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The Relevance of Accounting Information in a Stock Market Bubble: Evidence from Internet IPOs

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Abstract: Prior research shows that accounting information is relevant for stock valuation, failure prediction, performance evaluation, optimal contracting, and other decision-making contexts in relatively stable market settings. By contrast, accounting's role during stock market bubbles such as those involving a revolutionary emerging technology is the subject of considerable debate, and prominent market observers have alleged that outdated and flawed accounting practices contributed to the crash of the Internet-led high-tech bubble of the late 1990s. We address the issue of whether accounting data is informative in a stock market bubble by examining its failure prediction ability in the context of Internet IPOs, one of the most egregious and economically significant sectors of the high tech bubble. Our setting of young start-up firms is one in which there is relatively little room for managerial discretion with respect to accounting accruals; Internet firms' accounting earnings closely approximate operating cash flows. Yet in contrast to widespread criticisms of accounting and its alleged role in fueling the bubble, we find that accounting variables are highly informative for failure prediction; specifically, they are significant in explaining *ex post* realized Internet IPO failures. Using an existing IPO failure prediction methodology and two alternative definitions of innovative IPOs, we further show that *ex ante*, out-of-sample Internet IPO failure forecasts are associated with economically and statistically significant hedge returns. Our analyses suggest that the traditional financial reporting system could serve as an anchor during speculative bubbles.

Keywords: stock bubbles, IPO, Internet, failure prediction, high tech, innovation, risk assessment, accounting information, market crash

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1. INTRODUCTION

The dramatic rise and fall of the Internet sector remains the subject of much controversy, speculation and debate.[1] Influential economic observers have alleged, for example, that outdated and flawed accounting practices provided biased information contributing to inflated pricing that culminated in the crash of the high tech bubble of the late 1990s. The Chairman of President Clinton's Council of Economic Advisors and Nobel Laureate economist, Joseph Stiglitz, stated, 'bad accounting provided bad information, and part of the irrational exuberance was based on this bad information' (Stiglitz, 2003, p. 10). In a similar vein, prominent macroeconomist and Nobel prize winner Paul Krugman commented that poorly crafted accounting standards and compliant auditors aided in the excesses of the 1990s bull market (Krugman, 2004, p. 108). Other commentators suggest that the accounting principles are not to be blamed. Penman (2003), for example, argues that many of the accounting practices blamed for the debacle are reckless violations of sound principles of revenue recognition, expense matching and debt recognition, and are *not* the failure of the principles, per se. In light of these mixed but strongly held views, we examine whether the financial reporting system provided useful and reliable information for failure risk assessment in the context of an economically significant sector of the recent stock market 'bubble,' Internet IPOs.[2]

Accounting information has been shown to be valuable in many settings. Extant research contends that earnings, in particular, is the premier source of financial information, with investors and managers using earnings more than any other summary measure of performance (e.g., Liu, Nissim and Thomas, 2002; and Graham et al., 2005). Earnings also serve as key inputs for firm valuation (e.g., Biddle et al., 1995; and Francis et al., 2003). Corporate governance research provides evidence that accounting information is used for designing optimal contracts and for mitigating agency issues (see Bushman and Smith, 2001, for a review).

Most of this body of work examines the usefulness of accounting information in the context of established firms. Demers and Joos (2007) (hereafter DJ) extend this research to show that accounting fundamentals are also informative in assessing the failure risk of young firms (i.e., IPOs).[3] The purpose of the current study is to investigate whether accounting information is relevant even during extreme bubble-like conditions.[4] Our analysis is prompted by claims that the traditional financial reporting model, developed during the Industrial age, is not relevant for valuing

1 For example, Welch (2001) identifies stock market 'frenzies' such as the Internet bubble as one of the top 10 challenges yet to be addressed by empirical capital markets research. Ritter (2001) comments that the Internet bubble of 1999 will be to IPO researchers what the Great Depression of the 1930s is to macroeconomists.

2 It is empirically difficult to definitively test whether a bubble exists, and this is not the focus of the current study. We follow multiple recent studies that conclude that bubble-like conditions were present during this period (e.g., Ofek and Richardson, 2003; Brunnermeier and Nagel, 2004; and Griffin et al., 2006; among others).

3 Internet stocks were not included in the main DJ sample. In specification checks, DJ report that their results are robust to the inclusion of Internet stocks. Given, however, that Internet firms comprise less than 10% of their sample, it is not surprising that including them has little effect on their results. Further, this specification check is not, in our view, equivalent to stating that accounting was useful for the risk assessment of Internet IPOs that were subject to extreme euphoria and mispricing. Consequently, in order to address our specific research question, a separate, dedicated examination of the Internet sector is needed.

4 In Section 2(*ii*) we present descriptive evidence to support the characterization of Internet stocks during the late 1990s and early 2000 as being under 'bubble like conditions.'

innovative, intangibles laden companies (Lev and Zarowin, 1999), much less those in a revolutionary technology industry such as the Internet (Peel, 2001). Notably, such young start-up firms are subject to relatively little accounting discretion.[5]

Accordingly, our study is not an investigation of opportunistic accounting practices, earnings management, or discretionary accruals at the time of IPO. Rather, the goal of our paper is to extend prior research by examining whether fundamental accounting variables are informative in anchoring investors' valuation expectations even during the volatile developmental stage of a revolutionary technology industry.

The implications of our analysis are pertinent to investors and regulators who are concerned about extreme wealth erosions following the bursting of bubbles. In the two years following the Internet-driven crash of the NASDAQ Composite Index in March 2000, approximately $8.5 trillion dollars of shareholder wealth was lost (Stiglitz, 2003, p. 6). Moreover, the Internet 'bust' is generally considered to be the trigger for the much broader technology market recession that followed. Economic inefficiencies arising out of such tremendous resource misallocations and social welfare costs associated with such extreme shareholder wealth erosion pose a formidable challenge to academics, practitioners and regulators. The criticisms leveled at the accounting system in the wake of the Internet crash strike at the very heart of the accounting discipline because one of the fundamental roles of accounting information is to facilitate the efficient allocation of capital.

Our research design builds on the predominantly accounting-based IPO failure prediction methodology developed by DJ (2007). In developing their model, DJ specifically exclude the anomalous Internet IPOs from their sample; as a consequence, their results do not speak to our research question. In order to address our specific research question, we first analyze accounting indicators of Internet IPO firms that went public during the period 1992 through February 2000. We document that accounting fundamentals were very weak for the majority of Internet IPO firms despite the optimism expressed by investors about these companies. An example of this exuberance is the large first day returns to Internet IPOs, which averaged over 80%.[6] Yet by standard accounting risk metrics, these Internet IPOs exhibited very weak fundamentals at their IPO dates: 88% of Internet companies reported negative earnings in the year prior to their IPO, 91% of these firms had accumulated deficits, and many Internet firms did not even have revenues at the time of their IPOs. Our evidence is consistent with Penman's (2003) conjecture that in general during this period, momentum investing displaced fundamental investing. In the end, over 24% of publicly-traded Internet companies ultimately failed within five years of their IPO.[7] Probing further, we document that contrary to the criticisms leveled at 'bad' accounting data, numerous accounting indicators are significant in explaining *ex post* IPO failures. Moreover, the accounting indicators exhibit significant incremental explanatory power over competing non-accounting variables.

We also investigate the role of accounting information in the context of experiential learning. Specifically, we investigate whether investors could have used accounting fundamentals and the experiences of past IPOs of innovative companies to become

5 The one exception in the context of Internet firms relates to their sometimes questionable revenue recognition practices (see e.g., Trueman et al., 2001; Davis, 2002; and Bowen et al., 2002).

6 The first day return is defined as the difference between the closing price at the end of the first day of trading minus the offer price, scaled by the offer price.

7 The technical definition of 'failure' that we adopt for this study is explained in Section 4(*i*).

more informed about the heightened failure risk of Internet companies. Our approach presumes that the past experiences of firms that utilize innovative ideas or technologies are relevant for predicting failure in the Internet sector. In testing this idea, we use two approaches to define and identify innovative firms,[8] and we estimate the DJ model on each of the two resulting prediction samples. Using the failure parameter estimates derived from these fitted models to develop strictly out-of-sample failure forecasts, we find that a model using either definition of innovation successfully predicts Internet IPO failures. Furthermore, a hedge strategy of going long (short) in Internet IPOs with low (high) failure risk yields significant one-, two- and three-year post-IPO abnormal returns. These findings demonstrate the value of learning from the history of innovative firms' IPOs.

In sum, our analyses suggest that accounting systems did provide reliable information even during the extremely volatile developmental stage of the Internet sector. Our evidence confirms Penman's (2003) premise that the financial reporting system could serve as an anchor during speculative bubbles.

The rest of this paper is organized as follows. Section 2 provides historical background to the Internet and other revolutionary technology industry shakeouts. In Section 3, we define our samples of Internet and other innovative IPO firms, while Section 4 examines the association between IPO date accounting information and *ex post* realized Internet IPO firm failures. In Section 5, we present the results from our out-of-sample Internet IPO failure predictions and associated hedge returns. Section 6 provides concluding remarks.

