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The valuation of IPO and SEO firms

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Abstract

We examine the pricing of initial public offering (IPO) and seasoned equity offering (SEO) firms using a stochastic frontier methodology. The stochastic frontier framework models the difference between the maximum possible value of the firm and its actual market capitalization at the time of the offering as a function of observable firm characteristics. Using a new data set, we find that commonly used pricing factors do indeed influence valuation. Ceteris paribus, firms in industries with great earnings potential are more highly valued, and IPO firms are underpriced. Theories regarding underwriter reputation or windows of opportunity for equity issuance are not supported in our empirical results. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

Valuation plays a central role in corporate finance for several reasons. First, corporate control transactions such as hostile takeovers and management buyouts require the valuation of equity. Second, privately held corporations that need to set a price for their initial public offerings, or public firms that require further equity financing, must first establish the value of their equity. Finally, the estimated equity value is important in setting the capital structure of these issuing firms.

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Standard finance models imply that the value which the market places on a firm's equity should reflect the firm's expected future profitability. In the absence of data on the latter, it is common to use variables that might proxy for future profitability (e.g. net income, revenue, earnings per share, total assets, debt, industry affiliation, etc.) in an effort to value equity. One purpose of the present paper is to investigate the roles of various potential explanatory variables in valuing equity using a new, extensive data set involving many firms and many explanatory variables. However, it is often the case that firms, which are similar in terms of these observable characteristics will be valued quite differently by the market. We refer to this difference as "misvaluation". Accordingly, a second purpose of this paper is to investigate this misvaluation using stochastic frontier methods. The questions of particular interest are whether initial public offering (IPO) and seasoned equity offering (SEO) firms are valued in a different manner and whether they exhibit different patterns of misvaluation (e.g. are IPOs underpriced relative to SEOs?).

Using a sample of 2969 IPO and 3771 SEO firms between 1985 and 1998, we find that IPO firms are misvalued (e.g. underpriced), while SEO firms are almost efficiently priced. Furthermore, the market capitalization of an offering firm is positively related to net income, revenue, total assets, and underwriter fees, and negatively related to its debt level. Ceteris paribus, firms in industries with great earnings potential such as chemical products, computer, electronic equipment, scientific instruments, and communications are more highly valued, whereas firms in more traditional industries such as oil and gas, manufacturing, transportation and financial services are valued less. Finally, we find no evidence that underwriter reputation or macroeconomic factors are related to misvaluation.

Hunt-McCool et al. (1996) is the paper most closely related to our own. Their paper examines the IPO underpricing phenomenon using a stochastic frontier methodology. The authors stress that the advantage of stochastic frontier models is that they can be used to measure the extent of underpricing without using aftermarket information. This property could be very useful to corporate executives involved in IPOs when they select underwriters and determine the offer price. Hunt-McCool et al. (1996) conclude that the measure of premarket underpricing cannot explain away most anomalies in aftermarket returns and that the measure of IPO underpricing is sensitive to the issue period (e.g. hot versus nonhot IPO periods). The contributions of our work can be illustrated in contrast to their methodology. A first difference is that we apply the stochastic frontier modeling approach to both IPO and SEO firms. By construction, the stochastic frontier methodology uses firms that are efficiently priced (e.g. not misvalued) to estimate the frontier, and then misvalued firms are measured relative to this frontier. This of course, assumes that some of the firms are efficient. Seen in this way, it is interesting to see what happens if we include data both on firms that we expect to be undervalued (e.g. most IPO firms) and on those that we expect to be efficiently priced (e.g. many SEO firms). This is an important distinction between our paper and the work of Hunt-McCool et al. (1996). The latter only uses data on IPOs and cannot answer general questions such as, "Are IPOs underpriced?". They can only answer questions such as, "Are some IPOs underpriced relative to other IPOs?". However, if all IPO firms are massively and equally mispriced, their econometric methodology will misleadingly indicate full efficiency (e.g. with no efficient firms to define the pricing frontier, the frontier will be fit through misvalued IPO firms). In sum, it is important to include SEO firms to help define the efficient pricing frontier. Of course, if SEOs are consistently overpriced, then IPOs may appear underpriced using our approach even if they are efficiently priced. Furthermore, apparent undervaluation may simply reflect the influence of omitted explanatory variables. Such qualifications must be kept in mind when interpreting our results. Nevertheless, we feel that the stochastic frontier methodology, using both IPOs and SEOs, provides a new and interesting way of looking at the data and even if our findings are not definitive, they are suggestive.

A second contrast with the work of Hunt-McCool et al. (1996) is our use of the market value of common equity as the dependent variable. Hunt-McCool et al. (1996) use the offer price as a dependent variable. Since the market value of common shares is more comparable across firms than the stock price, we would argue that our approach is more sensible and our results have more general implications.

Third, by explicitly modeling misvaluation at the time of the offering as a function of observable firm characteristics, we categorize firm-specific characteristics into pricing factors and factors that are associated with misvaluation. Hence, our paper offers further evidence on the determinants of time-varying adverse selection costs in equity issues.

Finally, the Bayesian approach adopted in this paper overcomes some statistical problems which plague stochastic frontier models (see e.g. Koop et al., 1995, 1997, 2000). For instance using classical econometric methods, it is impossible to get consistent estimates and confidence intervals 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.

In summary, our work combines two distinct areas of research—the valuation literature and the stochastic frontier literature—to shed light on the determination of market capitalization in the equity issuing process. The rest of the paper proceeds as follows. In the next section, we describe the data before introducing the stochastic frontier model in Section 3. Our choice of explanatory variables are discussed in Section 4. We report the empirical results in Section 5 and conclude in Section 6.

2. Data

The initial sample of domestic US public equity offerings consists of 6828 IPOs and 6403 SEOs for the period between 1985 and 1998 (obtained from Securities

Data Corporation (SDC)). For inclusion in the final sample, we impose the following criteria. First, issuing firms must have an offer price exceeding US$1 and a market capitalization of at least US$20 million in December 1998 purchasing power. Similar criteria have been used by Ritter (1991) and Teoh et al. (1998a) in choosing their IPO samples. The first filter reduces the IPO sample from 6828 to 5737 firms, and the SEO sample from 6403 to 5851 firms. Second, issuing firms must have available accounting data in the year prior to the offering. It appears that the data availability on debt and earnings per share (EPS) is the poorest. More specifically, the lack of availability of debt and EPS data reduces IPO firms from 5737 to 3642, a hefty 37% reduction in the IPO sample; and the lack of availability of debt and EPS data reduces SEO firms from 5851 to 4409, a 25% reduction in the SEO sample. In the end, the second filter further reduces the IPO sample to 2969 firms and the SEO sample to 3771 firms.[1] The offer price is taken from SDC or, if omitted there, from Standard and Poor's Daily Stock Price Record. Firm-specific information at the (prior) fiscal year end that is closest to the IPO or SEO offer date is also taken from SDC or, if not available, from Compustat, Moody's or Annual Reports in Lexis/Nexis. The 6740 equity offers (including both IPOs and SEOs) were conducted by 4880 different companies, with only 12 firms conducting more than five SEOs during the 1985–1998 sample period. Overall, these offers represent 54% of the aggregate gross proceeds (in December 1998 purchasing power) of all firms issuing equity in the 1985–1998 period. Tables 1–4 provide descriptive statistics for 2969 IPO and 3771 SEO firms in our sample.

