THE CORRELATION IN CORPORATE DEFAULTS: EVIDENCE FROM NON-FINANCIAL LISTED COMPANIES IN SRI LANKA

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ABSTRACT

Default correlation is the extent to which one company's default causes another's default. It measures the relationship between a firm's individual default probability and the joint default probability among firms. This study makes theoretical contributions by examining the degree of default correlation among non-financial listed firms in terms of credit quality, time horizon, systematic risk, firm size, and liquidity. The researcher selected 550 firm-year observations (240 for default and 310 for non-default) consisting of 55 non-financial listed companies in Sri Lanka from 2012 to 2021. The default firms are selected using the three criteria during the selection period: suffering from losses, having negative net worth, or suffering from negative operating cash flows for more than three consecutive years. The non-default firms are selected by a couple with the default firms based on the same industry and the highest market capitalization. Altman's (1968) Z-score model is used to determine the credit ratings as high, medium, and low. The study follows Lucas's (1995) proposed standard binomial approach to measure the default correlation. The study revealed that time horizon, poor credit ratings, high beta, and small size increase the default correlation in the Sri Lankan context; however, liquidity is not a good measurement for default correlation analysis in Sri Lankan context. Credit risk management could underestimate the portfolio credit risk without considering the default correlation. The dynamic nature of default correlation shows that an increment in default risk of individual credit assets engages with a disproportionate increment in portfolio credit assets.

Keywords: ***Bankruptcy Prediction, Credit Quality, Credit Risk Management, Default Correlation***

1. INTRODUCTION

The banking industry has paid attention to credit risk management over the past three decades. This situation drastically impacted the banking and financial sectors worldwide, and various changes happened in different economic conditions. The credit risk of a bank can be categorized into default risk and concentration risk (Fernando, Li & Hou, 2020). Default risk is the risk the lender will face due to failure to make complete and timely payment of the principal and interest by the borrower, according to their debt security agreement. Credit concentration risk occurs when a significant amount of loans is subjected to the specific economic sector or business group whose performance has decreased, with the potential of producing losses large enough to impact the entire bank's health. Therefore, estimating individual and

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corporate customers' default probability is crucial in credit risk management. Similarly, recognizing the default correlation significantly contributes to managing a bank’s credit concentration risk.

Default correlation is the extent to which one company's default causes another's default (Fernando et al., 2020). It measures the relationship between a firm’s individual default probability and the joint default probability among firms. Default correlation arises due to the fact that the success of each individual company depends on the health of their specific industry or the state of the general economy; Therefore, to a certain extent, all the companies suffer or prosper together (Lucas, 1995).

Before the default correlation analysis, default prediction analysis evolved from the 1930s, for example, Altman in 1968. Studies on the default correlation came into the discussion with the financial crisis of 2007 and 2008. Das et al. (2007) describe three reasons for default clustering: contagious effect, cyclical correlation, and learning from default. A comparable pattern of associated risk factors among enterprises gives rise to cyclical correlation. Interest rates, inflation, GDP, business cycle, and stock market performance are typical economic indicators (Li & Chen, 2018). According to Duffie (1998), the overall default rates are associated with changes in general interest rates. In addition, Duffie et al. (2007) discover that variations in default probabilities are similarly influenced by changes in personal income growth and term structure levels. De Servigny and Renault (2002) state that recessionary periods are likelier than non-recessionary ones to see a joint default. Due to their susceptibility to broader economic conditions, businesses are significantly negatively impacted during a recession or financial crisis. Li and Chen (2018) suggest that firms with a low beta, which represents a systematic risk, have a high default correlation.

According to the contagion effect, when one company defaults, it inevitably causes another company to do the same. For instance, a subsidiary business's default causes its parent company to default. As a result, buyer-supplier relationships between tightly related businesses are where clustering default phenomena are typically found. The early research on the contagion effect primarily focuses on stock market information (Lang & Stulz, 1992). The contagion effect is attributed in later studies to elements connected to the sector. They find a positive correlation among credit derivatives because of the contagion effect and a negative correlation because of competitiveness (Jorion & Zhang, 2007). They believe that companies with similar cash flows cause the contagion effect. As a result, they use equity, industry concentration, and leverage to assess the correlation between bankrupt firms and their competitors.

Learning from defaults is the third reason for the default correlation. For instance, the failures of Worldcom and Enron highlight the significance of regulatory reforms to business irregularities that have impacted the surviving companies (Das et al., 2007). Learning from others indicates that the cause of one company's default may also exist in other companies; hence, identifying or disclosing such causes may be advantageous to the various stakeholders of other organizations.

