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IPO Pricing Efficiency in China's A-Share Market: A Stochastic Frontier Analysis

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Abstract

Initial Public Offerings (IPOs) have long been a focal point in financial research, attracting significant academic and practical attention. This study examines the pricing efficiency of IPOs across various industries and sectors in China's A-share market by analyzing data from 2,846 companies listed between January 2014 and July 2024. Using the Stochastic Frontier Analysis (SFA) model, we evaluate inefficiencies in IPO pricing, categorizing the independent variables into financial metrics (e.g., earnings per share, net assets, total assets) and pricing-related factors (e.g., financing scale, issuance costs, firm age, market conditions). The findings demonstrate that financial metrics exert a more significant influence on pricing efficiency than pricing-related factors. Moreover, notable differences in pricing efficiency are observed across industries and sectors, with the SME board exhibiting the highest efficiency and the comprehensive board showing the lowest, reflecting the unique characteristics and performance dynamics of each market segment. This study further identifies structural issues in China's IPO system, highlighting how lower issuance prices stimulate speculative behavior while limiting the market's capacity to support economic development. These insights contribute to a deeper understanding of IPO pricing mechanisms and provide valuable guidance for enhancing market efficiency.

Keywords: A-share Market, China, IPO Pricing Efficiency, Stochastic Frontier Analysis (SFA), Underpricing

1. Introduction

1.1 Rational of the Study

In the A-share market, Initial Public Offerings (IPOs) serve as a critical mechanism for corporate financing and offer the public valuable investment opportunities. However, the efficiency of IPO pricing remains a subject of debate due to its profound implications for market stability, investor confidence, and resource allocation. Mispricing—whether in the form of underpricing or overpricing—can lead to distortions in investment decisions and company valuations, underscoring the need for accurate and efficient IPO pricing (Reid-Grant, M. Y. (2018). This study advances existing research by employing the Stochastic Frontier Analysis (SFA) model to evaluate pricing efficiency within the A-share market, a context distinguished by its unique regulatory environment and operational characteristics. Unlike conventional approaches such as Ordinary Least Squares (OLS), the SFA model is specifically designed to identify inefficiencies, offering a more nuanced understanding of the dynamics underlying IPO pricing (Mohamad, Hassan, & Bader, 2008).

The primary hypothesis of this study posits that IPO pricing efficiency is significantly influenced by financial indicators such as earnings per share, net assets, and total assets, alongside pricing-related factors including fundraising size, cost per share, company age, and market conditions. The secondary hypothesis suggests that notable differences in IPO pricing efficiency exist across sectors and industries within the A-share market. Grounded in market efficiency theory, this approach enables the estimation of an "ideal" IPO price and the measurement of inefficiencies. The findings aim to provide actionable insights for regulators, underwriters, and companies seeking to enhance pricing mechanisms and reduce mispricing risks. Furthermore, these insights may assist investors in devising more informed strategies for navigating the A-share market.

1.2 Importance of the Problem

Initial Public Offerings (IPOs) have garnered significant attention from academia, businesses, and regulatory authorities due to their critical role in corporate financing and market development. Globally, IPO underpricing is a prevalent phenomenon, but it is particularly acute in China’s capital market, often referred to as the "IPO underpricing puzzle." This term describes the practice of setting IPO prices below their market value, leading to substantial price surges upon listing (Haque, 2024). Such underpricing distorts resource allocation, undermines investor interests, and disrupts market stability. While much of the existing research on IPO pricing efficiency in China focuses on the secondary market—where underpricing remains pronounced—studies examining efficiency in the primary market are relatively limited. Excessive underpricing indicates that IPOs are systematically undervalued, resulting in insufficient capital raised during the initial offering. This compels companies to seek alternative financing channels, such as private equity or debt, thereby increasing financing costs and financial risk (Cumming & Johan, 2013). Furthermore, prior studies often concentrate on specific sectors or policies, such as the Growth Enterprise Market or registration-based reforms, without providing a comprehensive market-wide analysis. Recent reforms to the A-share IPO system have revealed persistent inefficiencies in the IPO process, partly attributable to irrational investor behavior and inadequate investor education. This study addresses these gaps by employing Stochastic Frontier Analysis (SFA) to evaluate IPO pricing efficiency in the primary market, emphasizing firm fundamentals. The primary objective is to estimate an optimal IPO price that accurately reflects firms intrinsic value, thereby contributing to a deeper understanding of IPO pricing dynamics. Additionally, by analyzing various sectors and industries within the A-share market, this study offers a holistic perspective on the evolving trends and inefficiencies in IPO pricing, providing valuable insights for policymakers, underwriters, and market participants.

