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Evidence on Price Stabilization and Underpricing in Early IPO Returns

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ABSTRACT

Using data on 560 firm-commitment initial public offerings of common stock for the 1982–1983 period, we find that the cross-sectional distribution of one-day returns is modeled better as a mixture of two distributions, with the parameter estimates of one distribution being consistent with underpricing and the other with price stabilization. Further, the evidence that early IPO returns are drawn from a mixture distribution persists for at least four weeks. The implications of these results for the analysis of IPO returns are illustrated by examining the influence of a measure of ex ante price uncertainty on IPO pricing.

OF THE THREE ANOMALIES ASSOCIATED with initial public offerings (IPOs)—underpricing, "hot issue" markets, and long-run underperformance—the significant average underpricing of IPO issues is the best known and most widely studied. Empirical work documents the underpricing phenomenon in many countries with a stock market. In the United States, for example, the amount of short-run IPO underpricing was 15.3 percent over the 1960–1992 period using equal-weighted averages of initial returns (Ibbotson and Ritter (1995)). Numerous theoretical explanations have been offered for the large initial returns received by investors on new common stock. For the most part, these explanations focus on why underwriters might choose to (deliberately) underprice IPO shares. Included among the alternative reasons for underpricing are: the "winner's curse" (Rock (1986)), costly information acquisition (Benveniste and Spindt (1989)), cascades (Welch (1991)), information asymmetries between issuers and their investment bankers (Baron and Holmstrom (1980) and Baron (1982)), avoidance of legal liability (Tinic (1988)), signaling (Allen and Faulhaber (1989), Welch (1989), and Grinblatt and Hwang (1989)), regulatory constraints, wealth redistribution, and market incompleteness (Mauer and Senbet (1992)).

However, the evidence that these theories attempt to explain is based on the assumption that early IPO returns are drawn from a common distribution. This assumption is questionable given the arguments and evidence

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recently provided in Ruud (1993), Hanley, Kumar, and Seguin (1993), and Schultz and Zaman (1994) that some IPOs are price stabilized immediately after their issue, and some are not. Further, Ruud (1993) suggests that prior evidence of IPO underpricing may simply be attributable to incorrect modeling of the cross-sectional distribution of early IPO returns.

In this paper, we examine whether or not the cross-sectional distribution of early IPO returns represents a mixture of price-stabilized and underpriced issues. The evidence shows that the distribution of one-day returns is modeled better as a mixture of two distributions than as a single distribution. Further, the large positive estimated mean return for one IPO distribution is consistent with the effects of underpricing, while the near zero mean return for the other IPO distribution is consistent with the effects of price stabilization. Thus, our results lend support to recent work which suggests that underwriters use both underpricing and price stabilization to market IPOs (e.g., Chowdhry and Nanda (1996) and Benveniste, Busaba, and Wilhelm (1996)).

We also find that the observed cross-sectional distribution of early IPO returns is modeled better as a mixture of two distributions for up to four weeks after the offer date. This result suggests either that price stabilization continues for up to a month, which is unlikely for both regulatory and cost reasons, or that the underwriter's choice between price stabilization and underpricing is influenced by characteristics of the issue that are reflected in market prices after underwriter price support ceases.

These results are important because they suggest that future theoretical and empirical work on the pricing of IPOs should account for the stylized fact that early IPO returns are not sampled from a common univariate distribution. To illustrate the importance of this finding for the analysis of IPO returns, we examine the influence of ex ante price uncertainty on the pricing of IPOs. The results of the application illustrate the importance of accounting for the heterogeneity of IPO returns in empirical analysis of these returns.

The remainder of the paper is organized as follows. Section I presents the distributional models that are estimated and tested, along with a description of the estimation and testing procedures. Section II describes the sample of firm-commitment initial public offerings of common stock and presents test results and parameter estimates of the distributional models studied. Section III shows the effect of IPO heterogeneity on regression analysis of early IPO returns. Section IV concludes the paper.

