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Impact of market-based finance on SMEs failure

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ABSTRACT

Capital Market-Based financing for Small and Medium-sized Enterprises (SMEs) is increasingly viewed as complementary to traditional bank-based financing for SMEs. In response, policymakers are recognising the need for better access of SMEs to capital markets and are making efforts to remove major impediments to their participation in capital markets. Thus, SMEs listed on stock exchanges benefit from better access to finance and reduced information asymmetry than their unlisted counterparts. This in turn shall lead to lower failure likelihood of listed SMEs. In this study, we empirically test this hypothesis and report that listed SMEs enjoy a lower likelihood of financial distress and bankruptcy than their unlisted counterparts. Although factors affecting financial distress of both listed and unlisted SMEs are almost identical, Average Marginal Effects of respective factors are strikingly higher for their unlisted counterparts. This suggests a higher vulnerability of unlisted SMEs due to changes in financial ratios. Due to the extremely low number of legal bankruptcy events, our hypothesis finds weak support when bankruptcy is used as the dependent variable in the regression analysis. Broadly, our findings support the view that stock exchange listing can relieve SMEs from external financing constraints, thus reducing their failure likelihood.

1. Introduction

Access to finance for Small and Medium-sized Enterprises (SMEs) is a perennial problem for policy makers, and thus an area worthy of scholarly debate. For several reasons, access to external finance is unanimously considered to be the most important factor hindering SMEs growth, development (e.g. Beck and Demirguc-Kunt, 2006; Ardic et al., 2012), and potentially their failure. Several reasons such as insufficient collateral, poor creditworthiness, short/no credit history, underdeveloped bank-borrower relationships, high transaction costs, and information asymmetry, contribute toward the difficulty that they face in obtaining commercial bank financing, especially long-term borrowings. This problem became more severe with the unfolding of the financial crisis toward the end of 2007. During the crisis period, SMEs suffered from severe credit constraints and many had to rely on trade credits to meet their financing needs (Carbó-Valverde et al., 2016). Belgian SMEs with a large proportion of long-term debt maturing at the beginning of the crisis faced difficulties in renewing their loans due to the negative credit supply shock, and thus were left underinvested (Vermoesen et al., 2013). This crisis also had a significant detrimental impact on the ability of innovative SMEs to access external finance (Lee et al., 2015). Further, empirical evidence also suggests that the increasing market power of banks leads to higher credit constraints for SMEs (Love and Martínez Pería, 2015; Ryan et al., 2014), and thus a complementary source to traditional bank-based financing for SMEs might be an appropriate alternative choice.

Considering the limited use of alternative sources of financing by SMEs (Berger and Udell, 2006), efforts are being made to understand the factors affecting their participation in capital markets (see Bongini et al., 2017) and make their financial structure less dependent on bank financing (see OECD, 2015). This could be particularly relieving in conservative economic scenarios when bank lending decisions become increasingly selective due to banks' own balance sheet constraints, and the rising default likelihood of its borrowers (European Central Bank, 2014). Although trade credit, factoring and leasing might be viewed as closer substitutes to bank lending (Ferrando and Mavrakis, 2017), these alternative sources are primarily dependent upon their level of business activity, which gets adversely affected during economic downturns, and thus leads to constrained access to such alternatives.

While stock exchange listing could relieve them from financing constraints (Kim, 1999), listing might be difficult due to admission requirements and disclosure regulations (see Gao et al., 2013). This realization has led to the emergence of stock markets with relaxed admission requirements and disclosure regulations specifically targeting SMEs (e.g. Alternative Investment Market of the London Stock Exchange). Thereby, they may relax their overdependence on lending

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Table 1
Sample industrial classification.

Industry code	SIC code	Industry	Included/Excluded
1	< 1000	Agriculture, Forestry, Fishing	Included
2	1000 to < 1500	Mining	Included
3	1500 to < 1800	Construction	Included
4	2000 to < 4000	Manufacturing	Included
5	5000 to < 5200	Wholesale Trade	Included
6	5200 to < 6000	Retail Trade	Included
7	7000 to < 8900	Services	Included
Excluded	4000 to < 5000	Transportation, Communications & Public Utilities	Excluded
Excluded	6000 to < 6800	Finance, Insurance & Real Estate	Excluded
Excluded	9100 to < 10,000	Public Administration	Excluded

Notes: This table reports Standard Industrial Classification (SIC) of US firms. SIC Code is a four digit code that represents a given industrial sectors. The last column reports the industrial sectors that we included or excluded from our sample.

institutions/banks for external financing by listing themselves in stock exchanges, consequently removing the financial barriers hindering their growth and competitiveness. This further reduces information asymmetry between firms and external investors, which in turn can make access to external finance easier. As a consequence, listed SMEs are expected to experience lower likelihood of failure than their unlisted counterparts. Thus, in this study we hypothesize that the financial distress and bankruptcy likelihood of listed SMEs are lower than their unlisted counterparts, primarily due to their ability to access external market-based (equity) finance.

Considering the discussion above, we believe it is important to understand the impact of market-based finance on SMEs failure likelihood for several reasons. Improved understanding of the difference between credit risk behaviour of listed and unlisted SMEs shall allow for: (i) better pricing of credit risk by lending institutions; (ii) improved investment decisions by capital market investors; (iii) better allocation of resources by policymakers and regulators in developing capital markets targeted toward encouraging participation from small companies; and (iv) reduced constraints to external financing for SMEs. Thus we contribute to the fast growing literature on SMEs failure and their financing constraints (e.g. Bassetto and Kalatzis, 2011) by investigating whether Stock Exchange listing reduces SMEs likelihood of financial distress and bankruptcy. In particular we examine if there are significant differences in the determinants of financial distress and bankruptcy of listed and unlisted SMEs.

We empirically test our hypothesis using a sample of listed and unlisted SMEs in the United States covering a sampling period between 1985 and 2016. Firm level annual accounting information and monthly/daily stock prices data are sourced from the Compustat database. Considering the suggestion by Gupta et al. (2017), we use panel logistic regression to perform univariate and multivariate one-year financial distress and bankruptcy prediction models for listed and unlisted SMEs respectively. Twelve financial ratios with established reputations for financial distress/bankruptcy prediction in earlier studies are used as accounting covariates (see among others Altman and Sabato, 2007; Gupta et al., 2017) along with a number of appropriate control variables. In order to understand any complementary explanatory power of market variables in explaining financial distress and bankruptcy of listed SMEs, we also estimate our regression models supplementing five market variables in line with suggestions from Shumway (2001) and Campbell et al., (2008). Our definition of financial distress based on firms' financial performance is adapted from Keasey et al. (2015), and firms that filed for legal bankruptcy under Chapter 7/11 are considered to be bankrupt.

Based on our empirical findings, we report significant differences between failure hazards of listed and unlisted SMEs. At any given age, the failure (survival) rate of unlisted SMEs is significantly higher (lower) than their listed counterparts. Although an identical set of financial ratios are significant in discriminating between financially distressed and censored groups of listed and unlisted SMEs in univariate analysis, we observe significant difference in the weights of regression coefficients of respective covariates of listed and unlisted SMEs. *Average Marginal Effects* (AME) of respective covariates for the unlisted group of firms is strikingly higher than for their listed counterparts, suggesting higher vulnerability of unlisted firms due to changes in their financial position. However, univariate regression estimates using bankruptcy as a dependent variable reveal striking differences in the factors affecting the bankruptcy likelihood of listed and unlisted SMEs. Although all twelve accounting covariates are significant in predicting bankruptcy for the unlisted group of SMEs, only seven are significant predictors for listed SMEs. Moreover, values of AMEs for mutually significant covariates are much lower for listed firms. This may be explained by the fact that listed firms are discounted much earlier than their unlisted counterparts due to their lower information asymmetry. These univariate regression results support our hypothesis that listing reduces SMEs risk of failure; as a consequence listed SMEs shall be less vulnerable to financial distress and bankruptcy risk than their unlisted counterparts.

Results obtained in our multivariate analysis are also broadly consistent with our univariate findings. We adopt the multivariate model building strategy suggested by Gupta et al. (2017) and find empirical evidence in support of our hypothesis. Out of twelve significant covariates in the univariate analysis, we find nine covariates are significant in predicting the financial distress likelihood of listed SMEs over the one-year period, with significant values of AME and excellent within-sample and out-of-sample classification performance. Multivariate models developed supplementing significant market variables reflects the complementary nature of market information in predicting financial distress of listed SMEs. Broadly, the significance of respective accounting covariates remains unchanged, and four market variables enter significantly into the multivariate model. However, our primary interest lies in the comparative performance between multivariate models developed using accounting ratios for listed and unlisted SMEs. Out of twelve highly significant covariates in univariate analysis, eight enter significantly into the multivariate setup. We also find few differences in the factors affecting financial distress likelihood of listed and unlisted SMEs. Comparison of AMEs of respective accounting covariates further reinforces our hypothesis. AME for all accounting covariates are significantly higher for unlisted SMEs than their listed counterparts, as observed in the univariate analysis. This suggests that unlisted SMEs are more vulnerable to changing financial positions, unlike listed SMEs.

