

	<h1 style="margin: 0;">GOMAL UNIVERSITY</h1> <h2 style="margin: 0;">JOURNAL OF RESEARCH</h2> <p style="margin: 0;">Gomal University, Dera Ismail Khan, Khyber Pakhtunkhwa, Pakistan</p> <p style="margin: 0;">ISSN:1019-8180 (Print)                      ISSN: 2708-1737 (Online)</p>		
	<p style="margin: 0;"><b>Website</b></p> <p style="margin: 0;"><a href="http://www.gujr.com.pk">www.gujr.com.pk</a></p>	<p style="margin: 0;"><b>HEC Recognized</b></p> <p style="margin: 0;"><a href="#">Social Sciences (Multidisciplinary)</a></p>	


## THE FIRM'S FAILURE PROCESSES IN ASIAN MAJOR ECONOMIES: THE APPLICATION OF CLUSTERING TECHNIQUES

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KEYWORDS	ABSTRACT
Financial Ratios, Default Risk, Clustering Techniques, Bankrupt Firms, Asian Economies	<p>The objective of this study is to examine firm's failure processes (FFPs) by applying different clustering techniques on the dataset of 520 bankrupt manufacturing firms from various Asian countries and divide them into two groups based on their governance scoring reported by international governance index. The short-term failure is quite high in countries where governance scoring is low while long term failure is more prominent in high ranked countries. This shows three motivated FFPs and in case of dominant FFP, the study finds that firm's default risk befits increase shortly even earlier the bankruptcy is confirmed. The accumulated and annual profitability of firm is the most significant predictor of firm's failure risk for all the three firms' FFPs for the firms having failure probability more than 50%. Results of the study provide an important breakthrough in research of bankruptcy forecast and practices, precisely in terms of exploring the most significant determinants. This study also fills the gap by addressing the ignored area of constituents of failure risks during various FFPs.</p> <div style="text-align: center;">  </div> <p style="text-align: right; color: red;"><i>2020 Gomal University Journal of Research</i></p>
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### INTRODUCTION

Firm failure is a universal phenomenon and remains one of the everlasting topics in research; however, the literature never seems to be balanced and failure prediction domains have been represented by number of scholars with lack of contextual demonstration (Sun, Li, Huang, & He, 2014; Amankwah, 2016). The research follows the stage theory of business failure, which highlights that a firm faces numerous observable stages before its failure (Amankwah, 2016). Recently, the research has mostly focused on firm's turn-around (James, 2016; Mann & Byun, 2017; Zorn, Norman, Butler & Bhussar, 2017); besides, the researchers concentrating different phases lead to the bankruptcy lacks consensus (Amankwah, 2016; Horvathova & Mokrisova,

2018). There are several studies that conceptualized the FFPs (Lukson, 2018) and recently empirics have also been re-emerging (Nummela, Saarenketo & Loane, S. (2016); Lukason & Laitinen, 2019). However, there exist certain unexplored essential dimensions that need to be explored.

The firm's failure processes consider failing firm's behavior in long term; whereas, prediction studies often concentrate shorter performance version (Laitinen & Lukason, 2014). The long term enables stakeholders to these phases, re-address the courses of action, and probability to shun the crises. The evidences show that businesses fail for several reasons that vary across culture, economies and legal structure. However, there are certain reasons which are more common likewise generating adequate revenues to survive (Laitinen, Lukason & Suvas, 2014). Similarly, in the recession phase of the economic cycle, firms tend to generate lower revenues and often get out of the business. The firm specific factors such as the capital structure also affects firms. A firm with higher debt to equity ratio third, the firms are also exposed to the financial constraints, if a business struggles then getting new is susceptible to bankruptcy in long-term. Finally, the businesses also face failure due to lack of planning and ultimately to the bankruptcy.

### **Problem Statement**

The firm failure is a well-established phenomenon in business research. The researchers have investigated the FFPs that provide enough evidences how this process diverges with regard to financial state evolution in different stages. As D'Aveni (1989) highlighted initially that we can differentiate FFPs in perspective to failure risk development around time. However, he didn't intricate the relationship of FFP phases and risk of failure. We attempt to unveil how diverse phases of FFPs vary with regard to failure risk in Asia and propose a conceptual model based on other theoretical sources provided by D'Aveni (1989). Furthermore, to disclose diverse FFPs and validate the conceptual model, Altman, Iwanicz, Laitinen and Suvas (2017) modified Z-Score model is used to estimate firm's default risk and a diversity of clustering approaches. In contrast to earlier findings, this study applied most appropriate theory of FFPs for suitable empirical solution in accordance with the Scott (1981) probabilistic theory of the bankruptcy besides highlighting the important financial ratios that can be used in the future research studies.

### **Objective of Study**

The study aims to investigate various FFPs applying the failure risk and rank the significance of failure risk determinants at various stages of FFPs. The remaining of the paper is formatted with the manner like review on literature documents the theoretical and empirical work in the FFPs context. The research methodology explains the data sample and period along with the empirical strategy. In results and discussion section, a detailed analysis and their tables are interpreted and compared with other empirical studies. Finally, study is concluded in the last section.

## **LITERATURE REVIEW**

### **Firm's Failure Processes**

Argenti (1976) is the pioneering study in the field of FFPs that identified three failure stages with the decline in firm's financial condition. Since then, most of the researchers focused the

reasons of the firm's failure, signs of pre-failure or both (Ooghe & Prijcker, 2008; Lukason & Laitinen, 2016). The researchers detected failure reasons with qualitative data while ignoring the happening of specific event (Laitinen et al., 2014); Lukason & Laitinen, 2019). Resultantly, firm's default causes are explained with the financial ratios (Lukason & Laitinen, 2016; Jardin, 2017; Serrano, Nieto & Valbuena, 2019). Moreover, the court insolvency declaration has been used as most popular definition in failure research bankruptcy (Amankwah & Wang, 2019). In case of bankruptcy, it is rational as inability to pay unsettled debt and event time is predicted and identified (Lukason & Laitinen, 2016; Kliestik, Valaskova, Lazaroiu, Kovacova & Vrbka, 2020).

