IPO Failure Risk:
Determinants and Pricing Consequences

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Abstract

While a large body of research examines different aspects of the post-IPO stock return performance of new listings, little has been documented regarding the firm-specific characteristics that are associated with IPO failures. We contribute to the IPO literature by developing an IPO failure prediction model that includes both financial and non-financial variables that are known to the market as of the IPO date. We find significant differences in the failure models that are applicable to non-tech, combined high tech and Internet, and high tech only IPO samples, and the structural differences across the models are largely driven by accounting-based proxies for firms' investments in intangible assets. Most importantly, we document that our estimated probabilities of failure as of the IPO date are significantly negatively associated with one-year and two-year post-IPO abnormal returns. The pseudo-hedge returns available from a strategy of going long (short) in firms with low (high) estimated probability of failure are economically significant and these results are robust to the use of an alternative failure probability model, four-factor and simple market-adjusted abnormal returns models, and BHAR versus CAR returns calculations. In contrast to Brav, *et al.* (2000), we also document that the long-run (one- and two-year) negative abnormal returns IPO anomaly survives in the four-factor model, however this result holds only for non-tech firms.

1. Introduction

In a recent broad descriptive study, Fama and French (2004) document a dramatic decline in the survival rates of newly listed firms over the past several decades. Beginning with Ritter (1991), a vast literature also documents the IPO long-run underperformance anomaly.[1] In this study we intersect these two literatures by investigating the relation between the likelihood of IPO firm failure and long-run post-IPO returns. We first estimate and cross-validate an IPO failure prediction model, and then we examine whether the estimated firm-specific probabilities of failure are related to one-year and two-year post-IPO returns. Our results suggest that there is a significant negative relation between the estimated probabilities of failure and subsequently realized abnormal returns over each of the two time intervals. Furthermore, a pseudo-hedge strategy of going short and long in the high and low failure risk portfolios, respectively, yields returns of economically significant magnitudes over each of the one- and two-year time horizons. These results are broadly consistent with the findings of Dichev (1998) who documents that the likelihood of distress is negatively correlated with monthly returns in a non-IPO, general cross-sectional setting. We also document a mean negative abnormal return over each of the one- and two-year horizons after controlling for the three Fama-French (1993) risk factors and the Carhart (1997) momentum factor, but only for the sample of non-technology firms over our 1985-2000 IPO time period. This finding contrasts the cross-sectional four-factor model results of Brav, Geczy and Gompers (2000) as well as our own full sample results, and suggests that an IPO long-run returns anomaly may still exist, but that it resides only in the non-tech sector. Our results further suggest that the contradictory findings in the prior IPO long-run returns literature may be due in part to changing sample compositions across the non-tech and tech sector dimensions.

While a large body of research examines the post-offering stock return performance of IPOs, surprisingly little has been documented concerning the firm-specific factors that are associated with post-IPO firm failure.[2] In terms of efficient pricing and ultimately the

[1] See Draho (2004) for a recent summary of this literature.
[2] Several exceptions are Seguin and Smoller (1997), Schultz (1993), Willenborg and McKeown (2001), and Weber and Willenborg (2003), however each of these studies adopts a more limited perspective than that

assessment of failure probability, IPO firms are characteristically different from firms that have a history of being publicly traded in that there is a relative paucity of information concerning IPO firms, and thus potentially greater uncertainty associated with their valuation and assessed likelihood of failure (Weber and Willenborg (2003)). We address this gap in the literature by developing an IPO failure prediction model that includes as explanatory variables only information items that are available at the IPO date, including financial statement data, market related information, and firm-specific IPO deal-related variables that the prior IPO literature has associated with short- and long-term measures of IPO returns. In cross-validation tests we document that for the prediction of failure within 5 years of IPO, our model dominates a benchmark (non-IPO-specific) classical failure prediction model that is due to Zmijewski (1984) (as updated by Shumway (2001)). We find that proxies for underwriter prestige, audit quality, the "hotness" of the IPO market, firm age, offer price, and various accounting measures of financial leverage, pre-IPO performance, and investments in intangible assets, are all significant determinants of post-IPO failure.

Contemporaneous with the declining survival rates of new lists, Fama and French (2004) document a decline in new list profitability and an increase in the firms' expected growth prospects, characteristics that are consistent with the profile of young technology firms. Ritter and Welch (2002) similarly report that technology stocks have significantly increased as a percentage of all IPO offerings since the 1980's, and particularly so during the late 1990's and 2000.[3] Yet despite this growing importance of the technology sector, even the extant non-IPO-specific bankruptcy and failure prediction models are largely premised upon an "old economy" perspective of the firm. So-called "old economy" or non-tech firms are generally characterized by having more assets in place relative to growth

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which we pursue. Specifically, Seguin and Smoller (1997) examine only the association between offering share price and mortality, whereas Schultz (1993) explores many facets of unit IPOs, of which survivorship relative to non-unit IPOs is only one aspect. Neither study controls for other candidate economic determinants of failure such as ownership characteristics or accounting-based fundamental measures of firm performance. Willenborg and McKeown (2001) and Weber and Willenborg (2003) examine different aspects of the role of auditors and audit reports in predicting post-IPO firm failure.

[3] Ritter and Welch (2002) exclude biotechnology from their definition of technology firms. Had biotech been included, the rise in the percentage of technology IPOs would be even more dramatic.

options, and they tend to be financed by a combination of both debt and equity.[4] In contrast, technology companies are predominantly equity-financed, rely heavily upon intangible assets, and often report significant accounting losses resulting from their high levels of expenditures on research and development ("R&D").[5] All of the well-established failure prediction models (e.g., Altman (1968); Ohlson (1980); Zmijewski (1984); and Shumway (2001), amongst others) are essentially premised upon an assets-in-place perspective of the firm in that their hypothesized determinants of failure largely include only proxies for leverage, liquidity, debt servicing ability, and the current year's profitability.[6] In this study, we explicitly acknowledge the fundamental economic differences in the asset and liability structures across the technology and non-technology sectors of the economy by estimating separate IPO failure prediction models for these two broad categories of firms. As expected, we find that a significantly different structural model of IPO firm failure applies to non-technology versus high-technology-oriented firms, and the differences across the two sectors relate primarily to the greater importance of intangible assets in the tech sector. Robustness tests indicate that the differences across the tech and non-tech samples are not simply driven by the inclusion of Internet firms in the technology-oriented group. We also find that the association between our estimated failure probabilities at the time of IPO and one- and two-year post-IPO abnormal returns is materially different across the tech and non-tech sectors, further suggesting that this dichotomization of the IPO universe yields economically insightful results.

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[4] The technical classifications of "new economy" (i.e., high tech and Internet) and "old economy" firms are more specifically defined in terms of SIC codes in Section 3.

[5] Expenditures on R&D are expensed under generally accepted accounting practices in the US. Accordingly, even while making significant investments in internally developed intellectual property, many high tech firms report accounting losses, as well as negative cash flows from operations, for multiple successive years. Indeed, for start-up stage technology firms, patterns of recurring and/or increasing losses can be an indication of success (Joos and Zhdanov (2004)), which is precisely the opposite inference that one would draw from the same pattern of losses for old economy, assets-in-place companies.

[6] While Shumway (2001) considers financial structure related variables similar to those in the earlier failure prediction literature, his approach offers a considerable improvement over the earlier failure models in that he also adds market-based measures such as realized stock return variability to the prediction model. This additional explanatory variable should help to capture aspects of the operating risks inherent in technology firms, which we consider to be distinct from the predominantly financial structure related risks that are included in the prior failure models. Unfortunately no such market-based measures are available for companies as of their IPO dates, and accordingly Shumway (2001)'s significant improvements in the failure prediction arena do not help in the particular setting of IPO firms.

Our study makes several contributions to the literature. First, we contribute to the IPO literature by developing a failure model that is particular to the IPO setting, and we show that this model outperforms a leading accounting-based benchmark model due to Zmijewski (1984) across both the technology and non-technology sectors of the IPO universe. Second, we contribute to the failure prediction literature by improving upon the existing models that are largely leverage- and liquidity-based and thus premised upon an assets-in-place perspective of the firm. Our improvements derive from including variables that capture the likelihood of failure in the context of a high technology setting. We find that the failure prediction models estimated for each of these two broad sectors of the economy are structurally different, and these structural differences are largely determined by accounting-based proxies for firms' investments in intangible assets which prove to be significantly more important to technology-oriented companies relative to non-tech firms. Third, in contrast to the findings of Brav, *et al.* (2000) we present evidence to suggest that the long-run IPO underperformance anomaly persists even after controlling for the four standard factors, but this anomaly remains only in the non-tech sector. Finally, we add to the IPO anomalies literature by documenting a significant negative correlation between the probability of failure and one-year and two-year post-IPO returns. The pseudo-hedge returns from a long-short strategy in low-high estimated risk of failure firms are economically significant and robust across alternative IPO failure prediction models and abnormal returns calculations.

The balance of this paper is organized as follows. In Section 2 we describe our sample selection process and data sources, and we provide descriptive statistics related to the firms included in our IPO samples. Section 3 explains our IPO failure prediction model and presents the results from our failure prediction analyses. In Section 4 we document the relation between our estimated failure probabilities and long-run abnormal returns, while Section 5 provides a summary and conclusion to our study.

2. Sample Selection, Data Description, and Descriptive Statistics

2.1 Sample Selection and New Economy Classifications

Using the SDC New Issues database, we select all US IPOs for the period of January 1985 through December 2000, excluding rights issues, unit offerings, spin-offs, REITs, and ADRs. This results in a total of 5,603 IPOs.[7] After imposing data restrictions, we are left with 3,990 IPOs with which to conduct our analyses.

We define firms to be "high tech" companies if either SDC identifies them as high tech or if they fall into one of the fourteen high tech SIC codes established by Francis and Schipper (1999), and we exclude from this group all firms that are identified as Internet firms as described below. This results in a sample of 1980 non-Internet high technology firms.

