1989			B. Period: 1990-2000					
Intercept	-0.104***	-0.093**	-0.085***	0.210***	0.209***	0.201***	0.199***	0.041	0.200***
	(-2.95)	(-2.71)	(-2.95)	(10.86)	(11.18)	(10.35)	(10.60)	(1.06)	(10.67)
AGE	-0.0021*	-0.0010*	-0.0021**	-0.0039***	-0.0032***	-0.0039***	-0.0032***	-0.0034***	-0.0032***
	(-1.92)	(-1.85)	(-1.99)	(-5.44)	(-4.57)	(-5.49)	(-4.65)	(-4.84)	(-4.61)
PROCEEDS	6.806***	7.101***	6.878***	2.089**	1.451*	2.193**	1.438*	1.428*	1.165
	(3.10)	(3.24)	(3.15)	(2.37)	(1.68)	(2.55)	(1.71)	(1.71)	(1.35)
MANAGER_SHARE	1.470**			0.998***	0.741***				
	(2.04)			(4.33)	(3.28)				
TOPMANAGER		0.059				0.116***	0.097***		
		(0.12)				(4.45)	(4.59)		
VENTURE	0.141***	0.146***	0.137***	0.197***	0.184***	0.195***	0.181***	0.164***	0.186***
	(3.34)	(3.68)	(3.44)	(9.30)	(8.92)	(9.19)	(9.79)	(7.81)	(9.02)
HIGHTECH	0.029	0.024	0.036	0.182***		0.182***			
	(0.56)	(0.54)	(0.69)	(7.33)		(7.31)			
INTERNET					0.380***		0.378***	0.376***	0.375***
					(13.03)		(13.01)	(12.98)	(12.09)
IB_SHARE									0.111***
									(4.36)
CM_RATING			0.019**					0.028***	
			(2.03)					(5.47)	
N	768	768	768	2,558	2,558	2,558	2,558	2,558	2,558
R^2	0.054	0.051	0.051	0.102	0.139	0.105	0.143	0.146	0.145
Adjusted R^2	0.047	0.045	0.045	0.099	0.138	0.103	0.141	0.144	0.143

TABLE 5. A Logit Model for the Probability of Negative Performance Delisting

This table presents the regression results of the logit model where the dependent variable is the probability that the firm will be delisted for negative performance. We define a negative performance-related delisting $(d_{ti} = 1)$ any firm that had a CRSP delisting codes equal to 500, or in the range of 520-591. We used information from Bloomberg Financial to verify all CRSP negative delistings and restrict our sample to only those firms that resulted in an adverse outcome to investors. The control group in the logit sample $(d_{ti} = 0)$ consists of all active firms trading on the three major exchanges (firms with a delisting code of 100). The sample excludes all acquired or merged firms (delisting codes 200-290), exchanged or liquidated stocks (400-490), or firms that became a foreign securities (900-903). Panel A in the table reports logit regressions for the combined sample of IPO firms as well as firms that did not issue stock during the period. Panels B and C present logit results for the IPO sample.

The logit regression included the following independent variables: For IPOs, the variable YEARS_LISTED is the age of the firm after going public (measured in years); for nonIPO firms, YEARS_LISTED is the age of the firm since attaining its last exchange listing. In some cases, YEARS_LISTED for nonIPO firms may reflect the actual age of the firm since going public before 1980. SIZE is the log of market capitalization of the firm; VOLATILITY is the average monthly standard deviations of daily CRSP percent returns of the firm in year $(t-1)$; EXCESS_RETURN represents the average excess CRSP percent return of the firm in year $(t-1)$; WCAP is ratio of working capital to total assets (percent); SALES is total sales to assets (percent); ROA is the after-tax rate of return divided by total assets (percent); QRATIO is the ratio market value of assets plus liabilities divided by total book value assets minus goodwill (percent); R&D represents per share R&D expenditures; AMEX is 1 if firm is listed on the American Stock Exchange, 0 otherwise; NYSE is 1 if firm is listed on the New York Stock Exchange, 0 otherwise; IPO is a dummy indicator for an issuing firm; HIGHTECH is a binary indicator of high tech companies; INTERNET is a dummy indicator for Internet firms; SPINOFF is a dummy variable for IPO spin-offs; VENTURE indicates venture capital funding; MANAGER_SHARE is the percent market share of the lead IPO underwriter in each decade; IB_SHARE measures the overall investment banking share of the lead manager (IPO underwriting services, domestic corporate debt, M&A advising). All accounting financial ratios and market-based variables are as of year $(t-1)$. The regression includes yearly dummy controls (time-effects) not reported in the table because of space limitations. The symbols (*), (**), and (***) indicate statistical significance at he 10-, 5-, and 1-percent level. The Pseudo R^2 measures the goodness fit of the logit model (see Estrella (1998)).