### **FFPs in Previous Studies**

Consequently, the study considers FFP as path-way represented with firms' financial position till its bankruptcy is professed. The earlier studies have consensus on three kinds of FFPs e.g. Argenti (1976) suggested three stages of FFPs as: i) the firms never in affirmation stage; ii) the sudden decline in the high performing firm; and iii) a firm experiencing step by step decline. Though Argenti (1976) proposed three FFPs based on case study evidences by applying firms' financial health, but was unable to provide guidelines for measuring firm's financial position. A highly insightful method was suggested by D'Aveni (1989), he applied a customized D-score to depict FFPs wrapping five years pre-bankruptcy declaration. D'Aveni (1989) dyed three theoretical FFPs titled; sudden, gradual or lingers failing firms. The firm exposed to sudden bankruptcy are non-viable even less than 1-year to bankruptcy notice and it happens swiftly; steadily failing firms face issues with visible decline in 2-3 years before bankruptcy assertion; and lingers firms become non-viable even pre-bankruptcy. He supported his theoretical FFPs model by clustering the D-scores which was measured on equity to debt ratio and managerial stature.

Similarly, Laitinen (1991) authenticated existence of three different FFPs by applying factor analysis on six theoretically supported financial variables including growth variable and five financial ratios and named three FFPs as chronic, revenue financing, and severe failure firms. He reported negative value of return on assets (ROA) 4 years pre-bankruptcy for chronic FFP, 2 years pre-bankruptcy for revenue financing FFP and one year pre-bankruptcy for acute FFP. This shows strong similarities between findings of Laitinen (1991) and D'Aveni (1989) and established the presence of three types of FFPs. Nonetheless, they differ in the opinion as to conclude when a firm becomes poor in performance or exposed to high failure risk. Based on these studies, this study contends with existence of 3 theoretical kinds of FFPs and these are portrayed as follows depending upon failure risk development. In the 2<sup>nd</sup> kind of FFP, we can observe high failure risk even 2-3 years before bankruptcy and prevails until firm is dissolved. This is called medium range FFP. In the last stage of FFP, one can detect high failure risk even for more than 3 years before bankruptcy and prevails until firm is dissolved. It is called long-range FFP.

### ***Failure Risk & Contributors at Different Stages of FFPs***

Most of the contemporary researchers have applied classical statistical analysis methods for analyzing FFPs (Flores & Garcia, 2017; Lukason & Laitinen, 2016). These studies used either Laitinen (1991) model or its extended form. Based on findings of these studies, we can discern different FFPs by erratic levels of solidity, profitability and liquidity. Importantly, no one has applied failure risk factors in different FFPs and consider varying contribution of failure risk at

various phases of FFPs. Laitinen (1993) developed stage theory of FFPs which indicates that different failure predictors are useful in various phases of FFPs. This study focuses on methods of calculating variables for these stages rather than seeing role of financial ratios describing diverse financial realms to failure risk for these FFPs phases. The research showed liquidity, profitability and leverage ratios are the significant determinants of firm failure (Sun et al., 2014).

According to the bankruptcy theory, a firm is in a gambler ruin framework where equity and profitability are the main determinants of firm's performance (Scott, 1981). Similarly, Beaver's (1966) cash flows theory of bankruptcy pointed out that debt increase adds to the likelihood of bankruptcy. Similarly, Altman et al. (2017) provided evidences in line with failure prediction models by applying four theoretically justified financial ratios over the dataset of European firms. Henceforward, this study focuses the theoretical prospects of failure risk determinants of the various phases of FFPs and combined the results into the conceptual framework offered as under:

Table 1 Interconnections of FFPs Stages with Failure Risk and Financial Domain

Time Distance	Short Term Failure Processes (SFFP)		
	Financial dominion	Financial domain level	Determinants of Failure risk
Long-run	Liquidity ratio	Average/High	Failure risk is not observable
	Profitability ratio	Average/High	
	Leverage ratio	Low/average/high	
Mid-run	Liquidity ratio	Average/High	Failure risk is not observable
	Profitability ratio	Average/High	
	Leverage ratio	Low/average/high	
Short-run	Liquidity ratio	Low/Average	Failure risk might be observable. Negative profitability is the most significance determinant.
	Profitability ratio	Low/Average	
	Leverage ratio	High/Average	

Table 1a Interconnections of FFPs Stages with Failure Risk & Financial Domain (Continued)

Time Distance	Medium Term Failure Processes (MFFP)		Long Term Failure Processes (LFFP)	
	Financial domain level	Determinants of Failure risk	Financial domain level	Determinants of Failure risk
Long-Run	Average/High	Failure risk is not observable	Average	Failure risk is observable. Profitability and financial leverage have significance role in bankruptcy.
	Average/High		Low	
	Low/average/high		High	
Mid-Run	Average	Failure risk is observable. Negative profitability followed by financial leverage.	Average	Failure risk is observable. Profitability and financial leverage have significance role in the bankruptcy.
	Low		Low	
	Average/high		High	
Short-Run	Low	Risk is observable. Profitability along with financial domains are vital.	Low	Failure risk is observable. Each financial domain contributes but their exact role is not observed.
	Low		Low	
	High		High	

Table 1 provides consolidated results based conceptual model of different stages of FFPs. The study mainly focuses on theoretical prospects about the failure risk determinants of various phases of FFPs. As offered in theoretical model, observable failure risk may not be presented for SFFP in period t<sub>1</sub>, so these firms are not expected to show any problem in medium or long run through financial ratio. Hence, various prediction models can follow such a tendency in case when prediction accuracies decreases form t<sub>2</sub> and onwards and poor performance signs are invisible. Based on “probabilistic bankruptcy theory” (Scott, 1981), this study expects that firms adopting SFFP are prone to high level as they have observed extreme financial losses in short run which are outcome of ineffective management or worst environmental conditions (Lukason & Vissak, 2019). Hence, if failure risk is less 50% in t<sub>1</sub>; it is expected to be related to negative annual profitability. MFFP failure risk is visible either in t<sub>2</sub> or t<sub>3</sub>. These firms are expected to face regular increase in losses; but speed may vary across firms. It is in line with (Laitinen & Lukason, 2014; Jardin, 2017) and represents notion highlighted in theory by Scott (1981).