Consistent with prior studies in the Internet sector (e.g., Hand (2001); and Demers and Lev (2001)) we define Internet companies as those firms that earn the majority of their revenues as a result of the existence of the Internet.[8] There does not currently exist a standard SIC code or other official classification system with which to identify Internet companies, and therefore a listing of all initial public offerings of Internet-related companies was compiled from several sources. We began with the InternetStockList™ (provided by internet.com at http://www.internetnews.com/stocks/list/), a frequently cited and authoritative list of currently trading Internet companies. Because the InternetStockList™ exhibits a survivorship bias (i.e., only currently trading companies are included on the list), we also referred to the Morgan Stanley Dean Witter (2002) ("MSDW") *Technology and Internet IPO Yearbook (8th ed.)*. The MSDW yearbook provides a comprehensive listing of all technology and Internet IPO's for the 1980-2000 period, including firms that have subsequently been acquired or delisted. Our sample consists of 309 Internet companies that undertook initial public offerings prior to the end of 2000 and for which all necessary

[7] Many IPO studies exclude stocks with offer prices below various "penny stock" thresholds (e.g., Ritter (1991), Ibbotson and Jaffe (1975)). We do not deliberately exclude any IPOs on the basis of their issue price, but rather control for this directly in our multivariate tests. However, we rely on data from Ritter to identify firm founding dates, and this data set effectively eliminates firms with smaller offering prices. Because firm age is significant in virtually every one of our regression specifications, this variable cannot be ignored and thus data availability on firm age becomes a binding constraint for our study.

[8] This definition was originally established by internet.com, an Internet industry portal site, in order to distinguish between "pure play" Internet companies and entities that would exist without the Internet generating a majority of their revenues.

data are available. The remaining 1708 firms that are not classified as either Internet or non-Internet technology IPOs are labeled as non-technology companies.

Figure 1 presents a frequency distribution of Internet, non-Internet technology, and non-technology IPOs by calendar year. The most obvious feature of the IPO market depicted is the increasing proportion of high tech and Internet firms relative to non-tech firms, particularly since 1995. As is also evident from the graph, there have been several waves of IPO "hot issues markets" and the IPOs exhibit clustering patterns over time that are consistent with the general phenomenon documented by Ibbotson and Jaffe (1975), Ritter (1984), and Lowry and Schwert (2002), amongst others. During the "hot issues" market of 1999, for example, 206 out of the 348 IPOs included in our study were Internet stocks. Furthermore, in untabulated results we find that there are much higher levels of industry clusterings at the 3-digit SIC code level within the high tech sample than in the old economy group of IPOs.

2.2 Data Description

Market values, stock returns, Fama-French (1993) and Carhart (1997) momentum factors, and delisting events are obtained from the Center for Research in Security Prices (CRSP) databases. Data related to IPO deal characteristics, pre- and immediately post-IPO venture capital and insider ownership levels are derived from the SDC New Issues Database, while auditing and accounting data are obtained from the Compustat database. We use the SDC Corporate Restructurings database to identify Chapter 7 and Chapter 11 filings and we also obtain bankruptcy filing data from **www.bankruptcydata.com**.[9] Carter-Manaster underwriter reputation rankings and firm founding dates are provided by Jay Ritter.[10]

[9] As discussed in greater detail in Section 4, we define "failure" using CRSP delisting codes, however as a specification check on our dependent variable we rely on the SDC Corporate Restructurings and www.bankruptcydata.com databases.

[10] We thank Jay Ritter for making his underwriter reputation rankings and firm founding dates publicly available at http://bear.cba.ufl.edu/ritter/ipodata.htm, and Stavros Peristiani of the Federal Reserve Bank of New York for providing us with the Carter-Manaster ranking data matched to the IPO firms in our sample.

2.3 Sample Firm Descriptive Characteristics

Table 1 provides the definitions of the variables used in all of the subsequent tables. Table 2 presents the descriptive statistics for firms in the non-tech, combined high tech and Internet, and high tech only sectors, respectively, that are included in the failure and returns analyses reported in subsequent sections. In untabulated results we find that the p-values for differences between the variables listed in Table 2 are all significant for the non-tech versus non-Internet high tech samples, and the technology versus Internet only samples, respectively. As shown, approximately 21% of combined high tech and Internet firms, 16% of technology stocks, and 20% of the non-tech companies in our sample failed within 5 years of going public.[11]

The average age of Internet stocks at the time of their IPO was just 5 years (untabulated), compared to ages of 9 years and 18 years for technology and non-tech firms, respectively. The mean (median) CPI-adjusted proceeds raised by non-tech, combined high tech and Internet ("combined tech"), and high tech only sample firms was \$56 (\$30) million, \$50 (\$36) million, and \$47 (\$33) million, respectively. The average (median) CPI-adjusted market value of Internet stocks at the end of their first day of trading (*mv_ipodt*) was \$1,095 (\$506) million (untabulated), which dwarfs the \$352 (\$130) million and \$224 (\$96) million market values of high tech and non-tech firms, respectively. While the average initial returns, *FirstDayRet*, for all three samples are positive, consistent with what has been documented extensively in prior IPO studies, the mean (median) untabulated initial returns to Internet stocks of 85% (50%) are extremely high relative to firms in both the high tech and non-tech sectors. The frequency of VC backing is also very dissimilar across the samples, with 78% of Internet firms, 62% of non-Internet high tech firms, and only 23% of non-tech firms being VC-backed. A greater proportion of high tech firms than non-tech companies are audited by Big-8 or national level audit firms, while technology firms also have more prestigious underwriters (*CM_rank*) than non-high tech firms.

[11] The definition of firm failure adopted in this study is explained at length in Section 4, however at this point we note that data with respect to failures is available only until the end of 2003, and hence for firms that went public in 1999 or 2000 a full 5 years have not yet elapsed at the time of our determination of their fate. Since a disproportionate number of Internet and high tech firms went public during this period, it is likely that the 5-year failure rates are somewhat understated for each of these sectors. The definition of failure that we adopt is designed to at least partially address this potential problem.

In terms of their pre-IPO accounting-based performance measures, a greater proportion of Internet (combined tech) companies relative to high tech (non-tech) firms report accumulated deficits (*AccumDeficitDummy*) and net losses (*LossDummy*) for the year prior to IPO, while the leverage ratios (*leverage*) for non-tech firms are predictably higher than those for the combined tech sample. The ratio of R&D expenditures to total assets (*RD_TA*) prior to IPO is highest for the technology only sample whereas for non-tech firms the mean and median of the R&D expenditure ratio is close to zero.

Overall, the descriptive statistics suggest that the two major sectors, non-tech versus combined tech, are very different from one another along many economically important dimensions: the presence and/or prestige of information intermediaries; age at the time of IPO; firm size; and pre-IPO financial performance. Furthermore, Internet firms differ considerably from non-Internet high tech firms along many of these same dimensions.

3. IPO Failure Prediction

In this section we develop an IPO failure prediction model and assess its performance using both cross-validation tests as well as comparisons to a classic benchmark failure prediction model that is well established in the prior literature. Our logit-based failure prediction model uses financial accounting, as well as IPO timing and deal related data as explanatory variables. Given the documented differences in the failure rates of high technology versus non-technology firms, as well as the fundamentally different economic characteristics of these entities, we separately apply our IPO failure prediction model to these two samples. We also present results for the sample of high tech firms excluding Internet companies as a specification check to ensure that the anomalous nature of the Internet sector (see, e.g., Bartov, Mohanram and Seethamraju (2002)) is not driving the combined tech results.

3.1 Classification of Failures

In order to dichotomize the sample firms into failures and non-failures, we begin by identifying corporate delistings from the CRSP events file. We first classify firms as "failures" within the first five years subsequent to their IPO if their CRSP delisting codes are in the 400-range ("liquidations") or the 500-range ("dropped"), excluding firms with delisting codes of 501-503 ("stopped trading on current exchange to move to NYSE, AMEX, or Nasdaq") and 573 ("delisted by company request – gone private").[12] We also classify as failures all firms with share prices at or below $1.00 per share as of the end of 2003, the last date for which CRSP data is available. All other firms that did not fail during their 6th year subsequent to IPO are considered to be "non-failures."[13] This classification results in a total of 795 firms (19.9%) out of our original sample of IPOs being classified as failures, with the remaining 3195 firms (80.1%) being classified as non-failures.

As a further specification check on our dependent variable, we use the SDC Corporate Restructurings Database and data provided by www.bankruptcydata.com in order to identify any further bankruptcy or corporate reorganization filings by the firms in our samples. We classify as failures all firms that are identified in either the SDC Restructurings database or the www.bankruptcydata.com database and that don't have a CRSP code of 100 ("active"). Most of the incremental firms identified by the reorganization and bankruptcy databases have CRSP delisting codes in the 200 and 300 ranges, indicating that they were delisted due to mergers or exchanges of stock. Thus, this alternative classification rule would seem to pick up those firms that were sold in "fire sales" or equivalent. For failed firms, we select the earliest of the firm's Chapter 7 or 11 filing date and their delisting date as the date of failure. This failure classification rule results in a total of 811 firms (20.3%) out of our original sample of IPOs being classified as failures, with the remaining 3179 firms (79.7%) being classified as non-failures. We use this latter, more comprehensive definition of failure in our multivariate analyses, however our reported results are not sensitive to the alternative definition.

Figure 2A provides a graphical description of the number of firm failures per year for each year post-IPO and for each of the three sample classifications. As is evident from the graph, the amount of time that it takes for ultimately failing firms to realize their fate is somewhat longer for technology firms, in keeping with the longer investment cycles

[12] Our CRSP-based definition is similar to, but slightly broader than, those adopted by Beatty (1993), Schultz (1993), and Weber and Willenborg (2003), each of whom use CRSP delisting codes 550-572 and 574-584. Our results are not sensitive to this alternative definition of failure.

[13] In order to minimize the noise in the dichotomization of our sample, we follow the common convention in the failure literature of removing from the pool of "non-failed" firms all of those firms that are known to have failed in the year subsequent to the prediction year (i.e., year 6 in this case).

underlying R&D activities. This finding is consistent with prior results in the industrial organizational economics literature (e.g., Agarwal (1996)), wherein it is documented that the uncertainty associated with viability is resolved more quickly for non-technology firms. At the other extreme, Internet firms that were doomed to failure realized their fates much more quickly. This latter finding is consistent with our intuition that firms operating in a more turbulent environment are less likely to cope, and the descriptive evidence regarding the Internet industry is also broadly consistent with the findings of Audretsch (1995) who suggests that a turbulent environment coupled with learning will result in high rates of entry and high rates of failure within an industry.

