The Variability of IPO Initial Returns

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The monthly volatility of IPO initial returns is substantial and fluctuates dramatically over time. Moreover, the monthly volatility of initial returns is significantly positively correlated with monthly mean initial returns. This contrasts strongly with the strong negative correlation between the mean and volatility of secondary-market returns. Consistent with IPO theory, our empirical findings suggest that information asymmetry about the firm's market value drives this positive correlation. Specifically, months in which a greater portion of the offerings are for companies for which information asymmetry is likely to be a problem tend to have higher average initial returns and a higher volatility of initial returns. Moreover, information asymmetry proxies are able to explain much of the positive correlation between average initial returns and the variability of initial returns, and the same proxies are significantly associated with both the level and dispersion of initial returns at the firm level.

Key words: IPO, Underpricing, Cycles, Information Asymmetry, Conditional Heteroskedasticity, Volatility

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1. Introduction

A substantial body of literature focuses on the average initial returns to initial public offerings (IPOs). These initial returns are large, averaging 22% over the 1965–2004 period. For investors that can buy IPOs at the offer price, IPOs are clearly a good short-run investment. Theory, however, tells us that investors should care about risk in addition to expected return: investors prefer higher returns but also lower risk, and little is known about the volatility or dispersion of IPO returns during the first days of trading. We seek to fill this gap in the literature by examining the dispersion of IPO initial returns, measured as the volatility of initial returns across all firms going public.

Initial returns to IPOs are highly dispersed within each month. As a first step toward understanding this IPO initial return volatility, we compare it to the time-varying volatility of secondary-market returns. Assuming that market risk affects both market-wide returns and IPO initial returns, one might expect the two series to behave similarly. The time-varying volatility of market-wide returns has received considerable attention in recent literature;[1] we know that it is both highly autocorrelated and strongly negatively related to average market-wide returns. We find that the dispersion of initial returns is similar in some ways to the market volatility series, but very different in other ways. Specifically, similar to market-wide volatility, we find that the dispersion of initial returns is highly autocorrelated across months. However, in contrast to the *negative* relation between market returns and market volatility, we find that average IPO initial returns and the dispersion of initial returns (both measured across all IPOs within each month) are highly and significantly *positively* correlated.

This fundamental distributional difference between IPO initial returns and aggregate market returns is potentially related to the fact that IPO initial returns are economically different from the returns to stocks that are already publicly traded. Secondary market returns represent the difference between two market prices. In contrast, IPO initial returns represent the difference between market-clearing prices at

[1] For example, French, Schwert, and Stambaugh (1987) and Schwert (1989) are among the early studies in this voluminous literature.

the end of the measurement interval and prices formed in a non-market setting by the issuer and its investment bank. We appeal to IPO theory to gain insight into the ways in which this important difference affects the volatility of IPO initial returns.

The pricing of an IPO is a complex process. Although the issuer and its investment bank know considerably more about the firm's own prospects than any single market participant does, market participants as a whole know more than the firm about one critical input to the IPO pricing process: the aggregate demand for the firm's shares (see, e.g., Rock (1986)). Aggregate demand uncertainty is one of the principal problems facing issuers and their investment banks when attempting to price an IPO, and uncertainty about aggregate demand for IPO stocks varies in both the time series (it is higher at some points in time than others) and the cross section (it is higher for some types of firms than others).

By definition, the initiation of trading resolves this information asymmetry between the issuing firm and the market, i.e., trading resolves the firm's uncertainty about the market's aggregate demand. At this point, the information of all market participants becomes incorporated into the price. Beatty and Ritter (1986) predict that the difference between the market price and the offer price, i.e., the initial return, will be systematically related to this information asymmetry between firms and the market.[2] Specifically, companies for which information asymmetry is greater will tend to be more underpriced on average. Moreover, aggregate demand for the firm's stock is difficult to estimate precisely for high-information-asymmetry companies, implying that initial returns for these firms will be dispersed because aggregate demand is underestimated for some by more than for others. Extending these propositions to a time-series context, periods with greater uncertainty about demand for IPO stocks should be characterized by higher average initial returns and a greater dispersion of initial returns, i.e., the mean and volatility of IPO initial returns should be positively correlated. This prediction stands in stark contrast to returns on seasoned stocks, and it is exactly what we observe in the data.

[2] This prediction represents an extension of Rock's (1986) model.

Variation in the level of issuers' uncertainty about demand for IPO stocks can be caused both by changes in market-wide uncertainty (reflected in changes market volatility) and by changes in the types of firms going public. We explore both these time-series and cross-sectional influences, thereby providing evidence on the extent to which each contributes to the dispersion in IPO initial returns. We find that time-series changes in market volatility are significantly related to the large increase in IPO initial return volatility during the internet-NASDAQ bubble period. However, they are not a significant factor during the remainder of our 35-year sample period. Our results suggest that the variation in IPO initial return volatility over time is predominantly driven by cross-sectional effects, i.e., by changes in the types of companies going public in different periods. Initial return volatility is especially high in and around months with many technology firms going public and when many young firms are offering stock to the public for the first time. Furthermore, a substantial fraction of the correlation between the monthly average and dispersion of initial returns can be explained by firm-specific proxies for information asymmetry. We interpret this as evidence that information asymmetry about the demand for IPO stocks is the most important determinant of the dispersion of initial IPO returns.

The remainder of this paper proceeds as follows. Section 2 analyzes the unconditional dispersion of IPO initial returns and the time-variation in the dispersion of IPO returns. Section 3 relates the dispersion of IPO initial returns to the time series behavior of the volatility of stock market returns. Section 4 examines various firm- and deal-specific factors that are likely to influence initial IPO returns to see how much of the dispersion of IPO returns is attributable to the characteristics of the issuing firms. Finally, section 5 synthesizes the results from the preceding sections and presents concluding remarks.

2. IPO Return Data

2.1 Data Sources and Definitions

To assemble our dataset of IPOs between 1965 and 2004, we combine data from several sources. We begin with a sample of IPOs between 1965 and 1973 (excluding 1968) that were used by Downes and

Heinkel (1982) and Ritter (1984b).[3] We fill in data for 1968 by identifying company names and offer dates for IPOs listed in the *Wall Street Journal Index* and then collecting after-market prices from *The Bank and Quotation Record*. For the 1975-1984 period, we use Jay Ritter's (1991) hand-collected data. Finally, we use data from Securities Data Company (SDC) and from the Securities and Exchange Commission (S.E.C.) Registered Offering Statistics (ROS) database. We look through all of the offerings to ensure that none are double-counted because they were listed in multiple databases. In cases where offerings are in multiple databases (e.g., a 1980 IPO in the Ritter 1975-1984 database, the SDC database, and/or the ROS database), we rely first on hand-collected data, second on the SDC data, and last on the ROS data. Finally, from these samples we exclude unit IPOs, closed-end funds, real estate investment trusts (REITs), and American Depositary Receipts (ADRs).

As described in Table 1, these datasets provide us with a total of 11,598 offerings. For each offering we must obtain the initial return. For any IPO included in the Center for Research in Securities Prices (CRSP) database, we obtain the aftermarket price on the 21st day of trading, and the initial return equals the percent difference between this aftermarket price and the offer price.[4] Among those IPOs not included in CRSP, we calculate the initial return using the closing price at the end of the first month of trading (as we do not have price data on the twenty-first trading day). To ensure that our results are not disproportionately affected by extremely small firms, our main analyses restrict the sample to firms with an offer price of at least $5. After requiring that firms have both initial return data and an offer price of at least $5 our dataset consists of 8,608 IPOs: 575 from the 1965-1973 Ritter data, 369 from the 1968 *Wall Street Journal Index* data, 1,187 from the 1975-1984 Ritter data, 17 from ROS, and 6,460 from SDC.

[3] While the 1968 data were included in the original Downes and Heinkel (1982) data, they were lost and therefore not available to us.

[4] We measure returns through the 21st trading day to control for the wide-spread practice of secondary-market price support.

2.2 Descriptive Statistics

Consistent with the findings of prior literature, our sample IPOs are significantly underpriced: the 8,608 IPOs between 1965 and 2004 have a mean initial return of 22%. However, few offerings are underpriced by exactly this amount. In fact, only 500 of our 8,608 sample offerings have an initial return between 20 and 25%. The standard deviation of initial returns is over 55%. Figure 1a illustrates this dispersion. Specifically, Figure 1a shows the histogram of the 8,608 monthly initial returns to IPO investors from 1965-2004, along with a Normal distribution with the same mean and standard deviation as this sample. In addition to having a high standard deviation, the initial return distribution is highly positively skewed and fat-tailed.

