THE INTERNATIONAL JOURNAL OF BUSINESS & MANAGEMENT

Predicting Business Failure for Small Medium Enterprises (SMEs): The Role of Financial Ratios

Nekhasius Agus Sunarjanto
Lecturer, Widya Mandala Catholic University of Surabaya, Indonesia
Herlina Yoka Roida
Lecturer, Widya Mandala Catholic University of Surabaya, Indonesia
Agnes Utari Widyaningdyah
Lecturer, Widya Mandala Catholic University of Surabaya, Indonesia

Abstract:
Business failure identification is an effort of early warning system of business activities in every single scale, including small medium enterprises. Mostly, business failure identification conducts in banking sector or big enterprises to detect potential bankruptcy. Since 1968, Altman already set business clasification model with Z-Score. The different result in classification is because of: First, modelling technique used in classification such as Discriminant Analysis Model, logit model, probit model or survival analysis; Secondly, data released from enterprises; Thirdly, the definition failure or not failure depends on local enterprises; Lastly, there is no standard result of testing. This research briefly reconstrucs business classification model that could contribute to develop classification model of SMEs in Indonesia as early warning system, respectively.

Keywords: *Failure, Closure, Discriminant analysis, Small Medium Enterprises (SMEs)*

1. Introduction

SMEs play crucial roles in most economies. The aims of SME as an entity must be survive for the long time until unlimited time. The oldest company in the world is *Stora Kopparberg Bergslags Aktiebolag* from Sweden with the age of more than 722 years old since 1288. If business units are same as organism, then why did some SMEs die sooner than others? How long survival rate of SMEs? On the other side, early warning system is important to mitigate business failure of SMEs.

Meanwhile, big enterprises characteristic is different with SMEs. It means that business risk and financial risk potentially are relatively high. The simple management of SMEs is contributed to early warning system of business failure. On the other hand, the existence of SMEs and contribution to the most Indonesia economy dominate mostly Indonesia society. From 42.452 million business entities, there are 41.8 million (98.5%) micro enterprises. Only less than 650.000 are small and medium enterprises, also approximately less than 2000 are big enterprises (Menenkop, 2004). This number increases significantly around 50 million SMEs with 56% contribution to GDP.

Based on Sunarjanto and Roida (2013), the risk preferences of SMEs owners influence the degree of business risk and financial risk of SMEs. The argumentation is SMEs consider that high cost of transaction or interest rates, complicated procedures and failure risk are not equivalent with the amount of funds from financial institutions. It shows that risk preferences will impact funding sources of SMEs.

Financial distress condition of SMEs depends several factors. First, *cash flows solvability* that measure by EBITDA (profitability) of SMEs. Secondly, location of SMEs shows accesability of SMEs to get financial access from financial institutions. SMEs are located in urban areas less under financial distress than in remote areas. which is most likely remote area location if they located in remote areas. Thirdly, industry sector is refer to degree of complication that need skill and competence of SMEs (Sunarjanto and Roida, 2014) .

In the long run, financial risk will impact to survival rate of SMEs. The survival rate of SMEs is determined by the degree of risk tolerance (Roida and Sunarjanto, 2011). This study focuses on business failure classification formulation as failure early warning system of SMEs. Moreover, this research will emphasis fit indicators of discriminant analysis from financial ratios which was conducted by previous studies (Edminster, 1972; Merton, 1974, dan Altman, 1968). So, model reconstruction is conducted by *added value*, profitability, solvability and liquidity of SMEs in Surabaya.

This research will detect which indicators that relevant to detect financial failure and non-financial closure of SME. This work is a first part of reconstruction business failure model. The classification is divided into two categories: failure (financially) and closure (non-financial). Business failure could be caused by mismanage in finance or because of non-financial reason such as decreasing demand of the product.

