JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 45, No. 5, Oct. 2010, pp. 1253–1278

doi:10.1017/S0022109010000487

What Drove the Increase in Idiosyncratic Volatility during the Internet Boom?

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Abstract

Aggregate idiosyncratic volatility spiked nearly fivefold during the Internet boom of the late 1990s, dwarfing in magnitude a moderately increasing trend. While some researchers argue that this rise in idiosyncratic risk was the result of changes in the characteristics of public firms, others argue that it was driven by the changing sentiment of irrational traders. We present evidence that the marketwide decline in maturity of the typical public firm can explain most of the increase in firm-specific risk during the Internet boom. Controlling for firm maturity, we find no evidence that investor sentiment drives idiosyncratic risk throughout the Internet boom.

I. Introduction

The volatility of the average public firm has fluctuated significantly over the past 40 years. While market volatility has not changed substantially, firm-specific risk has increased. For example, recent studies by Campbell, Lettau, Malkiel, and Xu (CLMX) (2001), Xu and Malkiel (2003), Fama and French (2004), Wei and Zhang (2006), and Jin and Myers (2006) document that, over a 4-decade period from the early 1960s to the end of the 1990s, U.S. public firms exhibit increasing firm-specific return volatility, more volatile income and earnings, lower profitability, and lower survival rates. The recurring theme in these studies is that firm-specific risk, however defined, has been increasing.

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To explain this phenomenon, recent studies argue that the increasing trend in idiosyncratic risk is driven by changes in firm characteristics. For example, Brown and Kapadia (2007) show an increasing trend in new listings by riskier companies, while Cao, Simin, and Zhao (2008) find that there is no long-term trend in idiosyncratic risk after controlling for growth options.

However, as we show in this paper, the modest positive trend in firm-specific volatility documented by CLMX (2001) is a second-order phenomenon compared to the large spike in idiosyncratic risk during the late 1990s. Since previous studies focus only on explaining the modest linear trend in volatility, it is unclear whether systematic changes in the fundamentals of public firms can explain one of the largest increases in idiosyncratic volatility in U.S. history.

This is important because there is considerable debate on what drives idiosyncratic volatility during the Internet boom of the late 1990s. On the one hand, Pastor and Veronesi (2006) suggest a rational response to an increase in uncertainty about future profitability. On the other hand, Brandt, Brav, Graham, and Kumar (2010) argue that this spike in idiosyncratic risk was driven by irrational "noise" traders and show that volatility during the Internet boom is positively correlated with the trading of retail investors.

In this paper, we show that the spike in firm-specific risk in the late 1990s can be explained by the interaction of 2 reinforcing factors: a dramatic increase in the number of new listings, and a simultaneous decline in the age of the firm at initial public offering (IPO). As a result, the proportion of equity market capitalization represented by young firms increases for 3 decades, reaching a peak in the late 1990s. Since young firms have expected cash flows that are further in the future, having more of these firms in the sample can lead to a significant change in aggregate measures of idiosyncratic risk.

Consistent with this hypothesis, we find that the proportion of young firms in the market explains most of the spike in volatility during the late 1990s. Moreover, we find that, conditional on measures of firm maturity (e.g., size, profitability, asset tangibility), there is little evidence of any abnormal spike in idiosyncratic volatility even during the Internet boom of the late 1990s.

Of course, the decision to go public is not exogenous. If young, high idiosyncratic risk firms are more likely to issue public equity when waves of investor sentiment (SENT) are high, then we cannot say to what extent the correlation between age and risk is either rational or behavioral. Simply put, firm age and SENT may be endogenously determined. To address this issue, we incorporate several proxies for SENT, following Baker and Wurgler (2006). Indeed, we do find evidence that SENT is unconditionally correlated with idiosyncratic volatility. However, the explanatory power of firm age overwhelms SENT. In regression specifications that include both firm age and investor sentiment, SENT is either not significant or is negatively related to idiosyncratic risk. In short, we find little support for the behavioral sentiment interpretation of the firm age results.

To the extent that the age of a firm is a proxy for uncertainty regarding future growth rates, these results support Pastor and Veronesi's (2003) argument that volatility declines as investors rationally learn more about the profitability of the firms. Further, our results support the intuition in Pastor and Veronesi (2006) in that much of the rise in idiosyncratic risk throughout the late 1990s can be explained by fundamentals.

Our interpretation contrasts with that of Brandt et al. (2010), who argue that the Internet boom spike in idiosyncratic risk is driven by noise traders. As we show, there is little evidence of any abnormal spike in idiosyncratic risk during the Internet boom after conditioning on age and other measures of firm maturity. However, this does not necessarily contradict the evidence in Brandt et al. Since trading behavior is unlikely to have a causal effect on firm maturity (in fact, trading volume is included in our sentiment index), one could argue that the evidence in Brandt et al. reflects an increase in the dispersion of beliefs among investors as they learn about profitability.

The paper proceeds as follows. Section II describes the sample and methods. Section III examines the time-series behavior of idiosyncratic risk, while Section IV looks at the time series of firm characteristics and SENT. Section V tests the effect of firm age and sentiment on idiosyncratic risk. In Section VI we perform several robustness checks, while Section VII concludes.

II. Sample, Data, and Methodology

A. Sample Description

This study draws on data from a variety of sources. First, we follow CLMX (2001) in constructing measures of firm-specific risk from the Center for Research in Security Prices (CRSP) daily and monthly returns files. Methods, data filters, and summary statistics for idiosyncratic risk are detailed in Section II.B.

Another central variable for the analysis is the age of the firm. To construct this variable, we use data collected by Jovanovic and Rousseau (2001) on the date of first incorporation and/or original founding for a large sample of firms between 1926 and 1997. In addition, we use founding dates for IPOs from Loughran and Ritter (2004).[1] Further, we supplement this database using incorporation and founding dates collected from various issues of *Mergent Manuals*, published by Moody's Investors Service. We use the earliest available date of the founding date or incorporation date to determine the age of the firm. If these data are unavailable, we consider the age of the firm as a missing value.

In our final sample, we have detailed age at IPO data on 13,366 public firms with 7,142 founding dates and 11,720 incorporation dates over our entire sample period from 1926 to 2006. In all years, the sample of firms for which we have age data represents over 94% of the total market capitalization of all New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ firms. The majority of firms that have missing incorporation date are small over-the-counter (OTC) issues.

It is important to note that this methodology differs from the common alternative of using the firm's earliest occurrence on CRSP. Using the first CRSP

[1]These data were collected from a variety of sources. See Jovanovic and Rousseau (2001) and Loughran and Ritter (2004) for a detailed description of their data collection methods.

appearance can induce a significant bias in proxies for firm age because the age of the typical firm at its IPO date has fallen dramatically over the last 40 years. Ignoring this trend underestimates the age of older firms later in the sample. The bias is particularly severe with the inclusion of NASDAQ firms in the CRSP database in the early 1970s (many of which existed for many years but traded on pink sheets).

Finally, we collect firm-specific information (market-to-book (MKBK) ratio, total assets, etc.) from Compustat. The final sample consists of all firms for which we have age at IPO data and that merge with the CRSP and Compustat databases. Given that the sample period covers a long period of time, summary statistics are not generally informative, but our sample of firms represents the lion's share of the market, and most of the firm-specific data that we collect are representative of the population with similar means, medians, standard deviations, etc.

B. Construction of Firm-Level Volatility

There are a number of ways to construct a measure of idiosyncratic risk. Of course, one may construct estimates directly by adjusting total risk for the variation in nondiversifiable risk factors identified from a specific asset pricing model (e.g., the capital asset pricing model (CAPM)). The drawback lies in selecting an asset pricing model that all readers would agree on. Instead, we follow CLMX (2001), who propose an indirect method of constructing aggregate firm-specific risk. Intuitively, this measure estimates the idiosyncratic risk of a "typical" firm by averaging deviations from market returns over firms within an industry and then averaging the measure over industries. This approach is attractive because it avoids having to calculate a large number of betas and covariances. Since we are focusing on the time-series properties of large portfolios of firms, it is unlikely that methodological differences will affect our main results. For example, we note that Bali, Cakici, Yan, and Zhang (2005) and Malkiel and Xu (2002) employ different methods and find essentially the same time-series patterns as in CLMX. In the Appendix we provide a brief review of the methodology.

Figure 1 presents the estimates of annual and monthly idiosyncratic volatility, FIRM_t, for 1926–2006. The annual (monthly) series is idiosyncratic volatility estimated from the CRSP monthly (daily) returns file. Three casual inferences are apparent. First, idiosyncratic volatility exhibits a negative trend in the 1930s and 1940s after experiencing a spike around the Great Depression of the early 1930s. Second, consistent with the evidence in CLMX (2001), there appears to be a modest positive trend in idiosyncratic volatility beginning in the early 1950s. Finally, there is a remarkable jump in firm-level volatility during the Internet boom in the late 1990s, followed by a return to more typical idiosyncratic volatility levels. Indeed, while idiosyncratic risk averages 0.05 over the entire sample, it is nearly 5 times higher at the peak of the Internet boom. After 2001 idiosyncratic risk experiences a sharp decline to a level of just under 0.04 at the end of 2006.