1.3 Describe Relevant Scholarship

IPO pricing efficiency has long been a focal point in financial economics, underpinned by multiple theoretical frameworks. Among these, asymmetric information theory is particularly influential. Rock (1986) introduced the "Winner's Curse" model, which argues that uninformed investors are at a disadvantage due to adverse selection, prompting issuers to deliberately underprice IPOs to attract their participation. This perspective is further enriched by signaling theory, as proposed by Allen and Faulhaber (1989), which posits that high-quality firms intentionally underprice their IPOs to signal strong future profitability to investors. Meanwhile, behavioral finance theory, advanced by scholars such as Shiller (2000), emphasizes the role of investor sentiment and psychological biases in driving market inefficiencies and pricing deviations. Lastly, institutional economics theory highlights the influence of regulatory frameworks and market structures on IPO pricing efficiency, with unique implications for emerging markets like China. Building on these theoretical foundations, both domestic and international scholarship has extensively investigated IPO pricing efficiency. Beatty and Ritter (1986) were pioneers in this field, demonstrating that investors often set IPO prices deliberately below intrinsic value in the primary market, leading to inefficiencies in pricing. Their findings provided a cornerstone for subsequent studies. For example, Ekkayokkaya and Pengniti (2012), in an empirical study of Thailand’s market, confirmed similar patterns of deliberate underpricing, aligning with the conclusions drawn by earlier research. In the context of the Chinese market, particularly the A-share market, numerous studies have employed traditional Ordinary Least Squares (OLS) regression models to analyze the determinants of IPO pricing. For instance, He and Lu (2010), Li et al. (2014), and Duan et al. (2018) proposed theoretical hypotheses from various perspectives, including public information, institutional design, and disparities in institutional quotations, and conducted empirical tests to validate these hypotheses. While these studies address IPO pricing efficiency in China’s market, they share a common limitation: they primarily examine the marginal impact of specific systems or factors on IPO pricing efficiency, without a systemic analysis of overall pricing efficiency. Specifically, there is a lack of comprehensive discussion regarding differences in equity capital pricing efficiency across various sectors and industries within the current Chinese capital market environment. Moreover, the reliance on traditional linear regression models fails to adequately capture inefficiencies in the pricing process, limiting their ability to provide a holistic interpretation of the A-share market.

In the process of new stock issuance, three key price indicators are typically emphasized: the IPO issuance price, the first-day closing price in the secondary market, and the intrinsic value of the stock. Ideally, analyzing the deviations between primary and secondary market prices, relative to the first-day closing price, constitutes the core of pricing efficiency analysis. However, since the intrinsic value of new stocks is unobservable, existing literature often relies on the efficient market hypothesis, which assumes that the first-day closing price reflects a company's intrinsic value. As a result, the difference between the first-day closing price and the IPO issuance price is used to calculate the IPO underpricing rate, serving as a proxy for the efficiency of new stock issuances. On the other hand, due to investor sentiment and information asymmetry, the first-day closing price in the secondary market may not accurately reflect a stock's intrinsic value, potentially introducing biases when the underpricing rate is used directly for analysis. With advancements in analytical tools within technological economics, many scholars have incorporated intrinsic unobservable factors into the IPO pricing process by employing Stochastic Frontier Analysis (SFA) to study pricing efficiency. Benveniste, L. M., Busaba, W. Y., & Wilhelm Jr, W. J. (1996) were the first to apply the stochastic frontier model to IPO pricing research, concluding that the underpricing phenomenon in the U.S. stock market is primarily driven by underpricing in the primary market. In the Chinese A-share market, Liu Yuhui and Shen Keting (2011) pioneered the application of the SFA method, finding that limited supply forms the institutional basis for high underpricing. Unlike in developed Western markets, subsequent studies by Zheng and Zhang (2012), Zhang and Li (2017), and Huang et al. (2017) used the SFA model to analyze A-share pricing efficiency across different periods. These studies found that premium effects in the secondary market are the main drivers of China's high underpricing phenomenon, while the influence of the primary market is relatively weaker.

Despite the application of advanced tools such as Stochastic Frontier Analysis (SFA), previous research has highlighted significant disparities in IPO pricing efficiency within the Chinese market. These findings have spurred discussions about the influence of factors such as market structure, regulatory environment, and investor behavior on IPO pricing mechanisms. In the Chinese context, unique characteristics like limited supply and distinctive market systems may result in IPO pricing phenomena that differ from those in other markets (Chi & Padgett, 2005). Building on this, the present study employs a larger and more comprehensive dataset spanning multiple A-share market sectors to conduct a broader analysis of IPO pricing efficiency. This research examines differences in pricing efficiency across industries, aiming to reflect the specific conditions of China's capital market. Additionally, it seeks to explore the potential factors driving these differences and their impact on the IPO pricing mechanism.

1.4 State Hypotheses and Their Correspondence to Research Design

Building on the work of Hunt-McCool, Koh, & Francis (1996), which identifies corporate value, risk conditions, and market environment as key determinants of IPO pricing, this study focuses on analyzing issue prices in A-share market IPOs. Before exploring the phenomenon of IPO underpricing, a model is developed to examine the factors influencing IPO pricing, with particular attention to pricing differences across sectors and industries and their underlying causes.

Hypothesis 1: IPO pricing efficiency is significantly influenced by financial indicators (e.g., earnings per share, net assets, total assets) and pricing-related factors (e.g., fundraising size, cost per share, company age, market conditions).

Hypothesis 2: Significant differences exist in IPO pricing efficiency across sectors and industries within the A-share market.

To test these hypotheses, this study adopts methodologies from Hunt-McCool et al. (1996) and Kumbhakar and Lovell (2012) and employs a Stochastic Frontier Analysis (SFA) model. By integrating firm-specific variables, the model allows for precise measurement of IPO pricing efficiency differences across sectors and industries, providing empirical support for the proposed hypotheses. Furthermore, the research design enables an in-depth analysis of the relationship between IPO pricing efficiency and corporate characteristics, thereby offering a robust basis for hypothesis verification.

2. Method

This study employs a cross-sectional research design to estimate and analyze the IPO pricing efficiency of sample firms using the Stochastic Frontier Analysis (SFA) model. Unlike experimental designs that assign firms to treatment conditions, this approach observes natural IPO pricing behaviors. By comparing pricing efficiency across different periods and sectors, the study identifies horizontal trends within the A-share market.