Table 1 presents the temporal distribution of our sample in terms of number of issues. There were a substantial number of IPOs and SEOs in each sample year. Notably, 1986, 1992, 1993, and 1996 were the highest volume years, and the period between the October 1987 market crash and the February 1991 Gulf war victory was the period of lowest issuing volume. The observed clustering of equity issues is consistent with the widely held belief of the investment community that certain periods offer a window of opportunity in which equity is less likely to be misvalued. Later in the paper, we will investigate this conjecture by including the issue–volume defined dummies (to be defined in Section 4) in the misvaluation distribution. Overall, the temporal distribution of our sample is similar to Teoh et al. (1998a,b).

Table 2 presents the temporal distribution of our sample in terms of total proceeds, measured in December 1998 purchasing power. There are sizable

[1] The sample attrition experienced here is typical of IPO and SEO studies. For example, in Teoh et al. (1998a), they start with an IPO sample of 5171 firms and, after imposing similar filtering rules, they end up with 1649 firms in the final sample, a retention rate of 32%. In Teoh et al. (1998b), the final SEO sample of 1265 firms is obtained from a much larger initial sample of 6386 firms, a retention rate of 20%. Finally, in Choe et al. (1993), they initially have 5694 SEOs over the 1971–1991 period. After requiring the return data to be available from CRSP, the final sample contains 1456 SEOs.

Table 1
Sample characteristics: issues distribution

Year	Number of IPOs	Number of SEOs	Total number of offers	Percentage
1985	121	214	335	5.0
1986	307	317	624	9.3
1987	217	199	416	6.2
1988	88	92	180	2.7
1989	79	151	230	3.4
1990	78	123	201	3.0
1991	211	328	539	8.0
1992	267	345	612	9.1
1993	343	432	775	11.5
1994	244	233	477	7.1
1995	243	359	602	8.9
1996	381	414	795	11.8
1997	237	343	580	8.6
1998	153	221	374	5.5
Total	2969	3771	6740	100

The sample consists of 2969 US IPO firms and 3771 US firms conducting seasoned equity offerings in the period between 1985 and 1998 with an offer price of at least US$1 and a market capitalization of US$20 million in December 1998 purchasing power. The sample firm must also have sufficient accounting data in the year prior to the offering. The distribution of the sample by IPO or SEO year is reported.

Table 2
Sample characteristics: proceeds distribution

Year	IPO proceeds	SEO proceeds	Total proceeds	Percentage
1985	6.19	15.00	21.19	3.8
1986	17.54	22.12	39.66	7.2
1987	13.38	14.35	27.73	5.0
1988	4.08	5.30	9.39	1.7
1989	5.30	8.04	13.34	2.4
1990	3.82	8.82	12.64	2.3
1991	14.37	28.38	42.75	7.7
1992	18.79	32.75	51.54	9.3
1993	25.52	40.00	65.52	11.8
1994	13.89	21.30	35.19	6.4
1995	17.47	35.47	52.93	9.6
1996	30.38	43.69	74.07	13.4
1997	17.15	37.38	54.54	9.8
1998	19.19	34.18	53.37	9.6
Total	207.08	346.77	553.85	100

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Table 3
Sample characteristics: industry distribution

Industry	Two-digit SIC codes	IPO sample	SEO sample	Full sample	Percentage
Oil and gas	13, 29	57	169	226	3.4
Chemical products	28	156	247	403	6.0
Manufacturing	30–34	125	151	276	4.1
Computers	35, 73	529	453	982	14.6
Electronic equipment	36	230	213	443	6.6
Transportation	37, 39, 40–42, 44, 45	179	203	382	5.7
Scientific instruments	38	152	152	304	4.5
Communications	48	108	118	226	3.4
Utilities	49	47	214	261	3.9
Retail	53, 54, 56, 57, 59	194	234	428	6.4
Financial services	60–65, 67	396	732	1128	16.7
Health	80	133	139	272	4.0
All others	1, 2, 6, 7, 8, 9, 10, 15,...	663	746	1409	20.7
Total		2969	3771	6740	100

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variations in the volume of equity issues, and the general pattern in volume is similar to that in terms of number of issues as reported in Table 1.

Table 3 provides a breakdown of SIC codes of our equity offering firms. The presence of 74 separate two-digit SIC codes, with 28 of these representing at least 1% of the sample (68 issuers), indicates a wide selection of industries. It appears that about 80% of all offers arise from the 12 industries defined in Table 3. Not surprisingly for our sampling period of 1985–1998, there is a much higher

Note to Table 4:
This table presents summary statistics of the IPO and SEO samples. There are 2969 IPO and 3771 SEO firms. All accounting data are measured in the year prior to the offer. MVCS is the market value of common stock. Initial day return is obtained as the percentage difference between the first day closing price and the offer price. EPS is the earnings per share. Debt is the sum of the long-term, short-term and subordinate debt. Fees are the total fees paid to the underwriters in an issue. Top 5 is a dummy variable, it equals one if the lead manager of the offer belongs to the top five underwriters ranked by market shares, and zero otherwise. NBER Upturn is a business cycle dummy variable constructed using the NBER chronology, it equals one if the issue month is an NBER peak, and zero otherwise. Hot is an issue volume dummy variable, it equals one if the volume of the issuing month exceeds the top quartile, and zero otherwise. Cold is another issue volume dummy variable, it equals one if the volume of the issuing month falls below the bottom quartile, and zero otherwise. Exchange is a dummy variable that equals one if the shares of the issuing firm are traded on NYSE, AMEX or NASDAQ, and zero otherwise. Repeat is a dummy variable that equals one if the issuer made multiple offers during the 1985–1998 sample period (including the case when the first time it is an IPO), and zero otherwise.

concentration of IPOs and SEOs in the computer, electronic and financial services industries than for the samples reported in Teoh et al. (1998a,b). Note that the IPO sample in Teoh et al. (1998a) covers the period between 1980 and 1992, while the SEO sample in Teoh et al. (1998b) covers the period between 1976 and 1989. Both of their samples include a high percentage of offers made in more traditional industries, such as food products, paper and paper products, durable goods, entertainment services, etc. Other than the higher concentration in the top 12 industries as tabulated in Table 3, and the decline in offers made in some traditional industries, the general industry characteristics are similar between our

Table 4
Sample characteristics of IPO and SEO firms: a comparison

Variable	IPO sample		SEO sample		*P*-value from	
	Mean	Median	Mean	Median	*T*-test	Wilcoxon
Panel A: immediate post-offering firm characteristics						
Offer price (US$)	12.23	12.00	22.21	19.50	0.0001	0.0001
Number of shares ('000s)	14 187	7420	26 686	13 111	0.0001	0.0001
MVCS (US$ million)	225.54	85.01	748.91	243.68	0.0001	0.0001
Initial day return (%)	11.06	4.95	2.43	0.79	0.0001	0.0001
Panel B: pricing factors						
Net income (US$ million)	4.43	2.10	17.23	6.30	0.0001	0.0001
Revenue (US$ million)	203.49	44.40	805.32	125.90	0.0001	0.0001
EPS (US$)	1.33	0.41	0.72	0.75	0.2953	0.0001
Total assets (US$ million)	385.25	39.70	2221.54	185.50	0.0001	0.0001
Debt (US$ million)	148.25	6.60	737.84	42.20	0.0001	0.0001
Fees (US$ million)	3.43	1.93	3.13	2.10	0.0222	0.0078
Oil and gas	0.02	0	0.04	0	0.0001	0.0001
Chemical products	0.05	0	0.07	0	0.0242	0.0259
Manufacturing	0.04	0	0.04	0	0.6729	0.6720
Computers	0.18	0	0.12	0	0.0001	0.0001
Electronic equipment	0.08	0	0.06	0	0.0007	0.0006
Transportation	0.06	0	0.05	0	0.2581	0.2550
Scientific instruments	0.05	0	0.04	0	0.0349	0.0325
Communications	0.04	0	0.03	0	0.2538	0.2497
Utilities	0.02	0	0.06	0	0.0001	0.0001
Retail	0.07	0	0.06	0	0.5836	0.5825
Financial services	0.13	0	0.19	0	0.0001	0.0001
Health	0.04	0	0.04	0	0.1041	0.1003
Panel C: misvaluation factors						
Top 5	0.19	0	0.27	0	0.0001	0.0001
NBER Upturn	0.99	1	0.98	1	0.0005	0.0008
Hot	0.39	0	0.41	0	0.1746	0.1749
Cold	0.11	0	0.11	0	0.5149	0.5158
Exchange	0.89	1	0.96	1	0.0001	0.0001
Repeat	0.31	0	0.61	1	0.0001	0.0001