Besides that, a recent study by Li and Chen (2018) found that poor credit ratings, high beta, illiquidity, and small size could disproportionately increase the degree of default correlation during a recession. They use Lucas's (1995) method to estimate default correlation by choosing realized historical default data from the U.S. market from 1992 to 2013.

Recently, Fernando et al. (2019) systematically investigated the impact of corporate governance on the correlation in corporate defaults. They also used to realize historical default data in the U.S. between 2000 and 2015 to test the default correlation using Lucas's (1995) method. Their empirical results found that firms with concentrated ownership, low board effectiveness, low financial transparency and disclosures, and higher shareholder rights have a higher default correlation. Fernando et al. (2019) extended the reasons proposed by Das et al. (2007), founding that corporate governance practices of firms significantly affect the clustered default risk among firms.

When considering the Sri Lankan context, some studies have been conducted about corporate default prediction. Fernando et al. (2019) have reported a comparative study about the effectiveness of corporate governance variables such as ownership structure, shareholder rights, financial transparency, and board effectiveness in default prediction between an emerging market (Sri Lanka) and a mature market (USA) using the 730 Sri Lankan and 3280 USA firm-year observations from 2000 to 2015. Lakshan and Wijekoon (2012) investigated the influence of corporate governance characteristics on the corporate failure of listed companies in Sri Lanka using a sample of 70 default companies and 70 non-default companies listed on the Colombo Stock Exchange (CSE) from 2002 to 2008. Samarakoon and Hasan (2003) have investigated the ability of three versions of Altman's Z-Score distress prediction model to predict corporate distress in the emerging market of Sri Lanka. They conclude that the model has a remarkable degree of accuracy in predicting corporate distress using financial ratios, even in smaller emerging markets. Gunathilaka (2014) investigated the discriminant power of the Sri Lankan Companies' solvency test in identifying firms' insolvency and whether the Z-score models of Altman and Springate appropriately predict financial distress in Sri Lanka.

Thus, based on the literature review, no studies were found to study the correlation among credit defaults of companies in Sri Lanka. Past studies of default correlation only investigated in the USA context (Li & Chen. 2018; Fernando et al., 2019). Therefore, based on those studies, this study contributes to the extant literature by investigating the correlation effect of credit default in the Sri Lankan context. The rest of the paper is organized into four sections. Section 2 reviews the literature relating to default correlation. Section 3 describes the research methodology. Section 4 discusses the results and findings, and Section 5 summarises and concludes the paper.

2. LITERATURE REVIEW

2.1. Credit Default Theory

Credit default theory is explained the financial failure of a firm. This theory represents a systematic understanding of the causes that directly lead to the effects associated with loan defaults (Sy, 2007). This theory provides direct causal links between the macroeconomic causes of the changing economic environment and their microeconomic effects on changing personal or corporate financial conditions, leading to possible loan defaults (Sy, 2007).

2.2. Factors Affecting Default Correlation

As Das et al. (2007) proposed, three main broader areas create default correlation: Cyclical correlation, contagious mechanism, and learning from default. According to cyclical correlation, firms depend on economic factors, for example, interest rates, GDP, and stock return. Cyclical correlation implies that firms will default as clusters if co-movements in common factors such as GDP led to correlated changes in conditional default probabilities (Chava & Jarrow, 2004). Contagious mechanisms explain that one firm default can increase the probability of another firm default. At the first stage of the contagion, an immediate market effect is reflected, leading to broader credit spreads of other obligors. In the second stage, stronger interactions reflect defaults with other bonds (Schonbucher, 2003). Jorion and Zhang (2007) explain the contagion effects with industry characteristics. The last one is learning from default. If other companies' default, this information provides valuable information to assess their companies' default probabilities (Giesecke, 2004).

Li and Chen (2018) studied the default correlation using realized default data based on the USA. They used Luca's method (1995) to estimate default correlation and Altman's (1968) Z-score model to measure the firm's credit quality. Their results were helpful in the implications of credit risk measurement and management. By considering the findings, the researcher has concluded that default correlation increases with time horizon, high beta, low credit quality, small size, and illiquidity.