The Stochastic Frontier Analysis (SFA) model, originally developed in 1977 for analyzing production efficiency, has since been adapted for various applications, including IPO pricing. Hunt-McCool et al. (1996) were among the first to apply the SFA model in this context, using pre-IPO data to estimate efficient offer prices. Their approach decomposed IPO underpricing into two components: technical inefficiency and random disturbances. An offer price closer to the stochastic frontier was deemed more efficient, while deviations from the frontier reflected underpricing. By distinguishing disturbance factors from technical inefficiency, the SFA model provides more nuanced and realistic insights into pricing dynamics.

In this study, the SFA model is applied to estimate an optimal IPO price based on fundamental company indicators, aiming to approximate each firm's intrinsic value. An efficiency indicator (EFF) is then constructed by comparing the actual offering price to the estimated intrinsic value. This indicator serves as a metric for assessing IPO pricing efficiency, providing a quantitative evaluation of the reasonableness of initial offer prices.

The SFA model is expressed as follows:

$$y_i = x_i\beta + \varepsilon_i \quad \varepsilon_i = v_i + u_i \tag{1}$$

Where y_i represents the initial offering price of company, x_i is the set of indicators affecting IPO pricing; β is the parameter to be estimated for the corresponding indicators; and ε_i is referred to as the composite error term. The term u_i represents technical inefficiency, which is the deviation between the initial offering price and the optimal price, while v_i is the random disturbance term, reflecting errors caused by external shocks. It is assumed that both the random disturbance term v and the technical inefficiency term u follow a normal distribution. Specifically, $v_i \sim iidN\left(0, \sigma^2\right)$ and $u_i \sim iidN\left(0, \sigma^2\right)$, and u_i and v_i are independent of each other, such that $cov\ (v_i, u_i) = 0$.

By estimating the parameters in the above model, the Maximum Likelihood Estimation (MLE) values of the parameters can be obtained, along with the value of y, where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and$y = \frac{\sigma_u^2}{\sigma^2}$. The value of y indicates whether the company is on the frontier. If $y = 0$, it means that all deviations from the production frontier are due to v_i(random noise); if $y = 1$, it indicates that the deviation from the efficient production frontier is due to u_i (inefficiency). Using MLE allows for the estimation of each stock's optimal price, which can then be compared to its offering price to derive the IPO pricing efficiency EFF_i. The formula for calculating EFF_i is as follows:

$$\mathrm{EFF}_i = \frac{E(P_i \mid u_i, X_i)}{E(P_i \mid u_i = 0, X_i)} \tag{2}$$

2.1 Variable

2.1.1 Dependent Variable

The dependent variable, ln(op), represents the natural logarithm of the IPO firm's listing issue price. Using the logarithmic transformation of the stock price helps address potential heteroscedasticity in the model, thereby improving the robustness and reliability of the estimation results.

2.1.2 Explanatory Variable

Table 1. Variable Description

Variable Type	Variable Name	Variable Symbol	Variable Description
Financial Metrics	Earnings Per Share	ln_EPS	Latest EPS disclosed before IPO
	Net Asset Value	ln_NAV	Latest net asset value per share disclosed before IPO
	Total Assets	ln_TA	Log of total assets before IPO
	Debt-to-Asset Ratio	DAR	Total liabilities to total assets ratio before IPO
	Return on Equity	ROE	Return on equity in the first year
Pricing Metrics	Total Capital Raised	ln_TCR	Log of net proceeds from IPO
	Actual Issuance Cost Per Share	AICPS	Per share issuance cost of the IPO
	Company Age	AGE	Years from company establishment to IPO
	Market Temperature	MT	Month-over-month change rate in new account openings.

In selecting explanatory variables, this chapter builds on a review of existing literature, particularly the approaches of Liu Yuhui & Shen Keting (2011) and Luo Qi & Wu Jingdong (2017), while also considering other relevant studies. Based on this foundation, the explanatory variables in the stochastic frontier model are categorized into two main groups: pricing factors, which directly affect the value of the IPO, and efficiency factors, which influence the efficiency of the IPO pricing process.

2.2 Research Design

This study focuses on China's A-share market, the largest stock market in the country, encompassing various segments of the Shanghai and Shenzhen Stock Exchanges, including the main board, SME board, and ChiNext. The A-share market leads the nation in trading volume and the number of listed companies, with frequent new stock issuances. As the primary market for Chinese investors, the A-share market quickly incorporates market information into stock prices, making it a pivotal component of China's capital market. Given its central role and dynamic nature, the A-share market serves as an ideal subject for analyzing IPO pricing efficiency.

2.3 Sources of Data

The data used in this study primarily originates from the Guotai Junan database, which provides comprehensive IPO-related information. To control for factors influencing pricing efficiency in the primary market, additional accounting data was obtained from the Wind database. Secondary market data, including metrics such as the number of accounts opened, was sourced from the official websites of the China Securities Regulatory Commission (CSRC) and the China Listed Companies Association. The sample comprises data from 2,846 companies listed on the A-share market between January 2014 and July 2024.

2.4 Research Model Development

This study analyzes initial public offerings (IPOs) within China' s A-share market using the Stochastic Frontier Analysis (SFA) model. The selection of variables is guided by established theoretical frameworks and empirical evidence. By leveraging the inefficiency estimates derived from the SFA model, the study calculates the EFF pricing efficiency metric to evaluate IPO pricing efficiency across various sectors and industries. This approach offers insights into the determinants of pricing efficiency and its variability within the A-share market.

