Economics Bulletin

Volume 45, Issue 2

Impact of stock exchange listing on financial stability of small and medium enterprises: evidence from BSE SME platform in India

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Abstract

The study empirically investigates the impact of stock exchange listing on the financial stability of Indian Small and Medium Enterprises (SMEs). The study uses an unbalanced panel of sixty-four listed Indian SMEs from 2012 to 2023 and seeks to explore the performance of the selected SMEs before and after listing. It explores the impact of listing in two ways: first, using a fixed-effects panel regression it explores if listing helps SMEs improve their financial stability and second, using a fixed-effects ordered logit regression it explores if listing helps SMEs enter a higher zone of financial stability. Financial stability is measured by Altman's Z''-Score (2005). The Z''-Scores are used as the dependent variable in the first model while Z''-Score zones are used as ordered dependent variable in the second model. The listing dummy is the main independent variable for both models, the study uses control variables including company-related factors and macroeconomic variables including a pandemic dummy. The study finds significant impact of stock exchange listing in improving SMEs' financial stability and helping them enter a higher financial stability zone. Hence, the study suggests that access to capital market can benefit SMEs to raise funds through newer channels, and thus can enhance their financial stability by lowering the probability of failure faced through obstacles in accessing external finance. The insignificant pandemic dummy shows risk-resilient nature of SMEs.

Citation: Sanchita Saha and Gagari Chakrabarti, (2025) "Impact of stock exchange listing on financial stability of small and medium enterprises: evidence from BSE SME platform in India", *Economics Bulletin*, Volume 45, Issue 2, pages 928-943
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Submitted: January 30, 2025. **Published:** June 30, 2025.

1. Introduction

Small and Medium Enterprises (SMEs) play a crucial role in driving economic growth and fostering inclusive development across nations worldwide. Their role is particularly pivotal in emerging nations where they help create employment[1], promote equitable distribution of wealth and income, alleviate poverty, increase exports, and thus add to foreign exchange reserves. In overpopulated emerging nations, SMEs create many informal jobs, absorbing the growing workforce. SMEs are vital for India also. As per India's revised MSME definition (2020), small enterprises must have an investment in plant and machinery/equipment up to Rs. 10 crores, and medium enterprises up to Rs. 50 crores, with annual turnover not exceeding Rs. 50 crores and Rs. 250 crores, respectively.[2] While SMEs contribute about 40% to India's industrial production and exports,[3] they face significant financial challenges that could impede their growth. A key issue is the efficient management of operations and finances (Subramanian and Nehru, 2012). Adopting modern technologies and hiring skilled managers requires adequate funding, yet obtaining financial support from banks and other institutions is not easy. Factors like insufficient collateral, lack of credit history, poor creditworthiness, high transaction costs, weak bank-borrower relationships, and information asymmetry make it difficult for SMEs to secure long-term funds from commercial banks, hindering their growth and increasing the risk of financial failure (Gupta and Gregoriou, 2018). In fact, financially distressed firms are often financially constrained (Bassetto and Kalatzis, 2011). Credit supply channels for SMEs contract further during crises, increasing their dependence on trade credit (Carbó-Valverde et al., 2016). Stock market listing can be an alternative way to raise funds (Kim, 1999), but accessing the equity market is often costly due to factors like stringent admission and listing requirements, lack of liquidity, educational gaps, limited ecosystems, and tax treatment (Nassr and Wehinger, 2016). In 2012, the Indian government set up a special platform for SMEs on the BSE and NSE. To facilitate fundraising, both the BSE SME Exchange and NSE Emerge relaxed certain listing criteria. However, to ensure investor protection, the minimum application amount and trading lot were kept higher on these SME platforms compared to the main boards (Ganguly, 2022). Literature suggests a positive relationship between small business lending and bank profitability (Kolari and Shin, 2004; Berger, 2006; Altman and Sabato, 2007). However, lending to SMEs is riskier than lending to larger firms, as SMEs may either grow into large corporations or fail within a few years of incorporation (Altman and Sabato, 2007). Given the crucial role of SMEs as subsidiaries to large industries in an economy, several studies have attempted to model financial distress in SMEs, focusing on both developed (Altman and Sabato, 2007; Keasey et al., 2015; Gupta et al., 2017) and developing nations (Abdullah et al., 2016). Altman and Sabato (2007) developed a useful credit risk model for the U.S. SMEs. Studies have also attempted to predict the distress of SMEs in different countries (Yazdanfar and Ohman,2019; Mselmi et al., 2017; Madrid-Guijarro et al., 2011; Quintiliani,2017; Abdullah et al.,2008). Altman's Z-Score models are widely used in literature to predict financial distress of firms and to identify factors affecting the probability of their bankruptcy (Charalambakis and Garrett, 2015; Tsai, 2013; Rim and Roy,2014; Sulphey and Nisa, 2013; Begović et al., 2014). In fact, according to the World Bank Group, the Z-Score is a common measure of stability at the institutional level. Altman (1968, 1977, 1995) developed these models employing Multiple Discriminant Analysis to predict corporate bankruptcy. The discriminant score or Z-Score categorizes a firm's financial health into three zones: 'bankrupt', 'non-bankrupt', and 'zone of ignorance'. Altman et al. (1995) later adapted