The steady accumulation of losses results negative profitability. The case of medium-run, firm yearly profitability is considered as most important determinants while accumulated profits in the short-run. The study predicts accumulated profit as not the mere determinants in the short and medium run. In the short run, firms are already exposed to severe problems in different major domains and these might be important determinants of firm's failure but it's difficult to predict exact determinant. For long run, study expects failure risk  $\leq 50\%$ , so, it's impossible to outline any determinant for this stage. Similarly, for long failure process, the firms are exposed to high risk throughout the observed stages, so these firms face low or negative annual profits, low accrued profits and high financial leverage throughout failure stages (Ooghe & Prijcker, 2008). For this stage, it's not possible to rank the determinants of failure risk, thus it remains an empirical question. Despite of such situation, the continuous loss transforms accrued profit into negative with the passage of time. In financial mathematical sense, annual profitability is most vital determinants of firm's failure before bankruptcy declaration. Study ignores liquidity as failure risk until t<sub>1</sub> as firms in long-term failure manage to stay liquid despite of continuous loss.

## **RESEARCH METHODOLOGY**

The data of 520 bankrupt manufacturing firms from Asia were extracted using COMPUSTAT database for last 5 years i.e. from January 2014 to December 2018 and their descriptive stats are presented in table 2. For analysis, the study used data of only those firms whose data was known despite bankruptcy. Moreover, countries having data of less than 10 firms are excluded from the sample to justify the results. The nature of firms such as importing and exporting is not considered in the sample. The inclusion of data from Asian major economies authenticates our results as this guarantees specific country biasness. For each firm included in the sample, the date of bankruptcy was known exactly. Applying the financial statement data from t<sub>1</sub> to t<sub>5</sub>, theoretical FFPs are identified and corresponding empirical FFPs are investigated. Empirical FFPs are known applying relatively larger variety of clustering than prior empirical research on FFPs.

### **Asian Economies**

The Asian economy consists of more than four billion people which are around 60% of global population. Asian economies particularly China, India and Malaysia are the fastest growing in

the region (Kumar, 2019) and considered as the largest continental economy with respect to both GDP and PPP of the World. Eastern Asia and ASEAN countries are mainly dependent on the manufacturing industry for growth. The sample firms of study for analysis are considered from Singapore, Taiwan, Japan, Malaysia, Hong Kong, South Korea, and Thailand (in upper ranked) and Bangladesh, China, India, Indonesia, Pakistan, Sri Lanka, Turkey and UAE (in lower ranked).

### **Theoretical FFPs and their construction**

This study constructed variables based on closed theoretical justification and each firm is assigned one theoretical FFP by applying logistic bankruptcy forecasting based on Model-2 created by Altman et al. (2017: 154). They assigned equal weights to bankrupted and non-bankrupted firms. Based on this, critical probability of bankruptcy is 0.5 for detecting firms. Furthermore, the linear logit score applying the logistic transformation is applied in order to calculate the weighted probability. The Model-2 is applied to discover theoretical FFPs as if the value of Altman's Model 2 transformed logit score is:  $< 0.5$  before  $t_1$ , it is treated as short term FFPs (SFFP);  $> 0.5$  before either in  $t_2$  or  $t_3$  and remains  $> 0.5$  for all succeeding years, it is treated as medium term firm's failure process (MFFP);  $> 0.5$  before  $t_3$  and remains  $> 0.5$  for all succeeding years, it is treated as medium long firm's failure process (LFFP). By far, Altman et al. (2017) discriminate and logit models are nearly matched in AUCs value 0.743 and 0.745 respectively and it minimizes such threat. In addition, such approach is useful when the fact is declared before declaration of bankruptcy, e.g. a firm may be exposed to high bankruptcy risk in  $t_2$  and  $t_3$  but not in time  $t_1$ , and thus being categorized as SFFP. Altogether, study doesn't consider this risk fluctuation, and the approach used is in line to theoretical FFPs of D'Aveni (1989).

### **Empirical FFPs and their construction**

In order to detect FFPs empirically, study applied 4 different clustering methods on diverse groups of factors for last 5 years pre-bankruptcy declaration. The used clustering techniques are composite of 2 famous classical techniques (k-means & k-medians) and unique techniques (expectation maximization (E-max) and canopy clustering (Cc)). Most of researchers used k-means and k-medians for observing FFPs while no study has used canopy clustering (Cc) for detecting FFPs. Study used STATA for k-means and k-medians clustering while expectation maximization (E-max) and canopy clustering (Cc) is done in WEKA 3.8.0 software. Three theoretical FFPs exist; the study sets three clustering methods for the purpose of the analysis. Each clustering method is used in eight (8) various sets of factors as mentioned in table 2. This constructs 32 various clustering methods each of determinant which represents unique cluster result.

The study used 8 varying sets of factors based on Altman et al. (2017) bankruptcy prediction model. Four ratios are used, discriminant bankruptcy scores, logistic regression bankruptcy scores, transformed logistic regression bankruptcy scores. This study used four types of inputs with max. Likelihood factor analysis pre-clustering and this makes equal sets of 8 input variable. Studies used financial parameters with factor analysis pre clustering (Laitinen & Lukason, 2014; Lukason & Laitinen, 2016). The aim of this technique is to standardize the variable and remove their interdependence else the clustering approaches may unable to realize well with financial variables since distributions of financial variables are skewed and there exists several outliers.