sample and those of Teoh et al. (1998a,b). To account for different earnings potential and pricing practices across industries, later in our stochastic frontier model, we include industry dummies as pricing factors.

Table 4 compares sample characteristics of IPO firms with those of SEO firms. In Panel A of Table 4, we present some immediate post-offering firm characteristics. The offering prices in IPOs average about US$12.23 per share (median US$12.20), while the average offering price in SEOs is about US$22.21 per share (median US$19.50). The differences in both the mean and median offer prices are statistically significant. In terms of the number of shares outstanding after the offer, IPOs are also significantly smaller with mean number of shares outstanding at 14 187 000 (median 7 420 000) as compared to 26 686 000 shares (median 13 111 000) after SEOs. As a result, it is not surprising to find that the mean market capitalization (MVCS) of IPOs is about US$226 million and the median is about US$85 million, about one third of the values for SEOs that have the mean market capitalization of about US$749 million (median US$244 million). Consistent with the existing evidence on IPO underpricing (e.g. Kim and Ritter, 1999; Teoh et al., 1998a; Hunt-McCool et al., 1996; Ritter, 1991), IPOs in our sample on average experience a much larger first day price runup at 11.06% (median 4.95%) as compared to the runup of 2.43% (median 0.79%) of an average SEO in our sample.

3. Stochastic frontier modeling

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

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

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

where $\boldsymbol{\beta}$ 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; e.g. 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 ($i = 1, \dots, N$),

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

where $0 < \tau_i < 1$ is the efficiency of firm i, with values of τ_i near one implying a firm is near full efficiency, and ε_i reflects measurement error. It is standard to take logs of Eq. (2) and assume $f(\cdot)$ is log linear in X, yielding,[2]

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

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 $N(0, \sigma^2)$ 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 $0 < \tau_i < 1$, it follows that $u_i > 0$. It is this latter fact that allows us to distinguish between the two errors in Eq. (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 becomes 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 et al. (1996) use a Normal truncated at the point zero. Meeusen and van den Broeck (1977) and Koop et al. (1997) use an exponential distribution. Van den Broeck et al. (1994) and Koop et al. (1995) extend this by working with Erlang distributions (e.g. Gamma distributions with integer degrees of freedom). Here, we work with an exponential distribution.[3] This efficiency distribution for firm i depends on one unknown parameter, the mean, which we denote by λ_i.

In the present paper, we interpret the “output” y as being the market value of an offering firm’s equity (e.g. 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. net income, revenue, earnings per share, total assets, debt levels, and industry affiliation), which can be interpreted as “inputs”, x, used for producing the stock market value. The “production frontier”, now called the “valuation frontier”, captures the maximum that investors are willing to pay for shares in a firm with given characteristics. In the present paper, we refer to x as “pricing factors”. If two firms with similar values for pricing factors are yielding different stock market values, this is evidence that the equity of one of the firms is misvalued (relative to its characteristics). This underpricing is labelled “inefficiency” in the stochastic frontier literature and “misvaluation” in the present paper.

We use the 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 et al., 1994; Koop et al., 1997, 2000). Of particular

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

[3] In an earlier version of this paper (Koop and Li, 1998), we worked with the Erlang distribution (of which the exponential is a special case). However, empirical results were qualitatively similar for the various members of the Erlang class and, accordingly, we focus here only on the simpler exponential distribution.

interest is the fact that adoption of the Bayesian methods allows us to calculate point estimates and standard deviations of any feature of interest including u_i, the measure of misvaluation in Eq. (3). The latter feature is often of primary importance yet, as Jondrow et al. (1982) demonstrate, non-Bayesian point estimates are inconsistent. Furthermore, it is difficult to obtain meaningful standard errors for u_i using non-Bayesian approaches.[4]

Above, we have stressed that stochastic frontier models require the specification of a distribution for the measure of misvaluation u_i. Early work tended to assume that these mispricings were drawn from some common distributions (e.g. $\lambda_i \equiv \lambda$ for all i). However, Koop et al. (2000) reason that this might be too restrictive an assumption. For instance, it might be the case that firm- and issue period-specific characteristics as suggested in Choe et al. (1993) and Bayless and Chaplinsky (1996) or type of offers (IPOs versus SEOs) should be related to misvaluation. We can model such features by allowing the misvaluation distribution to depend on m observable characteristics of firm i, w_{ij} where $j = 1, \dots, m$.[5] In particular, we assume u_i to be distributed as an exponential distribution with mean λ_i where,

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

where $\phi_j > 0$ for $j = 1, \dots, m$. The preceding specification is chosen since it fulfills the technical requirement that the mean of the misvaluation distribution is positive.

It is worth stressing that in such a specification, we can directly test whether a particular firm characteristic tends to be associated with misvaluation. Note that if $\phi_j = 1$, then the jth firm characteristic has no effect on the misvaluation distribution, whereas if $\phi_j > 1$ (< 1) then the jth characteristic is associated with a lower (higher) degree of misvaluation. For instance, w_{i2} is a dummy variable that equals one if firm i makes an SEO, and zero otherwise. Then a finding of $\phi_2 > 1$ is associated with IPO underpricing. As shown in Koop et al. (2000), the Bayesian approach allows us both to estimate ϕ_2 and to statistically test whether it is equal to one or not.

To summarize, in the framework of Eqs. (3) and (4), the researcher is forced to draw on theory to decide whether a variable is an input in the valuation equation (in which case it belongs in x) or whether it should affect the level of mispricing (in which case it belongs in w). Alternative methods typically just enter all possible explanatory variables as x's (e.g. as explanatory variables which enter linearly in a regression model).

[4] It is possibly for these reasons that Hunt-McCool et al. (1996) never provide firm-specific estimates of underpricing.

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

4. The explanatory variables

In Section 3, we have outlined a framework where the dependent variable is the market value of common equity. The variables used to explain the dependent variable are broken down into "pricing factors" that are expected to directly affect the value of a stock and "misvaluation factors". In this section, we motivate why we label some of our explanatory variables as the former and some as the latter.

4.1. The pricing factors

We draw on standard finance theories to select explanatory variables that are expected to influence valuation of equity issuing firms. In Myers and Majluf (1984), investors use information about issuing firms to condition their assessment of firm value. Firms that issue in line with the predictions of capital structure theory are likely to be viewed by investors as having a reason for issue and hence, be valued fairly. Consistent with the above argument, we use issuer characteristics such as profitability, level of operations, risk, and underwriter fees as pricing factors in obtaining our valuation frontier.