[1] https://www.worldbank.org/en/topic/smefinance

[2] According to Ministry of Micro, Small & Medium Enterprises, Government of India.

[3] According to the report of Department of Scientific and Industrial Research, Government of India.

the Z″-Score model for emerging market corporations by removing the sales-to-total assets ratio to reduce industry sensitivity and using the book value of equity instead of market value. This version applies to both private and public manufacturing and non-manufacturing firms. Rettobjaan (2020) used this model to predict corporate bankruptcy among the listed SMEs in Indonesia and found that liquidity, profitability, and age have a significant negative impact, while debt structure has a significant positive impact on corporate bankruptcy. Singh and Rastogi (2022) examined how promoters' ownership, financial performance, and market competition affect the financial distress of listed SMEs in India, using the Altman Z-Score (1968) during and before COVID-19. They found that crises like COVID-19 can alter the impact of these determinants on financial distress. Wellalage and Locke (2012) identified factors such as ownership structure, ownership type, and geographical location as negatively impacting the financial health of small firms, potentially leading to bankruptcy. Environmental conditions and internal factors such as training, planning, innovation, technology, quality, and other strategic variables can also impact a firm's financial distress (Madrid-Guijarro et al., 2011). Limited access to formal credits and the resulting underinvestment have been pivotal for SME bankruptcy (Gupta and Gregoriou, 2017). They further emphasize that access to capital market can reduce the information asymmetry, and the probability of failure is lower among listed U.S. SMEs than their unlisted counterparts. Kulkarni and Chirputkar (2014), Verma et al. (2020), and Dey and Sharma (2021) explored these issues in the Indian context. Access to the capital market might help the financially sick SMEs and once listed on the stock exchange, raising funds from other sources like private equity, right shares, FPO, or ECBs/ ADRs/GDRs would be easier. They can have more equity in their capital structure to achieve an optimum debt-equity ratio and to reduce overall weighted average cost of capital (Kulkarni and Chirputkar, 2014). Verma et al. (2020) explored the financing choices of listed SMEs in India. The SMEs prefer current liabilities and total reserves as well as short-term debts over long-term debts. The choices are similar for both listed and unlisted SMEs. The preference for short-term debt may, however, be due to India's underdeveloped debt market (Rajamani, 2021). Dey and Sharma (2020) found that access to the stock market did not improve the financial performance of selected Indian SMEs. However, Tripathi et al. (2017), Dhamija and Arora (2017), Ibrahim (2018), and Shroff and Sengupta (2016) found the opposite, emphasizing that SME IPOs outperformed main board IPOs.

There is however a lack of literature on the failure and financial instability of Indian SMEs. Although many studies have analysed the impact of stock exchange listing on SMEs' financing and performance, the comparison of pre- and post-listing financial stability in Indian SMEs remains unexplored in the literature. This is exactly where the present study intervenes. Specifically, we pose the following set of questions:

Q1: Does stock exchange listing have a positive impact on the financial stability of Indian SMEs?

Q2: Does stock exchange listing enable SMEs to enter a higher stability zone compared to their pre-listing state?

The study adds to the existing literature by introducing a new aspect in impact evaluation of stock exchange listings of SMEs. Unlike prior studies that rely on cross-sectional comparisons between listed and unlisted firms, our within-firm longitudinal approach tracks the same firms before and after listing, which offers several advantages in addressing endogeneity.

