

The Variability of IPO Initial Returns

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 - Michelle Lowry, Micah Officer, and G. William Schwert
- Interesting blend of time series and cross sectional modeling issues
- Research question is motivated by the apparent difficulty that issuing firms and underwriters have in setting IPO prices anywhere near the subsequent secondary market price (i.e., IPO underpricing)

Decreasing uncertainty is a supposed advantage of bookbuilding

- Collect information about investors' demand for IPO stock
- Reward investors for providing value-relevant information
- Decrease uncertainty regarding aftermarket valuation

How “good” is bookbuilding?

- We know underpricing is large on avg
 - Lots of explanations that suggest IBs are underpricing IPO co’s deliberately
- How “certain” is level of underpricing?
 - Would underwriters be deliberately uncertain about aftermkt price?
 - Derrien and Womack

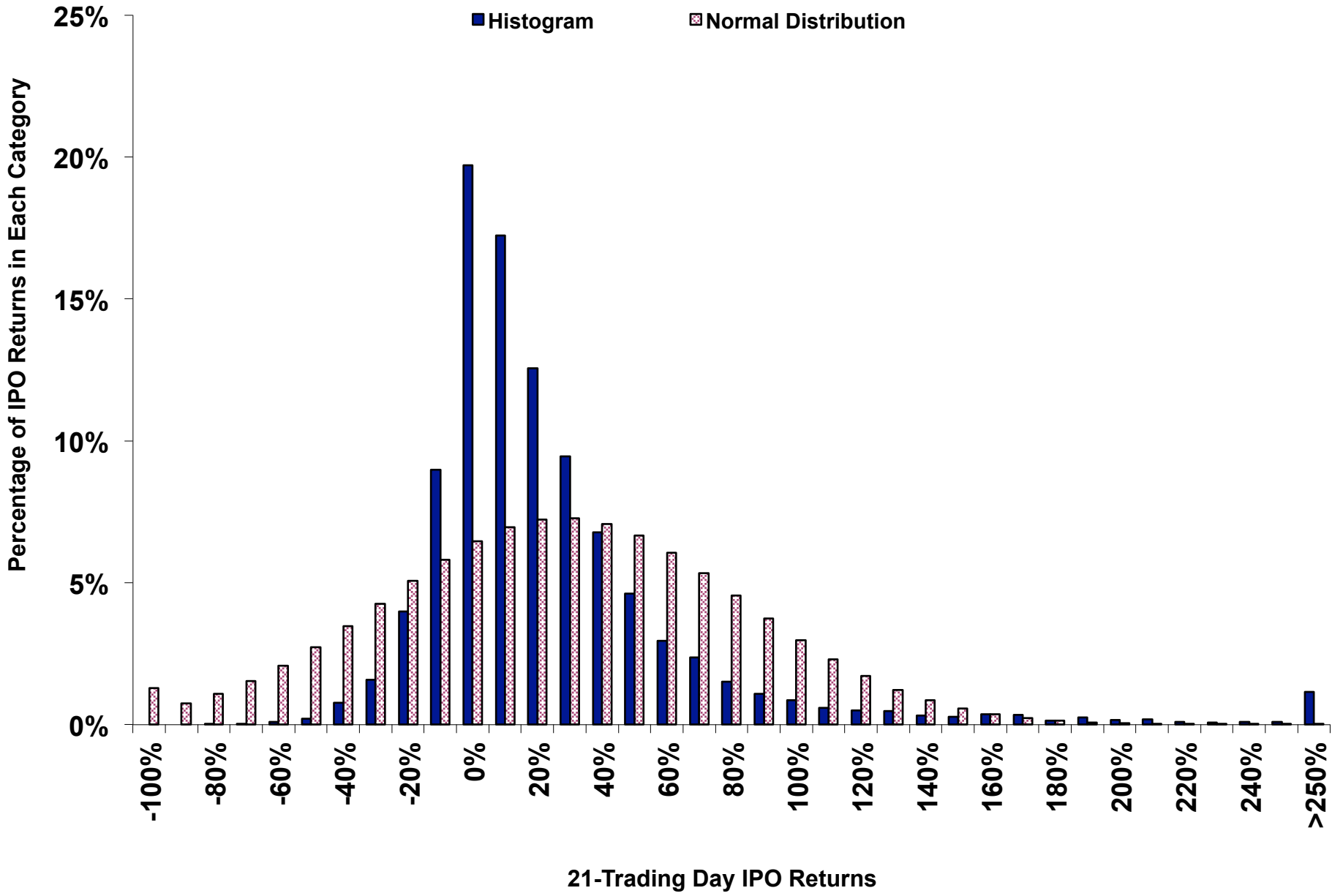
Measurement issues: How well can IBs value IPOs?