2. HISTORICAL BACKGROUND

(i) The Rise and Fall of the Internet Sector

Figure 1 presents a time series chart of the market value of publicly-traded Internet firms beginning with the inception of the industry in 1992, when America Online first went public, through to the end of 2003. For comparison, the figure also includes a line depicting the aggregate market capitalization of the NASDAQ (excluding Internet firms, and scaled by a factor of ten for greater comparability with the Internet industry), as well as a line showing the average market capitalization of NYSE firms (scaled by a factor of 20 for comparability). It is evident from the graph that the Internet sector experienced a spectacular rise followed by an equally dramatic fall. In contrast, the lines for the market values of the non-Internet NASDAQ and NYSE firms are relatively flat. In terms of wealth change, the market value of publicly-traded Internet companies declined by over $1 trillion from its peak in March 2000, settling down to approximately $282 billion by March 2002 (Morgan Stanley Dean Witter, 2002).[9]

(ii) Internet Companies and the Speculative Bubble

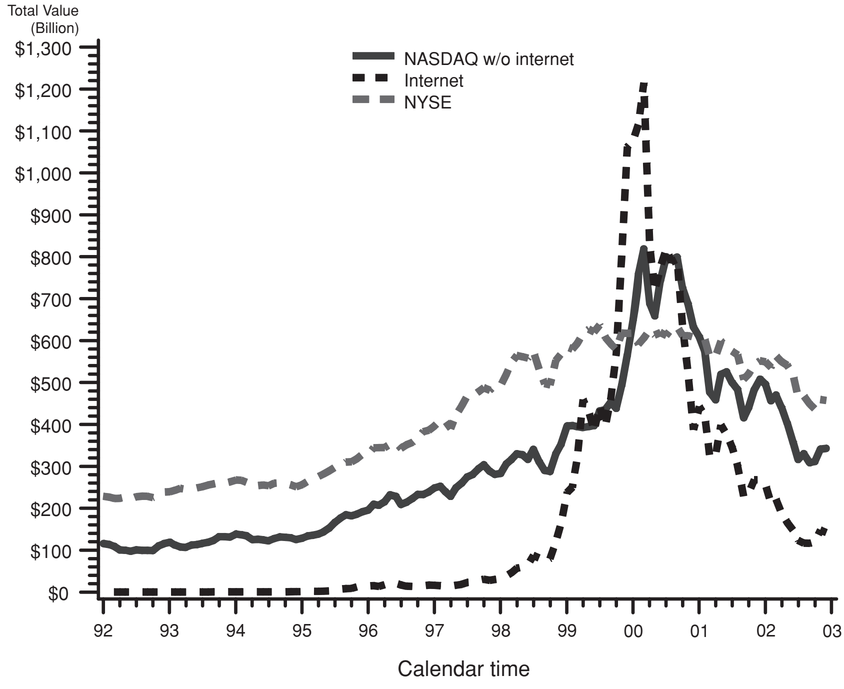
The empirical facts quoted above suggest that a bubble-like condition was present during the spectacular rise of the Internet companies. Academic and anecdotal

8 Section 3(*ii*) explains in detail our definitions of innovation.

9 Morgan Stanley's 8th edition of their *Technology IPO Yearbook* issued in March 2002 is the last to categorize the Internet as a separate sector.

Figure 1

Total Market Capitalization: Internet Industry versus Nasdaq and NYSE



Notes:
Nasdaq without Internet represents the market capitalization of all NASDAQ firms excluding Internet firms, scaled by a factor of 10. NYSE represents the market capitalization of all NYSE firms scaled by a factor of 20. All dollar amounts are inflation-adjusted and stated in January 2003 dollars.

evidence supports this notion. Barber and Odean (2001) identify several market conditions that are conducive to the formation of speculative bubbles: (1) the availability of large amounts of capital; (2) significant uncertainty regarding firm valuation; and (3) an inexperienced but active investor clientele. With respect to the first condition, the enormous flow of capital into the stock market and venture capital funds in the 1990s has been well documented (e.g., Perkins and Perkins, 1999; Leibowitz, 2000; and Mahar, 2003). Consistent with the second condition that the valuations of Internet firms were highly uncertain, our untabulated analyses using a range-based volatility estimator reveal that Internet stock volatilities are significantly higher than those of a matched pair sample of non-Internet high tech firms. The third condition, the role of unsophisticated investors in the growth and subsequent crash of the Internet sector, has not yet been thoroughly investigated. Anecdotal stories in the popular press are replete with claims and concerns that unsophisticated investors, including day traders and individuals managing their own 401(*k*) plans, formed a big part of the market for Internet stocks (e.g., Cassidy, 2002; and Mahar, 2003). Likewise, academics such as Ofek and Richardson (2003) argue that institutional investors underweighted Internet stocks in their portfolios. Our untabulated analyses using the Trade and Quotes (TAQ) database suggest that there was an abnormally high level of large trades in Internet stocks from 1997 through mid-1999, while the 'unsophisticated' trading activity was insignificantly different from a sample of matched-pair high tech firms even in the latter part of 1999 and early 2000. However, trade size is an imperfect and noisy proxy for investor sophistication. In the absence of more refined data, the role of investor clientele in the Internet bubble remains inconclusive. Overall, the Internet industry exhibits many of the characteristics alleged to be associated with a speculative 'bubble.' There was widespread exuberance during the boom years of Internet stocks, and these stocks experienced abnormally heavy trading volumes and abnormally high levels of volatility.

In addition to conditions associated with their timing or setting, there are several characteristics of Internet IPOs that differ from other IPOs. For example, Internet companies are much more likely to report a loss and an accumulated deficit in the year prior to IPO; they have higher mean levels of accumulated deficits; lower average sales levels; and higher spending on selling, general and administrative ('SG&A') expenses. Taken together, the evidence suggests that Internet companies are unusual and unique. Consequently, examining the Internet setting may provide useful new insights concerning the role of accounting information during speculative bubbles that cannot be gleaned from research investigating IPO firms during stable market conditions.

(iii) Historical Precedents

The exuberance of the Internet market was not unprecedented. Economic historians have documented that one of the hallmarks of speculative bubbles is the 'new era' thinking that often accompanies significant technological or financial innovations. Previous well-known bubbles include those associated with tulip hybrids in Holland in the 17th century, the advent of joint stock companies in the 18th century (e.g., the Mississippi and the South Sea Bubbles), the expansion of railroads in Great Britain and the US in the 19th century, the emergence of auto and aviation industries in the early and middle part of the 20th century, and the introduction of the microchip and personal computers in the late 20th century.[10] Such 'new era' thinking was clearly evident in the midst of the Internet bubble. For example, Bill Gates declared in 1995 that:

> the surging popularity of the Internet is the most important single development in the computer industry since the IBM PC was introduced... Like the PC, the Internet is a tidal wave (Gates, 1995).

Likewise, a prominent Silicon Valley venture capitalist, Donald Valentine, aptly captured the public mindset during the height of the Internet mania when he stated that:

> we have never had something so disproportionally publicized by everybody in the world as the greatest coming of anything ever as the Internet (in Perkins and Perkins, 1999, p. 13).

In addition to this 'new era' thinking, the Internet sector shared another similarity with nascent stage industries that emerge out of the commercialization of a new revolutionary technology. These nascent industries exhibit a well-documented pattern involving an initial explosion in the number of companies competing in the sector

10 See Galbraith (1993), Kindleberger (2000) and Shiller (2000) for detailed historical perspectives.

followed by significant shakeouts when rationalization of the industry occurs. By the end of our sample period, over 24% of Internet companies had failed within five years of their IPO. Prior shakeout industries include rubber tires, televisions, and penicillin in earlier eras; each of these sectors underwent a similar rapid proliferation followed by significant numbers of firm failures (Klepper, 2002). Another prominent example is the US auto industry, which consisted of 270 firms in the early 1900s before shrinking to a small oligopoly for most of the century (Mazzucato, 2002). Indeed, the eventual shakeout of the Internet industry was well-anticipated by some astute market observers.[11]

However, despite cautionary warnings and many historical precedents, most Internet investors did not appear to heed the lessons of history. This may not be altogether surprising; Galbraith (1993) observed that another key contributing factor to speculative bubbles is the 'extreme brevity of the financial memory.' As the pace of technological innovation continues to accelerate, history suggests that proliferations of firms competing to monetize the latest technologies will ensue, and the frequency of catastrophic industry shakeouts will increase. Consequently, in order to avoid repeated shareholder wealth erosions and the other economic woes that accompany major shakeouts, it is important to investigate whether investors and other stakeholders could learn from history to use accounting information to better assess failure probabilities in the early stages of innovative companies in revolutionary technology industries.

3. SAMPLE SELECTION AND DATA DESCRIPTION

(i) *IPO Sampling Frame and Internet Sample*

We begin by selecting all US IPOs for the period of January 1982 through February 2000 from the SDC New Issues database, excluding rights issues, unit offerings, spin-offs, REITs and ADRs.[12] We choose the year 1982 as the beginning of our prediction window because this is generally viewed as the start of the extended bull market (e.g., Evans, 2003; and Mahar, 2003).[13] Because we are interested in examining accounting's role in 'bubble' conditions, we end our sample in February 2000 as early March 2000 marks the very obvious beginning of the unwinding of the Internet bubble (see e.g., Figure 1 in Demers and Lev, 2001).[14] Consistent with prior studies in the Internet sector (e.g., 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.[15] Currently no standard SIC code or other official classification system exists for identifying Internet

11 These observers include: the founding editors of *Red Herring* magazine (Perkins and Perkins, 1999); the now infamous Internet analyst, Henry Blodget (Ackman, 2003); AOL Chairman, Steve Case (*Dallas Morning News*, 1997); and Federal Reserve Chairman, Alan Greenspan (Greenspan, 1999); among others.

12 Some prior IPO studies exclude stocks with offer prices below various 'penny stock' thresholds (e.g., Ritter, 1991; and Ibbotson and Jaffe, 1975). We do not exclude any IPO firms from our initial sample simply on the basis of their issue price, but rather we employ controls for this in our multivariate tests.

13 Our results are not sensitive to selecting 1980, for example, a somewhat more arbitrary date, as the starting point for the failure estimation model.

14 The decision to end the sample period in February 2000 does not bias towards our findings. The out-of-sample abnormal returns results reported in Section 5 are stronger if we include all Internet IPOs through calendar year 2000 for which we have the necessary data.

15 This definition was originally established by internet.com, an Internet industry portal site, in order to distinguish between 'pure play' Internet companies versus entities that would generate the majority of their revenues independent of the existence of the Internet.

companies. We, therefore, define the sample of Internet IPOs to be the superset of all IPOs that have been identified as Internet companies by prior IPO researchers. Specifically, we include all Internet IPOs identified by Demers and Lewellen (2003), Ofek and Richardson (2003), or Ritter.[16] Our final sample consists of 356 Internet companies that undertook initial public offerings by the end of February 2000 and for which data is available.