However, our multivariate results are not appropriately reliable for regression models estimated using bankruptcy as the dependent variable. This is due to an extremely low number of bankruptcy events (28 for listed SMEs with accounting variables, and 21 for listed SMEs with accounting and market variables) in our sample. Only two accounting covariates are significant with mostly insignificant values of control and market variables. We understand that this is a serious drawback of this study, but the appropriate solution to this problem

Table 2
Sample description.

Year	Financially distressed firms						Bankrupt firms					
	Listed firms			Unlisted firms			Listed firms			Unlisted firms		
	Distressed	Total	% Distressed	Distressed	Total	% Distressed	Bankrupt	Total	% Bankrupt	Bankrupt	Total	% Bankrupt
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1985	50	805	6.21	294	1460	20.13	4	805	0.49	27	1460	1.84
1986	57	872	6.53	333	1496	22.25	4	872	0.45	28	1496	1.87
1987	63	900	7.00	337	1515	22.24	5	900	0.55	21	1515	1.38
1988	60	854	7.02	289	1419	20.36	3	854	0.35	25	1419	1.76
1989	52	793	6.55	325	1372	23.68	3	793	0.37	24	1372	1.74
1990	53	770	6.88	299	1301	22.98	0	770	0.00	27	1301	2.07
1991	55	831	6.61	281	1250	22.48	1	831	0.12	16	1250	1.28
1992	60	899	6.67	238	1237	19.24	3	899	0.33	11	1237	0.88
1993	50	958	5.21	209	1269	16.46	2	958	0.20	15	1269	1.18
1994	48	948	5.06	200	1250	16.00	2	948	0.21	6	1250	0.48
1995	59	969	6.08	206	1270	16.22	1	969	0.10	6	1270	0.47
1996	61	1095	5.57	237	1408	16.83	3	1095	0.27	11	1408	0.78
1997	53	1029	5.15	253	1394	18.14	2	1029	0.19	9	1394	0.64
1998	79	909	8.69	276	1275	21.64	1	909	0.11	12	1275	0.94
1999	120	1010	11.88	307	1298	23.65	0	1010	0.00	10	1298	0.77
2000	94	835	11.25	320	1284	24.92	0	835	0.00	6	1284	0.46
2001	68	750	9.06	360	1230	29.26	0	750	0.00	7	1230	0.56
2002	84	702	11.96	388	1096	35.40	0	702	0.00	3	1096	0.27
2003	117	721	16.22	333	969	34.36	1	721	0.13	6	969	0.61
2004	94	690	13.62	297	931	31.90	0	690	0.00	3	931	0.32
2005	71	626	11.34	231	843	27.40	0	626	0.00	4	843	0.47
2006	75	573	13.08	241	790	30.50	0	573	0.00	5	790	0.63
2007	65	519	12.52	221	727	30.39	0	519	0.00	2	727	0.27
2008	64	440	14.54	203	642	31.61	0	440	0.00	3	642	0.46
2009	82	450	18.22	230	588	39.11	2	450	0.44	2	588	0.34
2010	85	452	18.80	208	548	37.95	0	452	0.00	1	548	0.18
2011	68	415	16.38	158	498	31.72	0	415	0.00	0	498	0.00
2012	73	438	16.66	197	513	38.40	0	438	0.00	0	513	0.00
2013	97	493	19.67	225	544	41.36	0	493	0.00	1	544	0.18
2014	93	496	18.75	224	560	40.00	0	496	0.00	1	560	0.17
2015	90	490	18.36	184	476	38.65	0	490	0.00	1	476	0.21
2016	15	90	16.66	42	104	40.38	0	90	0.00	0	104	0.00

Notes: This table presents annual details of financially distressed and bankrupt firms for listed and unlisted SMEs respectively. Column 1 lists years followed by the number of listed SMEs in financial distress in that year (column 2), total number of listed SMEs in the database in that year (column 3), and percentage of financially distressed listed SMEs in that year (column 4). Subsequent columns show similar information for financially distressed unlisted SMEs (columns 5, 6 and 7), bankrupt listed SMEs (columns 8, 9 and 10), and finally bankrupt unlisted SMEs (columns 11, 12 and 13).

would require a sample with greater frequency of bankruptcy events. However, for the unlisted group of firms, we have 247 bankruptcy events and the multivariate model developed looks much more reasonable than its listed counterpart. Out of twelve accounting variables, five enter significantly into the multivariate model with significant control variables.

The remainder of the paper is structured in the following way: the next section presents discussion on our sample, covariates, and descriptive statistics; Section 3 outlines our empirical methods, followed by discussion on univariate and multivariate estimates; and Section 4 concludes our study.

2. Sample, covariates and descriptive statistics

This section provides discussion related to the source and use of dataset, selection of explanatory variables and their summary statistics.

2.1. Sample description

We sourced firm-level accounting and market information for the United States SMEs from the Compustat database. We consider a firm a SME if it reports less than 250 employees[1]. Considering significant changes that were introduced in the Bankruptcy Reform Act of 1978, our sampling period runs from 1985 until 2016. We do this to avoid any structural bias that may arise in our estimations due to different bankruptcy regimes. Furthermore, firms with Standard Industrial Classification (SIC) codes from 6000 through 6999 (financial firms), and 4900 through 4949 (regulated utilities), are excluded from the sample (see Table 1). We also exclude subsidiary firms (if 'stock ownership code' (Compustat data item 'stko') is '1' (subsidiary of a

[1] In line with several existing studies (see among others Beck and Demirguc-Kunt, 2006; Carbó-Valverde et al., 2016), we follow the European Commission's definition of SMEs and define SMEs as those firms with fewer than 250 employees; micro firms with fewer than 10 employees; small firms with fewer than 50 but greater than 9 employees; and medium firms with fewer than 250 but greater than 49 employees. We are aware of the fact that the US Small Business Administration (SBA) defines SMEs differently. Broadly, it considers a firm a SME if it has less than 500 employees and an annual turnover of less than $7.5 million. However, their precise definition varies across industrial sectors to reflect industry differences. For instance, a mining firm with less than 1000 employees, a general building and heavy construction firm with annual turnover of less than $36.5 million, and a manufacturing firm with less than 1500 employees, are all classified as small businesses as per SBA. This may not be a convenient workable definition from the lender's point of view. Many of these firms are too big to be called SMEs in the real sense, despite being classified as small firms as per SBA. They do this primarily to determine the eligibility of a firm for SBA financial assistance, or for its other programs. Thus we follow a more appropriate and popular definition of SMEs provided by the European Union for this study. The most popular study on predicting bankruptcy of US SMEs by Altman and Sabato (2007) also follows the European Union's definition of SMEs.

publicly traded company) or '2' (subsidiary of a company that is not publicly traded) in the Compustat database). We consider a SME as listed if it is publicly traded in any of the three popular exchanges, i.e. NYSE, AMEX and NASDAQ (Compustat data item 'exchg' is 11 (NYSE), 12 (AMEX) or 14 (NASDAQ)) and unlisted otherwise (Compustat data item 'exchg' is 1 (non-traded company), 13 (OTC Bulletin Board) or 19 (Other OTC)).

Table 2 reports annual rates of financial distress and bankruptcy of listed and unlisted SMEs respectively. As we see in Table 2, for any given year the rate of financial distress is much higher for unlisted SMEs than for their listed counterparts. This phenomenon is also persistent for our sample of bankrupt firms. This provides preliminary support to our hypothesis that listed SMEs face lower financial constraints, and this transmits into their higher survival or lower distress rate. The number of firms entering the state of financial distress in any given year is sufficiently large to establish the empirical validation, however lower annual bankruptcy rates raise scepticism. Before the year 2000, numbers of bankruptcies were at-least in double digits, with a maximum of 28 for the unlisted group of firms (see columns 11, 12 and 13 of Table 2). However there is barely any bankruptcy filing in year 2000 and onwards. This problem of extremely low or no bankruptcy filing is more severe for our group of listed SMEs (see columns 8, 9 and 10 of Table 2). This is expected to have deterrent impact on our regression analysis; however computations presented in Table 2 are clearly in favour of our hypothesis.