III. The Time-Series Behavior of Idiosyncratic Risk

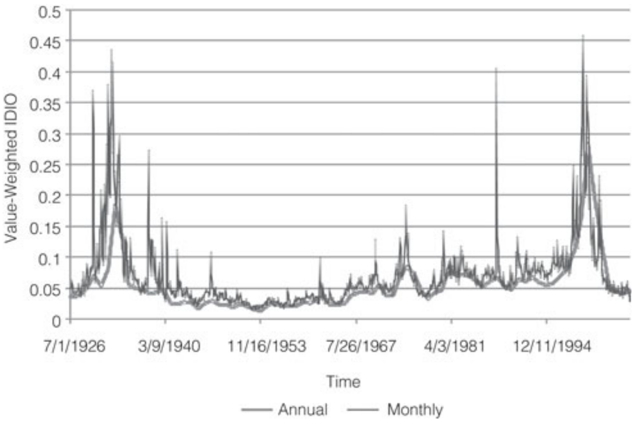
In this section we present a more formal analysis of the transition dynamics in idiosyncratic risk over the sample period. Motivation for this analysis

FIGURE 1

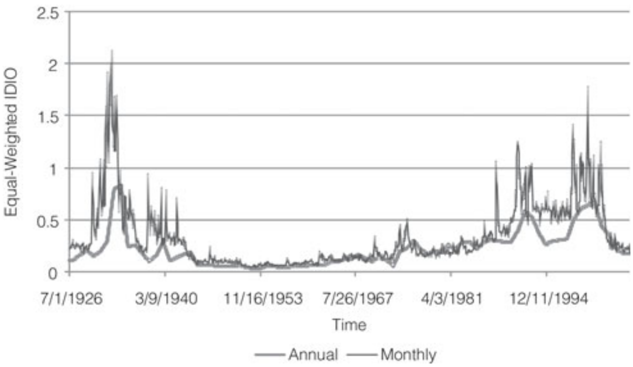
Firm-Level Volatility

Figure 1 depicts the time-series behavior of idiosyncratic volatility over the period 1926–2006 for value- and equal-weighted portfolios. The annual series is idiosyncratic volatility estimated annually from the CRSP monthly return file. The monthly series is annualized idiosyncratic volatility estimated monthly from the CRSP daily return file.

Graph A. Value-Weighted Idiosyncratic Volatility



Graph B. Equal-Weighted Idiosyncratic Volatility



is twofold. First, we confirm the findings of previous studies in our sample. Second, these results are the benchmark we use in subsequent sections to evaluate the effect of firm maturity on idiosyncratic volatility.

We begin by estimating simple linear trend models as in previous studies and then build a regime-switching model to incorporate the periodic episodes of high idiosyncratic risk. Finally, we allow for a more general model that incorporates both trending behavior and periodic high idiosyncratic regimes.

A. Linear Trend Models

We use both the monthly and annual series for 4 different sample periods to estimate the following specification:

$$\text{FIRM}_t \quad = \quad \alpha + \gamma t + \varepsilon_t. \tag{1}$$

The 4 sample periods are the full sample (1926–2006), a postwar sample (1945–2006), a recent sample (1965–2006), and finally the CLMX (2001) sample (1963–1998). Motivation for using different sample periods is straightforward. Casual inspection of Figure 1 shows that, to the extent idiosyncratic risk experienced a multidecade rise, it did so beginning roughly in the post-WWII period, so we examine 1945–2006. We include the recent sample period (1965–2006) separately because this is the time period for which we have sentiment data at the monthly level. Finally, we include the CLMX period for completeness.[2] Our analysis is also performed separately for the value- and equal-weighted series.

Table 1 reports the results from our estimation of equation (1) for the various time series. The results are consistent with past studies. While there is little evidence of a positive trend in idiosyncratic volatility over the period 1926–2006, there is evidence that idiosyncratic volatility has been increasing since the end of World War II. For example, the coefficient of the linear trend is positive and significantly different from 0 over the period 1946–2006 for both the value- and equal-weighted series. As expected, we also find an increasing trend for the recent sample period (post-1965) and the CLMX (2001) period.[3]

Overall, the results in Table 1 are consistent with past studies and indicate a positive trend in firm risk over the latter half of the 20th century. However, our analysis also points to some interesting transition dynamics. Casual interpretation of the data suggests that the time series of firm risk does not exhibit a constant linear trend over the 20th century, but there is a positive trend roughly between 1950 and 2000. Further, while there have been several large increases in idiosyncratic volatility, a primary feature of the data is a spike that starts in the early- to mid-1990s, peaks in 2000, and falls sharply thereafter, which coincides with the Internet boom (and bust) of the late 1990s.

B. Regime-Shifting Model of Idiosyncratic Risk

The periodic differences documented above suggest that a more flexible model of the data may be useful in describing the variation in idiosyncratic risk. Regime-switching models are particularly well designed to capture discrete changes in the economic forces that generate the data (e.g., wars, depressions, bubbles). In this section we use a simple regime-switching model to describe the behavior of idiosyncratic risk.

We estimate a 2-state regime-shifting model where FIRM_t is assumed to be conditionally normal. That is, the mean and variance for FIRM_t depend on the regime state, $S_{it} = i$, for $i = 1, 2$. S_t evolves according to a 1st-order Markov

[2]The postwar period is reported in Table 1 annually and the recent period monthly to conform with the SENT data that we examine in Section IV. The same rationale drives the reported frequencies in Table 3.

[3]In all of our tests, our statistical inference is based on Newey-West (1987) standard errors. In unreported tests, we also confirm the basic statistical features of the data using standard errors based on Vogelsang (1998) trend tests.

TABLE 1

Linear Trend Regressions for Various Subperiods

Table 1 reports linear trend regressions examining the behavior of average idiosyncratic risk for value- and equal-weighted portfolios. Average idiosyncratic firm variance (FIRM) is estimated from the CRSP monthly and daily return files for the annual and monthly series, respectively. Ordinary least squares (OLS) regression estimates are presented for the following linear trend model:

$$\text{FIRM}_t = \alpha + \gamma t + \varepsilon_t.$$

Here t-statistics (reported below coefficient estimates) are based on Newey-West (1987) standard errors.

Sample	Constant ($\hat{\alpha}$)	Trend × 10^3 ($\hat{\gamma}$)	N	Adjusted R^2
Panel A. Value-Weighted FIRM				
Full sample: Annual (1926–2006)	0.029	0.635	81	0.10
	[1.62]	[1.43]		
Postwar: Annual (1945–2006)	–0.019	1.51	61	0.36
	[–1.01]	[2.94]		
Full sample: Monthly (1926–2006)	0.061	0.018	948	0.01
	[4.04]	[0.66]		
Recent: Monthly (1965–2006)	0.003	0.107	492	0.09
	[0.08]	[2.02]		
CLMX sample: Monthly (1963–1998)	–0.005	0.112	432	0.22
	[–0.41]	[5.84]		
Panel B. Equal-Weighted FIRM				
Full sample: Annual (1926–2006)	0.107	2.856	81	0.12
	[1.26]	[1.65]		
Postwar: Annual (1945–2006)	–0.156	7.543	61	0.64
	[–2.76]	[5.19]		
Full sample: Monthly (1926–2006)	0.242	0.257	948	0.05
	[2.69]	[1.68]		
Recent: Monthly (1965–2006)	–0.424	1.21	492	0.33
	[–2.46]	[4.41]		
CLMX sample: Monthly (1963–1998)	–0.699	1.674	432	0.59
	[–6.43]	[9.23]		

process as in $S_{t+1} = \Pi S_t$ with transition probability matrix

$$\Pi = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}. \tag{2}$$

In this model, the parameters of the transition matrix determine the probability of continuation in the regime. That is, $p = \Pr(S_{t+1} = 1 | S_t = 1)$ and $q = \Pr(S_{t+1} = 2 | S_t = 2)$. We can describe the conditional distribution of FIRM_t as

$$\text{FIRM}_t | S_t \sim \left\{ \begin{array}{ll} N(\mu_1, \sigma_1), & \text{if } S_t = 1 \\ N(\mu_2, \sigma_2), & \text{if } S_t = 2 \end{array} \right\}. \tag{3}$$

With the conditional distribution and transition matrix specified, estimation of the parameters $(p, q, \mu_1, \mu_2, \sigma_1, \sigma_2)$ is straightforward via maximum likelihood.

Table 2 presents the results of the estimation. The high-idiosyncratic-risk regime (Regime 1) has a mean roughly 4 times larger than the low-idiosyncratic-risk regime (0.164 vs. 0.046) and a substantially higher variance. As expected, there is a high degree of persistence in the regime, with both transition probabilities above 0.96 (i.e., the regimes are generally long-lived).