(Continued next page)

TABLE 5A. A Logit Model for the Probability of Negative Performance Delisting: IPOs and NonIPOs

EXPLANATORY VARIABLES	PERIOD: 1980-2000	1980-1989	1990-2000
INTERCEPT	4.979***	4.651***	6.265***
	(622.93)	(171.23)	(553.66)
YEARS_LISTED	-0.010**	-0.014*	-0.017***
	(6.61)	(2.85)	(14.58)
SIZE	-0.865***	-0.805***	-0.973***
	(1573.22)	(401.78)	(1229.38)
VOLATILITY	0.022***	0.011***	0.023***
	(184.41)	(14.61)	(136.59)
EXCESS_RETURN	-0.004***	-0.001	-0.005***
	(118.68)	(1.83)	(113.91)
ROA	-0.014***	-0.013***	-0.015***
	(356.73)	(119.48)	(243.27)
WCAP	-0.017***	-0.018***	-0.017***
	(428.94)	(195.38)	(270.49)
QRATIO	0.000	0.000	0.000**
	(0.58)	(0.02)	(6.38)
R&D	-0.200**	0.188	-0.306***
	(6.45)	(1.21)	(11.64)
SALES	0.000	0.000	0.000
	(1.54)	(0.00)	(0.84)
AMEX	-0.489***	-0.186	-0.700***
	(31.37)	(1.48)	(40.08)
NYSE	0.700***	-0.355	0.956***
	(34.42)	(1.00)	(51.54)
IPO	0.384***	-0.093	0.259***
	(45.05)	(0.69)	(12.37)
HIGHTECH	0.139	-0.189	
	(2.54)	(1.31)	
INTERNET			2.047***
			(112.22)
LR χ^2 test	8,331***	2,534***	6,095***
Delistings	2,616	909	1,707
Nondelistings	39,976	13,033	26,943
Concordant Ratio (%)	93.8	92.0	95.2
Discordant Ratio (%)	6.0	7.8	4.6
Pseudo R^2	0.225	0.204	0.250

TABLE 5B. A Logit Model for the Probability of Negative Performance Delisting: IPO Sample Only

