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Abstract

We examine the pricing of initial public offering (IPO), seasoned equity offering (SEO) and post-Chapter 11 firms using a stochastic frontier methodology. The stochastic frontier framework allows us to model "inefficiency" or the difference between a firm's maximum predicted and its actual market capitalization at the time of the offering as a function of observable firm characteristics. Data for the analysis are comprised of 833 IPOs, 1,846 SEOs and 55 post-Chapter 11 firms between 1990 and 1996. At issue both the IPO and post-Chapter 11 firms are underpriced, while the SEO firms are almost efficiently priced. Furthermore, the market capitalization of an offering firm is positively related to size, sales and net income, negatively related to its debt level. Finally, offering firms tend to receive a poor market valuation in bad economic times.

1 Introduction

The motivation for our research comes from studies in several areas of corporate finance. First, initial public offerings (IPOs) of common equities experience underpricing over the first few days of trading, and their long-run performance is dismal.[1] Theories to explain IPO underpricing fall into three categories: asymmetric information among the issuer, the investment banker, and the outside investors; price support by underwriters in the after-market; and corporate ownership and control considerations (see Jenkinson and Ljungqvist 1996, pages 41-111 for a survey). On the other hand, Aggarwal and Rivoli (1990), Ibbotson, Sindelar and Ritter (1988) and Ritter (1991) conclude that the long-run underperformance of IPOs is consistent with the notion that many firms went public near the peak of industry-specific fads and investors were overoptimistic about the firms' prospects. Second, studies of seasoned equity offerings (SEOs) have focused on announcement period returns and long-run stock returns. Masulis and Korwar (1986) and Mikkelson and Partch (1986) document a decrease in share value at the issue announcement, Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) report that firms making SEOs substantially underperform a sample of matched firms. Finally, for firms emerging from Chapter 11 bankruptcy, Eberhart, Altman and Aggarwal (1997) and Wagner and van de Voorde (1995) find some evidence of short-run underpricing and long-run over-performance using different benchmarks. All these results cast doubt on the informational efficiency of the equity market and point to the potential mispricing going on at the time when firms come to the market for cash.

The objective of this paper is to shed light on factors that determine the market capitalization of equity issuing firms and in particular, firm characteristics that relate to *underpricing* using the stochastic frontier modelling approach. In some aspects, a firm issuing/trading common equities upon emergence from Chapter 11 is similar to an initial public offering, and initial public offerings share many features with seasoned equity offerings. Our study

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[1] In the IPO literature, underpricing is defined as the percentage difference between the first day closing bid price and the initial offer price.

integrates the IPO underpricing, SEO and bankruptcy literatures and makes contributions in the following directions.

First, we work with an analytically tractable and intuitively sensible concept of underpricing by adopting a stochastic frontier model for the pricing equation. This framework allows us to measure the size of underpricing for each of our sample firms, which itself is an important piece of information to management, stakeholders and investors in general. Second, the Bayesian approach adopted in this paper overcomes some statistical problems which plague stochastic frontier models (Koop, Steel and Osiewalski, 1995). For instance, using classical econometric methods, it is impossible to get consistent estimates and standard errors for measures of firm-specific underpricing. Since the latter is a crucial quantity, the fact that our Bayesian approach provides exact finite sample results is quite important. Third, by explicitly modelling pricing "inefficiency" at the time of the offering as a function of observable firm characteristics, we categorize firm-specific characteristics into the pricing factors, and factors that are associated with mispricing. Finally, we work on a unique and comprehensive equity offering data set.

Using a sample of 833 IPOs, 1,846 SEOs and 55 post-Chapter 11 firms, we find that at issue both the IPO and post-Chapter 11 firms are underpriced, while the SEO firms are almost efficiently priced. Furthermore, the market capitalization of an offering firm is positively related to size, sales and net income, negatively related to its debt level. Finally, offering firms tend to receive a poor market valuation in bad economic times.

In the next section, we give a brief review of the Chapter 11 bankruptcy and related IPO, SEO literature. The sampling scheme and data are described in Section 3. Section 4 introduces the stochastic frontier model and Section 5 reports some results. We conclude in Section 6.

2   Literature Review

The 1978 U.S. Bankruptcy Reform Act was rewritten for two scenarios. Under the new code, once a firm files for bankruptcy, it faces the option of liquidating under Chapter 7 or reorganizing in Chapter 11.

Under a Chapter 11 filing, the existing management of the firm usually remains in control (debtor-in-possession) and the firm continues operating as a going concern while a reorganization plan is negotiated among the firm's claimants. Once the plan is approved by all concerned parties, the Chapter 11 reorganization is completed and the firm emerges from Chapter 11.

When public firms emerge from Chapter 11 bankruptcy, they resemble initial public offerings in two aspects. First, they often cancel the old stock and distribute an entirely different share to the stakeholders of the firm. Second, there are some major changes made to the firm's capital structure due to the implementation of the Chapter 11 reorganization plan. On the other hand, there are also some distinct differences between the shares issued by the post-Chapter 11 firms and those in the regular initial public offerings. Primarily, there is neither an explicit offer price nor underwriters in the issuing process. Second, the concepts of underpricing and first trading day can be quite blurred, and the first day return is obtained on the second day of trading upon emergence from Chapter 11. That is, for some formerly bankrupt firms, there are no new shares issued upon emergence or only additional shares are introduced. In these cases, the first trading day is defined as the emergence day stipulated in the reorganization plan or announced by the firm in the business press.

In contrast, seasoned equity offerings share more similarities to initial public offerings, including an explicit offer price, the involvement of underwriters in the issuing process and the transfer of some of the ownership rights in the company from existing to new shareholders. On the other hand, since SEO firms have publicly traded shares outstanding, the market value of these shares are well established. The information asymmetry is of less concern to

potential investors than those of IPO or post-Chapter 11 firms. Hence, it is less likely for the shares of SEO firms to be mispriced.

Hunt-McCool, Koh and Francis (1996) examine the IPO underpricing phenomenon using the stochastic frontier methodology. The advantage of these stochastic frontier models is that it can be used to measure the extent of underpricing without using aftermarket information. This property turns out to be very useful to decision makers involved in IPOs when they select underwriters and determine the offer price. Hunt-McCool *et al.* (1996) conclude that the measure of pre-market underpricing cannot explain away most anomalies in aftermarket returns and that the measure of IPO underpricing is sensitive to the market period (hot versus non-hot IPO periods).

