FIN 540
The Variability of IPO Initial Returns

- *Journal of Finance* 65 (April 2010) 425-465
  - with Michelle Lowry and Micah Officer
- 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)

What do we know about IPO initial returns?

- IPOs have high first-day returns, on average
- For investors that can get in at the offer price, IPOs are clearly a good short-run investment

What don't we know about IPO initial returns

- How certain can investors be of earning a certain initial return?
- How certain can companies be of obtaining a certain market capitalization?

Decreasing uncertainty is a supposed advantage of bookbuilding

- Collect information about investors' demand for IPO stock
- Reward investors for providing value-relevant information
- Decrease <u>uncertainty</u> 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

Outline

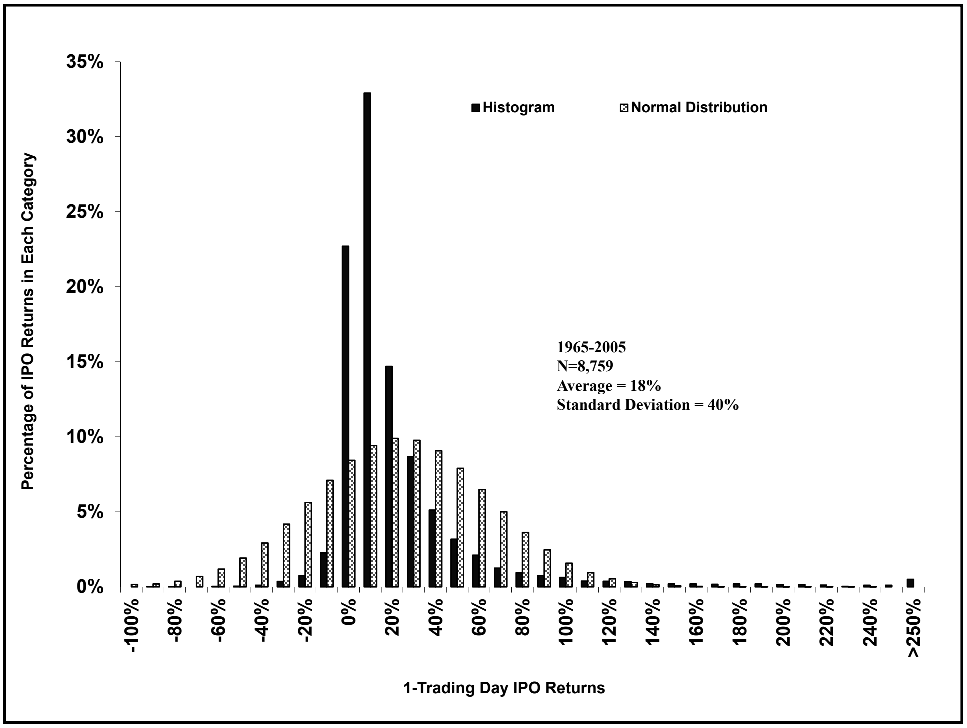
1. How certain are IBs regarding aftermkt prices of IPOs?
2. What factors affect IBs' ability to precisely estimate IPO firm value?
3. What do findings suggest about the bookbuilding process?

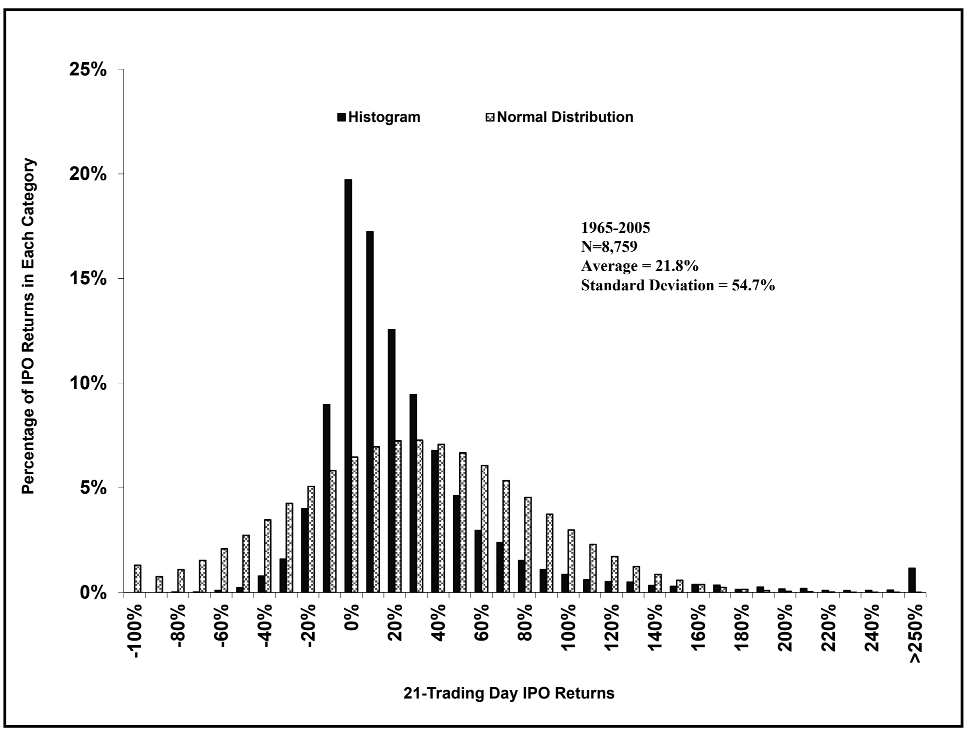
Measurement issues: How well can IBs value IPOs?