By focusing on the same entities over time, we are able to control for unobserved time-invariant firm-specific characteristics such as managerial quality, risk preferences, and business models—factors that could otherwise confound the observed relationship between listing and financial stability. This design treats the IPO event as a quasi-natural intervention, allowing us to approximate a quasi-experimental setup that strengthens causal inference and reduces sample selection bias. Furthermore, we employ a fixed-effects model, which helps control for firm-level heterogeneity and time-invariant omitted variables, providing an additional safeguard against endogeneity issues that are often present in cross-sectional analyses.

Moreover, we have used Altman’s Z″-Score (2005), which is better suited for assessing the financial stability of emerging market manufacturing and non-manufacturing, private and public companies. Altman's versions of models categorize companies into three zones: distressed, grey (slightly distressed), and safe (non-distressed), unlike other prediction models that classify companies as distressed or non-distressed only. Kane et al. (2006) utilized Altman’s Z-Score cutoffs to distinguish between healthy and distressed firms. In this study, we have used the adapted Z”-Score zones as a tool to capture the direction and degree of change in financial stability before and after listing. This multi-state framework helps us assess whether listing aids firms in moving from more distressed to less distressed states and allows us to examine whether stock exchange listing can function as a remedial strategy for firms facing financial adversity —a key concern in SME survival and growth literature. It is another contribution of this study to the existing literature.

Our use of Z”-Score zones is grounded in a well-established body of literature on multi-state financial distress prediction (Turetsky & McEwen, 2001; Tsai, 2013; Farooq et al., 2018; Sun et al., 2021). These studies emphasize that financial distress is a gradual process with transitional stages, not a binary event. Before reaching the point of bankruptcy, companies typically pass through various stages of financial distress. As such, distinguishing between firms experiencing mild financial difficulties and those in severe distress is crucial (Tsai, 2013). Farooq et al. (2018) highlighted that recovery from financial distress is possible, though the likelihood varies depending on the severity of the current distressed state. Hence, early identification of distress at an initial stage can enable firms to take timely and appropriate corrective actions. The study thus provides insights into how listing can help SMEs raise capital and avoid potential failures caused by credit constraints.

After this introductory section, the trajectory of the remaining sections is as follows: Section 2 describes the data and the selected variables. Section 3 explains the research methodology used. Section 4 presents the estimation results, and Section 5 concludes the study with key insights and implications.

2. Data and Variables

2.1 Data

Financial statement data was collected from the official websites of SMEs and the Bombay Stock Exchange. Macroeconomic data were collected from the World Bank Group. The study uses an unbalanced panel of 64 non-financial companies listed on the BSE SME Platform from FY 2011-2012 to FY 2022-2023. Since a dedicated platform for SMEs in India was established in 2012, data could be taken from FY 2011-2012 only. Companies were selected based on the availability of at least one year of financial statement data before and after listing. Use of an unbalanced panel enhances the sample size and addresses generalizability issues.

2.2 Description of the variables

The sample includes both manufacturing and non-manufacturing companies, with data from both their pre-listing and post-listing periods. Therefore, using the Z″-Score model (2005) is justified as a measure of financial stability, as it incorporates both manufacturing and non-manufacturing companies, whether publicly or privately owned, in emerging countries. The Z″-Score (Altman, 2005) model is as follows:

Z″ = 3.25+6.56T1+3.26T2+6.72T3+1.05T4

Where: T1 = (Current Assets-Current Liabilities) / Total Assets
T2 = Retained Earnings / Total Assets
T3 = Earnings before Interest and Taxes / Total Assets
T4 = Book Value of Equity / Total Liabilities

Zones of Discrimination: Altman presented three zones of discrimination for the model, as under:

- Z″ > 5.85 - Safe Zone
- 4.15 < Z″< 5.85 - Grey Zone
- Z″ < 4.15 - Distress Zone

2.2.1. Dependent Variables

- **Z″-Score:** We use Altman's Z″-Score values as the continuous dependent variable to explore the impact of stock market listing on the financial stability of SMEs.
- **Z″-Score Zone:** Z″-Score zones are taken as an ordered dependent variable (0 for distressed,1 for grey, and 2 for safe) to check if stock market listing helps SMEs to enter a higher stability zone.

2.2.2. Independent Variable

Q1 and Q2 use the same set of independent variables as the two questions are related, and the dependent variable in Q2 is deduced from that of Q1.

Listing is the independent variable in this study. A major challenge for SMEs is raising external funds. Smaller firms rely more on banks than larger ones, as they often cannot access capital markets (Thampy, 2010). Bank financing is limited by collateral and high interest costs, so capital market access can simplify fundraising. This provides SMEs with an additional source of finance, improving their financial health and stability (Gupta and Gregoriou, 2017; Kulkarni and Chirputkar, 2014).