(ii) Identification of Innovating Firms for Prediction Sample

For our tests involving out-of-sample failure predictions, we expect that firms that use or develop innovative ideas or technologies will provide the most relevant prediction sample for the Internet sector that we focus on in this study. We recognize that innovation is a complex and multi-faceted attribute, and our purpose here is not to provide the definitive taxonomy of what constitutes 'innovation.' Rather, we are interested in the information properties of accounting in the context of 'bubble' industries, the closest prediction sample for which we consider to be other innovative firms. Recognizing that 'innovation' is not a well-defined concept, we adopt two approaches to identify and define our prediction sample of innovative firms. To the extent that our samples suffer from misclassification, the use of two distinct samples will bias against the possibility of developing forecasting models that have out-of-sample predictive power.

Our first definition of 'innovative' IPO firms relies primarily upon accounting-based measures of R&D activities for classifying firms as 'high tech.' The rationale behind this definition is that R&D-intensive firms are investing significantly in developing innovative technologies. We define IPO firms to be 'high tech' if they fulfill any one of the following three criteria: (1) the ratio of their research and development (R&D) expenses to sales is greater than 5%; (2) the ratio of their R&D expenses to total assets is greater than 5%; or (3) they have been classified as Internet firms.[17] This generates a sample of 2,015 high tech IPO firms. Our second definition takes a much broader perspective and assumes that companies that were listed on the NASDAQ at the time of their IPOs employ significant innovative ideas and/or technologies, and thus they constitute a representative sample of 'innovators.' This definition generates a sample of 3,900 IPO firms during the period of our study. Figure 2 presents a histogram of Internet, high tech, and NASDAQ IPO firms over time.[18]

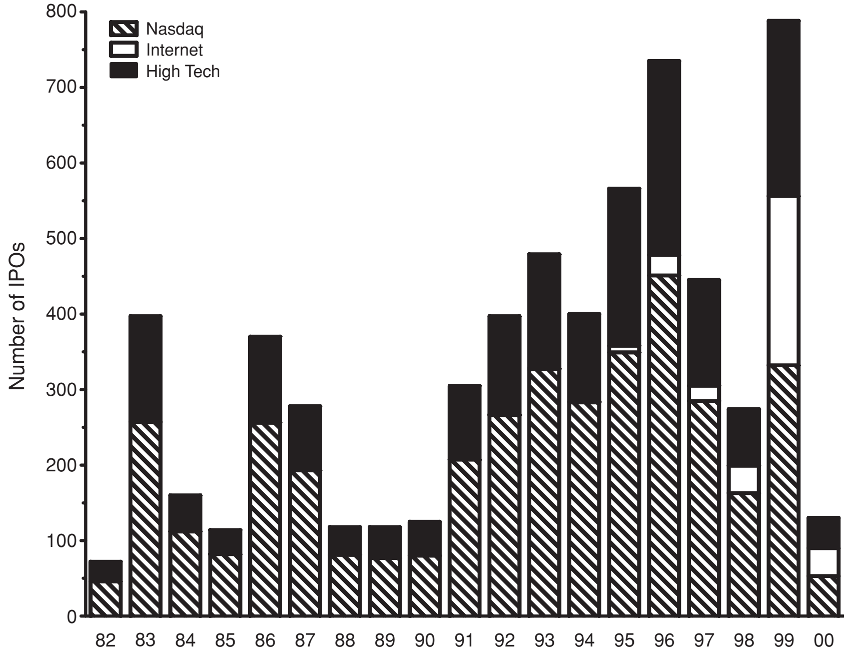
16 The Ofek and Richardson (2003) list is available at http://pages.stern.nyu.edu/~eofek/InternetDatabase.prn, while Ritter's Internet IPOs are found at http://bear.cba.ufl.edu/ritter/ipodata.htm

17 The 5% threshold is supported by prior research by Chan, Lakonishok and Sougiannis (2001) who report that the average R&D to sales ratio for firms in the fourth quartile of their sample (i.e., high technology intensive firms) is approximately 5.7%, and by Francis and Schipper (1999) who report that firms in their research intensive industry classification have an average R&D to total assets ratio of approximately 9%. An alternative classification scheme would rely upon the SDC categorization of 'high tech' firms. This option is problematic, however, because we have detected many misclassifications in the SDC database (e.g., retail drug stores and Health Maintenance Organizations are sometimes included in SDC's 'high tech' category). Yet another alternative is to directly adopt the Francis and Schipper (1999) industry classifications to assign firms into the 'high tech' category. Their classification scheme, however, has been formulated using data that largely predate our sample period. When we apply the Francis and Schipper classification scheme to our sample, we find that in many cases firms with high levels of R&D spending have been classified as 'non-tech' companies, while firms with very low or zero R&D spending have been classified as 'high tech' companies. Consequently, we decide to use a direct R&D spending cutoff to classify firms as 'high tech' or 'innovative.'

18 Note that these definitions are not mutually exclusive, and IPO firms may be simultaneously included in more than one of these IPO categories.

Figure 2

Number of IPOs for Period January 1982 – February 2000



(iii) Data Sources

Data related to IPO deal characteristics, pre- and immediately post-IPO venture capital and insider ownership levels are obtained from the SDC New Issues Database, while auditing and accounting data are taken from Compustat. Data related to Internet firms' significant shareholder(s) are hand collected from issuing companies' prospectuses and S-1 Registration filings. Market values, stock returns, and delisting events are obtained from the Center for Research in Security Prices (CRSP) databases, while financial statement variables are derived from the Compustat files. Carter-Manaster underwriter reputation rankings and firm founding dates are provided by Jay Ritter.[19]

(iv) Descriptive Statistics

Table 1 presents descriptive statistics for the Internet, high tech, and NASDAQ IPO samples. The Appendix provides detailed definitions of all of the variables appearing in each of the tables. All dollar-valued variables are CPI-adjusted and stated in 2004 dollars. As shown, the rate of failure within five years of IPO is over 24% for Internet firms, compared to just 14% and 18% for high tech and NASDAQ IPOs; this difference

19 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.

Table 1
Descriptive Statistics of Selected Variables

	Internet Sample		*High-Tech Sample*		*Nasdaq Sample*	
Variable	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Number of IPOs	356		2015		3900	
Failure within 5 years (0–1)	0.242	0	0.143	0	0.182	0
Market value at IPO (*mln*)	1,139.7	487.3	335.2	122.7	255.9	101.6
IPO *proceeds* (*mln*)	73.3	58.5	40.9	31.4	38.9	28.6
firm age at IPO (*years*)	5.193	4	9.084	6	11.750	7
CM_*rank* (underwriter prestige)	7.975	8.1	6.810	8.1	6.491	8.1
Venture-backed (0–1)	0.753	1	0.638	1	0.456	0
Hot issue (avg initial return prior 90 days)	0.643	0.630	0.238	0.153	0.210	0.145
IPO *day initial return*	0.859	0.511	0.282	0.094	0.221	0.079
Offer price	17.048	16.255	14.909	14.223	14.799	14.157
Leverage	0.144	0.106	0.212	0.158	0.298	0.248
R&D/*total assets*	0.379	0.204	0.800	0.407	0.408	0.045
R&D (*mln*)	3.48	1.80	5.26	2.81	2.35	0.25
*log*R&D	1.062	1.023	1.394	1.338	0.707	0.220
SGA	15.36	11.16	12.85	7.07	12.56	6.35
*log*SGA	2.436	2.498	2.083	2.088	2.023	1.996
Negative net income (0-1)	0.875	1	0.551	1	0.428	0
Accumulated deficits (0-1)	0.913	1	0.700	1	0.565	1
log Accumulated deficits	−2.43	−2.666	−1.624	−1.686	−1.194	−0.540
Sales (*mln*)	21.4	9.6	43.739	13.860	70.068	22.467
logSales	2.177	2.258	2.486	2.629	2.980	3.112

Notes:
Means and medians of firm characteristics are calculated at the date of IPO for each of three samples over the period January 1982 through February 2000: Internet firms, high-tech firms (based on R&D/total asset and R&D/sales > 5%), and Nasdaq firms (excluding SIC 0 and 1 industries). The variables are defined in the Appendix.

is significant at the 0.01 level.[20] As documented in prior studies (e.g., Demers and Lewellen, 2003), the statistics presented in Table 1 confirm that Internet IPOs raise more proceeds ($p < 0.001$), have higher market capitalizations ($p < 0.0001$), and are associated with greater initial returns ($p<0.0001$) at the time of IPO than other firms. Internet firms are also younger ($p < 0.0001$), have more prestigious underwriters (as evidenced by the higher CM_*rank* variable, $p < 0.0001$), are issued during hotter IPO markets ($p < 0.0001$), and are more likely to be venture-backed ($p < 0.0001$). In terms of accounting-based measures of performance, the descriptive statistics summarized in Table 1 reflect Internet firms' early stage of activities and lack of profitability at the time of IPO, as previously described in Section 2. In addition, the Internet companies' average pre-IPO expenditures on R&D and selling, general, and administrative expenses ('SG&A') are consistent with our Internet sample consisting of

20 By comparison, Fama and French (2004) report that the probability that a seasoned firm becomes delisted within ten years rises from 15.6% for the seasoned firms of 1973 to 17.9% for the cohorts of 1980–1991. The ten-year delist rate for new lists rises further, from 16.9% for the 1973 cohort to 44.2% for the 1980–1991 cohorts. Thus, more than two in five of the new lists of 1980–1991 are delisted within ten years for poor performance.

both technology-focused and business-to-consumer retail-oriented (e.g., Amazon and Pets.com) innovative firms.