The regime-switching model identifies 3 sustained periods of high idiosyncratic risk surrounding the Great Depression (August 1929–December 1934),

TABLE 2

A Regime-Shifting Model of Idiosyncratic Risk (1926–2006)

Table 2 reports results from a 2-state regime-switching model for idiosyncratic risk. Idiosyncratic risk (FIRM_t) is constructed as average idiosyncratic firm variance estimated monthly from the CRSP daily return file. The sample period is 1926–2006. Idiosyncratic risk is modeled as conditionally normal with means and variances that depend on the regime state $S_{it} = i$, for i = 1, 2, where S_{it} evolves according to a 1st-order Markov process as in $S_{t+1} = \Pi S_t$ with transition probability matrix

$$\Pi = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}.$$

Here p and q are transition probabilities, where $p = \Pr(S_{t+1} = 1 | S_t = 1)$ and $q = \Pr(S_{t+1} = 2 | S_t = 2)$. Based on these assumptions, the conditional distribution of FIRM_t is defined as

$$\text{FIRM}_t | S_{t-1} \text{ distributed as } \left\{ \begin{array}{ll} N(\mu_1, \sigma_1), & \text{if } S_t = 1 \\ N(\mu_2, \sigma_2), & \text{if } S_t = 2 \end{array} \right\}.$$

Estimation of the parameters$(p, q, \mu_1, \mu_2, \sigma_1, \sigma_2)$ is performed via maximum likelihood.

Parameter	Estimate	Standard Error
Panel A. Regime 1		
Transition probability (p)	0.965	0.0240
Mean (μ_1)	0.164	0.0086
Std. dev. (σ_1)	0.082	0.0048
Panel B. Regime 2		
Transition probability (q)	0.996	0.0035
Mean (μ_2)	0.046	0.0007
Std. dev. (σ_2)	0.018	0.0006

the oil crisis (November 1973–March 1975), and the Internet boom (October 1995–October 2002). Other short-lived regimes also arise in the late 1930s and the October 1987 stock market crash. Overall, the evidence points to periodic episodes of high idiosyncratic risk generally associated with significant economic events.

C. A General Model of Idiosyncratic Risk

Having identified periodic episodes of high idiosyncratic risk in the regime-switching model, we now move back to a linear regression framework and augment the linear trend regression of Section III.A to reflect the periodic episodes of high idiosyncratic risk identified in the regime-switching model. Our model is

$$\text{(4)} \qquad \begin{aligned} \text{FIRM}_t &= \alpha + \gamma t + \beta_1 \text{GREAT\_CRASH} + \beta_2 \text{OIL} \\ &\quad + \beta_3 \text{OCT\_1987} + \beta_4 \text{BOOM} + \varepsilon_t. \end{aligned}$$

We regress FIRM_t on a linear time trend along with a set of dummy variables that capture some of the large structural breaks in the series. Based on the results from the regime-shifting model, we include dummy variables for the Great Depression (GREAT_CRASH), the oil shock of the early 1970s (OIL), the market crash of 1987 (OCT_1987), and the Internet boom (BOOM). This approach allows a clean estimate of the magnitude of the jump in firm-specific risk in the late 1990s. Idiosyncratic volatility experienced large spikes during these periods of economic uncertainty and structural changes. Our primary goal is to gauge the behavior of idiosyncratic volatility during the Internet boom, and this regression allows us to examine this period directly.

Table 3 presents the results of our analysis. As expected, the coefficients on the dummy variables indicate that idiosyncratic risk is high during the Great Depression, the oil shock, the market crash of 1987, and the Internet boom. The idiosyncratic risk spikes of the Great Depression and the Internet boom are noticeably greater than the other events.

TABLE 3

The Time-Series Behavior of Idiosyncratic Risk

Table 3 reports regressions examining the behavior of monthly and annual series of idiosyncratic risk for value- and equal-weighted portfolios. The dependent variable is the average idiosyncratic firm variance estimated either annually from the CRSP monthly return file or monthly from the CRSP daily return file. BOOM, a dummy variable for the Internet boom period, is equal to 1 if the observation occurs between 1997 and 2002 for the value-weighted series and between 1995 and 2002 for the equal-weighted series, and 0 otherwise. The OCT_1987 is an indicator variable equal to 1 if the observation occurs in 1987, and 0 otherwise. Here OIL takes a value of 1 during 1973–1975 and GREAT_CRASH takes a value of 1 during 1929–1933. The *t*-statistics (reported below coefficient estimates) are based on Newey-West (1987) standard errors.

	Annual Series				Monthly Series			
	Value-Weighted		Equal-Weighted		Value-Weighted		Equal-Weighted	
	1926–2006	1946–2006	1926–2006	1946–2006	1946–2006	1966–2006	1946–2006	1966–2006
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Linear trend $\times 10^3$	0.52	0.834	3.585	6.188	0.069	0.018	0.807	0.888
	[3.30]	[4.28]	[2.95]	[4.11]	[5.28]	[0.86]	[5.26]	[2.82]
BOOM	0.077	0.071	0.189	0.142	0.068	0.074	0.277	0.263
	[2.31]	[2.14]	[2.18]	[2.60]	[2.88]	[3.09]	[3.29]	[2.57]
OCT_1987	0.016	0.014	0.051	0.035	0.342	0.341	0.685	0.681
	[3.91]	[2.79]	[1.44]	[0.89]	[92.79]	[115.77]	[14.35]	[14.12]
OIL	0.032	0.034	0.042	0.059	0.057	0.048	0.126	0.135
	[9.42]	[10.36]	[1.45]	[2.34]	[7.50]	[5.98]	[3.28]	[3.76]
GREAT_CRASH	0.074		0.373					
	[4.30]		[3.10]					
Constant	0.019	0.003	0.028	–0.112	0.012	0.051	–0.187	–0.243
	[2.70]	[0.35]	[0.57]	[2.07]	[1.85]	[3.61]	[2.78]	[1.29]
Observations	81	61	81	61	732	492	732	492
R^2	0.54	0.59	0.47	0.7	0.54	0.44	0.6	0.43

To put these results in perspective, consider the economic magnitude of the increase in idiosyncratic risk during the Internet boom. The coefficient on the Internet dummy variable for the full-sample value-weighted series (column 1 of Table 3) suggests that idiosyncratic risk is more than twice as large during the Internet boom. For the equal-weighted series (column 3 of Table 3), the economic magnitude is similar.

Even conditional on the inclusion of dummy variables for the high-state regimes, there is still significant evidence of a trend. Indeed, over the complete 1926–2006 time period, both equal- and value-weighted series exhibit a positive, statistically significant trend. Neither series did so prior to the inclusion of the controls; the Great Depression appears to have masked the effect. Further, a strong positive trend exists in the postwar period. The lone exception to these positive trend findings is the value-weighted series from 1966–2006, where no discernible time trend remains.

IV. Time-Series Patterns in Firm Characteristics and Investor Sentiment

A. Time-Series Behavior of Firm Age

Table 1 documents a significant positive trend in unconditional idiosyncratic risk over the last 4 decades, and Table 3 shows a large rise in idiosyncratic risk during the Internet boom of the late 1990s. In this section, we examine 2 possible sources of these changes in firm-specific risk: firm characteristics and SENT.

To test whether the maturity of the typical public firm has changed over time, we construct a measure of the average age of a firm at the time of its IPO. Figure 2 provides a time series of the average and median age of the firm at IPO, where age at IPO is measured as the difference between the minimum of the founding or incorporation date and the listing date.

Graph A of Figure 2 shows that before the early 1950s, the average age of firms at IPO is volatile but roughly increasing over time. However, there is a significant and steady decline in the age of the average or median firm at IPO from approximately 40 years in the early 1960s to less than 5 years by 2000, consistent with Jovanovic and Rousseau (2001). This decline is followed by an increase to 12 years by 2006. The effect of this change is a decline in the vintage of IPOs after the early 1960s on a large scale, only recently reversed. Since this trend represents a secular shift in the sample of public firms, it could have a significant effect on aggregate estimates of firm risk for decades. Most notable, however, is the substantial effect that it may have in the latter part of the sample.

Graph B of Figure 2 presents the number of IPOs in our sample period between 1926 and 2006 for which we have incorporation or founding data. Consistent with previous studies, the data show a substantial increase in the number of IPOs over the sample period, from the early 1980s through about 2002.[4] Overall, there has been a positive trend in the number of firms raising public equity over this time period, with the number of firms going public each year being an order of magnitude larger by the end of the 1990s.[5]

To see the effect that these patterns in IPO behavior have had on the composition of public firms, Table 4 presents the distribution of firm age over time. This table shows that the proportion of firms less than 5 years old increases from 2.7% in 1965 to 12.8% in 2000 at the peak of the Internet boom. This proportion declines significantly to the 1960s levels after the demise of the Internet boom. Similar patterns are found for firms that are less than 10 or 20 years old. Table 4 also shows that the average (median) age of public firms has decreased from 53 (49) years old in 1965 to 31 (17) years old in 2000. Overall, this evidence

[4]Our data only represent a sample of all IPOs. In unreported results, we compare our sample to the data from Ritter (2001) on the total number of IPOs (with an offer price greater than $5). The time-series properties of our sample closely relate to Ritter's data, with a correlation larger than 0.90.