Our research extends Hunt-McCool *et al.*'s (1996) work in following ways: 1) We apply the stochastic frontier modelling approach to a relatively neglected area of research, namely, the underpricing phenomenon observed for firms emerging from Chapter 11 bankruptcy. For comparison, we also include a sample of IPO and SEO firms in our study.[2] 2) We extend their model to allow for firm-specific characteristics to directly affect the degree of underpricing. 3) In contrast to Hunt-McCool *et al.*'s (1996) exclusive focus on a truncated normal formulation of the one-sided error term (which is the inefficiency measure used in the stochastic frontier literature, and the underpricing measure used in their IPO study), we allow alternative distribution assumptions on this pivotal one-sided error term. Hence we do not start with an arbitrary distribution for underpricing but consider several differing possibilities. 4) Our estimation is Bayesian which enables us to take into account both the modelling uncertainty (with respect to different error term specifications) as well as the estimation uncertainty. 5) Our Bayesian approach provides exact finite sample results on measures of firm-specific underpricing.

In summary, our work combines four distinct areas of research—the IPO underpricing,

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[2] This is extremely important in stochastic frontier modelling. Loosely speaking, the efficient firms define the frontier against which underpricing is measured. If only inefficient firms are included, the frontier will be mismeasured. To avoid this risk, we take a wide variety of firms of various types. Since Hunt-McCool *et al.* include only IPO firms, they may be mismeasuring the pricing frontier.

SEO, Chapter 11 bankruptcy and the stochastic frontier literatures—and focuses on the determination of market capitalization in the equity issuing process.

3 Data

To collect data on post-Chapter 11 firms, we first went through various issues of the Moody's Investors Service's special report on corporate bond defaults.[3]

According to the Moody's, default takes place if there is any missed or delayed disbursement of interest and/or principal, bankruptcy, receivership, or distressed exchange. Between 1990 to 1995, the total number of bond defaults reported by the Moody's is 341. We exclude defaults from our final sample based on the following criteria: 1) firms with dubious defaults, such as those where payments were made afterwards, agreement was reached with creditors, or exchange offers were completed (58 firms); 2) foreign based (20 firms); 3) subsidiaries, or otherwise affiliated with another firm on the list (17 firms); 4) firms that were eventually liquidated (5 firms); 5) insurance companies (4 firms); 6) firms that were acquired (3 firms); 7) firms that filed Chapter 7 (6 firms); 8) firms that are in the savings, loans, banking and REIT industries (22 firms); 9) firms that never filed Chapter 11 (24); and 10) firms that were too small to obtain additional information on their defaults (20). In the end, we obtain 162 valid defaults for the period 1990-1995 that eventually filed for Chapter 11.

Information on these bankrupt firms' Chapter 11 filing, confirmation of the reorganization plan and emergence from Chapter 11 is obtained by searching through the Bankruptcy Datasource in Lexis/Nexis, the Capital Changes Reporter, various issues of the Moody's manuals and the Bankruptcy Yearbook and Almanac. Of these 162 bankruptcy filings in our sample, 55 firms emerged from Chapter 11 with equity trading on the NYSE, AMEX or NASDAQ.

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[3]Starting in 1991, the Global Credit Research Division of the Moody's Investors Service annually publishes reports on bonds that were rated by the Moody's and went into default in the previous year. We thank Ms. Dawn Wall at the Moody's Investors Service for kindly providing us past issues of the Moody's special reports on corporate bond defaults.

In order to obtain accurate information on the first trading day closing price upon emergence (P_0), we cross-check both the CRSP tapes and the Standard and Poor's Daily Stock Price Record (SPDSPR) for the earliest record on trading upon emergence from Chapter 11. There are 26 (out of 55) firms which have their first post-bankruptcy trading recorded in SPDSPR. The average lag between the SPDSPR coverage and CRSP coverage is 27 days (median 20 days), which is similar to what Eberhart *et al.* (1997) find.

The sample of initial public offerings and seasoned equity offerings is retrieved from the U.S. new issues data base of the Securities Data Corp. For the sample period 6/1990-6/1996, we obtain 2,605 IPOs and 2,698 SEOs after excluding unit offers, rights offers and ADRs and restricting the exchange in which the issuer's shares are traded to be NYSE, AMEX or NASDAQ. After dropping issuers with incomplete data, we end up with 833 IPOs and 1,846 SEOs.

Firm-specific information at the financial year end that is closest (prior) to the IPO, SEO offer date or the Chapter 11 emergence date, is retrieved from Compustat, the Capital Changes Reporter, the Bankruptcy Datasource and Annual Reports in Lexis/Nexis. Table 1 presents a temporal breakdown of our sample firms. Table 2 provides some summary statistics for our sample of 833 IPOs, 1,846 SEOs and 55 post-bankruptcy firms. We find that compared with IPO and post-Chapter 11 firms, SEO firms are higher in offer price, larger in size, sales and more profitable.

4   Stochastic Frontier Modelling

The stochastic frontier model, developed by Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977), has been widely used in many areas of economics. However, it has been most commonly used in microeconomic studies of production relationship, and we shall adopt the terminology of this literature to describe the basic ideas underlying stochastic frontier modelling.

Standard textbook models of production state that the amount of output produced by

the i'th firm, Y_i, should depend on the inputs used in the production process, X_i, where X_i is a $k \times 1$ vector of inputs. The production technology used for transforming inputs into outputs is given by:

$$Y_i = f(X_i, \beta), \tag{1}$$

where β is a vector of parameters and $f(\cdot)$ describes the maximum possible output that can be obtained from a given level of inputs.