Table 2 Clustering Strategies based on 8 different Variables &amp; 4 Clustering Techniques

Clustering Method: Altman et al. (2017)	K-mean	K-median	E-max	Cc
Study based 4 financial ratios	Cl1	Cl9	Cl17	Cl25
Model-1 based discriminant model scores	Cl2	Cl10	Cl18	Cl26
Model-2 based logit model scores	Cl3	Cl11	Cl19	Cl27
Model-2 based transformed logit model scores	Cl4	Cl12	Cl20	Cl28
Study based factored 4 financial ratio	Cl5	Cl13	Cl21	Cl29
Model-1 based factored discriminant model	Cl6	Cl14	Cl22	Cl30
Model-2 based factored logit model scores	Cl7	Cl15	Cl23	Cl31
Model-2 based factored transformed logit model	Cl8	Cl16	Cl24	Cl32

### Inter-connection of theoretical and empirical FFPs

Each firm follows one of theoretical FFPs which results that each of the 3 empirically perceived clusters will represent 1 of 3 failure stages. In an ideal situation, the match of the empirically detected clusters and the theoretical assignments proves the theory, but in reality the results are mostly other way around. In order to the major three clusters with 32 cluster solutions of theoretical FFPs, the study needed an algorithm. The best way is to achieve desired results through an assignment as per cluster solution which should maximize the weighted average classification for the theoretical FFPs. Finally, study chooses cluster solution with the maximum weighted average classification rate and all clusters with value >50% of theoretically correct cases. Thus, use of this solution helps to analyze "real-life situation", with quite ties to ideal-life situation. The theoretical assignment helps as alternative for statistical cluster distinctiveness measures.

### Failure risk components and their contribution

The study conducted examination of the components of firm's default risk in a sequential way. After findings the most appropriate theoretically cluster solution, the behavior is studied of 4 financial ratios to dig out the determinant of failure risk development. To serve this purpose, each variable, for each entity in sample, the values of 4 financial ratios from Altman's Model 2 is multiplied by its corresponding coefficient. Then median of these multiplied financial ratios is calculated for clusters. Subsequently, values of these medians are matched and the largest value represents the most significant contributor in determining default risk associated with different factors. Lastly, study will conclude occurrence of various failure processes in Asian market.

## RESULTS AND DISCUSSION

In table 3, all the firms are divided into three groups i.e. 322 firms represent short-FFP, 144 firms' medium-FFP and remaining 54 represents long-FFP across different countries. These groups are further split into 2 groups i.e. high corporate governance ranked countries and low ranked countries based on their governance scoring. In case of higher ranked, results showed similar firm failure percentage for short and long term FFP. This shows that firms operating in more efficient governance structure are less likely to be bankrupt in short-FFP. In contrast, short-FFP is higher in case of lower ranked countries (almost 36%). This shows governance has significant role in FFPs. The medium-FFP is highest in case of lower ranked countries. The overall results showed that short-FFP represents 28.66%, medium-FFP is 36.69% and long-

FFP share is 33.39%. Sample contradicts with findings in D'Aveni (1989) who practiced nearly 10% short-FFP. Finding resembles with earlier sample of Laitinen (1991) study where reported significant share of short-FFP. From this, study achieves share of each stage is subject to sample distribution.

Table 3 Country-wise Frequencies of three FFPs based on Best Cluster Solution C8

	Short-FFP	%age	Medium-FFP	%age	Long-FFP	%age	Total
Higher Ranked Countries							
Singapore	2	6.90	7	24.14	10	34.48	29
Taiwan	4	19.05	5	23.81	12	57.14	21
Japan	7	13.46	16	30.77	29	55.77	52
Malaysia	21	31.34	23	34.33	23	34.33	67
Hong Kong	11	29.73	17	45.95	9	24.32	37
Higher Ranked Countries							
South Korea	5	12.20	23	56.10	15	36.59	41
Thailand	7	17.95	19	48.72	13	33.33	39
High Ranked Overall	57	19.93	110	38.46	111	38.81	286

Table 3a Country-wise Frequencies of three FFPs- Best Cluster Solution C8 (Continued)

Lower Ranked Countries							
	Short-FFP	%age	Medium-FFP	%age	Long-FFP	%age	Total
Bangladesh	13	50.00	5	19.23	8	30.77	26
China	12	29.27	21	51.22	8	19.51	41
India	21	24.42	39	45.35	26	30.23	86
Indonesia	17	31.48	16	29.63	21	38.89	54
Pakistan	21	34.43	23	37.70	17	27.87	61
Sri Lanka	7	36.84	6	31.58	6	31.58	19
Turkey	18	51.43	9	25.71	8	22.86	35
United Arab Emirates	16	59.26	4	14.81	7	25.93	27
Low Ranked Overall	125	35.82	123	35.24	101	28.94	349
Total	182	28.66	233	36.69	212	33.39	635

More so, a clustering strategy is used and 32 different clusters (CL) are presented in table 4. The results depicted a significant variation in numbers for each clusters. This indicates ability of each cluster to detect FFPs diverges largely. Furthermore, the smallest cluster's size varies from 4.38% to 43.35%, the largest sample varies from 20.83% to 89.79% and median cluster varies from 5.83% to 71.56%. Similarly, study assigned one of three theoretical FFPs to each detected empirically clusters. Table 4 also shows that highest average accuracy of classification is obtained over solution CL8 (68.98%). The variation in total accuracy is observed between 41.43% for CL9 to 68.98% for CL8. Solution CL8 denotes to K-means clustering which is based on the factored transformed logit model scores from Altman's Model2. The worst clustering strategy is result of K-medians clustering using 4 financial ratios from Altman (2017) as input variables.



