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The Variability of IPO Initial Returns

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ABSTRACT

The monthly volatility of IPO initial returns is substantial, fluctuates dramatically over time, and is considerably larger during "hot" IPO markets. Consistent with IPO theory, the volatility of initial returns is higher for firms that are more difficult to value because of higher information asymmetry. Our findings highlight underwriters' difficulty in valuing companies characterized by high uncertainty, and raise serious questions about the efficacy of the traditional firm-commitment IPO process. One implication of our results is that alternate mechanisms, such as auctions, could be beneficial for firms that value price discovery over the auxiliary services provided by underwriters.

INITIAL PUBLIC OFFERINGS (IPOS) are underpriced on average: The secondary market trading price of a stock is on average much higher than its IPO price. A number of academic papers note that the equity in private companies with uncertain prospects is inherently difficult to value, and they posit that underpricing is an efficient response to the complexity of this valuation problem.[1] In contrast, others have questioned whether the IPO price-setting process results in excess underpricing of IPO stocks.

This article proposes a new metric for evaluating the pricing of IPOs in traditional firm-commitment offerings: the volatility of initial returns to IPO stocks. We find that there is considerable volatility in initial returns. To the extent that the IPO price is a forecast of the secondary market price for the stock, these forecasts are not only biased downward (underpricing), but the range of the

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[1]See, for example, Rock (1986), Beatty and Ritter (1986), Welch (1992), and Benveniste and Spindt (1989), among others.

forecast (or pricing) errors is huge. While underpricing[2] averages 22% between 1965 and 2005, a relatively small portion of offerings have underpricing that is close to this average: Only about 5% of the initial returns are between 20% and 25%. Moreover, nearly one-third of the initial returns are negative. The standard deviation of these initial returns over the 1965 to 2005 period is 55%.

If one considers IPO initial return volatility to be a proxy for the difficulty of pricing IPOs, then one could reasonably expect this volatility to change over time with changes in the complexity of the pricing problem. Consistent with this intuition, we find that the volatility of initial returns fluctuates greatly over time. While prior literature shows the existence of hot IPO markets characterized by extremely high initial returns (see, for example, Ibbotson, Sindelar, and Ritter (1988, 1994)), we find that these hot markets are also characterized by extraordinarily high variability of initial returns. That is, there is a strong positive correlation between the mean and the volatility of initial returns over time.

These descriptive statistics suggest that the level of uncertainty surrounding IPO firms, and correspondingly, underwriters' ability to value these firms, varies over time. 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 in the IPO pricing process: the aggregate demand for the firm's shares (see, for example, Rock (1986)). Aggregate demand uncertainty is one of the principal problems facing issuers and their investment banks when attempting to price an IPO. By definition, the initiation of trading resolves this information asymmetry between the issuing firm and the market; that is, 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.

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). To understand these effects, we examine both variation in the types of firms going public and variation in market-wide conditions.

To the extent that the complexity of the pricing problem is greater for certain types of firms than others, one would expect greater pricing errors when the sample of firms going public contains a larger fraction of highly uncertain firms. A number of theories support this intuition and predict that an investment bank's pricing of an offering should be related to the level of information asymmetry surrounding the company. For example, Beatty and Ritter's (1986) extension of Rock (1986) predicts that companies characterized by higher information asymmetry will tend to be more underpriced on average, a prediction

[2] As discussed in more detail later, to avoid the effects of price support we measure initial returns as the percent change from the offer price to the closing price on the 21st day of trading.

that has received considerable empirical support (see, for example, Michaely and Shaw (1994)). As noted by Ritter (1984a) and Sherman and Titman (2002), information asymmetry should also affect the precision of the price-setting process. Specifically, it should be more difficult to estimate precisely the value of a firm that is characterized by high information asymmetry: Firms with higher uncertainty should have a higher volatility of initial returns. Our results are consistent with these models. In particular, we find that IPO initial return variability is considerably higher when the fraction of difficult-to-value companies going public (young, small, and technology firms) is higher. Given that these types of firms also have higher underpricing on average, this result is also consistent with the positive relation between the mean and volatility of underpricing noted above.

Our findings provide some evidence that the complexity of the pricing problem is also sensitive to market-wide conditions. Specifically, market-wide uncertainty related to IPO-type firms is higher during some periods than others, making it harder for underwriters and investors to accurately value IPOs. Our results on the importance of market conditions complement those of Pástor and Veronesi (2005) and Pástor, Taylor, and Veronesi (2009). Pástor and Veronesi analyze the importance of market-wide uncertainty on firms' decisions to go public. Conditional on going public, we find that similar factors also affect the pricing of the stock.[3]

The results in this article suggest that the complexity of the pricing problem is related to both firm-specific and market-wide factors, and that this complexity limits underwriters' ability to accurately value IPOs. Existing evidence suggests that price discovery is only one of a number of services provided by underwriters, and accurate price discovery may not always be underwriters' primary objective (see, for example, Krigman, Shaw, and Womack (2001) and Houston, James, and Karceski (2006)). Yet even if price discovery is a secondary objective, it is difficult to conjecture why underwriters would deliberately *overprice* one-third of IPO offerings. Furthermore, it may be the case that other services obtained via the bookbuilding method (for example, price support, analyst coverage, market making, placement of shares with long-term investors) can also be packaged with alternative price discovery methods, such as IPO auctions, while also improving the accuracy of IPO price discovery.

Unlike traditional firm-commitment offerings, auctions incorporate the information of all market participants into the setting of the offer price. It is this knowledge of aggregate market demand that gives auctions an advantage over traditional firm-commitment offerings and potentially contributes to more accurate pricing. In a preliminary analysis of a small sample of U.S. IPOs placed using an auction format, we find significant differences in the accuracy of price

[3] Edelen and Kadlec (2005) find that market conditions also affect how aggressively issuers will price the offering. Their findings suggest that variation in issuers' pricing behavior in response to market conditions may also contribute to observed fluctuations in initial returns and/or the dispersion of initial returns over time.

discovery during the IPO period (that is, a significantly lower level and volatility of initial returns for auction IPOs) but little difference in the provision of auxiliary services (analyst coverage and market making) to issuers. The size of the U.S. auction IPO sample limits our power to draw strong conclusions about the relative advantages of the two IPO placement methods available to issuers, but the evidence suggests that the efficacy of the price-setting process cannot explain the dominance of the book building method for IPOs in the United States. Perhaps many issuers place a very high value on underwriters' ability to guarantee certain post-IPO services, such as market making or analyst coverage. In fact, for some issuers, such services may be more important than the most accurate pricing at the time of the IPO, and, as suggested above, it may even be the case that underwriters are not striving to minimize pricing errors but rather are placing more effort in the provision of these auxiliary services. However, other issuers, such as Google, are likely to obtain substantial analyst coverage, market making, etc., regardless of how they structure their IPO. Such issuers are likely to find an IPO auction to be the better alternative.

Our conclusions regarding the difficulty underwriters have in pricing IPOs in traditional firm-commitment offerings are consistent with the findings of Derrien and Womack (2003) and Degeorge, Derrien, and Womack (2007) for the French market. Subsequent to this article, Degeorge, Derrien, and Womack (2010) analyze detailed information from the U.S. market and reach similar conclusions. In contrast, there is a large literature on the accuracy of earnings forecasts, even though the earnings forecasting problem seems relatively easy compared with setting IPO prices, in the sense that the dispersion of forecast errors is much larger for IPO prices.[4]

Our results raise serious questions about the efficacy of the traditional firm-commitment underwritten IPO process, in the sense that the volatility of the pricing errors reflected in initial IPO returns is extremely large, especially for certain types of firms and during "hot market" periods. The patterns observed in the volatility of initial returns over time and across different types of issues illustrate underwriters' difficulty in valuing companies characterized by high uncertainty.

The remainder of this article proceeds as follows. Section I analyzes the unconditional dispersion of IPO initial returns and the time-variation in the dispersion of IPO returns. Section II 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. Section III investigates the influence of market conditions on initial return volatility, and Section IV discusses other possible influences on the variation of initial returns. Based on our findings about initial return volatility, Section V presents some exploratory evidence on the ability of auction methods to improve price discovery when placing IPOs. Section VI summarizes our results and presents concluding remarks.

[4]For example, Gu and Wu (2003) find that the standard deviation of the errors in analysts' forecasts of quarterly earnings, scaled by the prior stock price, is 2.7%.

Table I
Sources of IPO Data, 1965–2005

Initial returns are measured as the percent difference between the aftermarket price on the 21st day of trading and the offer price.

Data Source	Sample Period	Number of IPOs	One-Month Initial Return Available	IPO Price ≥ $5.00
Downes and Heinkel (1982) and Ritter (1984b)[a]	1965–1973 (not 1968)	635	604	573
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	1,394	46	16
Securities Data Corporation (SDC) Database[d]	1970–2005	7,786	6,925	6,614
Total	1965–2005	11,734	9,477	8,759

[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.

I. IPO Return Data

A. Data Sources and Definitions

To assemble our data set of IPOs between 1965 and 2005, 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).[5] 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 to 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 examine 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 (for example, a 1980 IPO in the Ritter 1975 to 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 I, these data sets provide us with 11,734 offerings. To ensure that our results are not disproportionately affected by extremely small firms, we restrict the sample to firms with an offer price of at least $5. After requiring that firms have initial return data and an offer price of at least $5,

[5]The original Downes and Heinkel (1982) data do not include information from 1968.

our data set consists of 8,759 IPOs: 573 from the 1965 to 1973 Ritter data, 369 from the 1968 *Wall Street Journal Index* data, 1,187 from the 1975 to 1984 Ritter data, 16 from ROS, and 6,614 from SDC.

B. Descriptive Statistics

The first question we address is how best to measure the initial return to IPO investors, or equivalently, the pricing error realized by the issuing firm as measured by the percent difference between the IPO price and the subsequent secondary trading market price. Ruud (1993) and Hanley, Kumar, and Seguin (1993) find that underwriter price stabilization activities influence the trading prices of IPO stocks in the days immediately following the offering. Consistent with this result, we find that 12% of the IPOs in our sample have a 0% initial return—a far greater portion of the sample than would be expected in a random draw. To increase the probability that our measure of the aftermarket price is a true reflection of market value, we employ monthly (rather than daily) initial returns in all of our reported analyses. Specifically, 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. For 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 21st trading day). Consistent with price stabilization activities having subsided by this point, the proportion of monthly initial returns exactly equal to 0% is much smaller (4% of the sample) and there are substantially more negative initial returns.

Figure 1 shows the distribution of monthly initial returns to IPOs over a 41-year period. The 8,759 IPOs between 1965 and 2005 have an average monthly initial return of 22% and a large standard deviation of over 55%. Figure 1 also shows 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) and Loughran and Ritter (2004) note that the 1998 to 2000 period exhibits unusual dispersion of IPO returns. A closer inspection of the chronology of firms going public in 1998 to 2000 shows that the first very high IPO initial return is for eBay, which went public on September 24, 1998 (the 1-day IPO return was 163% and the 21-day return was 81%). 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 article we define the "IPO bubble period" as September 1998 to August 2000.

Figure 1 also shows the summary statistics of IPO initial returns after omitting the IPOs that occurred during this IPO bubble period. The average IPO return omitting the bubble period is only 15%, about two-thirds the size for the complete sample, and the standard deviation is also about one-third lower at 34%. Both skewness and kurtosis are similarly much lower.