Lowry and Schwert (2002, 2004) note that the 1998-1999 period exhibits unusual dispersion of IPO returns. A closer inspection of the chronology of firms going public in 1998-2000 shows that the first very large IPO initial return is for eBay, which went public on September 24, 1998 (the one-day IPO return was 163.2% and the 21-day return was 81.3%). The end of the hot IPO market seems to have occurred in September 2000, as the number of IPOs fell to 21 from 59 in August, while the average IPO initial return fell to 33.1% from 66.2% in August. Thus, throughout the paper we define the internet-NASDAQ bubble period as September 1998 – August 2000.

Figure 1b shows the same histogram of IPO initial returns after omitting the IPOs that occurred during this internet-NASDAQ bubble period. While the histogram is still skewed and fat-tailed, it is more normal looking than the all-inclusive 1965-2004 sample, because there are so many very large IPO returns in the September 1998-August 2000 period. The average IPO return in Fig. 1b is only 15.1%, about two-thirds the size of the corresponding statistic in Fig. 1a, and the standard deviation is also about one-third lower at 34.5%.

Figure 2 shows the monthly mean and standard deviation of IPO initial returns, as well as the number of IPOs per month, from 1965-2004. It is clear from this graph that both the level and the dispersion of IPO initial returns both follow persistent cycles, with high average IPO initial returns and high standard deviations occurring at roughly the same time. Ibbotson and Jaffe (1975), Ibbotson, Sindelar, and Ritter (1988, 1994), and Lowry and Schwert (2002, 2004) have noted this 'hot issues' phenomenon in the number of new issues per month and also in the average initial return per month, but the strong and similar pattern in the dispersion of initial returns is one of the contributions of this paper.

Table 2 contains the descriptive statistics underlying Figure 2. Each month we calculate the mean and standard deviation of initial returns for all IPOs during the month.[5] Columns 2, 3, and 4 show the time-series mean, median, and standard deviation of these two monthly statistics. Column 5 shows the correlation between the monthly mean and standard deviation. Finally, the last six columns show autocorrelations (up to six lags) of the initial return mean and standard deviation measures.

The cross-sectional standard deviation of IPO initial returns is about twice as large as the average IPO initial return, the two statistics are strongly positively correlated (0.863 in the 1965-2004 period), and the autocorrelations of the initial return dispersion are generally similar to those of the initial return mean.[6] Table 2 also contains these same summary statistics for the 1965-1980, 1981-1990, and 1991-2004 subperiods, as well as for the 1991 – 2004 subperiod after excluding the September 1998-August 2000 internet-NASDAQ bubble period. Omitting the data from September 1998-August 2000 makes the remainder of the 1991-2004 period look very similar to the earlier sample periods in terms of the mean, dispersion, and autocorrelations of both initial return means and initial return standard deviations.

This evidence strongly suggests that the conditional distribution of IPO initial returns changes substantially over time, that some of these changes are predictable, and that the average initial return is strongly positively associated with the cross-sectional dispersion of IPO initial returns. The subsequent sections of this paper examine these findings in greater detail, relating the cross-sectional dispersion of IPO initial returns to IPO market conditions, secondary-market volatility, and the characteristics of the

[5] The standard deviation of initial returns is only calculated in months with at least three IPOs. As a result, in Table 2 the number of observations for mean initial returns (i.e., the number of months in which we can calculate this statistic) exceeds the number of observations for the standard deviation of initial returns.

[6] The positive relation between average IPO returns and cross-sectional standard deviations within months partially explains the strong positive skewness and kurtosis shown in the frequency distribution in Figure 1a (see, for example, Clark (1973)).

types of firms that go public at different points in time. The nature of these relations highlights many important facets of the economics underlying the IPO pricing process.

3. Correlations with Market and Firm-specific Stock Volatility

3.1 The Relation between IPO Initial Return Volatility and Market-wide Measures of Volatility

One obvious factor that could explain the strong cycles in the dispersion of IPO returns is the well-known persistence in the volatility of stock market returns. We thus relate the monthly volatility of IPO initial returns to market-wide volatility measures. Monthly initial returns have both time-series and cross-sectional dimensions: the IPOs (by definition) are for different firms, implying a cross-sectional component, and the IPOs occur at different points in the month, implying a time-series component. Therefore, we examine market volatility measures computed in both the time-series and cross-section. The time-series metrics are the traditional monthly standard deviations of daily returns (e.g. Schwert (1989)), computed using equal-weighted portfolios of all firms on CRSP, and also for the sub-sample of firms listed on NASDAQ.[7] The cross-section measures are the standard deviations of firm-specific monthly cumulative returns, again estimated using all firms on CRSP and for the sub-sample of firms listed on NASDAQ.[8]

While the time-series volatility metrics are common in the literature, the cross-section measures are less frequently employed as measures of return volatility. Bessembinder, Chan, and Seguin (1996) are perhaps the first to use such a metric, and they interpret the cross-sectional volatility of returns as an aggregate measure of firm-specific information flows.[9] Stivers (2003) is the first paper to systematically analyze this cross-sectional measure of return volatility and its relation with traditional time-series

[7] We also used value-weighted (by market capitalization) portfolios, but focus on the equal-weighted market portfolios since they are most comparable to our equal-weighted portfolios of IPO returns.

[8] To compute a time-series standard deviation for a given month, we determine the index returns on each day within a month, and then take the standard deviation across these daily index returns. In contrast, to compute a cross-sectional standard deviation for a given month, we first determine the monthly return of each firm in the market, and then take the standard deviation across these N monthly returns.

[9] Bessembinder, Chan, and Seguin (1996) use the mean absolute deviation of abnormal returns, while we employ the standard deviation of raw returns.

measures of volatility, and Stivers labels this measure 'return dispersion.' He shows that in a simple market model, return dispersion computed using raw returns has two components: one related to the dispersion of beta among the sample firms and one related to the volatility of the firm-specific components of stock returns. In the context of a single- or multi-factor model, the latter component can be interpreted as the average firm-specific residual variance. As in Bessembinder, Chan, and Seguin (1996), we use this measure of return dispersion as a proxy for the aggregate flow of firm-specific information, in the sense that months with high flows of information about firm-specific factors will have greater dispersion of firm-specific returns and thus greater average firm-specific residual volatility.

The time-series and cross-sectional measures of volatility that we employ are closely related to the disaggregated volatility measures in Campbell, Lettau, Malkiel, and Xu (2001) [henceforth CLMX]. CLMX decompose traditional time-series metrics of return volatility into market-related, industry-related, and firm-specific components. To gain more insight into the economics behind our time-series and cross-sectional volatility measures, we compute our volatility measures on a value-weighted basis and calculate the correlations between these measures and the CLMX measures (which are similarly value-weighted). Not surprisingly, our traditional time-series volatility measure is highly correlated with CLMX's market volatility component (correlation coefficient = 0.99), as the two series are nearly the same. Our cross-sectional measure of volatility should be strongly related to CLMX's firm-specific measure of volatility, because CLMX's firm-specific volatility component is essentially the value-weighted, average time-series variance of residuals from a simple one factor model (where firm return equals industry return plus a residual). Apart from the weighting scheme and a slightly different return generating model, this is almost exactly the same as a value-weighted cross-sectional volatility measure (as illustrated by Stivers' (2003) exposition, discussed above). Consistent with this intuition, a value-weighted cross-sectional volatility measure has a correlation of 0.79 with the CLMX firm volatility component.

These correlations suggest that our time-series and cross-sectional return volatility measures are capturing significantly different aspects of aggregate return variance. Time-series volatility measures, as traditionally employed in the literature on return volatility, reflect aggregate market return volatility – the extent of movements in stock indices within the month. On the other hand, our cross-sectional return dispersion measures capture aggregate firm-specific volatility – the extent to which firm-specific information flows cause stock prices to move in different directions, or change by different magnitudes, within the month. In this sense, the cross-sectional volatility measures reflect 'market-wide' firm-specific information flows: months with lots of firm-specific news are characterized by greater cross-sectional return dispersion, while months in which most of the news that moves stock prices is related to systematic factors affecting all firms are characterized by lower cross-sectional return dispersion.

Table 3 examines whether initial return volatility covaries with either of these measures of market volatility over time, where both initial return volatility and market volatility are measured at the monthly interval. Looking at the first row, in the full sample from 1965–2004, there is a strong positive correlation between IPO initial return volatility and the cross-sectional measure of market volatility (correlation of 0.25, significant at the 1% level). In contrast, the correlation between IPO initial return volatility and the time-series measure of volatility is only 0.07 and not significantly different from zero. These correlations suggest that the factors that cause initial returns to IPO stocks to be dispersed within a month have little association with market-wide 'news' that causes time-series variation in aggregate indices, but a much closer association with firm-specific factors that also cause spreads in secondary-market returns.

The second row of Table 3 shows similar correlations, substituting the NASDAQ Index for the market-wide Index. Similar to the correlations with the market-wide index shown in row (1), the correlation between initial return volatility and the cross-sectional standard deviation of NASDAQ returns is significantly positive. In addition, there is some association between time-series volatility in the NASDAQ portfolio and IPO initial return volatility, indicating that a subset of market-wide news, specifically news concerning NASDAQ firms (which tend to be younger, smaller, and concentrated in high-tech industries), is positively related to IPO initial return dispersion. This conclusion is reasonable give that NASDAQ firms tend to more closely resemble an average firm going through an IPO, compared to firms listed on the NYSE.