- We want the difference between
 - IB valuation *Offer Price*
 - Mkt valuation *Aftermkt Price*
- Appropriate offer price – unambiguous
 - Appropriate mkt price – less clear

Measurement issues: Effects of price support

- After-market price support causes a lot of one-day initial returns (IRs) equal to zero, or very small negative numbers
- Measuring IRs using after-market prices 21 trading days (one month) after the IPO avoids the problems of price support

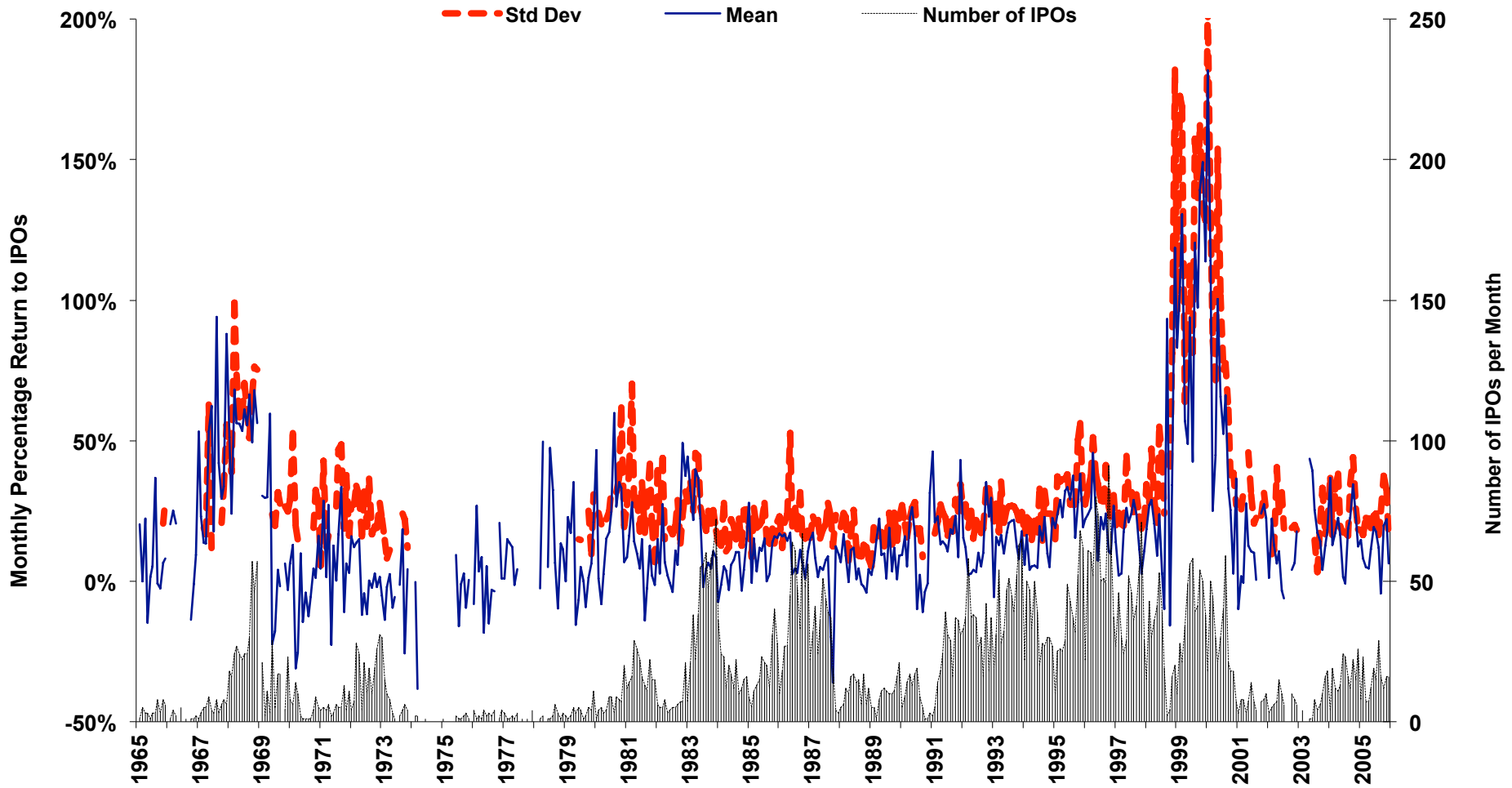
Frequency Distribution of First-month IPO Returns, 1965-2005, IPO Price > \$4.99