Table 4 Each Cluster Size, Firm Division into Three FFPs and Clustering Accuracy

Sol	Cluster 1 size	FFPs	Cluster 2 size	FFPs	Cluster 3 size	FFPs	Smallest Cluster	Largest Cluster	Medium Cluster	Cluster Accuracy
CL1	84	Medium	60	Long	491	Short	9.3%	77.39%	13.12%	45.9%
CL2	157	Medium	57	Long	421	Short	8.8%	66.45%	24.72%	48.4%
CL3	68	Long	362	Short	205	Medium	10.5%	57.29%	32.17%	64.0%
CL4	102	Medium	439	Short	94	Long	8.4%	76.42%	15.15%	64.3%
CL5	208	Medium	365	Short	62	Long	9.7%	57.13%	33.14%	64.8%
CL6	97	Medium	480	Short	58	Long	9.0%	76.01%	14.91%	65.2%
CL7	246	Medium	318	Short	71	Long	11.4%	49.92%	38.65%	66.0%
CL8	102	Medium	462	Short	71	Long	10.9%	73.01%	16.05%	68.9%
CL9	121	Long	105	Medium	409	Short	18.8%	58.51%	22.69%	41.4%
CL10	157	Medium	192	Long	286	Short	31.2%	43.11%	25.61%	55.1%
CL11	198	Long	163	Short	274	Medium	31.4%	25.93%	42.63%	54.1%
CL12	186	Short	319	Medium	130	Long	17.9%	31.20%	50.81%	50.3%
CL13	209	Long	152	Short	274	Medium	43.3%	24.31%	32.33%	52.9%
CL14	208	Short	316	Medium	111	Long	19.2%	31.77%	48.95%	50.0%
CL15	97	Long	372	Short	166	Medium	15.5%	43.35%	41.09%	63.9%
CL16	127	Long	304	Medium	204	Short	19.8%	31.36%	48.78%	48.8%
CL17	198	Short	282	Medium	155	Long	24.8%	30.31%	44.81%	53.0%
CL18	117	Long	198	Medium	320	Short	18.3%	50.32%	31.36%	47.0%

Table 4a Each Cluster Size, Firm Division into Three FFPs and Clustering Accuracy (Continued)

Sol	Cluster 1 Size	FFPs	Cluster 2 Size	FFPs	Cluster 3 Size	FFPs	Smallest Cluster	Largest Cluster	Medium Cluster	Cluster Accuracy
CL19	326	Medium	134	Short	175	Long	27.7%	21.64%	50.65%	53.6%
CL20	112	Medium	454	Short	69	Long	8.9%	73.01%	18.07%	66.5%
CL21	312	Medium	142	Short	181	Long	28.4%	22.61%	48.95%	54.0%
CL22	409	Short	141	Medium	85	Long	10.0%	68.64%	21.31%	66.4%
CL23	142	Short	291	Medium	202	Long	30.2%	22.61%	47.16%	54.0%
CL24	409	Short	150	Medium	76	Long	10.2%	64.83%	24.88%	65.4%
CL25	512	Short	49	Medium	74	Long	6.8%	84.68%	8.51%	50.4%
CL26	565	Short	40	Medium	30	Long	4.3%	89.79%	5.83%	47.1%
CL27	410	Medium	171	Short	54	Long	7.6%	27.31%	65.07%	61.9%
CL28	520	Short	51	Medium	64	Long	5.5%	85.82%	8.59%	60.0%
CL29	390	Medium	182	Short	63	Long	7.6%	29.74%	62.64%	62.7%
CL30	539	Short	57	Medium	39	Long	6.0%	85.17%	8.83%	60.5%
CL31	465	Medium	142	Short	28	Long	7.6%	20.83%	71.56%	56.0%
CL32	499	Short	56	Medium	80	Long	12.4%	78.77%	8.75%	42.5%

Subsequently, only those clusters having values >50% is included for analysis. Now, there are only 8 solutions available having clusters >50% (table 5). This makes them a binding solution for advance analysis. All valid clusters are bolded and underlined in the table below which are represented by CL4, CL6, CL8, CL20, CL22, CL24, CL28 and CL30 because their value in all three clusters >50%. Likelihood between theoretical and empirical FFPs for appropriate cluster solution CL8 are highlighted. Decisively, varying clustering approaches sometimes lead to high disparity in shares of different FFPs. The empirics highlights that K-mean clustering provides best matches with theoretical FFPs; while, K-median in inefficient in this matching technique. So, either of transformed logit model/discriminant mode scores are helpful as input variable in clustering.

Table 5 Shares of Theoretically Correct Processes in Overall 32 Solutions

Solutions	Accuracy Cluster1	Accuracy Cluster2	Accuracy Cluster3	Solutions	Accuracy Cluster1	Accuracy Cluster2	Accuracy Cluster3
CL1	14.90%	64.80%	48.98%	CL17	78.57%	33.57%	51.00%
CL2	23.06%	73.98%	54.49%	CL18	52.35%	28.47%	56.74%
CL3	88.67%	68.98%	47.24%	CL19	35.61%	91.33%	49.19%
CL4	58.98%	63.37%	83.37%	CL20	62.65%	65.51%	86.80%
CL5	48.16%	69.90%	91.84%	CL21	35.61%	90.31%	95.62%
CL6	61.53%	63.67%	83.78%	CL22	66.12%	58.57%	87.23%
CL7	47.04%	76.02%	86.84%	CL23	90.31%	35.82%	90.42%
CL8	70.10%	66.12%	86.12%	CL24	67.14%	54.49%	89.67%
CL9	52.76%	14.90%	48.06%	CL25	50.41%	16.53%	50.04%
CL10	48.47%	41.53%	68.88%	CL26	49.49%	17.04%	71.72%
CL11	40.20%	97.86%	37.86%	CL27	42.65%	98.37%	39.42%
CL12	83.98%	29.08%	51.53%	CL28	57.65%	60.61%	53.66%
CL13	40.92%	97.96%	36.63%	CL29	43.06%	95.92%	38.14%
CL14	82.76%	28.06%	51.84%	CL30	58.06%	60.82%	53.97%
CL15	73.37%	80.71%	42.86%	CL31	39.29%	98.88%	44.62%
CL16	47.04%	26.73%	84.39%	CL32	47.14%	61.43%	87.87%