4. HISTORICAL DETERMINANTS OF INTERNET IPO FAILURES

Our first set of empirical tests explores the factors associated with Internet IPO firm failures; specifically, we examine whether accounting information that is available at the time of IPO is associated with *ex post* realized failures. In the following subsections we define our dependent and independent variables, together with predictions regarding the latter's explanatory role for failure probability. We then present our within-sample Internet IPO logistical regression results.

(i) Definition of Failure

We use the CRSP events file to identify corporate de-listings for the firms in our sample. We 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').[21] All other firms that did not fail during their 6th year subsequent to IPO are considered not to have failed. In order to minimize the noise in the dichotomization of our sample, we follow the common convention in the literature of removing from the pool of 'non-failures,' firms that are known to have failed in the year subsequent to the prediction year (i.e., year 6 in this case). These classifications result in a total of 86 (24%) of Internet firms, 288 (14%) of high tech firms, and 710 (18%) of NASDAQ firms being classified as failures.

(ii) Accounting-Based Indicators of Failure Risk

We consider a number of accounting indicators of risk as well as pre-IPO firm performance measures as explanatory variables for Internet IPO failures. We describe these variables and the rationale for their inclusion in our model below. Variable definitions are summarized in the Appendix. First, we expect that pre-IPO sales levels (*logSales*) will be negatively associated with IPO-failure realizations since sales may either serve as a proxy for size and/or an indicator of product demand and the extent of the customer base. Higher gross margins (GM) are an indication of a firm's premium pricing power and their efficiency in producing and delivering their products or services. Thus, this variable is expected to be negatively associated with IPO failures. If advertising expenses (*logAdvertising*) reflect a successful investment in intangible assets such as customer lists and brand names, then we expect a negative association between this variable and failure risk. However, many Internet firms were perceived to be spending excessively on advertising during the early years of the Internet boom, in which case higher values

21 Our CRSP-based definition is identical to that of Demers and Joos (2007), and similar to, but slightly broader than, those adopted by Beatty (1993) and Schultz (1993). An alternative definition of 'failure' would also include firms that are 'economic failures,' such as those, e.g., whose share prices have declined by some stated threshold such as 80% or 90% subsequent to the initial offering. To the extent that we have excluded these firms from our definition of failure, our dependent variables may contain measurement error and this biases against our finding significant results.

of *logAdvertising* would be positively associated with failure risk. We expect that firms that are spending more heavily on R&D at the time of IPO are further along in the development of their products, and that they have successfully met earlier R&D-based milestones in order to garner higher levels of pre-IPO capital. Accordingly, we expect R&D expenses (*log*RD) to be negatively associated with failure, consistent with Demers and Joos (2007) who directly document this result for their sample of high-tech IPOs and with Guo et al. (2007) who find that R&D is positively associated with long-term performance for US IPOs that went public before the bubble years.[22]

Leverage, defined as total liabilities divided by the sum of total pre-IPO assets plus IPO proceeds, is a financial structure risk that is expected to be positively associated with failure, consistent with extensive prior findings in the non-IPO failure literature (e.g., Altman, 1968; Ohlson, 1980; and Zmijewski, 1984), as well as with Peristiani (2003) and Demers and Joos (2007) in an IPO-specific setting. As previously noted, over 91% of Internet IPO firms have accumulated deficits at the time of going public. We define *logAccumDeficits* to be negative 1 times the natural log of the absolute value of the firm's accumulated deficits, or 0 for firms with positive retained earnings. Although they are a 'sunk cost,' the cumulative pre-IPO losses are nevertheless expected to serve as an indication of the continued riskiness of the firm's prospects (Demers and Joos, 2007). We expect that higher past levels of accumulated losses are an indication of higher failure risk, and thus we expect a negative coefficient on the negatively-valued *logAccumDeficits* variable.

We acknowledge that the accounting measures that we use as pre-determined explanatory variables may contain aspects of endogeneity. However, these concerns are likely to be less severe in our particular setting because most material expenditures made by Internet firms (R&D, product development, marketing) are required to be expensed (i.e., there is no accounting discretion available with respect to these expenditures, and thus no room for manipulation or signaling). Further, some important accounting estimates and policy choices such as those related to depreciation or inventory cost-flow assumptions, are not relevant to IPO stage Internet firms.[23]

(iii) Other Candidate Determinants of Failure

We also consider a number of other candidate variables for explaining the failures of newly public Internet companies, including proxies for IPO pricing, deal, and firm characteristics as well as the role of expert informational intermediaries.

22 Our multivariate model includes all of the key components of Internet firms' earnings, and permits the coefficients on the components to differ. As a specification check, we also examine a model that includes an earnings summary figure (scaled by sales), and allow separate coefficients for positive and negative earnings. The explanatory power of this model, captured by the pseudo-R^2, is 8.5% compared to 17% for the earnings components model reported in our tables. Consistent with economic intuition and prior accounting research, we conclude that the earnings components model is the superior specification.

23 Of the accounting variables included in our models, the one that is most likely to be susceptible to the endogeneity concern is revenue (i.e., *logSales* in our model). Indeed, Internet firms' revenue recognition practices have been the subject of previous academic study (e.g., Trueman et al., 2001; Bowen et al., 2002; and Davis, 2002). In the context of our setting, one could argue that opportunistic managers might inflate revenue to raise more capital at the time of IPO. However, any such endogeneity will decrease the predictive power of our models in the out-of-sample failure prediction analyses reported in Section 5, ultimately biasing against finding the significant hedge returns that we document there. Hence, even though the endogeneity concern cannot be completely ruled out, it is clearly not helping to over-reject the null. If anything, it is likely to be biasing against us finding significant results.

Based upon prior studies (e.g., Seguin and Smoller, 1997; Fernando et al., 2004; and Demers and Joos, 2007), we include the IPO offering price per share (*offer_price*) and expect this variable to be inversely related to failure.[24] *IPO day initial returns*, which are defined as the increase from the offer price to the closing price on the first day of trading, have been shown to be related to IPO risk (Beatty and Ritter, 1986). If this variable captures some notion of valuation uncertainty as of the IPO date, we expect that this risk proxy will be positively associated with IPO failure probabilities. We also consider the potential signaling value of IPO lock up provisions, and measure the variable *lockup days* as the number of days post-IPO during which insiders are forbidden to sell their shares. Lockup provisions may either provide a signal of firm quality or may be an indication of (and control mechanism against) moral hazard problems (Brav and Gompers, 2003). This suggests the potential for either a positive or negative association with failure risk depending upon which factor dominates, on average, for our sample firms.

Following the conventional wisdom in the financial markets and popular press, as well as the evidence documented in prior academic studies (e.g., Loughran and Ritter, 2004; Coakley, Hadass and Wood, 2007; and Demers and Joos, 2007), we expect that IPOs that are issued during a 'hot market' are of lower quality and thus at greater risk of failure. We capture this construct empirically with *hot issue market*, a variable defined as the average first day returns to all IPOs issued during the 90 days prior to the firm's own IPO date. In addition to this notion of timing the IPO within the buoyancy of the general capital markets, both anecdotal accounts in the Internet sector specifically (e.g., Perkins and Perkins, 1999), as well as the prior industrial organizational literature more generally (e.g., Klepper and Simons, 2000), suggest that early entrants into a revolutionary new industry are more likely to survive the sector's shakeout since these firms are likely to have met a higher 'quality hurdle' in order to be taken public at the inception of a new industry. We measure the variable IPO *vintage* as the number of months that have elapsed between the date of the first Internet IPO (i.e., AOL in 1992) and the target firm's IPO date, and we expect that firms with larger values for IPO *vintage* (i.e., firms that went public later in the life cycle of the industry) will be more likely to fail. In addition, we include *firm age* (Fama and French, 2004) and expect that firms that are older at the time of their IPO will be more established in their customer, supplier, and labor markets, and thus will be less likely to fail.

We consider a number of variables related to the presence of expert informational intermediaries in the IPO firm. First, we include an indicator variable (*Big*6-*national auditor*) which we set equal to 1 if the firm's auditor is either a Big-6 or national level firm, and 0 otherwise. We expect that this proxy for the quality of the auditor will be negatively associated with failure (Titman and Trueman, 1986; Michaely and Shaw, 1995; and Weber and Willenborg, 2003). Similarly, we include the Carter-Manaster rank (CM_*rank*) associated with the firm's lead underwriter, which is a well-established variable in the IPO literature to capture the prestige of the firm's underwriter (Carter and Manaster, 1990; Megginson and Weiss, 1991; and Schultz, 1993; amongst others). Higher values of CM_*rank* indicate higher levels of underwriter prestige, and thus we expect this variable to be negatively associated with failure. We also include a dummy

24 There is no strong economic intuition for why this variable should be associated with poor post-IPO performance or failure. One might expect that the firm could simply issue half as many shares for twice the price per share, e.g., in order to raise the same amount of proceeds and avoid a small share price. Despite this obvious logic, there is strong prior empirical support for this explanatory variable, and thus we include it in order to avoid a potential correlated omitted variables problem.

variable (*venture-backed*) to capture the presence of a venture capitalist in the IPO firm, and we expect this variable to be negatively associated with failure as the VC plays a certification role for the quality of the firm because she has reputational capital at stake should the firm fail (Brav and Gompers, 1997; and Jain and Kini, 2000).[25,26]

We include several additional variables which may capture further aspects of either quality signaling and/or monitoring. First, we define *insider ownership* retention as the percentage of common stock retained by officers and directors at the time of IPO. Both the agency theory (e.g., Jensen and Meckling, 1976) and the signaling hypothesis (e.g., Leland and Pyle, 1977) suggest that firms with higher levels of retained ownership by insiders will experience superior performance. Although the empirical evidence on this issue in the IPO setting remains mixed (see Jain and Kini, 1994; Hensler et al., 1997; and Jain and Kini, 1999 and 2000), based upon theory we expect to find a negative association between *insider ownership* and the probability of firm failure. We also define an indicator variable, *strategic investor,* that is set equal to 1 when there is a strategic investor from within the IPO firm's industry who owns 5% or more of the firm's outstanding shares at the time of IPO, and 0 otherwise. Strategic investors are pathways for the exchange of resources and they also play a signaling role, conveying status and recognition in both the firm's product and investor markets (e.g., Stuart, 2000; and Perkins and Perkins, 1999).[27] We expect that firms that have a strategic investor in their ownership structure at the time that they go public are less likely to fail because they have available the added benefit of the expertise and/or industry and financial connections that these investors bring to the new venture.[28]