However, the bottom panel of Table 3 indicates that the importance of both cross-sectional and time-series volatility measures is driven by the internet-NASDAQ bubble period.[10] Removing the bubble period from the sample reduces the correlations between IPO initial return dispersion and both time-series and cross-sectional measures of volatility considerably; outside the bubble period the correlation between IPO initial return volatility and the cross-sectional standard deviation of returns is actually significantly negative. In sum, across the vast majority of our sample period, there is no significant positive association between IPO initial return variability and measures of market-wide volatility, whether measured in the time-series or cross-section and whether measured for all firms on the CRSP database or for NASDAQ firms only.

3.2 The Relation between the Mean and Dispersion of IPO Initial Returns

One of the striking results in Table 2 and Figure 2 is that average IPO initial returns are strongly positively correlated with IPO initial return volatility. In contrast, the stylized fact from studies of the time-series behavior of stock market volatility is that time-series volatility and contemporaneous returns are negatively related (see, e.g., French, Schwert, and Stambaugh (1987)). Table 4 illustrates this disparity by showing the correlations between average monthly returns to the market portfolios and contemporaneous time-series and cross-sectional measures of volatility. For either the market-wide portfolio (all stocks available on the CRSP database) or the NASDAQ portfolio, there is a strong negative correlation between the time-series volatility of monthly returns and the realized return to the portfolio during the month (correlations on the order of -0.35 and statistically significant). A comparison of the full sample results shown in the top panel with those in the bottom panel where the internet bubble is excluded indicate that this relation is strong both within and outside of this bubble period. French, Schwert, and Stambaugh (1987) explain this negative relation as a by-product of the positive association

[10] This is consistent with the evidence in Schwert (2002), who shows that technology firms' volatility was unusually high during this period.

between volatility and risk premiums – when volatility rises (unexpectedly), risk premiums increase, inducing a fall in stock prices (holding expectations of future cash flows constant).

In sharp contrast, the correlations between portfolio returns and cross-sectional standard deviations are large and positive for both portfolios in both panels of Table 4 (correlations between 0.43 and 0.56). This is consistent with Ang and Chen's (2002) findings on the relative movements in stocks: they report that stocks tend to move together more when aggregate indices fall and less when they rise. Ang and Chen's evidence implies that the cross-sectional dispersion for the aggregate market would be higher when returns are high and lower when returns are low, which is exactly what we find. The strong positive correlation between the average and dispersion of IPO initial returns (correlation of 0.86 in the full sample) suggests that the dynamics are similar among IPO firms. The next section focuses on understanding the economics behind this phenomenon, in the context of the IPO pricing process.

4. Why Are Average IPO Initial Returns and IPO Initial Return Volatility Related?

To understand the factors underlying the strong positive correlation between the mean and standard deviation of monthly initial returns, we appeal to the IPO literature. In an extension of Rock's (1986) model, Beatty and Ritter (1986) make specific predictions regarding the relation between firm characteristics and the level of underpricing. We consider whether these same characteristics are potentially also related to the dispersion of underpricing.

Rock's model relies on the assumption that a group of market participants (the 'informed') know more than the all other investors (including the issuing firm and its investment bank) about the aggregate demand for the firm's shares and the after-market prospects for the offering. When a firm and its investment bank face greater ex-ante information asymmetry about the value that informed investors will place on an issue, an IPO will have greater *expected* underpricing because representative (uninformed) investors face a larger adverse selection problem (Rock, 1986, and Beatty and Ritter, 1986). Moreover, because the costs of learning about high information asymmetry offerings are higher, investors require greater compensation for becoming informed about such issues (Ritter, 1984a). This suggests that IPOs for firms with greater information asymmetry will have higher initial returns on average, a prediction that has received considerable empirical support (see, e.g., Beatty and Ritter (1986), Ritter (1984a), and Michaely and Shaw (1991)).

As noted in Ritter (1984a), however, there is a second cross-sectional implication of Rock's model: the variability of initial returns should be higher when issuing firms face greater information asymmetry with respect to the after-market price of IPO stocks.[11] Specifically, the information asymmetry faced by certain types of firms generates 'risk' or 'uncertainty' about the after-market price. This uncertainty is related to the fact that, for high-risk issues, the aggregate demand at the offering price is more difficult to estimate. As a result, aggregate demand for the firm's stock can be forecast less precisely for high-risk issues than for low-risk issues.

Extending these ideas to a time-series context suggests a positive relation between the mean and volatility of initial returns. Suppose that during certain periods the companies going public face greater ex-ante information asymmetry and are therefore high-risk issuers. We would expect the initial returns during such periods to have a high mean (to compensate investors for the greater costs of becoming informed) and a high dispersion (because the aggregate demand for such issues is difficult to estimate). This positive relation between the mean and standard deviation is precisely what we observe in the data, and in this section we attempt to discern whether information asymmetry contributes to this positive correlation.

As Ritter (1984a) discusses, the key to adapting Rock's model to data is identifying the right proxies for information asymmetry ('risk' or 'uncertainty'). The appropriate measure would capture the uncertainty that uninformed investors have regarding the secondary-market price. Consistent with this objective, studies of the relation between information asymmetry and initial returns have typically focused on firm- and offer-specific sources of uncertainty, for example firm age and underwriter rank.

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[11] Ritter (1984a), p.221, especially Figure 3 and the discussion thereof.

We take a slightly different approach, by considering the effects of changing levels of information asymmetry over time driven by changes in the types of firms going public. Section 4.1 examines whether the average characteristics of firms going public each month are correlated with the mean and standard deviation of initial returns during the month. Section 4.2 investigates whether these same average characteristics contribute to the positive correlation between the mean and standard deviation of monthly initial IPO returns. Finally, section 4.3 directly examines the extent to which both the level and dispersion of initial IPO returns are related to firm-specific sources of information asymmetry in a time-series context.

4.1 Descriptive Evidence

Our measures of firm- and offer-specific characteristics, which proxy for information asymmetry, include:

(1) **Rank** is the underwriter rank, from Carter and Manaster (1990), as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004). Carter and Manaster suggest that highly ranked underwriters can successfully decrease the amount of information asymmetry surrounding an offering (suggesting a negative relation between rank and underpricing). However, Loughran and Ritter (2004) note that, in recent years, issuers' increased focus on analyst coverage rather than pricing implies that issuers may accept lower offer prices (i.e., greater underpricing) to obtain the best analyst coverage. Because the highly ranked underwriters tend to have the best analysts, this suggests a positive relation between underpricing and rank.

(2) **Log(Shares)** equals the logarithm of the number of shares (in millions) offered in the IPO. Less information tends to be available about smaller offerings, suggesting that information asymmetry will be greater for such issues.

(3) **Tech** equals one if the firm is in a high tech industry [biotech, computer equipment, electronics, communications, and general technology (as defined by SDC)], and zero otherwise. The value of technology firms tends to be much harder to estimate precisely, suggesting that information asymmetry will be greater for such firms.

(4) **VC** equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise. Similar to the underwriter rank logic,

Barry, Muscarella, and Vetsuypens (1991) and Megginson and Weiss (1991) suggest that venture capitalists potentially decrease the amount of information asymmetry surrounding an offering.

(5) **NASDAQ** equals one if the IPO is listed on NASDAQ, and zero otherwise. The Small, young, high-tech firms tend to list on NASDAQ, suggesting that information asymmetry will be especially high for these firms.

(6) **NYSE** equals one if the IPO is listed on the New York Stock Exchange, and zero otherwise. In contrast to Nasdaq, more established firms tend to go public on the NYSE, suggesting that information asymmetry for these firms will be relatively low.

(7) **Log(Firm Age + 1)** equals the logarithm of (1 plus) the number of years since the firm was founded, measured at the time of the IPO. There is likely to be more information asymmetry regarding the secondary-market pricing of the stocks of young firms.

(8) **|Price Update|** is the absolute value of the percentage change between the offer price and the middle of the range of prices in the prospectus. This represents a proxy for the amount of learning that occurs during the registration period when the IPO is first marketed to investors. Substantial learning (i.e., a higher absolute value of price update) is more likely in firms that are subject to more information asymmetry.

Table 5 shows correlations between the monthly average characteristics of firms going public and the monthly means and standard deviations of initial returns. In the first two columns, correlations are computed using the full sample from 1981–2004, the sample period with sufficient IPO characteristic data from SDC. The final two columns contain the same correlations after omitting the internet-NASDAQ bubble period.