Krinsky and Rotenberg (1989) and Ritter (1984) have shown a positive relationship between historical accounting information and firm value. The first set of pricing factors we include in the valuation equation relates to profitability. According to Teoh et al. (1998b), cashflows are the ultimate "bottom line" for valuation. We use net income and sales revenue over the 12-month period before the offer (as reported in the firm's prospectus) as proxies for the profitability of a firm. Following Kim and Ritter (1999), we also include earnings per share (EPS) in the fiscal year prior to the offer to measure a firm's ability to generate income for shareholders. On the other hand, past performance does not necessarily represent future performance, especially in the case of IPOs. Following Kim and Ritter (1999), Ritter (1991) and Downes and Heinkel (1982), we introduce 12 industry dummy variables (listed in Table 3) as the proxy for (perceived) earnings potential. Finally, to control for the level of operations, total assets is also included in the valuation equation.

Default risk is measured by total debt, which is the sum of long-term debt, short-term debt and subordinate debt. We expect that firms with a heavy burden of debt have a greater chance of bankruptcy, and as a result, ceteris paribus, the market value of a firm is negatively associated with its debt level.[6]

Another factor which is related to the value of the firm is the total compensation paid to the underwriter. According to Hughes (1986), underwriters' compensation will be higher for companies that are more likely to suffer from the

[6] A referee has pointed out that the variance of EPS prior to the offer date could be used as a proxy for the perceived risk of IPOs at the time of offering. We have some EPS data for our sample of IPOs prior to the offering, but the data points are insufficient for us to obtain a valid measure of variance. In future work, we plan to collect more data and use the variance of EPS as our measure of risk.

information asymmetry problem. This variable is defined as total fees paid by the issuing firm.

Panel B of Table 4 presents summary statistics of the pricing factors. SEO firms in our sample are more profitable. The mean net income of IPO firms is about US$4.43 million (median US$2.10 million), while the mean net income of SEO firms is about US$17.23 million (median US$6.30 million). Both the mean and the median are statistically different across the two groups of firms. The same holds true for the mean and median sales revenue. In terms of earnings per share (EPS), IPO firms in our sample are doing as well as SEO firms. The mean EPS of US$1.33 for IPOs is not statistically different from that of SEOs. We use total assets prior to the offer to measure the level of operations. As expected, the mean total assets of IPO firms is about US$385 million, only one-fifth of the mean total assets of SEO firms. One might argue that the very large mean value we get for the total assets of an average SEO firm (US$2221.54 million) could be driven by a few extreme observations in the sample. When comparing the median total assets of IPOs versus that of SEOs, we see the same result: the median total assets of IPOs (US$39.7 million) is about one-fifth of the median total assets of SEOs (US$185.5 million). The difference in size between IPO and SEO firms could be explained by the difference in the number of years since incorporation. Unfortunately, the data on the year of incorporation is so poor (e.g. less than 30% of the sample firms have it) that we have been unable to get reliable measurements for this variable. Finally, SEO firms in our sample on average have a much higher debt level (mean US$738 million, median US$42 million) than their IPO counterparts (mean US$148 million, median US$6.6 million).

The Fees variable indicates that IPOs pay significantly more to their underwriters than SEOs do. The mean total fees paid by IPO firms to their group of underwriters is about US$3.43 million (median US$1.93 million), while the mean fees paid by SEO firms is about US$3.13 million (median US$2.10 million). This result is consistent with the fact that IPO firms tend to be younger firms and the underwriting of IPOs is more involved.[7]

The industry distribution across the IPO and SEO samples can be summarized as follows. Over the 1985–1998 sample period, there is a higher concentration of IPOs compared to SEOs in the computer, electronic equipment and scientific instrument industries. In contrast, there is a higher concentration of SEOs in more traditional industries such as oil and gas, chemical products, utilities and financial services. The industry distribution across the IPO and SEO samples is similar for manufacturing, transportation, communications, retail and health industries.

[7] Chen and Ritter (2000) find that during 1995–1998, 90% of IPOs raising between US$20 and US$80 million have spread (fees/gross proceeds) of exactly 7%. In our sample of IPOs during 1985–1998, the average spread is 2.4%. Given that our sample covers a longer period and the average size of the offerings in our sample is bigger than that in Chen and Ritter (2000), it seems reasonable for our IPO sample to have varying and lower (than 7%) spreads.

4.2. The misvaluation factors

The extended stochastic frontier model adopted in this paper allows for firm- and issue period-specific characteristics to directly affect misvaluation.

Mispricing is costly to the issuing firms. Therefore, low risk firms attempt to reveal their low risk characteristic to the market. According to Carter and Manaster (1990), one way they can do so is by selecting underwriters with high prestige. This implies that offers underwritten by reputable Wall Street firms will be less likely to be misvalued at the time of offering. We rank all underwriters by their market shares over the 1985–1998 sample period, and create a dummy variable Top 5 that equals one if the lead underwriter of a deal belongs to the top five investment banks, and zero otherwise.[8] We expect the coefficient associated with this underwriter reputation dummy variable to be greater than one in the misvaluation distribution.

According to Choe et al. (1993), the adverse selection effects of equity offerings decrease when more promising economic conditions for new investment exist. As a result, there will be less of a mispricing problem during economic booms. In this paper, we introduce a dummy variable NBER Upturn that equals one if the economy is at an upturn based on the NBER business cycle chronology and zero otherwise.[9]

On the other hand, Bayless and Chaplinsky (1996) point out that periods selected by equity issue–volume differ rather markedly from those selected using macroeconomic criteria. They believe that there is not a simple and direct link between the business cycle and the decision to issue. Instead Bayless and Chaplinsky (1996) use the aggregate issue–volume to designate hot versus nonhot issue periods for seasoned equity. The rationale behind their designation of issue periods is as follows. If information costs are a significant deterrent to equity issue, then reductions in adverse selection costs should stimulate firms to issue equity. Ritter (1991) finds that issuers are successfully timing new issues to take advantage of windows of opportunity and the cost of external equity capital of issuers in high-volume years is lowest and their post IPO performance fares the worst. Following Bayless and Chaplinsky (1996), we introduce two issue–volume defined dummy variables Hot and Cold. First, we rank the monthly equity issue

[8] The top five underwriters ranked by market shares over the 1985–1998 sample period are Merrill-Lynch, Goldman, Sachs, Morgan Stanley Dean Witter, Salomon Smith Barney and Lehman Brothers according to Securities Data. In Carter and Manaster (1990), the rankings of underwriters are determined by examining the actual issue announcements available either from the Investment Dealer's Digest or from The Wall Street Journal. They assign an integer rank, zero to nine, for each underwriter in the announcement according to its position. Four out of our top five underwriters overlap with their top five ranked underwriters.

[9] The NBER defines a recession as a recurring period of decline in total output, income, employment and trade that usually lasts from 6 months to a year and is marked by widespread contractions in many sectors of the economy.

volume in December 1998 purchasing power into quartiles.[10] High volume issue periods (Hot) are months where the equity volume of the month exceeds the upper quartile. Low volume issue periods (Cold) are months where the equity volume of the month falls below the lower quartile. We use the offers falling between the upper and lower quartile cutoffs as the benchmark for normal periods. We expect that firms issuing in the hot market years are less likely to be undervalued (more likely to be overvalued).