(iv) Empirical Results of Within-Sample Internet Logistic Regressions

The results of the logit regressions of realized Internet firm failures on the candidate accounting and other IPO-related information are presented in Table 2 for the 281

25 Chahine et al. (2007) document that retained VC ownership in UK IPOs is negatively associated with underpricing, which they interpret as evidence that VCs play a certifying role in UK IPOs, consistent with most of the prior US-based research. By contrast, the same authors document that VC ownership in France is positively associated with IPO initial returns, which they interpret to be indicative of French VCs having a tendency to grandstand as suggested by Gompers (1996). Chahine et al. (2007) do not, however, speak to the role of VCs in the longer-term performance of the French and UK IPOs in their study. Wang et al. (2003) find that VC-backed Singaporean IPOs exhibit both lower levels of underpricing but also inferior post-IPO operating performance, suggesting a relatively more complicated role for VCs in the Singapore IPO market.
26 In their study of UK IPOs, Coakley et al. (2007) find that VCs play the expected certification role during the non-bubble years covered by their sample period, however, they document a significantly negative relationship between post-IPO operating performance and VC board representation for their UK IPOs during the 1998–2000 bubble years. Their results do not necessarily lead to similar predictions for our US-based IPO sample, however, since the VC-backed IPOs in the Coakley et al. (2007) study are fundamentally different from the prototypical VC-backed US IPO in that very few of their UK VC-backed companies are early stage IPOs.
27 Strategic investors in the Internet sector would include, e.g., technology firms, other larger Internet firms, and consumer-oriented companies from traditional (i.e., off-line) retailing or media industries in which the Internet firm seeks to operate. Examples of each of these respective categories include Intel, AOL, and Barnes and Noble bookstores (which applied their bricks and mortar bookselling expertise to the Internet space with barnesandnoble.com).
28 As a specification check, we also include the book-to-market ratio as an explanatory variable, with the book value of equity being defined as pre-IPO shareholders' equity plus the proceeds raised from the IPO and market being defined as the number of shares outstanding multiplied by the offer price per share. This variable is not significant at traditional levels ($p = 0.2122$).

Table 2

Logistic Regression Estimation: Explaining Failure Within Five Years of IPO for Internet IPOs Over the Period March 1992 Through February 2000

	Predicted	*Accounting Model*		*Non-Accounting Model*		*Full Model*	
	Signs	*Coefficient*	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*
Intercept		−1.275	0.006	−17.798	0.047	−23.397	0.046
logSales	−	−0.613	0.001			−0.622	0.002
Gross profitmargin	−	0.077	0.889			0.489	0.459
*log*RD	−	−0.546	0.018			−0.419	0.115
logAdvertising	?	0.389	0.054			0.486	0.032
Leverage	+	3.583	0.010			4.327	0.013
logAccumDeficits	−	−0.348	0.055			−0.852	0.001
Offer price	−			−0.072	0.095	−0.084	0.046
IPO *day initial return*	+			−0.244	0.255	−0.132	0.571
Hot issue market	+			0.770	0.355	0.515	0.596
*log*IPO*vintage*	+			4.645	0.028	5.932	0.032
logAge	−			−0.897	0.004	−0.951	0.015
*Big*6*-national auditor* (0/1)	−			−0.932	0.252	−0.992	0.252
Venture-backed (0/1)	−			−1.186	0.005	−2.093	0.000
CM_*rank*	−			0.026	0.813	0.019	0.886
Strategic investor (0/1)	−			−0.150	0.665	−0.639	0.115
Insider ownership	−			−0.017	0.062	−0.022	0.031
Failures within 5 years		57		57		57	
Total obs.		281		281		281	
Log likelihood		−125.43		−118.16		−100.24	
Nagelkerke R^2		0.172		0.243		0.402	
Hosmer-Lemeshow χ^2		5.987		6.715		2.550	
Hosmer-Lemeshow *p*-value		0.649		0.568		0.959	
χ^2 test accounting variables = 0						26.682	<0.0001

Notes:
Logistic regression estimates (and *p*-values of Wald tests) for Internet IPO firms over the period March 1992 through February 2000. The dependent variable is an indicator equal to one if the firm failed within 5 years of its IPO. The other variables are defined in the Appendix. The Log likelihood value, Nagelkerke R^2 and Hosmer-Lemeshow statistic are goodness of fit measures. The chi-squared test for the full model tests the linear hypothesis that all of the coefficients on the accounting variables are zero.

Internet firms for which the extended set of variables is available.[29] The first column presents a strictly accounting-based model. In the absence of other information, five out of the six accounting variables are significant at the 10% level using two-sided tests. The pseudo-R^2 is almost 17%, suggesting that the group of accounting variables together have considerable power for explaining realized Internet IPO failures. Further,

29 We are unable to obtain prospectus data for all of the Internet IPO firms. In univariate tests, we have verified that the subset of 281 observations for which we have data are not significantly different from the observations for which we do not have complete data. Furthermore, we have estimated a restricted regression model on all 356 observations and find that it is not significantly different from the same model estimated on the dataset of 281 observations.

the insignificant Hosmer-Lemeshow goodness-of-fit statistics suggests that there is no evidence of lack of model fit.

The negative coefficient on *logsales* suggests that large firms, or those that otherwise have more established customer and revenue bases at the time of going public, are less risky, as expected. The firms' pre-IPO *gross profit margin* percentage does not explain firm failure. Consistent with expectations, the negative coefficient on *log*RD suggests that firms that are spending more heavily on R&D activities in the year prior to going public are less risky. Since such funding for a young, start-up stage firm is typically advanced in stages as the firm meets various technological benchmarks, this result is consistent with the intuition that firms at more advanced stages in their technological development and that have received sizable pre-IPO capital, are less likely to fail. The level of Internet firms' spending on advertising, *logAdvertising*, provides an opposite indication as it is positively associated with failure risk. This result suggests that, on average, heavy pre-IPO advertising spending by Internet firms was a wasteful use of resources rather than a positive investment in intangible brands or profit-generating customer bases. Consistent with prior failure prediction studies, we find that *leverage* is positively related to Internet firms' likelihood of failure. The accounting system's balance sheet tally of the firm's accumulated net losses, *logAccumDeficits* (a negatively-valued variable), apparently captures an aspect of the firm's ongoing riskiness as it is also significant in the accounting-only logit model. Overall, in the absence of competing variables, accounting information offers significant explanatory power for *ex post* realized Internet IPO failures.

The second column of Table 2 presents the results of a regression containing only the non-accounting candidate variables. The overall explanatory power of the non-accounting model is over 24%, which is considerably higher than the accounting-only model. As shown, five out of eleven of the variables have significant coefficients, and all of the significant coefficients carry the predicted sign.

The third column of Table 2 presents the fully specified model. The pseudo-R^2 of this combined model is over 40%. Allowing for a one-sided test on the variables for which we have directional predictions, none of the accounting variables lose significance in the presence of the competing non-accounting variables, and the significance of many of the non-accounting variables is enhanced by the inclusion of accounting indicators of failure risk. The reported chi-square statistic for the fully-specified model strongly refutes the null hypothesis that all of the accounting variables are equal to zero ($p < 0.0001$). Taken together, these findings suggest that accounting and non-accounting information variables are complementary indicators of Internet firms' failure risk as of the IPO date.

Although poor firm performance is often preceded by earnings management maneuvers, our parsimonious model does not include any variables designed to proxy for such managerial earnings manipulations because there is likely to be very little accounting discretion available to the executives of the early stage start-up firms represented by our Internet IPO sample. Nevertheless, in untabulated analyses we also estimate the accounting-only and full-model regressions reported in Table 2 after including a variable to capture accounting accruals.[30] Not surprisingly, none of the

30 We define total accruals to be net income before extraordinary items (data18) minus cash flows from operations (data308). Collins and Hribar (2002) suggest that total accruals is likely to be the most appropriate

inferences regarding the coefficients on the variables reported in Table 2 are affected, and the accruals variable is far from significant in each case ($p > 0.52$).

Overall, the results presented in this section provide strong preliminary evidence that the accounting variables reported by our early-stage sample firms are highly informative in explaining the failure risk of IPOs in one of the most dramatic stock market bubble industries in modern history.

5. OUT-OF-SAMPLE FAILURE PREDICTION

The previous analyses suggest that as-reported accounting data are informative in explaining *historical* Internet IPO failures. In this section, we investigate whether accounting information, apart from being informative in explaining *ex post* failure risk, has predictive value for Internet IPO failures. Our tests here examine whether pseudo hedge strategies (based on the predictive power of accounting information) yield profitable results.

(i) Innovating Firm IPO Failure Prediction Models

We investigate whether accounting data can be used to learn from the history of prior innovative IPO firms' experience to predict the failure probabilities of Internet IPO firms. Our objective in this test is not to develop an 'optimal' failure prediction model for the Internet IPO firms, but rather to determine whether an established failure prediction methodology for high tech IPO firms (the DJ, 2007 model) is useful for predicting Internet failures.[31] The explanatory variables in the DJ model include underwriter prestige (CM_*rank*), *offer_price, leverage, log*RD, *logAccumDeficit* and *logSales*. The motivation for each of these variables, as well as the expected signs of their coefficients, are as previously explained in Section 4.