The Population Regression Model:

$$\begin{aligned}\ln(OP_i) = \beta_0 + \beta_1 \ln(EPS_i) + \beta_2 \ln(NAV_i) + \beta_3 \ln(TA_i) + \beta_4 DAR_i + \beta_5 ROE_i \\ + \beta_6 \ln(TCR_i) + \beta_7 \ln(AICPS_i) + \beta_8 AGE_i + \beta_9 MT_i + u_i\end{aligned} \tag{3}$$

ln(OP) The natural logarithm of the IPO price.

ln(EPS) The natural logarithm of earnings per share.

ln(NAV) The natural logarithm of net asset value per share.

ln(TA) The natural logarithm of total assets.

DAR Debt-to-asset ratio

ROE Return on equity

ln(TCR) The natural logarithm of total capital raised

ln(AICPS) The natural logarithm of issuance cost per share

AGE Company age in years

MT Market temperature (monthly change in new accounts)

u_i Error term, consisting of inefficiency (u_i*) and random noise (v_i)

The model parameters are estimated using Maximum Likelihood Estimation (MLE), which allows for the decomposition of the error term into inefficiency and noise components. This decomposition enables a more accurate assessment of IPO pricing efficiency by isolating the inefficiency effects from random market fluctuations.

An efficiency indicator (EFF) is then constructed by comparing the actual offering price to the estimated intrinsic value derived from the SFA model. The formula for calculating EFF is as follows:

$$EFF_i = \frac{\ln(OP_i)}{\ln(OP_i^*)} \tag{4}$$

$\ln(OP_i)$:Actual IPO offering price.

$\ln(OP_i^*)$:Estimated optimal IPO price based on firm fundamentals

An EFF value of 1 indicates that the IPO pricing is fully efficient, aligning perfectly with the intrinsic value. Values below 1 suggest underpricing, while values above 1 indicate overpricing. This metric provides a quantitative assessment of the reasonableness of initial offer prices, facilitating comparisons across firms, sectors, and market conditions.

3. Descriptive Statistical Analysis

The descriptive statistics for the variables are shown in the table above. Most variables, particularly the price variables, approximate a normal distribution after logarithmic transformation. This meets the requirements for regression analysis, including Stochastic Frontier Analysis (SFA), enabling the next steps in the analysis.

Table 2. Descriptive statistics of variables

Variable	Variable	Count	Mean	SD	Min	Max
Opening Pricing	OP	2846	24.49	26.95	1.22	557.80
Earnings Per Share	EPS	2846	1.00	0.98	-10.82	21.99
Net Asset Value	NAV	2846	5.58	3.30	0.09	55.81
Total Assets	TA	2830	9537	166085	32	8265622
Debt-to-Asset Ratio	DAR	2830	0.46	0.20	0.02	2.12
Return on Equity	ROE	2828	23.64	37.07	-843.95	819.72
Total Capital Raised	TCR	2846	103.27	233.63	4.47	4869.54
Issuance Cost	AICPS	2846	2.31	1.95	0.01	23.71
Company Age	AGE	2846	15.52	5.81	3.22	61.07
Market Temperature	MT	2784	0.07	0.45	-0.47	3.35

Based on the empirical results, the correlation coefficients among all explanatory variables were analyzed to assess potential multicollinearity. The findings, presented in the accompanying table, indicate that most explanatory variables exhibit low correlation coefficients, suggesting minimal multicollinearity within the model. Notably, no significant correlations were identified among the efficiency factor variables introduced in this chapter. The only moderate correlations observed were between EPS and NAV, as well as between firm size and total assets; however, these coefficients remain below the commonly accepted threshold of 0.75. Therefore, it can be concluded that the dataset used in this study does not suffer from substantial multicollinearity, ensuring the reliability of the regression analysis.

Table 3. Correlation matrix of variables

	ln OP	ln EPS	ln NAV	ln TA	DAR	ROE	ln TCR	ln AICPS	AGE	MT
ln OP	1									
ln EPS	0.715***	1								
ln NAV	0.592***	0.731***	1							
ln TA	-0.323***	-0.232***	0.005	1						
DAR	-0.112***	-0.086***	-0.115***	0.408***	1					
ROE	0.055***	0.141***	0.018	-0.079***	0.064***	1				
ln TCR	0.463***	0.219***	0.170***	0.505***	0.187***	-0.033*	1			
ln AICPS	0.720***	0.637***	0.520***	-0.628***	-0.221***	0.052***	-0.026	1		
AGE	-0.028	0.016	0.089***	0.127***	-0.003	-0.061***	-0.011	-0.011	1	
MT	-0.017	0.004	0.022	-0.004	0.004	0.012	-0.023	-0.015	-0.006	1

Finally, scatter plots were generated to visualize the relationships between selected explanatory variables and the issue price, the dependent variable. The plots reveal a relatively strong linear correlation between the issue price and traditional pricing indicators, particularly EPS and NAV per share. In contrast, efficiency indicators such as

Company Age and Market Temperature exhibit weaker correlations with the issue price. These findings suggest that in the context of IPO pricing in China, traditional pricing indicators like EPS play a more significant role, while efficiency indicators reflecting institutional effectiveness have a comparatively limited impact. In the following section, we conduct more rigorous regression analyses to further explore these relationships.