I. Modeling, Estimating, and Testing Different Distributional Models for Early IPO Returns

A. Distributional Models

In this section, we describe how we test whether or not the cross-sectional distribution of early IPO returns is better described as a single distribution of returns or as a mixture of two return distributions: one for price-supported issues and another for unsupported issues. To accomplish this, we develop a finite mixture of distributions, or mixture distribution, model for the cross-sectional distribution of early IPO returns. This particular approach is used widely in situations where an observed sample of data can be viewed as coming from two or more populations mixed in varying proportions (see McLachlan and Basford (1988)). Mixture distributions have been applied successfully to several topics in economics and finance, ranging from modeling the influence of trading volume on return volatility (Andersen (1996)) to the value at risk in risk management (Venkataraman (1997)).

For the null hypothesis in conducting our tests, we assume that the early returns of supported and unsupported issues are independent and identically distributed return observations sampled from a common univariate normal distribution. As noted by Kon (1984), the normality hypothesis is crucial to many models of stock returns, and the above hypothesis underlies prior IPO empirical research. The corresponding sample likelihood function is

$$L = f(r_1;\theta)f(r_2;\theta)\ldots f(r_n;\theta) = \prod_{i=1}^{n} f(r_i;\theta) \tag{1}$$

where

$$f(r_i;\theta) = f(r_i;\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{1}{2}\left(\frac{r_i-\mu}{\sigma}\right)^2\right], \qquad r_i = 1,\ldots,n, \tag{2}$$

and r_i represents the observed return for the ith observation. To obtain maximum-likelihood estimates of μ and σ, we form the log-likelihood function (i.e., ln L), take its derivatives with respect to μ and σ, and solve the resulting first-order conditions.

For the alternative hypothesis, the mixture distribution hypothesis, we assume that there is a return distribution for supported issues (i.e., IPOs whose prices are supported by the underwriting syndicate in aftermarket trading) and a separate return distribution for unsupported issues (i.e., IPOs whose prices are not supported by the underwriting syndicate in aftermarket trading). To estimate the parameters of such a mixture distribution using the maximum-likelihood approach, a characterization of the distribution for each sample observation must be specified. We assume each component of our estimated mixture distribution is a univariate normal distribution. For such a two-component mixture of univariate normal distributions model, the following mixture density for the ith observation in the sample holds,

$$f(r_i;p_1,\theta_1,\theta_2) = p_1 f_1(r_i;\theta_1) + p_2 f_2(r_i;\theta_2), \tag{3}$$