2. Literature Review

2.1. Discriminant Analysis Model

Basically, discriminant model is a model to categorize whether business units fail or not. The first to do in discriminant analysis is estimating discriminant. Defining dependent variable as category of failure or not failure and financial ratios as independent variables. Altman (1968) estimated the fuction as:

$Z = 1{,}2\ X1 + 1{,}4\ X2 + 3{,}3\ X3 + 0{,}6\ X2 + 1{,}0\ X5$………………………..(1)

Where
X1 = Working capital / Total asset ratio
X2 = Retained earnings / Total asset ratio
X3 = EBIT / Total asset ratio
X4 = Market value of equity / Book value of equity ratio
X5 = Sales / Total asset ratio

Then, Altman (1983) extended previous model for non-public units. The new model is:

$Z = 0{,}717\ X1 + 0{,}847\ X2 + 3{,}107\ X3 + 0{,}420\ X2 + 0{,}998\ X5$....................(2)

Where
X1 = Working capital / Total asset ratio
X2 = Retained earnings / Total asset ratio
X3 = EBIT / Total asset ratio
X4 = Book value of equity / Book value of total debt
X5 = Sales / Total asset ratio

The application of model in several countries is different and adjusted for some reasons:

1) Modeling technique used
Multiple Discriminant Analysis (MDA) is a popular tecnique to clasify business failure. Some researcher developed other techniques such as logit analysis (Suominen, 1988), probit analysis (Swanson and Tybout, 1988), decision tree analysis, *Bayesian Discriminant Analysis*, survival analysis and neural analysis. However, until now MDA is still applied in some countries (Altman et.al., 1979; Bhatia, 1988; Cahill, 1981; Altman et.al., 1995; Bidin, 1988; Ta and Seah, 1981; Unal, 1988; Pascale, 1988)
2) Data released of business units
Sample size and data sources are the essential things to validate robustness of this model. Availability data in developed countries is different with developing countries. Developed countries have long history regarding business failure and availability data.
3) The definition of failure and not failure
Business failure definition depends on local condition such as local culture which embeded with every business entities. The most important thing is how early business failure detect and prevent.
4) Test result.
Test result is not only answer the model statistically significant, but also could report type I error and type II error in this analisis and result test.

2.2. Business Failure Classification in Developing Countries

To determine SMEs whether under failure or not condition is not easy. SMEs with high financial distress tend to reduce their loan to financial institutions compare with SMEs with low financial distress (Ross, et.al, 2010). The problem is sometimes SMEs owner never make a report regarding their conditions that could disturb their sustainabilities. Mostly SMEs closed their business not only because of financial problem (Watson & Everett, 1996), technical reasons such as lack of human resourses and no demand, make SMEs so fluctuative operasionally (Roida& Sunarjanto, 2012). This is supported by Headd (2003) findings that a third SMEs closed their business because they unsuccesful run their business. So, it is important to distinguish the term of *failure* and *closur*e (Gilson & Vetsuypens, 1993), whether SMEs classified as a failure because of financial reason or unsuccesful in their business.

Categorizing SMEs under failure or not is firstly by factor analysis. To collect all variables used in MDA model in developing countries is the preliminary step in this study.

1) Brazil
Classification model that applied in Brazil is a MDA that developed by Altman et.al (1979):
$Z = 0{,}717\ X1 + 0{,}847\ X2 + 3{,}107\ X3 + 0{,}420\ X2 + 0{,}998\ X5$...............................(3)
Where
X1 = Working capital / Total asset ratio
X2 = Retained earnings / Total asset ratio
X3 = EBIT / Total asset ratio
X4 = Book value of equity / Book value of total debt
X5 = Sales / Total asset ratio

2) India
Classification model in India is develped by Bhatia (1988) with categorize ill units (unit that loss their cash flows during two years). The model is using seven variables:
X1 = Curent asset / Current liabilities
X2 = Stock of finish goods / Sales
X3 = EAT / Total asset
X4 = Interest / Value of Output
X5 = Cash flows / Total debt
X6 = Working capital / Total asset
X7 = Sales / Total asset
3) Malaysia
Bidin (1988) was developed classification model with MDA model.
X1 = Operational earning / Total debt
X2 = Curent asset / Current liabilities
X3 = EAT / *Paid –up capital*
X4 = Sales/ Working capital
X5 = Curent asset – stocks - curent liabilities/ EBIT
X6 = Total shareholder's funds / Total debt
X7 = Common stocks / Employment capital
4) Singapore
Clasification model in Singapura developed by Ta and Seah (1981). It was simplier than MDA model.
X1 = Total debt / Equity
X2 = EBT / Sales
X3 = EBT / Equity
X4 = Interest payment / EBIT
5) Turkey
MDA was developed as a measurement model by Unal (1988). This model is applied six variables:
X1 = EBIT / Total asset
X2 = Working capital / Sales
X3 = Long term debt / Total asset
X4 = Total debt/ Total asset
X5 = Quick asset / Inventory
X6 = Quick asset / Short term debt
6) Uruguay
Pascale (1988) developed classification by reducing variables used:
X1 = Sales / Total debt
X2 =EAT / Total asset
X3 = Long term debt / Total debt