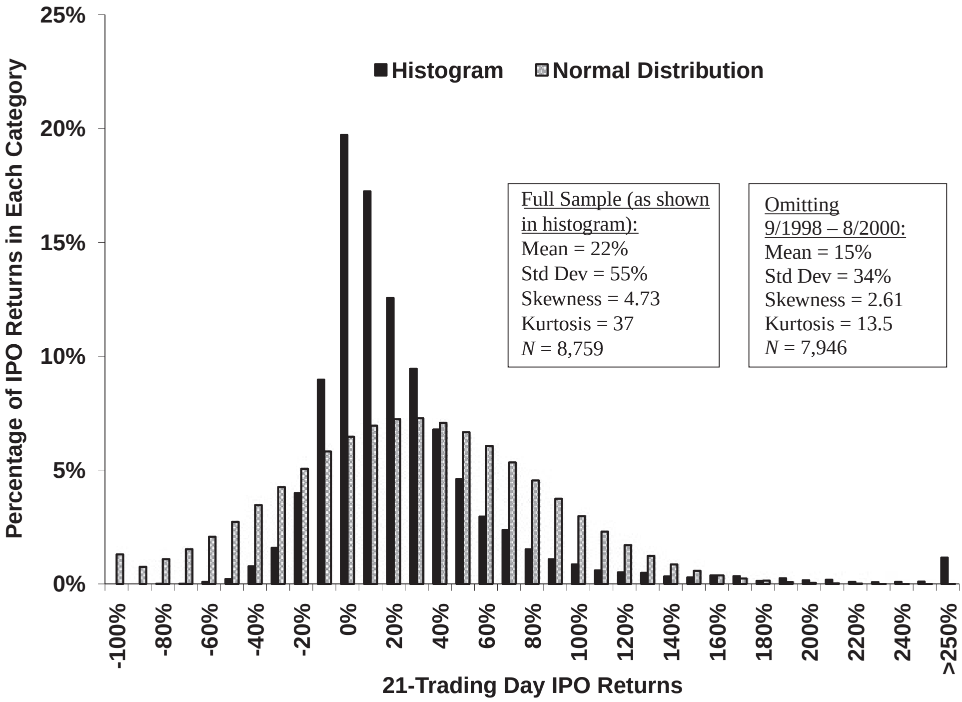

Figure 1. Frequency distribution of first-month IPO returns, 1965–2005. Distribution of initial returns to IPO investments, defined as the percent difference between the aftermarket price on the 21st day of trading and the offer price.

Figure 2 shows the monthly mean and standard deviation of IPO initial returns, as well as the number of IPOs per month, from 1965 to 2005. Both the level and dispersion of IPO initial returns follow persistent cycles, with high average IPO initial returns and high standard deviations within a month occurring at roughly the same time. Ibbotson and Jaffe (1975), Ibbotson et al. (1988, 1994), Lowry (2003), 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 article.

Table II contains the descriptive statistics underlying Figure 2. Each month we calculate the average and standard deviation of initial returns for all IPOs during the month.[6] 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

[6]The standard deviation of initial returns is only calculated in months with at least four IPOs. As a result, in Table II 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.

Table II

Descriptive Statistics on the Monthly Mean and Volatility of IPO Initial Returns

Each month, the average and standard deviation of initial returns are measured across all firms that went public during that month. Initial returns are measured as the percent difference between the aftermarket price on the 21st day of trading and the offer price. The summary statistics in this table reflect the monthly time series of these cross-sectional averages and standard deviations, σ. Corr represents the correlation between the averages and standard deviations over time. Months for which there is only one IPO yield an estimate of the average IPO initial return, but not an estimate of the standard deviation. Months with four or more IPOs yield an estimate of the cross-sectional standard deviation.

						Autocorrelations: Lags					
	N	Mean	Median	Std. Dev.	Corr.	1	2	3	4	5	6
				1965–2005							
Average IPO initial return	456	0.166	0.119	0.256		0.64	0.58	0.58	0.50	0.47	0.45
Cross-sectional σ of IPO IRs	372	0.318	0.242	0.279	0.877	0.73	0.68	0.69	0.64	0.59	0.57
				1965–1980							
Average IPO initial return	162	0.121	0.053	0.237		0.49	0.46	0.46	0.47	0.42	0.35
Cross-sectional σ of IPO IRs	91	0.311	0.251	0.202	0.799	0.37	0.30	0.45	0.41	0.26	0.26
				1981–1990							
Average IPO initial return	120	0.092	0.085	0.120		0.48	0.28	0.16	0.12	0.00	0.05
Cross-sectional σ of IPO IRs	114	0.216	0.202	0.097	0.542	0.24	0.21	0.11	0.24	0.13	0.14
				1991–2005							
Average IPO initial return	174	0.258	0.184	0.310		0.69	0.62	0.64	0.50	0.47	0.47
Cross-sectional σ of IPO IRs	167	0.391	0.266	0.364	0.925	0.79	0.73	0.73	0.65	0.63	0.59
				1991–2005 (omitting September 1998–August 2000)							
Average IPO initial return	150	0.162	0.164	0.113		0.30	0.14	0.01	0.01	0.03	−0.03
Cross-sectional σ of IPO IRs	144	0.266	0.247	0.097	0.500	0.29	0.12	0.10	0.10	0.19	0.24

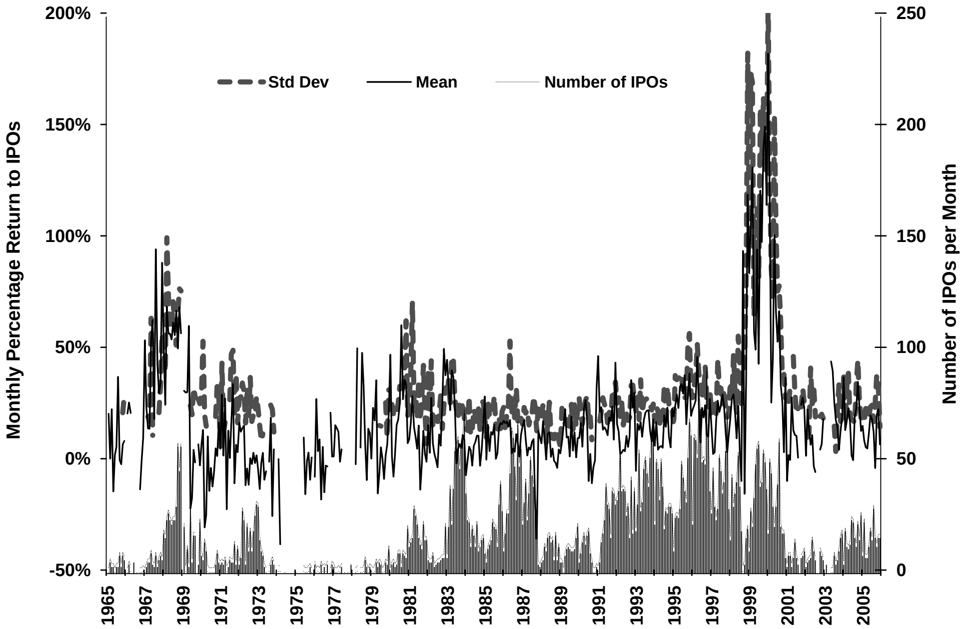

Figure 2. Mean and standard deviation of initial returns to IPOs and the number of IPOs by month, 1965 to 2005. Initial returns are defined as the percent difference between the aftermarket price on the 21st day of trading and the offer price. Each month, the initial returns of each IPO during that month are calculated. 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 (shown on the right Y-axis).

last six columns show autocorrelations (up to six lags) of the initial return average and standard deviation measures. The table shows that 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 (0.877 in the 1965 to 2005 period), and the autocorrelations of the initial return dispersion are generally similar to those of the initial return average.[7] Table II also contains these same summary statistics for the 1965 to 1980, 1981 to 1990, and 1991 to 2005 subperiods, as well as for the 1991 to 2005 subperiod after excluding the September 1998 to August 2000 IPO bubble period. Omitting the data from September 1998 to August 2000 makes the remainder of the 1991 to 2005 period look very similar to the earlier sample periods in terms of the mean, dispersion, and autocorrelations of both initial return averages and standard deviations.

The evidence in Table II strongly suggests that the conditional distribution of IPO initial returns changes substantially over time, that some of these

[7]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 1 (see, for example, Clark (1973)).

changes are predictable, and that the average initial return is strongly positively associated with the cross-sectional dispersion of IPO initial returns. This comovement of the average and standard deviation, and the high standard deviation in months with many deals, are consistent with the fact that the initial return series is highly skewed, as seen in Figure 1. Our objective in this article is to examine the economic factors that drive these statistical patterns. What causes the standard deviation of initial returns to be positively correlated with average initial returns, that is, what causes the distribution of initial returns to be positively skewed? The subsequent sections of this article examine these empirical patterns in detail, relating the dispersion of IPO initial returns to IPO market conditions, to the characteristics of the types of firms that go public at different points in time, and to secondary-market volatility.

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

There is considerable variation in the types of firms that go public. Some firms are over 100 years old, are from well-established industries, and are broadly covered in the media even before filing an IPO. In contrast, other firms are less than 1 year old, are from new industries that are not well understood by the market, and have received little or no media coverage prior to the IPO. Underwriters presumably find it more difficult to value firms about which the market's aggregate demand for shares is more uncertain, that is, for which information asymmetry (as defined in Rock (1986)) is higher. Investment banks may overvalue some and drastically undervalue others, suggesting that the dispersion of underpricing across these types of firms will be quite substantial. In contrast, the greater amount of information available about more established firms should enable underwriters to more precisely estimate market demand for their shares, and therefore more accurately value these companies, meaning the dispersion of initial returns across these firms will be relatively low.

The idea that the dispersion of initial returns is related to the amount of information available about the firm was first suggested by Ritter (1984a), in an extension of Rock (1986) and Beatty and Ritter (1986). Specifically, Ritter (1984a) notes that IPO firms that are characterized by greater information asymmetry should have both greater average initial returns and a greater variability of initial returns.

Extending these ideas to a time-series context, clustering in the types of firms going public will cause time-series patterns in both the mean and the variability of initial returns. Suppose that during certain periods there is greater ex-ante information asymmetry about the companies going public. We would expect initial returns during such periods to have a high mean (to compensate investors for the greater costs of becoming informed) and high dispersion (because the underwriters will find it especially difficult to estimate the value of such issues). Consistent with these ideas, Figure 2 and Table II depict a positive relation between the mean and standard deviation. The remainder of this section more directly examines the extent to which the fluctuations in initial return volatility reflect underwriters' ability to value the types of firms going public at various points in time. In other words, during some periods a greater portion of the IPOs are relatively easy to value, while in other periods more firms are quite difficult to value. Specifically, Section A 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. Sections B and C then directly examine the extent to which both the level and the uncertainty regarding individual firm initial returns are related to firm-specific sources of information asymmetry.

A. Descriptive Evidence

Our measures of firm- and offer-specific characteristics, which proxy for underwriters' ability to accurately estimate firm value, are as follows:

(1) *Rank* is the underwriter rank from Carter and Manaster (1990), as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004). If highly ranked underwriters are better able to estimate firm value, then we should observe 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 (that is, 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 underwriters will have more difficulty valuing 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 because it depends on growth options.

(4) *VC* equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise. If venture capitalists share information about the firm with underwriters, then underwriters may be better able to estimate firm value for such issues.

(5) *NASDAQ* equals one if the IPO is listed on NASDAQ, and zero otherwise. Small, young, high-tech firms tend to list on NASDAQ, suggesting that underwriters will find it more difficult to value 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 underwriters will be better able to value these firms.

(7) *Log*(*Firm Age* + 1) equals the logarithm of (one plus) the number of years since the firm was founded, measured at the time of the IPO. There is likely to be more uncertainty regarding the secondary-market pricing of the stocks of young firms. We use the Field-Ritter data set of founding dates (see Field and Karpoff (2002) and Loughran and Ritter (2004)).

(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 (that is, a higher absolute value of price update) is more likely for firms whose value is more uncertain.

Table III summarizes the variables we use in our subsequent correlation and regression tests. Table IV shows correlations between the monthly average characteristics of firms going public and the monthly averages and standard deviations of initial returns. In the first two columns, correlations are computed using the full sample from 1981 to 2005, the period with sufficient IPO characteristic data from SDC. The final two columns contain the same correlations after omitting the IPO bubble period.