Measurement issues: Effects of IPO Bubble

- September 1998-August 2000 was a period of:
 - Large average IRs
 - Large dispersion of IRs
 - Large number of IRs
- As a result, this part of our sample has the potential to dominate the results if pooled with the other data
 - Partly due to heteroskedasticity

IPO Market Cycles in Pricing, Offers, and Volatility



**Table II. IPO Returns and Volatilities Are
Autocorrelated and Cross Correlated**

	N	Mean	Median	Std Dev	Corr	Autocorrelations: Lags					
						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 Std Dev of IPO Initial Returns	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 Std Dev of IPO Initial Returns	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 Std Dev of IPO Initial Returns	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 Std Dev of IPO Initial Returns	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 Std Dev of IPO Initial Returns	144	0.266	0.247	0.097	0.500	0.29	0.12	0.10	0.10	0.19	0.24

What might drive the positive correlation between mean and volatility?

- IPOs characterized by greater information asymmetry tend to be underpriced more
 - Beatty and Ritter's (1986) extension of Rock (1986)
 - Sherman and Titman (2002) – effects of costly information
- Moreover, exact level of initial returns is more uncertain (when info asymmetry is high)
 - Because the value of these companies is harder to precisely estimate

Inferences from Simple Correlations

- Variation in types of firms going public has substantial effect on IR volatility
 - Periods with riskier firms going public have higher avg IRs & more volatile IRs
- Young, technology firms have more underpricing and more volatile underpricing
- When price updates are large, both the level and volatility of IRs are large

**Table IV. Firm & Deal Factors Related to
IPO Returns & Volatility**

	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 (0.016)	0.19 (0.002)	-0.04 (0.561)	-0.08 (0.235)
Average Log(Shares)	0.22 (0.000)	0.26 (0.000)	0.15 (0.008)	0.16 (0.015)
Percent Technology	0.48 (0.000)	0.52 (0.000)	0.26 (0.000)	0.27 (0.000)
Percent Venture Capital	0.30 (0.000)	0.32 (0.000)	0.15 (0.035)	0.11 (0.086)
Percent NYSE	-0.12 (0.006)	-0.07 (0.065)	-0.04 (0.540)	0.01 (0.890)
Percent NASDAQ	0.17 (0.000)	0.13 (0.003)	0.08 (0.163)	0.04 (0.517)
Average Log(Firm Age + 1)	-0.29 (0.000)	-0.34 (0.000)	-0.12 (0.037)	-0.29 (0.000)
Average Price Update 	0.50 (0.000)	0.61 (0.000)	0.08 (0.257)	0.19 (0.008)

The MLE is WLS Using a Similar Function for the Standard Deviation as for the Mean Return

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

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

Inferences from Cross-section Model

- Underwriter rank and NYSE or Nasdaq listing are associated with less volatility
- Other information asymmetry variables, like young, technology firms have more underpricing and more volatile underpricing
- When price updates are large, both the level and volatility of IRs are large