EXPLANATORY VARIABLES	PERIOD: 1980-2000	1980-1989	1990-2000	1980-1989	1990-2000	1990-2000
INTERCEPT	8.583***	3.817***	9.365***	3.779***	9.135***	9.283***
	(405.43)	(16.27)	(379.60)	(16.31)	(368.66)	(375.97)
YEARS_LISTED	0.002	0.061	0.003	0.059	-0.001	0.010
	(0.04)	(0.99)	(0.06)	(0.92)	(0.01)	(0.60)
SIZE	-1.117***	-0.807***	-1.208***	-0.791***	-1.239***	-1.203***
	(706.42)	(67.36)	(630.92)	(62.74)	(627.35)	(627.51)
VOLATILITY	0.025***	0.020**	0.027***	0.021**	0.027***	0.027***
	(72.02)	(5.85)	(69.10)	(6.34)	(68.82)	(70.07)
EXCESS_RETURN	-0.005***	-0.001	-0.006***	-0.001	-0.006***	-0.006***
	(54.78)	(0.39)	(59.03)	(0.46)	(54.86)	(60.03)
ROA	-0.014***	-0.012***	-0.015***	-0.012***	-0.015***	-0.015***
	(145.23)	(18.06)	(125.14)	(18.08)	(131.06)	(125.07)
WCAP	-0.019***	-0.021***	-0.019***	-0.022***	-0.019***	-0.019***
	(177.46)	(40.66)	(136.97)	(40.88)	(139.66)	(138.20)
QRATIO	-0.001***	0.000	-0.001***	0.000	-0.001***	-0.001***
	(12.77)	(0.13)	(15.45)	(0.06)	(11.99)	(15.44)
R&D	-0.295***	0.140	-0.357***	0.176	-0.370***	-0.344***
	(7.10)	(0.13)	(9.09)	(0.21)	(9.90)	(8.50)
SALES	0.001**	0.002*	0.001	0.002*	0.001	0.001*
	(5.18)	(3.23)	(2.57)	(3.57)	(1.67)	(2.83)
AMEX	-1.209***	-0.184	-1.452***	-0.144	-1.483***	-1.421***
	(38.69)	(0.20)	(43.57)	(0.12)	(45.21)	(42.08)
NYSE	0.851***	0.240	0.972***	0.340	1.006***	0.982***
	(20.16)	(0.08)	(23.52)	(0.15)	(25.82)	(24.01)
INTERNET	1.552***		1.620***		1.571***	1.617***
	(47.17)		(47.99)		(44.51)	(47.63)
SPINOFF	0.321**	-0.209	0.402**	-0.208	0.398**	0.385**
	(4.41)	(0.26)	(5.73)	(0.26)	(5.58)	(5.28)
VENTURE	0.195*	-0.511**	0.355***	-0.489*	0.301***	0.371***
	(3.64)	(3.88)	(9.79)	(3.58)	(6.86)	(10.76)
MANAGER_SHARE	0.074***	0.020	0.080***			
	(26.23)	(0.12)	(26.99)			
CM_RATING				-0.017	0.124***	
				(0.11)	(30.90)	
IB_SHARE						0.945***
						(23.27)
LR χ^2 test	3,815***	460***	3,412***	460***	3,418***	3,408***
Delistings	1,016	155	861	155	861	861
Nondelistings	15,365	2,280	13,085	2,280	13,085	13,085
Concordant Ratio (%)	95.6	92.6	96.3	92.6	96.3	96.3
Discordant Ratio (%)	4.2	7.1	3.6	7.1	3.6	3.6
Pseudo R^2	0.276	0.214	0.294	0.214	0.294	0.293

TABLE 5C. Investigating the Adverse Selection Hypothesis: IPO Sample Only

EXPLANATORY VARIABLES	PERIOD:	
	1990-2000	1990-2000
INTERCEPT	9.392***	9.472***
	(382.02)	(396.04)
YEARS_LISTED	0.001	-0.015
	(0.01)	(1.34)
SIZE	-1.209***	-1.200***
	(635.74)	(640.07)
VOLATILITY	0.027***	0.027***
	(69.97)	(69.83)
EXCESS_RETURN	-0.006***	-0.006***
	(58.85)	(59.72)
ROA	-0.015***	-0.014***
	(126.29)	(120.00)
WCAP	-0.019***	-0.018***
	(136.00)	(124.20)
QRATIO	-0.001***	-0.001**
	(15.19)	(4.85)
R&D	-0.351***	-0.392***
	(9.01)	(11.22)
SALES	0.001	0.001
	(2.34)	(1.26)
AMEX	-1.504***	-1.518***
	(46.64)	(48.39)
NYSE	0.988***	0.865***
	(24.45)	(19.07)
HIGHTECH		0.185
		(1.29)
HIGHTECH×TOPMANAGER		-0.078
		(0.05)
INTERNET	1.514***	
	(29.16)	
INTERNET×TOPMANAGER	0.301	
	(0.55)	
TOPMANAGER	0.661***	0.772***
	(26.80)	(36.01)
SPINOFF	0.432***	0.448***
	(6.69)	(7.26)
VENTURE	0.364***	0.372***
	(10.37)	(11.01)
LR χ^2 test	3,424***	3,379***
Delistings	863	863
Nondelistings	13,098	13,098
Concordant Ratio (%)	96.3	96.1
Discordant Ratio (%)	3.6	3.7
Pseudo R^2	0.295	0.290