Figure 2B provides a graphical depiction of firm failures in calendar time. The trend towards higher numbers of failures in later years is expected by construction as our sample of IPOs only begins in 1985 (and few firms fail within just a year or two of IPO), and the number of firms going public each year has also increased over time. Clearly there is a clustering of failures in 2001, the year after the Internet and technology "bubbles" burst in March through September of 2000, and this clustering is especially true for Internet stocks.

3.2 Determinants of Firm Failure

3.2.1 Expert Informational Intermediaries: Underwriters, Venture Capitalists, & Auditors

Underwriter prestige plays a certification role at the time that a company goes public. Prior evidence suggests that IPO firms with higher prestige underwriters earn lower first day returns, consistent with there being a lower level of risk and information asymmetry associated with these offerings (Carter and Manaster (1990); Megginson and Weiss (1991)). In a more comparable analysis to our setting, Schultz (1993) finds that the probability of firm failure within either two or three years of IPO is negatively associated with underwriter prestige. We use Ritter (2002)'s modified Carter-Manaster rankings as our proxy for underwriter prestige. High prestige underwriters have higher Carter-Manaster rankings, so we expect a negative association between our prestige measure (*CM_rank*) and the probability of failure in each of our samples.

Brav and Gompers (1997) find that over the long-term (5 years), venture-backed IPOs outperform nonventure-backed firms, but only when returns are weighted equally. The results of Jain and Kini (2000) indicate that venture capitalist ("VC") involvement improves the survival profile of IPO issuers. Accordingly, we include an indicator variable (*VCdummy*) for whether a company was VC-backed at the time of IPO and we expect that VC-backed firms are less likely to fail than nonventure-backed firms in each of our samples.

Signaling models such as that of Titman and Trueman (1986) suggest that higher quality firms will employ higher quality auditors in order to signal their quality to the market at the time of their IPO. Consistent with this, Michaely and Shaw (1995) document empirically that more prestigious auditors are associated with IPO firms that seem *a priori* less risky, that the market subsequently perceives to be less risky, and that are less likely to fail. For a sample of non-VC backed microcap IPOs, Weber and Willenborg (2003) find that the pre-IPO opinions of higher quality auditors are more predictive of post-IPO negative stock delistings. In the preceding and other prior studies (e.g., Beatty (1989), Hogan (1997), and Willenborg and McKeown (2001)) audit "quality" is empirically defined by the size of the audit firm rendering the opinion (e.g., Big-8 and national level CPA firms versus others). In the reported results we use an indicator variable (*Big8Natl*) that is equal to one if the auditor is a "Big-8" firm (or in later periods "Big-6," or "Final-4") or if it is a national level audit firm, and zero otherwise.[14]

3.2.2 IPO Timing – "Hot Issues Markets"

The phenomenon of "hot markets" for IPOs, where there are periods of significantly greater numbers of new issues and higher average initial returns per month, has been well documented in the IPO literature since Ibbotson and Jaffe (1975). Lowry and Schwert

[14] The audit firm is identified from the Compustat database where available, or alternatively from the SDC database. *Big-8Natl* is set to one where Compustat annual data item #149 is equal to 1-8, 11, 17, 19, 20, 21, 24, or 27. The Compustat auditor variable is not available for non-Big-8 national firms prior to 1988, and hence any national firms for which SDC is also incomplete will be incorrectly coded as having been audited by a non-Big-8, non-national firm. Hence our indicator variable is noisy for pre-1988 nationally audited firms, which biases against our finding this variable to be significant.

(2002) suggest that there is a lead-lag relation between the two series, where periods of high and rising initial returns tend to be followed by spurts of higher IPO volume. Financial market observers, particularly during the exuberant market for technology stocks in the late 1990s, have suggested that periods of high initial returns to IPOs are associated with excessive demand for IPOs and that this high demand subsequently attracts new issues of a lower quality being taken to market (see e.g., Perkins and Perkins (1999) or Loughran and Ritter (2004)). We therefore include a proxy variable for whether an IPO has been issued in a "hot market" and expect that firms that are taken public during periods of such high demand are of lower quality and thus are more likely to fail. We define our hot markets proxy, *IPOmkt30days*, as the average initial returns to all IPOs in the thirty days prior to the firm's IPO, and we expect this variable to have a positive coefficient.

3.2.3 Firm Age, Initial Returns, and Issue Share Price

Consistent with prior studies (e.g., Weber and Willenborg (2003)), firm age (*logAge*) is defined as the natural log of (1+ the number of years from the firm's incorporation date to the date of its IPO). There is greater uncertainty associated with newer firms that do not have a record of past performance, and therefore we expect *logAge* to have a negative coefficient as more established firms have a lower risk of failure within a few years of IPO.

As explained by Ritter (1984) in relation to Rock (1986)'s model and further formalized by Beatty and Ritter (1986), there is a monotonic relation between the (expected) underpricing of an IPO and investors' uncertainty regarding its value. We therefore include initial returns in our prediction model and we expect this variable to be positively associated with the probability of failure. Consistent with other studies in the IPO literature, we define first day initial returns (*FirstDayRet*) as the closing price on the first day of trading minus the offer price, all scaled by the offer price.

Prior studies (e.g., Seguin and Smoller (1997) and Fernando, Krishnamurthy and Spindt (2004)) document that IPO offering price per share is a significant determinant of attrition. Accordingly, we control for the IPO offer price (*offer_price*) and expect a negative association between this variable and the probability of failure.

3.2.4 Growth Options Versus Assets in Place

We first include the natural log of one plus research and development expenses for the year prior to IPO (*logRD*). This variable captures the scale of the firm's expenditures on R&D and thus is expected to provide an indication of the stage of the firm's research activities for firms in the high tech sample (Joos and Zhdanov (2004)). The scale of R&D expenditures may also serve as an indication of the amount of pre-IPO funding that has been raised and made available for spending on R&D, which similarly serves as a proxy for the company's stage of development and/or the non-public capital markets' positive assessment of the company's R&D prospects. We expect that technology firms that are at a more advanced stage of research and that are spending more heavily on R&D at the time of IPO are less likely to fail, and hence we expect a negative association between *logRD* and firm failure for high tech companies. For non-technology firms, we might expect that the risk of failure increases with their relative proportion of growth opportunities to assets-in-place and hence higher levels of R&D would be positively associated with the likelihood of failure.[15] Alternatively, R&D may simply be immaterial to this non-tech sample, in which case we would expect the coefficient on *logRD* to be insignificant. In either case, to the extant that the scale of R&D spending proxies for the firm's investments in intangible assets, we expect the coefficient on this variable will be significantly different across the high tech and non-tech sectors.

We also include the log of one plus selling, general, and administrative expenses, *logSGA*. If, as we intend, this variable is a good proxy for the firm's investments in intangible assets such as brand names, then we expect this variable to be negatively associated with firm failure.[16] Alternatively, if this variable captures more of the firm's general and administrative expenses rather than the desired sales and marketing expenditures, higher levels of this variable could be an indication of the firm's inefficiency and thus we would expect this variable to be negatively related to firm failure.

[15] In untabulated results, we also run the non-technology sample model with R&D scaled by total assets in order to capture this notion of the relative proportion of growth opportunities to assets-in-place. The results are unchanged, and hence we report the model that simply includes *logRD* in order to be consistent with the high tech and Internet + high tech sample specifications.

[16] Marketing expenses would clearly be a better proxy for the firm's investment in brand names and related intangible assets. Unfortunately, separate disclosure of marketing (or selling) expenses is not required by either GAAP or the SEC and hence SG&A is the closest available alternative measure.

We attempt to capture the level of competitiveness of the firm's industry, or the market pricing power of the firm, by including the gross profit margin percentage (*GrossMargin*). The gross profit margin is calculated as sales minus cost of goods sold, all divided by sales, and this variable is expected to be negatively related to failure as higher margins are indicative of better brand names, higher pricing power, and generally less competitive conditions in the firm's product markets.

We also include a variable to capture the firms' accumulated deficits (i.e., negative retained earnings). We define *logAccumDeficit* to be equal to negative one times the natural log of the absolute value of retained earnings for firms with accumulated deficits, and zero otherwise. By definition, firms with high negative retained earnings balances have a history of losses, but in the technology sector these losses are presumed to be the result of expenditures on the creation of intangible assets. The accumulated deficit reflects the total net amount of money that has been spent towards the creation of these assets, and also indicates a minimum bound on the accumulated amount of pre-IPO financing that the firm has been successful in apprehending. For technology firms, if large accumulated deficits reflect past success in their R&D activities and thus in obtaining pre-IPO rounds of financing, we expect to find a positive association between the negatively valued *logAccumDeficit* and the probability of failure (i.e., tech firms with higher accumulated deficits are less likely to fail). Alternatively, even in the high tech sector, the large accumulated losses may simply be an indication of a riskier firm, a firm that has more uncertain prospects as to its ability to ultimately generate a profit. In this case, *logAccumDeficit* would have a negative coefficient. In the non-tech sector higher levels of past losses may similarly be indicative of past investments in other forms of non-R&D-related intangible assets (e.g., building a customer list or a brand name) or may simply represent start-up losses as the firm builds itself up to operations of a profitable scale. In either case, we expect that intangible assets are relatively less important to non-tech firms, and that start-up losses incurred by more tangible asset-intensive firms represent a different economic phenomenon than technology firms' investments in intellectual capital. Accordingly, we expect the coefficient on *logAccumDeficit* to be significantly different across the high tech and non-tech sectors.

Finally, we include the variable *logSales,* which is defined as the natural log of one plus total revenue for the fiscal year prior to IPO. Firms that are more established in their product markets are expected to be less risky than firms that have yet to produce substantial revenues. Furthermore, *logSales* may also serve as a proxy for firm size, and prior studies have found that size is negatively associated with the probability of IPO firm failure (Schultz (1993); Hensler, Rutherford and Springer (1997); and Peristiani (2003)). Hence, we expect a negative relation between *logSales* and the probability of firm failure for all three of our sample specifications.

3.2.5 Leverage

Various measures of leverage have been documented to be important predictors of firm failure in non-IPO settings (e.g., Altman (1968); Ohlson (1980); Zmijewski (1984); Shumway (2001); and Hillegeist, Keating, Cram and Lundstedt (2004)). We define *leverage* as of the date of IPO to be total liabilities divided the sum of total assets plus the proceeds raised at the date of IPO. Consistent with the results of prior studies, we expect the probability of bankruptcy to be increasing in leverage for all firms. However, the role of leverage may be different for non-technology versus high tech firms since firms with more tangible assets in place are more likely to have significant debt as a natural part of their financial structure whereas the long-term financing of high tech firms is predominantly in the form of equity.