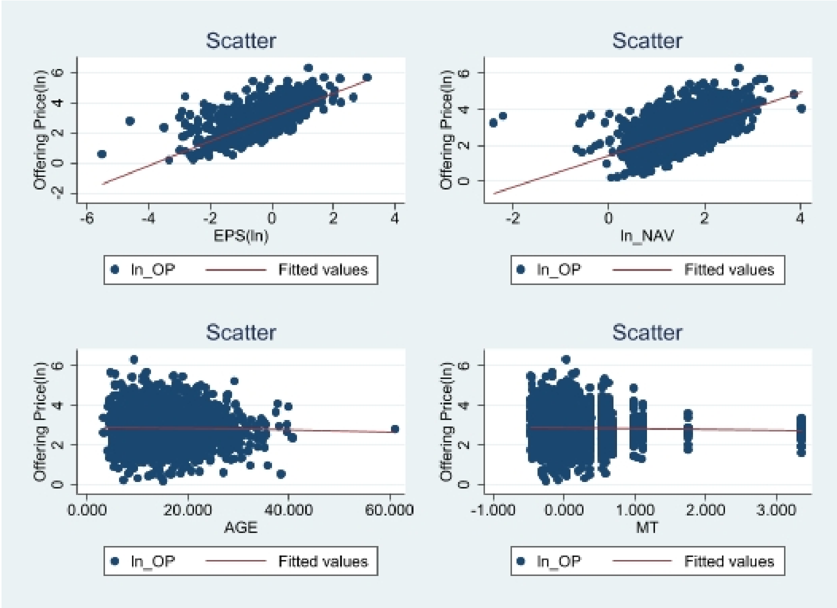

Figure 1. Scatter plots of offering price (ln OP) against key variables

3.1 Statistics and Data Analysis

3.1.1 Baseline Regression Results

In this study, we first conducted a baseline regression using the above model. We estimated the model parameters through the Maximum Likelihood Estimation (MLE) method, gradually adding explanatory variables to refine the parameter selection. Specifically, given that efficiency factors were found to have limited explanatory power in China' s capital market, a regression relying solely on these factors could lead to model convergence issues. Therefore, we started with pricing factors and incrementally added other explanatory variables to achieve a more robust model estimation. The detailed regression results are presented in the table below.

Table 4. Regression results of factors influencing offering price (ln OP)

	(1)ln_OP	(2)ln_OP	(3)ln_OP	(4)ln_OP	(5)ln_OP
Frontier					
ln_EPS	0.798^{***}		0.544^{***}	0.134^{***}	0.133^{***}
	(58.88)		(27.42)	(16.18)	(16.13)
ln_NAV		0.881^{***}	0.403^{***}	0.219^{***}	0.218^{***}
		(39.17)	(14.41)	(18.38)	(18.37)
ln_TA			-0.128^{***}	-0.160^{***}	-0.166^{***}
			(-16.39)	(-26.65)	(-26.60)
DAR				0.155^{***}	0.152^{***}
				(7.37)	(7.24)
ROE				0.000152	0.000152
				(1.44)	(1.45)
ln_TCR				0.553^{***}	0.554^{***}
				(83.37)	(83.28)
ln_AICPS				0.511^{***}	0.513^{***}
				(57.47)	(57.90)
AGE				0.000894	0.000964
				(1.44)	(1.56)

MT				-0.0146*	-0.0142*
				(-1.94)	(-1.89)
_cons	3.037***	1.491***	3.190***	1.166***	1.214***
	(134.03)	(24.71)	(46.84)	(33.16)	(32.83)
lnsig2u	-8.130***	-7.768*	-8.315**	-5.228***	-5.253***
_cons	(-3.46)	(-1.69)	(-2.16)	(-25.66)	(-25.57)
lnsig2v	-1.287***	-0.891***	-1.418***	-3.647***	-3.655***
_cons	(-47.92)	(-33.10)	(-52.52)	(-79.47)	(-79.93)
Year	NO	NO	NO	YES	YES
Industry	NO	NO	NO	NO	YES
loglik	-2166.9	-2772.3	-1979.5	842.2	856.6
N	2789	2846	2774	2710	2710

Notes. t statistics in parentheses;

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the IPO pricing regression model, the unobservable efficiency factor (lnsig2u) is statistically significant at the 10% level in Equation (2) and at the 5% level in Equation (3), indicating that the IPO pricing process does not fully achieve efficiency. To provide a more accurate assessment of IPO pricing efficiency, this study employs a stochastic frontier model. The results of the Likelihood Ratio (LR) test confirm significant differences between the stochastic frontier model and traditional OLS regression, highlighting the superior ability of the stochastic frontier model to address efficiency bias.

In the regression results for pricing factors, the coefficients for earnings per share (EPS) and net assets per share (NAV) are both positive and statistically significant at the 1% level. These findings suggest that firms with higher earnings and net assets tend to achieve higher IPO prices. Conversely, firm size is significantly negatively correlated with IPO pricing, indicating that smaller firms often set higher prices to expand their capital capacity. Additionally, the positive correlation between leverage and IPO pricing implies that firms with greater financial risk are more likely to adopt higher pricing strategies, consistent with speculative behavior. Both offering size and issuance costs are positively associated with IPO prices at the 1% significance level, while firm age does not exhibit a significant effect on IPO pricing.

3.2 Regression Results Based on Different Models

To evaluate the robustness of the baseline regression model, various alternative stochastic frontier models were employed. Columns (1) and (2) in the table above present stochastic frontier models with error terms assuming a half-normal distribution and an exponential distribution, respectively. Columns (3) and (4) incorporate recent advances in heterogeneous stochastic frontier models, utilizing EPS and NAV per share as sources of heterogeneity to enhance model fit for IPO firms. For comparison, a traditional OLS linear regression model is included in column (5) to highlight differences in model performance.