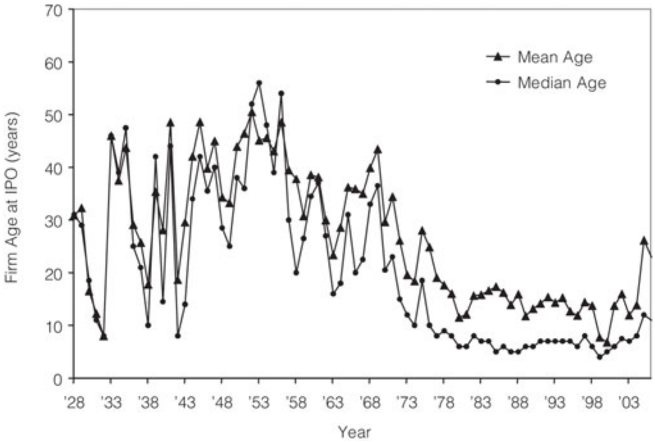
[5]These patterns are not simply an artifact of NASDAQ stocks. In unreported results, we verify that the increase in both the number of IPOs and the decrease in IPO vintage are not driven by a particular market segment or exchange type.

FIGURE 2

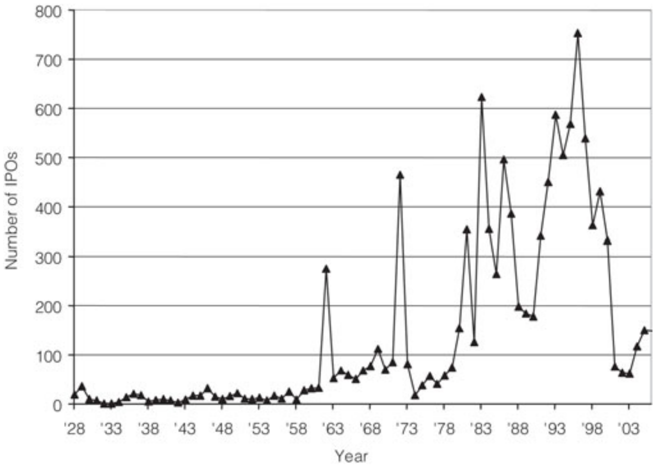
The Age of the Firm at IPO and IPO Activity

Figure 2 presents a time series of the average and median age of a firm at the time of its initial public offering (IPO) of equity. The age of the firms is constructed as the number of years between initial listing and the minimum of the founding date or the date of first incorporation. Equal-weighted cross-sectional means and annual medians are computed each year using all IPOs for which incorporation or founding data are available. The total number of IPOs used is also provided. The number of IPOs is constructed as the number of new listings on the NYSE, AMEX, and NASDAQ.

Graph A. Age of the Firm at IPO



Graph B. Number of IPOs



indicates that changes in IPO behavior have significantly changed the age of the average public firm, particularly in the late 1990s.

Because of its role in value-weighted measures, we also examine whether the market value of "young" firms has increased over time. To do this, we compute w_t^Y, the proportion of total market capitalization represented by "young" firms. Figure 3 presents a time series of the proportion of the total market capitalization comprised of young firms, where young is defined to be less than or equal to 20

TABLE 4

Distribution of Firm Age through Time

Table 4 presents the distribution of firm age over the period 1965–2006. The age of the firms is constructed as the number of years between initial listing and the minimum of the founding date or the date of first incorporation. Equal-weighted cross-sectional means and annual medians are computed each year using all IPOs for which incorporation or founding data are available. The total number of firms is also provided.

		Percentage of Firms Aged Less Than								
Year	*N*	5	10	20	50	Mean Age	Std. Dev.	5th Percentile	Median	95th Percentile
1965	1,393	2.7	8.5	18.7	52.4	53	33	7	49	115
1970	1,620	3.0	7.8	20.9	54.0	52	34	9	46	119
1975	2,976	4.6	17.7	34.0	64.2	43	34	6	37	106
1980	2,873	3.9	10.4	31.2	60.5	45	35	7	34	112
1985	3,830	12.2	25.3	46.6	70.2	37	36	3	24	109
1990	3,960	9.9	28.7	46.6	73.6	36	36	4	22	112
1995	5,481	11.7	30.5	54.8	79.2	32	35	3	17	108
2000	5,772	12.8	27.8	57.7	80.2	31	34	4	17	107
2006	3,717	1.3	9.6	36.7	74.2	40	36	9	25	119

years old.[6] Figure 3 shows a generally negative trend in the proportion of young firms until the mid-1950s, followed by a substantial positive trend in the proportion of young firms thereafter. For example, the proportion of total market capitalization represented by firms aged 20 or younger was roughly 5% of the market in the early 1960s, rose to about 12% in the early 1990s, and increased to around 20% by the late 1990s. Finally, this measure also spikes in the late 1990s, with a peak in 2000 of about 31% and a subsequent steep decline back to about 14% by mid-2003, coinciding with the Internet boom and bust.

FIGURE 3

Market Value of Young Firms as a Proportion of the Total Equity Market

Figure 3 presents a time series of the market value of equity of young firms as a proportion of total equity market capitalization. The sample includes all CRSP common stocks. Young firms are defined as firms that are less than or equal to 20 years old. Market value is constructed annually as the share price times the number of shares outstanding. Firm age is constructed for each firm year as the difference between the calendar year and the minimum of the listing year, date of first incorporation, or founding date, depending on availability.

[6]This finding is robust to the definition of what constitutes a "young" firm. We find similar results if we define as young those firms that are less than 10 or 5 years old.

The increase in young firms in the market is economically significant. Particularly in value-weighted portfolios, the shift in total market capitalization representing young firms could have a dramatic effect on idiosyncratic risk. For example, if the youngest firms are small, high-MKBK, high-idiosyncratic-risk firms, then this pattern would imply that as the portfolio weight of the market shifts toward young firms, one would expect to find an increase in idiosyncratic risk. Further, the substantial increase in this proportion in the late 1990s coincides with a dramatic multiyear rise in idiosyncratic risk.

B. The Properties of Young and Old Firms

In this section, we briefly describe the characteristics of the sample firms and the relationship between age, risk, and investment opportunities. Since age is highly correlated with firm size, we begin by first partitioning the sample into size deciles. Decile rankings are formed on market capitalization each year. Each size decile is then partitioned into 10 subgroups based on age deciles. The age of the firm is measured as the difference between the sample year and the minimum of the year of the firm's incorporation or founding. To avoid any distortions in our sample over time, we start in 1974, after the introduction of NASDAQ.[7]

For each age-size portfolio we compute equal-weighted cross-sectional averages of our variables. Idiosyncratic risk is measured for each firm as the annualized standard deviation of residuals from a market model regression for each firm based on daily returns each year. MKBK ratio is defined as the sum of market value of equity and the book value of total debt divided by the book value of assets. Capital expenditure to net property, plant, and equipment (PPE) is equal to capital expenditure scaled by total PPE, net of depreciation and amortization expense. Total debt, book assets, book equity, capital expenditures, and net PPE are collected from Compustat.

Table 5 presents the univariate statistics. As expected, Panel A of Table 5 shows a clear relationship between firm age and idiosyncratic risk. For all size deciles, the old firms are significantly less risky than the young firms. Even for the largest 10% of the firms, there is a 26% difference in firm-specific risk between the youngest and oldest age deciles.

Panels B and C of Table 5 show that the relationship between idiosyncratic risk and firm age is a natural consequence of a firm's changing investment opportunity over its life cycle. As expected, the age of the firm is negatively related to proxies for the present value of future growth opportunities. Independent of firm size, younger firms have a higher MKBK ratio, and a higher rate of capital expenditures relative to their net PPE. In each case, the difference between old and young firms is statistically significant in all size deciles.

The differences in investment opportunities between the oldest and the youngest firms are also economically large. For example, Table 5 shows that in the smallest size decile the youngest firms have a 91% higher MKBK ratio than the oldest firms (1.38 compared to 0.72), and a 100% larger ratio of capital expenditures to net PPE (0.10 compared to 0.05). These findings are consistent with

[7] All of our results are qualitatively similar if we start the sample in 1962 instead.

TABLE 5

The Effect of Age on Idiosyncratic Risk and Investment Opportunities: Univariate Analysis

Table 5 presents a comparison of equal-weighted portfolio means for idiosyncratic risk and different measures of investment opportunities by decile of market value of equity and firm age. Portfolios are formed by first partitioning the sample into deciles based on market capitalization. Each size decile is then partitioned into 10 subgroups based on age deciles. Decile rankings are calculated at the end of each year. Nominal market values are deflated by the average market value each year before ranking. The age of the firm is constructed as the difference between the sample year and the year of firm's incorporation or founding. Idiosyncratic risk is measured as the annualized standard deviation of residuals from a market model regression for each firm based on daily returns each year. Market-to-book (MKBK) ratio is defined as the sum of market value of equity and the book value of total debt divided by the book value of assets. Capital expenditures to net property, plant, and equipment (PPE) is based on reported capital expenditures divided by total PPE, net of depreciation and amortization expense. Total assets, book equity, capital expenditures, and net PPE are collected from Compustat. Reported averages are based on equal-weighted cross-sectional means. The significance levels of the differences are based on a 2-tailed t-test with a sampling frequency for each cell given by the number of firms in each cell. ***, **, and * denote significantly different from 0 at the 1%, 5%, and 10% levels, respectively. The sample comprises the period 1974–2006.