- 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


35%
30%
25%
20%
15%
10%
5%
0%
Percentage of IPO Returns in Each Category
Histogram
Normal Distribution
1965-2005
N=8,759
Average = 18%
Standard Deviation = 40%
-100%
-80%
-60%
-40%
-20%
0%
20%
40%
60%
80%
100%
120%
140%
160%
180%
200%
220%
240%
>250%
1-Trading Day IPO Returns


25%
20%
15%
10%
5%
0%
Percentage of IPO Returns in Each Category
Histogram
Normal Distribution
1965-2005
N=8,759
Average = 21.8%
Standard Deviation = 54.7%
-100%
-80%
-60%
-40%
-20%
0%
20%
40%
60%
80%
100%
120%
140%
160%
180%
200%
220%
240%
>250%
21-Trading Day IPO Returns

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

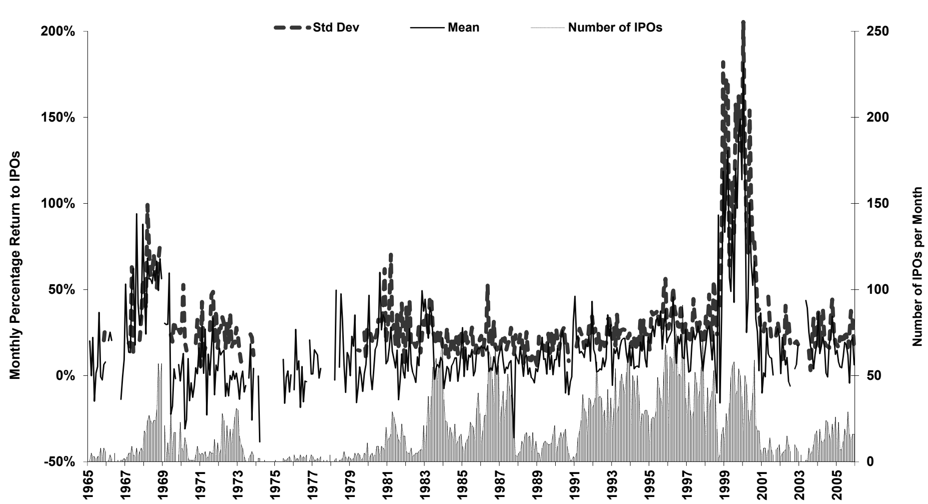
Sources of IPO Data (Table I)

Data Source	Sample	# IPOs	With 1-mth IR, OP ≥ $5
Downes and Heinkel (1982); Ritter (1984)	1965-73 (not ‘68)	635	573
WSJ Index	1968	395	369
Ritter (1991)	1975-84	1,524	1,187
ROS	1977-88	1,394	16
SDC	1970-2005	7,786	6,614
Total	1965-2005	11,734	8,759

Effects of IPO Cycles

- It's well known that IPO markets have shown strong cycles in the number of IPOs and in IRs
- We extend this by also measuring the volatility of IRs
  - Std Dev of initial returns, across all IPOs each mth
  - Initial Return = $\dfrac{\text{Price Day 21} - \text{Offer Price}}{\text{Offer Price}}$

IPO Market Cycles in Pricing, Offers, and Volatility



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

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)

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

Variation in firm type: examine in more depth

1. Estimate cross-sectional regressions of initial returns on information asymmetry proxies
2. Calculate correlations between mthly mean and volatility of fitted values (from regressions)

Variation in firm type: examine in more depth

- IF: correlation between mthly mean and volatility of *raw* initial returns is driven by variation in info asymmetry of firms going public over time
- THEN: we should observe same correlation in mthly mean and volatility of fitted values
  - where fitted values ~ portion of initial return attributable to information asymmetry