Months in which a greater proportion of firms are subject to higher levels of information asymmetry should exhibit both higher average initial returns 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 backed by venture capital, in months when the average offering is smaller and by a younger firm, in months when more companies list on NASDAQ rather than the NYSE, and in months when the average absolute value of the price update is higher.

Consistent with our predictions, 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 a higher mean and standard deviation of initial returns, while months with more firms listing on the 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 our predictions.

The positive correlation of the average and standard deviation of initial returns with underwriter rank suggests that issuers' focus on analyst coverage dominates any incremental skill that highly ranked underwriters have in accurately valuing companies—perhaps issuers' focus on analyst coverage rather than pricing leads highly ranked underwriters to exert less effort on accurately pricing the issue.

Finally, the positive correlations of the average and standard deviation of initial returns with venture capital backing and shares offered are not consistent

Table III
Variable Definitions

Variable	Definition
IPO initial return	The percent difference between the closing price on the 21st day of trading and the offer price
Underwriter rank	The average Carter–Manaster (1990) underwriter ranking score, as updated by Carter, Dark, and Singh (1998) and Loughran and Ritter (2004)
Log(Shares)	The logarithm of the number of shares (in millions) offered in the IPO
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
Venture capital dummy	Equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise
NYSE dummy	Equals one if the IPO firm will be listed on the New York Stock Exchange, and zero otherwise
NASDAQ dummy	Equals one if the IPO firm will be listed on NASDAQ, and zero otherwise
Log(Firm Age + 1)	The logarithm of the number of years since the firm was founded at the time of the IPO plus one
|Price update|	The absolute value of the percentage change between the middle of the range of prices in the initial registration statement and the offer price
Bubble period	Equals one between September 1998 and August 2000, and zero otherwise
Number of Rec.'s	Maximum number of analysts providing a recommendation during the 6 months following listing
% with Buy Rec.	Percentage of those analysts that recommend a buy or strong buy
Market makers	Number of market makers on the 21st trading day following listing
Turnover	Average daily turnover (trading volume/shares outstanding) in months two through four following listing (that is, excluding the first month after listing)
Fama–French Wholesale-Retail dummy, FF9	Equals one if the IPO firm has an SIC code between 5000–5999, 7200–7299, or 7600–7699, and zero otherwise
Time variable, MTH	Equals one in March 1999 and increments by one each succeeding month.

with our predictions. The positive correlations with venture capital backing potentially indicate that companies backed by venture capitalists tend to be riskier or characterized by greater information asymmetry than other companies, which would bias against finding that venture-backed IPOs are priced more accurately. Thus, venture backing may be picking up a risky industry effect, rather than the effect of venture capitalists' incremental ability to decrease uncertainty. Similar dynamics potentially also affect the underwriter rank coefficient.

When the IPO bubble period is excluded from the sample, the correlations become smaller, and several are not reliably different from zero. Looking at the last two columns, the strongest effects are for the technology and firm age variables: Months in which more firms are from high-technology industries

Table IV

Correlations between the Moments of IPO Initial Returns and IPO Market Characteristics

This table shows correlations between the monthly averages and standard deviations of IPO initial returns and monthly average IPO market characteristics. The sample consists of IPOs between 1981 and 2005 with data available for inclusion in the subsequent regression tests. See Table III for variable definitions. The p-values, in parentheses, use White's (1980) heteroskedasticity-consistent standard errors.

	1981–2005		1981–2005 (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	0.14	0.19	−0.04	−0.08
	(0.016)	(0.002)	(0.561)	(0.235)
Average log(Shares)	0.22	0.26	0.15	0.16
	(0.000)	(0.000)	(0.008)	(0.015)
Percent technology	0.48	0.52	0.26	0.27
	(0.000)	(0.000)	(0.000)	(0.000)
Percent venture capital	0.30	0.32	0.15	0.11
	(0.000)	(0.000)	(0.035)	(0.086)
Percent NYSE	−0.12	−0.07	−0.04	0.01
	(0.006)	(0.065)	(0.540)	(0.890)
Percent NASDAQ	0.17	0.13	0.08	0.04
	(0.000)	(0.003)	(0.163)	(0.517)
Average log(Firm Age + 1)	−0.29	−0.34	−0.12	−0.29
	(0.000)	(0.000)	(0.037)	(0.000)
Average |Price update|	0.50	0.61	0.08	0.19
	(0.000)	(0.000)	(0.257)	(0.008)

and months in which the average firm is younger exhibit a 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 subsample, and the coefficient (although insignificant) is now consistent with highly ranked underwriters having more skill in valuing companies: Months in which more IPO firms are advised by higher ranked advisors have lower variability of initial returns.

In sum, these results in Table IV 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 that are more difficult for underwriters to value, both average initial returns and the standard deviation of initial returns tend to be higher.

B. The Effects of Firm-Specific Information Asymmetry on IPO Initial Return Dispersion

The findings in the previous section suggest that changes in the types of firms going public affect both the level and the variance of monthly initial returns.

Table V examines this proposition more directly. Specifically, Table V shows the results of maximum likelihood estimation, where both the level and the variance of initial returns are modeled as a function of firm- and offer-specific characteristics

$$\begin{aligned}\mathrm{IR}_i &= \beta_0 + \beta_1\,\mathrm{Rank}_i + \beta_2\,\mathrm{Log}(\mathrm{Shares}_i) + \beta_3\,\mathrm{Tech}_i + \beta_4\,\mathrm{VC}_i + \beta_5\,\mathrm{NYSE}_i \\ &\quad + \beta_6\,\mathrm{NASDAQ}_i + \beta_7\,\mathrm{Log}(\mathrm{Firm\,Age}_i + 1) + \beta_8\,|\mathrm{Price\,Update}_i| + \varepsilon_i. \quad (1)\end{aligned}$$

$$\begin{aligned}\mathrm{Log}(\sigma^2(\varepsilon_i)) &= \gamma_0 + \gamma_1\,\mathrm{Rank}_i + \gamma_2\,\mathrm{Log}(\mathrm{Shares}_i) + \gamma_3\,\mathrm{Tech}_i + \gamma_4\mathrm{VC}_i + \gamma_5\,\mathrm{NYSE}_i \\ &\quad + \gamma_6\,\mathrm{NASDAQ}_i + \gamma_7\,\mathrm{Log}(\mathrm{Firm\,Age}_i + 1) + \gamma_8\,|\mathrm{Price\,Update}_i|. \quad (2)\end{aligned}$$

The variance of the error from the regression model in (1), ε_i, is assumed to be related to the same firm- and offer-specific characteristics that are posited to affect the level of initial returns, and following Greene (1993, pp. 405–407) we assume that the log of the variance of the regression error follows the model shown in (2). Maximum likelihood estimation (MLE) of (1) and (2) is essentially weighted least squares estimation of (1) using the standard deviations $\sigma(\varepsilon_i)$ as weights. The advantage of this approach is that it enables us to estimate the influence of each characteristic on both the level and the uncertainty of firm-level initial returns.

As a benchmark against which to compare the MLE results, Table V also shows cross-sectional OLS regressions of initial returns on this same set of firm- and offer-specific characteristics (that is, equation (1)). Table V shows both OLS and MLE results for three different specifications: Column (a) includes the entire sample period, modeling initial returns as shown in equations (1) and (2); column (b) includes the entire sample period, adding an indicator variable (Bubble dummy) that equals one if the IPO occurs between September 1998 and August 2000, and zero otherwise; and column (c) omits all of the observations between September 1998 and August 2000.

In column (b), the coefficient on the IPO bubble indicator in the MLE mean equation implies that average IPO returns were 45% higher during these 24 months, holding other characteristics of the deals constant. Moreover, in both columns (b) and (c), many of the coefficients on the firm- and deal-characteristic variables are different from those in column (a). This indicates that restricting coefficients on all explanatory variables to be constant throughout the entire sample period (including the IPO bubble period) causes misspecification and biased inferences, a conclusion that is consistent with the findings of Loughran and Ritter (2004) and Lowry and Schwert (2004). To avoid such biases without completely omitting the bubble period (arguably an important time in the IPO market), we focus our discussion on column (b).

Focusing first on the mean effect in the MLE results, most findings are consistent with the OLS regressions and with prior literature. Consistent with Loughran and Ritter (2002), Lowry and Schwert (2004), Ritter (1991), and Beatty and Ritter (1986), we find that technology firms, firms with venture capital backing, younger firms, and NASDAQ firms have the most

Table V

Relation between the Mean and Variance of Initial Returns and Firm-Specific Proxies for Information Asymmetry

The columns labeled OLS show cross-sectional regressions of IPO initial returns on firm- and offer-specific characteristics. The sample consists of all IPOs between 1981 and 2005. See Table III for variable definitions. 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.

The columns labeled MLE show maximum likelihood estimates of these cross-sectional regressions where the log of the variance of the IPO initial return is assumed to be linearly related to the same characteristics that are included in the mean equation (for example, Greene (1993), pp. 405–407). The large sample standard errors are used to calculate the t-statistics in parentheses under the coefficient estimates. The log-likelihoods show the improvement achieved by accounting for heteroskedasticity compared with OLS.

	(a) 1981–2005			(b) 1981–2005			(c) 1981–2005, Omitting Bubble		
		MLE			MLE			MLE	
	OLS	Mean	Variance	OLS	Mean	Variance	OLS	Mean	Variance
Intercept	−0.654	−0.188	−6.325	0.181	−0.035	−2.344	−0.117	−0.058	−2.763
	(−5.87)	(−2.61)	(−31.61)	(1.75)	(−0.45)	(−9.49)	(−1.71)	(−0.72)	(−10.18)
Underwriter rank	0.010	0.000	−0.001	0.011	−0.002	−0.044	−0.001	−0.003	−0.061
	(3.06)	(−0.20)	(−0.24)	(3.50)	(−0.98)	(−9.12)	(−0.48)	(−1.28)	(−11.79)
Log(Shares)	0.038	0.017	0.267	−0.020	0.007	0.017	0.011	0.009	0.056
	(4.77)	(3.29)	(17.51)	(−2.64)	(1.27)	(0.95)	(2.43)	(1.66)	(2.84)
Technology dummy	0.123	0.099	0.998	0.060	0.046	0.444	0.048	0.043	0.451
	(9.61)	(6.43)	(51.19)	(5.13)	(4.45)	(15.68)	(5.44)	(4.06)	(14.28)
Venture capital dummy	0.037	0.031	0.300	0.041	0.019	0.154	0.012	0.016	0.121
	(2.41)	(2.37)	(14.53)	(2.84)	(1.94)	(5.18)	(1.35)	(1.62)	(3.47)

(*continued*)

Table V—*Continued*

	(a) 1981–2005			(b) 1981–2005			(c) 1981–2005, Omitting Bubble		
		MLE			MLE			MLE	
	OLS	Mean	Variance	OLS	Mean	Variance	OLS	Mean	Variance
NYSE dummy	0.039	0.044	−0.787	0.078	0.060	−0.657	0.059	0.059	−0.725
	(1.31)	(1.67)	(−13.42)	(2.68)	(1.83)	(−10.47)	(2.33)	(1.73)	(−11.35)
NASDAQ dummy	0.138	0.080	0.204	0.099	0.071	−0.204	0.078	0.069	−0.257
	(5.16)	(3.26)	(5.27)	(3.77)	(2.26)	(−4.83)	(3.30)	(2.10)	(−5.84)
Log(Firm age + 1)	−0.033	−0.013	−0.280	−0.021	−0.011	−0.176	−0.013	−0.010	−0.162
	(−6.81)	(−3.36)	(−30.07)	(−4.69)	(−2.98)	(−15.51)	(−4.16)	(−2.77)	(−13.49)
|Price update|	0.969	0.238	2.820	0.739	0.206	1.730	0.241	0.174	1.767
	(8.89)	(4.70)	(40.46)	(7.32)	(5.07)	(17.59)	(6.02)	(4.08)	(14.87)
Bubble dummy (9/1998–8/2000)				0.620	0.445	2.335			
				(14.78)	(8.93)	(60.97)			
R^2	0.142			0.240			0.030		
Log-likelihood	−5,169.620	−2,875.73		−4,752.578	−1,844.798		−1,079.842	−702.7833	
Sample size		6,840			6,840			6,103	

underpricing. We also find that firms listing on the NYSE have higher initial returns than firms listing on either Amex or the OTC, a result that is inconsistent with predictions. Underwriter rank has a significantly positive coefficient in the OLS specification, which is inconsistent with Carter and Manaster's (1990) reputation hypothesis, but it becomes insignificant in the maximum likelihood estimation.[8] 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 2.06% higher initial return (t-statistic = 5.07) in the MLE mean equation.