Months in which a greater proportion of firms are subject to higher levels of information asymmetry should exhibit both higher mean and a higher standard deviation of initial returns. Specifically, we expect initial returns to be high and more volatile in months when a lower fraction of offerings is underwritten by highly ranked banks or backed by venture capital, months when the average offering is smaller and by a younger firm, months when more companies list on NASDAQ rather than NYSE, and months when the average absolute value of the price update is higher.

Consistent with the information asymmetry hypothesis, both average initial returns and the dispersion of initial returns are substantially higher in months when the firms offering stock are (on average) younger, and when a greater proportion of IPO firms are in high-tech industries. Also, months with more firms listing on NASDAQ tend to have higher initial returns, while months with more firms listing on NYSE tend to have lower initial returns. To the extent that the absolute price update reflects the amount of learning that occurs during the registration period when the IPO is first marketed to investors, the strong positive correlations between this variable and both average initial returns and the dispersion of initial returns are similarly consistent with information asymmetry. The positive correlations of the average and standard deviation of initial returns with underwriter rank, venture capital backing, and shares offered are not consistent with our predictions.

When the internet-NASDAQ bubble period is excluded from the sample, the correlations become much smaller, and many are not reliably different from zero. Firm industry and firm age provide the strongest support for the effects of information asymmetry: months in which more firms are from high technology industries and months in which the average firm is younger exhibit higher average and a higher standard deviation of initial returns. In addition, the correlation between average underwriter rank and the standard deviation of IPO initial returns changes sign in this sub-sample, and it is now consistent with the information asymmetry hypothesis: months in which more IPO firms are advised by higher ranked advisors have lower variability of initial returns. These results provide suggestive evidence regarding the factors underlying the positive relation between the average and standard deviation of initial returns: when a greater fraction of the IPOs represent firms about which investors face greater ex-ante information asymmetry, both average initial returns and the standard deviation of initial returns tend to be higher.

4.2 Regression Analysis

Evidence in the previous section indicates that the portion of 'high information asymmetry' firms in a month contributes positively to both the mean and the standard deviation of initial returns in that month. This suggests that the positive correlation between the mean and standard deviation of monthly initial returns is driven, at least partly, by fluctuations in the types of firms going public over time. Tables 6 and 7 investigate this proposition more directly.

Table 6 contains cross-sectional regressions of initial returns on various firm- and offer-specific characteristics, where these characteristics are intended to proxy for the level of information asymmetry regarding the secondary-market pricing of the issue (and thus the uncertainty regarding the initial return). Specifically, Table 6 contains estimates of several variants of the following regression:

$$\begin{aligned} IR_i = \alpha + \beta_1 \text{Rank}_i + \beta_2 \text{Log}(\text{Shares}_i) + \beta_3 \text{Tech}_i + \beta_4 \text{VC}_i + \beta_5 \text{NYSE}_i + \beta_6 \text{NASDAQ}_i \\ + \beta_7 \text{Log}(\text{Firm Age}_i + 1) + \beta_8 |\text{Price Update}_i| + \beta_9 \text{Bubble}_i + \varepsilon_i. \end{aligned} \quad (1)$$

IR is the IPO initial return, defined as the percent difference between the offer price and the closing price on the 21st day of trading (as described in section 2.1). Bubble equals one if the IPO occurs between September 1998 and August 2000, and zero otherwise. All other variables are defined above.

The primary purpose of the cross-sectional regressions shown in Table 6 is to identify firm and deal characteristics that are likely to be systematically related to initial returns so that we can aggregate the predictions and the prediction errors from these models (at the monthly level) to learn more about the role that information asymmetry plays in explaining the cycles in IPO initial return volatility. While these cross-sectional regressions have many potential statistical problems (for example, correlations in regression errors arising from the time clustering of IPOs), these problems are unlikely to bias the aggregation of predictions and prediction errors.

Our objective is to assess the importance of firm-specific measures of information asymmetry, rather than the recent state of the IPO market. Consistent with this objective, the regression in column (1) of Table 6 includes only firm-specific measures (i.e. excluding the internet-NASDAQ bubble indicator variable). To examine the extent to which the extreme conditions during the internet-NASDAQ IPO bubble of the late 1990s affect our regression estimates, columns (2) and (3) in Table 6 account for this period in two different ways. Column (2) includes an indicator variable that allows the average IPO return to be different between September 1998 and August 2000 (Eq. (1)). Column (3) omits all of the observations between September 1998 and August 2000.

The regressions in Table 6 highlight the importance of the bubble period to the overall 1981-2004 sample. In column (2), the coefficient on the internet-NASDAQ bubble indicator variable implies that average IPO returns were 62% higher during these 24 months, holding other characteristics of the deals constant. Moreover, in both columns (2) and (3), many of the coefficients on the firm- and deal-characteristic variables are different than those in column (1). This indicates that restricting coefficients on all explanatory variables to be constant throughout the entire sample period (including the internet-NASDAQ bubble period, as shown in column (1)) causes misspecification and biased inferences, a conclusion that is consistent with the findings of Lowry and Schwert (2004). As a result, we focus on the regressions shown in columns (2) and (3).

Looking at column (2) of Table 6, results are broadly consistent with those reported in prior literature. Consistent with Loughran and Ritter (2002), Megginson and Weiss (1991), Lowry and Schwert (2004), Ritter (1991), and Beatty and Ritter (1986) we find that smaller offerings, technology firms, firms with venture capital backing, NASDAQ firms, and younger firms have the most underpricing. The positive coefficient on underwriter rank is inconsistent with Carter and Manaster's (1990) reputation hypothesis, but consistent with the findings of Cooney, Singh, Carter, and Dark (2001) and Loughran and Ritter (2004). We also find that firms listing on NYSE have higher initial returns than firms listing on either Amex or the OTC, a result that is inconsistent with predictions. Finally, we find that the absolute value of the price update has a large, positive effect on the initial return. This is consistent with the effect of learning about unexpected investor demand during the book-building period. An absolute price update of 10% is associated with a 10% higher initial return (t-statistic = 8.69).

As mentioned above, the primary purpose of Table 6 is to obtain estimates of the ways in which firm- and deal-specific information asymmetry affect the pricing of each IPO. We use these estimates to investigate whether these same factors contribute to the positive correlation between the monthly mean and standard deviation of initial returns. To achieve this, we aggregate at the monthly level the predicted and residual values of each observation from the Table 6 regressions. We then calculate the mean and standard deviation, across all IPOs in each month, of both these predicted and residual values. Table 7 shows these means, standard deviations, and most importantly the correlations between the means and standard deviations across the raw data, fitted values, and residuals.

Specifically, in each of the three panels of Table 7, the first row represents the sample average of the monthly mean initial return measures (i.e., raw initial returns in the first column, predicted initial returns in the second column, and residual initial returns in the third column). The second row shows the sample average of the monthly standard deviations of the initial return measures. Finally, the third row shows the correlation between the mean and standard deviation, at the monthly interval.

Looking at the top panel in Table 7, we see that the fitted values from the column (2) regression in Table 6 (which employs the entire sample period and includes a dummy variable for the internet-NASDAQ bubble period) captures many of the features of the raw initial returns. Although the regression only explains 24% of the variation in initial returns, the characteristics of the fitted values are similar to those of the raw data. Most importantly, the correlation between the mean and standard deviation of the fitted values is 0.65, compared to 0.91 in the raw data. In contrast, the analogous correlation for the residuals is only 0.36. Consistent with Beatty and Ritter's and Ritter's (1984a) extensions of Rock's model, this suggests that the time variation in information asymmetry results in a significantly positive correlation between the mean and volatility of initial returns, a result that we first found surprising because it is so different from what we observe in secondary market returns.

The second panel in Table 7 is similar, with the exception that the cross-sectional regression of initial returns is estimated on a rolling sample of the previous 500 IPOs. This estimation method accounts more generally for the fact that many determinants of initial returns are not constant over time (see, e.g., Lowry and Schwert, 2004). After accounting for such fluctuations, the importance of information asymmetry as a determinant of the positive correlation between the mean and volatility of initial returns appears even stronger. The correlation between the mean and standard deviation of the fitted values is 0.85, which is very close to the correlation of 0.93 observed in the raw data for the same sample period.

Finally, the last panel shows similar results after omitting the internet-NASDAQ bubble period. Due to the unique characteristics of this period, we want to ensure that results are robust to excluding it. While the correlation between the mean and standard deviation in the raw data is weaker (0.56), the predicted values from the cross-sectional regressions continue to explain a substantial portion of this relation (correlation = 0.39).

In sum, the extensions of Rock's model assert that some IPOs are characterized by greater uncertainty about aggregate demand for the stock and, as a result, about the aftermarket price of the stock. For issues that are characterized by greater information asymmetry, underpricing should be higher on average and more dispersed within the month. Our results suggest that the level of such uncertainty varies over time, resulting in strong patterns in both the mean and volatility of IPO initial returns. Specifically, a substantial portion of the positive correlation between the mean and standard deviation of initial returns is explained by changes in firm- and offer-specific information asymmetry over time.