Age Decile	Smallest Size Decile	Size Decile 4	Size Decile 7	Largest Size Decile
Panel A. Idiosyncratic Risk				
Youngest	14.27	9.84	8.12	5.51
2	13.80	9.01	7.54	5.14
3	13.20	9.04	7.29	5.01
4	13.04	8.89	6.82	4.92
5	12.99	8.92	6.51	4.52
6	12.72	8.75	6.32	4.26
7	12.52	8.38	5.87	4.24
8	12.11	7.82	5.56	4.07
9	11.72	6.89	5.18	4.11
Oldest	10.30	6.75	4.94	4.08
Difference (10) – (1)	–3.97***	–3.09***	–3.18***	–1.43***
Panel B. MKBK Ratio				
Youngest	1.38	1.37	1.35	0.96
2	1.15	1.36	1.54	1.03
3	1.06	1.38	1.47	1.00
4	1.00	1.43	1.26	1.18
5	1.04	1.36	1.32	0.97
6	1.07	1.28	1.21	0.91
7	1.00	1.17	1.28	0.91
8	0.85	1.11	1.14	1.05
9	0.84	1.07	1.01	1.13
Oldest	0.72	0.78	1.04	0.90
Difference (10) – (1)	–0.66***	–0.58***	–0.31***	–0.06**
Panel C. Capital Expenditures to Net PPE				
Youngest	0.10	0.12	0.11	0.08
2	0.09	0.10	0.10	0.08
3	0.08	0.09	0.09	0.09
4	0.08	0.09	0.08	0.08
5	0.07	0.08	0.09	0.08
6	0.06	0.08	0.08	0.07
7	0.06	0.08	0.08	0.07
8	0.06	0.07	0.07	0.07
9	0.05	0.06	0.07	0.07
Oldest	0.05	0.06	0.06	0.06
Difference (10) – (1)	–0.06***	–0.06***	–0.04***	–0.02*

those of Pastor and Veronesi (2003), who argue that young firms have less certainty over future growth rates, which leads to both higher MKBK ratios as well as higher firm-specific risk. These results show that the increasing propensity of firms to issue public equity at an earlier stage of their life cycle raises the idiosyncratic risk of the typical public firm.

C. The Time Series of Young and Old Firms Separately

Our basic hypothesis can be represented by describing aggregate idiosyncratic risk, FIRM_t, as a linear combination of both "old" and "young" idiosyncratic risk:

$$\mathrm{FIRM}_t = w_t^Y \mathrm{FIRM}_t^Y + (1 - w_t^Y)\mathrm{FIRM}_t^O, \tag{5}$$

where FIRM_t^O and FIRM_t^Y represent the idiosyncratic risk of old and young firms at time t, respectively, and w_t^Y continues to represent the proportion of the total market comprised of young firms at time t. Fluctuations in aggregate idiosyncratic risk may be driven by old or young groups either separately or together. A natural question then is whether the idiosyncratic risk of old firms exhibits similar patterns.

To test whether the aggregate idiosyncratic risk of old and young firms exhibits similar time-series behavior, we first form subsamples based on firm age. Each year, we form 2 portfolios of the 500 oldest and 500 youngest firms and compute the annual firm-specific risk as the residual from market model regressions. Value-weighted average idiosyncratic volatilities for each group are then computed, forming separate age-group proxies for FIRM_t^Y and FIRM_t^O.

Figure 4 presents the time series of FIRM_t^Y and FIRM_t^O along with the full sample aggregate measure, FIRM_t. Two qualitative patterns are clear. First, while the old portfolio has substantially lower idiosyncratic risk than the young portfolio throughout the sample, neither portfolio shows any clear trending behavior prior to the mid-1990s. Second, the full sample aggregate measure does appear to trend upward as the proportion of young firms in the market rises.

We also perform more formal trend tests for our 3 portfolios: FIRM_t, FIRM_t^Y, and FIRM_t^O. For each series, we estimate simple ordinary least squares (OLS) trend test regressions including the Internet boom dummy variable. The results (not reported in a table) are familiar: a positive and significant linear trend, a positive and significant coefficient on the Internet boom period, and a high coefficient of determination. In contrast, neither FIRM_t^Y nor FIRM_t^O exhibits such a trend. Since the time trends are not significant, the large positive coefficient for the aggregate group appears to be driven by the changes in the relative weights of these portfolios.

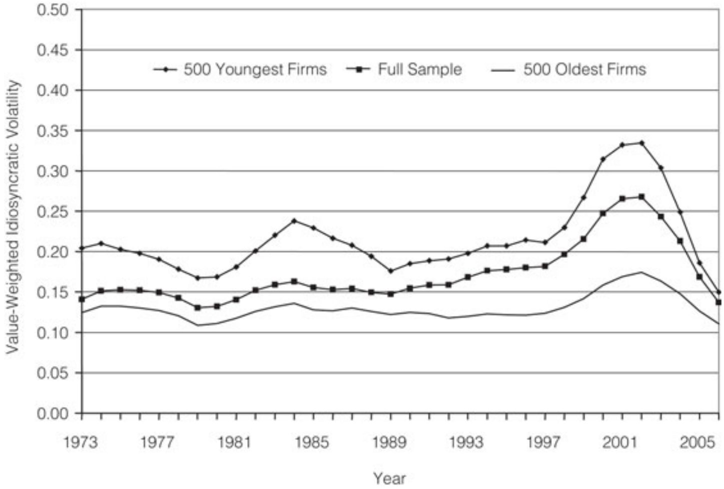
D. Investor Sentiment and Idiosyncratic Risk

In Sections IV.B and IV.C, we show that idiosyncratic risk is correlated with firm age. However, since the choice to do an IPO is endogenous, younger firms may decide to go public during periods of "irrational exuberance" (e.g., SENT is high). Thus, age may proxy for an underlying relation between idiosyncratic risk and SENT. To investigate this, we perform a simple univariate sort into periods of high and low SENT. First, we classify each month (year) into quintiles (terciles) based on the level of the SENT. Following Baker and Wurgler (2006), we use a composite index (SENT) that captures the common component of 6 proxies for investor sentiment:

FIGURE 4

Firm-Level Volatility for Age Cohorts

Figure 4 depicts the time-series behavior of value-weighted idiosyncratic volatility for old and young groups of firms. Each year, separate portfolios are formed for the 500 youngest and oldest firms in the sample based on firm age. The age of the firm is constructed as the number of years between initial listing and the minimum of the founding date or the date of first incorporation. The annual series are estimated from the CRSP monthly return file.



i) the average difference between net asset values of closed-end funds and their market value (closed-end fund discount),

ii) the share volume to average shares listed in the NYSE (share turnover),

iii) the number of IPOs,

iv) the average first-day returns of IPOs,

v) the share of equity issues in total equity and debt issues (equity share), and

vi) the difference in MKBK ratio of dividend payers versus nonpayers.

The advantage of using a composite index is that we do not need to rely on one particular variable to measure SENT. However, our results are similar whether we use the composite index or any of the individual variables.

Table 6 presents the results of our analysis. For the value-weighted series, there is a monotonic increase in idiosyncratic risk across either monthly quintiles or annual terciles. For the equal-weighted series, the increase is not monotonic, but there is clearly an increase in idiosyncratic risk in months with higher-than-average SENT. In all cases, the periods of lowest sentiment have both statistically and economically significant lower idiosyncratic risk. The difference is economically meaningful. For example, the difference in idiosyncratic risk between the 1st and 5th monthly quintiles for the equal-weighted series is 0.15, which is nearly as large as the increase during the Internet boom. The results in Table 6 indicate that we need to control for SENT in our regressions to be able to distinguish the rational hypothesis from the behavioral hypothesis.

TABLE 6

Investor Sentiment and Idiosyncratic Risk: Univariate Analysis

Table 6 presents a comparison of average idiosyncratic risk during periods of high and low SENT for both the monthly and annual idiosyncratic risk series. Panel A presents the average level of idiosyncratic risk for monthly series (1966–2006) for quintiles based on the level of SENT. Monthly idiosyncratic risk is estimated from the CRSP daily return file. Panel B presents the average level of idiosyncratic risk for the annual series (1934–2006) for terciles based on the level of SENT. Annual idiosyncratic firm variance is estimated from the CRSP monthly return file. Monthly and annual SENT are measured using the Baker and Wurgler (2006) sentiment index.