Turning to the variance portion of the MLE, we find that the firm and offer characteristics that predict average underpricing are even more strongly related to the volatility of underpricing. The signs of the coefficients in the mean equations are almost always the same as in the variance equation, and the asymptotic test statistics are generally much larger in the variance equation. The exceptions are the exchange listing indicator dummies, which the model predicts to have small positive effects on the incremental mean initial return but negative effects on the variability of initial returns.

Overall, our findings are consistent with our predictions, and with earlier literature suggesting that information asymmetry should affect both the level of the offer price and the precision of the price-setting process (see, for example, Beatty and Ritter (1986), Ritter (1984a), and Sherman and Titman (2002)). When the types of firms going public are especially difficult to value, both the mean and the variability of initial returns are relatively high. In contrast, when the types of firms going public are easier to value, both the mean and the variability of initial returns are substantially lower. Comparison of the log-likelihoods of the OLS regressions with the maximum likelihood estimates (that account for differences in the variability of IPO initial returns) shows that modeling the uncertainty of IPO initial returns is a substantial improvement in explaining the behavior of these data. For example, using a conventional large sample test, twice the difference of the log-likelihoods would have a χ^2 distribution with degrees of freedom equal to the number of explanatory variables in (2). P-values for these tests (of the null hypothesis that the maximum likelihood estimation does not improve the fit of the model over the OLS estimation) are all close to zero.

The strength of the relations between IPO firm characteristics and the volatility of initial returns in Table V suggests that variation in the types of firms going public over time may also contribute to the time-series patterns in initial return volatility. Table IV provides suggestive evidence in support of this conjecture; however, the results from Table V enable us to examine the conjecture more directly. Specifically, the fitted values of initial returns, as obtained from the MLE estimates in column (a) of Table V, should represent the

[8]The finding of a positive coefficient for underwriter rank is consistent with the results of Cooney et al. (2001) and Loughran and Ritter (2004).

portion of initial returns that is attributable to information asymmetry.[9] For example, to the extent that there is more information asymmetry about young firms, we expect underpricing for these firms to be greater and the pricing to be less precise—their *expected* initial return would be higher and the dispersion of *expected* initial returns greater, ceteris paribus, than an older firm. Thus, Figures 3 and 4 aggregate the expected initial returns from Table V by month, and plot the monthly mean and volatility of both raw and expected initial returns. If variation over time in the types of firms going public contributes to the time-series patterns in raw initial returns, then we should observe similar patterns in the fitted values of initial returns as we see in the raw data. Figures 3 and 4 show that this is in fact the case. The averages and standard deviations of IPO initial returns co-move with the averages and standard deviations of the predictions from the MLE model. Therefore, this figure shows that some of the serial correlation in both average returns and standard deviations can be explained by time clustering of the types of firms that have IPOs at different times.

C. Time-Series Variation in IPO Initial Returns and Return Dispersion

To the extent that the relation between initial returns and the types of firms going public has both cross-sectional and time-series components (as suggested by Table V and Figures 3 and 4), there are obvious benefits to modeling these effects jointly. Moreover, there are likely to be additional time-series factors, such as varying market conditions, which also affect the pricing of IPOs. Therefore, we treat the sequence of IPOs in our sample period as a time-series process, thereby enabling us to examine the effects of firm characteristics on the level of underpricing, the effects of firm characteristics on the precision of underpricing, and the time-series dynamics between IPOs adjacent to one another in time (that is, due to both clustering in firm type and variation in market conditions).

Treating the 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.[10] Nonetheless, the use of Box and 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 regressions.

Column (a) in Table VI replicates the MLE model shown in column (a) of Table V. This serves as a baseline model against which to compare the alternative specifications that capture the time-variation in both the level and the

[9]Note that we choose to use the fitted values from column (a), which capture only the effects of firm-specific information asymmetry and do not control for any time-series effects. The next section more directly models time-series effects.

[10]In cases where there are multiple IPOs on a single calendar day, we randomly order the offerings.

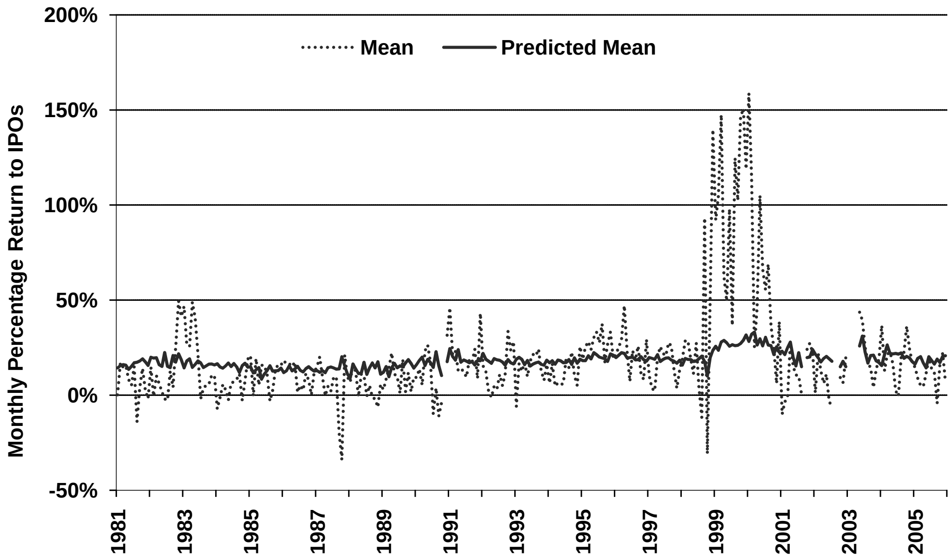

Figure 3. Actual and predicted average of IPO initial returns by month, 1981–2005. Initial returns are defined as the percent difference between the aftermarket price on the 21st day of trading and the offer price. Each month, the initial returns of each IPO during that month are calculated. The dotted line represents average initial returns during the month. The solid line represents average predicted initial returns during the month from the MLE model in column (a) of Table V

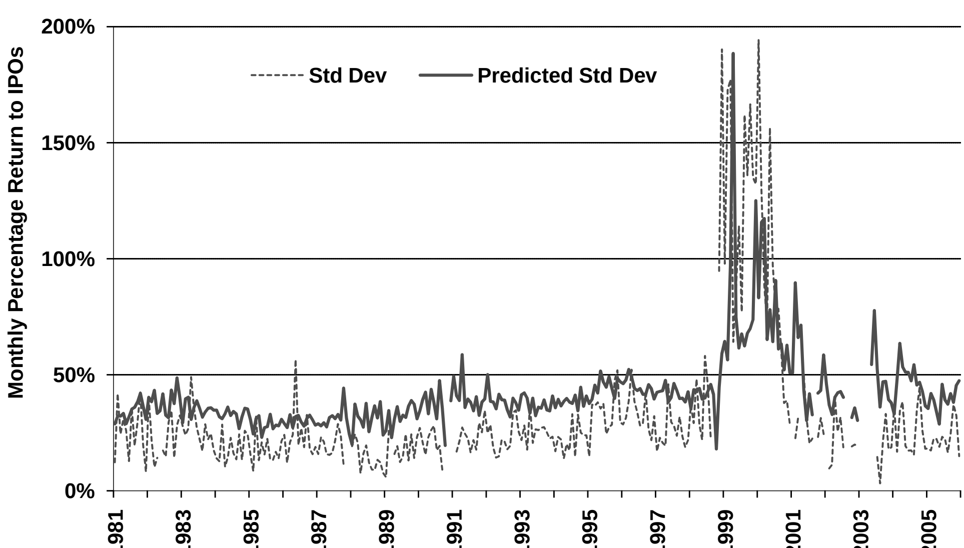

Figure 4. Actual and predicted volatility of IPO initial returns by month, 1981–2005. The dotted line represents the standard deviation of IPO initial returns. The solid line represents the standard deviation of the predicted initial returns from the model in column (a) of Table V.

Table VI

Relation between Initial Returns and Firm-Specific Proxies for Information Asymmetry, with ARMA(1,1) Errors and EGARCH(1,1) Conditional Volatility, 1981–2005

This table shows maximum likelihood estimates of these cross-sectional regressions where the log of the variance of the IPO initial return is assumed to be linearly related to the same characteristics that are included in the mean equation (for example, Greene (1993), pp. 405–407). The sample consists of IPOs between 1981 and 2005, ordered by the date of the offer. See Table III for variable definitions. The large sample standard errors are used to calculate the t-statistics in parentheses under the coefficient estimates. The Ljung and Box (1979) Q-statistic is based on the first 20 lags of the autocorrelation function of the standardized residuals (or the squared standardized residuals) and has an asymptotic χ^2 distribution under the hypothesis of no autocorrelation. The data are ordered according to the offer date of the IPO, but they are not equally spaced in time. The models in columns (b) and (c) estimate ARMA(1,1) models (Box and Jenkins (1976)) to correct for the autocorrelation of the residuals in the mean equation (1). The model in column (c) includes an EGARCH(1,1) model (Nelson (1991)) in (3) that corrects for autocorrelation in the conditional variance of the residuals from the mean equation (1). The log-likelihoods show the improvement achieved by accounting for autocorrelation in the mean equation and in the conditional variance.

$$\mathrm{IR}_i = \beta_0 + \beta_1 \mathrm{Rank}_i + \beta_2 \mathrm{Log(Shares}_i) + \beta_3 \mathrm{Tech}_i + \beta_4 \mathrm{VC}_i + \beta_5 \mathrm{NYSE}_i + \beta_6 \mathrm{NASDAQ}_i + \beta_7 \mathrm{Log(Firm\,Age}_i + 1) + \beta_8 |\mathrm{Price\,Update}_i| + [(1-\theta L)/(1-\phi L)]\varepsilon_i. \quad (1)$$

$$\mathrm{Log}(\sigma^2(\varepsilon_i)) = \gamma_0 + \gamma_1\,\mathrm{Rank}_i + \gamma_2 \mathrm{Log(Shares}_i) + \gamma_3\,\mathrm{Tech}_i + \gamma_4\,\mathrm{VC}_i + \gamma_5\,\mathrm{NYSE}_i + \gamma_6\,\mathrm{NASDAQ}_i + \gamma_7\,\mathrm{Log(Firm\,Age}_i + 1) + \gamma_8\,|\mathrm{Price\,Update}_i|. \quad (2).$$

$$\text{EGARCH model}: \log(\sigma_t^2) = \omega + \alpha \log\left[\varepsilon_{i-1}^2/\sigma^2(\varepsilon_{i-1})\right] + \delta \log\left(\sigma_{t-1}^2\right). \quad (3)$$

$$\mathrm{Var}(\varepsilon_i) = \sigma_t^2 \cdot \sigma^2(\varepsilon_i). \quad (4)$$