Next, this study will analyze all possible variables that already applied for clasification model in developing countries. Then, it will be selected the suitable variables for SMEs in Indonesia.

2.3. Alternatives Method Business Failure Measurement

Business failure clasification has already developed during recent decades, such the fuzzy rule-based classification model, logit model, CUSUM model, dynamic event history analysis, cathastrophe theory, chaos theory model, multidimentional scaling, linear goal progamming, the multi-criteria decision approach, rough set analysis, expected systems, and self organizing map. Besides discriminant model, there are several popular models that already used:

First, survival analysis is an analysis based on asumption that failure or not depends on same population within groups (Lane et.al., 1986; Luoma dan Laitinen, 1991; Kauffman dan Wang, 2001). This model is not asume there is dicotomy of dependent variable (Shumway, 1999). The based concept of this model is a hazard rate of SMEs. As consequence, failure probability in the future will depend on survival ability of SMEs. In other words, the measurement uses countinues times and formulated in CoxProportional Hazard Model. Hazard model assumes that every unit has hazard proportional than other business units.

Focus of survival analysisis to determine factors of dependent variables that influence hazard rate and not determine by actual hazard rate (Yang and Temple, 2000). Value of hazard function could not interpret directly as failure probability (Laitinen and Kankaanpaa, 1999). However, this model does not design as predictor of business failure clasification. The calculation of survival times uses data implicitly as a baseline failure process (Luoma dan Leitenen, 1991).

Second, decision tress is a model that does not need complex statistic requirement because it could use qualitative data to make a decision. Problem raises in probability specification and could create error clasification cost. This model is hard to apply(Joos et.al, 1998; Frydman, 1985).

Third, neural networks is a model that does not need tight assumption. It could be applied in complex model and use qualitative data. But this model has weakness such as dificult to interpret, need good quality data, variables that used must be well selected, need long process and sometimes unlogic network (Atiya, 2001; Yang et.al, 1999).

3. Data Set and Variables

This study is empirical research to test variables as a predictor of business failure classification of SMEs. The source of the empirical data is based on Industrial Department Surabaya Municipal City Trade data of Small and Medium Enterprises in 2009 to 2015. The sample is representative of Surabaya City SMEs. The observation includes 263 SMEs but only 50 SMEs which eligible in financial report along those durations. Total observationis 300, 50 SMEs in 6 years.

3.1. Variables Identification

Selected variables in this research are 22 independent variables as shown in Table 1. Dependent variable (Y) is business condition of SMEs, categorized as failure and not failure.

1) Dependent Variable

This research use two dependent variables to assess the probability to be failed: Failure and Closure. (1) Failure is a condition that SMEs are financially failed. Classification used 1 refer to "*failure*" and 0 refer to "*non-failure*". The indicator in this research is if in last year SMEs decrease the level of current liabilities, then it is categorized as "*failure*" and vice versa from 2009 until 2015 as *non-failure*". (2) Closure is a condition that SMEs are non-financially failed. The classification used 1 refer to *"closure"*and 0 refer to *"non-closure*". The measurement of closure is the decreasing number of sales that could indicate decreasing demand from 2009 to 2015.