However, in practice, firms may not achieve maximum output; i.e. they may not be efficient. If we allow for firm-specific inefficiency and the usual measurement error that econometricians add, we obtain the following stochastic frontier model for firm i ($i = 1, .., N$):

$$Y_i = f(X_i, \beta)\tau_i\varepsilon_i, \tag{2}$$

where $0 \leq \tau_i \leq 1$ is the efficiency of firm i, $\tau_i = 1$ implies a firm is fully efficient and ε_i reflects measurement error. It is standard to take logs of Equation (2) and assume $f(\cdot)$ is log linear in X, yielding:[4]

$$y_i = x_i'\beta + v_i - u_i, \tag{3}$$

where $y_i = \ln(Y_i)$, $x_i = \ln(X_i)$, $v_i = \ln(\varepsilon_i)$ and $u_i = -\ln(\tau_i)$. We make the usual assumption that v_i is N(0,σ^2) and is distributed independently of u_i. It is common to refer to u_i as inefficiency since higher values of this variable are associated with lower efficiency. Given $0 \leq \tau_i \leq 1$, it follows that $u_i \geq 0$. It is this latter fact that allows us to distinguish between the two errors in Equation (3). Common distributions for u_i are the truncated Normal or various members of the Gamma class. Ritter and Simar (1997) have noted some identification problems which occur if we allow the distribution of u_i to be too flexible. For instance, the truncated Normal distribution become indistinguishable from the Normal if the truncation point is too far out in the tail of the distribution. The unrestricted Gamma distribution runs into similar problems. For this reason, researchers have worked with restricted versions of these general classes. Hunt-McCool, Koh and Francis (1996) use a Normal truncated at the

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[4]Or, if translog technology is assumed, then $f(.)$ is log linear in X and powers of X.

point zero. Meeusen and van den Broeck (1977) and Koop, Osiewalski and Steel (1997) use an exponential distribution (i.e. a Gamma distribution with degrees of freedom, ν, equal to two).[5] Van den Broeck, Koop, Osiewalski and Steel (1994) and Koop, Steel and Osiewalski (1995) extend this by working with Erlang distributions (i.e. Gamma distributions with $\nu = 2, 4$ or 6).

Here, we also work with Erlang distributions. These allow for a wide variety of shapes for the pricing inefficiency distribution. Given that financial theory offers us little guidance into the precise form for this distribution (other than the fact that it is non-negative), investigating different possible shapes could be important. Note that the Erlang distribution with $\nu = 2$ is the exponential distribution which has a mode at 0 (as does the truncated Normal distribution used by Hunt-McCool, Koh and Francis, 1996). The Erlang distributions with degrees of freedom equal to 4 or 6 free up this possibly restrictive assumption and allow for a wide variety of distributional shapes (see Poirier, 1995, page 102 or our Figure 1). Formally, if we let $f_G(.|a, b)$ indicate the Gamma distribution with a degrees of freedom and mean b, then we consider three different distributions for u_i, viz., $f_G(u_i|\nu, \nu\lambda_i)$ for $\nu = 2, 4, 6$ and λ_i is a parameter to be estimated.

In the present paper, we interpret the "output" as being the market value of an offering firm's equity (i.e. the offer price times the number of shares outstanding after the issue). Investors establish this by looking at various factors relating to the future profitability of the firm (e.g. sales, assets, net income and debt levels, etc.) which can be interpreted as "inputs", x, used for producing stock market value. The "production frontier" captures the maximum that investors are willing to pay for shares in a firm with a given level of inputs (firm characteristics). If two firms with similar levels of x are yielding different stock market values, this is evidence that one of the firm's stocks is underpriced (relative to its "input"). This underpricing is labelled "inefficiency" in the stochastic frontier methodology. Hence, we

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[5]Note that there are two common ways of parameterizing the Gamma distribution (see Poirier, 1995, pages 98-102). The first is in terms of a shape and scale parameter, the second in terms of a degrees of freedom and mean parameter. We choose the latter parameterization.

argue that the stochastic frontier model is well-suited for addressing the issue of underpricing of stocks when firms come to the market for cash.

In practice, the stochastic frontier methodology uses firms that are efficiently priced to estimate the frontier, and then underpriced firms are measured relative to this frontier. This, of course, assumes that some of the firms are efficient. Seen in this way, it is important to include data both on firms that we expect to be underpriced (e.g. IPO firms or firms emerging from bankruptcy) and those that we expect to be efficiently priced (e.g. SEO firms). This is an important distinction between our work and Hunt-McCool *et al.* (1996). The latter only uses data on IPOs and cannot answer general questions such as "Are IPOs underpriced?" They can answer questions such as "Are some IPOs underpriced relative to other IPOs?" However, if all IPO firms are massively and equally underpriced, the econometric methodology will misleadingly indicate full efficiency (i.e. with no efficient firms to define the pricing frontier, the frontier will be fit through the underpriced firms).

We use Bayesian methods to estimate the stochastic frontier model described above. The advantages of such an approach are described in some previous work (e.g. van den Broeck, Koop, Osiewalski and Steel, 1994 or Koop, Osiewalski and Steel, 1998). Of particular interest is the fact that adoption of Bayesian methods allows us to calculate point estimates and standard deviations of any feature of interest including τ_i in Equation (2). The latter feature is often of primary importance yet, as Jondrow, Lovell, Materov and Schmidt (1982) demonstrate, non-Bayesian point estimates are not consistent. Furthermore, it is difficult to obtain meaningful standard errors for τ_i using non-Bayesian approaches.[6]

Above, we have stressed that stochastic frontier models require the specification of a distribution for u_i, which we will call from now on the "underpricing" instead of inefficiency. Early work tended to assume that these underpricings were drawn from some common distributions (i.e. $\lambda_i \equiv \lambda$ for all i). However, Koop, Osiewalski and Steel (1998) reason that this might be too restrictive an assumption. For instance, it might be the case that firm-

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[6]It is possibly for these reasons that Hunt-McCool, Koh and Francis (1996) never provide firm-specific estimates of underpricing.

specific characteristics or type of offers (IPOs, SEOs or post-Chapter 11 offerings) should be related with underpricing. From a statistical standpoint, this implies that the underpricing distribution in Equation (3) should depend on m observable characteristics of firm i, w_{ij} where $j = 1, .., m$.[7] In Koop *et al.* (1998), it is assumed that underpricing u_i is distributed as an exponential distribution with mean λ_i, where

$$\lambda_i = \prod_{j=1}^{m} \phi_j^{-w_{ij}}. \tag{4}$$

The preceding specification is chosen since it ensures that the mean of the underpricing distribution is positive (which it has to be). In the present paper, we adopt this specification in Equation (4) for λ_i. It is worth stressing that, in such a specification, we can directly test whether a particular firm characteristic tends to be associated with underpricing. For instance, we can construct a bankrupt status dummy variable (e.g. $w_{i2} = 1$ if firm i is emerging from Chapter 11, $= 0$ otherwise) and include it in the underpricing distribution Equation (4). If firms emerging from bankruptcy are underpriced then $\phi_2 < 1$ and we can both estimate ϕ_2 and statistically test whether it is greater than one or not.