	(a)	(b)	(c)
Intercept	−0.188	0.183	0.169
	(−2.61)	(2.50)	(12.15)
Underwriter rank	0.000	0.002	0.004
	(−0.20)	(1.06)	(10.88)
Log(Shares)	0.017	−0.011	−0.010
	(3.29)	(−2.07)	(−10.91)
Technology dummy	0.099	0.067	0.069
	(6.43)	(4.75)	(53.84)
Venture capital dummy	0.031	0.030	0.043
	(2.37)	(2.49)	(36.28)
NYSE dummy	0.044	0.060	0.064
	(1.67)	(2.27)	(15.00)
Nasdaq dummy	0.080	0.072	0.061
	(3.26)	(2.86)	(15.26)
Log(Firm age + 1)	−0.013	−0.009	−0.012
	(−3.36)	(−2.46)	(−27.61)
|Price update|	0.238	0.249	0.153
	(4.70)	(5.34)	(20.97)
AR(1), ϕ		0.948	0.963
		(203.13)	(803.07)
MA(1), θ		0.905	0.911
		(122.23)	(496.25)
Variance intercept, γ_0	−6.325	−7.044	1.303
	(−31.61)	(−39.77)	(5.20)
Underwriter rank	−0.001	−0.016	−0.027
	(−0.24)	(−4.03)	(−7.54)

(*continued*)

Table VI—*Continued*

	(a)	(b)	(c)
Log(Shares)	0.267	0.325	−0.167
	(17.51)	(23.87)	(−10.89)
Technology dummy	0.998	0.904	0.379
	(51.19)	(47.62)	(17.31)
Venture capital dummy	0.300	0.255	0.255
	(14.53)	(12.88)	(10.51)
NYSE dummy	−0.787	−0.686	−0.467
	(−13.42)	(−12.17)	(−7.49)
Nasdaq dummy	0.204	0.174	−0.046
	(5.27)	(4.68)	(−1.28)
Log(Firm age + 1)	−0.280	−0.284	−0.182
	(−30.07)	(−31.94)	(−19.23)
|Price update|	2.820	2.661	1.475
	(40.46)	(39.99)	(19.47)
ARCH intercept, ω			0.025
			(31.19)
ARCH, α			0.016
			(30.39)
GARCH, δ			0.984
			(1,730.14)
Ljung-Box Q-statistic (20 lags)	2,848	129	57
(p-value)	(0.000)	(0.000)	(0.000)
Ljung-Box Q-statistic (20 lags, squared residuals)	301	317	67
(p-value)	(0.000)	(0.000)	(0.000)
Log-likelihood	−2,875.73	−2,611.20	−1,684.83
Sample Size	6,840	6,839	6,839

volatility of initial returns. In Column (b) we add an ARMA(1,1) process to the mean equation in column (a). The AR coefficient estimate is close to one, and the MA coefficient estimate is slightly lower, but also highly significant. The relative magnitude of the AR and MA terms indicates that the residual autocorrelations are small but very persistent, a common pattern in financial time series.[11] After adding these time-series terms, the Ljung and Box (1979) Q-statistic, which measures the joint significance for the first 20 lags of the residual autocorrelation function, drops from 2,848 to 129, suggesting that the specification has improved dramatically.

While the ARMA terms control for autocorrelation in the level of initial returns, Figure 2, Table II, and Figure 4 show that there also exist strong cycles in the volatility of initial returns. Consistent with this evidence, the Ljung-Box Q-statistic for the squared residuals, which is used to identify persistent residual heteroskedasticity, shows substantial time-varying heteroskedasticity (Q-statistic of 317, p-value = 0.000 in column (b) of Table VI). The final column adds terms to capture such autoregressive conditional heteroskedasticity

[11] As discussed in Schwert (1987), ARMA(1,1) models similar to this occur frequently in financial and economic data, for example, CPI inflation and measures of stock volatility.

(ARCH; see Engle (1982)).

Specifically, in column (c) of Table VI we add an EGARCH(1,1) process to the ARMA(1,1) model in column (b),

$$\log\left(\sigma_t^2\right) = \omega + \alpha \log\left[\varepsilon_{i-1}^2/\sigma^2(\varepsilon_{i-1})\right] + \delta \log\left(\sigma_{t-1}^2\right). \tag{3}$$

Thus, the variance of the error of the mean equation, ε_i, is the product of the EGARCH factor from (3), σ_t^2, and the cross-sectional factor from (2), $\sigma^2(\varepsilon_{i-1})$,

$$\mathrm{Var}(\varepsilon_i) = \sigma_t^2 \cdot \sigma^2(\varepsilon_i). \tag{4}$$

By capturing the time-series persistence in both the level and the variance of initial returns, this model should best capture the dynamics first observed in Figure 2. The first thing to note is that the standard errors for the coefficients in the mean equation (1) are much lower after adding the EGARCH factors to the model. This reflects the fact that the EGARCH model does a better job making the weighted least squares adjustment than just using the cross-sectional variance model shown in column (b).[12] Also, some of the coefficients of the information asymmetry variables in the variance equation (2) change substantially after including the EGARCH parameters in the model. For example, larger offers, as reflected in Log(Shares), have significantly lower variability of initial returns after accounting for time-variation in the volatility of returns in the IPO market. Also, the increase in uncertainty about technology IPOs is much smaller and IPOs listed on NASDAQ no longer have greater initial return volatility after taking into account the EGARCH parameters. These changes are driven by the fact that the EGARCH specification accounts for time-series effects in both the mean equation and the volatility equation, thereby reducing the influence of the IPO bubble period (which had very high variability).

Finally, the EGARCH parameters indicate that the residual variance is very persistent (the GARCH parameter is 0.984). Consistent with the patterns in raw initial returns seen in Table II and Figure 2, the EGARCH model suggests that the persistence in the mean and variance of initial returns are driven by similar factors. Finally, the Ljung-Box Q-statistic for the squared residuals is much smaller in column (c), a value of 67, implying that most of the conditional heteroskedasticity has been modeled adequately.

The evidence presented here supports the conclusion that firm characteristics that one could naturally expect to be associated with greater uncertainty about the aftermarket price of the IPO stock are reliably associated with higher, and more variable, initial returns. Technology companies, young firms, and companies about which there is greater price discovery during the IPO registration period have significantly higher dispersion of initial returns than

[12]We suspect that the increase in the t-statistics in the mean equation in column (c) is too large. However, given that nearly all the information asymmetry variables are reliably different from zero in column (b)—before we improve the specification by adding the GARCH terms—the exact magnitude of the increase in significance between column (b) and (c) is relatively unimportant.

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 VI 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 IPO bubble period.

III. The Relation between the Dispersion of IPO Initial Returns and Market Volatility

The significance of the time-series variables in Table VI suggests that other factors, beyond firm characteristics, have an important effect on IPO pricing. One additional factor that could explain the strong cycles in the dispersion of IPO returns is the well-known persistence in the volatility of secondary stock market returns. In particular, the peak in both the average level and the standard deviation of the initial returns to IPOs during the IPO bubble period is reminiscent of the high volatility of NASDAQ stock returns during this period (for example, Schwert (2002)). It seems plausible that both underwriters and investors would have greater difficulty valuing IPO firms when the level of market-wide uncertainty about prices and value is especially high.

To provide descriptive evidence on the importance of market-wide uncertainty, Figure 5 shows the implied volatility of the Standard & Poor's composite index (VIX) and the NASDAQ composite index (VXN), both from the Chicago Board Options Exchange (CBOE). Notably, there does seem to be a pronounced jump in market volatility in late August 1998. However, the biggest increases in market volatility on NASDAQ occurred starting in early 2000 and continued through the end of 2001. Figure 6 shows the ratio of these measures of volatility from 1995 to 2005. To the extent that the volatility of the NASDAQ index reflects uncertainty about the value of growth options, this ratio should mimic the uncertainty in IPO pricing. The September 1998 to August 2000 period is identified by the dashed line in Figure 6. It is clear from Figure 6 that market uncertainty about the value of NASDAQ stocks began to rise from a historically low level relative to S&P volatility in September 1998 and it continued to rise throughout the IPO boom period. However, NASDAQ market volatility remained high until July 2002, long after the IPO market had been very quiet in terms of average initial returns, the volatility of initial returns, and the number of IPOs. Thus, this figure provides preliminary evidence that is inconsistent with the notion that secondary market volatility explains the volatility of IPO initial returns.

To investigate more rigorously the link between market-wide volatility and our measures of the monthly volatility of IPO initial returns, we first must determine the appropriate measure(s) of market-wide volatility. 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

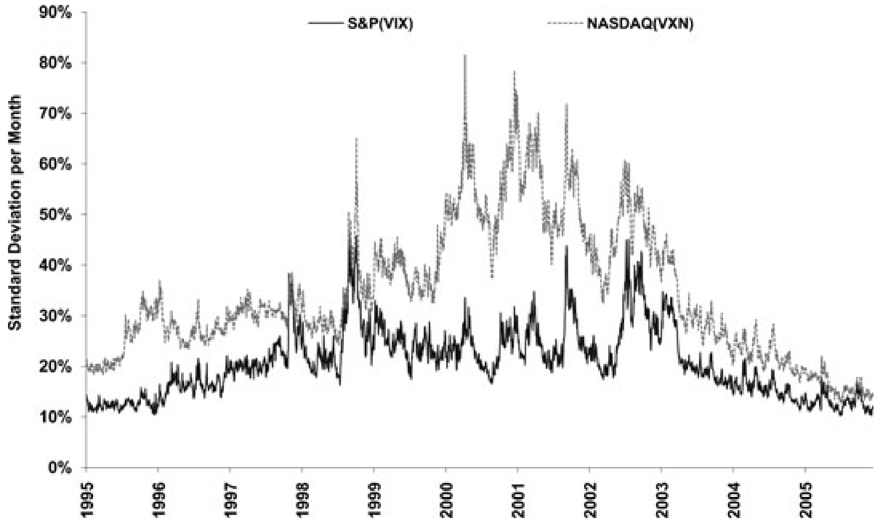

Figure 5. Implied volatility of S&P and NASDAQ composite indexes, 1995–2005. Monthly standard deviations of returns to the S&P (VIX) and NASDAQ (VXN) composite indexes implied by option prices from the CBOE.

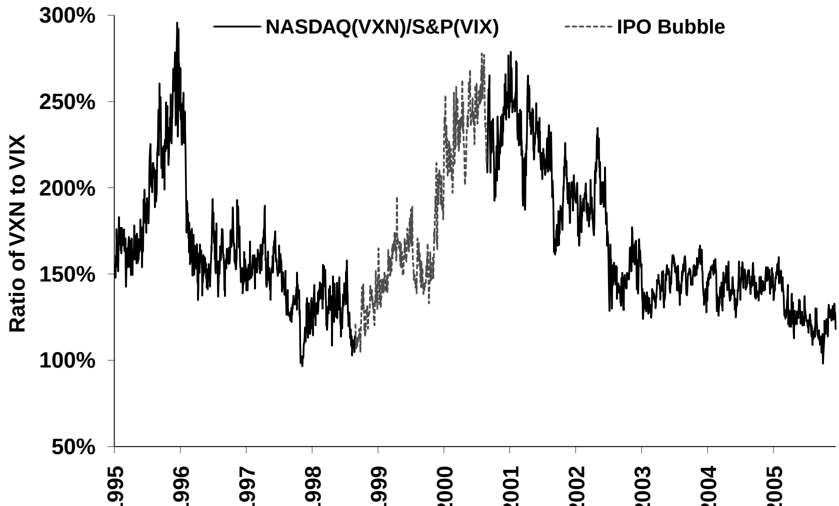

Figure 6. Ratio of implied volatility of NASDAQ to S&P composite indexes, 1995–2005. The "IPO bubble period" from September 1998 through August 2000 is identified by the dashed line.

traditional monthly standard deviations of daily returns (for example, Schwert (1989)), computed using equal-weighted portfolios of all firms listed on NASDAQ.[13] The cross-section measures are the standard deviations of firm-specific monthly cumulative returns, again estimated using all firms listed on NASDAQ.[14]

These time-series and cross-sectional return volatility measures capture different aspects of aggregate return variance.[15] 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 to change by different magnitudes, within the month (see, for example, Bessembinder, Chan, and Seguin (1996) and Stivers (2003)). In this sense, the cross-sectional volatility measures reflect "market-wide" firm-specific information flows: Months with greater amounts 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 VII examines the importance of market conditions in the context of the model used in Table VI, but also including the cross-sectional dispersion and time-series volatility measures discussed above. Column (a) in Table VII shows the estimates of the mean equation (1), while column (b) shows estimates of the two parts of the variance in equations (2) and (3). For each IPO, both the cross-sectional dispersion and the time-series volatility are calculated over the 21 trading days prior to the offer date. The results in Table VII provide some evidence that NASDAQ time-series return volatility helps explain the level and volatility of IPO initial returns. Average initial returns and the volatility of initial returns are higher when the NASDAQ time-series return volatility is unusually high, such as occurred during the IPO bubble period. There is weak evidence that average initial returns are higher when the NASDAQ cross-sectional return volatility is unusually high, but there seems to be no incremental link with initial return volatility.