4.3 The Effects of Firm-specific Information Asymmetry on IPO Initial Return Dispersion

The previous section provided strong support for Beatty and Ritter's and for Ritter's applications of Rock's model in an aggregated time-series framework. This section tests the same ideas on a firm-specific basis, by treating the sequence of IPOs in our sample period as a time-series process. As discussed earlier, many prior papers have employed cross-sectional regressions of initial returns on firm- and offer-specific variables to show that the level of initial returns is positively related to measures of information asymmetry. Table 8 increases our understanding of the pricing of IPOs by capturing not only the cross-sectional characteristics of initial returns, but also the time-series dynamics. Second, in addition to examining the determinants of the *level* of initial returns, our specifications enable us to also investigate the factors that affect the *volatility* of initial returns.

Treating this sample of IPO initial returns as the realization of a time series process is somewhat unusual, because the individual observations represent different firms. The observations are ordered so that they are sequential, but they are not equally spaced in calendar time.[12] Nonetheless, the use of Box-Jenkins (1976) ARMA models to account for residual autocorrelation and the use of Nelson's (1991) EGARCH models to account for residual heteroskedasticity allow us to substantially improve the statistical specification of our models. The EGARCH specification allows us to directly test whether our information asymmetry variables are related to both the level of and the variability of IPO initial returns in similar ways.[13]

Column (1) replicates the regression shown in column (1) of Table 6. As described above, this regression restricts the coefficient estimates to be the same across the entire 1981 – 2004 period. This serves as a baseline regression against which to compare the alternative specifications that capture the time-variation in both the level and the volatility of initial returns. Column (2) adds an ARMA(1,1) process to the baseline regression in column (1). The coefficient on the AR(1) term is close to 1, and the MA term is slightly lower, but also highly significant. As discussed in Schwert (1987), ARMA(1,1) models similar to this occur frequently in financial and economic data, including CPI inflation and measures of stock volatility. The relative magnitude of the AR and MA terms indicates that the residual autocorrelations are small but very persistent. After adding these time-series terms, the Ljung-Box (1979) Q-statistic, which measures the joint significance for the first 20 lags of the residual autocorrelation function, drops from 4,107 to 64, suggesting that the specification has improved dramatically.

[12] In cases where there are multiple IPOs on a single calendar day we randomly order the offerings.
[13] We use Eviews version 5.1 to estimate all of the ARMA and EGARCH models.

While the ARMA terms control for autocorrelation in the level of initial returns, Figure 2 and Table 2 showed that there also exists strong cycles in the volatility of initial returns. Thus, for each regression we also calculate the Ljung-Box Q-statistic for the squared residuals, which is used to identify persistent residual heteroskedasticity. Not surprisingly, we find substantial time-varying heteroskedasticity (Q-statistic equals 1,143, p-value=0.000 in column (2)). This implies the need for some form of autoregressive conditional heteroskedasticity (ARCH) model of the type introduced by Engle (1982).

To address this issue, column (3) adds an EGARCH(1,1) process to the ARMA(1,1) model in column (2). The first thing to note is that the coefficients on several of the explanatory variables change substantially. For example, underwriter rank, which was significantly positive in column (2), is now insignificantly different from zero. These changes are driven by the fact that the EGARCH specification essentially produces weighted least squares estimates, thereby reducing the influence of the internet-NASDAQ bubble period (which had very high variability). Thus, the estimates of the parameters of the regression model look more like the estimates in columns (2) or (3) of Table 6, which adjusted for the internet-NASDAQ bubble period by either adding a differential intercept (column (2)) or by completely omitting that data (column(3)). Finally, consistent with the patterns in raw initial returns shown in Figure 2, the EGARCH parameters indicate that the residual variance is very persistent (the GARCH parameter is 0.997).

Moreover, the asymmetric ARCH coefficient in column (3) is positive (0.031, with an asymptotic t-statistic of 2.61), indicating that unusually large IPO initial returns are associated with a higher variability of subsequent residuals, while unusually low initial returns are associated with a lower variability of subsequent residuals. In light of the very persistent nature of both the level and variance of initial returns, this is broadly consistent with the strong positive correlation between the level and standard deviation of initial returns, as shown in Table 2 and as discussed by Ritter (1984a). As noted previously, this contrasts sharply with what we have come to expect from studies of the variability of secondary-market returns, where positive shocks to returns are followed by low subsequent volatility.

Finally, the Ljung-Box Q-statistic for the squared residuals is much smaller in column (3), a value of 23, with a p-value of 0.205, implying that most if not all of the conditional heteroskedasticity has been modeled adequately.

Column (4) of Table 8 adds the information asymmetry variables to the EGARCH(1,1) process in column (3). This specification allows us to simultaneously examine whether these firm-specific factors affect both the level and variability of IPO initial returns, as suggested by our earlier evidence. Consistent with our expectations, several of the information asymmetry proxies are significantly related to both the mean and the variance of initial returns in the predicted direction. For example, the coefficients on the Technology indicator variable imply that the level of the IPO initial return and also its variability are reliably larger for technology firms (*t*-statistics of 2.45 and 4.47, respectively). Venture-backed IPO's have marginally lower initial return variability (*t*-statistic of -1.84), and firms with large absolute price updates (suggesting more learning during the book building process) have reliably larger IPO initial returns and variability of initial returns (*t*-statistics of 5.53 and 4.87). Finally, consistent with older firms being subject to less information asymmetry, firm age is significantly negatively related to both the level of initial returns (*t*-statistic of -3.32) and the dispersion of IPO initial returns (*t*-statistic of -2.36).

Thus, our most direct tests are strongly consistent with Beatty and Ritter's (1986) and Ritter's (1984a) interpretations of Rock's (1986) model, implying that firm-specific information asymmetry plays a predictable role in both the level and the dispersion of IPO initial returns. The evidence presented here supports the conclusion that firm characteristics that one could naturally expect to be associated with greater uncertainty about demand for the IPO stock and, therefore, about the aftermarket price of the IPO stock, are reliably associated with higher, and more variable, initial returns. Technology companies, companies not backed by a venture capitalist, young firms, and companies about which there is greater price discovery during the IPO registration period have significantly higher dispersion of initial returns than the remainder of the sample. Our tests are also more powerful than those offered previously in this literature: the combined ARMA/EGARCH models in Table 8 jointly model the time-dependence of the data that makes the simpler statistical analysis typically used in the IPO literature problematic, particularly for any sample that includes the Internet bubble period.

5. Conclusion

This paper documents the monthly dispersion of IPO initial returns, and demonstrates that the volatility of initial returns is large on average but varies considerably over time. The dispersion of initial IPO returns each month has a strong positive correlation with average initial returns each month (underpricing) over the 1965–2004 period. This relation is stronger in data from the internet-NASDAQ bubble period (September 1998 to August 2000), but persistently positive across all sub-periods analyzed, and contrasts markedly with the negative correlation between the volatility and mean of secondary-market returns. We hypothesize that the difference stems from the fact that initial returns are fundamentally different from secondary-market returns: initial returns represent the percent difference between the market price and a price set by companies and their underwriters, while secondary-market returns represent the percent difference between two market prices. While companies and their underwriters might have the best information about company-specific information, they face considerable uncertainty about market demand for the issue. Rock (1986), Beatty and Ritter (1986), and Ritter (1984a) hypothesize that this uncertainty about the aggregate demand for IPO stocks generates both higher underpricing (because representative investors face greater costs of becoming informed) and greater dispersion of initial returns (because aggregate demand is underestimated for some issues by more than for others).

While a wide body of prior literature has examined the relation between information asymmetry and the *level* of initial returns, very little evidence exists on the relation between such information asymmetry measures and the *volatility* of initial returns. Through a combination of cross-sectional and time-series analyses, we provide strong support for the volatility prediction first noted in Ritter (1984a). Specifically, we show that periods when more high-information-asymmetry companies are going public tend to have a higher volatility of initial returns. The strong positive correlation between the monthly mean and volatility of initial returns is at least partially attributable to variation in the types of companies going public over time, and specifically to time-series variation in the amount of information asymmetry about companies undertaking an IPO.

This study has several important implications. First, while many researchers have shown that IPO stocks are risky investments over the long-run, we show that they are risky even in the first few weeks of trading. While average initial returns are high, investors are not guaranteed to receive exactly this return and the dispersion in realized initial returns can be considerable. Second, this risk is highest in periods when average returns are highest. Investors should be aware that the precise initial return to an IPO is most uncertain during hot IPO markets, a pattern that is not constrained to any particular period over the past 30 years, but persists, to a varying degree, through all sub-periods. Finally, our research also demonstrates the importance of uncertainty about aggregate market demand in determining both the level and volatility of initial returns. The process of marketing of an issue to institutional investors, for example during the road show, appears able to resolve only a relatively small portion of this uncertainty. Issues for which the most learning occurs during the registration period (suggesting particularly high information asymmetry at the filing date), are characterized by the highest average and the highest volatility of initial returns (suggesting particularly high information asymmetry at the offering date).