2.2. Covariates

2.2.1. Dependent variables

This study employs two binary dependent variables (Financial Distress and Bankruptcy) to establish the empirical validation. A firm which files for legal bankruptcy under Chapter 7/11 is considered to be Bankrupt with value of the dependent variable equalling to 1 and 0 otherwise. In this study we also use financial distress as a dependent variable beside legal bankruptcy, with the presumption that it is the primary reason behind bankruptcy and always precedes the bankruptcy filing event. Also, bankruptcy filings are becoming an increasingly rare phenomenon; this might be due to active bankruptcy resolution support provided by the government, and an increasing number of out of court settlements (see Blazy et al., 2013). Thus a mechanism to identify distressed firms is operationally more relevant than waiting until a firm files for bankruptcy as the last resort. Further, filing for legal bankruptcy is the least efficient exit strategy for SMEs (Balcaen et al., 2012) and distress definitions based on bankruptcy laws are inefficient in comparison to distress definitions based on firms' financial performance (see Gupta et al., 2017). Thus, following Keasey et al. (2015), a SME experiencing financial distress is defined as one that satisfies the following: (i) its expenses exceed earnings during two consecutive years; (ii) its total debt exceeds net worth during those two years in (i); and (iii) it records negative growth in net worth during the same consecutive periods in (i) and (ii). Additionally, a firm is also recorded as financially distressed in the year immediately following these distress events.

2.2.2. Independent variables

Our empirical analysis employs financial ratios that have established reputations as significant predictors of SMEs default risk. The adopted accounting covariates (see Panel A of Table 3) assess firms' performance on liquidity, solvency, activity, profitability and interest coverage dimensions. Specifically, we incorporate covariates from popular studies on SMEs bankruptcy such as Altman and Sabato (2007), Lin et al. (2012), and Gupta et al. (2017).[2] To restrict the influence of outliers, the range of all accounting variables are restricted to within their 5th and 95th percentile values. For our sample of listed SMEs, we also estimate our regression models supplementing market variables (see Panel B of Table 3) suggested by Shumway (2001) and Campbell et al. (2008).

2.2.3. Control variables

As suggested by Gupta et al. (2015) we control for the diversity between micro, small and medium firms by employing dummy variables for micro (fewer than 10 employees) and small (fewer than 50 but greater than 9 employees) firms in all our multivariate models. To control the volatility in the macroeconomic environment affecting specific industrial sectors, we calculate an additional measure of industry risk (RISK) as the failure rate (number of firms experiencing the event of interest in the respective industrial sector in a given year/ total number of firms in that industrial sector in that year) in each of the seven industrial sectors in a given year. Higher values indicate a higher risk of default, and vice versa. The risks of financial distress and bankruptcy are denoted by RISKFD and RISKB respectively (see Panel C of Table 3). To account for any duration dependence due to firms' age, we employ natural logarithm of firms' annual age (AGE) in our multivariate models. We proxy a firm's age as the earliest year for which annual financial information is available for that firm in the Compustat database.

2.3. Descriptive statistics

Table 4 reports key descriptive measures of our 12 accounting variables and 5 market variables. Measures are reported for listed and unlisted SMEs separately for respective samples of financially distressed and bankrupt groups of firms. Initial inspection of descriptive statistics is useful in evaluating the variability of covariates and potential bias that may arise in the multivariate setup due to unexpected extreme variations. We expect the mean of covariates that exhibit a positive relationship with the failure risk to be higher for the distressed or bankrupt group than for the healthy or censored group (e.g. see the variable TLTA in Table 4) of firms. On the contrary, the mean of covariates that shows a negative relationship with the failure risk is expected to be lower for the default group than for their healthy counterparts (e.g. see variable CETL in Table 3). Mean, median and standard deviation of all covariates are as we expect for the respective group of listed and unlisted SMEs, except CTA (for listed financially distressed SMEs), MB (for listed financially distressed SMEs), TCTA (for listed Bankrupt SMEs), and STDEBV. Their mean value for the distressed/bankrupt group is contrary to our expectation. A look at the mean and median values of respective covariates reveals that most of the accounting variables show skewed distribution, with STDEBV and TTA exhibiting extreme skewness. In comparison, the mean and median values of market variables are sufficiently close (except MB) for both financially distressed and bankrupt group of SMEs. When interpreting these distributions, it is important to keep in mind that we weight every firm-year observation equally. This has two important implications. First, these distributions might be dominated by the behaviour of relatively small/large companies. Second, these distributions reflect the influence of both cross-sectional and time-series variation. However, this should not be a problem in our regression analysis, as our methodology does not require any normality or linear assumption.

Strong correlation among explanatory variables might raise serious multicollinearity issues in our multivariate models. The correlation matrix presented in Table 5 provides evidence that some of the covariates are strongly correlated with each other. For example, FETA exhibits moderate to strong correlation with six other covariates. This is also the case with TCTA and LCR. RETA shows strong positive correlation of approximately 0.72 with EBITDATA, supporting the expectation that SMEs primarily rely on internal sources for their

[2] Altman et al. (2010) and Gupta et al. (2017) provide detailed discussions of the covariates selected as well as their relationship with the probability of a default.

Table 3
List of explanatory variable.

Variable	Definition	Compustat data item
	Panel A: Accounting Variables	
EBITDATA	Earnings before interest taxes depreciation and amortization/total assets	EBITDA/AT
STDEBV	Short term debt/equity book value	DLC/SEQ
CTA	Cash and short-term investments/total assets	CHE/AT
RETA	Retained earnings/total assets	RE/AT
CETL	Capital employed/total liabilities	(AT – LCT)/LT
TLTA	Total liabilities/total assets	LT/AT
CAG	Capital growth; calculated as ($Capital_t$ / $Capital_{t-1}$) - 1	(AT - LCT)
TTA	Taxes/total assets	TXT/AT
LCR	ln(current assets/current liabilities)	ln(ACT/LCT)
TCTA	Trade creditors/total assets	AP/AT
FETA	Financial Expense/total assets	XINT/AT
FES	Financial Expense/sale	XINT/SALE
	Panel B: Market Variables	
EXRETAVG	Weighted average of monthly log excess return relative to value-weighted S & P 500 return over the previous 12 months period (EXRETAVG), calculated as: $EXRETAVG_{t-1,t-12}=$ $\frac{1-\varnothing}{1-\varnothing^{12}}(EXRET_{t-1}+\ldots+\varnothing^{11}EXRET_{t-12})$ Where; $EXRET_{i,t} = log(1{+}Return_{i,t}){-}log(1{+}Return_{S\,\&\,P500,t})$ Missing values of EXRETAVG are replaced with the cross-sectional mean of EXRET.	
RSIZE	Logarithm of each firm's size relative to S & P 500 market capitalization (RSIZE), calculated as: $RSIZE_{i,t} = log\left(\frac{Firm\ Market\ Equity_{i,t}}{\text{Total S \& P Market Value}_t}\right)$	
PRICE	Log of price per share winsorized at 5%	PRCC_F
MB	Firm's Market-to-book ratio	PRCC_F×CSHO/SEQ
SIGMA	Standard Deviation of past three months daily return	
	Panel C: Control Variables	
Micro	Dummy variable (Number of employees < 10 = 1 and 0 otherwise)	EMP
Small	Dummy variable (10 = < Number of employees < 50 = 1 and 0 otherwise)	EMP
AGE	Natural logarithm of firms' annual age	
RISKFD	Financial distress rate (number of firms experiencing a financial distress event in the respective industrial sector in a given year/total number of firms in that industrial sector in that year) in each of the seven industrial sectors in a given year.	
RISKB	Bankruptcy rate (number of firms a experiencing bankruptcy event in the respective industrial sector in a given year/total number of firms in that industrial sector in that year) in each of the seven industrial sectors in a given year.	

Notes: This table lists the set of covariates along with their respective definitions that we used for our empirical analysis. The last column presents the specific Compustat data items that we used to estimate the covariates. Panel A list the set of accounting variables, Panel B lists the set of market variables and Panel C lists the set of control variables that we use in this study.

funding requirements. In order to address this issue of multicollinearity effectively while developing multivariate models, we follow the suggestion by Gupta et al. (2017) and use a selection procedure of covariates based on their Average Marginal Effects, obtained from the univariate analysis. Among the market variables, only RSIZE is strongly correlated with PRICE, and they all exhibit low or moderate correlation with accounting variables. Moreover, casual observation of mean of respective covariates for listed and unlisted group of SMEs reveal striking differences in their values. Thus we are initially motivated to believe that weights/significance of respective regression coefficients might be different for listed and unlisted SMEs.

3. Empirical methods and findings

In this section we explain the choice of statistical model that we use to perform regression analysis, followed by results and discussion on univariate regression analysis of respective covariates. Finally, we report and discuss multivariate regression results for our samples of listed and unlisted SMEs.