[13]We also analyzed value-weighted (by market capitalization) portfolios, but we focus here on the equal-weighted market portfolios since they are most comparable to our equal-weighted portfolios of IPO returns. In addition, we analyzed portfolios that cover all of the firms listed on the NYSE, Amex, and NASDAQ with similar results.

[14]To compute a time-series standard deviation for a given 21-day period, we determine the index returns for each day within the period, and then take the standard deviation across these daily index returns. In contrast, to compute a cross-sectional standard deviation for a given 21-day period, we first determine the 21-day return for each firm in the market, and then take the standard deviation across these N 21-day returns.

[15]Our time-series and cross-sectional volatility measures are closely related to the disaggregated volatility measures in Campbell et al. (2001, CLMX). Specifically, our time-series volatility measure is highly correlated with CLMX's market volatility component, and our cross-sectional measure is strongly related to CLMX's firm-specific volatility component.

Table VII

Relation between Initial Returns and Firm-Specific Proxies for Information Asymmetry, as well as Market Volatility Measures, with ARMA(1,1) Errors and EGARCH(1,1) Conditional Volatility, 1981–2005

This table shows maximum likelihood estimates of these cross-sectional regressions where the log of the variance of the IPO initial return is assumed to be linearly related to the same characteristics that are included in the mean equation (for example, Greene (1993), pp. 405–407). The sample consists of IPOs between 1981 and 2005, ordered by the date of the offer. The estimates of the mean equation (1) are shown in column (a). The estimates of the variance equations (2) and (3) are shown in column (b). See Table III for variable definitions. The variable s_{t-1}^2 is the time-series variance of the returns to the equal-weighted portfolio of NASDAQ stocks from CRSP for the 21-trading days ending at day $t-1$. The variable c_{t-1}^2 is the cross-sectional variance of the 21-trading-day returns to stocks on NASDAQ ending at day $t-1$. The large sample standard errors are used to calculate the t-statistics in parentheses under the coefficient estimates. The Ljung and Box (1979) Q-statistic is based on the first 20 lags of the autocorrelation function of the standardized residuals (or the squared standardized residuals) and has an asymptotic χ^2 distribution under the hypothesis of no autocorrelation. The data are ordered according to the offer date of the IPO, but they are not equally spaced in time. The ARMA(1,1) models (Box and Jenkins (1976)) correct for the autocorrelation of the residuals in the mean equation (1). The EGARCH(1,1) model (Nelson (1991)) in (3) corrects for autocorrelation in the conditional variance of the residuals from the mean equation (1).

$$\begin{aligned}\mathrm{IR}_i = {} & \beta_0 + \beta_1\,\mathrm{Rank}_i + \beta_2\,\mathrm{Log(Shares}_i) + \beta_3\,\mathrm{Tech}_i + \beta_4\,\mathrm{VC}_i + \beta_5\,\mathrm{NYSE}_i \\ & + \beta_6\,\mathrm{NASDAQ}_i + \beta_7\,\mathrm{Log(Firm\,Age}_i + 1) + \beta_8\,|\mathrm{Price\,Update}_i| + \beta_9 \log(s_{t-1}^2) \\ & + \beta_{10}\log(c_{t-1}^2) + [(1-\theta L)/(1-\phi L)]\varepsilon_i. \quad (1)\end{aligned}$$

$$\begin{aligned}\mathrm{Log}(\sigma^2(\varepsilon_i)) = {} & \gamma_0 + \gamma_1\,\mathrm{Rank}_i + \gamma_2\,\mathrm{Log(Shares}_i) + \gamma_3\,\mathrm{Tech}_i + \gamma_4\,\mathrm{VC}_i + \gamma_5\,\mathrm{NYSE}_i \\ & + \gamma_6\,\mathrm{NASDAQ}_i + \gamma_7\,\mathrm{Log(Firm\,Age}_i + 1) + \gamma_8\,|\mathrm{Price\,Update}_i|. \quad (2)\end{aligned}$$

$$\text{EGARCH model}: \log(\sigma_t^2) = \omega + \alpha \log\left[\varepsilon_{i-1}^2/\sigma^2(\varepsilon_{i-1})\right] + \delta_1 \log\left(\sigma_{t-1}^2\right) + \delta_2 \log\left(s_{t-1}^2\right) + \delta_3 \log\left(c_{t-1}^2\right). \quad (3)$$

$$\mathrm{Var}(\varepsilon_i) = \sigma_t^2 \cdot \sigma^2(\varepsilon_i). \quad (4)$$

	(a) Mean Equation (1)	(b) Variance Equations (2) and (3)
Intercept	0.204	1.425
	(21.38)	(5.41)
Underwriter rank	0.003	−0.031
	(13.76)	(−8.11)
Log(Shares)	−0.010	−0.156
	(−19.63)	(−9.41)
Technology dummy	0.068	0.326
	(67.84)	(13.95)
Venture capital dummy	0.024	0.258
	(15.53)	(9.81)
NYSE dummy	0.050	−0.620
	(30.18)	(−8.61)
Nasdaq dummy	0.046	−0.231
	(27.28)	(−5.01)
Log(Firm age + 1)	−0.006	−0.179
	(−12.89)	(−18.19)
|Price update|	0.232	1.547
	(89.18)	(18.34)

(*continued*)

Table VII—*Continued*

	(a) Mean Equation (1)	(b) Variance Equations (2) and (3)
Market volatility, time-series, Log(s^2_{t-1})	0.950	0.124
	(11.07)	(5.24)
Market dispersion, cross-sectional, Log(c^2_{t-1})	0.136	−0.009
	(4.73)	(−1.32)
AR(1), ϕ	0.956	
	(870.50)	
MA(1), θ	0.891	
	(378.24)	
ARCH intercept, ω		0.028
		(11.80)
ARCH, α		0.019
		(24.49)
GARCH, δ_1		0.981
		(1,212.04)
Ljung-Box Q-statistic (20 lags)	46	
(p-value)	(0.001)	
Ljung-Box Q-statistic (20 lags, squared residuals)	58	
(p-value)	(0.000)	
Log-likelihood	−1,660.55	
Sample size	6,839	

In sum, we conclude that while IPO initial returns volatility appears to be affected by the secondary market volatility of returns, these effects are small when compared to the associations with variation in the types of firms going public.

Our examination of the relation between secondary market volatility and IPO initial return volatility relates to the findings of Pástor and Veronesi (2005). Pástor and Veronesi hypothesize that more firms choose to go public when market-wide ex ante uncertainty about the future profitability of young firms is high, as higher uncertainty increases the option value of going public. Pástor and Veronesi use the incremental return volatility (in excess of market return volatility) of recently completed IPOs as one proxy for ex ante uncertainty about future profitability. In addition to being positively related to companies' decisions to go public, this uncertainty should also increase the difficulty that underwriters face when pricing the stocks of IPO firms and, therefore, the extent of the pricing errors. In other words, high *ex ante uncertainty* (about profitability) should cause many firms to go public and we should observe high *ex post variability* of initial returns for the firms that choose to go public. The fact that IPO initial return volatility appears to be strongly positively correlated with IPO volume (Figure 2) provides some independent support for the Pástor and Veronesi model. However, our finding that changes in the types of firms going public have a much more substantial effect on the variability of IPO initial returns than changes in secondary market volatility indicates that the direct implication of the Pástor and Veronesi model can only partly explain IPO initial return variability.[16]

Figures 7 and 8 show how the model in Table VII explains the time-series patterns of both the level and the volatility of IPO initial returns. Compared with Figures 3 and 4, which only reflect the variation in the types of firms going public over time, Figures 7 and 8 also reflect time-varying conditions in the IPO and secondary capital markets. It is clear that the models in Tables VI and VII substantially improve the explanatory power of the model by capturing the large time-series movements in IPO initial returns and their volatility, especially during the IPO bubble period.

IV. Other Factors That Might Affect Volatility of IPO Initial Returns

Prior literature in the IPO area includes a number of other models that relate to initial returns. While data limitations prevent us from examining each of these empirically, we briefly discuss several of these models. At the end of the section, we argue that these factors are not likely to be the primary drivers of the observed time-series patterns in initial returns.

Loughran and Ritter (2002) argue that prospect theory can explain part of the underpricing seen in IPO markets. In effect, equity owners who see their wealth increase due to large increases in the secondary market stock price after an IPO do not feel too bad about the fact that they could have raised more money in the IPO by setting a higher IPO price. Of course, unless the post-IPO market price of the stock is higher than it would be if the IPO had not been underpriced, there is no connection between the high value of the stock and the loss associated with underpricing, so prospect theory implies irrational behavior by the decision-makers of issuing firms.

Ljungqvist and Wilhelm (2003) argue that lower CEO ownership and smaller secondary components of IPOs in the late 1990s led to less sensitivity to IPO underpricing. They find some evidence that this factor explains part of the variation in underpricing in the 1999 to 2000 period. They also argue that directed allocations of underpriced IPOs to "friends and family" led to a desire for underpricing by the executives of firms undergoing IPOs.[17]

Loughran and Ritter (2004) suggest that during the IPO bubble period many issuers had objective functions that focused on things other than maximizing

[16] It is possible that market conditions also affect the type of firm going public (not just the decision to go public), suggesting that the coefficient on market volatility underestimates the true importance of market conditions for subsequent IPO initial return volatility. Alternatively, it may be that the volatility of secondary market returns is a poor proxy for ex ante uncertainty about future profitability (the key component in the Pástor and Veronesi model), even for segments of the secondary market that are most closely related to IPO firms (for example, NASDAQ firms).

[17] However, Lowry and Murphy (2007) suggest that the high levels of underpricing may lead more firms to adopt friends and family programs, rather than friends and family programs leading to more underpricing.