2.2.3. Control Variables

Age: Older Companies tend to gain more experience, expertise, and reserves compared to younger firms (Campa and Kedia, 2002; Villalonga, 2004). Hence, the likelihood of failure decreases with the company's age (Bandyopadhyay, 2006; Tulsian, 2014).

Size: Generally, the large companies have the advantages of economies of scale, diversification of the product or service, and reputation over small companies. Large firms usually have better access to the capital market and more financing options. As suggested by Agarwal and Taffler (2008), a high value of the size variable should have a negative impact on the firm's probability of financial distress. Carling et al. (2007) found the same as Agarwal and Taffler that large-sized firms are less likely to go bankrupt. According to Gertler and Gilchrist (1993), as large-sized firms have better access to credit, it is expected to be more resilient to the negative shock compared to smaller ones.

Cost-to-Income ratio: The ratio measures a company's efficiency in managing expenses, indicating how much it should spend to generate one unit of income. A lower cost-to-income ratio implies higher operating profit and lower chances of bankruptcy (Kosmidou et al., 2005).

Internal Growth Rate: This is the highest rate of growth that a company can attain without raising external finance (Kouser et al., 2012). A higher internal growth rate increases a company's self-sufficiency, reducing its reliance on external financing and borrowing costs during distress. This, in turn, lowers the likelihood of its failure (Singh and Rastogi, 2022).

Cashflow to Current Liabilities: This ratio is a cashflow-based liquidity metric that measures a firm's ability to meet its short-term financial obligations with the cash generated by its activity. A higher ratio indicates a lower likelihood of a firm entering financial distress. This cashflow-based ratio is employed in other studies as well (Khoja et al.,2019; Tinoco and Wilson, 2013; Rizzo et al., 2020). Several studies have found incremental predictive power of cashflow-based ratios in corporate bankruptcy (Beaver, 1966; Gilbert et al., 1990; Sung et al., 1999; Ravisankar et al., 2010; Tang and Yan, 2010).

Interest Rate: Small firms with no access to the capital market and listed firms suffering from low liquidity in the equity market depend on banks for external financing. Higher interest rates lead to increased borrowing costs and reduced financial stability of firms. In fact, a 1% hike in interest rates results in a 14% decline in profits for SMEs (Kulkarni and Chirputkar, 2014).

Financial Crisis: Financial crises disrupt global and domestic demand and supply chains and lead to environmental uncertainties. Thus, macroeconomic turbulences can impact firms' operations and financing activities, which in turn affect their financial stability (Tinoco and Wilson, 2013; Bhattacharjee and Han, 2014; Kim and Upneja, 2021). This study takes COVID-19 pandemic as the crisis. FY 2020-2021 is taken as the impact year since the lockdown in India was imposed on 24^{th} March, 2020, just 7 days before the end of FY 2019-2020 (Singh and Rastogi, 2022).

Inflation Rate: Inflation is a well-known macroeconomic indicator widely used in bankruptcy prediction models. Although its impact on corporate bankruptcy is questionable and ambiguous. Wadhwani (1986) suggested that inflation can create cashflow problems due to imperfect credit markets and cause bankruptcy. According to Jones (2017), high inflation means uncertainty in the economy that very likely negatively impacts corporate activity and therefore can increase the default event. Others found a positive relationship between inflation and the likelihood of firm failure (Mare, 2015; Tinco and Wilson, 2013). On the other hand, Qu (2008) suggested that high inflation can increase risk-taking capacity of investors as a fear of reduced purchasing power, thus increasing the supply of credit lower the firm's probability of default.

Real GDP Growth Rate: The real GDP growth rate serves as a proxy for overall economic growth. Generally, the probability of firm failure tends to decrease when the economy is experiencing strong growth (Jones, 2017). Carling et al. (2006) found that during the sample period of their study, corporate default rates declined as macroeconomic conditions improved. Similarly, Tang and Yan (2010) demonstrated that the GDP growth rate is a significant predictor of average credit spreads. Specifically, their findings suggest that, on average, a one-percent increase in the GDP growth rate leads to a reduction in credit spreads by 6 to 7 basis points.

Table I describes the variables, while Tables II and III show the distribution of IPOs over time and the distribution of total listed and non-listed observations, respectively. Table IV lists the descriptive statistics for them.