2) Independent Variables

To predict the probability of failure or not failure, financial ratios are used in MDA model based on experience in developing countries. These ratios are:

X1	Working capital / Total asset
X2	Retained earnings / Total asset
X3	EBIT / Total asset
X4	Book value of equity / Book value of debt
X5	Sales / Total asset
X6	Working capital / Total asset
X7	Current asset / Current liabilities
X8	EAT / Paid –up capital
X9	Sales/ Working capital
X10	Total shareholder's funds / Total debt
X11	Equity / Employment capital
X12	EBT / Sales
X13	EBT / Equity
X14	Interest payment / EBIT
X15	Working capital / Sales
X16	Long term debt / Total asset
X17	Total debt/ Total asset
X18	Quick asset / Inventory
X19	Quick asset/ Short term debt
X20	Sales / Total debt
X21	EAT / Total asset
X22	Long term debt / Total debt

Table 1: The Altman Ratios

4. Methodology and Result

Two empirical models of probability to be failed are setimated to test the hypothesis. Model 1 and Model 2 used a logit model to explain whether SMEs possible to be failed financially. Model 2 used a logit model, as well to estimate the probability to be failed non-financially. In both cases, methodology has been adjusted to process panel data as consideration on the existence of individual effects and provides consistency of the coefficient. Table 1 gives details of the models.

Model 1 is statistically significant below 0.5% level. It means the potential impacts on the variables on SMEs probability of failure is statistically supported. However, the model shows only three variables this research as an independent variable, Working capital / Total asset, Current asset / Current liabilities, and Quick asset / Inventoryare potentially to be indicator of business failure. In other words, working capital management could explain SMEs'to be in financial distress on not. Model 2 reveals also significant in 0.5% level that Current asset / Current liabilities and Quick asset / Inventory or working capital management also related to the second dimension of business fail which is closure.

	Model 1 (Failure, Financial)	Model 2 (Closure, Non-Financial)
Working capital / Total asset	4.0520*	1.3590
EBIT / Total asset	-1.5782	2.6953
Current asset / Current liabilities	0.3692*	-0.1488*
EBT / Sales	6.1715	-7.870
Working capital / Sales	-1.9543	3.4217
Quick asset / Inventory	-0.7432*	-0.3407*
Prob (LR statistic)	0.0000*	0.0150*
McFadden R Squared	0.2313	0.0511

Table 2: Empirical Model
Note. * *Significant level 0.05*

5. Discussion and Conclusion

Different theoretical and methodology perspectives provide different results with previous study by Altman. To determine SMEs whether under failure or not condition is not easy, especially with data availability. The finding is consistent with Ross, et.al. (2010) that SMEs with high financial distress tend to reduce their loan to financial institutions compare with SMEs with low financial distress (Ross, et.al, 2010). Probability to be failed based on Model 1 depends on how SMEs manage their working capital. It is showed by the ratio of working capital to total assets and liquidity of SMEs. As good as SMEs manage this ratio, the financial distress will avoided. However, the ratio of quick assets to inventory will negative impact to probability to be failed. As much as SMEs have a large number of inventory, the cash flows from operations will influence financial cash flows of SMEs.

Mostly SMEs closed their business not only because of financial problem (Watson & Everett, 1996), technical reasons such as lack of human resourses and no demand, make SMEs so fluctuative operasionally (Roida& Sunarjanto, 2012). This is supported by Headd (2003) findings that a third SMEs closed their business because they unsuccesful run their business. Model 2 try to distinguish *failure* and *closur*e (Gilson & Vetsuypens, 1993). SMEs could be lassified as a failure because of unsuccesful in their business. By looking at the decreasing of demand that end up with decreasing number of sales, closure could be indicate from Current asset / Current liabilities and Quick asset / Inventory. Both of them reflects the liquidity condition of SMEs.

The explanation from our findings is there is one indicator that could indicate the business failure, both financially and non-financially: Liquidity. Liquidity will reflect the ability of SMEs to manage their working capital. Also, it supports the condition of SMEs which mostly finance their investment in a short term. Working capital is a crucial part of SMEs, the sustainability of SMEs will depend on how management maintain current asset and current liability. There is a consistent indicator to detect both failure business financially and non-financially from short term indicator.

Despite this, the results on business failure classification of SMEs cover few number of financial ratio and are not conclusive as it might be expected a consideration of previous theoretical findings. The limitation of this study should be a consideration for the next research. First, this research is a replication and research development from previous study in big companies, so the same methodology could be applicable, but different characteristic of SMEs in Indonesia. Second, there are others qualitative variables besides financial variables included in this research that give more contribution to influence business failure or distress of SMEs. Lastly, this research did not include SMEs' life cycle as a consideration of sustainability of SMEs.