Table 5. Regression results using different model specifications

	(1)Half-Normal Distribution	(2)Exponential Distribution	(3)Half-Normal Heterogeneity SFA	(4)Half-Normal Heterogeneity SFA	(5)Linear Regression OLS
	ln_OP	ln_OP	ln_OP	ln_OP	ln_OP
ln_EPS	0.132***	0.133***	0.0932***	0.131***	0.132***
	(15.80)	(16.13)	(9.41)	(15.80)	(15.73)
ln_NAV	0.224***	0.218***	0.224***	0.174***	0.224***
	(18.72)	(18.37)	(18.34)	(12.03)	(18.63)
ln_TA	-0.170***	-0.166***	-0.167***	-0.168***	-0.170***
	(-27.35)	(-26.60)	(-26.62)	(-26.92)	(-27.22)
DAR	0.161***	0.152***	0.163***	0.161***	0.161***
	(7.64)	(7.24)	(7.74)	(7.65)	(7.61)
ROE	0.000149	0.000152	0.000166	0.000150	0.000149
	(1.42)	(1.45)	(1.55)	(1.44)	(1.42)
ln_TCR	0.550***	0.554***	0.552***	0.553***	0.550***

	(84.59)	(83.28)	(82.88)	(83.93)	(84.20)
ln_AICPS	0.512***	0.513***	0.510***	0.509***	0.512***
	(57.64)	(57.90)	(57.00)	(57.11)	(57.38)
AGE	0.00100	0.000964	0.00104*	0.00101	0.00100
	(1.61)	(1.56)	(1.67)	(1.62)	(1.60)
MT	-0.014*	-0.014*	-0.015**	-0.014*	-0.013***
	(-1.78)	(-1.89)	(-1.98)	(-1.85)	(-1.77)
_cons	1.159***	1.214***	1.210***	1.303***	1.157***
	(18.06)	(32.83)	(31.14)	(32.52)	(31.26)
Vsigma	-3.463***	-3.655***	-3.607***	-3.607***	
_cons	(-126.17)	(-79.93)	(-79.84)	(-71.53)	
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES
loglik	846.4	856.6	858.3	853.8	846.4
N	2710	2710	2710	2710	2710

Notes. t statistics in parentheses;

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A comprehensive comparison of regression results from various models demonstrates that the final regression outcomes, under different error term assumptions, exhibit a high degree of robustness. Key variables in the baseline regression, such as EPS and NAV, remain statistically significant across models, indicating a certain level of generalizability. A detailed examination of coefficient differences reveals minimal variations in the signs and significance of pricing-related variables, while efficiency-related variables show slight differences. For instance, the "Market Temperature" variable is statistically significant at the 1% level in the OLS model and at the 10% level in the SFA model, highlighting minor variations in significance levels across methodologies. Overall, the consistency in variable signs and significance aligns with expectations, affirming the robustness of the regression framework. Accordingly, the half-normal SFA model from the baseline regression will be primarily used for further subgroup analyses.

3.3 Grouped Regression Results

3.3.1 Regression Results Based on Samples from Different Sub-industries

Table 6 presents regression results for samples from different industries. Significant differences in production, operations, and business logic across industries may lead to variations in production functions and error terms. Although the regression equation controls for industry fixed effects, inter-industry differences could still introduce bias. To address this, we conducted grouped regressions across five industries classified by the Guotai Junan database. The results provide insights into industry-specific characteristics and their impact on the regression outcomes.

Table 6. Regression results based on samples from different sub-industries

	(1)Public	(2)Commercial	(3)Industrial	(4)Integrated	(5)Financial
	ln_OP	ln_OP	ln_OP	ln_OP	ln_OP
ln_EPS	0.137***	0.193***	0.125***	0.262**	0.247*
	(7.17)	(3.11)	(13.37)	(1.98)	(1.79)
ln_NAV	0.179***	0.235***	0.224***	0.423***	0.0835
	(6.64)	(3.28)	(16.60)	(2.84)	(0.53)
ln_TA	-0.156***	-0.0935**	-0.181***	-0.132*	-0.0285
	(-12.53)	(-2.46)	(-24.59)	(-1.82)	(-0.28)
DAR	0.124***	0.370***	0.144***	0.216	-0.0175
	(2.80)	(3.25)	(5.98)	(0.52)	(-0.06)
ROE	0.000122	0.00433***	0.0000908	0.0123***	0.00859***
	(0.55)	(2.84)	(0.78)	(3.05)	(3.07)
ln_TCR	0.567***	0.473***	0.563***	0.332***	0.347***
	(41.67)	(14.47)	(72.69)	(3.28)	(3.17)
ln_AICPS	0.523***	0.531***	0.518***	0.167***	0.697***

	(30.03)	(11.06)	(49.52)	(2.92)	(3.96)
AGE	0.0000409	0.00222	0.00120*	0.0100	0.0140**
	(0.03)	(0.77)	(1.66)	(1.50)	(2.14)
MT	-0.0191	0.0341	-0.0121	0.0251	0.0655
	(-1.16)	(0.66)	(-1.39)	(0.46)	(1.53)
_cons	1.281***	0.513	1.158***	1.125	0.931**
	(15.92)	(1.62)	(18.42)	(.)	(2.22)
lnsig2v	-3.940***	-4.284***	-3.486***	-31.52	-3.828***
_cons	(-17.28)	(-23.95)	(-110.87)	(-0.14)	(-15.46)
lnsig2u	-4.064***	-12.03	-12.98	-3.373***	-11.64
_cons	(-5.72)	(-0.07)	(-0.17)	(-13.91)	(-0.06)
EFF	89.64%	99.85%	99.87%	79.78%	99.76%
Year	YES	YES	YES	YES	YES
N	493	64	2032	34	33

Notes. t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression results show that in the financial sector, net asset value (NAV) is positive but not statistically significant, while earnings per share (EPS) is significant only at the 10% level. This suggests that NAV and EPS have limited influence on IPO pricing in this sector, likely due to unique industry characteristics. Financial institutions, such as banks and insurance companies, operate under strict regulations and face cyclical fluctuations, making their financial performance less predictable compared to other industries. As a result, IPO pricing for financial firms may rely more on non-financial factors or sector-specific valuation methods than traditional indicators like EPS or NAV.