Table V. Start by Ignoring Time Series Issues

	OLS	MLE	
		Mean	Variance
Intercept	0.181 (1.75)	-0.035 (-0.45)	-2.344 (-9.49)
Underwriter Rank	0.011 (3.50)	-0.002 (-0.98)	-0.044 (-9.12)
Log(Shares)	-0.020 (-2.64)	0.007 (1.27)	0.017 (0.95)
Technology Dummy	0.060 (5.13)	0.046 (4.45)	0.444 (15.68)
Venture Capital Dummy	0.041 (2.84)	0.019 (1.94)	0.154 (5.18)
NYSE Dummy	0.078 (2.68)	0.060 (1.83)	-0.657 (-10.47)
NASDAQ Dummy	0.099 (3.77)	0.071 (2.26)	-0.204 (-4.83)
Log(Firm Age + 1)	-0.021 (-4.69)	-0.011 (-2.98)	-0.176 (-15.51)
 Price Update 	0.739 (7.32)	0.206 (5.07)	1.730 (17.59)
Bubble Dummy (9/1998-8/2000)	0.620 (14.78)	0.445 (8.93)	2.335 (60.97)
R²	0.240		
Log-likelihood	-4752.578		-1844.798
Sample Size		6,840	

To Account for Autocorrelation of IPO Returns Add an ARMA(1,1) Model

This a little unusual, since the IPO returns are for different securities and they are not equally spaced through time

Effectively, we are treating these observations as coming from the “IPO return process,” which we assume is stationary

As you will see, this seems to work pretty well . . .

To Account for Autocorrelation of IPO Returns Add an ARMA(1,1) Model

$$\begin{aligned} IR_i = & \beta_0 + \beta_1 \text{Rank}_i + \beta_2 \text{Log}(\text{Shares}_i) + \beta_3 \text{Tech}_i \\ & + \beta_4 \text{VC}_i + \beta_5 \text{NYSE}_i + \beta_6 \text{NASDAQ}_i \\ & + \beta_7 \text{Log}(\text{Firm Age}_i + 1) + \beta_8 |\text{Price Update}_i| \\ & + [(1-\theta L)/(1-\phi L)] \varepsilon_i \end{aligned}$$

$\phi = .948, \theta = .905 \Rightarrow$ low, but persistent
autocorrelations of returns

Ljung-Box(20) drops from 2,848 to 129

Table VI. Reflect Time Series Issues in Mean Equation [ARMA(1,1)]

	Mean	Variance
Intercept	0.183 (2.50)	-7.044 (-39.77)
Underwriter Rank	0.002 (1.06)	-0.016 (-4.03)
Log(Shares)	-0.011 (-2.07)	0.325 (23.87)
Technology Dummy	0.067 (4.75)	0.904 (47.62)
Venture Capital Dummy	0.030 (2.49)	0.255 (12.88)
NYSE Dummy	0.060 (2.27)	-0.686 (-12.17)
NASDAQ Dummy	0.072 (2.86)	0.174 (4.68)
Log(Firm Age + 1)	-0.009 (-2.46)	-0.284 (-31.94)
 Price Update 	0.249 (5.34)	2.661 (39.99)
Bubble Dummy (9/1998-8/2000)	0.183 (2.50)	-7.044 (-39.77)
AR(1), ϕ	0.948 (203.13)	
MA(1), θ	0.905 (122.23)	
Ljung-Box Q-statistic (20 lags)	129	317
Log-likelihood		-2611.20
Sample Size		6,830

To Account for Autocorrelation of IPO Volatility Add an EGARCH(1,1) Model

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

EGARCH model:

$$\log(\sigma^2_t) = \omega + \alpha \log[\varepsilon_{i-1}^2 / \sigma^2(\varepsilon_{i-1})] + \delta \log(\sigma^2_{t-1})$$

$$\text{Var}(\varepsilon_i) = \sigma^2_t \cdot \sigma^2(\varepsilon_i)$$

Table VI. Reflect Time Series Issues in Mean and Variance Equations [EGARCH(1,1)]