TABLE 6. What Contributes to the Probability of Delisting? Looking at the Odds Ratio

This table reports the odds ratios for all explanatory factors included in the logit model. The odds ratio compares the probability of delisting under different scenarios. When the independent variable X is continuous, the ratio compares the probability that the issuer is delisted at the mean value X to the probability that the issuing firm is delisted after X increases by one standard deviation. Specifically,

$$odds\ ratio = \frac{P(issuing\ \ firm\ delists / \bar{X} + \sigma_X)}{P(issuing\ \ firm\ \ delists / \bar{X})}.$$

If X is a discrete binary variable, the odds ratio compares the probabilities that the firm is delisted under the two competing responses, that is,

$$odds\ ratio = \frac{P(issuing\ \ firm\ delists / X = 1)}{P(issuing\ \ firm\ delists / X = 0)}.$$

The binary independent variable TOPMANAGER indicates a top-tier underwriter (see Appendix A.3, for a list of the top lead managers). The odds ratio estimates are estimated from the logit regressions presented in Panel B of Table 5, representing only issuing firms. The only exception is the odds ratio for the binary variable IPO that is estimated from logit regression presented in the second and third column of Table 5A. For the IPO discrete variable, this measure represents

$$odds\ ratio = \frac{P(issuing\ \ firm\ delists / IPO = 1)}{P(nonissuing\ \ firm\ delists / IPO = 0)}.$$

Variables are defined in more detail in Table 5. The mean values for explanatory variables are computed over the entire panel sample. The symbols (*), (**), and (***) indicate that the odds ratio estimate is different from 1 at the 10-, 5-, and 1-percent level of significance.

Explanatory Variables	A. 1980-1989 Mean $\bar{X}$	A. 1980-1989 Odds Ratio	B. 1990-2000 Mean $\bar{X}$	B. 1990-2000 Odds Ratio
Continuous Variables				
YEARS_LISTED	2.40	1.125	4.81	1.013
SIZE	10.35	0.234***	11.36	0.086***
VOLATILITY	14.88	1.215	18.41	1.450***
EXCESS_RETURN	-2.20	0.938	0.62	0.664***
ROA	-5.17	0.698***	-9.15	0.625***
WCAP	30.74	0.539***	30.82	0.590***
QRATIO	210.13	1.048	265.22	0.750***
R&D	0.08	1.045	0.215	0.828***
SALES	126.89	1.202	113.24	1.078
CM_RATING	6.19	0.983	6.81	1.339***
MANAGER_SHARE	2.43	1.054	3.21	1.383***
Discrete Variables				
IPO	0.209	0.911	0.473	1.293***
IPO-1990 issuers only			0.310	1.529***
INTERNET-all firms			0.021	7.745***
INTERNET-issuers only			0.042	5.053***
SPINOFF	0.079	0.811	0.101	1.495**
VENTURE	0.277	0.600**	0.355	1.426***
TOPMANAGER	0.347	1.165	0.371	1.989***