To summarize, in the framework used here, Equations (3) and (4), the researcher is forced to draw on theory to decide whether a variable is an input in the production process (in which case it belongs in x) or whether it should effect the level of underpricing (in which case it belongs in w). Alternative methods typically just enter all possible explanatory variables as x's (i.e. as explanatory variables which enter linearly in a regression model).

5   Empirical Results from Stochastic Frontier Model

The output, y, used in stochastic frontier model is the log of market value of equity (i.e. the offer price times the number of shares outstanding after the issue).[8] For inputs, x, we use an

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[7]In practice, all of our $w_{ij}'s$ are 0-1 dummy variables. This greatly simplifies our computational methods. Furthermore, we always set $w_{i1} = 1$ (i.e. we put an intercept in the model).

[8]The use of market value as the dependant variable also distinguishes our work from Hunt-McCool *et al.*'s (1996). The latter uses stock price as a dependant variable. Since market value is more comparable across firms than price, we would argue that our approach is more sensible.

intercept and measures of debt, sales, net income, total assets, default premium and term premium. Variables that are positive for all firms are logged (except the intercept). Formally, we include an intercept and DEBT, ln(SALES), NI, ln(AT), ln(DEF) and ln(TERM) (see Appendix A for variable definitions). In the efficiency distribution Equation (4) an intercept is included along with 0-1 dummies for SEO and CH11 (post-Chapter 11 firms, IPO is the omitted dummy to avoid singularity problems) and a dummy, LBO, for whether the firm was involved in a leveraged buyout prior to the offer.

In preliminary investigations, we tried including an exchange code indicator (= 1 if firm is listed on NASDAQ, = 0 otherwise) and dummies for the year of the offering. Bayes factors indicated that these were not significant so they were dropped for the final runs report here. For what it is worth, note that the year 1996 seemed to be the hottest year for going to market (i.e. less underpricing occurred then), although this result was not statistically significant.

An advantage of the Bayesian approach is that, unlike traditional econometric approaches, we can derive the entire posterior distribution of the efficiency of any firm and, hence, can calculate both point estimates and standard deviations.[9] For the sake of brevity, we cannot present results for every firm here (2,734 of them). Instead, remember that the underpricing distribution varies across firms (i.e. depends on w). Since w is a vector of 0-1 dummies and some of these dummies are mutually exclusive (e.g. no firm is both CH11 and SEO), it can be seen that there are six different underpricing distributions in the model. In particular, if we divide firms into two groups depending on whether they were involved in a LBO or not, then within each group a firm could be either IPO, CH11 or SEO. Accordingly we can plot the efficiency distribution of each of these six types of firms. Each of these six distributions can be interpreted in several ways. For instance, the CH11/LBO distribution can be interpreted as the efficiency distribution of a typical CH11/LBO firm. Alternatively, it can be interpreted as summarizing the distribution of efficiency across all CH11/LBO firms. Or, it

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[9]To aid in interpretation, the underpricing distribution is transformed into an efficiency distribution as described in Section 4. Note that the efficiency distribution is bounded between 0 and 1 and a value of, say, 0.85 indicates that the market value of the firm is only 85% of the maximum it could be (or, equivalently, the firm is undervalued by 15%).

can be interpreted as a forecasted efficiency distribution for an unobserved CH11/LBO firm. For more explanation, formalization and computation details of this concept of the efficiency distribution of a typical firm, see van den Broeck, Koop, Osiewalski and Steel (1994), pages 279-280.

Figure 1 plots 18 efficiency distributions: one for each of the six types of firms, for each of our three models (i.e. for $\nu = 2, 4, 6$). Table 3 gives the means and standard deviations of these 18 distributions. These plots tell the most important parts of our empirical story.

First, the SEO firms tend to be quite efficient and there is little variability across firms. That is, the bulk of the probability in the efficiency distribution lies between 0.95 and 1, indicating it is rare for a SEO firm to be undervalued by more than 5%.

Second, the efficiency distributions of IPO and CH11 firms are extremely disperse and there is a great deal of evidence for underpricing. For instance, if we look at CH11/LBO firms the mean of the efficiency distribution is roughly 0.50, indicating that on average this class of firms is valued at only 50% of what our stochastic frontier model says it should be. However, the high standard deviation associated with this distribution indicates that some CH11/LBO firms are valued quite efficiently.

Third, if firms were involved in a LBO, they tend to be slightly underpriced, although (as we will discuss shortly), this result is not statistically significant.

Finally, results for the three different Erlang stochastic frontier models are qualitatively the same, indicating that our story is robust to widely differing alternative assumptions about the one-sided error in our model.

The efficiency distributions discussed above are directly interpretable and, hence, we have focused our discussion on them. For the sake of completeness, we also report information on the parameters in Equations (3) and (4) in Tables 5 and 4, respectively. For brevity we only present results for the Erlang model with $\nu = 6$, results for other models are very similar. Table 4 presents point estimates and standard deviations for the elements for the $\phi_i's$ as well as Bayes factors for testing $H_0 : \phi_i = 1$ against $H_1 : \phi_i \neq 1$, $i = 2, 3, 4$ (i.e. for

testing whether each variable in w, other than the intercept, is statistically significant).[10] As discussed above, SEO firms do seem to be more efficient (i.e. $\phi_2 > 1$) and CH11 firms less efficient (i.e. $\phi_3 < 1$). Furthermore, these results are both strongly significant. The point estimate of ϕ_4 indicates that LBO firms also tend to be less efficient, but the Bayes factor indicates that this result is not strongly significant.

Table 5 contains point estimates and standard deviations for the frontier parameters (i.e. β) in Equation (3), plus OLS estimates and standard errors.[11] It can be seen that OLS and stochastic frontier estimates are very similar. Both tell the story that sales, net income and book value of total assets are strongly positively, while debt and the term premium are strongly negatively associated with the market capitalization of the offering firm. The default premium is not statistically significant.

In summary, we find that at issue both the IPO and post-Chapter 11 firms are underpriced, while the SEO firms are almost efficiently priced. Furthermore, the market value of an offering firm's equity is positively related to size and profit, negatively related to its debt level. Finally, in bad economic times, offering firms tend to receive a poor market valuation.