3.3 Empirical Failure Prediction Results

Table 3 presents the results of logistic failure regressions for each of our three samples separately.[17] The last two columns of Table 3 report the p-values from pooled regression models for the interacted variables for the combined tech sample incremental to the non-tech sample, and the high tech only versus the combined Internet and high tech sample, respectively. In the following sections we discuss our failure model's overall performance,

[17] The reported results are for regressions that exclude extreme observations. We follow the recommendations proposed by Hosmer and Lemeshow (2000) in identifying extreme observations, which results in 4, 11, and 1 observations being deleted from the non-tech, high tech + Internet, and high tech only samples, respectively.

the prediction of failures for the tech versus non-tech samples, and the significance of individual explanatory variables, respectively.

3.3.1 Model Performance Assessment

In Table 3, the reported Hosmer-Lemeshow goodness-of-fit statistic is insignificant for each of our models, suggesting that the models fit the data well.[18] The reported Nagelkerke (1991) R^2 coefficient for the logit models range from approximately 23% for the non-tech model to approximately 32% for the combined tech sample, and suggest that the models explain a reasonable amount of the cross-sectional variation in firm failures across the three samples.[19]

We adopt a Receiver Operating Characteristic ("ROC") curve methodology in order to assess the predictive accuracy of our models (Hosmer and Lemeshow (2000)). The area under the ROC curve provides us with an absolute measure of our models' out-of-sample performance and facilitates a comparison of our models' performance to a classic benchmark failure model that is well established in the prior failure literature. A more detailed description of the calculation of the ROC curves is provided in the Appendix. The "out-of-sample" performance of our models is determined through cross validation wherein a random selection of 75% of the observations from each respective sample (i.e., non-tech, combined tech, and high tech only) is used to estimate a logistic regression model. The fitted model so derived is then applied to the remaining 25% of the observations in each respective sample. In order to arrive at the reported estimates, we repeat this process through 100 iterations.

As shown in Table 3, the area under the ROC curve, which is our measure of the model's cross-validated performance, is approximately 77%, 78%, and 82% for the non-tech, tech only, and combined tech samples, respectively. Each of the three sample's reported ROC

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[18] The Hosmer and Lemeshow (2000) statistic is distributed chi-square, and small p-values for the statistic indicate a lack of model fit.

[19] By comparison, Seguin and Smoller (1997) report of a maximum pseudo-R^2 of approximately 11%, Peristiani (2003) reports pseudo-R^2s in the range of 21% to 29% for a much larger cross-sectional sample of IPO firms, and Willenborg and McKeown (2001) claim pseudo-R^2s of approximately 21% to 25%. Schultz (1993) does not report R^2s for his logistic models of IPO failure.

levels is considered to be a good level of discrimination (Hosmer and Lemeshow (2000)). The sample that includes Internet firms has the highest pseudo-R^2 and ROC measures, indicating both good within-sample and out-of-sample fit to the model. This finding suggests that the relatively short time to failure for Internet firms helps to increase the predictive accuracy of the failure model for this sample.

We also compare the performance of our model to failure predictions derived from the classic Zmijewski (1984) model using the updated coefficient estimates for that model as provided by Shumway (2001). In Table 3 we report the areas under the ROC curves for the application of the updated Zmijewski model to each of our three samples. As shown, the Zmijewski model has little or no discriminatory power in any of the three sectors (ROC<0.70 in each case). Figure 3 presents a graphical comparison of the out-of-sample ROC curves generated from our model compared to those derived from the updated Zmijewski model for each of the IPO samples. As is evident from the graphs, our model dominates the Zmijewski models for each sample and over every probability threshold.

3.3.2 Determinants of Failure: Information Intermediary, Deal, & Timing Variables

The prestige of the firm's underwriter, as captured by the Carter-Manaster rank variable (*CM_Rank*) is negative and significant as expected for each of the non-tech and high tech only samples, suggesting that firms underwritten by higher prestige investment banks are less likely to fail within 5 years of their IPO. This result does not hold for the combined tech sample, suggesting that for Internet companies underwriters do not appear to play the same certification role as they do for the broader cross-section of firms.[20]

Inconsistent with the findings of Brav and Gompers (1997) who report that VC-backed firms have better returns over 5 years than non-VC-backed firms (when returns are equally-weighted), VC-backing is not a significant determinant of failure over 5 years for any of our three IPO samples. Having a Big-8 or national level auditor certify the firm's financial

[20] We note that this is not due to a time period effect. In untabulated results we find that the CM_Rank variable remains significant for a randomly selected sample of 310 high technology firms from the late 1990s.

statements for the year prior to IPO is associated with lower failure risk for non-tech firms, as expected, however the auditor variable is not significant for the other two samples.[21]

Our proxy for the "hotness" of the new issues market, *IPOmkt30days*, is positive and significant in all three regressions, although the magnitude of the coefficient is considerably larger for the combined tech model relative to the non-tech model. The findings suggest that the greater the returns to other IPOs in the thirty days prior to the company going public, the higher is that firm's probability of failure within five years of its IPO date. This finding is consistent with the notion that periods of high levels of demand for IPOs, which manifest as periods of higher average initial returns, are followed by the issuance of firms of lower (*ex post* realized) quality. Considering the mania that is alleged to have taken hold of the market for Internet IPOs, it is perhaps not surprising that the magnitude of the coefficient on this variable is significantly higher for the combined tech sample.

Consistent with expectations and with the results of prior studies, firms that are more mature (*logAge*) at the time of IPO are significantly less likely to fail within five years of going public, and this result holds across all three of our samples. Although an extensive prior IPO literature interprets the firm's first day underpricing (*FirstDayRet*) as an indication of uncertainty regarding the firm's value, this uncertainty is not ultimately associated with the likelihood of failure for any of our three samples. Finally, consistent with Seguin and Smoller (1997), we find that firms with a higher IPO offer price (*offer_price*) have a lower probability of failure, conditional upon the other variables included in our model.

3.3.3 Determinants of Failure: Accounting-Related Variables

Consistent with expectations, higher levels of pre-IPO R&D expenditures are associated with a lower likelihood of failure within 5 years of going public for the combined tech and high tech only samples, as captured by the negative and significant coefficient on *logRD* in

[21] The insignificance of the auditor variable for the combined tech sample is driven by the disproportionate effect of the non-Internet high-tech firms. In untabulated results we find that the auditor variable is negative and significant for the failure model applied to the sample of Internet only firms.

Table 3. In contrast, pre-IPO R&D spending is not a significant determinant of failure for non-tech firms.

Corporate expenditures on selling, general and administrative expenses (*logSGA*) are significantly positively associated with the likelihood of failure for each of our three samples, suggesting that this variable is capturing some element of inefficiency in the administration of the firm rather than a positive investment in intangible assets. Gross margin is significantly negatively associated with failure for the non-tech and high tech only samples, as expected. This finding is consistent with the notion that firms with greater pricing power in their product markets are less likely to fail. Gross margin was obviously not an informative metric regarding the prospects for Internet firms, as the variable becomes insignificant when Internet firms are added to the sample in the combined tech regression. Interestingly, the magnitudes of the coefficients are significantly different in economic as well as statistical terms across the non-tech versus combined tech sectors, further emphasizing the economic differences across these two groups of firms.

For both the high tech and combined tech samples *logAccumDeficit* is negatively and significantly associated with the likelihood of failure. Since *logAccumDeficit* is a negatively valued variable, the negative coefficient suggests that firms with higher accumulated deficits have a higher probability of failure. Hence, it seems that the accumulated deficits are capturing some dimension of increased uncertainty inherent in the firm’s business rather than serving as an indicator of reduced risk deriving from an IPO firm’s past successful investments in intangible assets. In the non-tech sector, the coefficient on *logAccumDeficit* is insignificant, consistent with the lesser expected importance of accumulated past investments in intangibles, as well as the much lower frequency of non-zero observations for this variable as previously documented in Table 2.
The coefficient on *logSales* is negative and significant for all three samples. As expected, higher levels of pre-IPO sales are associated with a lower probability of failure either because this variable captures the stage of development of the firm’s operations and/or because it serves as a proxy for size, where the latter is well known to be associated with lower risk.

Finally, *leverage* is positively associated with the likelihood of failure for firms in all three sectors of the economy, a finding that is consistent with the results from many past failure studies. Somewhat surprisingly, however, leverage is also positively associated with failure for non-Internet high tech companies, and the magnitudes of the coefficients on the leverage variable are not significantly different for firms across these three groups.

3.3.4 Is IPO Failure Prediction Different For High Tech Versus Non-Tech Firms?

In the previous section we identified individual coefficients that were significantly different across our three samples. We further address the question of whether a structurally different failure model applies to high tech versus non-tech firms using a logistic regression analogue to the linear regression based Chow test for structural differences across samples.[22] The test statistic reported in Table 3 has a chi-squared distribution with degrees of freedom equal to the number of coefficients being estimated by the model. As shown, the statistic is highly significant in both tests, suggesting that there is indeed a different failure model underlying the non-tech versus high tech firms, as well as the combined tech versus high tech only samples.

4. The Relation Between IPO Failure Risk and Abnormal Returns

In this section we relate our estimated probabilities of failure to one-year and two-year post-IPO abnormal returns. We find that a pseudo-hedge strategy of going long in firms with low estimated probabilities of failure and short in firms with high estimated failure generates economically significant abnormal returns over both a one- and two-year horizon. We present this evidence using both buy-and-hold abnormal returns (BHARs) as well as cumulative abnormal returns (CARs), using simple market-adjusted returns as well as Fama-French four-factor model adjusted returns, and for both our fitted failure prediction probabilities as well as those derived from the updated Zmijewski model. The results are robust across all such specifications.

[22] The limited dependent variable analog of the Chow test is described in greater detail in Chapter 19 of Greene (2000).

4.1 Four-Factor Model Regressions

We measure abnormal returns using the Fama and French (1993) three-factor model augmented by the Carhart (1997) momentum factor, using data for the four factors provided by CRSP. The returns are calculated beginning with the closing price on the first day of trading (i.e., they exclude IPO initial returns) and ending on the one-year and two-year anniversary dates, respectively, of the firm's IPO. We use equally-weighted returns in constructing the monthly portfolios and otherwise follow the standard procedure described in Draho (2004) for estimating the factor models and thus calculating abnormal returns in calendar time.