Figure 1: Number of IPOs by Year, 1980-2000

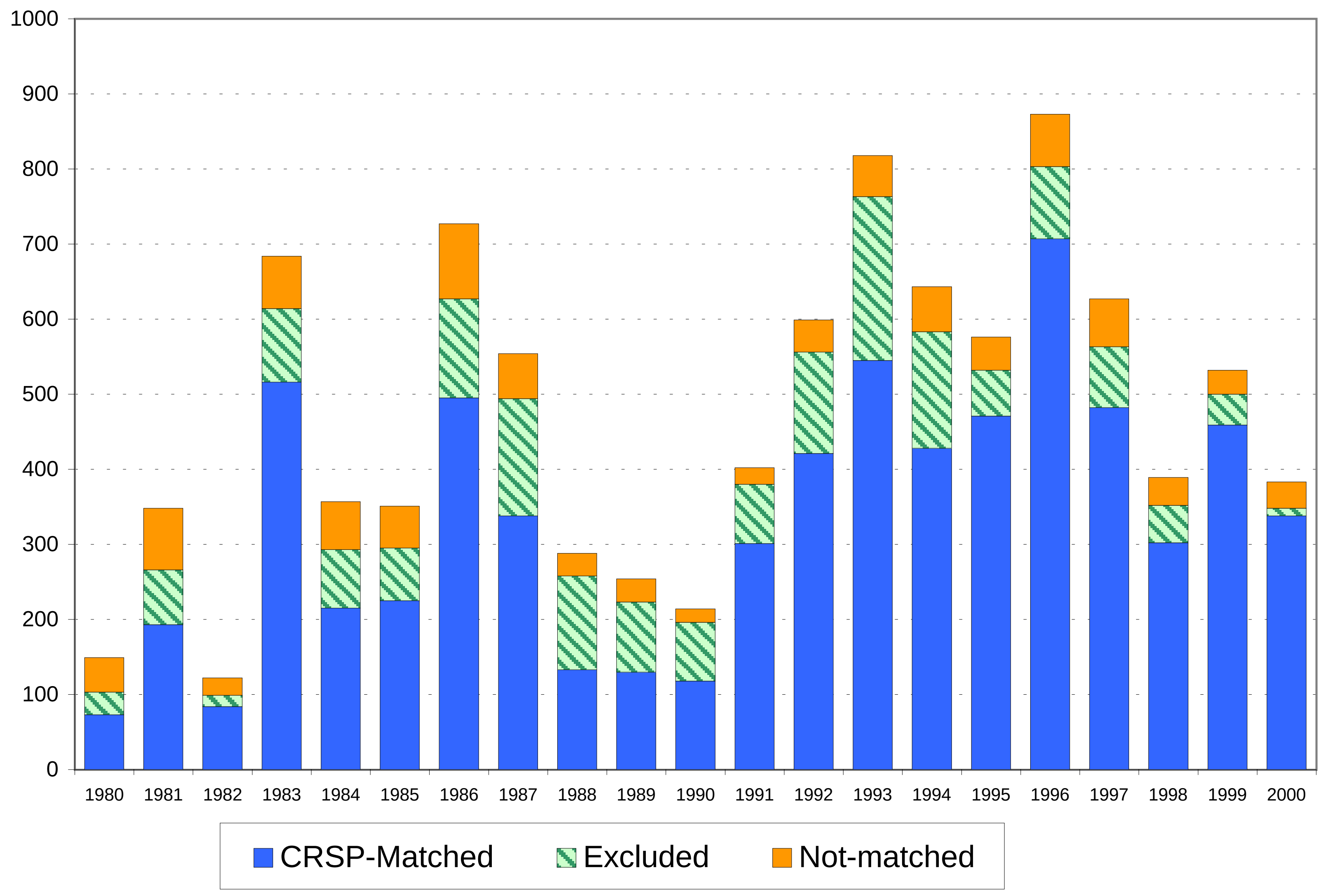
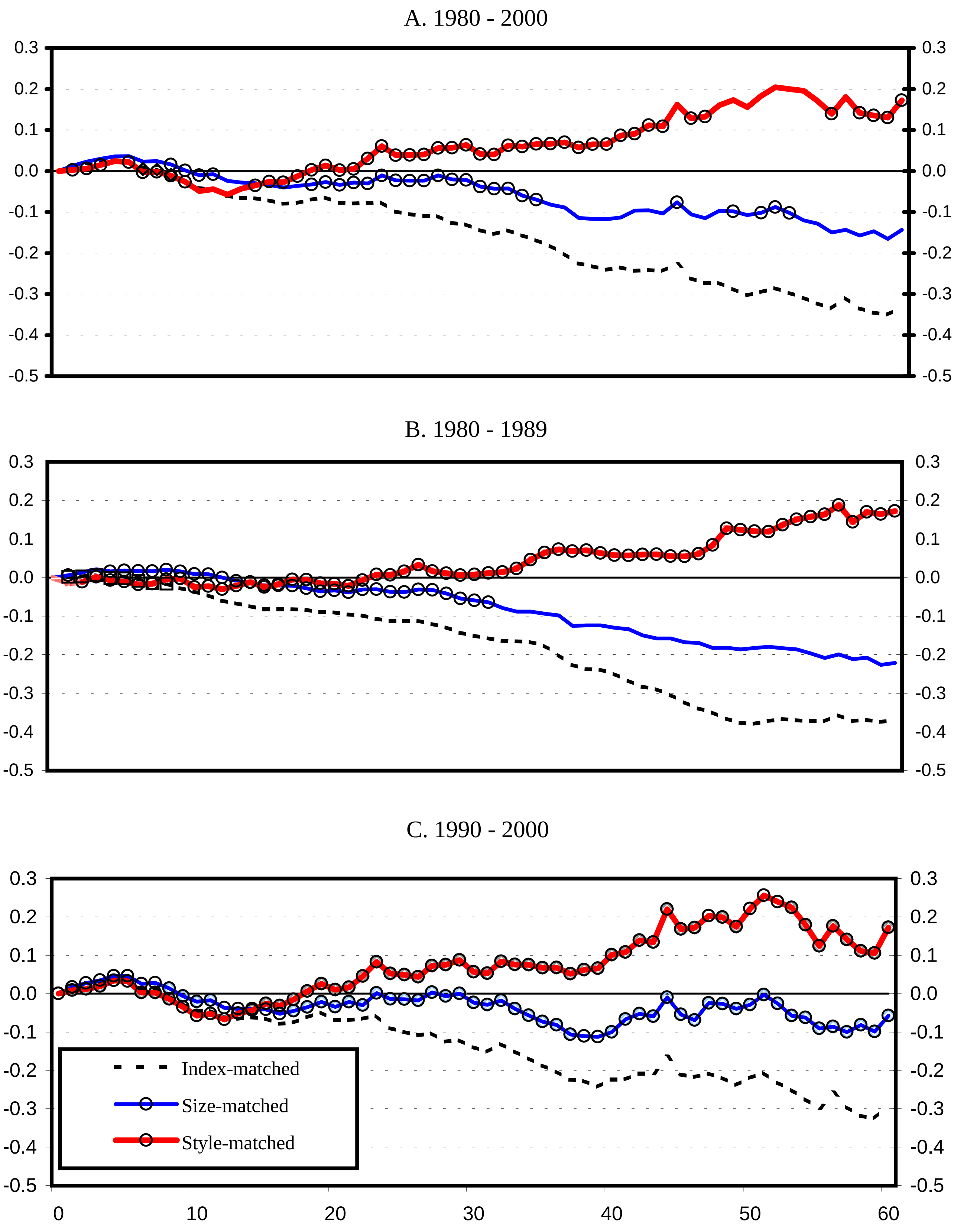