All the above issue timing factors are not specific to the firm (e.g. every firm which issues in a Hot period will have the same value for this variable). This provides further justification for considering these variables as reflecting misvaluation. That is, valuation should largely reflect firm-specific characteristics rather than timing of equity issuance.

As an aside, it is worth noting that other variables have been constructed to capture the ideas developed in Choe et al. (1993) and Bayless and Chaplinsky (1996) that market and macroeconomic conditions at the time of issue can affect investors' estimates of the value of equity, and result in clustering in equity issues. Following Bayless and Chaplinsky (1996), we obtained the measures of the change in the price–earnings ratio for the S&P 500 Stock Index, the change in the S&P 500 Stock Index, the change in the Index of Industrial Production, the default premium and the term premium (Fama and French, 1989) as proxies for aggregate economic conditions. The first three of these are the average level of the variable in the 3 months prior to issue relative to the average value of the variable in the last 24 months. The other two macro variables are measured over the 3 months preceding the offering announcement. However, in our empirical work we found them to be statistically insignificant (even if they were put in the valuation frontier or simply in an OLS regression). Furthermore, they are closely related to the NBER Upturn and the Hot/Cold dummies described above. To simplify the analysis we do not present empirical results involving these variables in this paper.

Valuation errors are also predicted when the uncertainty concerning the value of firm assets in place increases. In Choe et al. (1993), stock price volatility is included as a proxy to capture the potential negative impact on equity issuance activity of market uncertainty about the value of the firm's assets. We expect that volatile stock markets are associated with equity misvaluation. Our market risk variable is the daily S&P 500 return variance measured over the 3-month period prior to the month of the stock offering. However, in our preliminary analysis of the data we found that the risk variable is statistically insignificant (even if it is put in the valuation frontier or simply in an OLS regression). We opt not to include it in our final analysis.[11]

[10] Real dollar volume is monthly nominal issue volume (US$ millions) deflated by the monthly consumer price index.

[11] This provides some evidence that the results in our paper are not sensitive to the precise classification of at least some of the explanatory variables.

It is well known that listing on NYSE, AMEX and NASDAQ demands more stringent registration requirements. As a result, we would expect that firms with shares traded on these three exchanges are less likely to be mispriced. We introduce a dummy variable Exchange that equals one if the shares of the issuing firm are traded on NYSE, AMEX or NASDAQ, and equals zero otherwise.

Since the market does not have prior experience in valuing IPO firms, we would expect that the chances that they are mispriced are greater. Accordingly, we introduce a dummy variable SEO that equals one for a seasoned equity offering, and equals zero otherwise.

Along the same lines, if a public firm repetitively come to the market for fresh equity, the market should have a more accurate valuation of the equity of the firm. Hence, we expect that firms with multiple equity offers are less likely to be mispriced. We introduce a dummy variable Repeat that equals one if the firm comes to the market more than once for equity over the sample period (including the case when the first time it is an IPO), and equals zero otherwise.

Panel C of Table 4 presents summary statistics of the misvaluation factors. Overall, SEO firms are more likely to have a Top 5 underwriter as their lead underwriter and the shares of SEO firms are more likely to be traded on NYSE, AMEX or NASDAQ. On the other hand, IPOs are more likely to take place during the upturns of the NBER business cycle as compared to SEOs. We do not find significant difference between IPOs and SEOs based on the issue–volume defined indicators (e.g. hot and cold issue periods); both types of offers are more likely to occur in the hot issue periods. This finding is consistent with the pattern seen in Table 1 that there is clustering of IPOs and SEOs over the sample periods of 1986, 1992, 1993 and 1996. Finally, we see more repeat issuers in the SEO sample (61%) than in the IPO sample (31%). Note that our repeat dummy equals one if the firm comes to the market more than twice for equity over the 1985–1998 sample period (including the case when the first time it is an IPO). Overall, more than 72% of our sample (4880 firms) are first-time issuers on the market, and less than 7% of our sample come to the market for equity more than twice during the sample period.

5. Empirical results from stochastic frontier model

5.1. Basic findings

The output, y, used in the stochastic frontier model is the log of market value of common stock (MVCS, e.g. the offer price times the number of shares outstanding after the issue). The inputs or pricing factors, x, we use are discussed in Section 4.1. Further details and a listing of all variables are given in Table 4. Variables that are positive for all firms are logged (except the intercept). Formally, we include an intercept, net income, revenue, EPS, the log of total assets, the log of debt, the log of fees and industry affiliation in the valuation frontier Eq. (3). In the misvaluation distribution Eq. (4), an intercept is included along with the 0–1 dummies explained in Section 4.2 and labelled SEO, Top 5, NBER Upturn, Hot, Cold, Exchange, and Repeat.

Table 5 contains point estimates and standard deviations for the valuation frontier parameters (e.g. $\boldsymbol{\beta}$) in Eq. (3), plus OLS estimates and standard errors.[12] It can be seen that OLS and stochastic frontier estimates are very similar. Both tell the story that net income, revenue, book value of total assets, underwriter fees and earnings potential are strongly positively associated with the market value of the offering firm, while debt has a strong negative association. These results are consistent with those found in other studies, such as Hunt-McCool et al. (1996), and Kim and Ritter (1999). The only somewhat surprising thing is the lack of a role of earnings per share in explaining market value. According to Teoh et al. (1998a,b), it is a common practice that IPO and SEO firms raise reported earnings by altering discretionary accounting accruals. As a result, earnings per share becomes a less relevant pricing factor. Our result is consistent with the findings in Teoh et al. (1998a,b). In contrast, many of the industry dummies are highly significant, indicating the different profit potential in different industries is far more important than past accounting data. In particular, firms in industries with great earnings potential such as chemical products, computers, electronic equipment, scientific instruments, and communications are more highly valued, whereas firms in more traditional industries such as oil and gas, manufacturing, transportation and financial services are valued less than comparable firms in most other industries.[13] According to Choe et al. (1993), utility offerings are much more frequent and predictable and are less likely to be associated with adverse selection given the extensive regulation of industry profits and frequent regulatory pressure to undertake equity offerings. We find that utilities are more highly valued, which is consistent with the above explanation. On the other hand, the massive failure of Savings and Loans companies in the 1980s and the sovereign debt crises of many Third World countries in the 1990s probably explain the severe underpricing experienced by the financial services firms in our sample.

The posterior means and standard deviations of the coefficients on the variables in the misvaluation distribution (e.g. ϕ in Eq. (4)) are presented in Table 6. Remember that if $\phi_j > 1$, then misvaluation factor j is associated with a higher degree of efficiency (e.g. less misvaluation). If $\phi_j < 1$, then the factor is associated

[12] The intercept has a different interpretation in the stochastic frontier and OLS results and is not presented.

[13] A referee questioned whether financial firms should be dropped from our study since they have a capital structure, which is heavily oriented towards debt. We found that omitting these firms did not cause any substantive changes in our results.