6   Conclusion

In this paper, we examine the pricing of initial public offering, seasoned equity offering and post-Chapter 11 firms using the stochastic frontier methodology. In addition to the regular symmetric error term in the pricing equation, the stochastic frontier model introduces a systematic one-sided error term that captures pricing "inefficiency" or the difference between a firm's maximum predicted and its actual market capitalization at the time of the offering. To uncover the sources of mispricing, we further model the inefficiency distribution in the

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[10]Note that small values of the Bayes factor indicates $\phi_i \neq 1$, if the Bayes factor is roughly 1 then the model with $\phi_i = 1$ and $\phi_i \neq 1$ receive similar amounts of support from the data, and if the Bayes factor is larger than one then the variable is not statistically significant.

[11]The intercept has a different interpretation in the stochastic frontier and OLS results and is not presented. Note also that, as discussed in Appendix B, we have standardized the elements of y and x to have mean zero and standard deviation one. This makes it simple to interpret the magnitude of the elements of β.

pricing equation as a function of observable firm characteristics.

Data for the analysis are comprised of 833 IPOs, 1,846 SEOs and 55 post-Chapter 11 firms between 1990 and 1996. We find that at issue both the IPO and post-Chapter 11 firms are underpriced in comparison to the SEO firms. Furthermore, market capitalization of the offering firm is positively related to size, sales and net income, negatively related to its debt level. Finally, offering firms tend to receive a poor market valuation in bad economic times.

The advantage of stochastic frontier models is that they can be used to measure the level of mispricing in the premarket without resorting to the aftermarket information. This property is important to management of the offering firm in selecting underwriters and determining if the suggested offer price is appropriate. We believe the stochastic frontier approach has many more practical applications in financial economics.

Appendix A: Variable Definitions

Dependent Variables:

P_0: the offer price for the IPOs and SEOs, or the first day closing price upon emergence from bankruptcy for post-Chapter 11 firms

SHOUTS: the number of shares outstanding after the issue as recorded by the Securities Data Corp. or in the first month of trading upon emergence from Chapter 11 ('000s)

Independent Variables:

x **variables** (measured in the fiscal year end prior to the offer):

DEBT: the amount of long-term debt outstanding ($m)

SALES: total sales ($m)

NI: net income ($m)

AT: the book value of total assets ($m)

DEF: default premium, defined as the yield difference between Moody's Baa bonds and Aaa bonds

TERM: term premium, defined as the yield difference between 10-year government bonds and 3-month treasury bills

w **variables:**

SEO: dummy variable, equals 1 if the new issue is a SEO, 0 otherwise

CH11: dummy variable, equals 1 if the new issue is by a post-Chapter 11 firm, 0 otherwise

LBO: dummy variable, equals 1 if the issuer had a leveraged buyout before the offer, 0 otherwise

w_i's have no effect on pricing efficiency. For β we use a noninformative, improper, uniform prior.

The posterior corresponding to this prior is analytically intractable and must be analyzed using simulation methods. In particular, a Gibbs sampler with data augmentation can be set up for this model (see Koop, Steel and Osiewalski, 1995, or Koop, Osiewalski and Steel, 1997) involving the following conditional distributions.

For the frontier coefficients:

$$p(\beta|Data, \sigma^{-2}, \phi, u) = f_N(\beta|\widehat{\beta}, \sigma^2(x'x)^{-1}),$$

where $f_N(.|a, b)$ indicates the multivariate Normal distribution with mean a and covariance matrix b, x is an $N \times k$ matrix containing observations for all explanatory variables for all firms, y is an $N \times 1$ vector containing observations for the dependant variable for all firms, $u = (u_1, ..., u_N)'$, and

$$\widehat{\beta} = (x'x)^{-1}x'y.$$

For the measurement error precision:

$$p(\sigma^{-2}|Data, \beta, \phi, u) = f_G(\sigma^{-2}|n_0 + N, \frac{n_0 + N}{(n_0 + N)s_0^2 + (y - x\beta + u)'(y - x\beta + u)}).$$

For the parameters in the inefficiency distribution:

$$p(\phi_h|Data, \beta, \sigma^{-2}, \phi^{(-h)}, u) = f_G(\phi_h|\nu(n_h + 2\sum_{i=1}^{N} w_{ih}), \frac{\nu(n_h + 2\sum_{i=1}^{N} w_{ih})}{n_h s_h^2 + 2\sum_{i=1}^{N} w_{ih}u_i \prod_{j \neq h} \phi_j^{w_{ij}}}),$$

where $\phi^{(-h)} = (\phi_1, ..., \phi_{h-1}, \phi_{h+1}, ..., \phi_m)$. The w_{ih}'s must be 0-1 dummy variables for the preceding conditional to have a Gamma form. Note that, if n_i is set very near to zero, then all of the prior hyperparameters have a negligeable effect on the above distributions. In this sense, the empirical results in this paper are based on a noninformative prior.

For u:

$$p(u|Data, \beta, \sigma^{-2}, \phi, u) = f_N(u|x\beta - y - \sigma^2\eta, \sigma^2 I_N) \prod_{i=1}^{N} u_i^{\frac{\nu}{2}-1} I(u\epsilon R_+^N),$$

where $\eta = (\lambda_1^{-1}, ..., \lambda_N^{-1})'$, I_N is the $N \times N$ identity matrix and $I(\cdot)$ is the indicator function. That is, for $\nu = 2$, the conditional for u is truncated Normal. For $\nu = 4, 6$ the conditional does not have a convenient form. Nevertheless, we can draw from this distribution using the rejection methods described in Koop, Steel and Osiewalski (1995), pages 359-360.

A Gibbs sampler can be set up using the preceding conditional distributions which involve only the well-known Gamma, Normal and truncated Normal distributions. We calculate Bayes factors for testing whether $\phi_i = 1$ for $i = 2, .., m$ using the Savage-Dickey density ratio (see Verdinelli and Wasserman, 1995). In previous work with such models, Koop, Steel and Osiewalski (1995) have found that the Gibbs sampler is numerically well behaved. Hence, we do not provide numerical standard errors and convergence diagnostics. Our final results are based on 10,000 passes through the Gibbs sampler with an initial 1,000 discarded to mitigate initial condition effects. Experimental runs using different starting values indicate that initial condition effects are minimal. To avoid underflow/overflow problem, we standardize y and x so that individual variables have sample means of zero and standard deviation of one.