Table I. Description of the variables

Variables		Definitions
Dependent variable	Z"-Score	Altman's Z"-Score model is used as a proxy for Financial Stability
	Z"-Score Zones	Categorical Variable with three categories (safe zone =2; grey zone=1; distress zone =0)
Independent Variable	Listing	Dummy Variable (Pre-Listing Period=0 and Post-Listing Period =1)
Control Variable	Age	Age of the company
	Size	Log of total assets of the company
	Internal Growth Rate	Internal Growth Rate= Return on Assets×Retention Ratio/ (1-Return on Assets) ×Retention Ratio
	Cost to Income	Cost to Income Ratio= Total Expenses/Total Income; a proxy for measuring efficiency in expense management
	Cashflow to Current Liabilities	Cashflow to Current Liabilities= Total Cashflow/Current Liabilities; a cashflow based liquidity ratio
	Interest Rate	Repo Rate (a proxy for interest rate)
	Real GDP Growth Rate	A proxy for measuring direction of the overall economy
	Inflation Rate	A proxy for measuring overall economic condition
	Covid-19	Dummy Variable: Non-Covid Period=0 (FY2011-2012 to FY2019-2020 and from FY2021-2022 to FY2022-2023), and Covid Period=1(FY2020-2021)

Source: The authors

Table II. Distribution of IPOs over time

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
No. of IPOs	1	0	2	1	3	6	9	2	3	9	25	3

Source: The authors

Table III. Distribution of Listed and Non-Listed observations in the dataset

Listing	Frequency	Percentage
0. Non-listed observations	199	48.42
1. Listed observations	212	51.58
Total	411	100

Source: The author's calculation. Statistical software Stata14 has been used for the calculation.

Note: As seen in Table II, the distribution of IPOs across the study period is uneven, with clustering, particularly in 2022. The clustering in 2022 is mainly due to data availability. But we have tried to ensure a fairer distribution of the total observations between non-listed and listed observations, as seen in Table III. To ensure the robustness of our analysis, we have included only those BSE SME-listed companies for which both pre- and post-listing annual report data were obtainable. While the temporal clustering of IPOs could potentially influence the results, we have controlled for such effects by including macroeconomic variables, interest rate, real GDP growth rate, inflation rate, and the financial crisis COVID-19 in our analysis. These controls help account for time-specific external factors, thereby mitigating any biases arising from IPO concentration during certain years.

Table IV. Descriptive Statistics of the Variables

Variables	Mean	Median	Standard Deviation	Maximum	Minimum
Z″-Score	11.76	7.63	18.54	202.26	-2.96
Cost to Income	0.98	0.96	0.69	11.01	0
Age	13	12	7.23	39	1
Total Assets (Size)	37.70	22.48	46.87	305.51	0.01
Internal Growth Rate	0.05	0.02	0.10	0.91	-0.34
Cashflow to Current Liabilities	1.17	0.08	5.80	76.83	-0.01
Interest Rate	5.57	5.77	1.07	8	4
Real GDP Growth Rate	0.08	2.5	5.31	4.56	-12.50
Inflation Rate	5.37	5.13	1.36	10.02	3.33

Source: The author's calculation. Statistical software Stata14 has been used for the calculation.

Note: The summary statistics of all the continuous variables are presented in Table IV. The mean value of the dependent variable Z″-Score is 11.76. It suggests that on average the Indian SMEs selected for this study are in the safe zone which means their financial condition is stable. However, there is a high degree of dispersion in the Z″-Score because the sample of companies comprises various sectors with different ages. The mean value of the age variable is 13 years. The average size (measured by total assets) of the sample companies is 37.70 cr. The mean values of the variables cost-to-income ratio, internal growth rate and cashflow to current liabilities are 0.98, 0.05 and 1.17 respectively. The interest rate varies from 4% to 8% during the sampling period of this study while real GDP growth rate and inflation rate varies from 4.56% to -12.50% and 10.02% to 3.33% respectively.

3. Methodology

We start by describing the summary statistics of the variables and run the Fisher-type unit root test to check their stationarity. We employ two statistical methods depending on the nature of our two dependent variables. Based on the Hausman test, a fixed-effect static panel data model has been used to explore the first research question. And, depending on the significance of the OMODEL test and considering the unobserved time-invariant individual-specific effect, fixed-effects ordered logit regression is employed to explore the second research question.