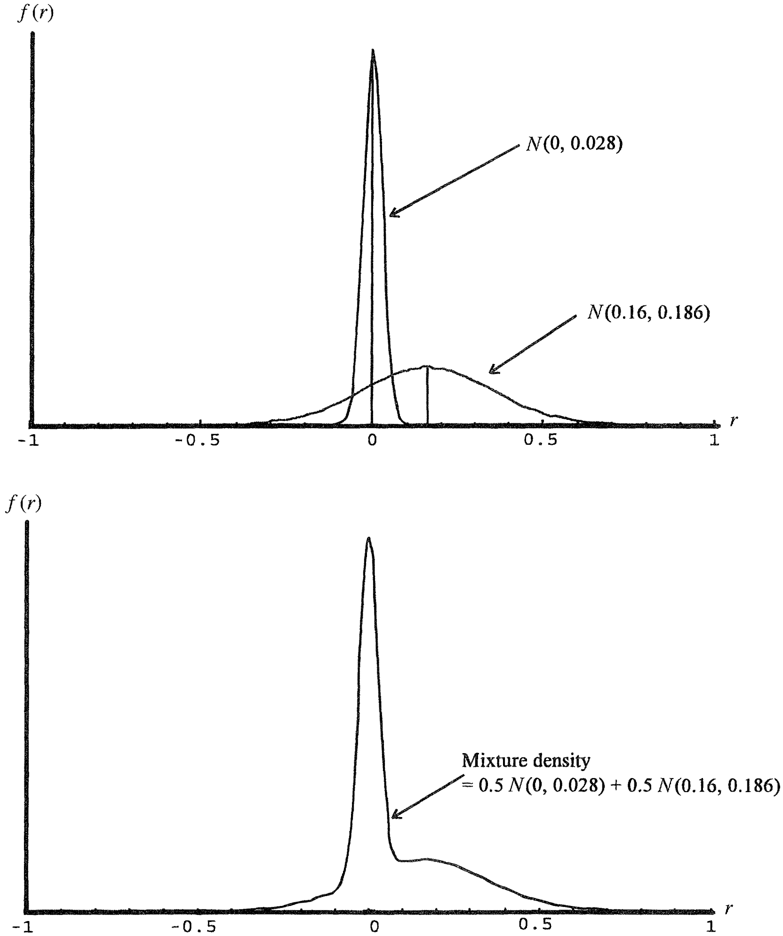

Figure 1. Mixture of two univariate normal densities. The first graph depicts two univariate normal densities and the second graph depicts a mixture of these densities.

where $p_2 = 1 - p_1$, and $f_1(\cdot)$, $f_2(\cdot)$ are different univariate distributions with parameter vectors $\theta_1 = (\mu_1, \sigma_1)$ and $\theta_2 = (\mu_2, \sigma_2)$. The weights, p_1 and p_2, denote the probabilities of observing r_i from each of the two distributions and are called the mixing proportions.[1] As an illustration of this distributional model, Figure 1 shows how two univariate normal densities might be combined to produce a mixture density.

[1] There is an alternative formulation of the mixtures density which incorporates an unobserved or missing indicator variable that is assigned the value 1 when an observation comes from a particular component density. However, the different formulations result in the same estimators.

Based on the mixture density function in equation (3), the sample likelihood function can be written as

$$L = f(r_1; p_1, \theta_1, \theta_2) \cdots f(r_n; p_1, \theta_1, \theta_2) = \prod_{i=1}^{n} f(r_i; p_1, \theta_1, \theta_2). \tag{4}$$

Taking the logarithm of equation (4) and imposing the mixing constraint $p_1 + p_2 = 1$, we form the constrained optimization problem: $\ln L - \lambda(p_1 + p_2 - 1)$, where the constraints $p_1 + p_2 = 1$, $p_1 \geq 0$, and $p_2 \geq 0$ are introduced using the Lagrange multiplier (λ). Maximization of the Lagrangian with respect to all the mixture model parameters yields their maximum-likelihood estimates.

B. Estimation Procedures

To derive numerical estimates of the parameters of the univariate normal distribution, we use a Newton–Raphson procedure to optimize the sample log-likelihood function. To obtain numerical estimates of the parameters of the mixture of distributions model, we must solve the constrained optimization problem discussed earlier. There are several numerical methods for doing this; we use the EM algorithm because it is widely used in mixture estimation and it has certain advantages over numerical optimization routines such as Newton–Raphson (see Hamilton (1994) or McLachlan and Basford (1988) for further discussion).[2] One shortcoming of the EM algorithm is that it does not produce standard errors for the mixture model parameter estimates. Consequently, we also compute mixture model parameters using a Newton–Raphson method for the M-step in the EM algorithm, and use the implied information matrix to conduct asymptotic t-tests of the statistical significance of the parameter estimates. Both estimation procedures produce the same estimated mixture model parameters.[3]

C. Testing Procedures

There are several methods proposed in the mixtures literature to test for the number of component distributions supported by the data, and no agreement on which method is best.[4] For this reason, we test the descriptive validity of the two-component mixture model using two statistics. First, we use

[2] It can be shown that each iteration of the EM algorithm increases the value of the likelihood function. Redner (1981) shows that if maximum likelihood parameter estimators exist for a mixture distribution with a compact parameter space, then the conditions of Wald (1949) can be used to demonstrate the estimators are strongly consistent (see Dempster, Laird, and Rubin (1977) for details on the EM algorithm).

[3] We use GAUSS code provided by James Hamilton for the first procedure and develop SHAZAM code for the second procedure.