	Value-Weighted Idiosyncratic Risk		Equal-Weighted Idiosyncratic Risk		
SENT	Mean	Std. Dev.	Mean	Std. Dev.	*N*
Panel A. Monthly Series (1966–2006)					
Low	0.063	0.027	0.273	0.161	99
2	0.063	0.026	0.447	0.294	98
3	0.082	0.047	0.566	0.343	99
4	0.088	0.043	0.525	0.262	98
High	0.102	0.077	0.429	0.315	98
Difference	0.039		0.156		
	[4.71]		[4.37]		
Panel B. Annual Series (1934–2006)					
Low	0.035	0.015	0.153	0.098	25
Medium	0.048	0.024	0.219	0.161	24
High	0.072	0.061	0.245	0.187	24
Difference	0.037		0.091		
	[2.96]		[2.14]		

V. Firm Age and Sentiment Effects on the Time Series of Idiosyncratic Risk

In this section we test the hypothesis that variations in idiosyncratic risk can be explained by systematic changes in the vintage of the typical public firm. To test whether changing weights on the age categories explain variations in idiosyncratic risk, we regress the level of idiosyncratic volatility at time *t* on the same set of conditioning variables that we used in Section III.C, but we now include our age measure and the sentiment index of Baker and Wurgler (2006) as additional explanatory variables. Our basic regression specification is

$$\text{(6)} \qquad \text{FIRM}_t = \alpha + \gamma t + \beta_1 \text{AGE}_t + \beta_2 \text{SENT}_t + \beta_3 \text{OIL} + \beta_4 \text{OCT\_1987} + \beta_5 \text{BOOM} + \varepsilon_t,$$

where $\text{AGE}_t = (1 - w_t^Y)$ and SENT_t represents the sentiment index. The indicators are the same as in Section III. To the extent that variation in the maturity of the average firm can explain changes in idiosyncratic risk, we expect the inclusion of age to have an effect on the time trend coefficient and the coefficient on the Internet boom dummy variable.

Table 7 presents the results from this analysis based on our annual sample from 1946 to 2006.[8] Consistent with our main hypothesis, the coefficient on AGE

[8]The annual SENT index is not available prior to 1934. The monthly SENT index is not available prior to 1966.

is negative and statistically significant in all specifications. Further, it appears that excluding AGE from the idiosyncratic volatility regression induces a positive linear trend.

TABLE 7

Fluctuations in Idiosyncratic Risk (Annual Series 1946–2006)

Table 7 reports regressions examining the behavior of annual series of idiosyncratic risk for value- and equal-weighted portfolios. The dependent variable is the average idiosyncratic firm variance estimated annually from the CRSP monthly return file. AGE is the proportion of the total market capitalization comprised of firms that are more than 20 years old. BOOM, a dummy variable for the Internet boom period, is equal to 1 if the observation occurs between 1997 and 2002 for the value-weighted series and between 1995 and 2002 for the equal-weighted series, and 0 otherwise. Here OCT_1987 is an indicator variable equal to 1 if the observation occurs in 1987, and 0 otherwise. OIL takes a value of 1 during 1973–1975. Annual investor sentiment (SENT) is measured using the Baker and Wurgler (2006) sentiment index. The *t*-statistics (reported below coefficient estimates) are based on Newey-West (1987) standard errors.

	Value Weighted			Equal Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Linear trend $\times 10^3$	0.834	–0.531	–0.531	6.188	2.046	2.046
	[4.28]	[0.87]	[0.83]	[4.11]	[1.29]	[1.28]
BOOM	0.071	0.031	0.029	0.142	0.021	0.022
	[2.14]	[1.27]	[1.18]	[2.60]	[0.26]	[0.27]
OCT_1987	0.014	–0.006	–0.003	0.035	–0.026	–0.026
	[2.79]	[0.58]	[0.35]	[0.89]	[0.80]	[0.81]
OIL	0.034	0.034	0.036	0.059	0.060	0.060
	[10.36]	[8.11]	[6.88]	[2.34]	[2.40]	[2.44]
AGE		–0.59	–0.576		–1.791	–1.796
		[2.28]	[2.18]		[4.03]	[3.98]
SENT			0.007			–0.003
			[1.79]			[0.30]
Constant	0.003	0.613	0.600	–0.112	1.741	1.746
	[0.35]	[2.29]	[2.20]	[2.07]	[3.71]	[3.67]
Observations	61	61	61	61	61	61
R^2	0.59	0.7	0.7	0.7	0.77	0.76

For both the value- and equal-weighted series, column 1 of Table 7 reports the results from the estimation of equation (6) without the inclusion of the AGE or sentiment variables, as reported in Table 3. Column 2 includes the AGE variable in the regression, and column 3 includes both AGE and sentiment. Several important results are illustrated.

First, the inclusion of AGE eliminates the significance of the coefficient on the time trend and reverses the sign of the estimated coefficient. Further, the significance of the coefficient on the Internet dummy variable also evaporates. This is true even for the coefficient on the October 1987 crash.[9] Lastly, the inclusion of the sentiment has only a negligible effect on the results. In neither the value- nor equal-weighted case is the coefficient on the sentiment index significant, and its inclusion does not appreciably change the magnitude of any other coefficient estimates.

The AGE result may not be surprising given the time-series properties of firm age documented previously. However, the economic magnitude of the effect

[9]The insignificance of the 1987 crash is not surprising in the annual regressions. The dummy variable is necessarily an indicator for the entire year of 1987, so the small increase in annual idiosyncratic risk caused by the 1-day fall is overshadowed by the effect of the AGE variable. The monthly regressions in Table 10 show that the coefficients on the crash dummy variable continue to be significant.

is large. For example, consider column 2 of Table 7. Based on the coefficient estimate on age of –0.59, we estimate that a 2-standard-deviation decrease (roughly 13 percentage points) in the market value proportion of old firms would increase idiosyncratic risk by roughly 1.5 standard deviations. Given that the proportion of old firms changes from a high of around 95% in the mid-1950s to a low of around 69% in 2000, this variation would indicate that idiosyncratic risk would increase from 0.020 in 1956 to roughly 0.17 by 2000, which accounts for almost two-thirds of the difference in those 2 periods (idiosyncratic risk hit a high that year at 0.283).

Table 8 presents the results of the same set of tests using the sample constructed at the monthly frequency. Once again, we find that the coefficient on age is consistently negative and statistically significant. Again, we find no evidence of any trend in idiosyncratic volatility after including AGE in the regressions, and the effect of sentiment on the regressions is negligible. There exists no remaining evidence of abnormal firm-specific risk during the Internet boom of the late 1990s after controlling for AGE.

TABLE 8

Fluctuations in Idiosyncratic Risk (Monthly Series 1966–2006)

Table 8 reports regressions examining the behavior of monthly series of idiosyncratic risk for value- and equal-weighted portfolios. The dependent variable is average idiosyncratic firm variance estimated monthly from the CRSP daily return file. AGE is the proportion of the total market capitalization comprised of firms that are more than 20 years old. BOOM, a dummy variable for the Internet boom period, is equal to 1 if the observation occurs between 1997 and 2002 for the value-weighted series and between 1995 and 2002 for the equal-weighted series, and 0 otherwise. OCT_1987 is an indicator variable equal to 1 if the observation occurs in 1987, and 0 otherwise. OIL takes a value of 1 during 1973–1975. Monthly investor sentiment (SENT) is measured using the Baker and Wurgler (2006) sentiment index. The *t*-statistics (reported below coefficient estimates) are based on Newey-West (1987) standard errors.

	Value Weighted			Equal Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Linear trend $\times 10^3$	0.018	–0.156	–0.151	0.888	–0.126	–0.133
	[0.86]	[2.71]	[2.59]	[2.82]	[0.37]	[0.41]
BOOM	0.074	0.022	0.022	0.263	–0.019	–0.008
	[3.09]	[1.36]	[1.36]	[2.57]	[0.18]	[0.08]
OCT_1987	0.341	0.314	0.316	0.681	0.521	0.500
	[115.77]	[32.59]	[32.10]	[14.12]	[9.48]	[8.70]
OIL	0.048	0.049	0.054	0.135	0.077	0.067
	[5.98]	[4.91]	[5.25]	[3.76]	[1.52]	[1.37]
AGE		–0.798	–0.772		–4.743	–4.655
		[2.96]	[2.84]		[4.14]	[4.34]
SENT			0.004			–0.061
			[1.50]			[2.91]
Constant	0.051	0.896	0.868	–2.430	4.754	4.678
	[3.61]	[3.16]	[3.04]	[1.29]	[3.85]	[4.03]
Observations	492	492	492	492	492	492
R^2	0.44	0.58	0.59	0.43	0.56	0.57

Overall, the evidence in Tables 7 and 8 supports the hypothesis that the positive trend in idiosyncratic volatility documented in previous studies is driven by the increasing number of young firms accessing the public equity markets. We show no remaining excess idiosyncratic risk during the Internet boom of the late 1990s after controlling for the substantial increase in the number of young firms during this period. Further, including a composite measure of SENT has no material effect on the results. Thus, our findings do not appear to be driven by behavioral effects.