Fixed-effects panel regression

The panel data model includes an individual-specific effect, α_i, in the error term. This time-invariant effect may or may not be correlated with the regressors. If it correlates with the regressors, the fixed-effects model (FEM) is preferred; otherwise, the random-effects model (REM) is used. The general fixed-effect model is described as (Johnston and Dinardo,1996):

$$Y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} \tag{1}$$

Where α_i, the individual-specific fixed effects term, is an unknown parameter to be estimated, and we assume that $cov(X_{it}, \alpha_i) \neq 0$. Y_{it} and X_{it} are the values of the dependent and independent variables respectively, for cross-section unit i at time t. β is the coefficient vector to be estimated, and ε_{it} is the error term that varies independently across time and individuals. In this study, Y_{it} is Z″-Score. Detailed descriptions of regressors are in Table I.

Fixed-effects ordered logit regression

Fixed-effects models are generally preferred when the unobserved individual-specific error term is correlated with the regressors that incorporate the endogeneity arising from time-invariant characteristics. Since the dependent variable in the second research question is ordinal, the fixed-effects ordered logit model is used in this study. This model is built upon the blow-up and cluster (BUC) estimator (Baetschmann et al., 2015), based on the conditional maximum likelihood estimator. This estimator has good properties and is almost as efficient as generalized method-of-moments and empirical likelihood estimators.

In the fixed-effects ordered logit model, the latent variable Y* connects the observable covariates X to the observable ordered dependent variable Y, where the dependent variable can take values 1,..., K. The functional relationship between the latent variable Y_{it}^* and covariates X_{it} is linear and it takes the following form (Baetschmann et al, 2020):

$$Y_{it}^* = X'_{it}\beta + \alpha_i + \varepsilon_{it};\ i = 1, \ldots, N \text{ and } t = 1, \ldots, T_i \text{ (for unbalanced panel data)}$$

Where α_i is the time-invariant individual-specific unobserved fixed-effect term correlated with X_{it}. The latent variable Y* is related to the observed ordered outcome variable Y_{it} through the thresholds τ_{ik} in the following way:

$$Y_{it} = k \quad \text{if} \quad \tau_{ik} < Y_{it}^* \leq \tau_{ik+1};\ k = 1, \ldots, K$$

We assume that the individual-specific thresholds are that the lowest and highest thresholds are plus and minus infinity, respectively, and the thresholds are increasing for each individual:

$$\tau_{i1} = -\infty;\ -\infty < \tau_{ik} < \tau_{ik+1} < \infty,\ \forall\ k = 2, \ldots, K-1;\ \tau_{ik+1} = \infty \tag{2a}$$

The time-varying unobservable error term ε_{it} is assumed to be independent and identically distributed with the standard logistic cumulative density function as follows:

$F(\varepsilon_{it} | X_{it}, \alpha_i) = F(\varepsilon_{it}) = 1/[1 + \exp(-\varepsilon_{it})] \equiv \Lambda(\varepsilon_{it})$

Hence, the probability of observing outcome k for individual i at time t is of the form:

$$\Pr(Y_{it} = k | X_{it}, \alpha_i) = \Lambda(\tau_{ik+1} - X'_{it}\beta - \alpha_i) - \Lambda(\tau_{ik} - X'_{it}\beta - \alpha_i) \quad (2b)$$

Where τ_{ik+1} and τ_{ik} represent thresholds, β is the slope coefficient of regressors and α_i is the fixed-effects term. Y_{it} is the ordered dependent variable, Z″-Score Zones, that assumes outcomes like 'Safe', 'Grey', and 'Distress'. Detailed description of regressors is in Table I.

4. Empirical Result

4.1 Panel unit root test:

All the variables are stationary as evidenced from the Fisher-type unit-root test based on the Augmented Dickey-Fuller test.

Table V: Panel Unit root test (Fisher-Type) results

Test Statistics	ln (Z″-Score)	Cost to Income	Internal Growth Rate	Cashflow to Current Liabilities	Size
Inverse chi-squared (122)	261.6441***	566.3509***	293.8284***	580.2662***	506.8787***
Inverse normal	0.1862	-6.7698***	-3.7328***	-9.1672***	-4.1094***
Inverse logit t (284)	-3.3328***	-16.1425***	-6.9249***	-17.8288***	-12.8049***
Modified inv. chi-squared	8.9398***	28.4467***	11.0002***	29.3375***	24.6393***

Source: The authors' calculation. Statistical software Stata14 has been used for the calculation.