In Table 4 we report White's heteroskedasticity-consistent results for the one-year and two-year returns intervals using the four-factor model on the full sample of IPOs from our entire sample period of 1985 through 2000, as well as each of the three IPO subsamples, respectively. Consistent with prior studies, the adjusted-R^2s for these regressions are quite high even for the subsamples, ranging from 82% to 88% in the one-year horizon and 88% to 91% in the case of the two-year interval.[23] As shown in the left-hand columns of Table 4, all of the factors are significant over the one-year horizon for each regression except for the momentum factor, which is only significant for the non-tech sample.[24] The results are similar over the two-year horizon depicted in the right-hand columns of Table 4, except that the momentum factor becomes negative and significant in every regression. For the pooled full sample regression, the signs and magnitudes of the coefficients are broadly consistent with those reported in previous studies (e.g., Brav, *et al.* (2000)). However, for the non-tech sample, the coefficient on HML is positive and significant over both the one-year and two-year returns intervals, whereas the negative coefficients on the HML factor in the two technology samples are approximately twice as large as those for the pooled model as well as those reported in prior studies. This finding is intuitive, and indeed somewhat mechanical, since the non-technology sample contains, on average, firms with higher book-

[23] The reported results are for regressions that exclude influential observations for which the studentized residual is greater than 2.0. The results are substantively similar for regressions that include the influential observations, except that the magnitude of the negatively valued intercept term becomes even larger for the non-technology sample.

[24] The significance of the momentum factor for the non-tech sample disappears in the one-year returns analysis when the "bubble" period (i.e., 1998 through March 2000) IPOs are excluded from the regressions.

to-market ratios. In other words, splitting the sample as we do between non-tech and technology is roughly similar to splitting the sample on the book-to-market ratio.

A further more economically interesting result is the finding that the intercept term is negative and significant at both the one-year and two-year time horizons, but only for the non-tech sample. The coefficient of approximately –0.005 for the non-tech sample in both time horizon regressions can be interpreted as the mean negative monthly abnormal return for the non-tech IPOs, and this corresponds to one-year (two-year) abnormal returns of approximately -6% (-12%). Our finding that a significant negative mean abnormal return survives for the non-tech sample even after the inclusion of the fourth (i.e., momentum) factor is consistent with the long-run negative abnormal returns IPO anomaly (see Draho (2004) for a recent summary of the literature). This finding contrasts the cross-sectional results of Brav, *et al.* (2000) as well as our own full sample results, and suggests that an IPO long-run returns anomaly may still exist, but that it resides only in the non-tech sector. Furthermore, our results suggest that the contradictory findings in the prior IPO long-run returns literature may be due in part to changing sample compositions across the non-tech and tech sector dimensions.

The insignificant intercept terms in the two-year technology regressions suggests that, on average, high tech firms are not subject to the IPO long-run underperformance anomaly over that interval. In the shorter one-year horizon, the intercept term is positive and significant for the technology samples over our entire sample period, suggesting that the mean abnormal returns to the technology samples are .6% (7%) per month (per year). However in untabulated results we find that this intercept term becomes statistically insignificant when the "bubble" period is excluded from the regressions. Overall, after controlling for the four factors, the evidence suggests that the IPO negative long-run abnormal returns anomaly is exclusive to the non-technology sector of the economy during the period of our study.

4.2 Pseudo-Hedge Returns

In Table 5 (6) we report the one-year (two-year) post-IPO buy-and-hold mean and median abnormal returns (BHARs) associated with each of the five failure probability portfolios derived from our logit-based failure model applied to our three IPO samples.[25] We also report returns for failure probability portfolios generated using the updated Zmijewski prediction model. The returns are calculated beginning with the closing price on the first day of trading (i.e., they exclude IPO initial returns) and ending on the one-year and two-year anniversary dates, respectively, of the firm's IPO. We report abnormal returns calculated by simply removing the annual Nasdaq return corresponding to each IPOs first-year return interval, as well as the abnormal returns generated using the previously reported four-factor model analyses. Although the magnitudes of the pseudo-hedge returns vary across the four-factor and simple market-adjusted returns model, the results are substantively similar across the two models and accordingly we discuss only the four-factor model results since this is arguably a more appropriate benchmark (Draho (2004)).

The overall picture that emerges from Tables 5 and 6 is that the estimated probability of failure as of the IPO date is highly negatively correlated with one-year and two-year post-IPO returns. This finding is consistent with the results of Dichev (1998), who documents that bankruptcy risk is negatively associated with returns in a non-IPO setting. We refer to the BHARs reported in Tables 5 and 6 as pseudo-hedge returns because the implicit hedge strategy underlying these tables is not fully implementable in practice for at least two reasons. First, the IPO dates are non-synchronous and thus it is not possible to simultaneously take long and short positions in the underlying stocks beginning at the close of their first day of trading. Second, there are likely to be restrictions to short-selling smaller, newly issued firms (see, e.g., Ritter and Welch (2002); Ofek and Richardson (2003)). Nevertheless, the quintile rankings of the failure probabilities and associated returns are suggestive of possible trading strategies involving going long in low probability firms and avoiding IPO firms with high probabilities of failure. Furthermore, over the two-year return interval in particular, the returns available on the long side of the hedge alone

[25] In order to implement the failure portfolio rankings, we use the average cross-validated failure probabilities from our logit-based IPO failure prediction model applied over 100 iterations as described in Section 3.3.1.

(i.e., a more readily implementable trading strategy) are of economically significant magnitudes.

As shown in Panel A of Table 5, for non-tech firms a pseudo-hedge four-factor model adjusted buy-and-hold abnormal return from going long in the lowest risk quintile and short in the highest risk quintile is approximately 17% (18%), on average, using our (Zmijewski's) failure prediction model for the one-year return interval. For the combined tech sample, the pseudo-hedge returns are approximately 24% and 16% for our logit-based model and the updated Zmijewski model, respectively. For the high tech only sample, the pseudo-hedge returns are approximately 13% using either our model or the Zmijewski probability of failure estimates.

The two-year BHAR results reported in Table 6 are similar, except that the magnitude of the returns increases considerably over the longer interval. Over two-years, the pseudo-hedge returns available in the non-tech sector are 38% using our model and just 24% using the Zmijewski estimates. For the combined tech (high tech only) sample, our failure model generates hedge returns of 67% (39%) compared to 46% (48%) for the Zmijewski model. The general finding that returns to our pseudo-hedge strategy increase considerably as the interval expands from one-year to two-years post-IPO is broadly consistent with the stylized fact documented by Loughran and Ritter (1995) and others that the abnormal returns to IPOs do not begin until the latter half of the first-year of trading. Figure 4 presents an alternative graphical depiction of these results for each of our IPO samples using a cumulative abnormal returns (CARs) framework. As is evident from the CAR plots, the abnormal returns to the high and low failure risk portfolios begin to diverge significantly by approximately 6 (5) months after IPO for the non-tech (combined tech) sample firms, whereas the high and low risk firms in the tech-only sample seem to begin their divergent trajectories immediately after IPO.

Overall, the evidence suggests that the IPO date estimated probability of failure (derived from either our model or the Zmijewski model) is significantly negatively associated with one-year and two-year ahead abnormal returns, and thus failure probabilities do not appear to be systematically priced into the market value of IPO stocks as of the close on their first day of trading. With the exception of the tech-only sample over the two-year horizon and (weakly) the non-tech sample over the one-year horizon, our failure model would seem to offer the greatest potential for generating economically significant pseudo-hedge abnormal returns.

5. Summary and Conclusion

While a large body of research examines different aspects of the post-IPO stock return performance of new listings, little has been documented regarding the firm-specific characteristics that are associated with corporate failures within 5 years of their IPO. We contribute to the IPO literature by developing an IPO failure prediction model that includes both financial and non-financial variables that are known to the market as of the IPO date. We find significant differences in the failure models that are applicable to non-tech, combined high tech and Internet, and high tech only IPO samples, and the structural differences across the models are largely driven by accounting-based proxies for firms' investments in intangible assets. Most importantly, we document that our estimated probabilities of failure as of the IPO date are significantly negatively associated with one-year and two-year post-IPO abnormal returns. The pseudo-hedge returns available from a strategy of going long (short) in firms with low (high) estimated probability of failure are economically significant and these results are robust to the use of an alternative failure probability model, four-factor and simple market-adjusted abnormal returns models, and BHAR versus CAR returns calculations. In contrast to Brav, *et al.* (2000), we also document that the long-run (one- and two-year) negative abnormal returns IPO anomaly survives in the four-factor model, but only for non-tech firms.

Appendix
Assessing Predictive Power Using ROC Curves

There are a number of alternative ways to demonstrate the (within or out-of-sample) performance of a logistic regression model. It is customary for logit studies to present a classification table, e.g., that cross-classifies the binary failure response variable with a prediction of whether failure=1 or 0. The prediction is that failure=1 when the estimated probability of failure exceeds some researcher-selected threshold (e.g., p=0.5). The limitations of this approach are that the table collapses continuous predicted probabilities of failure into binary ones, the choice of cutoff probability values is arbitrarily selected by the researcher and may not map into another reader's loss function with respect to the decision context at hand, and the predictive power reported this way is highly sensitive to the relative proportions of failed/non-failed companies in the sample (Agresti (2002)). In order to avoid some of these limitations, an alternative approach presents an entire table of cutoff points (e.g., every 10^{th} percentile) together with the percentage of failed/non-failed companies correctly classified, respectively, rather than to presume to know the reader's loss function. This is cumbersome, particularly where a number of different models are being tested.