8. References

i. Altman, E.I. (1968), 'Financial Ratios, Determinant Analysis and The Prediction of Corporate Bankruptcy', Journal of Finance, 23(4); 589-609.
ii. Altman, E.I. (1984), 'International Corporate Failure Model in Special Studies in Banking and Finance', Journal of Banking and Finance.
iii. Altman, E.I. (1993), Corporate Financial Distress, John Wiley and Sons, New York.
iv. Altman, E.I., Baidya, T., & Riberio-Dias, L.M., (1979), 'Assesing Potential Financing Problems of Firms in Brazil', Journal of International Business Studies.
v. Altman, E.I., & Narayanan, P., (1997), 'An International Survey of Business Failure Classification Models', Financial Markets, Institutions, Instruments, 6 (2): 1-57.
vi. Atiya, A.F., (2001), 'Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results, IEEE Transactions on Neural Networks, 12 (4), July 2001; 929-935.
vii. Berger, A.N., Frame, N.W.S., and Miller, N.H. (2005), 'Credit Scoring and The Availability, Price and Risk of Small Business Credit', Journal of Money, Credit and Banking, 37(2); 191-222.
viii. Berger, A.N., and Udell, G.F. (2006) 'A More Complete Conceptual Framework about SME Finance', Journal of Banking and Finance, 30(11): 2945-2966.
ix. Bhatia, U., (1988), 'Prediction Corporate Sickness in India', Studies in Banking and Finance, 7; 57-71.
x. Bidin, A.R., (1988), ' The Development of a Predictictive Model(PNB-Score) for Evaluating Performance of Companies Owned by The Government of Malaysia', Studies in Banking and Finance, 7;91-103.
xi. Copeland, T. and Weston, J.F., (1988), Financial Theory and Corporate Finance, Addison-Wesley.
xii. Crapp, H., and Stevenson, M. (1987), 'Development of a Method to Assess The Relevant Variables and Probability of Financial Distress', Australia Journal of Management, 12 (2); 221-236

xiii. De Young, R., Glennon, D., and Nigro, S.P. (2008), 'Borrower-Lender Distance, Credit Scoring and Loan Performance: Evidence from Informational-Opaque Small Business Borrowers', Journal of Financial Intermediation ,17(1); 113-143

xiv. Edminister, R.O. (1972), 'An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction', Journal of Finance and Quantitative Analysis, 7(2); 1477-1493.

xv. Fama, E.F. and Jensen, M.C. (1985), 'Organizational forms and investment decisions', Journal of Financial Economics 14(1) 101-119.

xvi. Frame, W.S., Srinivaran, A., and Woosley, L. (2001), 'The Effect of Credit Scoring on Small Business Lending', Journal of Money, Credit, and Banking 33(3); 813-825.

xvii. Frydman, H., Altman, E.I., and Kao, P.L., (1985), 'Introduction Recursive Partitioning for Financial Classification: The Case of financial Distress', Journal of Finance, 40 (1); 269-291.

xviii. Gilson, S.C., and Vetsuypens, M.R. (1993), 'CEO Compensation in Funancially Distressed Firms: An Empirical Analysis', Journal of Finance48(2); 425-458.

xix. Harner, M.M., (2011), Mitigating Financial Risk for Small Business Entrepreneurs, Ohio State Entrepreneur Business Law Journal 6(2) 469-489.

xx. Headd, B. (2003), 'Redifining Business Success: Distinguishing between Closure and Failure', Small Business Economics, 21(10), 51-61.

xxi. Jensen, M.C., and Meckling, W.H., (1976), 'Theory of the firm: managerial behavior, agency costs and ownership structure', Journal of Financial Economics 3(4): 305-360.

xxii. Joos, P., Vanhoof, K., Ooghe H., and Sierens, N. (1998), 'Credit Classification: A Comparation of Logit Models and Decision Trees, Proceedings Notes of The Workshop on Application of Machine Learning and Data Mining in Finance, 10th European Conference on Machine Learning, April 24, Germany; 59-72

xxiii. Kauffman, R.J. and Wang, B., (2001), 'The Success and Failure of Dotcoms: A Multi-Method Survival Analysis', Working Paper, 01-09, Management Information Systems Research Center, Carlson School of Management, University of Minnesota, Minneapolis, 1-7.