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Table 1. Frequency Distributions of Sample Firms

Year	IPO Firm	SEO Firm	Post-Chapter 11 Firm
1990	18	41	1
1991	139	306	7
1992	170	302	19
1993	184	393	17
1994	143	233	4
1995	96	345	6
1996	83	226	1
Total	833	1846	55

The data on IPOs and SEOs are obtained from the Securities
Data Corp. (6/1990-6/1996). The data on formerly bankrupt
firms are obtained from the Moody's Investors Service.

Table 2. Summary Statistics for Sample Firms

Variable	Mean	Std.	Min	Max
Panel A. Initial Public Offering Firms (833)				
P_0 ($)	11.49	4.11	3	28
SHOUTS ('000s)	10,485	13,045	525	163,966
DEBT ($m)	69	375	0.10	6,141
SALES ($m)	165	760	0.10	18,228
NI ($m)	-0.18	101	-2,861	207
AT ($m)	199	878	0.40	17,049
DEF (%)	0.79	0.19	0.55	1.50
TERM (%)	2.99	1.00	0.84	4.69
LBO	0.14	0.35	0	1
Panel B. Seasoned Equity Offering Firms (1,846)				
P_0 ($)	22.68	13.48	2.50	146.00
SHOUTS ('000s)	30,022	74,326	1,000	1,568,951
DEBT ($m)	415	3,056	0.10	85,481
SALES ($m)	1,065	6,556	0.20	160,741
NI ($m)	22	247	-4,130	6,201
AT ($m)	2,478	28,128	1.60	1,057,331
DEF (%)	0.77	0.18	0.55	1.50
TERM (%)	2.78	1.08	0.84	4.69
LBO	0	0	0	0
Panel C. Post-Chapter 11 Firms (55)				
P_0 ($)	8.72	7.63	0.94	40.63
SHOUTS ('000s)	24,508	25,083	12	116,226
DEBT ($m)	153	307	0	1,404
SALES ($m)	713	889	2	3,634
NI ($m)	-17	160	-436	748
AT ($m)	697	1,069	1.7	7,165
DEF (%)	0.79	0.17	0.57	1.50
TERM (%)	3.25	1.02	0.91	4.69
LBO	0.42	0.50	0	1

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Table 3. Posterior Properties of Efficiency Distributions

| | $\nu = 2$ | | $\nu = 4$ | | $\nu = 6$ | |
Firm Type	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
IPO/No LBO	0.852	0.129	0.793	0.126	0.771	0.118
SEO/No LBO	0.979	0.023	0.976	0.019	0.974	0.017
CH11/No LBO	0.604	0.265	0.527	0.221	0.501	0.193
IPO/LBO	0.777	0.182	0.706	0.167	0.674	0.153
SEO/LBO	0.965	0.038	0.963	0.029	0.959	0.027
CH11/LBO	0.483	0.295	0.401	0.236	0.361	0.201

For example, in the $\nu = 2$ case, an IPO with no leveraged buyout before the offer (IPO/No LBO) is underpriced by 15%.

Table 4. Posterior Properties of ϕ

		Mean	St. Dev.	Bayes Factor
ϕ_1	Intercept	11.538	3.191	—
ϕ_2	SEO	10.862	2.910	0.000
ϕ_3	CH11	0.352	0.071	4.6×10^{-10}
ϕ_4	LBO	0.650	0.122	0.374

Bayes factors give the evidence against H_0: $\phi_j = 1$. Very small Bayes factors correspond to the rejection of the null.

Table 5. Posterior and OLS Properties of β

| | | Stoch. Frontier | | Ordinary Least Sq. | |
		Mean	St. Dev.	Estimate	St. Error
β_2	DEBT	-0.030	0.016	-0.032	0.016
β_3	SALES	0.217	0.026	0.188	0.026
β_4	NI	0.079	0.015	0.083	0.158
β_5	AT	0.334	0.028	0.398	0.026
β_6	DEF	-0.009	0.016	-0.013	0.017
β_7	TERM	-0.078	0.016	-0.098	0.017

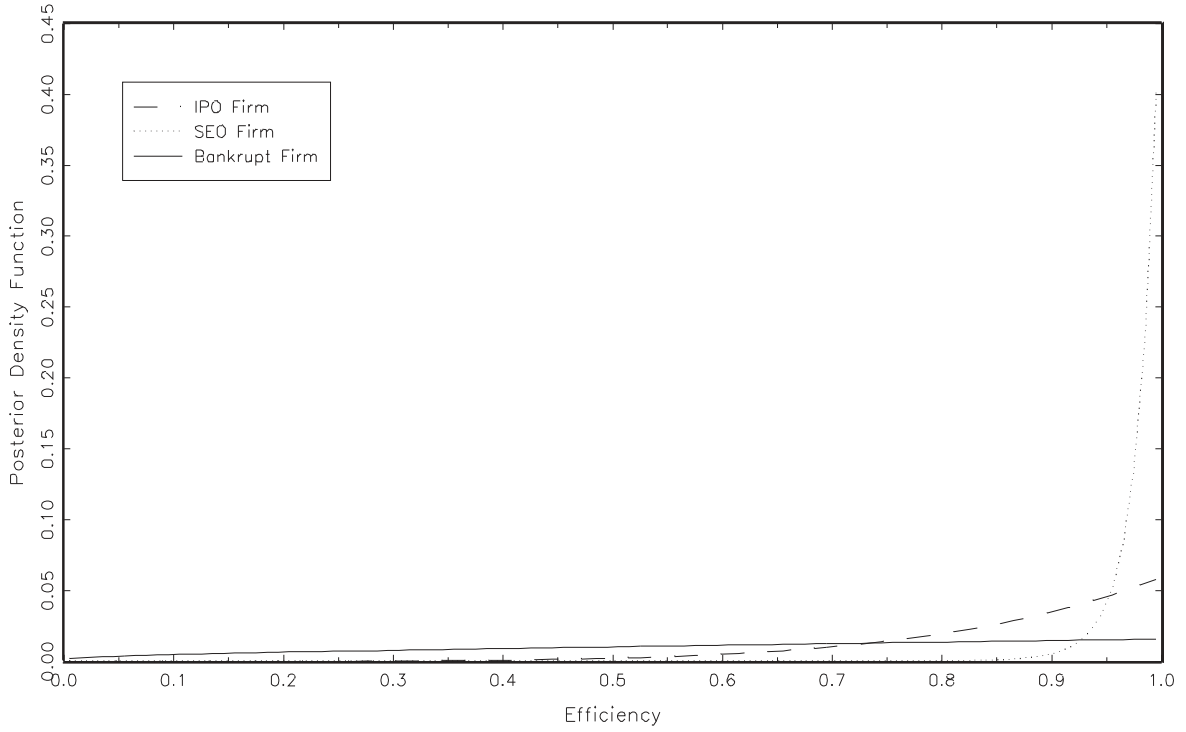Figure 1a: Efficiency Distribution (nu=2) for a Typical Firm: Non−LBO