Table 5
Posterior and OLS properties of $\boldsymbol{\beta}$ in Eq. (3)

	Stochastic Frontier Model		OLS regression	
	Mean	S.D.	Estimate	S.E.
Net income	8.4×10^{-4}	6.2×10^{-5}	8.8×10^{-4}	6.8×10^{-5}
Revenue	2.9×10^{-5}	2.6×10^{-6}	3.1×10^{-5}	2.9×10^{-6}
EPS	-4.5×10^{-5}	4.0×10^{-4}	-2.9×10^{-4}	3.6×10^{-4}
Total assets	0.375	0.008	0.423	0.008
Debt	−0.043	0.005	−0.054	0.005
Fees	0.752	0.010	0.699	0.010
Oil and gas	−0.174	0.042	−0.110	0.045
Chemical products	0.277	0.034	0.322	0.036
Manufacturing	−0.119	0.040	−0.137	0.042
Computers	0.172	0.026	0.175	0.027
Electronic equipment	0.186	0.033	0.191	0.035
Transportation	−0.162	0.035	−0.160	0.037
Scientific instruments	0.200	0.039	0.217	0.040
Communications	0.181	0.044	0.170	0.046
Utilities	0.206	0.040	0.245	0.044
Retail	−0.025	0.033	−0.029	0.035
Financial services	−0.532	0.026	−0.582	0.027
Health	−0.023	0.040	−0.017	0.042

This table presents point estimates and standard deviations for the valuation frontier parameters (i.e. $\boldsymbol{\beta}$ in Eq. (3)) under the stochastic frontier model, and point estimates and standard errors under the OLS regression, respectively. The sample consists of 2969 US IPO firms and 3771 US firms conducting seasoned equity offerings in the period between 1985 and 1998. The dependent variable is the market value of common equity, obtained as the product of the offer price and the number of shares outstanding after the issue.

with more misvaluation, and $\phi_j = 1$ indicates that the factor has no effect. Bayes factors for the latter hypothesis are presented in Table 6.

Clearly, the SEO variable is strongly significant with a magnitude indicating that IPOs are underpriced relative to SEOs. None of the other variables are strongly significant. There is some evidence in favor of the hypothesis that firms that have issued equity more than once are priced more efficiently than those who only issued equity a single time. The variables relating to the timing of issue (e.g. NBER Upturn, Hot and Cold) all seem to have no effect on the degree of misvaluation. The variables reflecting the trading location of the shares (Exchange) and the choice of underwriter (Top 5) are also insignificant. The latter result, combined with the important role of underwriter fees presented above (e.g. the Fees variable was very significant in the valuation frontier Eq. (3)) indicate that it is the amount of money spent on underwriting, rather than the choice of a particular underwriter, which is important.

The role of the explanatory variables in the misvaluation distribution can be partly understood through ϕ, but an examination of the misvaluation distributions

Table 6
Posterior properties of ϕ in Eq. (4)

	Mean	S.D.	Bayes factor
Intercept	4.288	2.144	–
SEO	25.197	5.318	0.000
Top 5	1.035	0.082	19.196
NBER upturn	0.758	0.294	4.223
Hot	1.074	0.069	14.152
Cold	0.993	0.103	15.903
Exchange	0.898	0.090	8.665
Repeat	1.202	0.082	0.713

This table presents point estimates and standard deviations of the coefficients on the variables in the misvaluation distribution (i.e. ϕ in Eq. (4)) under the stochastic frontier model. The sample consists of 2969 US IPO firms and 3771 US firms conducting seasoned equity offerings in the period between 1985 and 1998. Bayes factors give the evidence in favor of H_0: $\phi_j = 1$ (i.e. the factor j has no effect on misvaluation). Values of Bayes factors greater than one indicate support for H_0. SEO is a dummy variable that equals one if the offer is a seasoned equity offer, and zero otherwise. Top 5 is a dummy variable, it equals one if the lead manager of the offer belongs to the top five underwriters ranked by market shares, and zero otherwise. NBER upturn is a business cycle dummy variable constructed using the NBER chronology, it equals one if the issue month is an NBER peak, and zero otherwise. Hot is an issue volume dummy variable, it equals one if the volume of the issuing month exceeds the top quartile, and zero otherwise. Cold is another issue volume dummy variable, it equals one if the volume of the issuing month falls below the bottom quartile, and zero otherwise. Exchange is a dummy variable that equals one if the shares of the issuing firm are traded on NYSE, AMEX or NASDAQ, and zero otherwise. Repeat is a dummy variable that equals one if the issuer made multiple offers during the 1985–1998 sample period (including the case when the first time it is an IPO), and zero otherwise.

themselves is more informative. In the stochastic frontier literature, it is common to work with efficiency, τ_i, rather than inefficiency, u_i. As noted in Section 3, $\tau_i = \exp(-u_i)$ and, since efficiency is bounded between zero and one, it is easier to interpret. For instance, a value of 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 about 15%). Hence for the remainder of this paper, we will present results relating to misvaluation using τ_i. 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. Note that the underpricing distribution varies across firms (e.g. depends on $\boldsymbol{w}$, a vector containing an intercept and the 0–1 dummies) and hence, we cannot present results for every firm here (6740 of them). Instead, we group firms by their underpricing distributions. With seven dummy variables there are too many groups to be easily presented. We choose to focus on the SEO, Top 5 and Repeat dummies. In particular, we divide firms into eight groups depending on the values of these three dummies. For instance, SEO/Top 5/Repeat represents SEOs that were underwritten by the Top 5 investment banks and came to the market to issue equity more than once. We can derive an efficiency distribution corresponding to this group of firms. We refer to the result as the "Efficiency Distribution for a Typical Firm with SEO = 1, Top 5 = 1 and Repeat = 1". Each of these eight groups of firms has Hot = Cold = NBER Upturn = Exchange = 1. Since the coefficients on these latter variables are all very close to one, these choices have virtually no impact on the results. For more explanation, formalization and computation details of this type of efficiency distribution, see van den Broeck et al. (1994, pp. 279–280).

Fig. 1 plots the efficiency distributions for a typical firm in the eight groups along with the prior we use. Table 7 gives the means and standard deviations of these eight efficiency distributions. These plots tell the most important parts of our empirical story.

First, 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 firms are extremely disperse and there is a great deal of evidence for underpricing. The mean of the IPO efficiency distribution for each group of firms is in the region of 0.70–0.75. This indicates that, on average, IPO firms are valued at only 70–75% of what the valuation frontier says is the maximum possible. However, the high standard deviation associated with this distribution indicates that some individual IPO firms are valued quite efficiently and some very inefficiently.

Third, the lack of influence of the other explanatory variables on misvaluation (except possibly for Repeat having a minor role) is clearly visible in Fig. 1 and Tables 6 and 7.

Fourth, the prior we are using is quite noninformative. Furthermore, since the posterior efficiency distributions are very different from the prior, it is clear that the prior has little effect on our results.

5.2. Further discussion of results

As discussed in Section 3, the paper most related to ours is Hunt-McCool et al. (1996). These authors use a stochastic frontier methodology but only use IPO firms. We have argued above that this is not a good way to investigate IPO underpricing. Our approach addresses the issue of whether IPOs are underpriced relative to a valuation frontier determined by all issuing firms. The Hunt-McCool et al. approach addresses the issue of whether some IPOs are underpriced relative to other IPOs. It is instructive to ask what would have happened if we had adopted the Hunt-McCool et al. approach. Accordingly, we repeat all of our empirical analyses using only the 2969 IPO firms.