### Explanation of the most appropriate solution

For the purpose of discussion, the financial ratios of Altman's (2017) are used. These ratios are working capital to the total assets ratio (WC), earnings before interest and taxes to total assets ratio (ET), retained earnings to total assets ratio (RE) and book value of equity to total debt ratio (BE). Working capital ratio portray firm liquidity, earnings ratio represents profitability, retained earnings refers to accumulated profit and book value of equity ratio is meant to portray financial leverage. According to table 6, WC (liquidity) value is from 0.068 to 0.11 in case of short-SSP and negative value is also highlighted in t1. This implies that firms earning high losses (negative ET) during t1 and resulting negative accumulated profitability (RETA) during this period. Similarly, RE, ET, and BE also remained sustainable and positive from t1 to t5. Moreover, study also observed a drop of ET from t3 to t2. This shows that firms following short-FFP are exposed to mismanagement or unexpected environmental changes which causes their sudden failure (Thornhill & Amit, 2003). In case of medium-FFP, firms observe losses (negative earnings) already in in t3. These losses become so heavy and large in t1 and t2 that it considerably impacts the firms' liquidity making it negative in t3. This forces them for other sources of financing. For such firm, revenue financing could be best technique to resolve issue, but question arises whether attempted turnaround is successful/not (Trahms, Ndofor & Sirmon, 2013), they are indifferent/disappear by depending on original approach (Ooghe & Prijcker, 2008).

In case of long-FFP, firms' performance is ranked poor for the observed period. The negative value of ratios for entire period from t1 to t5 indicate that firms are in lingering stage (D'Aveni, 1989) and exposed to lasting failure. This makes firms to rely on additional capital to finance heavy losses for all periods which makes them more viable. However, majority of these firms involved in insolvency proceedings dissolving even many years earlier their bankruptcy was actually declared. As per median test results, median value of financial ratios are significantly

different for FFPs. The study observed the largest numbers of modifications of median values for short and long FFPs (19 times out of 20). In comparison of short-FFP with medium-FFP or medium-FFP with long-FFP, the study observed fewer differences for more than half of tests ran. The ratio of short and medium FFP tend to differ more just before failure, and resultantly, ratio values of medium and long FFPs for years further from firms failure. The study found similarity for short and medium FFPs, but vary from firms following long-FFP. Conclusively, firms falling in medium-FFP normally accumulate their problem in shorter version in comparison to firms following long-FFP. For the 3 FFPs, WC and RE values are negative for t1; firms' failure is condition to the liquidity and firmness bankruptcy as also documented in the literature.

Table 6 Three FFPs and their Mean Values for Best Cluster Solution (CL8)

Variables	WC1 <sup>13</sup>	WC2 <sup>13</sup>	WC3 <sup>123</sup>	WC4 <sup>23</sup>	WC5 <sup>23</sup>	RE1 <sup>13</sup>	RE2 <sup>123</sup>	RE3 <sup>123</sup>	RE4 <sup>123</sup>	RE5 <sup>23</sup>
S-FFP	-0.059	0.068	0.100	0.111	0.112	0.022	0.100	0.123	0.145	0.157
M-FFP	0.941	0.437	0.056	0.078	0.100	0.986	0.526	0.011	0.089	0.123
L-FFP	0.751	0.482	0.549	0.493	0.302	1.378	0.840	0.661	0.571	0.347
Total	0.213	0.017	0.056	0.067	0.078	0.168	0.033	0.078	0.100	0.123
Var.	ET1 <sup>12</sup>	ET2 <sup>123</sup>	ET3 <sup>13</sup>	ET4 <sup>23</sup>	ET5 <sup>23</sup>	BE1 <sup>13</sup>	BE2 <sup>13</sup>	BE3 <sup>123</sup>	BE4 <sup>23</sup>	BE5 <sup>23</sup>
S-FFP	0.134	0.011	0.033	0.044	0.044	0.067	0.257	0.280	0.302	0.325
M-FFP	0.403	0.392	0.089	0.033	0.033	0.482	0.291	0.078	0.246	0.302
L-FFP	0.179	0.089	0.100	0.224	0.078	0.538	0.370	0.336	0.280	0.089
Total	0.168	0.022	0.022	0.033	0.033	0.011	0.134	0.213	0.246	0.280
Var.	ZS1 <sup>13</sup>	ZS2 <sup>13</sup>	ZS3 <sup>123</sup>	ZS4 <sup>123</sup>	ZS5 <sup>23</sup>	Logit1 <sup>13</sup>	Logt2 <sup>13</sup>	Logt3 <sup>123</sup>	Logt4 <sup>123</sup>	Logt5 <sup>23</sup>
S-FFP	0.246	0.179	0.257	0.280	0.302	0.313	0.100	0.179	0.201	0.235
M-FFP	1.939	1.255	0.100	0.201	0.269	2.096	1.367	0.168	0.134	0.179
L-FFP	2.029	1.087	1.009	1.087	0.549	2.242	1.255	1.109	1.210	0.728
Total	0.571	0.022	0.179	0.235	0.257	0.650	0.044	0.100	0.157	0.179
Var.	TLogit1 <sup>1</sup>	TLogt2 <sup>13</sup>	TLogt3 <sup>123</sup>	TLogt4 <sup>12</sup>	TLogt5 <sup>23</sup>					
S-FFP	0.639	0.538	0.515	0.504	0.504					
M-FFP	0.975	0.863	0.605	0.526	0.515					
L-FFP	0.986	0.840	0.818	0.840	0.739					
Total	0.717	0.571	0.538	0.526	0.515					

**Failure Risk Components & Their Contribution**

In order to study the constituents of firm default risk, each observation of form observation 4 financial ratios from t1 and t5 is multiplied by its respective co-efficient obtained from Altman's Model-2. Table-7 below presents median value of outcome ratio after multiplication for three FFPs for t-1 to t-5. For short-FFP, the default risk is >50% only for t1 with negative ET (earnings) as most significant contributor to firm's failure risk. The finding is as per assumption of the study set in table 1 above and in line with earlier findings of Lukason et al. (2016). As in short-FFP, the study did not find any symptom of firm's failure before t-1, the firms observed heavy losses during t-1. This makes ET (earning) reasonably as most important determinants of failure risk. Results of short-FFP are supported by Scott's (1981) probabilistic theory of bankruptcy (negative equity is an outcome of negative profitability), even though the losses accumulate in a very short period of time. This is extremely surprising for listed firms as these firms are especially vulnerable to environmental pressures. It makes the management

role more critical (Lukson, 2018; Lukason & Minano, 2019) and exposes firms into “no man rule”.