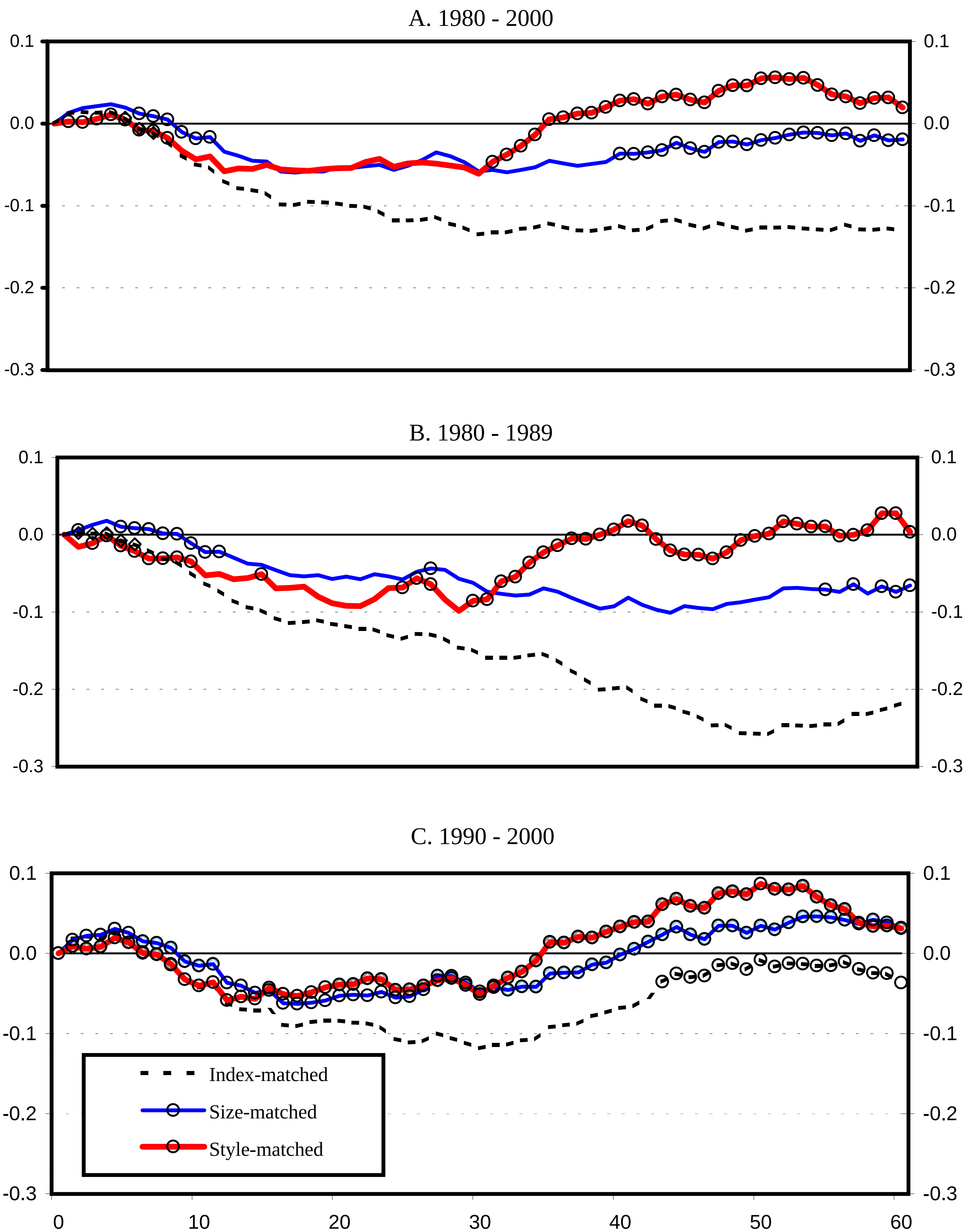