3.1. Panel logistic regression

Although we see a significant rise in the popularity of hazard models in modelling bankruptcy or financial distress events, we use panel logistic regression to establish our empirical validation in line with the findings of Gupta et al. (2017). They argue that the discrete-time hazard model with logit link is essentially a panel logistic model that controls for firms' age. We therefore assume that the marginal probability of a firm's financial distress or bankruptcy over the next year follows a logistic distribution that is estimated as follows:

$$P(Y_{it} = 1) = \frac{1}{1 + \exp(-\alpha - \beta X_{i,t-1})} \tag{1}$$

where Y_{it} is the dependent variable that equals one if the firm is in financial distress/bankrupt in the year t, and zero otherwise; and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous year. To capture any duration dependency, we use the natural logarithm of firms' annual age (AGE) as a control variable in our multivariate models.

Table 4
Descriptive statistics.

Variable	Financially distressed firms				Bankrupt firms			
	Listed		Unlisted		Listed		Unlisted	
	Distressed	Non-Distressed	Distressed	Non-Distressed	Bankrupt	Non-Bankrupt	Bankrupt	Non-Bankrupt
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EBITDATA								
Mean	-0.4474	-0.0407	-0.7723	-0.2049	-0.0998	-0.0808	-0.4184	-0.3459
Median	-0.2438	0.0626	-0.3376	3.21e-07	0.0304	0.0455	-0.1025	-0.0565
SD	0.6275	0.3422	0.9634	0.5949	0.4633	0.3987	0.8047	0.7461
Minimum	-2.7163	-2.7163	-2.7163	-2.7163	-2.4716	-2.7163	-2.7163	-2.7163
Maximum	0.2751	0.2751	0.2751	0.2751	0.2751	0.2751	0.2751	0.2751
STDEBV								
Mean	0.1048	0.1016	-0.0218	0.16422	0.1341	0.1019	0.1018	0.1197
Median	0.0073	0.0139	-0.0012	0.0370	4.86e-07	0.0135	-0.0046	0.0229
SD	0.5259	0.2569	0.6739	0.4464	0.4928	0.2941	0.5385	0.5184
Minimum	-0.8648	-0.8648	-0.8648	-0.8648	-0.8648	-0.8648	-0.8648	-0.8648
Maximum	1.3398	1.3398	1.3398	1.339	1.339	1.3398	1.3398	1.3398
CTA								
Mean	0.3420	0.3142	0.1608	0.2118	0.1543	0.3172	0.1643	0.1993
Median	0.2565	0.2311	0.0652	0.1087	0.1150	0.2341	0.0650	0.0962
SD	0.2969	0.2783	0.2172	0.2408	0.1624	0.2804	0.2394	0.2361
Minimum	0.0024	0.0024	0.0024	0.0024	0.0042	0.0024	0.0024	0.0024
Maximum	0.8850	0.8850	0.8850	0.8850	0.7767	0.8850	0.8850	0.8850
RETA								
Mean	-5.1102	-1.0834	-9.086	-2.7454	-1.8146	-1.4800	-6.4905	-4.3087
Median	-2.4755	-0.1135	-4.0122	-0.5265	-0.8056	-0.2031	-2.4034	-0.9486
SD	6.9482	3.0881	10.3607	6.0995	3.1702	3.8476	8.9668	7.8763
Minimum	-29.1461	-29.1461	-29.1461	-29.1461	-14.3784	-29.1461	-29.1461	-29.1461
Maximum	0.5035	0.5035	0.5035	0.5035	0.5035	0.5035	0.5035	0.5035
CETL								
Mean	1.1857	3.7522	0.3791	2.7290	2.4460	3.5008	0.6275	2.1561
Median	0.7774	2.5007	0.1983	1.5166	0.8445	2.2724	0.3170	1.1256
SD	1.9397	3.3794	1.2787	3.3085	4.0878	3.3527	1.4995	3.1148
Minimum	-0.5603	-0.5603	-0.5603	-0.5603	-0.5603	-0.5603	-0.5603	-0.5603
Maximum	13.0587	13.058	13.0587	13.0587	13.0587	13.0587	13.0587	13.0587
TLTA								
Mean	0.9755	0.3710	1.6469	0.6128	1.1248	0.4295	1.7501	0.8629
Median	0.7339	0.3154	1.1139	0.4576	0.8241	0.3406	1.3741	0.5675
SD	0.7819	0.2953	1.1878	0.6590	1.0052	0.4114	1.1636	0.9312
Minimum	0.0718	0.0718	0.0718	0.0718	0.0718	0.0718	0.0718	0.0718
Maximum	3.7170	3.7170	3.7170	3.7170	3.7170	3.7170	3.7170	3.7170
CAG								
Mean	0.1525	0.4351	-0.0018	0.2539	0.1531	0.4076	-0.1000	0.1927
Median	-0.1749	0.0918	-0.2418	0.0165	0.0264	0.0806	-0.1863	-0.0125
SD	1.3389	1.0760	1.2997	1.1231	1.0672	1.1079	1.1866	1.1744
Minimum	-1.4009	-1.4009	-1.4009	-1.4009	-1.4009	-1.4009	-1.4009	-1.400
Maximum	3.9583	3.9583	3.9583	3.9583	3.9583	3.9583	3.9583	3.9583
TTA								
Mean	0.0010	0.0156	0.0014	0.0083	0.0133	0.0142	0.0050	0.0066
Median	9.02e-08	0.0015	5.38e-07	6.12e-07	0.0020	0.0005	3.37e-07	5.88e-07
SD	0.0142	0.0290	0.0144	0.0241	0.0266	0.0283	0.0224	0.0222
Minimum	-0.0276	-0.0276	-0.0276	-0.0276	-0.0276	-0.0276	-0.0276	-0.0276
Maximum	0.0879	0.0879	0.0879	0.0879	0.0879	0.0879	0.0879	0.0879
LCR								
Mean	0.3804	1.1170	-0.6496	0.5449	0.5950	1.0451	-0.1936	0.2507
Median	0.3887	1.1202	-0.4709	0.5912	0.7665	1.0613	-0.0096	0.3676
SD	1.0589	0.8471	1.1876	1.1047	1.1185	0.8970	1.3571	1.2371
Minimum	-2.4365	-2.4365	-2.4365	-2.4365	-2.4365	-2.4365	-2.4365	-2.4365
Maximum	2.5579	2.5579	2.5579	2.5579	2.5579	2.5579	2.5579	0.5579
TCTA								
Mean	0.1367	0.0754	0.2850	0.1329	0.0632	0.0815	0.1920	0.1707
Median	0.0909	0.0554	0.2016	0.0885	0.0368	0.0573	0.0835	0.1052
SD	0.1472	0.0733	0.2344	0.1415	0.0674	0.0855	0.2278	0.1814
Minimum	0.0076	0.0076	0.0076	0.0076	0.0076	0.0076	0.0076	0.0076
Maximum	0.6895	0.6895	0.6895	0.6895	0.2835	0.6895	0.6895	0.6895
FETA								
Mean	0.0583	0.0163	0.1104	0.0359	0.0546	0.0203	0.0896	0.0542
Median	0.0338	0.0070	0.0683	0.0174	0.0247	0.0081	0.0598	0.0250
SD	0.0714	0.0285	0.1020	0.0570	0.0766	0.0372	0.0888	0.0777
Minimum	6.51e-08	6.51e-08	6.51e-08	6.51e-08	6.51e-08	6.51e-08	6.51e-08	6.51e-08
Maximum	0.2866	0.2866	0.2866	0.2866	0.2866	0.2866	0.2866	0.2866
FES								
Mean	0.1573	0.0434	0.2076	0.0750	0.06270	0.0546	0.1318	0.1079

(continued on next page)