Efficiency analysis reveals that the industrial (99.87%), commercial (99.85%), and financial (99.76%) sectors exhibit the highest pricing efficiency, reflecting strong alignment between their pricing models and market performance. The public sector follows with moderately high efficiency at 89.64%, while the integrated sector shows the lowest efficiency at 79.78%, indicating a greater gap between pricing models and market outcomes, likely due to its diverse structure. During the Maximum Likelihood Estimation (MLE) process, the integrated sector failed to converge, suggesting poorer model fit and pricing efficiency. In contrast, the commercial and industrial sectors demonstrated high efficiency, with minimal differences between stochastic frontier and OLS models.

3.3.2 Regression Results Based on Samples from Different Listing Boards

Table 7 presents regression analyses based on different listing boards. Since the establishment of the Shanghai and Shenzhen Stock Exchanges in 1990, China’s securities market has grown significantly over the past three decades. Due to differences in listing requirements, the Shenzhen Exchange introduced the SME Board in 2004 and the ChiNext Board in 2009, under the guidance of the State Council and the China Securities Regulatory Commission. These boards feature more lenient revenue and profit requirements compared to the Main Board. Similarly, in June 2019, the Shanghai Stock Exchange launched the STAR Market, offering flexible listing standards tailored for technology-driven enterprises.

To examine differences in pricing efficiency across boards, the sample was divided by listing location, and grouped regression analyses were conducted for each subsample. This approach aimed to determine whether significant disparities in pricing efficiency exist among the boards.

Table 7. Regression results based on samples from different listing boards

	(1) Main Board	(2) SME Board	(3)ChiNext Board	(4) STAR Market
	ln_OP	ln_OP	ln_OP	ln_OP
ln_OP				
ln_EPS	0.149***	0.387***	0.271***	0.0824***
	(8.62)	(12.47)	(14.22)	(5.63)
ln_NAV	0.213***	0.125***	0.219***	0.180***
	(9.70)	(4.26)	(10.62)	(6.84)
ln_TA	-0.176***	-0.102***	-0.145***	-0.123***
	(-14.37)	(-5.94)	(-13.13)	(-8.56)
DAR	0.122***	0.157***	0.173***	0.0531
	(3.50)	(2.75)	(4.23)	(1.29)
ROE	0.000165	0.000725	0.00112**	0.0000741
	(0.57)	(1.17)	(2.37)	(0.59)
ln_TCR	0.563***	0.377***	0.443***	0.571***
	(44.25)	(17.09)	(29.97)	(38.81)
ln_AICPS	0.504***	0.346***	0.393***	0.616***
	(31.45)	(15.04)	(25.21)	(30.22)
AGE	0.000835	0.00368***	0.000912	0.000946
	(0.82)	(2.82)	(0.89)	(0.56)
MT	-0.0167	-0.0220	-0.0141	0.0249
	(-1.43)	(-1.48)	(-1.22)	(0.85)
_cons	1.340***	1.609***	1.477***	0.760***
	(18.09)	(13.98)	(19.99)	(8.59)
lnsig2v	-3.840***	-3.976***	-3.732***	-3.438***
_cons	(-23.34)	(-54.93)	(-29.09)	(-24.30)
lnsig2u	-4.656***	-12.58	-4.199***	-4.401***
_cons	(-4.67)	(-0.15)	(-7.76)	(-4.75)
EFF	92.26%	99.85%	91.29%	91.79%
Year	YES	YES	YES	YES
Industry	YES	YES	YES	YES
N	1000	384	873	453

Notes. t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression results show that EPS and NAV are consistently significant across all boards, with the ChiNext Board placing the greatest emphasis on profitability (Z-value of 14.22). Total assets (TA) negatively impact IPO pricing across boards, indicating that larger firms are perceived as having lower growth potential. The SME Board demonstrates the highest pricing efficiency, as evidenced by the non-significance of the lnsig2u term, while differences in primary pricing factors between boards are minimal. Notably, market temperature shows opposite effects between the STAR Market and other boards, likely due to the STAR Market's unique pricing mechanisms.

Efficiency analysis reinforces these findings. The SME Board achieves the highest efficiency at 99.85%, reflecting a strong alignment between its pricing model and market performance. It is followed by the Main Board (92.26%), STAR Market (91.79%), and ChiNext Board (91.29%). Overall, pricing efficiency is high across all boards, with the SME Board leading in accuracy.