Figure 2: IPO Buy-and-Hold Geometric Returns, 1980-2000



The symbol 'o' indicates mean returns are not statistically different from zero.

Figure 3: IPO Cumulative Adjusted Returns, 1980-2000



The symbol 'o' indicates that mean returns are not statistically different from zero.

Figure 4: Kernel Density Estimate of Log Volatility
by Decade (Style-Matched Comparison)

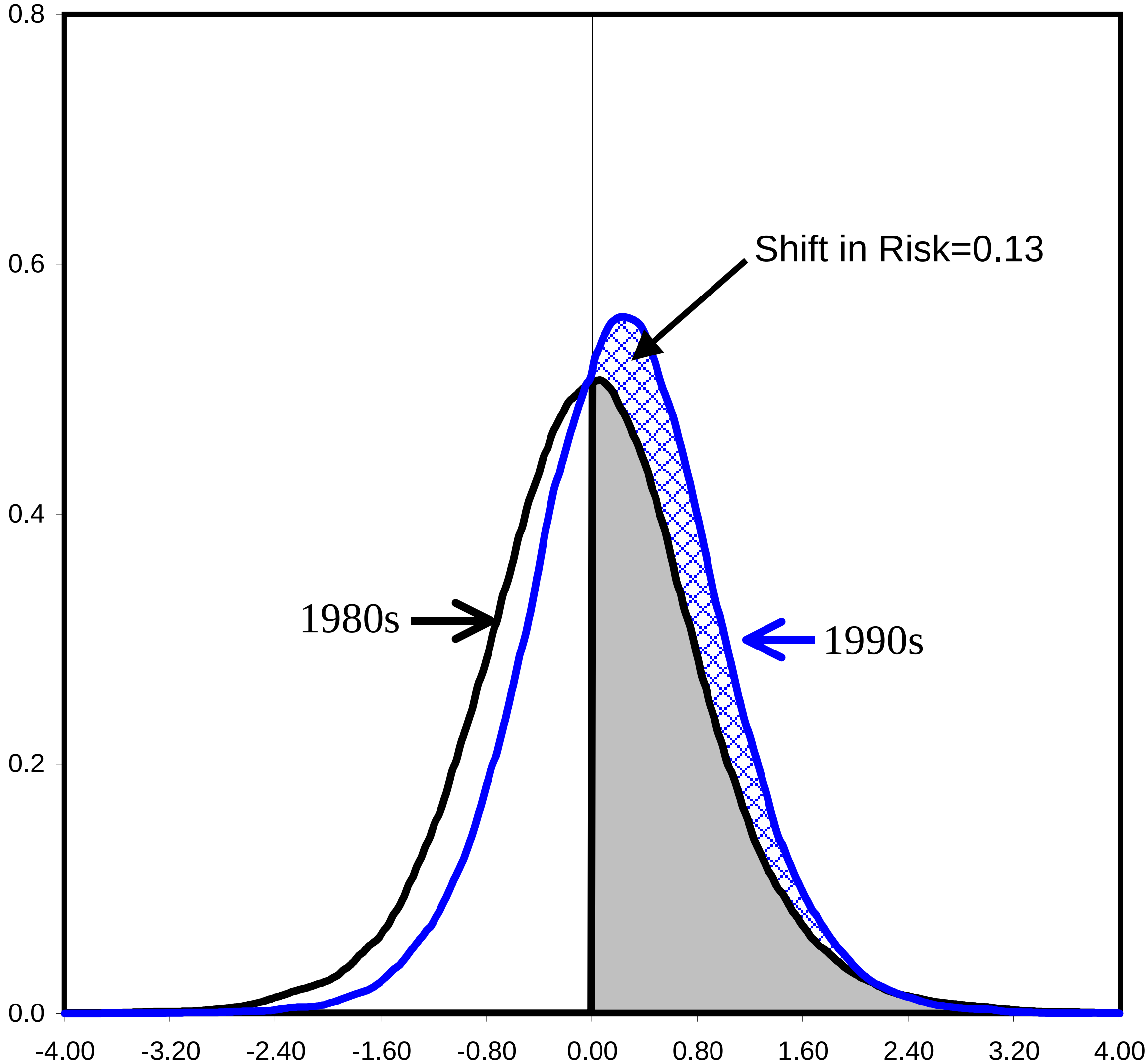


Figure 5. The Marginal Effect on the Survival of IPOs in the 1990s