Table 4 *(continued)*

Variable	Financially distressed firms				Bankrupt firms			
	Listed		Unlisted		Listed		Unlisted	
	Distressed	Non-Distressed	Distressed	Non-Distressed	Bankrupt	Non-Bankrupt	Bankrupt	Non-Bankrupt
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Median	0.0494	0.0091	0.0699	0.0175	0.0401	0.0105	0.0442	0.0240
SD	0.2219	0.1143	0.2556	0.1608	0.0753	0.1334	0.1960	0.1975
Minimum	1.20e-07	1.20e-07	1.20e-07	1.20e-07	1.20e-07	1.20e-07	1.20e-07	1.20e-07
Maximum	0.6969	0.6969	0.6969	0.6969	0.3874	0.6969	0.6969	0.6969
EXRETAVG								
Mean	-0.0245	-0.0140	–	–	-0.0440	-0.0148	–	–
Median	-0.0224	-0.0124	–	–	-0.0133	-0.0130	–	–
SD	0.0886	0.0652	–	–	0.1116	0.0675	–	–
Minimum	-0.5179	-0.5392	–	–	-0.3547	-0.5392	–	–
Maximum	0.5550	1.8033	–	–	0.0888	1.8033	–	–
RSIZE								
Mean	-12.3706	-11.8686	–	–	-12.3995	-11.9114	–	–
Median	-12.3559	-11.8511	–	–	-11.8353	-11.8817	–	–
SD	1.6217	1.3484	–	–	1.7010	1.3809	–	–
Minimum	-19.4562	-18.4861	–	–	-15.6499	-19.4562	–	–
Maximum	-7.1950	-5.6036	–	–	-10.2021	-5.6036	–	–
PRICE								
Mean	0.6940	1.5377	–	–	0.4519	1.4638	–	–
Median	0.7608	1.6582	–	–	0.5941	1.6034	–	–
SD	1.4274	1.1505	–	–	1.6711	1.2008	–	–
Minimum	5.5994	-5.5214	–	–	-2.7806	-5.5994	–	–
Maximum	5.0279	5.8327	–	–	2.7408	5.8327	–	–
MB								
Mean	3.6790	3.2490	–	–	2.0352	3.2892	–	–
Median	2.5912	2.1359	–	–	0.8808	2.1578	–	–
SD	6.6338	3.5578	–	–	4.2332	3.9327	–	–
Minimum	-6.5426	-6.5426	–	–	-6.5426	-6.5426	–	–
Maximum	16.8418	16.8418	–	–	13.8958	16.8418	–	–
SIGMA								
Mean	0.0618	0.0472	–	–	0.06121	0.0485	–	–
Median	0.0534	0.0415	–	–	0.0445	0.04245	–	–
SD	0.0342	0.0260	–	–	0.0457	0.0271	–	–
Minimum	0.0000	0.0000	–	–	0.01136	0.0000	–	–
Maximum	0.2464	0.2775	–	–	0.1618	0.2775	–	–

Notes: This table presents descriptive statistics measures of respective accounting and market covariates for financially distressed and bankrupt groups of listed and unlisted SMEs respectively.

3.2. Univariate regression and average marginal effects

To understand the statistical significance and relative importance of respective covariates in predicting the outcome variable, we use Eq. (1) to estimate univariate regression models for respective covariates, with financial distress and bankruptcy as dependent variables. In both cases the dependent variable has a binary outcome, where ‘1’ implies the firm has experienced the financial distress/bankruptcy event, and ‘0’ otherwise. Estimations are performed separately for the listed and unlisted groups of firms to understand whether listing has any impact on their statistical significance and *Average Marginal Effects* (AME[3]).

3.2.1. Financially distressed SMEs

Panel A of Table 6 reports results of univariate regression models estimated using financial distress as the dependent variable. Columns 3–6 report statistics pertaining to listed SMEs, while columns 7–9 report the same for unlisted SMEs. It emerges clearly that all accounting covariates are highly significant in discriminating financially distressed and censored firms for both listed and unlisted groups of SMEs. All respective covariates also bear excepted signs except STDEBV for the unlisted group of SMEs. We expect the sign of its coefficient to be positive, but it is negative. This might be due to the lower mean of STDEBV for the distressed group compared with the censored ones. What is really important and interesting is the value of AMEs of respective covariates. Comparisons of AMEs in columns 6 and 9 show that AME of respective accounting covariates are strikingly different for listed and unlisted groups of SMEs. Specifically, AMEs of all covariates are higher for unlisted SMEs than their listed counterparts. This implies that, although the same set of accounting covariates are statistically significant in explaining financial distress for both listed and unlisted firms, their impact is substantially higher on the unlisted group of SMEs. This suggests that default probabilities of listed SMEs are less affected by unit change in the value of respective covariates than unlisted SMEs. Overall, unlisted SMEs seem to be more vulnerable to financial distress due to changes in their financial ratios compared with listed SMEs. This supports our hypothesis that listed SMEs are less susceptible to financial distress than unlisted ones. This might be due to the fact that once a firm is listed, other factors besides accounting ratios also play a significant role in its survival likelihood. This is reinforced if one looks at the statistical significance of market variables in Panel A of Table 6. All five market variables are highly significant with their respective expected signs.

[3] In non-linear regression analysis, Marginal Effects is a useful way to examine the effect of changes in a given covariate on changes in the outcome variable, holding other covariates constant. These can be computed as marginal change (it is the partial derivative for continuous predictors) when a covariate changes by an infinitely small quantity and discrete change (for factor variables) when a covariate changes by a fixed quantity. Whereas, Average Marginal Effects (AME) of a given covariate is the average of its marginal effects computed for each observation at its observed value. Alternatively, AME can be interpreted as the change in the outcome (financial distress = 1, in our case) probabilities due to unit change in the given covariate, provided other covariates are held constant. See Long and Freese (2014) for detailed discussion on this topic.

Table 5
Correlation matrix.

Variable		1	2	3	4	5	6	7	8	9	10	11	12
EBITDATA	1	1.00											
STDEBV	2	0.24	1.00										
CTA	3	-0.14	-0.15	1.00									
RETA	4	0.72	0.25	-0.07	1.00								
CETL	5	0.19	-0.09	0.45	0.25	1.00							
TLTA	6	-0.60	-0.26	-0.19	-0.70	-0.51	1.00						
CAG	7	0.10	-0.01	0.16	0.10	0.16	-0.09	1.00					
TTA	8	0.25	-0.01	-0.00	0.16	0.08	-0.13	0.07	1.00				
LCR	9	0.41	0.03	0.51	0.47	0.68	-0.71	0.17	0.16	1.00			
TCTA	10	-0.54	-0.16	-0.22	-0.57	-0.43	0.70	-0.10	-0.10	-0.60	1.00		
FETA	11	-0.51	-0.20	-0.16	-0.57	-0.38	0.77	-0.08	-0.13	-0.58	0.52	1.00	
FES	12	-0.47	-0.15	0.03	-0.41	0.19	0.46	-0.01	-0.15	-0.37	0.24	0.64	1.00
EXRETAVG	13	0.19	-0.03	0.01	0.09	0.02	-0.06	0.11	0.13	0.06	-0.03	-0.07	-0.06
RSIZE	14	0.08	-0.15	0.33	0.19	0.23	-0.22	0.28	0.16	0.33	-0.29	-0.19	0.03
PRICE	15	0.27	-0.13	0.19	0.37	0.23	-0.32	0.26	0.29	0.34	-0.29	-0.30	-0.10
MB	16	-0.12	0.22	0.21	-0.08	0.00	-0.11	0.16	0.00	0.06	-0.01	-0.07	0.01
SIGMA	17	-0.22	0.07	-0.03	-0.21	-0.10	0.20	-0.04	-0.20	-0.20	0.18	0.19	0.07

		13	14	15	16	17
EXRETAVG	13	1.00				
RSIZE	14	0.23	1.00			
PRICE	15	0.31	0.73	1.00		
MB	16	0.20	0.34	0.26	1.00	
SIGMA	17	-0.15	-0.33	-0.45	-0.03	1.00

Notes: This table presents correlation among the covariates used in this study.

3.2.2. Bankrupt SMEs

Panel B of Table 6 reports univariate regression estimates obtained using bankruptcy as the dependent variable. Again, estimates are reported separately for listed and unlisted groups of SMEs. Here, results are strikingly different. Although all accounting covariates are significant in predicting the outcome variable for the unlisted group of SMEs, only 7 of them (CTA, CETL, TLTA, CAG, TCTA, FETA and FES) are significant predictors for the listed group of SMEs. Also, values of AMEs for mutually significant covariates are much lower for listed firms. This may be due to the fact that listed firms are discounted much earlier than their unlisted counterparts given their lower information asymmetry. Among the market variables, RSIZE and MB fail to be significant, while SIGMA is weakly significant. Although we find support in favour of our hypothesis, our results might be biased due to the very low number of bankruptcy events in our sample.

3.3. Multivariate regression analysis

Fig. 1 shows survival curves of the financially distressed and bankrupt group of firms estimated using the Kaplan-Meier estimator (see Cleves et al., 2010). At any given age, the survival curve of the listed group of SMEs is higher than their unlisted counterparts. This supports our hypothesis that SMEs using the capital market to access external finance enjoy lower levels of financial distress and bankruptcy likelihood. This is also evident from our results in the univariate analysis section. However, to test this hypothesis in the multivariate framework, we need to start with a multivariate model building strategy as we report strong to moderate correlation among some covariates in Table 5. We partially follow the model building strategy proposed by Gupta et al. (2017) to build our multivariate models. Specifically, considering the multicollinearity among the covariates, we introduce each covariate in turn into the multivariate setup based on the magnitude (sign is ignored) of their AME. For this, at first we rank[4] all of the covariates found significant in the univariate analysis based on the absolute value of their AME (see columns 6 and 10 in Table 6), and then start to introduce each covariate in turn into the multivariate setup in increasing order of the rank of their AME. The rationale is that the higher the value of AME, the higher the change in the predicted probability due to unit change in the covariate. Thus a covariate with a higher value of AME (e.g. FETA in Table 6) is more efficient in discriminating between distressed and censored firms than covariates with a lower value of AME (e.g. TLTA in Table 6). Further, if the introduction of a covariate affects the sign[5] of any previously added covariate, then that covariate is excluded from the multivariate model. This could happen due to multicollinearity among covariates; accordingly, their exclusion seems reasonable. Moreover, we believe that this method of covariate introduction while developing the multivariate models leaves us with the best set of covariates with expected sign of coefficients of respective covariates. However, this variable selection strategy is only applied to accounting variables. Market variables are excluded at this stage as we are initially interested in understanding the variability of accounting covariates across listed and unlisted groups of firms. After multivariate models for listed firms are developed, we then supplement those models with market variables to understand the marginal contribution that market variables make to the multivariate models developed using accounting ratios. We exclude RSIZE from our multivariate models as it shows a correlation of about 0.73 with PRICE and its AME is lower than AME of PRICE (see column 5 of Table 6). Additionally, we also employ all control variables listed in Panel C of Table 2 in all multivariate models.