xxiv. Knight, G., (2001), 'Entrepreneurship and Strategy in The International SME', Journal of International Management 7(3): 155-172.

xxv. Laitenen, T., and Kankaanpaa, M.m (1999), 'Comparative Analysis of Failure Prediction Methods: The Finnish Case', The European Accounting Review, 8 (1); 67-97.

xxvi. Lane, W.R., Looney, S.W., and Wangley, J.W., (1986), 'An Application of Cox Proportional Hazards Model to Bank Failure', Journal of Banking and Finance, 10; 511-531.

xxvii. Luoma,M., and Laitinen, E.K., (1991), 'Survival Analysis as A Tool for Company Failure Prediction', Omega International Journal of Management Science, 10 (6); 673-678.

xxviii. Michala, D., Grammatikos, T., and Filipe, S.F., 'Forecasting Distress in European SME Portfolios', Proceeding of The First International Conference on Finance and Banking, Sanur Bali, 11-12 December 2013.

xxix. Megginson, W.L., (1997), Corporate Finance Theory, Addison-Wesley.

xxx. Merton, R.C. (1974), 'On the Pricing of Corporate of Interest Rates', The Journal of Finance, 29(2), 449-470.

xxxi. Ooghe, H., and Balcaen, S., (2002), 'Are Failure Model Transferable from One Country to Another? : An Empirical study Using Belgian Financial statement', Working Paper, Sternpunt 001.

xxxii. Pascale, R., (1988), 'A Multivariate Model to Predict Firm Financial Problems: The Case of Uruguay', Studies in Banking and Finance, 7 (171-182).

xxxiii. Poza, E. (2004), Family Business, Thomson South-Western Publishing, Mason: Ohio.

xxxiv. Ross, S.A., Westefild, R., and Jaffe, J. (2010), Corporate Finance, 9th Edition, McGraw Hill/Irwin Series.

xxxv. Shrader, R.C., and Simon, M., (1997), 'Corporate versus Independent New Ventures: Resource, Strategy and Performance Differences', Journal of Business Venturing 12(1): 47-66.

xxxvi. Shumway, T., (1999), 'Forecasting Bankruptcy More Accurately: A Simple Hazard Model', Working Paper, University of Michigan Business School, USA, July 1999, 1-31.

xxxvii. Suominen, S.I., (1988), 'The Prediction of Bankruptcy in Finland', Studies in Banking and Finance, 7 (27-36).

xxxviii. Sunarjanto, N.A,&Roida, H.Y., 2013, 'Menerjemahkan Toleransi Risiko Pemilik UMKM Melalui Keputusan Penggunaan Modal yang Mengandung Risiko Bisnis dan Risiko Keuangan', Proceeding Konferensi Forum Manajemen Indonesia Ke-5 Pontianak, 23-24 Oktober 2013.

xxxix. Swanson, E and Tybout, J., (1988), 'Industrial Bankruptcy Determinants in Argentina', Studies in Banking and Finance, 7 (1-25).

xl. Ta, H.P., and Seah, L.H., (1981), 'Business Failure Prediction in Singapore', Studies in Banking and Finance, 7 (105-113).

xli. Unal, T., (1988), 'An Early Warning Model for Predicting Firm Failure in Turkey', Studies in Banking and Finance, 7 (141-170). Watson, J.E. (1993), 'Defining Small Business Failure', International Small Business Journal, 3(11); 35-48.

xlii. Yang Q.G., and Temple, P., (2000), 'The Hazard of Chinese Enterprises Under Reconstructing', paper presented at CEPR/ESRC Transition Economics and Chinese Economy Conference, Centre for Economic Reform and Transformation (CERT), 24/25 august 2000, Heriot-Watt, University Edinburg, 1-37.

xliii. Yang, Z.R., Platt, M.B., and Platt, H.D., (1999), 'Probabilistic Neural Networks in Bankruptcy Prediction', Journal of Business Research, 44 (2); 67-74.