VI. Robustness

In this section, we explore the robustness of our results. First, firm age may not capture all the aspects of firm maturity, so we employ firm-level estimations that control for other measures of maturity. The second set of tests demonstrates that our results are not driven by differences in IPO cohorts.

A. Firm-Level Analysis of the Time-Series Behavior of Idiosyncratic Risk

Other measures of firm maturity (e.g., profitability, asset tangibility, investment opportunities) may also explain the recent trends in idiosyncratic risk. These variables also tend to show some qualitative correlation with aggregate idiosyncratic risk in that they tend to trend over time and show substantial variation during the Internet boom of the late 1990s.

To test whether other characteristics of public firms can help explain long-run changes in idiosyncratic risk, we perform a 2-step approach following Fama and French (2001). The basic strategy is to estimate the relationship between idiosyncratic risk and firm characteristics in 1 base year and then use that estimation to forecast what idiosyncratic volatility would be in subsequent years, based on changes over time in the firm-level characteristics. If the time-series properties of the characteristics can fully explain changes in idiosyncratic risk, then the predicted values will match the actual values, and the residuals (or forecast errors) should average out to appear as a flat line over time.

To construct such a test, we first estimate the following cross-section regression equation for our base year of 1975:[10]

$$
\begin{aligned}
\text{(7)} \qquad \mathrm{IDIO}_{i,t} = {} & \alpha + \beta_1 \mathrm{AGE}_{i,t} + \beta_2 \mathrm{SIZE}_{i,t} + \beta_3 \mathrm{MKBK}_{i,t} \\
& + \beta_4 \mathrm{ROA}_{i,t} + \beta_5 \mathrm{EPS}_{i,t} + \beta_6 \mathrm{LEV}_{i,t} + \beta_7 \mathrm{DD}_{i,t} \\
& + \beta_8 \mathrm{AMEX}_{i,t} + \beta_9 \mathrm{NASDAQ}_{i,t} + \beta_{10} \mathrm{TANG}_{i,t} \\
& + \sum_{k=1}^{48} \gamma_k \mathrm{IND}_{k,i,t} + \varepsilon_{i,t},
\end{aligned}
$$

where IDIO is the log of the annualized standard deviation of residuals from a market model regression for each firm based on daily returns. At the firm level, age is straightforward to measure. We construct firm-level AGE as the log of the difference between the calendar year of the observation and the firm's founding date or date of incorporation. SIZE is the log of book assets, MKBK is the market-to-book ratio, ROA is the return on assets, EPS is the earnings per share, LEV is the log of 1 plus the ratio of total long-term debt to total equity, DD is a dummy variable equal to 1 if the firm pays dividends and 0 otherwise, TANG is net PPE scaled by assets, and IND are industry dummy variables based on the

[10]Results are not substantially different if we use a different base year (e.g., 1980, 1985).

Fama and French (1997) industry classification code. AMEX and NASDAQ are dummy variables for AMEX firms and NASDAQ firms, respectively.

With estimates of the parameters in equation (7), we forecast firm-level idiosyncratic risk using the observed firm-level characteristics risk in each subsequent year. We then calculate the unexpected level of idiosyncratic risk (the forecast error) by subtracting the predicted level from the actual level of idiosyncratic volatility (IDIO). That is, we construct residuals, $\hat{\varepsilon}_{i,t}$, over all i and t for all the sample firms observed after 1975. Finally, we then compute the sample mean of $\hat{\varepsilon}_{i,t}$ each year as the equal-weighted mean over all firms.

If aggregate idiosyncratic risk is driven by changes in the characteristics of public firms, we should find no trend or spike in the time series of average residuals. To test this hypothesis, we regress the average unexpected level of idiosyncratic volatility (average residuals) on a time trend and a dummy variable for the Internet boom. The results from this analysis are reported in Table 9. In this table, we show that without controlling for the measures of firm maturity, IDIO exhibits an abnormal spike during the Internet boom of the late 1990s, but no statistically significant trend (column 1). However, once we control for firm maturity, the coefficient of the Internet dummy variable becomes statistically and economically insignificant (column 2). Further, SENT does not affect the results and is not statistically significant.

TABLE 9

Firm-Level Analysis of the Time-Series Behavior of Idiosyncratic Risk

Table 9 reports regressions examining the time-series behavior of idiosyncratic risk controlling for firm characteristics. We use a 2-step approach to perform this analysis. In the 1st step, we use only data from 1975, and we regress the log of the annualized standard deviation of residuals from a market model regression for each firm, based on daily returns each year (IDIO) on the log of the difference between the calendar year of the observation and the firm's founding date or the date of incorporation (AGE), the log of deflated assets (SIZE), market-to-book (MKBK) ratio, return on assets (ROA), earnings per share (EPS), the log of 1 plus the ratio of total long-term debt to total equity (LEV), a dummy variable equal to 1 if the firm pays dividends and 0 otherwise (DD), net property, plant, and equipment (PPE) scaled by assets (TANG), industry dummy variables based on the Fama and French (1997) industry classification code (IND), and dummy variables for AMEX firms (AMEX) and NASDAQ firms (NASDAQ). In the 2nd step, we apply the estimated parameters from the 1st stage to all the sample firms observed after 1975 to estimate the predicted (expected) level of idiosyncratic risk given the characteristics of the firm. We then calculate the unexpected level of idiosyncratic risk $(\hat{\varepsilon}_{i,t})$ by subtracting the predicted level from the actual level of idiosyncratic volatility. With the estimated residuals, we then compute the sample mean of $\hat{\varepsilon}_{i,t}$ each year as the equal-weighted mean over all firms (AVERAGE $\hat{\varepsilon}_{i,t}$). Finally, we regress AVERAGE $\hat{\varepsilon}_{i,t}$ on a time trend, a dummy variable equal to 1 if the observation occurs between 1995 and 2002 (BOOM), and the annual sentiment index (SENT).

	Dependent Variable		
	Raw Data $\text{IDIO}_{i,t}$	AVERAGE $\hat{\varepsilon}_{i,t}$	
Linear trend × 10^3	–3.378 [0.42]	–1.571 [0.38]	–0.847 [0.18]
BOOM	0.332 [2.35]	0.111 [1.45]	0.13 [1.70]
SENT			–0.038 [1.50]
Constant	–3.758 [37.01]	–0.023 [0.45]	–0.040 [0.76]
Observations	32	32	32
R^2	0.31	0.01	0.01

Overall, conditional on the changing characteristics of listed firms, we find no abnormal time-series trend or spike in the underlying firm-specific risk measures. This is an important result because it indicates that the increase in volatility during the Internet boom can be explained by changes in firm fundamentals.

B. Cohort Effects

In this section, we examine the extent to which our results are driven by the risk characteristics of individual cohorts of young firms in our sample. Brown and Kapadia (2007) argue that recent cohorts of young firms are riskier than previous cohorts, and that it is the increased riskiness of these groups that drives the increase in idiosyncratic volatility initially reported by CLMX (2001).

To test whether there is an age effect on idiosyncratic risk independent of any cohort effect, we first construct the unconditional average idiosyncratic risk of firms by age. Next, we break the sample into 3 equal subperiods (1963–1977, 1978–1992, and 1993–2006) and compute the same average. Figure 5 presents the results across age portfolios. In Graph A, idiosyncratic risk consistently falls as firms get older, as expected. In Graph B, we see the same series for each IPO subperiod. As in Brown and Kapadia (2007), there is a cohort effect in the sense that the later subperiods show higher idiosyncratic risk regardless of their age. However, for each subsample cohort, there is a large and consistent decline in idiosyncratic risk as firm vintage increases. In fact, the decline is much larger in magnitude than the difference between the cohort portfolios for any given age.

To construct a more formal statistical test of the cohort effect, we break the sample of firms from 1963 to 2006 into 5 IPO cohorts by decade, as in Brown and Kapadia (2007). That is, we assign each firm a cohort dummy variable based on the decade in which the firm issued its IPO.[11] We then estimate a linear regression model of idiosyncratic risk (IDIO) that includes our AGE variable along with dummy variables for each year, dummy variables for each cohort, and lagged IDIO.

The results are presented in Table 10. In column 1, we see the familiar unconditional age effect on idiosyncratic risk documented in Figure 5. In contrast, column 2 presents results without the age effect but including the cohort dummy variables. Again, consistent with Brown and Kapadia (2007), the idiosyncratic risk of firms that list appears to increase over time. In column 3, we include both AGE and the cohort dummy variables. Both effects are present in the data, and the inclusion of the cohort dummy variables does not weaken the AGE effect presented in column 1, though the coefficient is somewhat smaller. On the other hand, including AGE in the regression does reduce the coefficients on the cohort dummy variables by roughly 50%. Columns 4–6 present similar evidence, including lagged idiosyncratic risk in the regressions. In short, both cohort and age are significant, but the age effect dominates the cohort effect.

[11] Any firm listing before 1960 is a separate cohort for this analysis.