A more intuitive, summary representation of classification accuracy is provided by the area under the ROC (Receiver Operating Characteristic) curve (Hosmer and Lemeshow (2000)).[26] The ROC curve generalizes the contingency table analysis by providing information on the performance of a model for all possible cut-off values. We estimate the ROC curves for our various regression models by first defining *sensitivity* and *specificity* in the following manner (Agresti (2002)):

$Sensitivity = P(\hat{y} = 1 \mid y = 1)$ = 1-Type I; and $Specificity = P(\hat{y} = 0 \mid y = 0)$ = 1-Type II.

and then plotting our estimates of sensitivity on the y-axis as a function of (1-specificity) on the x-axis using 100 estimated cutoff points. An example of the ROC curve is provided in Figure 3A, where three curves are plotted on the same graph, each depicting the out-of-sample predictive performance for our IPO failure prediction model applied to the old economy, high tech, and Internet sectors, respectively. As is evident from the axes, the area under the ROC curve ranges from 0 to 1, and provides a measure of the model's ability to *discriminate* between failures and non-failures. At every cutoff point on the curve, it is possible to obtain a measure of the Type I and Type II errors. In addition, the slope of the ROC at each point on the curve is a likelihood ratio of the probability of failure to non-failure for the specific model (Stein (2002)). An ROC=0.50, which is equivalent to a 45-degree line extending from the origin, represents a model that doesn't have discriminatory power beyond chance (i.e., it's equivalent to a coin toss), whereas at the other extreme an ROC $\geq$ 0.90 is essentially unheard of (Hosmer and Lemeshow (2000)). Each of the curves depicted in Figure 3A has ROC values that are greater than 70%, and thus all three are considered to have good discriminatory power.

[26] When the dependent variable is binary, as in the case of our logit model, the area under the ROC curve is equivalent to the more familiar *concordance index* (Agresti (2002)).

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Figure 1
Number of IPOs for period 1985-2000

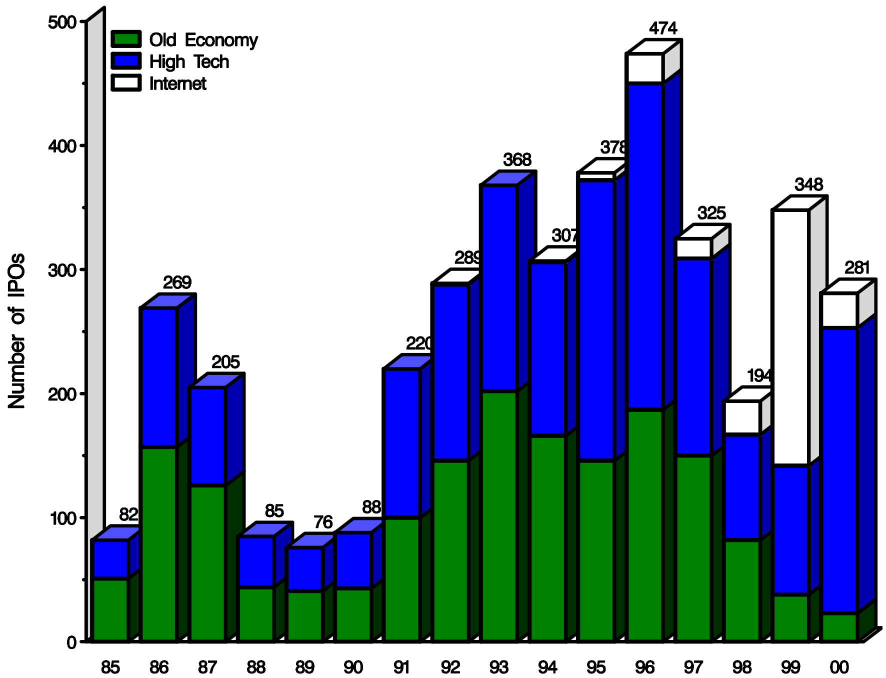
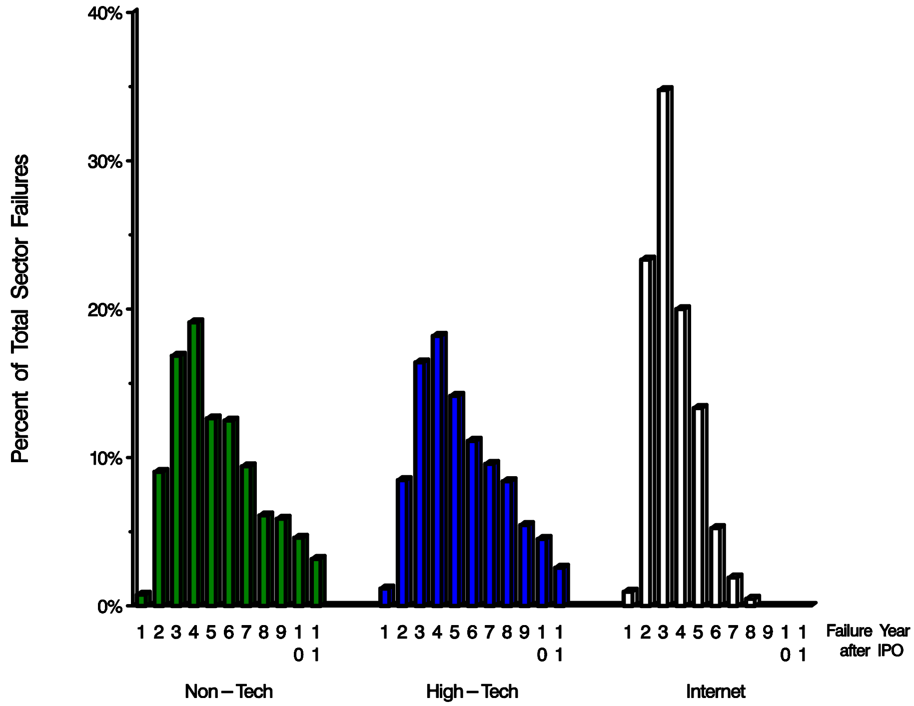
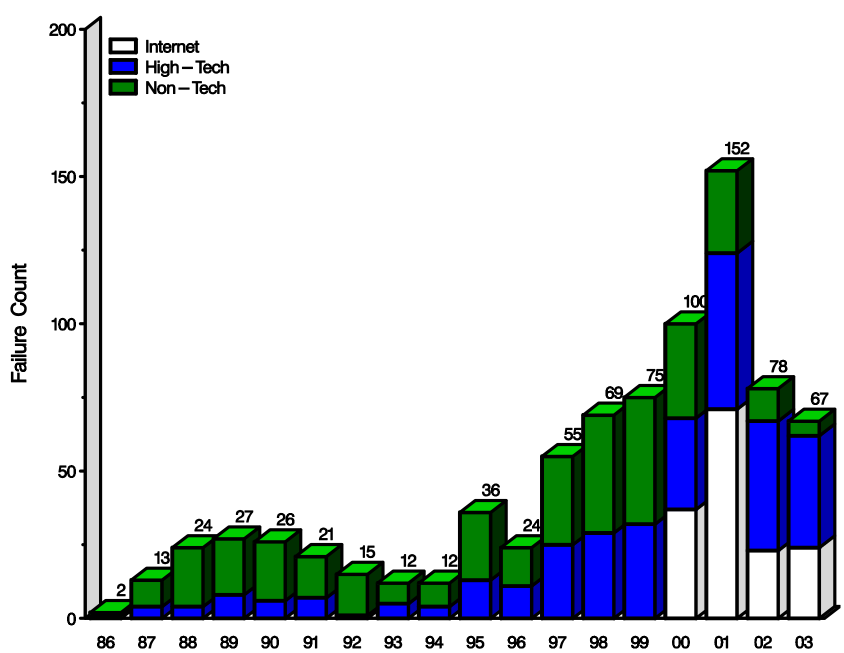


Figure 2
IPO Failures by Sector



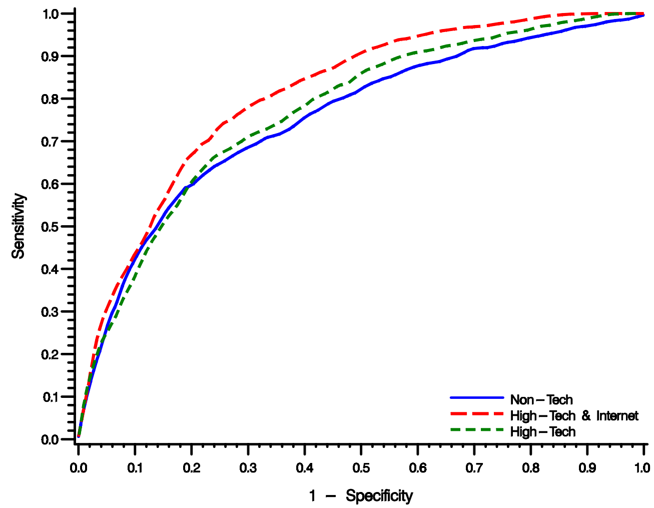
Panel A: Failure frequency in first eleven years after IPO by sector
(as percentage of total failures in the sector)



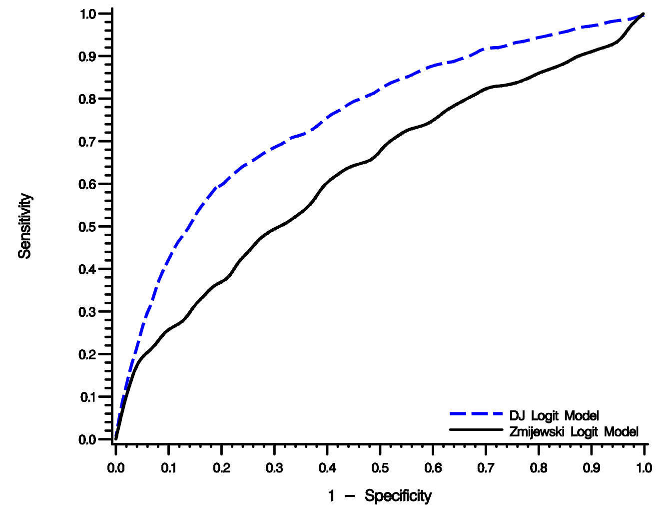
Panel B: IPO failure within 5 year of IPO date
count by sector and calendar year of failure