4.2 Correlation and Multicollinearity among Variables

Pearson's correlation explores the interdependence between dependent and independent variables and also among the independent variables. The observed relationships among variables are consistent with the findings in the literature, except for the variable size. However, a statistically significant relationship with the dependent variable is found between listing, internal growth, and cashflow to current liabilities. As expected, stock exchange listing, company age, internal growth rate, and cashflow to current liabilities are positively related, whereas cost-to-income ratio and the impact of COVID-19 are negatively related to a company's financial stability. To reduce the effect of multicollinearity among the regressors, variance inflation factor (VIF) test has also been performed. Since all variance inflation factors are below 5, the model is free from multicollinearity issues (Gujarati, 2009).

Table VI. Correlation and Multicollinearity analysis among the variables

	ln(Z″-Score)	Age	Size	Listing	Cost to Income	Internal Growth Rate	Cashflow to Current Liabilities	VIF
ln(Z″-Score)	1							
Age	0.0148	1						1.11
Size	-0.1587*	0.2644*	1					1.31
Listing	0.2327*	0.1319*	0.3654*	1				1.21
Cost to Income	-0.0332	0.038	0.0308	0.0811	1			1.08
Internal Growth Rate	0.1723*	-0.074	-0.161*	-0.117*	-0.230*	1		1.11
Cashflow to CL	0.3775*	0.0627	-0.190*	-0.0161	-0.0653	0.0126	1	1.07
Interest	0.0001	-0.1437*	-0.0639	0.0109	-0.0596	-0.0725	0.0527	3.4
Real GDP Growth	0.0376	0.0127	0.0571	0.0593	0.0316	-0.0081	0.0423	3.03
Inflation	0.0762	0.0138	0.0053	0.0785	0.0392	-0.0348	0.0003	1.43
Covid-19	-0.0122	0.0666	0.0195	-0.0541	0.072	0.0031	-0.0267	3.54

	Interest	Real GDP Growth	Inflation	Covid-19
Interest	1			
Real GDP Growth	0.2924*	1		
Inflation	-0.1401*	-0.4930*	1	
Covid-19	-0.6140*	0.3509*	-0.0677	1

Source: The authors' calculation. Statistical software Stata14 has been used for the calculation.

4.3 Estimation Results

4.3.1. Stock exchange listing and financial stability - result of panel regression

To enhance predictive power and reduce the impact of outliers, we transformed the dependent variable into the natural logarithm of Z″-Score values. Stock exchange listing was used as the main regressor of interest, while company age, size, cost-to-income ratio, internal growth rate, cashflow to current liabilities, interest rate, real GDP growth rate, inflation rate, and a pandemic dummy were included as control variables. The Hausman test chooses FEM over REM (p-value=0.0461). The result of Arellano-Bond rejects the presence of autocorrelation in first difference errors. As suggests in Table VII, only stock exchange listing and internal growth rate have significant impact on the outcome variable. Compared to the pre-listing periods, Z″-Scores increase by 1.40 points (e^0.34) in the post-listing periods, which is consistent with the literature (Gupta and Gregoriou, 2017; Kim, 1999). Moreover, one unit increase in the internal growth rate increases Z″-Score by 5.16 points (e^1.64). Other control variables, namely, company age, size, cost-to-income ratio, cashflow to current liabilities, and macro-economic factors like interest rate, real GDP growth rate, inflation rate, and pandemic, do not impact the outcome variable.

Table VII: Estimation result of the panel regression model

Model 1: Fixed-effects (within) regression	
Dependent Variable: ln(Z”-Score)	
Independent Variables	Coefficient
Listing	0.34(0.08) ***
Age	0.01(0.04)
Size	0.04(0.08)
Cost to Income	0.03(0.03)
Internal Growth Rate	1.64(0.79) **
Cashflow to Current Liabilities	0.03(0.02)
Interest Rate	0.00(0.06)
Real GDP Growth Rate	0.01(0.01)
Inflation Rate	0.04(0.03)
Covid-19 Period	-0.03(0.12)
Note: *** and ** indicate the level of significance at 1% and 5%, respectively. Robust standard errors are in parentheses.	
Prob > F = 0.0000	
Durbin-Wu-Hausman test, p-Value = 0.0461	
Arellano-Bond test for zero autocorrelation in first-differenced errors: Order1- p(0.3071) and Order 2- p(0.4790)	

Source: The authors' calculation. Statistical software Stata14 has been used for the estimation.