[4] See Dillon and Kumar (1994) for a summary of the arguments.

the likelihood ratio statistic. The sample likelihoods for both the null and alternative models are calculated using the maximum-likelihood estimates of the respective model parameters. To conduct the likelihood ratio test, we compute $\lambda = (L_N/L_A)$, where L_N denotes the sample likelihood for the null hypothesis of a common normal distribution and L_A denotes the sample likelihood for the alternative hypothesis of a mixture of two normal distributions. Wilks (1938) shows that $(-2 \ln \lambda)$ has an asymptotic Chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the two hypotheses, when the sampling distribution of λ under the null hypothesis is known.[5] Second, we use Akaike's information criterion (AIC) as proposed by Sclove (1977). This approach requires the researcher to choose the number of mixture components that minimizes the statistic, AIC $= -2 \ln L - td$, where $\ln L$ represents the log-likelihood function value of the distributional model, t represents the number of estimated parameters, and $d = 2$ for Akaike's information criterion.

II. Tests of the Mixture Distribution Hypothesis

A. Data

We identify our sample of IPOs from files collected by the Securities Data Corporation (SDC) and the Center for Research in Securities Prices (CRSP). We use the 1982–83 period to make our results comparable to those reported by Ruud (1993). SDC maintains files on all registered issues of securities with data primarily taken from public registration statements filed with the Securities and Exchange Commission. From the SDC files, we obtain a list of all firm-commitment initial public offerings of common stock. We then match the CUSIP and ticker symbol for each new issue to those in the current and historical CRSP stock files in order to collect stock price data from the CRSP files for each new issue. To be considered a match, either the ticker or CUSIP must match, and the CRSP starting date and the SDC offer date must coincide. We eliminate new equities issued in units of shares plus warrants to avoid separating the values of the share and the warrant. The final sample consists of 560 initial public offerings.[6]

[5] There are a number of variations of the likelihood ratio test in the mixture literature. However, there is no clear evidence of the superiority of one version over another.

[6] The discrepancy in the number of IPOs identified by Ruud ($n = 463$) and the number identified by us ($n = 560$) can probably be attributed to several factors. First, Ruud identifies her sample using only the SDC Common Stock files with two-week and four-week aftermarket stock price data. We use both the SDC and CRSP files to make our identifications of IPOs. Second, Ruud collects price data by hand from Standard and Poor's Daily Stock Price Records, whereas we use the CRSP files. Ruud deletes IPOs with missing price data for any of the holding periods from her sample. Miller and Reilly (1987) also study a sample of firm-commitment IPOs for the 1982–83 period. The discrepancy between our sample and theirs ($n = 510$) is probably due to the fact that they require bid-ask spreads, trading volume, and price data for up to 21 days after the issue date for each of the issues in their sample.

Table I

Summary Statistics for Our Sample of 560 Early Initial Public Offering Return Distributions, 1982–1983

All returns are calculated as continuously compounded, or logarithmic, returns. Excess kurtosis is calculated as sample kurtosis minus 3 (the value of kurtosis for the standard normal distribution).

	1-Day	1-Week	2-Week	3-Week	4-Week
Mean	0.097	0.096	0.103	0.106	0.112
Median	0.037	0.038	0.060	0.063	0.070
Minimum	−0.202	−0.333	−0.519	−0.545	−0.536
Maximum	0.865	0.989	0.891	0.983	0.895
Std. dev.	0.146	0.175	0.199	0.221	0.227
Skewness	1.87**	1.40**	0.89**	0.80**	0.67**
Excess kurtosis	4.16**	3.07**	1.58**	1.25**	0.87**

*Significant at the 5 percent level.
**Significant at the 1 percent level.

Like Ruud (1993), we compute logarithmic returns, $\ln(P_t/P_0)$, where t denotes time period t and P_0 denotes the offer price. To facilitate comparison of results, we make no adjustment for market movements. As noted by Kon (1984), limiting arguments imply that only logarithmic returns will be normally distributed. As a result, the use of logarithmic returns is consistent with both the null and alternative hypotheses specified in our tests.[7]

Table I presents summary statistics for the IPO returns of our sample firms over different horizons. Two interesting observations can be drawn from these statistics. First, our observed mean IPO return does not drop to zero as the horizon increases, as would be expected under Ruud's (1993) hypothesis that underwriter price-stabilization efforts account for the observed underpricing of IPOs documented in prior studies. Second, we find evidence that the distributions of IPO returns for different horizons are skewed and show positive excess kurtosis.