	Mean	Variance
Intercept	0.169 (12.15)	1.303 (5.20)
Underwriter Rank	0.004 (10.88)	-0.027 (-7.54)
Log(Shares)	-0.010 (-10.91)	-0.167 (-10.89)
Technology Dummy	0.069 (53.84)	0.379 (17.31)
Venture Capital Dummy	0.043 (36.28)	0.255 (10.51)
NYSE Dummy	0.064 (15.00)	-0.467 (-7.49)
NASDAQ Dummy	0.061 (15.26)	-0.046 (-1.28)
Log(Firm Age + 1)	-0.012 (-27.61)	-0.182 (-19.23)
 Price Update 	0.153 (20.97)	1.475 (19.47)
Bubble Dummy (9/1998-8/2000)	0.169 (12.15)	-7.044 (-39.77)
AR(1), ϕ / ARCH, α	0.963 (803.07)	0.016 (30.39)
MA(1), θ / GARCH, δ	0.911 (496.25)	0.984 (1730.14)
Ljung-Box Q-statistic (20 lags)	57	67
Log-likelihood		-1684.83
Sample Size		6,839

To Account for Autocorrelation of IPO Volatility Add an EGARCH(1,1) Model

ARCH intercept $\omega = .025$

ARCH coefficient $\alpha = .016$

GARCH coefficient $\delta = .984$

⇒ Very persistent time series volatility

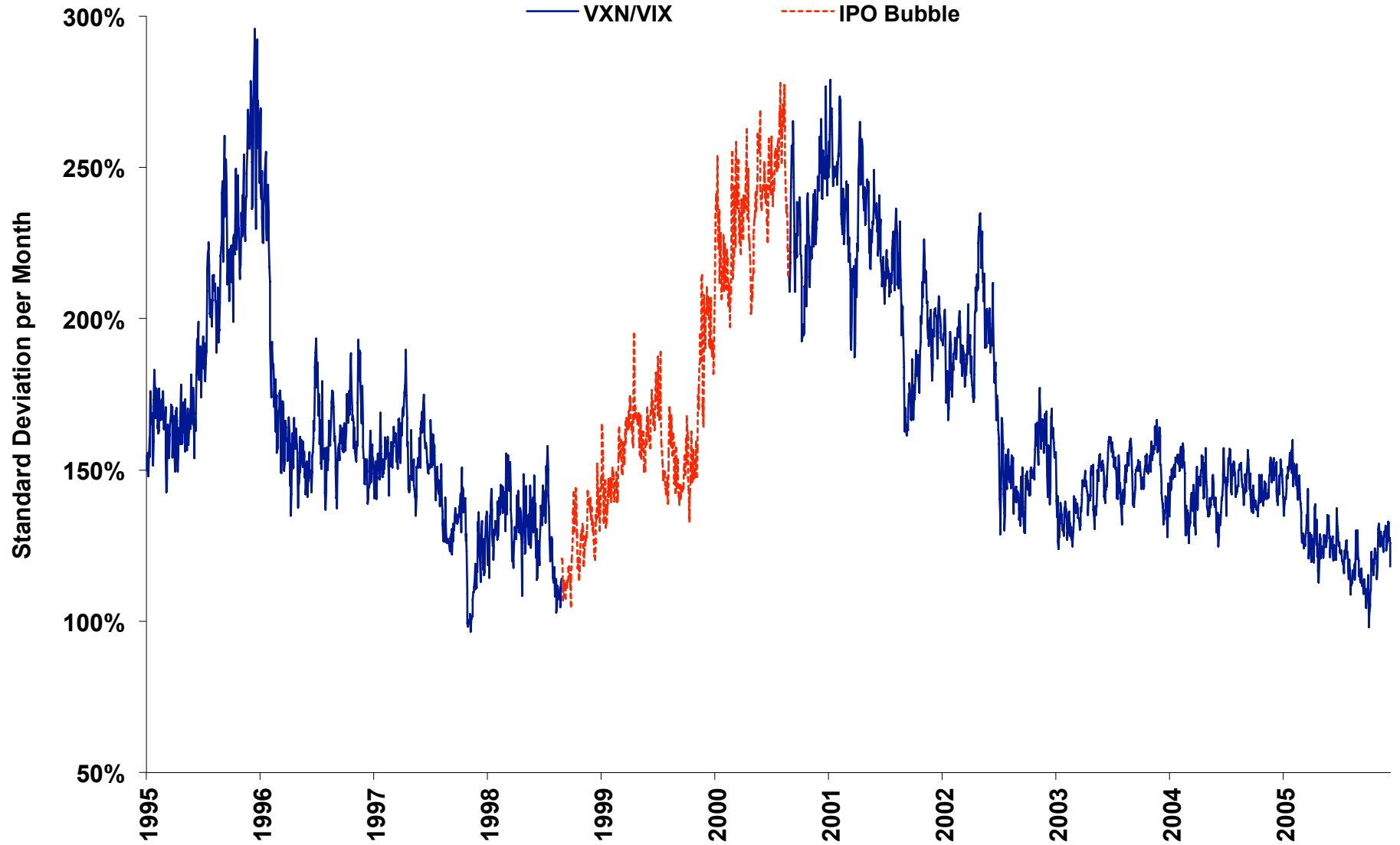
Ljung-Box(20) for autocorrelations drops to 57