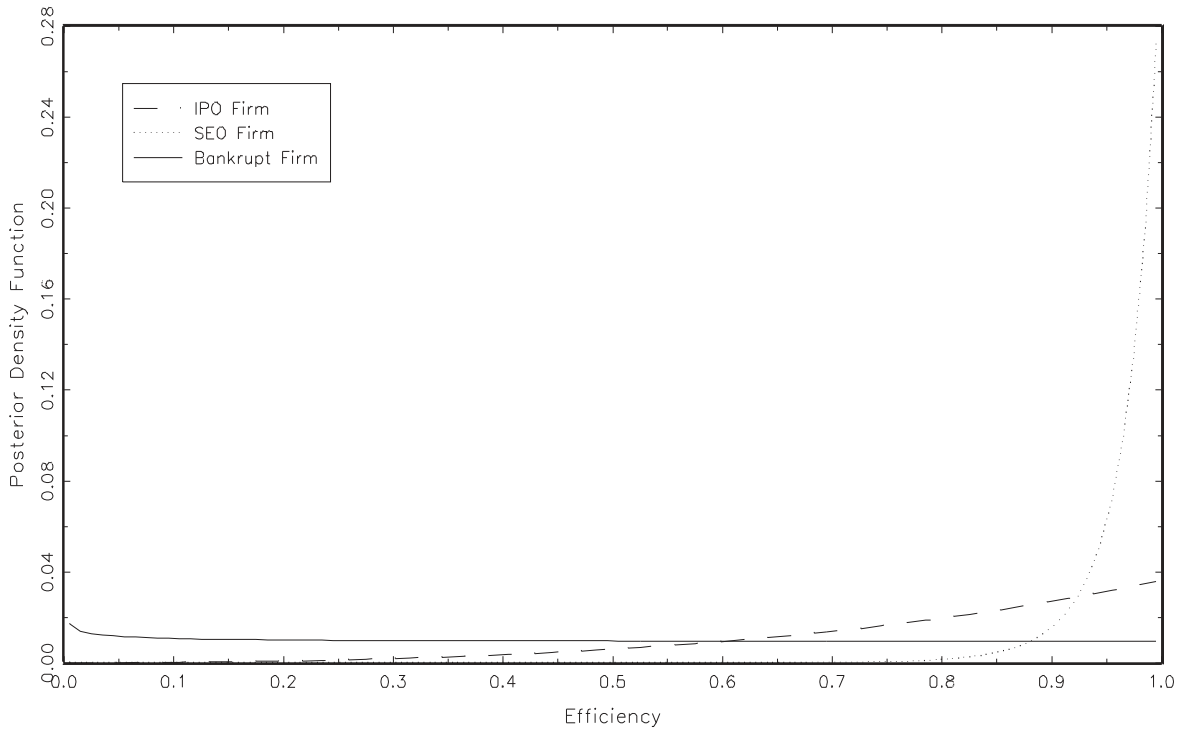Figure 1b: Efficiency Distribution (nu=2) for a Typical Firm: LBO

Figure 1c: Efficiency Distribution (nu=4) for a Typical Firm: Non-LBO
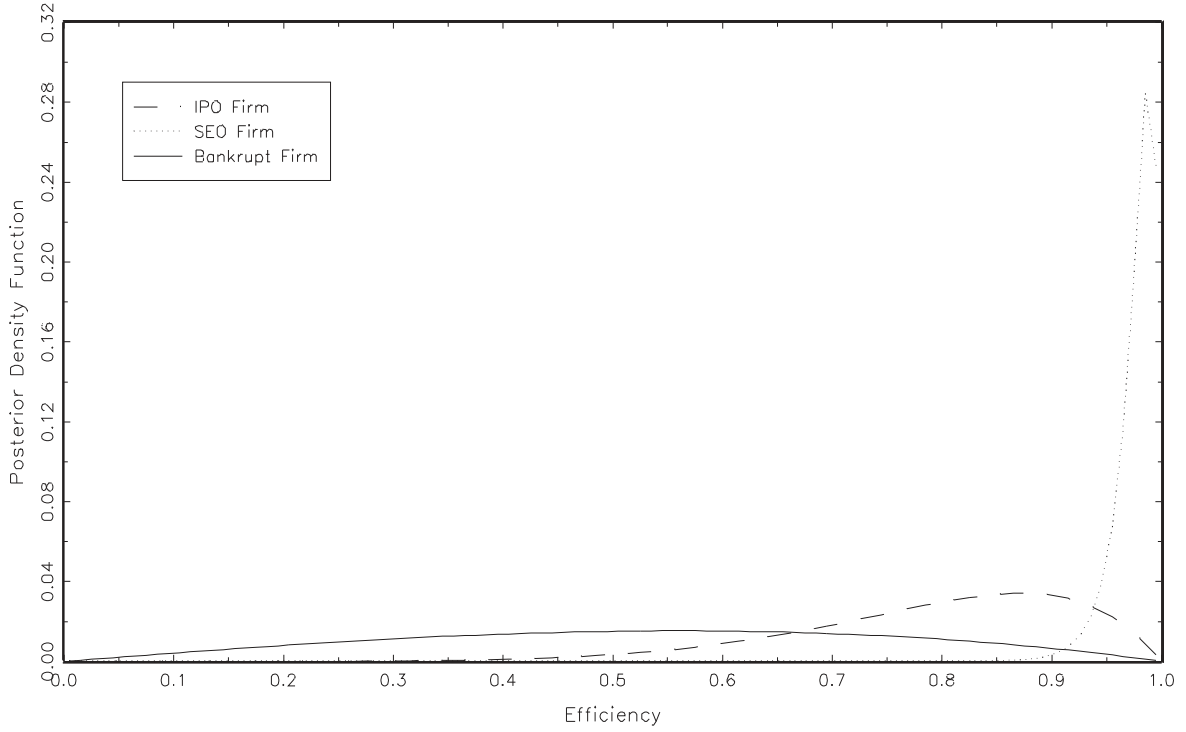