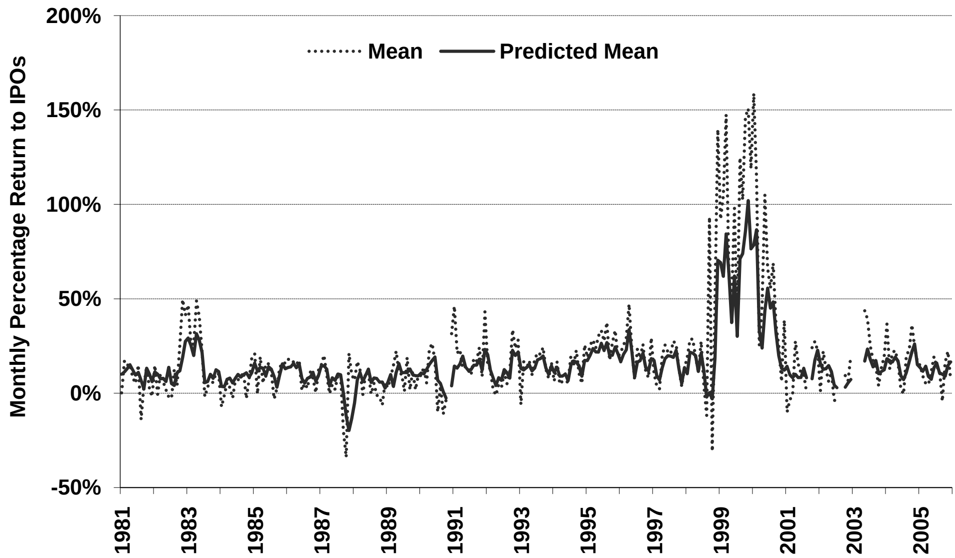

Figure 7. Actual and predicted average of IPO initial returns by month, 1981–2005. Initial returns are defined as the percent difference between the aftermarket price on the 21st day of trading and the offer price. Each month, the initial returns of each IPO during that month are calculated. The dotted line represents average initial returns during the month. The solid line represents average predicted initial returns during the month from the MLE model in column (a) of Table VII.

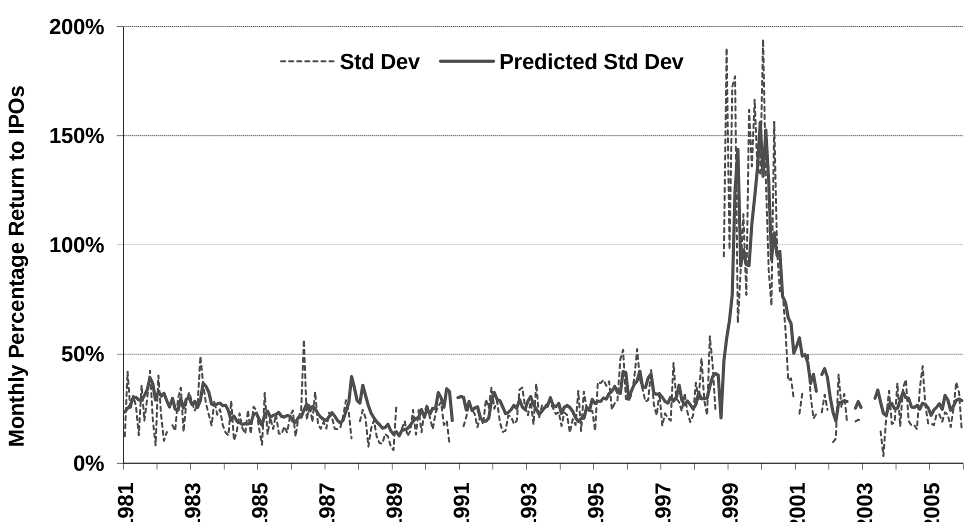

Figure 8. Actual and predicted volatility of IPO initial returns by month, 1981–2005. The dotted line represents the standard deviation of IPO initial returns. The solid line represents the standard deviation of the predicted initial returns from the model in column (b) of Table VII.

the proceeds from the IPO. In particular, they argue that decision-makers in the issuing firms sought payoffs from investment bankers in the form of allocations in the underpriced IPOs of other firms ("spinning"), so when their own firm went public they accepted underpricing as part of the quid pro quo exchange for the private benefits they received as investors in the underpriced IPOs of other firms. They also argue that issuing firms became very interested in coverage of their firms by securities analysts during this period, and perceived that an underpriced IPO would provide incentives for the underwriting firms to provide such analyst coverage.

We are unable to find data that would allow us to directly test whether these supply-related factors can explain the level and variability of underpricing over longer sample periods before and after the IPO bubble period. While many hypotheses have been proposed for the unusual underpricing behavior during the 1998 to 2000 period, as shown in Figure 2, there have been several other hot issues episodes in the IPO market before 1998, and most of the institutional factors that have been identified as being unusual in the 1998 to 2000 period were not present in the earlier episodes (to the best of our knowledge).

V. Implications of the High Volatility of IPO Initial Returns

The evidence in this article strongly suggests that the book building process (the conventional pricing mechanism for IPOs in the United States) has a difficult time setting IPO prices that come close to equating demand and supply. Across our 1965 to 2005 sample period, nearly one-third of IPOs have negative initial returns and another one-third have initial returns of 25% or more. This phenomenon is particularly pronounced in "hot issues" markets: The standard deviation of initial returns is 126% during the September 1998 to August 2000 IPO bubble period, compared to 30% during the remainder of our sample period.

At least a portion of this volatility in initial returns is driven by underwriters' tendency to incorporate only a portion of the information learned during the book-building period into the final offer price. While there is much evidence (for example, Hanley (1993), and recently Lowry and Schwert (2004)) that price updates that occur during the book-building period reflect some information about demand, there is also much evidence that underwriters and/or issuing firms are reluctant to adjust the IPO price upward sufficiently when they learn that there is substantial excess demand at the proposed IPO price. In fact, the results in this article suggest that IPOs in which underwriters revised the price by greater amounts (regardless of whether the revision was positive or negative) have larger pricing errors (as reflected in higher volatility of initial returns).

From the underwriters' perspective, it is arguably easy to see that a proposed IPO price is too low if the indications of interest are many multiples of the shares for sale in the IPO. However, it may be difficult to estimate the market-clearing price (that is, the price that would equate the supply of shares for sale with demand) if one only observes excess demand at the proposed IPO price.

Even if underwriters can confidently predict a "large" price increase after the IPO, they may remain quite uncertain about what the actual secondary market price will be.

In recent years, auctions have emerged as an alternative to the conventional book-building process for the pricing and distribution of shares in IPOs. In contrast to book-building methods, auction methods allow the overall market to determine the price at which demand for the IPO stock equals supply. Because, in theory, information from all market participants is used to set the offer price in auctions, there is little reason to expect large price changes in the secondary market for auction IPO stocks.

Derrien and Womack (2003) and Degeorge et al. (2007) compare the pricing of auction versus firm-commitment offerings in the French market and conclude that auctions are much better at identifying an IPO price that is close to the subsequent secondary market price. Consistent with our conclusions, they find that book building is at the greatest disadvantage during "hot issues" markets, when underpricing is largest and most uncertain. Institutional differences in the day on which the offer price is set in the various types of French offerings complicate interpretations of findings in these prior papers, and make it inappropriate to extrapolate results to the U.S. market.[18]

Table VIII contains a sample of 16 auction IPOs in the United States that were managed (or comanaged) by W.R. Hambrecht & Co.[19] All the IPOs in this sample are for firms that went public in the 1999 to 2005 time period and were listed on the NASDAQ. It is important to note that many of the IPO auctions conducted by W.R. Hambrecht were "dirty" auctions, meaning their offer price was set below the market clearing price.[20] The fact that W.R. Hambrecht chooses to run its auctions in this manner is consistent with Sherman (2005) and Jagannathan and Sherman (2006), who argue that the optimal IPO auction would give the auctioneer discretion in setting the offer price. As an example, Andover.net chose to price its offer at $18.00, considerably below the clearing price of $24.00. While this does not explain all of the initial return for Andover (its first-day initial return was 252%), the extent to which such practices are common throughout the sample potentially causes initial returns to be higher than they otherwise would be. With the notable exception of Google, the auctions are by small firms.

[18]At least a portion of the difference between auction and book-building methods in the French market potentially reflects the fact that the offer price is set further in advance for offers using book building (see, for example, Jagannathan and Sherman (2005)).

[19]http://www.wrhambrecht.com/comp/corpfin/completed_recent.html. This sample contains all auction IPOs managed by W.R. Hambrecht, with the exception of the Instinet IPO, for which only a small fraction of the shares offered in the IPO (2.4m out of 12.2m) were sold using the auction process. Subsequent to this paper, Degeorge et al. (2010) analyze detailed information from Hambrecht and reach similar conclusions.

[20]W.R. Hambrecht states on its website that the issuing company and the underwriters take "a number of economic and business factors into account in addition to the clearing price. The company may choose to sell shares at the clearing price, or it may offer the shares at a lower offering price."

Table VIII

Descriptive Statistics for U.S. Auction IPOs versus Comparable Firm-Commitment Underwritten IPOs, 1999–2005

This sample of auctions is from W.R. Hambrecht's OpenIPO process (http://www.wrhambrecht.com/comp/corpfin/completed_recent.html) through 12/31/2005, excluding Instinet (for which only a fraction of the IPO shares were sold in an auction format). FC is firm-commitment, and the propensity score matched sample of FC IPOs is generated from the probit model in Table IX (in which Auction is the explanatory variable). Specifically, we sort all IPOs by the propensity score and match each Auction IPO to the closest FC IPO with propensity score higher than the Auction IPO and to the closest FC IPO with propensity score lower than the Auction IPO. This produces two matched FC IPOs for each Auction IPO. See Table III for variable definitions.

Name	Filing Date	Proceeds ($m)	Number of Rec.'s	% with Buy Rec.	Market Makers	Turnover	First-day Initial Return	First-month Initial Return
Ravenswood Winery Inc	2/4/1999	$10.5	1	100%	12	0.4%	3.6%	0.6%
Salon.com	4/19/1999	26.2	1	100%	15	0.2%	−4.8%	8.3%
Andover.net Inc	9/16/1999	72.0	2	100%	17	2.3%	252.1%	116.7%
Nogatech Inc	3/14/2000	42.0	2	100%	17	1.1%	−21.6%	−42.4%
Peet's Coffee & Tea	10/13/2000	26.4	2	100%	27	0.9%	17.2%	6.3%
Briazz Inc	2/2/2001	16.0	–	–	18	0.6%	0.4%	−37.6%
Overstock.com Inc	3/5/2002	39.0	2	100%	24	0.3%	0.2%	3.8%
RedEnvelope Inc	6/13/2003	30.8	3	67%	15	1.8%	3.9%	−4.0%
Genitope Corp	8/6/2003	33.3	4	100%	17	0.4%	11.1%	36.1%
New River Pharmaceuticals	5/6/2004	33.6	3	100%	15	0.3%	−6.3%	−5.3%
Google Inc	4/29/2004	1, 666.4	27	52%	83	19.7%	18.0%	34.1%
BofI Holding Inc	3/11/2005	35.1	1	100%	20	0.2%	0.0%	−4.3%

(*continued*)

Table VIII—*Continued*

Name	Filing Date	Proceeds ($m)	Number of Rec.'s	% with Buy Rec.	Market Makers	Turnover	First-day Initial Return	First-month Initial Return
Morningstar Inc	4/8/2005	140.8	1	100%	28	0.3%	8.4%	18.6%
CryoCor Inc	4/5/2005	40.8	3	100%	21	0.5%	−1.2%	−23.9%
Avalon Pharmaceuticals Inc	5/3/2005	28.9	3	33%	17	0.3%	−9.6%	−46.4%
Dover Saddlery Inc	8/26/2005	27.5	2	50%	15	0.2%	2.5%	0.0%
Mean		141.8	3.8	86.8%	22.6	1.8%	17.1%	3.8%
Standard deviation							63.4%	38.6%
Mean excluding Andover.net							1.5%	−3.7%
Std dev excluding Andover.net							10.1%	25.0%
Mean for propensity score-matched FC IPOs		43.4	3.3	79.1%	16.8	0.9%	22.1%	38.3%
Std dev for propensity score-matched FC IPOs							46.8%	51.4%
Mean for propensity score-matched FC IPOs, excluding matches for Andover.net							22.0%	37.0%
Std dev for propensity score-matched FC IPOs, excluding matches for Andover.net							47.6%	50.7%

Table IX

Probit Model to Predict the Use of an Auction to Sell Shares in an Initial Public Offering