To visualize this evidence, we present in Figure 2 histograms for our sample of one-day, two-week, and four-week returns. Superimposed on each histogram in Figure 2 is a plot of the normal density using the sample mean and sample variance for each corresponding holding period. Inspection of these figures reveals that a common normal density function does not provide a very good fit to these observed returns. The pronounced lack of fit of the data to the common normal density is consistent with the significant skewness and excess kurtosis coefficients reported in Table I.

[7] Most prior research on the price behavior of IPOs uses arithmetic returns. To assess the sensitivity of our results to using logarithmic returns, we also conduct the analysis with one-day arithmetic returns. Since the mixture model estimates and inferences are qualitatively the same for both sets of returns, the results using arithmetic returns are not reported. As an aside, with right-skewed early IPO return distributions, logarithmic returns will have a lower mean than arithmetic returns. This implies that the use of logarithmic returns will actually bias our tests against finding evidence of a two-component mixture model in the data.

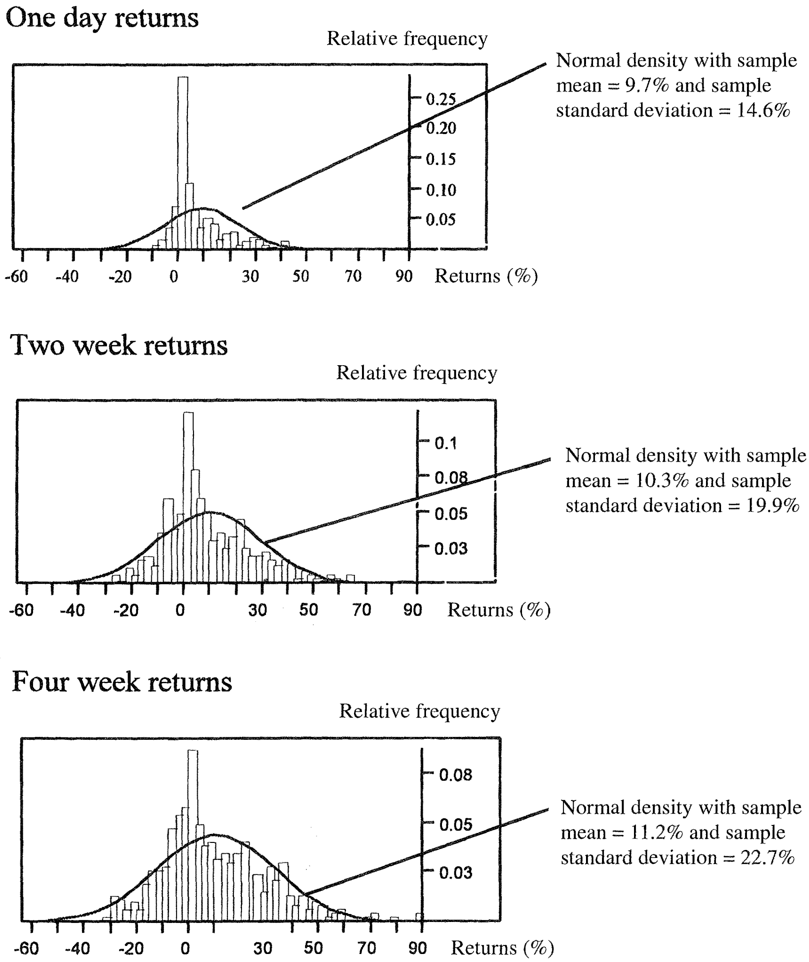

Figure 2. Selected histograms of early returns for our sample of 560 initial public offerings, 1982–83. These graphs represent histograms of sample returns for the one-day, two-week, and four-week holding periods. Superimposed on each histogram is the estimated normal density for those sample returns.

B. Results for One-Day Returns

We employ methods suggested by Fowlkes (1979) to obtain starting values for the EM algorithm used in computing maximum-likelihood estimates of the mixture model parameters. Using this approach, starting values for p_1, μ_1, μ_2, σ_1, and σ_2 are 0.50, -0.042, 0.138, 0.04, and 0.151, respectively. However, we find that our subsequent results are quite robust to variations in these starting values. The maximum-likelihood estimates of the mixture model parameters are presented in column 1 of Table II.