(a) Estimation of the Parsimonious Failure Model With Rolling Windows

We estimate the DJ failure prediction model on each of the respective high tech and NASDAQ samples using 10-year moving windows in order to ensure that our estimation process is updated, but not stale-dated, for each forecast year. For example, we estimate a logit failure prediction model using all high tech IPOs that went public between 1982 through 1991 in order to predict the likelihood of failure within five years for Internet firms undertaking IPOs in 1996. We also include in the estimation sample all IPO firms that went public after 1991 and that had failed by the end of 1995 since this information would be available to the market at the time of the Internet IPOs in 1996. In other words, we include all high tech IPOs that had survived for five years or that had

accruals measure for earnings management studies in various contexts (p. 110). Our definition of total accruals follows that of Collins and Hribar (2002), except that they use net income before extraordinary items and discontinued operations (data123) and cash flows from continuing operations (data308-data124). In IPO settings, extraordinary items and discontinued operations are practically never present in the year prior to the public offering, and hence our definition is operationally consistent with that of Collins and Hribar (2002). In the regression specification checks, we include the total accruals variable scaled by total assets.

31 Clearly, it is possible to further improve Internet IPO failure prediction by utilizing a more efficient and better specified model. To the extent that the DJ model is not optimal, our results will reflect a lower bound of the informativeness of accounting data.

failed by the end of 1995 in order to estimate a logit model to predict the failure of 1996 Internet IPOs. We then roll forward the estimation window by one year and re-estimate the failure model on all high tech IPOs that went public between 1983 through 1992 (or that had failed by the end of 1996) in order to predict the likelihood of failure for Internet firms undertaking IPOs in 1997, and so forth. We continue this procedure to arrive at a predicted probability of failure for each Internet IPO firm during the years 1996 through February 2000.

The resulting annual high tech IPO prediction model estimations are reported in the left columns of Table 3. We replicate this procedure using the NASDAQ IPO sample and report the annual prediction model estimations for this definition of innovative IPO firms in the right panel of Table 3.[32] The coefficient estimates within each sample panel are fairly consistent from year to year, as would be expected from the moving window estimation format. The coefficient estimates are also broadly consistent, in terms of sign and general magnitudes, across the two estimation samples. The Wald statistics reported in the lower half of Table 3 suggest that all of the coefficient estimates are significant at the 10% level or better (i.e., Wald > 2.71).

The forecasted probability of failure for each Internet firm is derived by fitting the relevant year's estimated IPO failure model coefficients as reported in Table 3 to the target Internet IPO. Thus, for each of the 344 Internet IPOs from 1996 through the end of February 2000 we generate an *ex ante* probability of failure based upon all available past innovative firms' IPO failure experience. We repeat this procedure for both prediction sample definitions of 'innovating' firms.[33]

(b) Contextual Failure Prediction Probabilities

As one might expect, most of the estimated failure probabilities as of the firms' IPO dates are small in absolute terms (otherwise it is unlikely that these firms would have survived the IPO process). For example, the average estimated failure likelihood for all of the Internet IPOs in our sample is just 8.7% (4.5%) using the NASDAQ (high-tech) failure prediction model. To place the small estimated failure probabilities into an appropriate context, we derive fitted probabilities of failure for each high tech (or, alternatively, NASDAQ) firm included in our estimation sample and we rank them. We then use the annual prediction models to generate an out-of-sample failure forecast for each Internet IPO firm. We include this forecasted probability of failure in the distribution of the fitted probabilities of the estimation sample and observe the rank or placement of the forecasted failure probability within the empirical distribution of failure estimates for the innovative firm samples. Firms included in the bottom (top) 33% probability of failure are considered to have low (high) estimated future likelihood of failure. We next examine our models' classification performance, and the returns

32 As a specification check, we have also included total accruals scaled by total assets as a candidate explanatory variable in the prediction model estimations, using IPO data beginning in 1988 when the necessary statement of cash flow data became available. Consistent with the results for the within-industry regressions reported in Table 2, this variable is never significant ($p > 0.41$).

33 We choose 1996 as the start of our out-of-sample prediction period for Internet IPOs because this is the year in which the Internet became publicly defined as a separate sector (e.g., the subsequently widely-cited ISDEX Internet stock index was initiated in 1996). From 1992 through 1995, only 12 Internet companies went public and hence our overall prediction and returns results are insensitive to the exclusion of this small number of early firms.

Table 3

Moving 10-Year Windows Logistic Regression Estimation Results: Predicting Failure within Five Years of IPO

	High-Tech IPO MODEL					*NASDAQ IPO MODEL*				
	1996	*1997*	*1998*	*1999*	*2000*	*1996*	*1997*	*1998*	*1999*	*2000*
					Coefficient Estimates					
Intercept	0.815	0.899	0.883	0.822	0.431	0.232	0.220	0.492	0.705	0.792
CM_*rank*	−0.298	−0.345	−0.352	−0.351	−0.308	−0.119	−0.143	−0.160	−0.134	−0.098
offer_price	−0.156	−0.118	−0.094	−0.097		−0.075	−0.078	−0.091	−0.109	−0.107
leverage	2.903	3.534	3.661	4.318	4.091	3.169	3.026	2.616	2.114	1.701
*log*RD	−0.956	−0.888	−1.144	−1.169	−0.483	−0.657	−0.626	−0.780	−0.693	−0.775
logAccumDeficit	−0.673	−0.501	−0.497	−0.464		−0.193	−0.152	−0.197	−0.225	−0.232
logSales	−0.652	−0.701	−0.652	−0.624	−0.826	−0.431	−0.395	−0.390	−0.389	−0.395
Failures within 5 yrs	58	69	82	90	96	268	287	311	361	425
Total obs.	512	610	683	781	879	1427	1642	1723	1924	2210
Nagelkerke R^2	0.521	0.533	0.520	0.548	0.461	0.367	0.350	0.363	0.362	0.349
					Wald Statistics					
Intercept	3.453	4.549	5.011	4.623	1.704	1.339	1.375	7.594	17.863	25.724
CM_*rank*	9.264	12.001	15.294	16.088	20.656	7.169	11.183	14.357	11.787	7.260
offer_price	7.263	5.357	4.052	3.979		19.977	20.641	20.235	29.159	32.844
leverage	5.151	9.789	12.394	16.914	22.833	36.274	38.467	31.352	23.477	18.619
*log*RD	2.825	2.974	6.499	8.468	3.497	10.840	11.225	18.046	18.853	32.187
logAccumDeficit	7.124	4.214	5.296	4.986		3.630	2.819	5.319	8.010	11.313
logSales	7.205	11.718	13.336	12.151	41.314	23.486	23.027	24.339	29.202	37.669

Notes:
Each column represents a logistic regression model that is estimated on a moving 10-year sample of firms with a known five year survival in the 10-year period before the IPO year indicated in the column header, or that had failed by the end of the year prior to the IPO year in the column heading. For example, for predicting the failure risk of 1998 IPOs, we use a 10-year moving estimation sample of IPO firms (high-tech and Nasdaq, respectively) that had survived for five years or that had failed by the end of 1997. All accounting variables are for the fiscal year immediately prior to the year of IPO. The logistic regressions only include variables with coefficients that are significantly different from zero and outliers have been removed when the deviance residual exceeds 2.5. The Wald statistic reported in the table has a chi-squared distribution with one degree of freedom. The high-tech model is based on a sample of high-tech firms with R&D/total assets or R&D/sales>0.05 and Internet firms. The Nasdaq model is based on Nasdaq IPO firms (excluding SIC 0 and 1 industries).

associated with the firms that our model identifies as having high and low failure risks, respectively.

(ii) Statistical Analysis and Benchmarking the IPO Failure Prediction Models

We begin by comparing the performance of our IPO failure prediction model with the Chava and Jarrow (2004) private company model (hereafter, 'Chava-Jarrow'). We focus on Chava-Jarrow because DJ find that this model performs best for high-tech IPOs.[34] Our formal comparison uses the Receiver Operating Characteristic ('ROC') curve methodology (Hosmer and Lemeshow, 2000) to assess the classification accuracy of all three models. The ROC curve provides information on the performance of a model for all possible cut-off values of Type I and Type II errors. The area under the ROC curve ranges between 0 and 1, where higher ROC values indicate that the underlying model has greater power to discriminate between failures and non-failures.[35]

The fitted ROC curves for each of the high-tech, Nasdaq, and Chava-Jarrow models are presented in Figure 3. The ROC curves associated with the Nasdaq and high-tech innovative IPO firm based models overlap most of the Type I/Type II error space, and the areas under the ROC curves are similar at about 68% and 70% for the high-tech and Nasdaq models, respectively. Both areas are consistent with a model of good discriminatory power. In contrast, the ROC curve associated with the Chava-Jarrow model falls below the other two ROC curves over the entire range of sensitivity and specificity values. The area value of 53% for the Chava-Jarrow ROC curve indicates that this model has almost no discriminatory power for identifying high versus low failure risk Internet IPOs (i.e., it is little better than chance). Based on this analysis, we conclude that the IPO firm failure prediction models provide strong statistical support for the notion that historical accounting information is informative in developing *ex ante* out-of-sample IPO failure risk assessments for bubble industry IPO firms.

(iii) Are Internet IPO Failure Predictions Associated with Abnormal Returns?