This table shows maximum likelihood estimates of a probit model to explain the choice to use an auction to sell shares in the IPO. The sample consists of IPOs between March 1999 and December 2005. See Table III for variable definitions. The large sample standard errors are used to calculate the t-statistics in parentheses under the coefficient estimates. The Pseudo-R^2 measures the goodness-of-fit of the model and the Likelihood Ratio Statistic measures the joint significance of the model with the p-value in parentheses.

$$\text{Auction}_i = \beta_0 + \beta_1 \text{Log}(\text{Shares}_i) + \beta_2 \text{Tech}_i + \beta_3 \text{VC}_i + \beta_4 \text{Log}(\text{Firm Age}_i + 1) + \beta_5 \text{FF9}_i + \beta_6 \text{MTH}_i$$

Intercept	1.875
	(0.49)
Log(Shares)	−0.693
	(−3.24)
Technology dummy, tech	0.574
	(1.88)
Venture capital dummy, VC	0.227
	(1.10)
Log(Firm age + 1)	0.241
	(2.04)
Fama–French wholesale/retail dummy, FF9	0.692
	(2.31)
Time variable, MTH	0.013
	(2.73)
Pseudo-R^2	0.167
Likelihood ratio statistic	28.7
(p-value)	(.000)

However, comparing auction IPOs to the full sample of traditional IPOs can be deceiving, as there is likely to be a selection bias in the type of firm undertaking an auction IPO. Therefore, we create a matched sample of firm-commitment IPOs over the 1999 to 2005 period by using a propensity-scoring method (Rosenbaum and Rubin (1983)). We first estimate a probit model to predict which types of firms chose the auction method between March 1999 and December 2005,

$$\begin{aligned}\text{Auction}_i = \beta_0 &+ \beta_1 \,\text{Log}(\text{Shares}_i) + \beta_2 \,\text{Tech}_i + \beta_3 \,\text{VC}_i \\ &+ \beta_4 \,\text{Log}(\text{Firm Age}_i + 1) + \beta_5 \,\text{FF9}_i + \beta_6 \,\text{MTH}_i. \end{aligned} \tag{5}$$

The variable FF9 equals one for firms in the wholesale/retail industry (Fama–French industry group 9, SIC codes 5000–5200, 7200–7299, and 7600–7699), and zero otherwise, MTH is a time trend variable, varying from 1 in the first month of our sample to 82 in the last month, and all other variables are as defined previously. The estimates of this model are shown in Table IX.

The results are not surprising. For example, larger firms, as represented by the number of shares offered, are less likely to choose auctions. Technology firms and wholesale and retail firms are more likely to use the auction method. In both cases, it is plausible that customers of the issuing firms could be a ready audience for purchases of the stock in the IPO. Also, older firms are more likely to use the auction method; again, firms without an existing customer base might benefit more from the selling efforts associated with firm-commitment IPOs. Finally, firms were more likely to choose the auction method the later in the sample period they were making the decision, which is consistent with the auction method gaining at least some credibility as an alternative for selling an IPO as more deals are completed. We try other specifications that include more of the Fama–French industry variables, for example, but they do not improve the fit of the model.

For every firm that chooses the auction IPO method in Table VIII, we select the two firms that choose traditional firm-commitment IPOs that have the closest propensity scores (predictions from the probit model) to the propensity score of the auction IPO firm. Specifically, we sort all IPOs by the propensity score and match each auction IPO to the closest firm-commitment IPO with propensity score higher than the auction IPO and to the closest firm-commitment IPO with propensity score lower than the auction IPO. By selecting matching firm-commitment IPOs with slightly higher and slightly lower propensity scores, the average propensity score for the matched firm-commitment IPO sample (0.0541) is very close to the average propensity score in the auction sample (0.0556).[21] As a result, we have a matched sample of 32 firm-commitment IPOs to compare with the 16 auction firms shown in Table VIII.[22] Due to the propensity score matching, these comparable firms that choose a firm-commitment offering are very similar to the firms that choose the auction format. For example, this matched sample of firm-commitment offerings is by firms that are also generally small, with average pre-IPO total assets of $143 million (compared to $1.1 billion average pre-IPO total assets for all firm-commitment IPOs over the same period).

Initial returns for auction IPOs look quite different from those for the matched sample of firm-commitment IPOs. For example, initial returns for the majority of auction IPOs are not very large, particularly given that many of these offerings occurred during the IPO bubble period, a time when traditional IPOs were underpriced by large amounts. As shown in Table VIII, average first-day initial returns across all 16 auction IPOs equal 17.1%, compared to an average of 22.1% for propensity score-matched firm-commitment IPOs over the same period.

Looking at the auction initial returns, we observe that there is one extreme outlier: Andover.net had a first-day initial return of 252%. Because the number of auctions is so small, this has a substantial effect on the sample statistics. We therefore calculate average initial returns after excluding this one outlier from the auction sample, and, for consistency, also excluding from the matched

[21]We selected firm-commitment IPOs without replacement so that the 32-matched firms are distinct.

[22]We thank anonymous referees and the Associate Editor for suggesting a propensity score matched sample approach. Using specific matching criteria, such as matching by pre-IPO assets and/or listing exchange, instead of propensity scores produces qualitatively similar results.

sample the two comparable firm-commitment IPOs that are matched to Andover.net by propensity scores. After excluding outliers from both samples, average first-day initial returns are 1.5% for the auctions, compared to 22% for the matched traditional IPOs.

In addition to being lower on average, initial returns of the auction IPOs also have considerably lower dispersion. After excluding Andover.net from the auction sample (and its matches from the firm-commitment IPO sample for consistency), the standard deviation of first-day initial returns for the auction sample is 10.1%, compared to 47.6% for similar firm-commitment IPO offerings. These same patterns are evident in first-month initial returns, which we rely on in this article to circumvent the effects of immediate post-offer price support by IPO advisors. Both the average and the standard deviation of initial returns are substantially lower for auctions than for matched firm-commitment IPOs.

While this evidence is somewhat preliminary due to the limited time series and small sample of auction IPOs, Table VIII suggests that auctions of IPO stocks result in considerably more accurate pricing than the conventional book-building approach for comparable offerings. Whether one focuses on first-day or first-month returns, auction IPOs are considerably less underpriced (in fact, barely underpriced at all on average after excluding Andover.net) and result in initial returns with a substantially lower standard deviation. As an additional estimate of the difference between auctions and firm-commitment offerings, we add an auction dummy to the GARCH models shown in Table VII, where the auction dummy equals one for each of the 16 auctions, and zero otherwise. Consistent with the descriptive statistics shown in Table VIII, the results (shown in the Internet Appendix available in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp) suggest that auctions have significantly lower underpricing than the firm-commitment offerings. However, the coefficient on the auction dummy is not significant in the volatility equation (but does have a negative coefficient). As before, given the small sample of auctions we interpret this evidence as suggestive of the benefits of auctions, but certainly not conclusive.

There are many things, in addition to the price-setting process, that differ between firm-commitment underwritten IPOs and IPOs that are sold through an auction process. For example, it is unlikely that the underwriter would provide price support services (effectively putting a bid order in at or slightly below the IPO price for a short period after the IPO) in an auction IPO. Also, since the underwriter has no real control over allocating underpriced IPO shares in an auction IPO, there is no opportunity for using IPO shares to provide benefits to selected investors. To the extent that conventional underwriters provide additional services, such as market-making or securities analysts' reports, which would not be economical on a stand-alone basis, some issuing firms might accept some level of underpricing as compensation for these follow-on services. On the other hand, for IPO firms that would attract an active investor following anyway, and for which many market-making firms are likely to compete, there is no reason to think that it is necessary to make side-payments to the IPO underwriter to acquire these tie-in services. Many of the examples of IPOs with the largest initial returns are firms that would be attractive to market-makers and to security analysts regardless of the process used to set the IPO price.

In any event, the argument that firm-commitment offerings are accompanied by the provision of auxiliary services, thereby justifying their higher and more volatile underpricing, relies on evidence that firm-commitment offerings are actually associated with higher levels of the provision of the services in question. Table VIII provides descriptive statistics on three auxiliary services that are generally thought to be associated with firm-commitment offerings: analyst following (the number of analysts providing a price recommendation within 6 months of listing and the strength of those recommendations), the number of market makers (measured on the 21st trading day following listing), and daily turnover (in months two through four following listing).

There is little evidence that those companies choosing to go public via the auction method are disadvantaged in any of these dimensions. Across all 16 auctions, the average number of analyst recommendations (provided in the month with the most recommendations in the 6 months following listing) is 3.8, compared to 3.3 for propensity score-matched firm-commitment IPOs over the same time period. Further, 87% of those analysts recommend a buy or strong buy for auction IPOs, compared to 79% of analysts with a similar recommendation for the matched firms undertaking a traditional IPO. Moreover, the auctions actually have a higher average number of market makers in the after-market than the matched firm-commitment offerings: 22.6 versus 16.8.[23] Postlisting trading volume (measured using average daily turnover in months two through four following listing) is also higher for firms that go public using the auction method compared to matched firm-commitment IPOs.

Like the other numbers in Table VIII, these comparisons are suggestive rather than conclusive. For example, using medians rather than means (which reduces the effect of the Google IPO on the auction sample) suggests that firm-commitment IPOs have slightly greater analyst following (three analysts at the median versus two for auction IPOs), but the strength of their recommendations (median of 100% buy recommendations for both groups), the number of market makers, and daily turnover is similar for firms going through firm-commitment or auction IPOs.

In sum, our results provide little support for the idea that companies obtain more nonprice-related benefits when they choose the firm-commitment method of underwriting. While there are other services that underwriters provide, for example, price support and discriminatory allocation, we do not have data to examine such issues. Certainly, we cannot rule out the relevance of such auxiliary services in a firm's decision between the auction and firm-commitment forms of going public. However, at a minimum, the extreme difficulties that underwriters appear to have in pricing IPOs suggests that many firms could benefit from improved price discovery by moving away from the traditional firm-commitment contract seen so often in the United States.

[23] All of the auction IPOs in Table VIII list on NASDAQ, and the number of market makers for the matched sample of firm-commitment IPOs is available for NASDAQ-listed IPOs only.

VI. Conclusion

This article documents the monthly dispersion of IPO initial returns, and demonstrates that the volatility of initial returns is large on average and 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 to 2005 period. This relation is stronger in data from the IPO bubble period (September 1998 to August 2000), but is persistently positive across all subperiods analyzed, and it contrasts markedly with the negative correlation between the volatility and mean of secondary market returns.

The large and time-varying volatility of IPO initial returns documented in this study suggests that underwriters have great difficulty in accurately valuing the shares of companies going public through IPOs. The process of marketing an issue to institutional investors, for example, during the road show, appears unable to resolve much of the uncertainty about aggregate market demand for the stock of IPO firms. If anything, we find the opposite: Issues for which the most learning occurs during the registration period (large absolute price updates) also have higher volatility of initial returns (that is, pricing errors). Furthermore, consistent with the notion that the complexity of the pricing problem in traditional firm-commitment offerings contributes to IPO initial return volatility, we report greater pricing errors (dispersion of initial returns) when a larger fraction of high information asymmetry firms (young technology firms) goes public and during hot markets, particularly the IPO bubble of the late 1990s.

Our results raise serious questions about the efficacy of the firm-commitment IPO underwriting process, as the volatility of the pricing errors reflected in initial IPO returns is extremely large, especially for firms with high information asymmetry and during hot market periods. We conjecture that alternative price discovery mechanisms, such as auction methods, could result in much more accurate price discovery in the pretrading period for IPO companies. In fact, in our sample period, those firms that chose to go public via the auction method experienced less underpricing and less variability of underpricing compared to other similar firms that did a firm-commitment IPO. Moreover, these auction IPO firms do not appear to have suffered in terms of the provision of auxiliary services: Levels of analyst coverage, favorability of analyst coverage, stock turnover, and number of market makers are similar across auction and matched firm-commitment offerings.

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