Table II

Maximum Likelihood Estimates of Two-Component Mixture Model Parameters

μ_1 and σ_1 denote the mean and standard deviation of the logarithmic returns of the first distribution; μ_2 and σ_2 denote the mean and standard deviation of the logarithmic returns of the second distribution; p_1 and p_2 represent the mixing proportions for the first and second distributions, respectively.

Mixture Parameter	One-Day Returns	One-Week Returns	Two-Week Returns	Four-Week Returns
μ_1	0.014	0.011	0.008	−0.012
μ_2	0.178	0.147	0.156	0.149
σ_1	0.024	0.036	0.058	0.058
σ_2	0.168	0.204	0.227	0.245
p_1	0.490	0.380	0.350	0.230
p_2	0.510	0.620	0.650	0.770

To test whether the estimated mixture distribution describes the data better than the estimated univariate normal distribution, we compute a likelihood ratio statistic and report the result in Table III. The Chi-square test statistic of 426 reported in the first row of the table is significant. On the basis of this test, we infer that the mixture of two univariate normal distributions fits the data better than does a common normal distribution. This inference is also confirmed by the AIC statistic. The value of the AIC statistic for the univariate normal distribution is 723,736.6, while its value for the mixture of two normal distributions is 4,155. Thus, Akaike's information criterion indicates the mixture of two normal distributions model fits the initial IPO return data better than the univariate normal distribution model does.

Focusing on the mixture model parameter estimates for one-day returns, we observe the following. First, the large positive estimated mean return of 17.8 percent for the second distribution is significantly greater than zero (t-statistic = 16.10). This parameter estimate is consistent with these issues representing underpriced IPOs. Second, for the first distribution, the mean return of 1.4 percent is near zero and the variance is very small. These estimates are consistent with these issues representing price-stabilized IPOs. However, the mean return of 1.4 percent is significantly different from zero (t-statistic = 7.75). This result suggests either that our assumption that the price-supported issues are normally distributed is reasonable and some underpriced issues are being captured in the first distribution, or that the distributional model of price-supported issues is misspecified.[8] Third, the mixing proportion estimate indicates that approx-

[8] Unfortunately, it is not possible to determine which of these explanations holds, since we do not know which issues were price stabilized and which were not. As a result, resolution of this issue is left to future research. Regardless of explanation, our mixture results are robust with respect to the specification of one component distribution of the mixture model.

Table III

Likelihood Ratio Tests for the Sample of 560 One-Day, One-Week, Two-Week, and Four-Week Initial Public Offering Returns, 1982–1983

All returns are calculated as continuously compounded, or logarithmic, returns. The reported likelihood ratios are equal to −2 times the natural logarithm of the ratios of the sample likelihood of the univariate normal density to the sample likelihood of the two-component mixture density. This ratio is asymptotically distributed as a Chi-square distribution with 2 degrees of freedom.

	Log of Likelihood Ratio	Chi-square	df	p-value
One-day returns	−213	426	2	0.00
One-week returns	−93	186	2	0.00
Two-week returns	−50	100	2	0.00
Four-week returns	−27	54	2	0.00

imately half (49 percent) of our sample of 560 IPOs appear to be associated with price-stabilization efforts after the first day of trading. Hanley et al. (1993) report a similar proportion for new equity issues that appear to receive aftermarket price support in their sample of 1,523 firm-commitment IPOs during the 1982–87 period. Overall the above estimates are consistent with the work of Chowdhry and Nanda (1996) and Benveniste et al. (1996) and do not provide support for the arguments that underwriters use only price stabilization (Ruud (1993)) or underpricing (prior IPO literature) as a marketing strategy for IPOs.

C. Stability of the Mixture Model for Longer Holding Periods

We now examine the descriptive validity of the two-component mixture model for successively longer holding periods. If, as Ruud (1993) argues, underwriters engage in price-stabilization efforts for an average of two to four days, then the observed cross-sectional distribution of IPO returns should converge to a common normal distribution from a two-component mixture of normal distributions within four weeks after their issue. On the other hand, Hanley et al. (1993) present evidence that suggests aftermarket price stabilization continues for 10 to 15 days after the offer date. Thus, evidence that the cross-sectional distribution of IPO returns is modeled better as a mixture of distributions for successively longer holding periods may simply reflect the persistence of price-support efforts by underwriters.