The dependent variable for these models has a binary outcome with financially distressed/bankrupt equalling ‘1’ and ‘0’ otherwise, while independent variables are the set of covariates found significant in the univariate regression analysis. The final set of multivariate hazard models reported for both listed and unlisted SMEs is estimated using observations from the entire sampling period available to us, thus we do not have separate test and holdout samples. In order to assess the within-sample classification performance of the models developed, we estimate area under Receiver Operating Characteristic curve[6] (AUROC) for respective models using the full estimation sample (i.e. from 1985 to 2016). For out-of-sample validation we first estimate the multi-

[4] Highest value gets rank ‘1’, second highest gets rank ‘2’ and so on.

[5] Coefficients with negative sign become positive and vice versa.

[6] See Gupta et al. (2017) for additional discussion on ROC curves.

Table 6
Univariate regression.

Variable	Sign	Listed SMEs				Unlisted SMEs			
		Coefficient	SE	AME	R	Coefficient	SE	AME	R
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Financially Distressed Firms									
Accounting Variables									
EBITDATA	–	-2.5973[a]	0.0892	-7.93[a]	6	-1.4195[a]	0.0329	-21.99[a]	6
STDEBV	+	0.2826[a]	0.0870	0.99[a]	10	-0.3612[a]	0.0344	-6.01[a]	11
CTA	–	-1.5500[a]	0.1680	-4.48[a]	7	-2.4354[a]	0.1039	-38.92[a]	5
RETA	–	-0.1893[a]	0.0081	-0.69[a]	12	-0.1013[a]	0.0028	-1.68[a]	12
CETL	–	-1.1801[a]	0.0399	-0.72[a]	11	-1.0085[a]	0.0219	-8.46[a]	9
TLTA	+	3.4940[a]	0.1119	8.47[a]	5	1.2872[a]	0.0271	20.75[a]	7
CAG	–	-1.3947[a]	0.0597	-3.42[a]	8	-0.4806[a]	0.0178	-7.80[a]	10
TTA	–	-33.8233[a]	1.8965	-112.06[a]	1	-27.5016[a]	1.1484	-440.29[a]	1
LCR	–	-1.3878[a]	0.0490	-2.97[a]	9	-1.0965[a]	0.0223	-15.55[a]	8
TCTA	+	7.5618[a]	0.3705	23.77[a]	3	4.7166[a]	0.1197	75.79[a]	3
FETA	+	15.8479[a]	0.7288	54.68[a]	2	10.0798[a]	0.2613	166.25[a]	2
FES	+	3.6450[a]	0.1929	13.42[a]	4	2.5223[a]	0.0997	41.58[a]	4
Market Variables									
EXRETAVG	–	-5.8849[a]	0.4531	-15.60[a]	2				
RSIZE	–	-0.6652[a]	0.0350	-1.37[a]	4				
MB	–	-0.0322[a]	0.0071	-0.08[a]	5				
SIGMA	+	15.7153[a]	1.1195	39.76[a]	1				
PRICE	–	-0.8078[a]	0.0339	-1.91[a]	3				
Panel B: Bankrupt Firms									
Accounting Variables									
EBITDATA	–	-0.7101	0.5181	-7.93e-05	–	-0.3069[a]	0.1231	-0.001[b]	11
STDEBV	+	0.3322	0.5422	8.69e-05	–	-0.5589[a]	0.1604	-0.005[a]	7
CTA	–	-4.2277[a]	1.6692	-0.001	3	-2.4929[a]	0.5164	-0.020[a]	3
RETA	–	-0.0527	0.0587	-1.62e-05	–	-0.0272[b]	0.0125	-2.2e-04[b]	12
CETL	–	-0.3552[b]	0.1604	-3.99e-05	6	-0.8694[a]	0.1067	-0.002[a]	10
TLTA	+	1.2998[a]	0.3194	8.48e-04	4	0.6945[a]	0.0906	0.005[a]	6
CAG	–	-0.7094[b]	0.3461	-1.86e-04	7	-0.4242[a]	0.0914	-0.003[a]	9
TTA	–	-11.3026	9.6082	-0.004	–	-11.5692[a]	4.6268	-0.100[b]	1
LCR	–	-1.5196	0.3163	-1.18e-04	–	-0.6973[a]	0.0832	-0.004[a]	8
TCTA	+	4.3895[b]	2.1920	0.001	2	2.9511[a]	0.4851	0.020[a]	4
FETA	+	15.5532[a]	3.7053	0.006	1	6.5106[a]	1.0942	0.040[a]	2
FES	+	2.8546[b]	1.3706	7.79e-04	5	1.0666[b]	0.4691	0.008[b]	5
Market Variables									
EXRETAVG	–	-6.2787[b]	2.9082	-0.002	2				
RSIZE	–	-0.1646	0.2069	-5.59e-05	–				
MB	–	-0.0263	0.0643	-9.70e-06	–				
SIGMA	+	13.1246[c]	6.8861	0.005	1				
PRICE	–	-0.7187[a]	0.2062	-5.42e-05	3				

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). This table reports results obtained from univariate regression analysis of respective covariates for listed and unlisted SMEs respectively. Column 2 presents the expected sign of the coefficients, while columns 3 and 7 report estimated coefficients of respective groups. In columns 4 and 8, 'SE' represents standard error of the respective estimated coefficients. AME is the Average Marginal Effects (AME) in percentage and reported in columns 5 and 9 for listed and unlisted SMEs respectively. 'R' in columns 6 and 10 show the rank of respective covariates in decreasing order of the absolute value of their respective AME. Panel A reports univariate estimates for financially distressed SMEs while Panel B reports similar information for bankrupt SMEs.

variate hazard model using observations until the year 2011. We use these estimates to predict the default probabilities for the year 2012. Then, we include 2012 in the estimation sample and predict default probabilities for 2013 and so on, until the year 2016. We then use these predicted probabilities from the year 2012 through to 2016 to estimate out-of-sample AUROC with a one-year prediction horizon for respective multivariate hazard models. AUROC of 1 denotes a model with perfect prediction accuracy, and 0.5 suggests no discrimination ability. In general there is no 'golden rule' regarding the value of AUROC, however anything between 0.7 and 0.8 is acceptable, while above 0.8 is considered to be excellent (see Hosmer Jr. et al., 2013).

3.3.1. Multivariate models for financially distressed SMEs

Panel A of Table 7 reports multivariate regression models developed using financial distress as the dependent variable. Considering our model building strategy as discussed earlier, out of twelve significant covariates in the univariate analysis, we find nine covariates suitable for developing the multivariate prediction model for listed SMEs. Columns 3, 4 and 5 report test results for the multivariate model developed using accounting ratios. All nine covariates are highly significant in predicting financial distress likelihood over the one-year horizon. Their respective AME are significant as well. Control variables RISKFD, Micro and AGE also exhibit significant explanatory power.

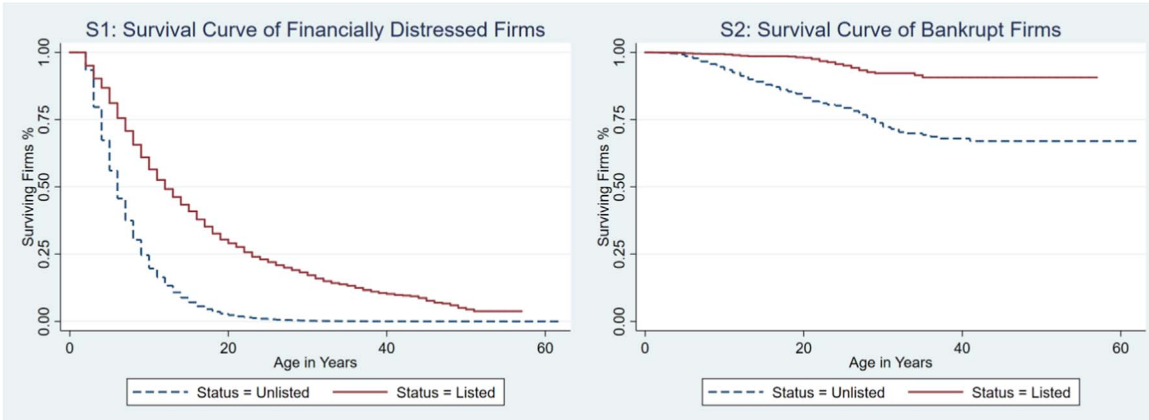

Fig. 1. Table of survival curves.