Figure3

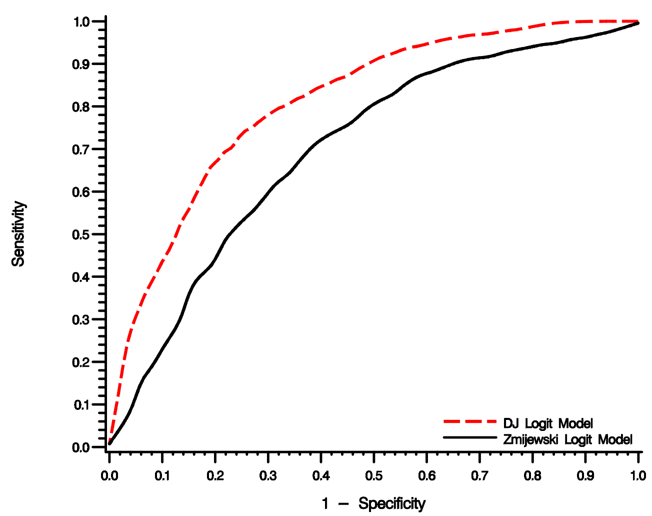
Receiver Operating Characteristic (ROC) curves: Comparing cross-validated failure prediction performance over total sample period



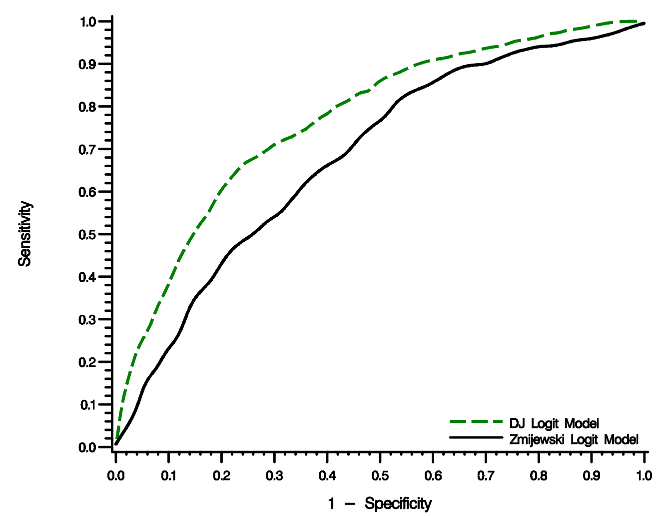
Panel A: DJ Logistic Regression Model Performance



Panel B: Non-Tech Sample – DJ vs Zmijewski Model Performance

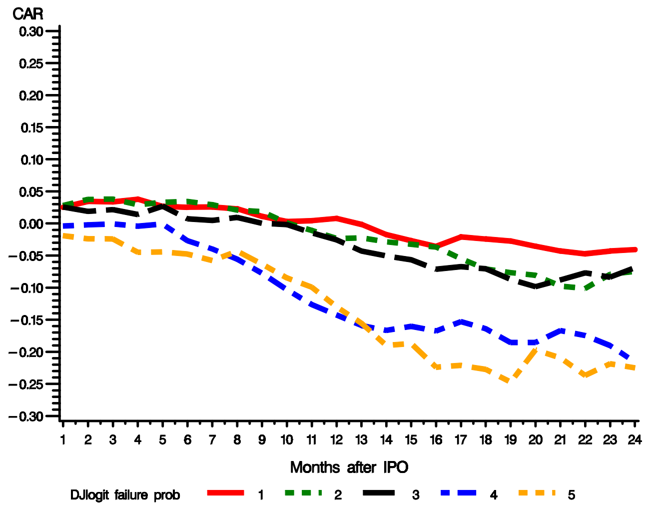


Panel C: High-Tech & Internet Sample – DJ vs Zmijewski Performance

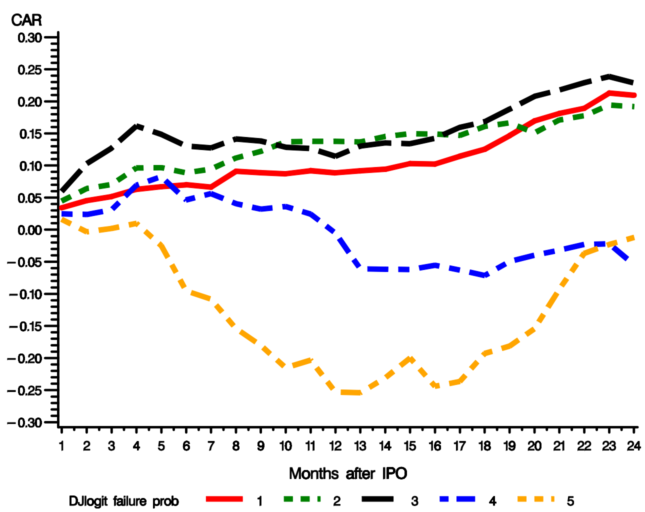


Panel D: High-Tech Sample – DJ vs Zmijewski Model Performance

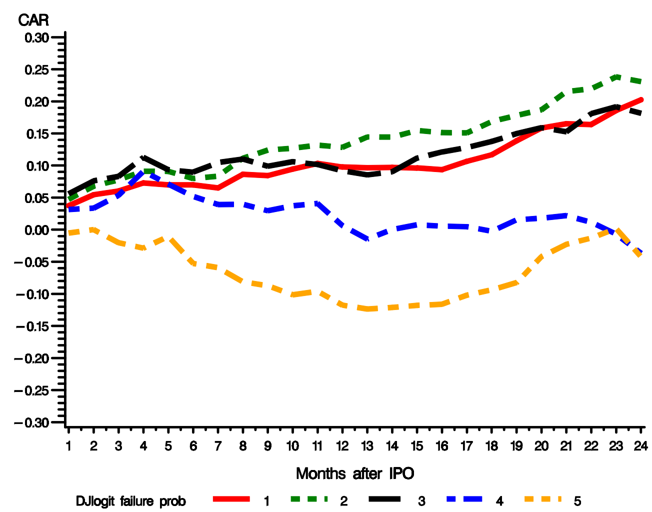
Figure 4
Cumulative Abnormal Return Plot over 2 Year Horizon after IPO Date
(DJ model is used to determine the 5 risk portfolios)



Panel A: Non-Tech sample



Panel B: High-Tech & Internet Sample



Panel C: High Tech Sample (without Internet Firms)

Table 1
Variable Definitions

Variable Name	Definition
failure	indicator variable equal to 1 if the firm failed within 5 years after IPO, 0 otherwise
mv_ipodt	stock market capitalization at the close of trading on the IPO date
proceeds	IPO proceeds (in millions – CPI adjusted)
NIdummy	indicator variable equal to 1 if the firm has negative earnings (data172), 0 otherwise
logaccumdeficit	accumulated deficit is negative log of retained earnings if the firm is in a deficit position, 0 otherwise
RD_TA	Research and development expense divided by total assets
age_ipodt	number of years since incorporation (measured at date of IPO)
CM_rank	Carter-Manaster underwriter reputation ranking
VCdummy	indicator variable set equal to 1 if the firm is VC backed at the time of IPO
Big8Natl	Indicator variable equal to 1 if firm has Big8 or national firm auditor, 0 otherwise
FirstDayRet	first day initial returns: closing price on the IPO date less offer price as % of offer price
offer_price	IPO offer price (CPI adjusted)
IPOmkt30days	average initial return to all IPOs in the thirty days prior to the firm's IPO
leverage	total liabilities divided the sum of total assets plus the proceeds raised at the date of IPO
logSGA	Natural log of selling, general and administrative expenses
grossmargin	ratio of sales minus cost of goods sold to sales
logrd	natural log of one plus R&D expense
logsales	natural log of one plus sales

Table 2
Descriptive Statistics: Non-Tech, High-Tech & Internet, and High-Tech IPOs period 1985-2000

	Non-Tech (A)		High-Tech & Int (B)		High-Tech (C)	
Variable	mean	median	mean	median	mean	median
failure	19.7%		20.8%		16.4%	
mv_ipodt	224.295	95.703	447.866	153.570	351.629	129.896
proceeds	56.482	30.070	50.375	36.285	47.143	32.952
NIdummy	0.255	0.000	0.571	1.000	0.521	1.000
accumdeficitdummy	0.389	0.000	0.718	1.000	0.684	1.000
RD_TA	0.031	0.000	0.516	0.272	0.542	0.280
age_ipodt	18.188	9.000	8.728	6.000	9.320	6.000
Logistic regression variables:						
CM_rank	6.704	8.100	7.216	8.100	7.089	8.100
VCdummy	0.226	0.000	0.637	1.000	0.615	1.000
Big8Natl	0.894	1.000	0.949	1.000	0.944	1.000
IPOmkt30days	0.179	0.135	0.308	0.170	0.251	0.158
logAge	2.336	2.303	1.980	1.946	2.041	1.946
FirstDayRet	0.115	0.054	0.310	0.115	0.226	0.094
offer_price	14.927	14.794	14.382	13.905	14.052	13.675
leverage	0.434	0.428	0.229	0.164	0.243	0.183
logRD	0.187	0.000	1.186	1.170	1.217	1.199
logSGA	2.170	2.048	1.954	2.095	1.923	2.063
grossmargin	0.322	0.310	0.402	0.421	0.402	0.420
logaccumdeficit	-0.797	0.000	-1.777	-1.907	-1.673	-1.694
logsales	4.024	4.164	2.664	2.761	2.753	2.890

Table 3
Logistic Regression Estimation: Predicting Failure within Five Years of IPO
Non-Tech, High-Tech & Internet, and High-Tech IPOs for period 1985-2000

	Non-Tech (A)		High-Tech & Int (B)		High-Tech (C)		Diff[*] (A) vs (B)	Diff (C) vs Int
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	p-value	p-value
Intercept	1.383	(0.000)	0.363	(0.228)	0.467	(0.146)	(0.012)	(0.791)
CM_rank	-0.097	(0.014)	-0.042	(0.245)	-0.099	(0.013)	(0.298)	(0.002)
VCdummy	-0.117	(0.499)	0.017	(0.913)	0.026	(0.878)	(0.563)	(0.131)
Big8Natl	-0.383	(0.051)	-0.385	(0.118)	-0.285	(0.271)	(0.998)	(0.129)
IPOmkt30days	0.743	(0.001)	2.274	(0.000)	1.462	(0.000)	(0.000)	(0.188)
logAge	-0.228	(0.000)	-0.428	(0.000)	-0.414	(0.000)	(0.084)	(0.115)
FirstDayRet	-0.263	(0.381)	-0.022	(0.837)	0.189	(0.211)	(0.450)	(0.016)
offer_price	-0.045	(0.009)	-0.078	(0.000)	-0.070	(0.000)	(0.155)	(0.874)
leverage	1.447	(0.000)	1.023	(0.008)	1.189	(0.003)	(0.452)	(0.252)
logRD	-0.263	(0.124)	-0.571	(0.000)	-0.415	(0.000)	(0.106)	(0.844)
logSGA	0.372	(0.000)	0.433	(0.000)	0.527	(0.000)	(0.652)	(0.014)
grossmargin	-0.972	(0.011)	-0.122	(0.599)	-0.532	(0.049)	(0.056)	(0.054)
logaccumdeficit	-0.043	(0.486)	-0.297	(0.000)	-0.212	(0.001)	(0.003)	(0.066)
logsales	-0.513	(0.000)	-0.419	(0.000)	-0.386	(0.000)	(0.409)	(0.569)
Failures / total obs	337 / 1708		474 / 2282		324 / 1980			
Log Likelihood	-716.72		-908.27		-734.61			
Nagelkerke R^2	0.227		0.316		0.235			
Hosmer-Lemeshow χ^2	7.985		8.128		11.880			
Hosmer-Lemeshow p-value	(0.435)		(0.421)		(0.157)			
ROC *within sample*	0.768		0.819		0.783			
ROC *out-of-sample*	0.754		0.811		0.770			
ROC Zmijewski	0.641		0.661		0.663			
Chow-Type χ^2							74.744	59.231
Chow-Type p-value							(0.999)	(0.998)