As far as medium-FFP is concerned, the study observed default risk is >50% for t2 and t3. Again, the firm's ET (profitability) is the most significant risk contributor to the firm failure. During medium-FFP, the firms faced heavy accumulated losses and at this stage RE (retained earnings) is declared as the most significant contributor as its takeovers ET (earnings) quite significantly. The transformation of ET into RE as significant risk contributor is quite logical in medium-FFP. In general, the findings are in line with the proposed concepts in table 1 above. Moreover, the medium-FFP is comparatively better reflection of Scott's (1981) theory than short-FFP. In case of long-FFP, RE is the most significant contributor during the entire period. As the firm closes to bankruptcy, the second important determinant of firm failure which is ET is taken over by WC. The study did not propose strict theoretical ranking of financial domains in table1; as how and which significant problems occur in diverse financial domains for long-FFP, is more an empirical question. According to D'Aveni (1989), firms falling in long-FFP category are more likely to delay their bankruptcy filing and, in the process, they undertake several unsuccessful survival and revival attempts (Ooghe & Prejcker, 2008; Kristof & Virag, 2020).

Results of current study of default risk providers for different FFPs highlights the significance of “Probabilistic theory of bankruptcy” in clarifying the content of FFPs. As per results of the current study, the firm's failure risk is >50% for all three stages of FFPs, and ET (earnings) and RE (retained earnings) is the most significant contributor in firm's failure risk in case of Asian context. As the study considers the listed firm in Asia, these firms are heavy loaded with equity financing followed by retained earnings. In case of analyzing different stages of short and medium FFPs, the failure risk is not>50% and the median value of financial ratio is quite similar. Hence, theoretical assumption could be empirically supported, that in case of failure risk development, only one FFP exists while considering the de facto moment of firm's failure. Still conclusive statement about this postulate demands about the exact situation of the firms in last year including the facts of delay of insolvency proceedings. Moreover, in case of long-FFP, the firm's failure risk is >50% and there is a dire need to apply longer time frame as it provides access to required information during the period when the firms were performing normally.

Table 7 Rankings of Factors of 3 FFPs of Best Cluster Solution C8 Based On Median Values

Ration Median Coefficient	Short-FFP		Medium-FFP		Long-FFP		Total	
	Medians	Rank	Medians	Rank	Medians	Rank	Medians	Rank
WC1	0.0424	2	0.4533	2	0.3587	2	0.1022	3
RE1	0.0152	1	0.8239	2	1.1511	3	0.1435	2
ET1	0.2283	3	0.6696	3	0.2924	1	0.2793	1
BE1	0.0011	4	0.0076	3	0.0087	4	0.0237	4

Table 7a Rankings of Factors of 3 FFPs of Best Cluster Solution C8 Based On Median Values

Ration Median Coefficient	Short-FFP		Medium-FFP		Long-FFP		Total	
	Medians	Rank	Medians	Rank	Medians	Rank	Medians	Rank
WC2	0.0391	2	0.2098	3	0.2315	2	0.0764	4
RE2	0.0891	1	0.4370	2	0.6978	1	0.0272	2

ET2	0.0098	3	0.6587	1	0.1522	3	0.0359	1
BE2	0.0043	4	0.0043	4	0.0065	4	0.0022	3
WC3	0.0467	2	0.0272	2	0.2663	3	0.0239	3
RE3	0.1076	1	0.0054	3	0.5576	1	0.0641	1
ET3	0.0535	3	0.1457	1	0.1652	2	0.0326	2
BE3	0.0043	4	0.0011	4	0.0054	4	0.0033	4
WC4	0.0489	3	0.0391	3	0.2359	3	0.0326	3
RE4	0.1217	1	0.0739	1	0.4753	1	0.0859	1
ET4	0.0707	2	0.0533	2	0.3761	2	0.0543	2
BE4	0.0054	4	0.0043	4	0.0043	4	0.0043	4
WC5	0.0533	2	0.0467	3	0.1435	3	0.0359	3
RE5	0.1283	1	0.1033	1	0.2880	1	0.1033	1
ET5	0.0728	3	0.0565	2	0.1304	2	0.0630	2
BE5	0.0054	4	0.0054	4	0.0011	4	0.0043	4

## CONCLUSION

The focus of the study remained the firm's failure risk determinants at 3 stages of FFPs. Based on analysis; study detected 3 theory-driven FFPs by applying bankruptcy probabilities from Altman's (2017) models. The study named 3 FFPs as short, medium and long FFP built on the failure risk occurrence over period. Furthermore, short-FFP is the most frequent out of three processes for that failure risk is unobservable until a year pre final declaration of bankruptcy. The firm's negative profitability is the largest contributor to failure risk in case of short-FFP in period t1. For medium-FFP, firm's annual and retained earnings are significant contributors of firm's failure risk depending on actual period before bankruptcy is viewed. Lastly, in case of long-FFP, firm's retained earnings are most significant contributor of firm's failure. Findings support the probabilistic bankruptcy prediction theory (Scott, 1981). Moreover, the study did not find any significant role of liquidity and leverage role in predicting the failure risk for three phases of FFPs. Study offers some practical implication based on bankruptcy forecast model. Firm's current year earning is most important contributor towards firm's bankruptcy. In case of three FFPs, firm's annual or accumulated profitability must be measured for predicting firm's bankruptcy.