TABLE 10

Cohort Regressions of Firm-Level Idiosyncratic Risk

Table 10 reports regressions of idiosyncratic risk for firms that issued their IPO in during different subperiods. We regress the log of the annualized standard deviation of residuals from a market model regression for each firm based on daily returns each year (IDIO) on the log of the difference between the calendar year of the observation and the firm's founding date or the date of incorporation (AGE) along with 5 dummy variables indicating the decade during which the firm issued its IPO. Firms that issued their IPOs prior 1963 form the base comparison group. All regressions also include dummy variables for each year (year-fixed-effects). The *t*-statistics, reported below coefficient estimates, are based on robust standard errors computed using both firm and year clustering.

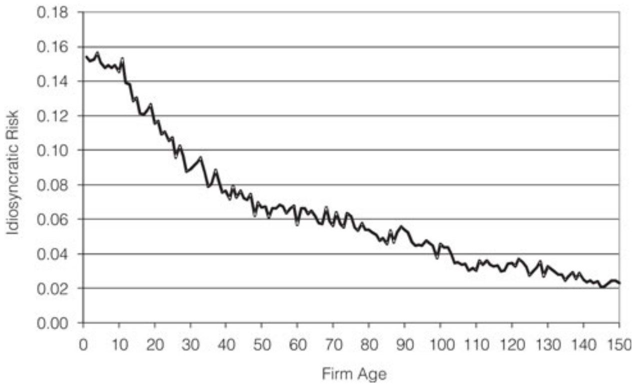
	Dependent Variable: log(IDIO)					
	(1)	(2)	(3)	(4)	(5)	(6)
AGE	–0.339		–0.203	–0.046		–0.029
	[–22.39]		[–21.12]	[–12.09]		[–9.07]
IPO cohort 1963–1969		0.168	0.094		0.024	0.015
		[15.55]	[8.78]		[6.16]	[3.81]
IPO cohort 1970–1979		0.263	0.152		0.041	0.027
		[20.86]	[12.20]		[7.37]	[4.85]
IPO cohort 1980–1989		0.405	0.262		0.059	0.041
		[22.83]	[14.43]		[7.61]	[5.14]
IPO cohort 1990–1999		0.502	0.332		0.071	0.050
		[22.00]	[15.45]		[9.07]	[6.67]
IPO cohort 2000–2006		0.544	0.360		0.078	0.056
		[27.90]	[19.08]		[12.44]	[8.92]
1-year lagged IDIO				0.804	0.801	0.793
				[73.46]	[74.91]	[75.19]
Constant	1.312	0.902	1.083	0.233	0.178	0.212
	[172.7]	[440.55]	[150.24]	[6.77]	[10.26]	[7.95]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,575	135,575	135,575	119,600	119,600	119,600
R^2	0.30	0.32	0.35	0.73	0.73	0.73

FIGURE 5

Average Idiosyncratic Risk across Age Portfolios

Figure 5 presents the value-weighted average idiosyncratic risk across portfolios formed on firm age. Portfolios are formed based on firm age on or founding date each year. The value-weighted average of idiosyncratic risk is formed for each age-year portfolio based on the year-end market capitalization within each age-year portfolio. Graph A presents the equal-weighted time-series averages computed for each age portfolio across all years (1963–2006) in the sample. Graph B presents the equal-weighted time-series average for each age portfolio for 3 cohort subsamples.

Graph A. Entire Sample

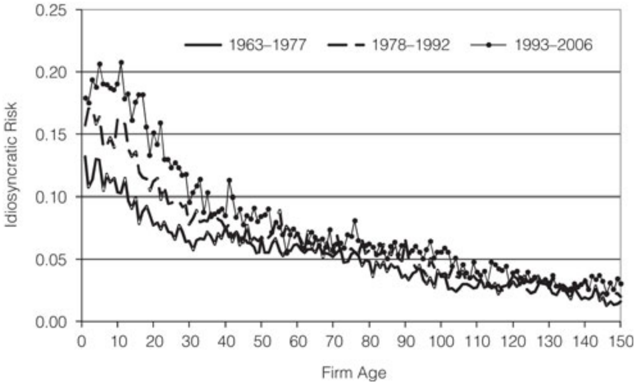


(continued on next page)

FIGURE 5 (continued)

Average Idiosyncratic Risk across Age Portfolios

Graph B. Cohort Subsamples



VII. Conclusion

This study shows that idiosyncratic risk is driven by the age characteristics of listed firms. The increased proportion of young firms in the market explains a large fraction of the increase in firm-specific risk during the Internet boom of the late 1990s. Further, when we control for other measures of firm maturity, no evidence of any abnormal spike in idiosyncratic risk during the Internet boom of the late 1990s is present. These results are important because they suggest that the recent behavior of aggregate idiosyncratic risk has been driven mainly by the changes in firms' characteristics and fundamentals, and not by the irrational behavior of noise traders. Further, they support Pastor and Veronesi's (2006) argument that the increase in volatility during the Internet boom was driven mainly by a systematic increase in firm-specific uncertainty about future profitability.

Over the past 40 years the age of the typical firm issuing public equity has fallen from almost 40 years in the 1960s to less than 5 years by the late 1990s. This suggests that U.S. capital markets have shown a variable, though generally increasing willingness to purchase equity claims on firms at earlier stages of their life cycles. This willingness seems to have peaked in the late 1990s. Our tests cannot reveal whether this is driven by changes in the demand for equity claims on young firms or changes in the supply of equity claims on young firms. To the extent that the fluctuations are driven by shifting supply, this may represent a general decline in the cost of equity capital (at least for young firms) in the post-WWII period, peaking and then subsiding during the Internet boom. Thus, the recent spike in idiosyncratic risk, rather than representing any deterioration in market quality or increase in irrationality, could actually represent an efficient mechanism for capital allocation, risk sharing, and social welfare.

Appendix. Construction of the Idiosyncratic Risk Measures

Our treatment closely follows CLMX (2001), who provide a detailed description of their methods. For convenience (and later reference), we briefly summarize the estimation methodology here. Let R_{mt} be the excess market return at time t, R_{it} be the excess return of industry i at time t, and R_{jit} be the excess return of firm j in industry i at time t. The firm returns R_{jit} are readily observable from daily prices, and dividends. R_{mt} and R_{it} are computed as

$$R_{it} = \sum_{j \in i} w_{jit} R_{jit}, \tag{A-1}$$

$$R_{mt} = \sum_{i} w_{it} R_{it}, \tag{A-2}$$

where w_{jit} is the percentage of market capitalization of firm j in industry i, and w_{it} is the percentage of market capitalization of industry i in the market. The sample volatility of the market at time t, denoted MKT_t, is computed as

$$\mathrm{MKT}_t = \sigma_{mt}^2 = \sum_{s \in t} (R_{ms} - \mu_{mt})^2, \tag{A-3}$$

where μ_{mt} is the time t mean excess market return.[12] We compute the volatility for a particular industry as

$$\hat{\sigma}_{\varepsilon it}^2 = \sum_{s \in t} \varepsilon_{is}^2, \tag{A-4}$$

where

$$\varepsilon_{is} = R_{is} - R_{ms} \tag{A-5}$$

is the industry-specific residual. We then average over industries to obtain average industry volatility:

$$\mathrm{IND}_t = \sum_{i} w_{it} \hat{\sigma}_{\varepsilon it}^2. \tag{A-6}$$

The time t return residual for an individual firm j in industry i is

$$\eta_{jit} = R_{jit} - R_{it}, \tag{A-7}$$

from which we can estimate firm-specific volatility for firm j,

$$\hat{\sigma}_{\eta jit}^2 = \sum_{s \in t} \eta_{jis}. \tag{A-8}$$

With the firm-specific volatilities, we can compute the average firm-specific volatility within an industry as

$$\hat{\sigma}_{\eta it}^2 = \sum_{j \in i} w_{jit} \hat{\sigma}_{\eta jit}^2. \tag{A-9}$$

Finally, we average over industries to obtain the CLMX measure of average firm variance:

$$\mathrm{FIRM}_t = \sum_{i} w_{it} \hat{\sigma}_{\eta it}^2. \tag{A-10}$$

The firm-level returns we examine are from the daily CRSP tape. NYSE-, AMEX-, and NASDAQ-traded common shares are included in the sample. The data for interest rates are

[12]This is a slight deviation from CLMX (2001) who assume a constant mean market return over the entire sample. We also replicate their methodology, and the results are almost identical.

taken from the CRSP T-bill term structure price file. The risk-free rate is computed from 30-day T-bills. The value- and equal-weighted measures of firm-level volatility (FIRM) that we compute are, as expected, almost equal to the measures reported by CLMX (2001). The correlation between our value- and equal-weighted series, and their respective series, for the overlapping portion of our sample is 0.993 and 0.987, respectively. The minor remaining differences may be attributed to such details as when market capitalization is sampled, the existence of the time-varying mean, or the routine updating of the CRSP data tapes.

In addition to constructing a monthly time series of idiosyncratic risk from the daily stock files, we also construct an annual time series from the CRSP monthly stock files. For this series, we follow exactly the same procedure as in the monthly series, save for using monthly observations to construct annual volatility estimates.

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