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Table 1

Sources of IPO Data

Data Source	Sample Period	Number of IPOs	One-month Initial Return Available	and IPO Price ≥ $5.00
Downes and Heinkel (1982) and Ritter (1984b) [a]	1965-1973 (not 1968)	640	607	575
Wall Street Journal Index [a]	1968	395	392	369
Ritter (1991) [b]	1975-1984	1,524	1,510	1,187
S.E.C. Registered Offering Statistics (ROS) Database [c]	1977-1988	1,407	47	17
Securities Data Corporation (SDC) Database [d]	1970-2004	7,632	6,747	6,460
Total	1965-2004	11,598	9,303	8,608

[a] http://schwert.ssb.rochester.edu/DownesHeinkelRitter.xls
[b] http://bear.cba.ufl.edu/ritter/IPO2609.xls
[c] http://www.archives.gov/research/electronic-records/sec.html#ros
[d] http://www.thomsonib.com/sp.asp

Initial returns are measured as the percent difference between the aftermarket price on the twenty-first day of trading and the offer price.

Table 2

Descriptive Statistics on the Monthly Volatility of Initial Returns

						Autocorrelations: Lags					
	N	Avg	Median	Std Dev	Corr	1	2	3	4	5	6
				1965 – 2004							
Mean IPO Return	443	0.167	0.118	0.258		0.63	0.58	0.58	0.50	0.46	0.45
Std Dev of IPO Returns	386	0.316	0.239	0.282	0.863	0.70	0.64	0.65	0.60	0.57	0.56
				1965 – 1980							
Mean IPO Return	161	0.120	0.050	0.240		0.48	0.45	0.46	0.46	0.42	0.35
Std Dev of IPO Returns	111	0.306	0.234	0.230	0.759	0.34	0.22	0.36	0.32	0.29	0.35
				1981 – 1990							
Mean IPO Return	120	0.093	0.085	0.124		0.48	0.29	0.18	0.14	0.02	0.06
Std Dev of IPO Returns	117	0.215	0.203	0.096	0.550	0.25	0.19	0.10	0.21	0.19	0.17
				1991 – 2004							
Mean IPO Return	162	0.267	0.191	0.312		0.68	0.62	0.64	0.49	0.47	0.47
Std Dev of IPO Returns	158	0.398	0.272	0.371	0.923	0.79	0.73	0.73	0.64	0.62	0.59
				1991 – 2004 (omitting Sept. 1998 – August 2000)							
Mean IPO Return	138	0.166	0.169	0.115		0.30	0.15	0.01	0.01	0.03	-0.03
Std Dev of IPO Returns	135	0.267	0.248	0.100	0.494	0.27	0.11	0.09	0.06	0.18	0.24

Each month, the mean and standard deviation of initial returns is measured across all firms that went public during that month. Initial returns are measured as the percent difference between the aftermarket price on the twenty-first day of trading and the offer price. Corr represents the correlation between the monthly means and standard deviations through time. Months for which there is only one or two IPOs yield an estimate of the mean IPO return, but not an estimate of the standard deviation. Months with three or more IPO's yield an estimate of the standard deviation.

Table 3

Correlations between volatility of initial returns and the time-series and cross-sectional volatility of market indices

	Time-series market volatility measure	Cross-sectional market volatility measure
	January 1965 – December 2004	
Correlation between IR volatility and Market-wide volatility	0.07	0.25***
Correlation between IR volatility and Nasdaq volatility	0.17***	0.24***
	January 1965 – December 2004, omitting September 1998 – August 2000	
Correlation between IR volatility and Market-wide volatility	0.00	-0.12**
Correlation between IR volatility and Nasdaq volatility	0.05	-0.12**

Initial Returns (IRs) are defined as the percent difference between the closing price on the twenty-first day of trading and the offer price. All IPO's between 1965 and 2004 with an offer price of at least $5 are included in the sample. To compute monthly volatility, we compute the daily return on the given portfolio (market-wide index or NASDAQ index). We then calculate the standard deviation of daily portfolio returns for all days in the month. To compute monthly cross-sectional volatility, we compute the monthly return on each stock in the given portfolio (market-wide index or NASDAQ index). We then calculate the standard deviation of these monthly returns across all firms in the portfolio. All portfolios use equal-weights.

** Significantly different from zero at the 5% level.
*** Significantly different from zero at the 1% level.

Table 4

Correlations between the returns to portfolios
and the time-series and cross-sectional volatility of the same portfolios

	Time-series market volatility measure	Cross-sectional market volatility measure
	January 1965 – December 2004	
Correlation between mean and volatility of Market-wide Index returns	-0.39***	0.43***
Correlation between mean and volatility of NASDAQ Index returns	-0.34***	0.56***
Correlation between mean and volatility of initial returns	0.86	
	January 1965 – December 2004, omitting September 1998 – August 2000	
Correlation between mean and volatility of Market-wide Index returns	-0.40***	0.43***
Correlation between mean and volatility of NASDAQ Index returns	-0.36***	0.54***
Correlation between mean and volatility of initial returns	0.69	

Initial returns are defined as the percent difference between the closing price on the twenty-first day of trading and the offer price. All IPO's between 1965 and 2004 with an offer price of at least $5 are included in the sample. To compute monthly volatility, we compute the daily return on the given portfolio (market-wide index or NASDAQ index). We then calculate the standard deviation of daily portfolio returns for all days in the month. To compute monthly cross-sectional volatility, we compute the monthly return on each stock in the given portfolio (market-wide index or NASDAQ index). We then calculate the standard deviation of these monthly returns across all firms in the portfolio. All portfolios use equal-weights.

** Significantly different from zero at the 5% level.
*** Significantly different from zero at the 1% level.

Table 5

Correlations between the moments of IPO initial returns and IPO market characteristics

	1981-2004		1981-2004 (omitting bubble)	
	Average IPO Initial Return	Std Dev of IPO Initial Returns	Average IPO Initial Return	Std Dev of IPO Initial Returns
Average Underwriter Rank	0.15**	0.17***	-0.04	-0.11*
Average Log(Shares)	0.25***	0.27***	0.17***	0.14**
Percent Technology	0.49***	0.48***	0.27***	0.25***
Percent Venture Capital	0.29***	0.25***	0.14*	0.08
Percent NYSE	-0.11**	-0.04	-0.03	0.01
Percent NASDAQ	0.16***	0.10**	0.08	0.03
Average Log(Firm Age + 1)	-0.29***	-0.31***	-0.11*	-0.27***
Average |Price Update|	0.50***	0.56***	0.08	0.14*

This table shows correlations between the monthly average and standard deviation of IPO initial returns and monthly average IPO market characteristics. The sample consists of all IPO's with an offer price of at least $5 that went public between 1981 and 2004. Initial returns are defined as the percent difference between the closing price on the twenty-first day of trading and the offer price. Underwriter Rank is the average Carter-Manaster (1990) underwriter ranking score, as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004). Log(Shares) is the logarithm of the number of shares (in millions) offered in the IPO. Percent Tech is the average of a Technology Dummy equals one if the firm is in a high tech industry [biotech, computer equipment, electronics, communications, and general technology (as defined by SDC)], and zero otherwise. Percent Venture Capital is the average of a Venture Capital Dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC)], and zero otherwise. Each month we determine the percent of firms listing on NYSE and NASDAQ. Log(Firm Age+1) is the logarithm of the number of years since the firm was founded at the time of the IPO plus one. |Price Update| is the absolute value of the percentage change between the offer price and the middle of the range of prices in the initial registration statement. The "bubble" period is defined to be between September 1998 and August 2000. The p-values use White's (1980) heteroskedasticity-consistent standard errors.

* Significantly different from zero at the 10% level.
** Significantly different from zero at the 5% level.
*** Significantly different from zero at the 1% level.