The within-sample AUROC is about 0.88, and out-of-sample AUROC is about 0.81. This shows excellent discriminatory performance of our multivariate model in identifying distressed and censored firms (see A1 and A2 in Fig. 2). The AME are reported in percentages, which state that TTA is the most powerful covariate with AME of around -48 followed by FETA with AME of around 7. The multivariate model developed supplementing market variables is reported in columns 6, 7 and 8. Broadly the significance of accounting covariates remains unchanged except RETA and FETA, and market variables EXRETAVG, MB, SIGMA (weakly significant) and PRICE enter significantly into the multivariate model. However we see a decline in AMEs of respective covariates in the presence of market variables (see columns 5 and 8 in Panel A of Table 7). This reflects the complementary nature of market information in predicting SMEs financial distress. Although the within-sample classification performance remains almost identical, but there is about a 5% increase in out-of-sample classification performance in the presence of market variables (see A3 and A4 in Fig. 2).

However, we are primarily interested in the comparative performance between multivariate models developed using accounting ratios for listed and unlisted SMEs. Columns 9, 10 and 11 in Panel B of Table 7 report the multivariate model for unlisted SMEs. Out of twelve highly significant covariates in univariate analysis, eight enter significantly into the multivariate setup. We also observe some differences in the factors affecting the default probability of listed and unlisted SMEs. For instance, STDEBV, RETA and FES are significant predictors for the listed group of SMEs, but they do not find a place in the model developed for unlisted SMEs, except for STDEBV being weakly significant. Unlike listed SMEs, LCR enters significantly into the multivariate model for unlisted SMEs, which emphasises the importance of liquidity on financial distress of unlisted SMEs. The model prediction performance is deemed to be excellent with AUROC values of above 0.8 (see A5 and A6 in Fig. 2). Finally, comparison of AMEs of respective accounting covariates reported in columns 5 and 11 reinforce our hypothesis. As observed in the univariate analysis section, here also AME for all covariates is significantly higher for unlisted SMEs than their listed counterparts (see columns 5 and 11 of Table 7). This suggests that unlisted SMEs are more vulnerable to the changing financial position, unlike listed SMEs.

3.3.2. Multivariate models for bankrupt SMEs

Panel B of Table 7 presents regression estimates using bankruptcy as the dependent variable. The effect of the extremely low number of bankruptcy events (28 for listed SMEs with accounting variables and 21 for listed SMEs with accounting and market variables) can be seen in the multivariate models. Only CTA and FETA are significant, however most of the control and market variables remain insignificant. Also, all AME values of respective covariates are insignificant. We understand that this is a serious drawback of this study, but the appropriate solution to this problem is beyond our control. With an increasingly low rate of bankruptcy filings, all we can suggest is to use an alternative mechanism like financial distress instead of legal bankruptcy filings to make relevant decisions, or to test it using legal bankruptcy data containing a sufficient number of bankruptcy events.

However, for unlisted group of firms, we have 247 bankruptcy events and the multivariate model developed looks much more reasonable than its listed counterpart. Out of twelve accounting variables, five enter significantly into the multivariate model with significant control variables. Although we report AUROC for these multivariate models, it might be unreliable considering the presence of a very low number of outcome events in our sample (see A7–A12 in Fig. 2).

4. Conclusion

SMEs are widely considered to be a fundamental component of an economy, and are viewed as an important route to recovery in the aftermath of the global financial crisis of 2008–2009. Given the increased importance of SMEs, a significant volume of academic literature on SMEs bankruptcy/financial distress has emerged in recent years (e.g. Altman and Sabato, 2007; Keasey et al., 2015; Gupta et al., 2017).

Access to external finance is unanimously considered to be the principal factor obstructing SMEs growth and development. This might be due to a lack of collateral and information asymmetries. Prolonged difficulty in accessing external finance may lead to financial distress or bankruptcy. Stock exchange listing could relieve SMEs from external financing constraints (Kim, 1999), consequently reducing their over-dependence on banks for external financing and, thereby, reducing their likelihood of failure.

We empirically test this hypothesis using a sample of listed and unlisted SMEs located in the United States covering the sampling period between 1985 and 2016. One-year financial distress and bankruptcy prediction models of listed and unlisted SMEs are estimated using panel logistic regression technique and a set of financial covariates with established significance of financial distress/bankruptcy prediction in prior studies. The definition of financial distress employed based on firms' financial performance is adapted from Keasey et al. (2015), and we consider a firm as bankrupt if it files for Chapter 7/11 bankruptcy.

We report significant differences between the failure risk of listed and unlisted SMEs. At any given age, the survival (hazard) likelihood of listed SMEs is significantly higher (lower) than their unlisted counterparts. In the univariate analysis, although an identical set of financial ratios is significant in discriminating between financially distressed and censored groups of listed and unlisted SMEs, we report significant differences in the weights of regression coefficients of respective

Table 7
Multivariate regression models.

Variable	Sign	Listed SMEs						Unlisted SMEs		
		Accounting Variables			Accounting + Market Variables			Accounting Variables		
		β	SE	AME	β	SE	AME	β	SE	AME
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Financially Distressed Firms										
EBITDATA	–	-1.6340^{a}	0.1152	-3.03^{a}	-1.6956^{a}	0.1437	-1.95^{a}	-0.8289^{a}	0.0417	-10.82^{a}
STDEBV	+	0.3746^{a}	0.0888	0.69^{a}	0.5590^{a}	0.1251	0.64^{a}	0.0585^{c}	0.0364	0.76^{c}
CTA	–	-1.1249^{a}	0.1877	-2.08^{a}	-0.5043^{b}	0.2269	-0.58^{b}	-1.0200^{a}	0.1269	-13.31^{a}
RETA	–	-0.0296^{a}	0.0109	-0.05^{a}	-0.0178	0.0134	-0.02	–	–	–
CETL	–	–	–	–	–	–	–	–	–	–
TLTA	+	–	–	–	–	–	–	–	–	–
CAG	–	-0.9063^{a}	0.0532	-1.68^{a}	-1.0113^{a}	0.0703	-1.16^{a}	-0.3623^{a}	0.0192	-4.73^{a}
TTA	–	-25.8403^{a}	2.1895	-47.95^{a}	-24.1643^{a}	2.5637	-27.83^{a}	-23.0114^{a}	1.3064	-300.43^{a}
LCR	–	–	–	–	–	–	–	-0.6444^{a}	0.0291	-8.41^{a}
TCTA	+	2.5850^{a}	0.4498	4.79^{a}	2.9353^{a}	0.5582	3.38^{a}	0.3348^{b}	0.1558	4.73^{b}
FETA	+	3.7301^{a}	0.9620	6.92^{a}	0.9593	1.2076	1.10	1.8423^{a}	0.3377	24.05^{a}
FES	+	2.4381^{a}	0.2736	4.52^{a}	3.2631^{a}	0.3281	3.75^{a}	–	–	–
EXRETAVG	–	–	–	–	-1.6824^{a}	0.5472	-1.93^{a}	–	–	–
RSIZE	–	–	–	–	–	–	–	–	–	–
MB	–	–	–	–	0.0206^{b}	0.0096	0.02^{b}	–	–	–
SIGMA	+	–	–	–	2.6305^{c}	1.5189	3.03^{c}	–	–	–
PRICE	–	–	–	–	-0.3066^{a}	0.0541	-0.35^{a}	–	–	–
Micro		-0.6439^{a}	0.1426	-1.19^{a}	-1.0632^{a}	0.1745	-1.22^{a}	0.4173^{a}	0.0690	5.44^{a}
Small		0.0653	0.0919	0.12	-0.1995^{c}	0.1107	-0.22^{c}	0.4011^{a}	0.0571	5.23^{a}
AGE		-0.2118^{a}	0.0741	-0.39^{a}	0.0136	0.0944	0.01	0.1675^{a}	0.0400	2.18^{a}
RISKFD	+	5.3348^{a}	0.7583	9.90^{a}	4.4440^{a}	0.9238	5.11^{a}	1.0432^{b}	0.4191	13.62^{b}
Constant		-3.8580^{a}	0.2144	–	-4.5701^{a}	0.3107	–	-2.2673^{a}	0.1170	–
Goodness of Fit		Value			Value			Value		
Wald chi2		1282.39^{a}			1045.11^{a}			3069.28^{a}		
Log likelihood		-4090.4301			-3174.1028			-11067.319		
AUROC										
Within Sample		0.8792			0.8870			0.8295		
Holdout Sample		0.8099			0.8461			0.8186		
Number of observations										
Distressed		1,798			1,390			6,760		
Censored		16,340			14,408			19,469		
Panel B: Bankrupt Firms										
EBITDATA	–	–	–	–	–	–	–	–	–	–
STDEBV	+	–	–	–	–	–	–	–	–	–
CTA	–	-3.2537^{c}	1.7384	-8.16e-04	-2.1179	1.8661	-1.45e-04	-1.8949^{a}	0.5248	-0.01^{b}
RETA	–	–	–	–	–	–	–	–	–	–
CETL	–	–	–	–	–	–	–	–	–	–
TLTA	+	–	–	–	–	–	–	–	–	–
CAG	–	–	–	–	–	–	–	-0.3092^{a}	0.0895	-0.002^{b}
TTA	–	–	–	–	–	–	–	-8.4212^{c}	4.9078	-0.07
LCR	–	–	–	–	–	–	–	–	–	–
TCTA	+	–	–	–	–	–	–	1.9866^{a}	0.5554	0.01^{b}
FETA	+	15.9876^{a}	4.0072	0.01	8.5400	5.8890	5.84e-04	3.9274^{a}	1.2612	0.03^{b}
FES	+	–	–	–	–	–	–	–	–	–
EXRETAVG	–	–	–	–	-4.4539	3.5486	-3.04e-04	–	–	–
RSIZE	–	–	–	–	–	–	–	–	–	–
MB	–	–	–	–	–	–	–	–	–	–
SIGMA	+	–	–	–	-0.0700	9.9581	-4.79e-06	–	–	–
PRICE	–	–	–	–	-0.5678^{c}	0.3126	-3.88e-05	–	–	–
Micro		-1.0788	1.2668	-2.71e-04	-1.1927	1.4507	-8.15e-05	0.5313^{c}	0.2958	0.004
Small		0.1480	0.6472	3.71e-05	0.0693	0.7980	4.74e-06	0.4936^{b}	0.2546	0.004
Age		-0.0493^{c}	0.4711	-1.24e-05	0.0576	0.6168	3.94e-06	0.5156^{a}	0.1833	0.004^{b}
RISKB	+	65.5401^{b}	28.2130	0.01	52.5831	35.3994	0.003	59.0356^{a}	10.4964	0.55^{b}
Constant		-12.511^{a}	1.4786	–	-13.3585	2.1086	–	-11.2812^{a}	0.6559	–
Goodness of Fit		Value			Value			Value		
Wald chi2		25.30^{a}			17.87^{b}			108.44^{a}		
Log likelihood		-156.5782			-116.0002			-1078.5337		
AUROC										