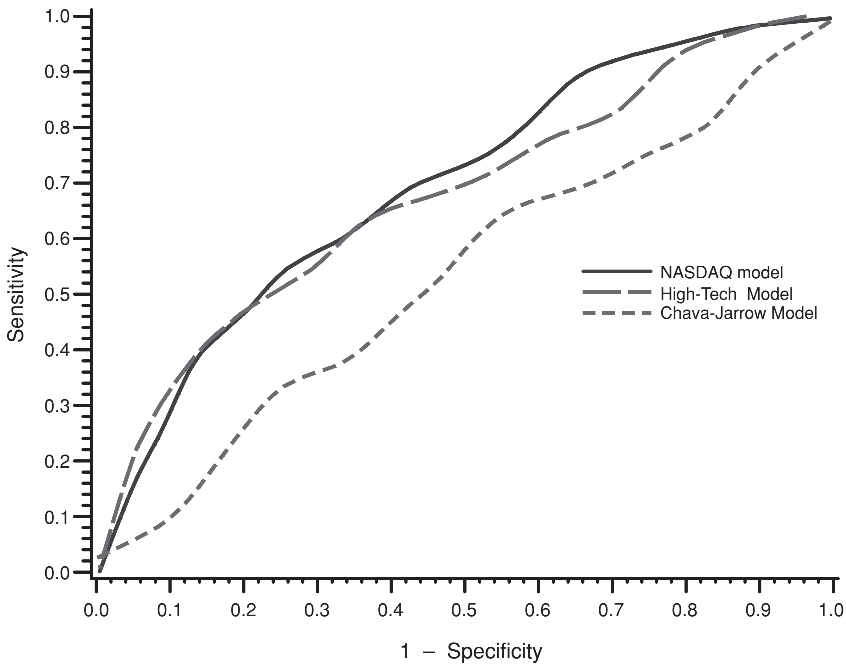
Having established the within sample risk-relevance of accounting information for explaining the *ex post* failures of bubble period IPOs, as well as the statistical validity of the out-of-sample predictive value of accounting variables for forecasting *ex ante* bubble period IPO failure risks, we next examine the returns consequences of failure predictions. Specifically, we investigate whether one can earn significant hedge returns from a strategy of going short (long) in Internet IPOs that our innovative IPO models predict to have high (low) failure risk.

34 We do not benchmark against the Shumway (2001) models because these models rely on market-derived variables (e.g., stock price momentum and volatility) as key inputs.

35 For a more detailed explanation of the ROC curve methodology and examples of its use in a failure prediction setting, please refer to Chava and Jarrow (2004) or Demers and Joos (2007).

Figure 3

Comparison of Predictive Performance of the Forecasting Models (ROC Curves) for the Internet Industry



Notes:
The Receiver Operating Characteristic (ROC) curve generalizes the Type I-Type II classification table analysis by providing information on the classification accuracy for all possible cut-off values. Sensitivity represents 1 – Type I, and specificity is 1-Type II. The figure shows the out-of-sample prediction accuracy for three different models. The Internet firms were not part of the estimation sample. The respective areas under the three curves are measured by the Concordance Index and represent the overall prediction accuracy of the failure model. A concordance index of 0.50 indicates no discrimination between failures and non-failures, whereas an index greater than 0.90 indicates an extremely high classification accuracy. The concordance indices are as follows for the Internet IPOs (period January 1996-February 2000):
1) High Tech IPO model 0.677
2) Nasdaq IPO model 0.696
3) Chava-Jarrow (2004) model 0.533

(a) Abnormal Returns Calculations

We accumulate returns starting from the first month subsequent to the month of IPO. Following Ang et al. (2007), we consider longer one-, two- and three-year return intervals in order to allow time for any anomalous post-IPO performance to be more fully revealed. For firms that delist prior to the end of the annual accumulation intervals, we complete the returns accumulation with the CRSP delisting return where available. For missing CRSP delisting returns, we set the delisting return to −0.55, consistent with the average missing delisting returns for Nasdaq stocks estimated by Shumway and Warther (1999). We then use Nasdaq-adjusted returns as our measure of 'abnormal' returns, which we calculate by subtracting the monthly return on the Nasdaq index from the firm-specific monthly return.

(b) Empirical Trading Strategy Results

Table 4 presents the raw and Nasdaq-adjusted one-, two and three-year buy-and-hold returns (BHARs) associated with Internet IPO firms that fall into the highest 33% and lowest 33% forecasted probabilities of failure, based upon forecasts derived from each of our high tech and NASDAQ IPO failure prediction models, respectively. Also shown for each model are the returns calculated using a zero-investment strategy of going long in low predicted probability of failure, and short in high predicted probability of failure, Internet IPOs. We refer to this zero-investment strategy as a pseudo-hedge strategy because traders may not be able to fully implement it in practice for the following 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 end of their first month of trading. Second, there may be some restrictions to short-selling smaller, newly issued firms (see e.g., Ritter and Welch, 2002; and Ofek and Richardson, 2003), although Edwards and Hanley (2007) suggest that these implementation constraints may not be as severe as the prior literature has presumed. Our methodology is otherwise implementable in the sense that no foresight is used either to forecast the probabilities of failure or to classify the IPOs into long and short investment portfolios.

In Panels A and B of Table 4 we calculate the statistical significance of the low-minus-high returns for the high tech and Nasdaq models, respectively, using a *t*-test for the difference in means from the two independent samples. As shown, the pseudo-hedge strategies based on either the high tech or NASDAQ definition of 'innovative' IPO firms yield statistically significant returns over the one-, two- and three-year post-IPO intervals, although the statistical significance of the abnormal returns declines somewhat over the longer intervals. The most notable observation from Table 4, however, is that the pseudo-hedge returns generated from our models are economically large. For example, the one-year abnormal returns available from the high tech model are 129%, while those for the same interval from the Nasdaq model are 79%. The economic magnitude of the abnormal returns declines over longer intervals, but remains impressive throughout the three-year post-IPO period examined. These findings are broadly consistent with Dichev (1998) and Campbell, Hilscher and Szilagyi (2008), who document (for large cross-sectional, non-IPO samples) that distress risk is not fully priced by the market. We note, however, that the pseudo-hedge returns generated by our failure models (using prior innovative IPO firm experience and applied to Internet bubble period IPOs) are significantly greater than those documented by these prior studies for the general cross-section of firms. Given the statistical reliability of our forecasting models and the extreme returns patterns in the Internet sector during the time period of our study (i.e., the very characteristic of the 'bubble' period that investors would like to profit from), our documentation of larger returns relative to prior cross-sectional results is perhaps not surprising. The combined economic and statistical significance of our returns enable us to strongly reject the null hypothesis that accounting data is uninformative in a bubble setting.

We acknowledge that there is a caveat associated with our use of Nasdaq-adjusted abnormal returns. Namely, Internet firms are likely to be riskier (i.e., in the sense of having larger *betas*) than non-Internet firms. Consequently, subtracting the Nasdaq returns from Internet stock returns may not be a sufficient adjustment for arriving at

Table 4

Buy-Hold Returns from Going Long (Short) in Forecasted Low (High) Failure Risk Portfolios of Internet IPOs: Jan 1996 to Feb 2000

		Raw Returns			*NASDAQ Adjusted Buy-Hold Abnormal Returns*			*Sharpe Ratio*		
Portfolio	*No. of Obs.*	*1 YR*	*2 YR*	*3 YR*	*1 YR*	*2 YR*	*3 YR*	*1 YR*	*2 YR*	*3 YR*
Panel A: High Tech IPO Model										
Low Failure Prob	66	147%	30%	3%	112%	41%	34%	0.854	0.153	−0.014
Medium Failure Prob	214	51%	−21%	−50%	26%	−10%	−22%	0.530	−0.280	−0.579
High Failure Prob	64	10%	−31%	−51%	−17%	−23%	−27%	0.082	−0.508	−0.797
Low Minus High Difference		137%	61%	54%	129%	64%	60%			
t-statistics of the Difference		(4.01)	(1.47)	(1.35)	(4.02)	(1.67)	(1.64)			
Panel B: Nasdaq IPO Model										
Low Failure Prob	176	89%	9%	2%	63%	19%	−27%	0.680	0.033	−0.247
Medium Failure Prob	135	31%	−37%	−27%	3%	−31%	−51%	0.368	−0.604	−0.716
High Failure Prob	33	11%	−41%	−35%	−17%	−35%	−62%	0.102	−0.714	−1.023
Low Minus High Difference		78%	50%	37%	79%	53%	35%			
t-statistics of the Difference		(3.14)	(1.98)	(1.96)	(3.52)	(2.15)	(1.66)			

Notes:
Mean holding returns and mean adjusted holding returns relative to the value-weighted NASDAQ benchmark over three horizons: 1, 2 and 3 years after the IPO date. We form portfolios of IPOs in the Internet industry for the period January 1996 through February 2000 (344 IPOs) based on the predicted failure probability at the IPO date. We classify as 'low,' 'medium' and 'high' failure risk those Internet firms with failure probabilities that fall into the lower, middle and upper third, respectively, of the probability distribution of each of the high-tech and Nasdaq estimation samples. Portfolio sizes are not necessarily equal. Low minus high represents the average difference between the low and high failure probability portfolio. The t-statistics for the difference in average returns are reported in parentheses. The Sharpe ratio is defined as the ratio of excess expected return (relative to the risk-free rate) to the standard deviation of the portfolio return, calculated on a monthly basis.

abnormal returns. In order to address this concern, we alternatively estimate abnormal returns using the Fama-French three-factor model. Although Lyon et al. (1999) argue that estimating abnormal returns using the Fama-French three-factor model would be inappropriate in our setting due to the severe time-clustering of our data, we nevertheless adopt this approach for an additional specification check. Untabulated analyses using the Fama-French three-factor approach generate significant abnormal hedge returns to a strategy of going long in the one-third of stocks that our model suggests to have low failure risk, and short in the one-third of stocks that our model suggests to have high failure risk. This hedge strategy is significant for both the high-tech and Nasdaq prediction model samples.

As a final specification check on our event time analyses, we also compute the Sharpe (1994) ratios associated with the three failure risk level portfolios generated from each of the high-tech and Nasdaq prediction models. These Sharpe ratios are presented in the right-hand columns of Table 4. Lending further corroboration to the two previous tests, the rank ordering of the Sharpe ratios is consistent with the notion of our high (low) IPO failure risk portfolios yielding lower (higher) risk-adjusted returns. Similar to the previous tests, the Sharpe ratios are also subject to some limitations. In particular, Sharpe ratios are sensitive to bear versus bull market conditions (Scholz and Wilkens, 2006), a problem that is likely to be heightened in our setting given that our returns accumulation periods extend over both euphoric and 'crash' conditions.