4. Conclusion and Discussion

This study analyzes the pricing efficiency of 2,846 IPO companies listed in China in recent years by constructing a stochastic frontier model and examining primary market issuance data. The empirical findings show that financial indicators, such as earnings per share (EPS), net assets (NAV), and total assets, as well as market conditions, significantly influence IPO pricing efficiency, although the degree of impact varies across sectors and boards. For instance, in the financial sector, traditional indicators like EPS and NAV display limited influence, likely due to industry-specific characteristics. Furthermore, pricing efficiency varies notably across sectors and boards: the SME Board demonstrates the highest efficiency while the integrated sector exhibits the lowest, reflecting distinct market dynamics and performance.

4.1 Comparison with Existing Literature

Our findings regarding the predominant role of financial metrics in determining IPO pricing align with existing research in both developed and emerging markets (Beatty & Ritter, 1986; Ekkayokkaya & Pengniti, 2012; Pan & Ma, 2022). Similar to studies on Thailand's market and other emerging markets, the Chinese A-share market shows that fundamental indicators like EPS and NAV are primary drivers of IPO pricing, while market sentiment variables (e.g., investor mood or "market temperature") exert relatively weaker explanatory power. In the Chinese context, our results are consistent with domestic studies (He & Lü, 2010; Huang, Zhou, & Yang, 2017) that emphasize the significant influence of financial performance on IPO pricing. However, this study extends previous research by providing a more granular analysis across different industries and listing boards, revealing that the SME Board achieves the highest pricing efficiency, whereas comprehensive boards lag behind. This contrasts with some international studies where market sentiment plays a more pronounced role (Makieła, Kowalski, & Mazur, 2022). Additionally, our findings resonate with Kartanaitė, Vaitkevičius, & Krušinskas (2022), who highlight the robustness of SFA models in capturing pricing inefficiencies compared to traditional OLS approaches. Conversely, some emerging market analyses suggest a stronger impact of behavioral factors on IPO pricing (Makieła et al., 2022). In our study, while behavioral factors like market temperature do influence IPO pricing, their impact is overshadowed by financial metrics, except in specific boards like the STAR Market where market sentiment becomes more significant. This nuanced understanding contributes to the broader discourse by demonstrating that the relative influence of financial versus behavioral factors can vary based on market structure and regulatory frameworks.

4.2 Theoretical Implications

Our findings support and extend several key theories in IPO research. First, asymmetric information theory (Rock, 1986) posits that issuers deliberately underprice IPOs to attract uninformed investors in the face of information asymmetry. Our results suggest that artificially suppressed offering prices in the Chinese A-share market mitigate risks arising from uneven information distribution, aligning with Nguyen (2020). Second, signaling theory (Allen & Faulhaber, 1989) argues that high-quality firms may underprice IPOs to signal robust future earnings potential. In our study, firms with stronger financial indicators (e.g., higher EPS) achieve better pricing outcomes, reinforcing the notion that credible signals of financial strength shape investor perceptions, as discussed by Makieła and Mazur (2022). Third, from a behavioral finance perspective (Shiller, 2000), while investor sentiment and psychological biases influence IPO pricing, especially on boards like the STAR Market, core financial metrics typically overshadow emotion-driven factors in driving IPO pricing efficiency. This is consistent with Nguyen (2020), who found that behavioral factors have a nuanced impact on IPO pricing depending on market conditions and regulatory environments. Finally, institutional economics theory highlights how variations in listing standards, regulatory oversight, and approval processes lead to different pricing outcomes across boards and industries. Our finding that the SME Board demonstrates notably high efficiency underscores the importance of transparent and established listing frameworks in aligning IPO pricing with firms' fundamental values, supporting the assertions of Makieła and Mazur (2022).

4.3 Practical Implications, Limitations, and Future Research

This study reveals inefficiencies in the current IPO issuance system—artificially suppressed issuance prices disrupt market equilibrium, transferring benefits from issuing companies to secondary market investors and fueling speculative trading in newly issued stocks. This "IPO always wins" phenomenon limits support for the real economy, which relies on capital, and reflects a "de-marketization" approach contrary to China's broader market-oriented reform goals. To address these issues, regulators and policymakers should refine IPO pricing mechanisms to reduce underpricing incentives and enhance transparency. Issuing firms and underwriters should emphasize reliable disclosure of financial indicators to optimize offer prices without excessively subsidizing the secondary market. Investors can benefit from recognizing that firm fundamentals remain strong determinants of

IPO pricing and long-term performance, despite the presence of speculative behavior.

However, the study faces certain limitations. Investor sentiment was proxied using aggregated account openings, which may not capture all behavioral nuances. Additionally, the cross-sectional SFA model limits the ability to capture temporal variations and dynamic changes in IPO pricing efficiency. Future research could incorporate additional proxies for investor education, underwriting reputation, or corporate governance factors to gain a more granular understanding of IPO pricing dynamics. Comparative studies across different emerging or developed markets would offer valuable cross-country perspectives on how varying institutional frameworks influence IPO pricing efficiency. Moreover, longitudinal studies are warranted to examine how ongoing regulatory reforms, such as the broader implementation of the registration-based IPO system, affect the efficacy of existing pricing mechanisms. Exploring alternative distributional assumptions and incorporating heteroskedasticity into the SFA model enhance model flexibility and accuracy. Finally, integrating secondary market performance indicators, such as post-IPO stock performance and trading volume, could provide a more comprehensive view of IPO pricing efficiency and its determinants.

In conclusion, by employing a stochastic frontier model on a large sample of Chinese IPOs, this study finds that financial metrics predominantly drive IPO pricing efficiency, though notable disparities exist across different industries and boards. These results both align with and extend classical theories—underscoring the importance of fundamental signals, market structure, and regulatory frameworks—and offer useful guidance for market stakeholders seeking to enhance the IPO issuance process.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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