4.3.2. Factors that help companies reach a better financial stability zone - estimation result of fixed-effects ordered logit regression model

Ordered logistic regression explores the factors that help companies reach a better financial stability zone. OMODEL test, based on the null hypothesis of no difference in the coefficients between the models, checks the validity of the proportional odds assumption. Acceptance of the null hypothesis implies that the proportional odds assumption is not violated, and the use of the ordered logit model is justified. The estimation results reveal that stock exchange listing, size, internal growth rate, and cashflow to current liabilities can significantly affect the Z″-Score Zone at 1%, 10%, and 5% level of significance, respectively (Table VIII).

Hence, with all other variables held constant, a move from the pre-listing to the post-listing period, the log odds of the companies being in a higher Z″-Score zone increase by 1.75. Similarly, with all other variables unchanged, a one-unit increase in internal growth rate increases the log odds of being in a higher level of Z″-Score zone by 15.92 and a one-unit increase in cashflow to current liabilities increases the same by log odds of 2.53, while one-unit increase in size increases the log odd of being in a higher zone by 0.86.

Table VIII. Estimation results of the Fixed-effects ordered logit regression model

Model 2: Fixed-effects ordered logit regression	
Dependent Variable: Z″-Score Zone	
Independent Variables	Coefficient
Listing	1.75(0.60) ***
Age	0.06(0.17)
Size	0.86(0.52) *
Cost to Income	0.19 (0.22)
Internal Growth Rate	15.92(8.24) **
Cashflow to Current Liabilities	2.53(1.12) **
Interest Rate (Repo Rate)	0.56(0.35)
Real GDP Growth Rate	-0.00(0.05)
Inflation Rate	0.10(0.13)
Covid-19 Period	0.91(0.79)
Note: ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively. Robust standard errors are in parentheses.	
Prob > F = 0.0000	
Likelihood-ratio test of proportionality of odds: p-value = 0.1060	

Source: The authors' calculation. Statistical software Stata14 has been used for the estimation.

5. Conclusion

The study empirically examines the impact of stock exchange listing on the financial stability of selected Indian SMEs, comparing their performance before and after listing. Financial stability of SMEs has been measured by Altman's Z″-Score (2005). These scores were developed to measure the credit risk of publicly and privately owned manufacturing as well as non-manufacturing firms in emerging countries. While stock exchange listing is the main predictor variable of the financial stability of firms, the study chooses other control variables based on the existing literature. These include firm-specific factors like company's age, size, cost-to-income ratio, internal growth rate, cashflow to current liabilities, and macroeconomic factors like interest rate, real GDP growth rate, inflation rate, and crises like the Covid-19 pandemic. We find stock exchange listing to be crucial in improving companies' Z″-Score value and, thus, the financial stability of Indian SMEs. This is consistent with the literature (Gupta and Gregoriou, 2017; Kim, 1999). Among the control variables, the internal growth rate, size and cashflow to current liabilities (liquidity) increase financial stability of the SMEs and help them reach a better stability state. Other control variables, including the pandemic dummy, have insignificant impact on financial stability. The insignificant impact of the pandemic is not in line with the existing literature (Tinoco and Wilson, 2013; Bhattacharjee and Han, 2014; Kim and Upneja, 2014). This may point towards the risk-resilient nature of Indian SMEs as hinted by Artini and Sandhi (2020). This resilience may be explained by the lower dependence of SMEs on debt financing. In general, SMEs prefer current liabilities and total reserves over debt financing in meeting their financing needs (Verma et al., 2020). During crises, SMEs may reduce financing costs and rely on their total reserves to maintain financial stability, despite a decline in overall income.

Therefore, access to the capital market can help SMEs raise funds through newer channels. More equity can help in expansion, innovation, and other business activities. Listing could enhance their financial stability by reducing the likelihood of failure caused by prolonged difficulties in accessing external finance. Listing improves the visibility, reputation, and credit score of SMEs, making fundraising easier from banks and like institutions. However, to ensure uninterrupted funding, SMEs should consistently perform well in generating operating revenues and demonstrate high growth over time following their listing. This will attract more investors and increase the liquidity of their shares. Failing to do so could result in the costs of listing outweighing the benefits. The study thus provides valuable insights to firms considering listing, highlighting how listing can help raise capital and mitigate the risk of failure due to credit constraints faced by SMEs.

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