Table 6

Relation between Initial Returns and Firm-Specific Proxies for Information Asymmetry

	(1) 1981-2004	(2) 1981-2004	(3) 1981-2004 Omitting Bubble
Intercept	-0.746	0.167	-0.160
	(-6.30)	(1.52)	(-2.24)
Underwriter Rank	0.009	0.011	-0.002
	(2.77)	(3.40)	(-0.67)
Log(Shares)	0.044	-0.019	0.014
	(5.24)	(-2.41)	(2.89)
Technology Dummy	0.126	0.062	0.050
	(9.60)	(5.16)	(5.53)
Venture Capital Dummy	0.036	0.041	0.011
	(2.33)	(2.83)	(1.19)
NYSE Dummy	0.039	0.081	0.062
	(1.28)	(2.73)	(2.44)
NASDAQ Dummy	0.146	0.107	0.085
	(5.32)	(4.00)	(3.54)
Log(Firm Age+ 1)	-0.034	-0.022	-0.014
	(-6.81)	(-4.85)	(-4.32)
|Price Update|	0.978	0.748	0.243
	(8.83)	(7.28)	(5.94)
Bubble Dummy (9/1998-8/2000)		0.615	
		(14.66)	
R^2	0.145	0.241	0.031
Sample Size	6,632	6,632	5,894

This table shows cross-sectional regressions of IPO initial returns on firm- and offer-specific characteristics. The sample consists of all IPO's with an offer price of at least $5 that went public between 1981 and 2004. Underwriter Rank is the average Carter-Manaster (1990) underwriter ranking score, as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004). Log(Shares) is the logarithm of the number of shares (in millions) offered in the IPO. The Technology Dummy equals one if the firm is in a high tech industry [biotech, computer equipment, electronics, communications, and general technology (as defined by SDC)], and zero otherwise. The Venture Capital Dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC)], and zero otherwise. The NYSE Dummy equals one if the IPO firm will be listed on the New York Stock Exchange, and zero otherwise. The Nasdaq Dummy equals one if the IPO firm will be listed on NASDAQ, and zero otherwise. Log(Firm Age+1) is the logarithm of the number of years since the firm was founded at the time of the IPO plus one. |Price Update| is the absolute value of the percentage change between the offer price and the middle of the range of prices in the initial registration statement. Bubble equals one if the IPO occurs between September 1998 and August 2000, and zero otherwise. The t-statistics, in parentheses, use White's (1980) heteroskedasticity-consistent standard errors. R^2 is the coefficient of determination, adjusted for degrees of freedom.

Table 7

Monthly means and standard deviations of predicted and residual initial returns, 1981 - 2004

	Whole Time Period: *Column 2, Table 6 regression*		
	Raw Data	Fitted Values	Residuals
Average Monthly Value	0.20	0.20	0.00
Std dev of values within each month, averaged across all months	0.32	0.12	0.33
Correlation between mean and standard deviation, monthly interval	0.91***	0.65***	0.36***
	Whole Time Period: *Column 2, Table 6 regression estimated on Rolling Sample of last 500 IPOs*		
	Raw Data	Fitted Values	Residuals
Average Monthly Value	0.21	0.21	-0.01
Std dev of values within each month, averaged across all months	0.33	0.14	0.34
Correlation between mean and standard deviation, monthly interval	0.93***	0.85***	0.29**
	Omitting Bubble Period (September 1998 – August 2000): *Column 3, Table 6 regression*		
	Raw Data	Fitted Values	Residuals
Average Monthly Value	0.14	0.14	-0.01
Std dev of values within each month, averaged across all months	0.24	0.05	0.24
Correlation between mean and standard deviation, monthly interval	0.56***	0.39***	0.47***

To compute Average Monthly Value, we calculate the average initial return each month, and then average this value across all months. For the standard deviation, we compute the standard deviation of initial returns across all IPOs each month, and then average this value across all months. The correlation represents the correlation between this mean and standard deviation at the monthly interval. Fitted values and residuals come from regressions in Table 6. In the second panel, the regression is continuously re-estimated, based on the previous 500 observations.

* Significantly different from zero at the 10% level.
** Significantly different from zero at the 5% level.
*** Significantly different from zero at the 1% level.

Table 8

Relation between IRs and Firm-Specific Proxies for Information Asymmetry, with ARMA(1,1) Errors and EGARCH(1,1) Conditional Volatility, 1981-2004

	(1)	(2)	(3)	(4)
Intercept	-0.746	0.599	0.234	0.249
	(-6.30)	(4.06)	(2.74)	(3.09)
Underwriter Rank	0.009	0.014	0.001	0.003
	(2.77)	(4.24)	(0.46)	(1.06)
Log(Shares)	0.044	-0.047	-0.009	-0.012
	(5.24)	(-4.71)	(-1.54)	(-2.05)
Technology Dummy	0.126	0.054	0.025	0.023
	(9.60)	(4.45)	(2.53)	(2.45)
Venture Capital Dummy	0.036	0.044	0.018	0.017
	(2.33)	(3.07)	(1.84)	(1.79)
NYSE Dummy	0.146	0.111	0.066	0.054
	(5.32)	(4.32)	(2.40)	(1.32)
Nasdaq Dummy	0.039	0.106	0.056	0.046
	(1.28)	(3.70)	(1.97)	(1.04)
Log(Firm Age+1)	-0.034	-0.018	-0.011	-0.011
	(-6.81)	(-3.97)	(-2.84)	(-3.32)
|Price Update|	0.978	0.785	0.210	0.200
	(8.83)	(8.03)	(5.84)	(5.53)
AR(1)		0.991	0.988	0.986
		(217.55)	(287.29)	(258.94)
MA(1)		0.925	0.919	0.921
		(77.48)	(116.70)	(106.06)

EGARCH model: $\log(\sigma^2_t) = \omega + \alpha\, |\varepsilon_{t-1}|/\sigma_{t-1} + \gamma\, \varepsilon_{t-1}/\sigma_{t-1} + \beta \log(\sigma^2_{t-1}) + \sum_{k=1}^{8} c_k X_{kt}$

	(1)	(2)	(3)	(4)
variance intercept, ω			-0.051	-0.184
			(-3.76)	(-0.81)
ARCH, α			0.063	0.150
			(3.38)	(3.29)
Asymmetric ARCH, γ			0.031	0.022
			(2.61)	(1.05)
GARCH, β			0.997	0.939
			(727.71)	(82.76)
Underwriter Rank				0.005
				(0.63)
Log(Shares)				0.008
				(0.45)

Table 8 (continued)

	(1)	(2)	(3)	(4)
Technology Dummy				0.159
				(4.47)
Venture Capital Dummy				-0.062
				(-1.84)
NYSE Dummy				-0.214
				(-0.81)
Nasdaq Dummy				-0.305
				(-0.95)
Log(Firm Age+1)				-0.045
				(-2.36)
|Price Update|				0.433
				(4.87)
Ljung-Box Q-statistic (20 lags)	4,107	64	25	22
(p-value)	(0.000)	(0.000)	(0.125)	(0.226)
Ljung-Box Q-statistic (20 lags, squared residuals)	1,392	1,143	23	13
(p-value)	(0.000)	(0.000)	(0.205)	(0.810)
R^2	0.145	0.284	0.250	0.248
Sample Size	6,632	6,631	6,631	6,631

This table shows regressions of IPO initial returns on firm- and offer-specific characteristics. The sample consists of all IPOs with an offer price of at least $5 that went public between 1981 and 2004, ordered by the date of the offer. The model in column (1) is the same as the model in column (1) of Table 6. Underwriter Rank is the average Carter-Manaster (1990) underwriter ranking score, as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004). Log(Shares) is the logarithm of the number of shares (in millions) offered in the IPO. The Technology Dummy equals one if the firm is in a high tech industry [biotech, computer equipment, electronics, communications, and general technology (as defined by SDC)], and zero otherwise. The Venture Capital Dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC)], and zero otherwise. The NYSE Dummy equals one if the IPO firm will be listed on the New York Stock Exchange, and zero otherwise. The Nasdaq Dummy equals one if the IPO firm will be listed on Nasdaq, and zero otherwise. Log(Firm Age+1) is the logarithm of the number of years since the firm was founded at the time of the IPO plus one. |Price Update| is the absolute value of the percentage change between the offer price and the middle of the range of prices in the initial registration statement. The t-statistics, in parentheses, use heteroskedasticity-consistent standard errors. The Ljung-Box (1979) Q-statistic is based on the first 20 lags of the residual autocorrelation function and has an asymptotic χ^2 distribution under the hypothesis of no autocorrelation. For the EGARCH models in columns (3) and (4), the Ljung-Box Q-statistic is based on the autocorrelations of the standardized residuals. R^2 is the coefficient of determination, adjusted for degrees of freedom.