(continued on next page)

Table 7 *(continued)*

Variable	Sign	Listed SMEs						Unlisted SMEs		
		Accounting Variables			Accounting + Market Variables			Accounting Variables		
		β	SE	AME	β	SE	AME	β	SE	AME
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Within Sample		0.7742			0.7609			0.7269		
Holdout Sample		0.4885			–			0.4525		
Number of observations										
Bankrupt		28			21			247		
Censored		18,110			15,782			25,982		

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). This table report results obtained from multivariate regression analysis of listed (columns 3–8) and unlisted (columns 9, 10 and 11) SMEs respectively. Column 2 presents the expected sign of the coefficients. 'SE' represents standard error of respective estimated coefficients, while AME is the Average Marginal Effects (AME) in percentage. Panel A reports multivariate regression estimates for financially distressed SMEs while Panel B reports similar information for bankrupt SMEs.

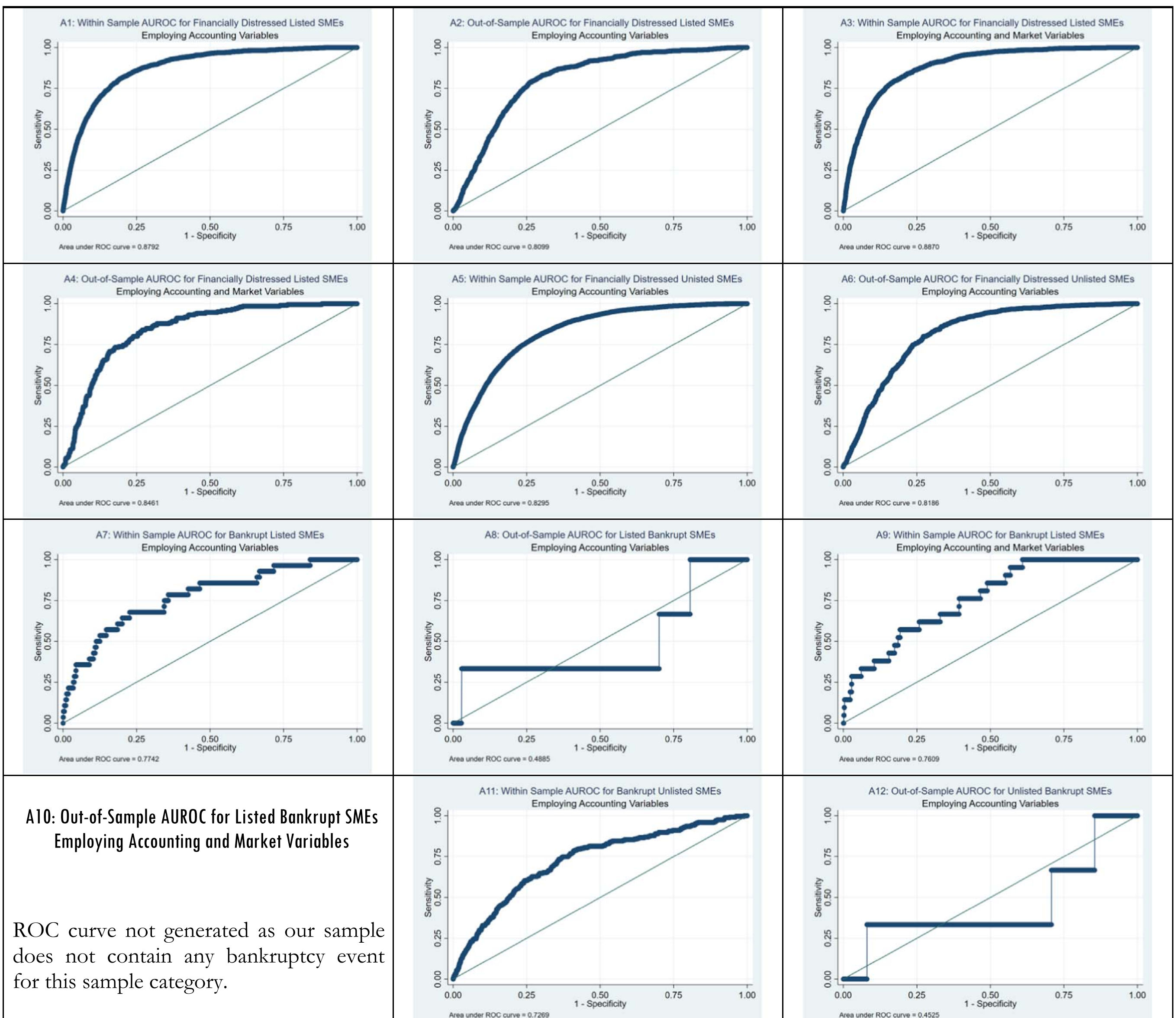

Fig. 2. Table of ROC Curves.

covariates of listed and unlisted SMEs. AME of respective covariates for the unlisted group of firms is strikingly higher than their listed counterparts, suggesting higher vulnerability of unlisted firms due to changes in financial ratios. Additionally, regression coefficients of mutually significant covariates in multivariate regression models for listed and unlisted SMEs also show striking differences in their weights. Our hypothesis is further reinforced when we compare AME of respective covariates for financial distress prediction models of listed and unlisted groups of firms. In line with our univariate estimates, AME of mutually significant covariates are significantly higher for unlisted SMEs than for listed ones. However, we report weak empirical evidence in support of our hypothesis when bankruptcy is used as the dependent variable. This is primarily due to the very low number of bankruptcy events in our sample. We understand that this is a serious drawback of this study, but the appropriate solution to this problem would require a sample with greater frequency of bankruptcy events.

We believe this study on the impact of market-based equity finance on SMEs failure likelihood shall be of relevance for several reasons. Our study leads to improved understanding of differences between credit risk behaviour of listed and unlisted SMEs. This in turn shall allow for: (i) better pricing of credit risk by lending institutions; (ii) improved investment decisions by capital market investors; (iii) better allocation of resources by policymakers and regulators in developing capital markets targeted toward encouraging participation from small companies; and (iv), as a consequence, reduced constraints to external financing for SMEs.

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