The results relating to the valuation frontier (not reported) are quite similar to those obtained with the full sample in Table 5, which provides some support for our pooling of the two types of offers. Table 8 presents results relating to the

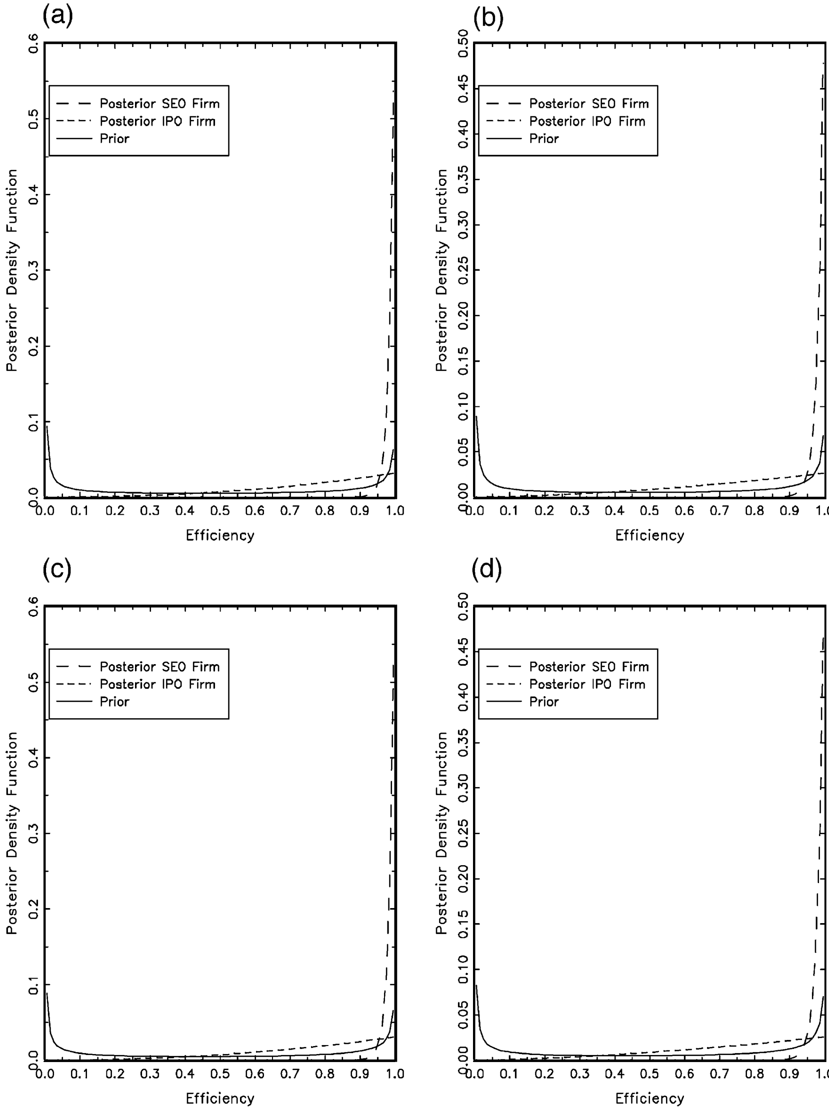

Fig. 1. (a) Eff. Dist. for a Typ. Firm: Top 5 = Rep. = 1. (b) Eff. Dist. for a Typ. Firm: Top 5 = 1, Rep. = 0. (c) Eff. Dist. for a Typ. Firm: Top 5 = 0, Rep. = 1. (d) Eff. Dist. for a Typ. Firm: Top 5 = Rep. = 0.

efficiency distribution in a similar way as Table 7. This table indicates a few interesting contrasts with Table 7. First, IPO firms now look much more efficient and there is very little evidence of underpricing. This is exactly what we would

Table 7
Posterior properties of efficiency distributions for different types of firms

Type of firm	Mean	S.D.
SEO/Top 5/Repeat	0.986	0.013
SEO/Top 5/No Repeat	0.984	0.016
SEO/No Top 5/Repeat	0.986	0.014
SEO/No Top 5/No Repeat	0.983	0.017
IPO/Top 5/Repeat	0.759	0.191
IPO/Top 5/No Repeat	0.724	0.210
IPO/No Top 5/Repeat	0.753	0.193
IPO/No Top 5/No Repeat	0.718	0.212

This table presents the posterior distributions of the efficiency measure τ in Eq. (2) for different groups of issuing firms. For instance, a value of 0.85 indicates that the market value of the issuing firm is only 85% of the maximum it could be, or equivalently, the firm is undervalued by about 15%. The sample consists of 2969 US IPO firms and 3771 US firms conducting seasoned equity offerings in the period between 1985 and 1998. We choose to focus on the SEO, Top 5 and Repeat dummies, and divide firms into eight groups depending on the values of these three dummies. For instance, SEO/Top 5/Repeat represents SEOs, which were underwritten by the top five investment banks and came to the market to issue equity more than once. Other types of firms can be interpreted similarly. Each of these eight groups of firms has Hot = Cold = NBER upturn = Exchange = 1.

expect. Since the data set no longer contains efficient SEO firms, the benchmark against which IPO firms are being compared is lower.[14]

Second, for IPO firms there is evidence that choosing an underwriter from the top five investment banks does have some effect. In particular, IPOs underwritten by the top five underwriters tend to be valued more highly than those which are not. This result presumably does not hold for SEO firms and, given the predominance of SEOs in the total sample, gets swamped when we use the entire data set. Apparently, underwriter certification is more important for IPO firms than for the SEO firms, a result that is consistent with Hughes (1986).

[14] Based on the results reported in Table 7, we see that IPO firms on average are undervalued by 25–30%, while Hunt-McCool et al. (1996) conclude that their sample of IPOs are on average underpriced by 8–9%. We attribute the drastic difference in results to the following factors. First, the sample is different. Hunt-McCool et al. (1996) use a data set covering 1035 IPOs over the period 1975–1984, and their first day return is 10%. We employ a more recent (covering the 1985–1998 period) and larger IPO data set (with 2969 observations), the first day return in our IPO sample is 11%. Hence, a small portion of the difference in results could be driven by the difference in data employed. Second, our methodology is an improved version of Hunt-McCool et al. (1996). We apply the stochastic frontier modeling approach to both IPO and SEO firms. Using only IPO firms (as did by Hunt-McCool et al. (1996)), we find the average IPO underpricing is much lower, at around 5% (see our Table 8). In sum, we are inclined to attribute the bulk of the difference in results on IPO underpricing to the difference in methodology employed.

Table 8
Posterior properties of efficiency distributions for different types of firms using only IPO firms

Type of firm	Mean	S.D.
IPO/Top 5/Repeat	0.988	0.013
IPO/Top 5/No Repeat	0.982	0.021
IPO/No Top 5/Repeat	0.931	0.074
IPO/No Top 5/No Repeat	0.891	0.108

This table presents the posterior distributions of the efficiency measure τ in Eq. (2) for different groups of IPO firms. For instance, a value of 0.85 indicates that the market value of the issuing firm is only 85% of the maximum it could be, or equivalently, the firm is undervalued by about 15%. The sample consists of 2969 US IPO firms in the period between 1985 and 1998. We choose to focus on the Top 5 and Repeat dummies, and divide firms into four groups depending on the values of these two dummies. For instance, IPO/Top 5/Repeat represents IPOs, which were underwritten by the top five investment banks and came to the market to issue equity more than once. Other types of firms can be interpreted similarly. Each of these four groups of firms has Hot = Cold = NBER upturn = Exchange = 1.

Third, for the other dummy variables (e.g. NBER Upturn, Hot, Cold, Exchange and Repeat) results are the same as with the entire sample, which provides further support for our pooling of the two types of offers.

The results relating to IPO underpricing relative to SEOs can be interpreted in two different ways. It is possible that the misvaluation we have found truly is underpricing. That is, for the reasons discussed in previous sections, the offer price of IPOs genuinely tends to be less than a fair valuation of the underlying worth of the issuing firm. Alternatively, it could be the case that the apparent misvaluation of IPOs arises because they are priced in a fundamentally different manner from SEOs. That is, we should not have assumed that IPOs and SEOs face a common valuation frontier.[15] If this is the case, the findings presented using just the IPO data indicate there is very little misvaluation.