Although each of the returns tests described above is subject to different limitations, the triangulated findings provided by consistent results across all three tests supports the robustness of our inferences.

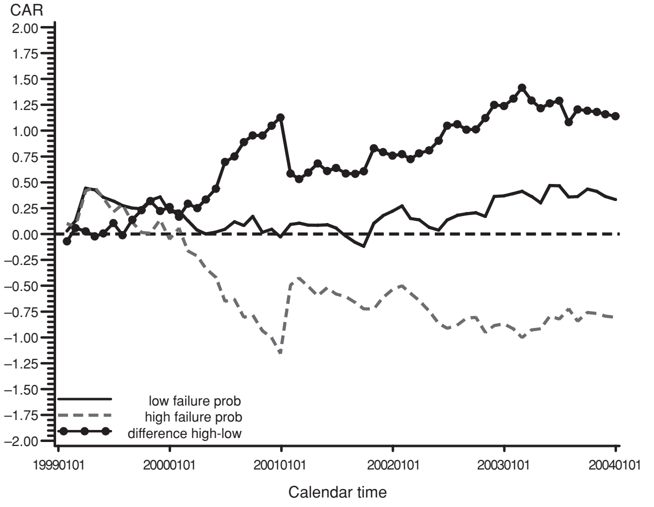
(c) Calendar Time IPO Returns

To further supplement the event time analyses, we present a more descriptive calendar time analysis following the methodology of Brav et al. (2000). For each firm in the sample, we estimate a time-series regression of returns on the three Fama French factors (MKTRF, SMB, HLM) purged of recent IPOs. We compute the abnormal returns for each firm in each month as the sum of the intercept and the residual in that month. Using individual abnormal returns we compute cumulative average monthly returns for a group of low (high) failure probability IPOs. Similar to the event time analyses, we assign Internet firms to either high or low risk portfolios based upon whether their predicted failure risk falls into the top or bottom third of the distribution of all fitted failure probabilities. We then compute and plot the monthly equally weighted averages of these individual firms' abnormal returns within each portfolio and cumulate these over time.

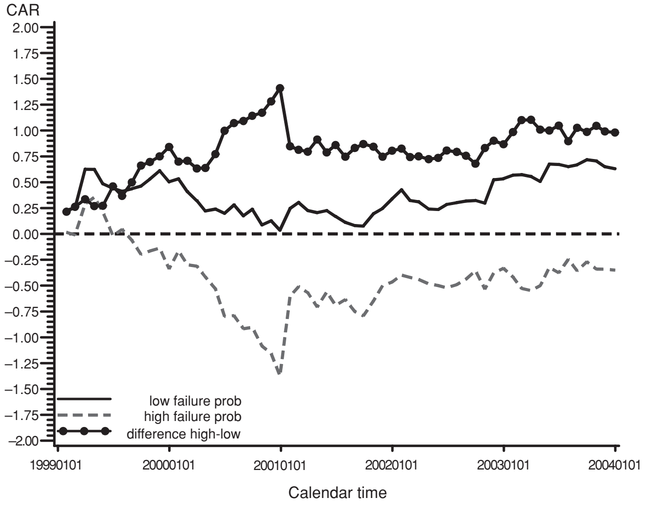
Figure 4 (Panel A and Panel B) presents the cumulative abnormal returns for both high and low failure risk groups generated using the high tech and NASDAQ failure prediction models, respectively. As shown in the calendar time plot, each of the innovative firm prediction models provides a meaningful separation between low and high risk failure firms; the abnormal returns to low and high failure risk firms diverge significantly from one another and straddle the zero baseline in the appropriate direction. Notably, the low risk Internet firms' abnormal returns are almost always greater than zero, suggesting that our prediction models could even be useful for

Figure 4

Panel A: Calendar Time Plot of Abnormal Returns Earned in the Forecasted Low and High Failure Probability Portfolios (High–Tech Failure Model)



Panel B: Calendar Time Plot of Abnormal Returns Earned in the Forecasted Low and High Failure Probability Portfolios (NASDAQ Failure Model)



Notes:
Calendar-time cumulative abnormal returns are computed in a manner similar to those in Figure 3 of Brav et al. (2000). For each firm in the sample, we estimate a time-series regression of returns on the three Fama French factors (MKTRF, SMB, HLM) purged of recent IPOs. We compute the abnormal returns for each firm in each month as the sum of the intercept and the residual in that month. Using individual abnormal returns we compute cumulative average monthly returns for a group of low (high) failure probability IPOs. Failure probability is determined at IPO date using the high tech (Panel A) and Nasdaq (Panel B) prediction models, respectively, and a firm falls within the low (high) failure probability group if its failure probability ranks among the lower (upper) third of the relevant estimation sample's failure probability distribution for the year before the IPO date.

trading strategies that do not involve a short side. Overall, these results are consistent with the event time analyses; there is long-term under-performance in the high failure risk groups and long-term over-performance in the low failure risk groups using either of the accounting-based ‘innovating firm’ prediction models to generate Internet IPO failure forecasts.

6. SUMMARY AND CONCLUSION

There has been widespread criticism that accounting does not provide useful information to assist in the efficient allocation of capital in dynamic, rapidly-evolving settings such as the Internet sector. Worse, ‘bad accounting’ is alleged to have contributed to the gross excesses that culminated in the bursting of the Internet and high tech stock market bubbles. These criticisms are directed at the very heart of accounting’s role in society because one of the primary goals of the financial accounting system is to provide reliable information to facilitate the efficient allocation of capital *irrespective of the period and setting in which the financial accounting rules are applied*.

We find that Internet IPO firms exhibited weak accounting fundamentals at the time they went public. These accounting fundamentals offer significant explanatory power in describing *ex post* Internet IPO failures. Such descriptive findings suggest that investors may have ignored, or at least heavily discounted, financial accounting information that is relevant for risk assessment. We find that investors could have used historical information about other innovative IPO firms to assist in their discrimination of Internet stocks. Using an existing IPO failure prediction methodology, we estimate Internet IPO failure forecasts using prior innovative IPO firms’ experiences. We document, for two definitions of ‘innovation,’ that predominantly accounting-based models provide strong discriminatory ability in predicting Internet failures. Further, we find that a pseudo-hedge strategy of going short (long) in Internet IPOs having high (low) failure risk yields economically and statistically significant returns over one-, two- and three-year intervals.

Our findings are consistent with the view that investors significantly underestimated the early warning signals provided by the financial accounting system during the euphoric rise of the Internet industry. Contrary to criticisms of accounting during this time period and setting, our results show that financial accounting information could serve as an anchor during such bubble periods.

Finally, there seems to be a tantalizing parallel between the Internet crash and the recent financial crisis concerning the role of accounting information. Just as many market observers blamed bad and outdated accounting information for the formation of the Internet bubble, many professionals similarly now allege that ‘fair value’ accounting contributed to the recent financial and credit crisis. Our study shows that the accounting information system provided early warning signals about the failure risks of Internet IPOs, but the market largely ignored these red flags. A fruitful avenue of future research would therefore be to revisit the question of the value-relevance of fair values to financial institutions, and to investigate the extent to which fair value accounting helped to reflect the underlying risks in the balance sheets of the banks and financial institutions that subsequently failed.

APPENDIX

Variable Definitions[36]

Variable	*Definition*
Big6-national auditor	Indicator variable equal to 1 if the firm has a big 6 or national auditor, 0 otherwise.
Buy-hold abnormal return	Raw return minus the NASDAQ index holding return over the same horizon.
Carter-Manaster rank	Underwriter reputation ranking developed in Carter and Manaster (1990).
Failure within 5 years	Indicator variable equal to 1 if the firm failed within 5 years after IPO, 0 otherwise.
Firm age at IPO	Number of years since incorporation (measured on the IPO date).
Gross profit margin	Total revenue (Data 12) minus cost of goods sold (Data 41), scaled by total revenue and expressed as a percentage.
Hot issue market	Average first day initial returns 90 days prior to a particular IPO.
Insider ownership	Combined ownership percentage of directors and executives after IPO.
IPO-*day initial return*	Closing price on the IPO date less offer price, scaled by the offer price (expressed as a percentage).
IPO *proceeds*	Proceeds from IPO (in December 2004, millions of dollars).
IPO *vintage*	Natural log of 1 plus number of months between March 1992 (IPO month of AOL) and the IPO month of the firm.
Leverage	Total liabilities (Data 6 – Data 216 – Data 38) divided by the sum of total assets (Data 6) plus IPO proceeds.
Lockup days	Number of days in the IPO lockup period.
Log accumulated deficits	Natural log of non-zero accumulated deficits (Data 36), 0 otherwise.
*Log*RD	Natural log of 1 plus R&D expense in 2004 dollars (Data 46 – Data 388).
*Log*SGA	Natural log of 1 plus selling, general & administrative expenses (Data 189) in Dec 2004 dollars.
Market value at IPO	Stock market capitalization at the close of trading on the IPO date (in December 2004, millions of dollars).
Negative income indicator	Indicator variable equal to 1 if the firm has negative income before extraordinary items (Data 18), 0 otherwise.
Offer price	IPO offer price (in Dec 2004 dollars).
Raw return (1, 2, 3 years)	Cumulative holding period return until the earlier of the cumulation horizon (1 or 2 or 3 years) or delisting.
Sales	Total revenue (Data 12) in December 2004 dollars.
SG&A	Selling, general & administrative expenses (Data 189) in Dec 2004 dollars.
Strategic investor	Indicator variable equal to 1 if the firm has a significant strategic investor; i.e., another firm in the same industry is mentioned as significant owner in the prospectus.
Venture-backed firm	Indicator variable equal to 1 if the firm is VC funded, 0 otherwise.

36 Data numbers mentioned in the Appendix refer to data items included in the Compustat annual tape.

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