(*) The difference between the coefficients in the respective columns is tested with a Wald test on the interactive term of the respective coefficient in the logistic regression for which the two samples are pooled. That is, an non-tech dummy variable is multiplied to each variable in a pooled Non-Tech-High Tech & Internet model to test for a (A) vs (B) difference, and an internet dummy variable is used in a pooled High Tech-Internet sample to test for a (C) vs Int difference.

Table 4
Four-Factor Time-Series Regressions on IPO rolling Portfolios, One and Two Year Horizon [(1)]

Variable	One Year Horizon				Two Year Horizon			
	Full Sample	Non-Tech	High-Tech & Internet	High-Tech	Full Sample	Non-Tech	High-Tech & Internet	High-Tech
Intercept	0.0020	-0.0050	0.0056	0.0059	-0.0010	-0.0046	0.0022	0.0025
	(0.94)	(-2.29)	(2.07)	(2.19)	(-0.54)	(-2.65)	(0.96)	(1.16)
RMRF	1.0880	1.1513	1.1027	1.0937	1.1069	1.1528	1.1008	1.0970
	(23.29)	(20.16)	(16.64)	(16.39)	(25.92)	(25.14)	(20.73)	(20.07)
SMB	1.2584	0.9456	1.2841	1.2883	1.0735	1.0458	1.1217	1.1330
	(15.44)	(9.13)	(13.43)	(12.36)	(14.42)	15.07)	(13.06)	(11.82)
HML	-0.5629	0.2175	-0.9111	-0.9057	-0.5373	0.2363	-0.9404	-0.9350
	(-6.94)	(2.40)	(-7.66)	(-7.51)	(-6.61)	(3.43)	(-8.89)	(-9.01)
Momentum	-0.1227	-0.1584	-0.1172	-0.1087	-0.1563	-0.2512	-0.1940	-0.1895
	(-1.57)	(-2.11)	(-1.46)	(-1.29)	(-2.72)	(-5.82)	(-3.12)	(-3.05)
R^2	0.91	0.82	0.88	0.88	0.91	0.88	0.91	0.91

(1) The four-factor model, i.e. the three Fama-French factor with the additional Carhart price momentum factor, is estimated over the entire 1985-2000 period with a regression of monthly equally weighted IPO portfolio returns on four factors. Portfolios of IPOs are formed by including all issues that were done within the previous year (two years). The four factors are: market return minus the risk-free rate (RMRF), returns on a portfolio of small firms minus returns on a portfolio of big firms (SMB), returns on a high book-to-market portfolio minus returns on a low book-to-market portfolio (HML), and returns on a high momentum portfolio minus returns on a low momentum portfolio (PR12). The t-statistics are White-adjusted for heteroskedasticity.

Table 5

Buy-and-Hold Abnormal Return over 1 Year Horizon across Five Failure Risk Portfolios (using DJ and Zmijewski model)

	DJ Failure Model				Zmijewski (1992) Failure Model			
	Market-Adjusted		Four-Factor Adjusted		Market-Adjusted		Four-Factor Adjusted	
Failure Risk Portfolio	Average Return	Median Return	Average Return	Median Return	Average Return	Median Return	Average Return	Median Return
PANEL A: Non-Tech One Year Buy-and-Hold Abnormal Returns								
1 (Low Risk)	-0.0195	-0.0679	0.0128	-0.0534	-0.0475	-0.1768	-0.0127	-0.1398
2	-0.0499	-0.1428	-0.0265	-0.1135	-0.1018	-0.2189	-0.0705	-0.1758
3	-0.0477	-0.1357	-0.0281	-0.1259	-0.0833	-0.2241	-0.0523	-0.1910
4	-0.2048	-0.3346	-0.1709	-0.2743	-0.0850	-0.1559	-0.0659	-0.1377
5 (High Risk)	-0.1893	-0.3852	-0.1608	-0.3638	-0.2172	-0.3102	-0.1954	-0.2869
PANEL B: High-Tech and Internet One Year Buy-and-Hold Abnormal Returns								
1 (Low Risk)	-0.0140	-0.1271	0.0795	-0.0431	-0.0375	-0.2095	0.0557	-0.1186
2	0.0550	-0.1474	0.1494	-0.0237	0.1005	-0.1341	0.1954	0.0089
3	-0.0028	-0.2623	0.1175	-0.0796	-0.0939	-0.2804	0.0114	-0.1401
4	-0.1323	-0.4336	-0.0383	-0.2363	-0.0871	-0.4209	-0.0136	-0.2412
5 (High Risk)	-0.2296	-0.6263	-0.1606	-0.3870	-0.2127	-0.5154	-0.1075	-0.2841
PANEL C: High-Tech One Year Buy-and-Hold Abnormal Returns								
1 (Low Risk)	-0.0164	-0.1310	0.0836	-0.0308	-0.0226	-0.1691	0.0761	-0.0765
2	0.0338	-0.2188	0.1507	-0.0819	0.0529	-0.1450	0.1518	-0.0159
3	-0.0587	-0.2461	0.0844	-0.0495	-0.0896	-0.2526	0.0352	-0.1012
4	-0.1684	-0.3875	-0.0423	-0.1799	-0.1204	-0.3594	0.0165	-0.1498
5 (High Risk)	-0.1768	-0.4464	-0.0487	-0.2393	-0.2169	-0.4481	-0.0521	-0.1898

The average and median buy-and-hold return for each failure risk porfolio is calculated by compounding the monthly four-factor adjusted returns over 12 months after IPO. The sector specific four-factor sensitivities reported in the previous table are used to calculate the expected return for each firm. The failure probability (risk) is determined from both the Zmijewski (1992) model, and from the DJ model as reported in table 3. We use a simulation procedure in which we randomly select 75% of the sample data to estimate the DJ model and apply the model to the 25% left-out sample. We repeat this procedure 200 times and compute the average cross-validated failure probability per firm. We then sort the firms into risk quintiles and report the average/median buy-and-hold abnormal returns.

Table 6

Buy-and-Hold Abnormal Return over Two Year Horizon across Five Failure Risk Portfolios (using DJ and Zmijewski model)

	DJ Failure Model				Zmijewski (1992) Failure Model			
	Market-Adjusted		Four-Factor Adjusted		Market-Adjusted		Four-Factor Adjusted	
Failure Risk Portfolio	Average Return	Median Return	Average Return	Median Return	Average Return	Median Return	Average Return	Median Return
PANEL A: Non-Tech Two Year Buy-and-Hold Abnormal Returns								
1 (Low Risk)	-0.0883	-0.2514	0.1946	0.0817	-0.1701	-0.3563	0.1697	-0.0459
2	-0.1229	-0.3044	0.1934	-0.0328	-0.2268	-0.4373	0.0746	-0.1784
3	-0.0990	-0.3207	0.2209	-0.0245	-0.2384	-0.4655	0.0659	-0.1647
4	-0.3371	-0.5688	-0.0170	-0.2657	-0.1479	-0.3910	0.1515	-0.1386
5 (High Risk)	-0.5017	-0.7695	-0.1849	-0.4881	-0.3789	-0.6045	-0.0682	-0.2968
PANEL B: High-Tech and Internet TwoYear Buy-and-Hold Abnormal Returns								
1 (Low Risk)	0.0861	-0.3449	0.4089	-0.0288	0.0022	-0.4141	0.2990	-0.1327
2	0.0665	-0.4352	0.3797	-0.1118	0.0727	-0.3943	0.3614	-0.0943
3	0.1069	-0.5182	0.3856	-0.2466	-0.0043	-0.5605	0.2517	-0.3141
4	-0.1178	-0.6428	0.0969	-0.4991	0.0570	-0.6540	0.2700	-0.4999
5 (High Risk)	-0.3621	-0.7733	-0.2608	-0.7485	-0.3402	-0.6833	-0.1651	-0.6238
PANEL C: High-Tech Two Year Buy-and-Hold Abnormal Returns								
1 (Low Risk)	-0.0028	-0.3772	0.3019	-0.0841	0.0173	-0.3925	0.3212	-0.1264
2	0.1399	-0.4683	0.4109	-0.1515	0.0426	-0.3445	0.3364	-0.0767
3	-0.1263	-0.4822	0.1406	-0.2274	-0.1535	-0.5065	0.1411	-0.2418
4	-0.2340	-0.6278	0.0132	-0.3843	-0.1153	-0.6028	0.1407	-0.3541
5 (High Risk)	-0.3543	-0.6892	-0.0850	-0.4554	-0.3697	-0.6506	-0.1555	-0.5368

The average and median buy-and-hold return for each failure risk porfolio is calculated by compounding the monthly four-factor adjusted returns over 24 months after IPO. The sector specific four-factor sensitivities reported in the previous table are used to calculate the expected return for each firm. The failure probability (risk) is determined from both the Zmijewski (1992) model, and from the DJ model as reported in table 3. We use a simulation procedure in which we randomly select 75% of the sample data to estimate the DJ model and apply the model to the 25% left-out sample. We repeat this procedure 200 times and compute the average cross-validated failure probability per firm. We then sort the firms into risk quintiles and report the average/median buy-and-hold returns.