Ljung-Box(20) for autocorrelations of squared residuals drops to 67
(from 317 for ARMA model)

Is IPO Volatility Related to Secondary Market Volatility?

- We know the IPO bubble period was also a period when market volatility was high
 - *Schwert (2002)*
- But, it turns out that the relative volatility of young/tech firms on NASDAQ (compared with S&P 500) rose during the IPO boom, but remained high long after the IPO market cooled off

Ratio of Implied Volatility of NASDAQ to S&P Composite Indexes, 1995-2005



Other Factors That Might Influence IPO Volatility

- Supply factors:
 - Prospect theory
 - *Loughran & Ritter (2002)*
 - Increased agency problems
 - *Ljungqvist & Wilhelm (2003) – friends & family*
 - *Loughran & Ritter (2004) – spinning & “analyst lust”*
- We have had difficulty thinking of empirical proxies to use over long time periods to measure these effects

Implications for Bookbuilding

- Volatility of initial returns highlights the difficulty IBs have in estimating the secondary market trading price
 - Particularly in “hot issues” markets
- Auction methods are much better suited to finding the market-clearing price
 - Even if an artificial “discount” is applied ex post to induce investors to invest in learning about the issuing firm
 - *Derrien & Womack (2003) and Degeorge, Derrien & Womack (2005)*

Evidence on US Auction IPOs

- 16 firms brought public using WH Hambrecht's OpenIPO process (Table VIII)
 - Compared with Firm-commitment underwritten issues matched using propensity scores within the 1999-2005 period
 - Average initial return and standard deviation of initial returns is much higher for firm-commitment deals
 - -3.7% vs. 37.0% average 21-day return for samples excluding outliers
 - 25.0% vs. 50.7% standard deviation for samples excluding outliers
 - Similar number of market makers and securities analysts for auctions as firm-commitment deals

Conclusion

- Evidence is consistent with time-varying information asymmetry story
- But the extreme persistence of IRs and volatility, given the characteristics of the offering, suggests that there are important aspects of uncertainty about the valuation of IPOs that are simply hard to predict
 - Suggests alternative methods for selling IPOs are worth considering – e.g., IPO auctions . . .

Conclusion

- The general approach of focusing on uncertainty has many possible applications in corporate finance as well as in capital markets areas
- Modeling uncertainty as a function of firm/deal characteristics gives a richer set of tools to look at information asymmetry and other similar questions

Conclusion

- Finally, modeling dispersion using both time series and cross sectional tools allows for better inference
- In much the same way that Mitch Petersen's paper on the importance of clustering in calculating standard errors for cross-sectional models used in corporate finance has become "state-of-the-art," correctly using WLS or MLE leads to much more reliable inferences for the "mean equation"