In short, we have two stories: “IPOs are underpriced” or “IPOs and SEOs are valued in completely different ways, but each is valued fairly efficiently by the market”. We cannot tell which of our two stories is the correct one due to lack of theoretical guidance. However, regardless of which story is correct, our stochastic frontier methods have highlighted important empirical regularities in the data that are worthy of further study by theorists and applied researchers.

We believe that we have made a strong argument why some explanatory variables should be considered pricing factors and others misvaluation factors. However, some might disagree with certain aspects of our classification. Perhaps the most controversial choice is classifying the macroeconomic variables as

[15] Evidence against this latter interpretation arises from the fact that the estimated frontiers using all the data and using just IPO data are quite similar (except for the intercept). It is hard to argue that IPOs and SEOs are fundamentally different, yet at the same time explanatory variables such as net income, revenue, total assets, debt, etc. influence IPOs and SEOs in such a similar manner.

misvaluation factors. Note however, that these are found to be insignificant (even if they are put in the valuation frontier) and hence, this classification choice is irrelevant for our empirical results. Furthermore, our decisions for variables relating to underwriters might be controversial. However, our empirical results (especially those which relate to the IPO underpricing issue) are qualitatively the same regardless of whether these variables are included as pricing or misvaluation factors.

6. Conclusion

In this paper, we have examined the pricing of IPOs and SEOs using a stochastic frontier methodology. The model introduces a systematic one-sided error term that captures misvaluation defined as the difference between the maximum value of the firm and its actual market capitalization at the time of the offering. To uncover the sources of mispricing, we further model the misvaluation distribution in the pricing equation as a function of observable firm- and issue period-specific characteristics.

Data for the analysis are comprised of 2969 IPO and 3771 SEO firms between the period of 1985 and 1998. Our estimated valuation frontier is reasonable. Measures of profitability, level of operations, risk and underwriter fees are found to have significant explanatory power. Ceteris paribus, firms in industries with great earnings potential such as chemical products, computers, electronic equipment, scientific instruments, and communications are more highly valued, whereas firms in more traditional industries such as oil and gas, manufacturing, transportation and financial services are valued less. The variables included to explain misvaluation are mostly insignificant. For instance, variables reflecting underwriter reputation or windows of opportunity are not significant. However, the dummy variable for whether the issue is a SEO or an IPO is highly significant, indicating that IPOs are underpriced relative to SEOs.

The advantage of stochastic frontier models is that they can be used to measure the level of mispricing in the premarket without resorting to 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 finance.

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Appendix A. Computational methods

Bayesian estimation is based on the posterior distribution, which is proportional to the likelihood function times the prior. Eqs. (3) and (4) given in Section 3 specify the likelihood functions which depend on the parameter vector $\boldsymbol{\theta} = (\beta', \sigma^{-2}, \phi')'$ where $\phi = (\phi_1, \ldots, \phi_m)'$. As discussed in Fernandez et al. (1997), proper priors are required for σ^{-2} and ϕ for the posterior and its moments to exist. We assume independent Gamma priors for these parameters. In particular, σ^{-2} is $f_G(\sigma^{-2} \mid n_0, s_0^{-2})$ and ϕ_h is $f_G(\phi_h \mid n_h, s_h^{-2})$, where $f_G(\cdot \mid a,b)$ is the Gamma distribution with a degrees of freedom and mean b (see Poirier, 1995, pages 98–99). Note that, if degrees of freedom are close to zero (relative to the sample size N), then the prior is noninformative relative to the data. Loosely speaking, a prior with n_h degrees of freedom contains as much information as a data set with n_h observations. Setting degrees of freedom close to zero results in a prior very close to the standard flat noninformative prior.

With these general considerations in mind, we elicit the following values for the prior hyperparameters. For σ^{-2}, we have very little prior information and, hence, set $n_0 = 10^{-6}$. With such a selection, the choice of s_0^{-2} does not matter much (see formulae below). For the record, we set $s_0^{-2} = 1$. In van den Broeck et al. (1994), a prior elicitation strategy is described for ϕ_1 for the case $m = 1$, which sets $n_1 = \nu$ and $s_1^{-2} = (1)/(-\ln(\tau^*))$. For this case, or for firms with $w_{ij} = 0$ for $j = 2, \ldots, m$, this prior is quite uninformative but implies prior median efficiency is τ^*, a natural quantity to elicit. Here we set $\tau^* = 0.90$. Note that $\phi_j = 1$ for $j = 2, \ldots m$ implies that w_{ij} has no effect on inefficiency (since one to any exponent is still one). This is a hypothesis we test in the paper. A common Bayesian practice is to centre the prior over the restriction being tested. This implies $s_j^{-2} = 1$ for $j = 2, \ldots, m$. In order to ensure a relatively noninformative prior we set $n_j = 1$ for $j = 2, \ldots, m$. Hence, we have used a relatively noninformative prior which is centered over the hypothesis that the 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 et al., 1995, 1997) involving the following conditional distributions.

For the frontier coefficients,

$$p(\beta \mid \text{Data}, \sigma^{-2}, \phi, u) = f_N\left(\beta \mid \hat{\beta}, \sigma^2 (x'x)^{-1}\right), \tag{A1}$$

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

$$\hat{\beta} = (x'x)^{-1} x'\boldsymbol{y}. \tag{A2}$$

For the measurement error precision,

$$p\left(\sigma^{-2}|\mathrm{Data},\beta,\phi,u\right) = f_{\mathrm{G}}\left(\sigma^{-2}|n_0+N, \frac{n_0+N}{(n_0+N)s_0^2+(y-x\beta+u)'(y-x\beta+u)}\right). \tag{A3}$$

For the parameters in the inefficiency distribution,

$$p\left(\phi_h|\mathrm{Data},\beta,\sigma^{-2},\phi^{(-h)},u\right) = f_{\mathrm{G}}\left(\phi_h|2\left(n_h+2\sum_{i=1}^{N} w_{ih}\right), \frac{2\left(n_h+2\sum_{i=1}^{N} w_{ih}\right)}{n_h s_h^2 + 2\sum_{i=1}^{N} w_{ih} u_i \prod_{j\neq h} \phi_j^{w_{ij}}}\right), \tag{A4}$$

where $\phi^{(-h)} = (\phi_1, \dots, \phi_{h-1}, \phi_{h+1}, \dots, \phi_m)$. 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 negligible effect on the above distributions. In this sense, the empirical results in this paper are based on a noninformative prior.

For u,

$$p\left(u|\mathrm{Data},\beta,\sigma^{-2},\phi,u\right) = f_{\mathrm{N}}\left(u|x\beta-y-\sigma^2\eta,\sigma^2\mathrm{I}_N\right)I\left(u\epsilon R_+^N\right), \tag{A5}$$

where $\eta = (\lambda_1^{-1}, \dots, \lambda_N^{-1})'$, $\mathbf{I}_N$ is the $N \times N$ identity matrix and $I(\cdot)$ is the indicator function. That is, the conditional for u is truncated Normal.

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 $i = 2, \dots, m$ using the Savage–Dickey density ratio (see Verdinelli and Wasserman, 1995). In previous work with such models, Koop et al. (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 50 000 passes through the Gibbs sampler with an initial 5000 discarded to mitigate initial condition effects. Experimental runs using different starting values indicate that initial condition effects are minimal.

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