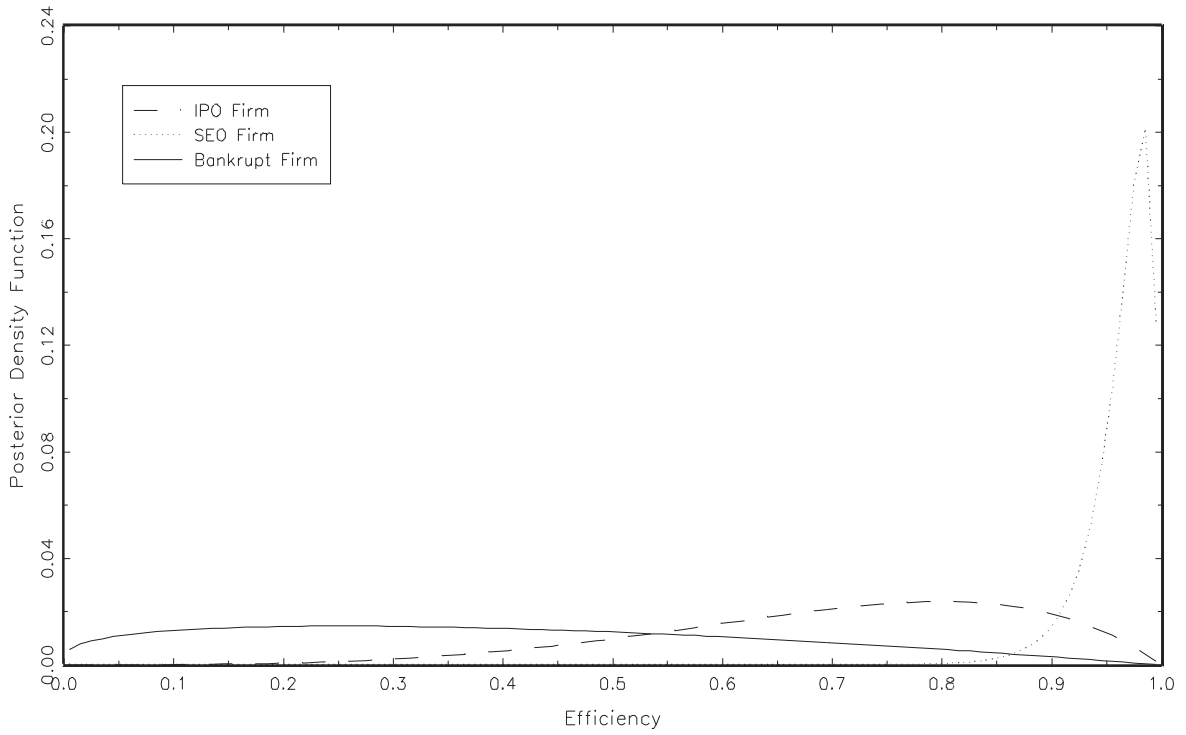Figure 1d: Efficiency Distribution (nu=4) for a Typical Firm: LBO

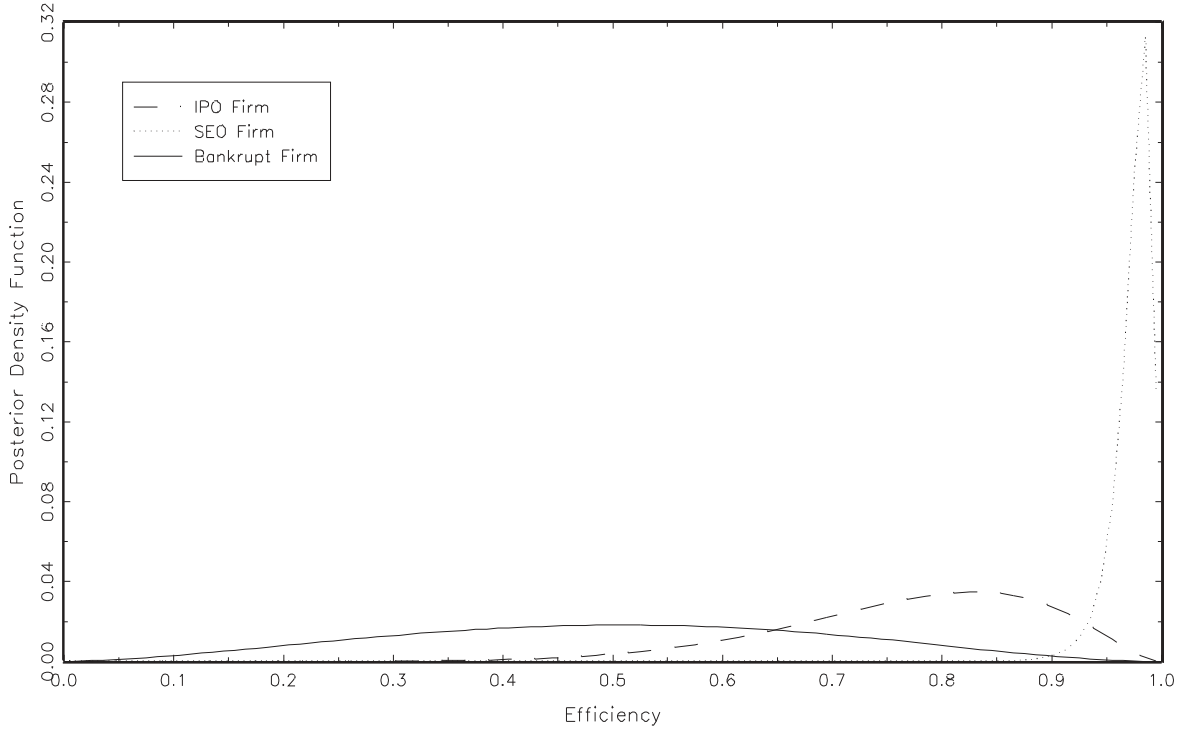Figure 1e: Efficiency Distribution (nu=6) for a Typical Firm: Non-LBO

Figure 1f: Efficiency Distribution (nu=6) for a Typical Firm: LBO