Table II presents parameter estimates for the two-component mixture model for one-week, two-week, and four-week returns.[9] Table III presents the likelihood ratio tests for the three longer holding periods. Although

[9] Starting values for the mixture model estimation using the longer holding periods are obtained using the procedure in Fowlkes (1979).

there is a decrease in the size of the test statistics as the holding period increases, all three Chi-square test statistics are significant. As with one-day returns, the likelihood ratio test indicates that a mixture of normals distribution fits the data better than a common normal distribution. Although not reported, the Akaike information criterion also confirms the results of the likelihood ratio tests.

Although the decay in the mixing proportion for the supported return distribution is consistent with a slow cessation of underwriter price-stabilization efforts, it is questionable that such efforts continue for up to four weeks after the offer date. First, Rule 10b-7 of the Securities Exchange Act of 1934 views price stabilization over an extended period of time as violating the antimanipulative provisions of the Exchange Act. Second, price support becomes increasingly costly the longer it is conducted. As noted by Chowdhry and Nanda (1996), large losses associated with stabilization activity may pose substantial liquidity problems and expose the underwriter to both potential bankruptcy and financial distress.

Further, the mean return of the price-supported distribution becomes insignificantly different from zero by the second week (t-statistic = 1.16). This result suggests that stabilization efforts have ended for the price-supported issues by the end of the second week, which is consistent with evidence presented in Hanley et al. (1993).

III. Implications for Future Work on IPO Returns

Our evidence that the cross-sectional distribution of early IPO returns is better described as a mixture distribution calls into question previous empirical work on IPO returns which is based on the assumption that early IPO returns are drawn from a single normal distribution. According to Dietz (1992), "[W]hen it comes to estimation of association between variables, nothing is as fatal as overlooking heterogeneities." Parameter estimates will be biased and inconsistent, and so little confidence can be placed in the validity of hypothesis tests based on analyses where researchers ignore the possibility that an observed sample of data is drawn from two or more populations mixed in varying proportions.

To illustrate how parameter estimates change when heterogeneity in a sample is accounted for in regression analysis, we use the following example. Since the work of Rock (1986), IPO research has argued for and found evidence of the influence of ex ante price uncertainty on IPO underpricing. We examine the influence of a measure of ex ante IPO price uncertainty on IPO returns for two cases: (1) our sample of IPO returns is assumed to come from a common distribution, and (2) our sample of IPO returns is assumed to come from a mixture distribution.

To accomplish this, we use a variant of the mixture of normal regressions model first developed in Hosmer (1974). We modify his method by employing our prior estimates of the mixing proportions in the sample log-likelihood

Table IV

Regression Analysis of One-Day Initial Public Offering Returns

Results from estimating a univariate normal regression model and a mixture of normal regressions model. All returns are calculated as continuously compounded, or logarithmic, returns. UM represents the ratio of the difference between the offer price and the mean of the high and low filing prices divided by the offer price. t-statistics are reported below coefficient estimates in parentheses. Supported issues are the ostensibly price-stabilized IPOs. Unsupported issues are the ostensibly underpriced issues.

		Mixture Regression Model	
	Univariate Normal Regression Model	"Supported" Issues	"Unsupported" Issues
Constant	−50.349	4.326	−101.19
	(−5.382)	(2.003)	(−5.530)
UM	65.400	−3.253	128.22
	(6.432)	(−1.346)	(6.486)

function in order to maintain consistency with our previous analysis.[10] Formally, we obtain parameter estimates that maximize the sample log-likelihood function of the following density:

$$f(r_{\text{IPO}}) = f(r_{\text{IPO}};\Theta_1,\Theta_2) = cN_1(r_{\text{IPO}};\mu_1,\sigma_1) + (1-c)N_2(r_{\text{IPO}};\mu_2,\sigma_2), \tag{5}$$

where

$$\mu_1 = a_{10} + a_{11}UM \quad \text{and} \quad \mu_2 = a_{20} + a_{21}UM, \tag{6}$$

and where UM is our measure of the ex ante IPO price uncertainty, c denotes the proportion of price-stabilized IPOs, and $(1 - c)$ denotes the proportion of underpriced IPOs. We calculate UM as the ratio of the difference between the offer price and the mean of the high and low filing prices divided by the offer price. We assume that the greater the relative deviation between the final offer price and the mean of the high and low filing prices, the greater the ex ante price uncertainty associated with a particular IPO. Data on the offer price, and the high and low filing prices for each sample IPO are obtained from the SDC files.