These factors may arrest the future problems in firm's failure. Moreover, about 3 quarters of firms follow a sequence, where the application of the bankruptcy prediction models depends on availability of the last annual report. However, the results are generalizable to the listed manufacturing firms only. Hence, entire ratios of in Altman's (2017) model excluding leverage might be affected by that sectorial distinctiveness. Moreover, the study is based on the existing conceptual models (i.e. Scott, 1981; D'Aveni, 1989; Altman's, 2017). Though the study provides unique implication in respect of FFPs, yet there are some prospects that need to be considered in future. The study can be extended to reveal all diverse mathematical groupings and a few other financial domains, like firm output/capability to generate future cash flows. In addition, study relied on three theoretical FFPs; there is possibility of more diversified pathway. Study can be extended to measure presence pre-bankruptcy informal/court supervised restructuring. Further, scholar can extend by considering failure risk development for surviving and bankrupt firms.

## REFERENCES

- Altman, E., Iwanicz, M., Laitinen, K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-Score model. *Journal of International Financial Management & Accounting*, 28 (2), 131–171.
- Amankwah, A. J. (2016). An integrative process model of organizational failure. *Journal of Business Research*, 69 (9), 3388–3397
- Amankwah, J., & Wang, X. (2019). Business failures around the world: Emerging trends and new research agenda.
- Argenti, J. (1976). *Corporate collapse: The causes and symptoms*. New York, NY:
- Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71.
- D'Aveni, R. (1989). The aftermath of organizational decline: A longitudinal study of the strategic and managerial characteristics of declining firms. *Academy of Management Journal*, 32 (3), 577–605.
- Jardin, P. (2017). Dynamics of firm financial evolution and bankruptcy prediction. *Expert Systems with Applications*, 75, 25–43.
- Flores, R., & Garcia, I. (2017). Dynamic analysis of different business failure process. *Problems and Perspectives in Management*, 15(2-3), 486–499.
- Horváthová, J., & Mokrišová, M. (2018). Risk of bankruptcy, its determinants and models. *Risks*, 6 (4), 117.
- James, S. D. (2016). Strategic bankruptcy: A stakeholder management perspective. *Journal of Business Research*, 69 (2), 492–499.
- Jimeno, I., Merayo, M., & Blasco, M. (2017). The failure processes and their relation to the business interruption moment. *International Journal of Managerial and Financial Accounting*, 9 (1), 68–83.
- Kliestik, T., Valaskova, K., Lazaroiu, G., Kovacova, M., & Vrbka, J. (2020). Remaining Financially Healthy and Competitive: The Role of Financial Predictors. *Journal of Competitiveness*, 12(1), 74.
- Kristóf, T., & Virág, M. (2020). A Comprehensive Review of Corporate Bankruptcy Prediction in Hungary. *Journal of Risk and Financial Management*, 13 (2), 35.
- Kumar, D. (2019). Causal Linkages among Advanced Emerging European and Asian Economies. *Theoretical Economics Letters*, 9 (1), 139-154.
- Laitinen, E., & Lukason, O. (2014). Do firm failure processes differ across countries: Evidence from Finland and Estonia. *Journal of Business Economics and Management*, 15 (5), 810–832.
- Laitinen, E., Lukason, O., & Suvas, A. (2014). Are firm failure processes different? Evidence from seven countries. *Investment Management and Financial Innovations*, 11 (4), 212–222.
- Lukason, O. (2018). Age and size dependencies of firm failure processes: an analysis of bankrupted Estonian firms. *International Journal of Law and Management*.
- Lukason, O., & Miñano, M. (2019). Bankruptcy Risk, Its Financial Determinants and Reporting Delays: Do Managers Have Anything to Hide? *Risks*, 7 (3), 77.
- Lukason, O., & Laitinen, E. K. (2016). Failure processes of old manufacturing firms in different European countries. *Investment Management and Financial Innovations*, 13 (2), 310–321.

- Lukason, O., & Laitinen, E. K. (2019). Firm failure processes and components of failure risk: An analysis of European bankrupt firms. *Journal of Business Research*, 98, 380-390.
- Lukason, O., & Vissak, T. (2019). Internationalization and failure risk patterns. *Review of International Business and Strategy* (upcoming).
- Mann, M., & Byun, E. (2017). To retrench or invest? Turnaround strategies during a recessionary time. *Journal of Business Research*, 80, 24-34.
- Nummela, N., Saarenketo, S., & Loane, S. (2016). The dynamics of failure in international new ventures: A case study of Finnish and Irish software companies. *International Small Business Journal*.
- Ooghe, H., & Prijcker, S. (2008). Failure processes and causes of company bankruptcy: A typology. *Management Decision*, 46 (2), 223-242.
- Scott, J. (1981). The probability of bankruptcy: A comparison of empirical predictions and theoretical models. *Journal of Banking & Finance*, 5 (3), 317-344.
- Serrano, C., Nieto, B., & Valbuena, M. (2019). The use of accounting anomalies indicators to predict business failure. *European Management Journal*, 37 (3), 353-375.
- Sun, J., Li, H., Huang, H., & He, Y. (2014). Predicting financial distress and corporate failure: A review from state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems*, 57, 41-56.
- Thornhill, S., & Amit, R. (2003). Learning about failure: Bankruptcy, firm age and resource-based view. *Organization Science*, 14 (5), 497-509.
- Trahms, C. A., Ndofor, H. A., & Sirmon, D. G. (2013). Organizational decline and turnaround. *Journal of Management*, 39 (5), 1277-1307.
- Zorn, M., Norman, M., Butler, C., & Bhussar, S. (2017). Cure or curse: Does downsizing increase the likelihood of bankruptcy? *Journal of Business Research*, 76, 24-33.