The data are ordered according to the offer date of the IPO, but they are not equally spaced in time. The models in columns (2)-(4) estimate ARMA(1,1) models [Box and Jenkins(1976)] for the residuals from the model to correct for the autocorrelation of the residuals in column (1), as reflected in the lower Ljung-Box Q-statistics. The Ljung-Box Q-statistics for squared residuals suggest substantial autocorrelation of the conditional variance of the residuals, so the model in column (3) includes an EGARCH(1,1) model for the conditional variance of IPO returns. The model in column (4) also includes the information asymmetry variables that are in the return equation in the conditional variance equation, $\log(\sigma^2_t) = \omega + \alpha\, |\varepsilon_{t-1}|/\sigma_{t-1} + \gamma\, \varepsilon_{t-1}/\sigma_{t-1} + \beta \log(\sigma^2_{t-1}) + \Sigma\, c_k\, X_{kt}$

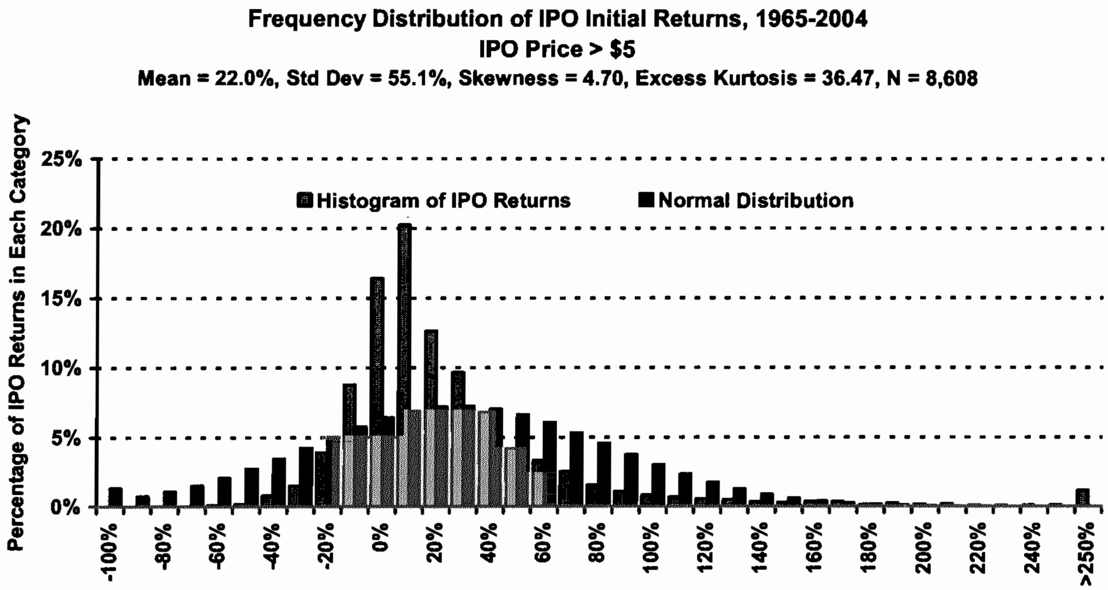

Fig. 1a. Distribution of initial returns to IPO investments, defined as the percent difference between the aftermarket price on the twenty-first day of trading and the offer price. A Normal distribution with the same mean and standard deviation is also shown to highlight the positive skewness and kurtosis of the distribution of IPO returns.

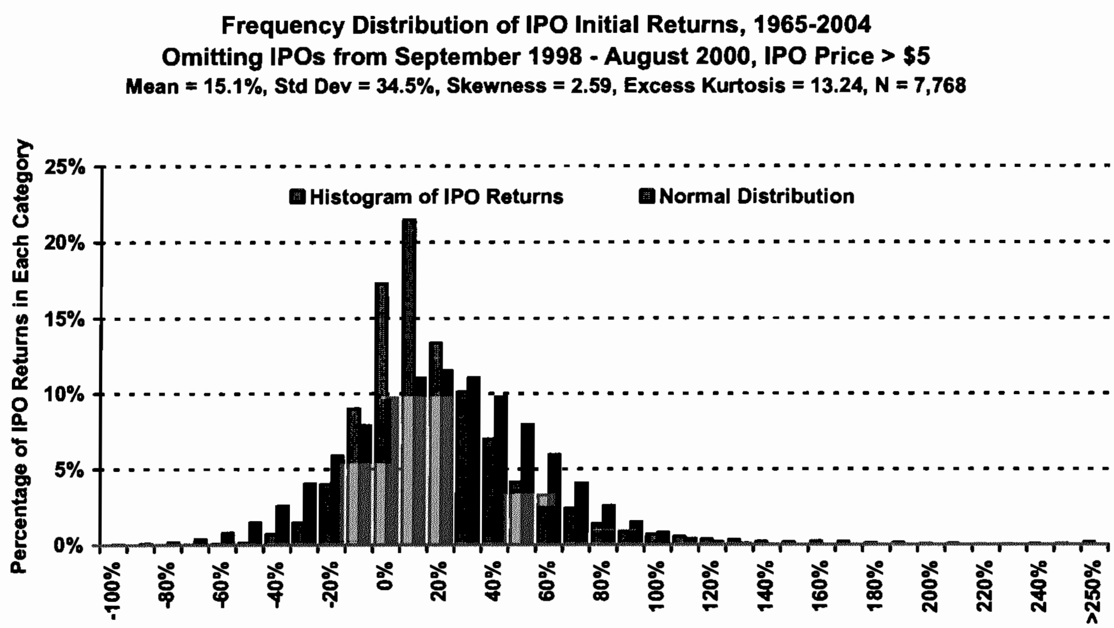

Fig. 1b. Distribution of initial returns to IPO investments, defined as the percent difference between the aftermarket price on the twenty-first day of trading and the offer price. A Normal distribution with the same mean and standard deviation is also shown to highlight the positive skewness and kurtosis of the distribution of IPO returns.

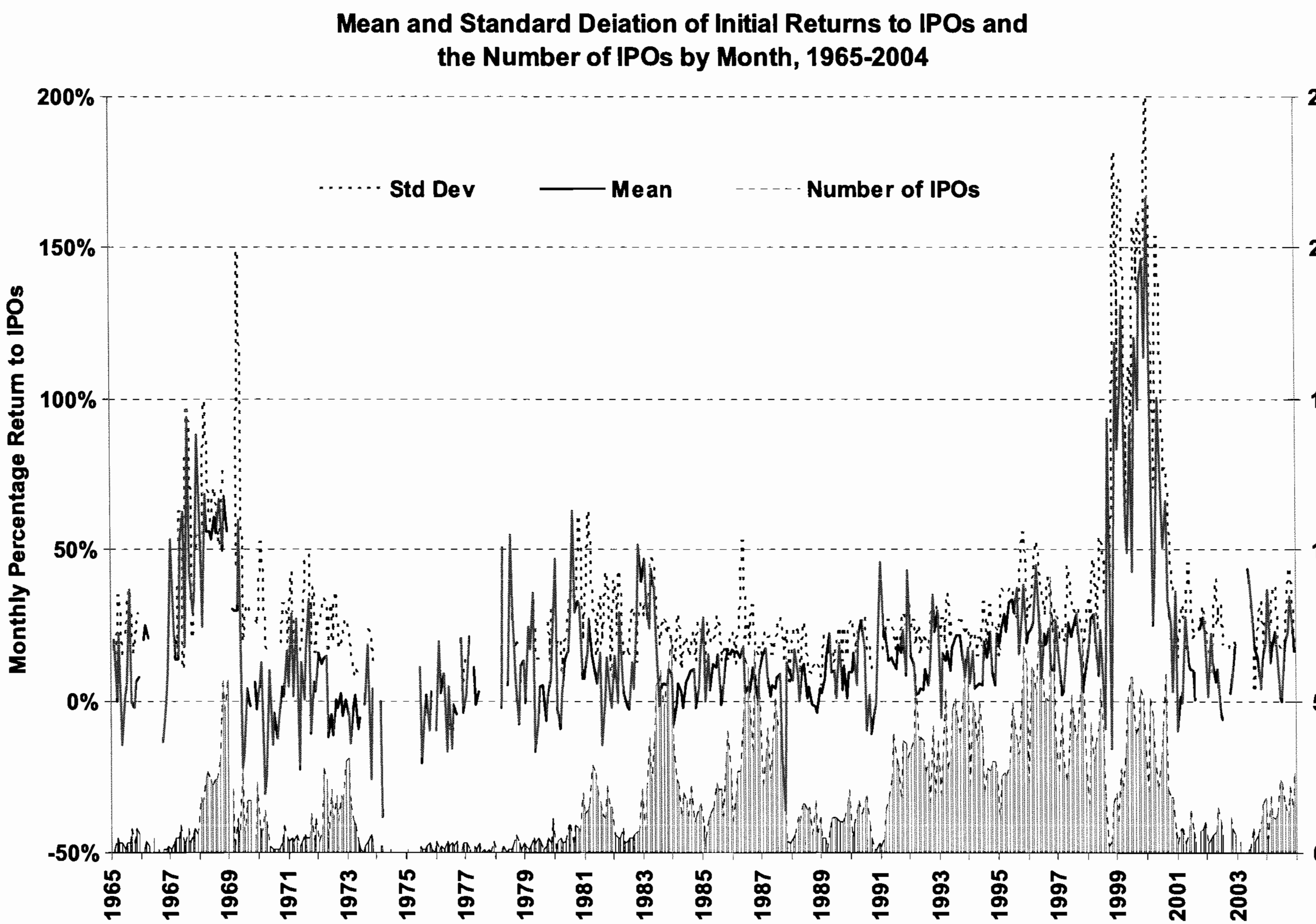

Fig. 2. Initial returns are defined as the percent difference between the aftermarket price on the twenty-first day of trading and the offer price. Each month, the initial returns of each IPO during that month are calculated. The sample consists of IPOs with an offer price of at least $5. The solid line represents average initial returns during the month, and the dotted line represents the standard deviation of these initial returns. The bars represent the number of IPOs per month.