The results obtained from maximizing the sample log-likelihood function for the univariate regression model and the mixture regression model are reported in Table IV. Consistent with prior research, the estimated

[10] Mixing proportions may change because one is now effectively studying mixtures of multivariate distributions. Our estimation procedure is one of several suggested by Dietz (1992) for estimating generalized linear models for heterogeneous samples. We implement this estimation procedure in SHAZAM.

univariate regression model suggests that the greater the ex ante price uncertainty associated with a particular IPO, the more it is underpriced.

The estimated mixture regression tells a more subtle story. For the ostensibly underpriced IPOs, increasing ex ante price uncertainty increases the underpricing of these IPOs. However, the estimated coefficient for our ex ante price uncertainty measure in the mixture regression is much larger than the estimated coefficient for this variable in the univariate regression model. This suggests that prior research has tended to underestimate the economic effect of ex ante price uncertainty on the degree of underpricing of underpriced IPOs.

Further, the mixture regression results suggest a different effect of ex ante price uncertainty for the price-supported IPOs. For these issues, although the coefficient is statistically insignificant, the sign of the coefficient for the ex ante price uncertainty measure is opposite in sign to that for the underpriced IPOs. What these results might suggest is that there is less ex ante price uncertainty associated with price-supported IPOs, which could explain why underwriters are willing to stabilize the prices of these issues. Regardless of interpretation, the mixture regression results illustrate how very different univariate and mixture regression results can be and why future research that tests alternative theories of IPO pricing should account for the fact that the cross-sectional distribution of early IPO returns is a mixture distribution.

IV. Summary

Previous empirical work on IPO pricing has assumed that early IPO returns are drawn from a common distribution. Recent research questions this assumption and previous evidence of IPO underpricing by noting that the prices of some IPOs are stabilized by their underwriters. Consistent with this recent research, we find evidence that a mixture of two normal distributions better describes the cross-sectional distribution of early IPO returns than does a univariate normal distribution.

Further, we find that the observed cross-sectional distribution of early IPO returns is better modeled by a mixture distribution for up to four weeks after the offer date. Possible explanations of these results include the notions that underwriter price stabilization lasts for up to four weeks, or that as price support ceases, important differences in the underlying characteristics of supported and underpriced issues are being reflected in their market prices. While the large difference in the estimated means of the supported and unsupported return distributions and the prohibitive costs of lengthy price-stabilization efforts lend support to the latter interpretation, explanation of these results requires further research.

Finally, our results suggest that little confidence can be placed in previous regression analyses of early IPO returns. Heterogeneity in sample IPO returns means that regression analyses of these returns must account for the heterogeneity or be of questionable validity. To illustrate this point, we examine the influence of a measure of ex ante price uncertainty on IPO returns. While the mixture regression results suggest that ex ante price uncertainty does increase the degree of underpricing of underpriced IPOs, the economic effect is much greater than previously estimated. Further, the mixture regression results find a different pattern for the influence of ex ante price uncertainty for the price-supported IPOs. These results illustrate why future empirical work on the pricing of IPOs should account for the fact that early IPO returns are drawn from a mixture distribution.

Although our results are consistent with the theoretical work of Chowdhry and Nanda (1996) and Benveniste et al. (1996), there are implications of their work that require further testing before it can be asserted which particular model of an underwriter's choice between price stabilization and underpricing is supported by the data. Moreover, Hanley et al. (1993) and Schultz and Zaman (1994) suggest other economic rationales for price stabilization which are unrelated to compensating initial investors for informational asymmetries. These other explanations include viewing stabilization as a put option to other dealers, as well as a way to prevent cascades or to avoid legal liability associated with a poorly performing new issue. Thus, additional research is needed to provide more insight into why some IPOs are price stabilized and others are not.

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