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

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

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

Start by Ignoring Time Series Issues

		MLE	
	OLS	Mean	Variance
Intercept	0.181	-0.035	-2.344
	(1.75)	(-0.45)	(-9.49)
Underwriter Rank	0.011	-0.002	-0.044
	(3.50)	(-0.98)	(-9.12)
Log(Shares)	-0.020	0.007	0.017
	(-2.64)	(1.27)	(0.95)
Technology Dummy	0.060	0.046	0.444
	(5.13)	(4.45)	(15.68)
Venture Capital Dummy	0.041	0.019	0.154
	(2.84)	(1.94)	(5.18)
NYSE Dummy	0.078	0.060	-0.657
	(2.68)	(1.83)	(-10.47)
NASDAQ Dummy	0.099	0.071	-0.204
	(3.77)	(2.26)	(-4.83)
Log(Firm Age + 1)	-0.021	-0.011	-0.176
	(-4.69)	(-2.98)	(-15.51)
|Price Update|	0.739	0.206	1.730
	(7.32)	(5.07)	(17.59)
Bubble Dummy (9/1998-8/2000)	0.620	0.445	2.335
	(14.78)	(8.93)	(60.97)
R^2	0.240		
Log-likelihood	-4752.578	-1844.798	
Sample Size		6,840	

Figure 3a. Actual and predicted average of IPO initial returns by month, 1981-2005

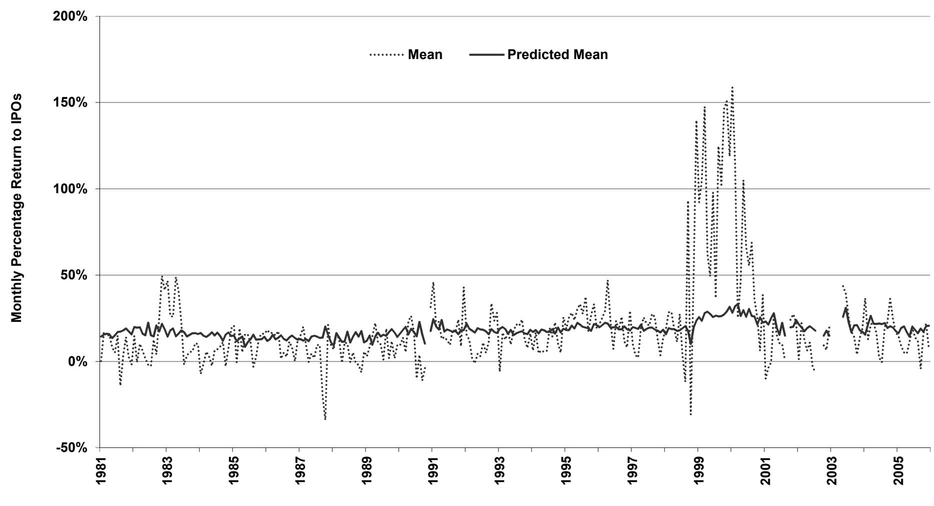
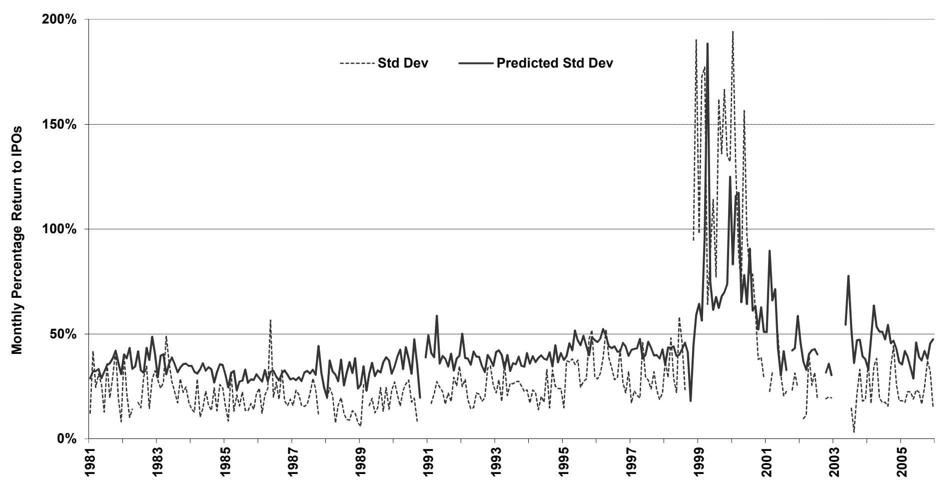


Figure 3b. Actual and predicted volatility of IPO initial returns by month, 1981-2005



Do Firm-specific Proxies for Information Asymmetry Drive Our Results?

- Previous table and figures provide support in a time-series framework (aggregated by month)
- But there is clearly time series behavior that is missed by the purely cross-sectional models
- Next table examines same issue using GARCH regressions to model individual firm IRs

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

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

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

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

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

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

<u>EGARCH model:</u>

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

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

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

ARCH intercept $\omega = .025$

ARCH coefficient $\alpha = .016$

GARCH coefficient $\delta = .984$
$\Rightarrow$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)

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)*

Preliminary 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 a propensity score model to predict the use of auctions between 1999-2005 period (in Table IX)
    - 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"