Fernando et al. (2019) have done a study on corporate governance and correlation in corporate defaults. This study is based on default data from 2000 to 2015 in the United States by using independent variables such as ownership, board effectiveness, financial transparency and disclosures, and shareholder rights while using degree of default correlation as a dependent variable. The researcher used Lucas's (1995) method to estimate default correlation. Their study found that concentrated ownership in ineffective boards, low financial transparency, and strong shareholder rights are associated with high default correlation. The following sections review the literature on the areas of credit quality,

2.3. Default Correlation Measurements

Different methods can be used to measure default correlation. Merton (1974) introduced a method named structural models which is based on asset correlations. Duffie and Singleton (1999) and Jarrow et al. (1997) introduced reduced-form models that focused on the default intensity dynamics. This approach has been expanded by

Davis and Lo (2001) and Jarrow and Yu (2001). They have expanded the model by accounting for default contagion and default clustering. The hybrid approach was developed by Kunisch and Uhrig-Homburg (2008) using the Poisson process with Merton-type conditions, while the copula framework has developed by Li (2000) and Giesecke (2003).

According to the structural model approach, when a company's assets are less than its debt, it is considered a default. However, there are assumptions to constrain the approach. The default can only occur at the bond's maturity, the debt's value is stable, and stock prices are normally distributed. However, firms could default before their asset value falls below their debt because their equity value has zero floors (Li & Chen, 2018).

Jorion and Zhang (2007) and Pianeti and Giacometti (2011) show an alternative measurement of default correlation using credit default swap (CDS) or bond spread data. However, Li and Chen (2018) argue that the CDSs and bond spread Data-based approach could only capture one side of the credit risk: credit loss due to downgrades but not the credit loss due to default. The approaches mentioned above do not based on realized default events; the standard binomial approach proposed by Lucas (1995) could measure default correlations based on actual default data. Moreover, this method is known as model-free estimation (Li & Chen, 2018).

2.4. Empirical Studies on Default Prediction in Sri Lankan Context

Lakshan and Wijekoon (2012) have studied corporate governance and corporate failure to examine the influence of corporate governance characteristics on the corporate failure of listed companies in Sri Lanka. According to the study, corporate governance is proxied by using board size, CEO duality, outside directors, outsiders' ownership, audit opinion, presence of an audit committee, and remuneration of board members. Researchers concluded that a negative relationship exists between corporate failure and outside director ratio, an audit committee's presence, and board members' remuneration. There is a positive relationship between corporate failure and CEO duality, and there is no relationship between corporate failure and Board size, auditor's opinion, and outside ownership.

Fernando et al. (2019) studied financial versus non-financial information for default prediction evidence from Sri Lanka and the USA. This study used data from the USA and Sri Lanka based on ownership structure and influence, shareholder rights and relations, financial transparency, board structure, and effectiveness. After analyzing all the collected data, the researcher concluded that corporate governance information is helpful in default prediction in both Sri Lanka and the United States.

Gunathilaka (2014) studied financial distress prediction using Alman Z-Score Models in Sri Lankan context. This study has been done based on default data from 2008 to 2012 in public companies in Sri Lanka, listed on Colombo Stock Exchange, using five sectors: manufacturing, food and beverage, hotels, service, diversified, health, chemical, and property. After analyzing all the collected data, the researcher concluded that Altman's Z-score model shows a higher degree of accuracy in predicting financial distress and insolvency under the solvency test, which does not mean that the firms cannot meet the capital maintenance. Finally, the study suggests that employing the Z-score model and the solvency test might produce better inputs for decisions while statutory compliance is respected. The extant literature on default prediction has been limited to individual default probabilities, and no studies in the Sri Lankan context have tested the default correlation or the portfolio credit risk management.

2.5. Hypotheses Development

According to previous studies and based on the above conceptual framework, the following hypotheses are developed to examine the degree of default correlation among firms regarding credit quality, time horizon, systematic risk, firm size, and liquidity.

Li and Chen (2018) argued that default correlations are asymmetric across firms of different credit quality. The low-credit quality firms are more vulnerable to unfavorable economic conditions because their ability to repay debt is lower. However, with higher credit quality, the ability to repay the debt is higher, making them less vulnerable to unfavorable economic conditions (Crouhy, Galai & Mark 2000). Das et al. (2007) show that default correlation in a high-default regime is higher than in a law default regime. Gersbach and Lipponer (2003) and Zhou (2001) also argue that default correlation among firms with poor credit ratings is higher than those with high credit ratings. Accordingly, the first hypothesis of the study is,

H_1: *Firms with poor (good) credit quality are associated with high (low) default correlation.*

The probability of the default correlation usually is low over the short time horizon due to the relatively infrequent nature of the default event (Li & Chen, 2018). In contrast to the longer time horizon, it can experience more default events, and the likelihood of default correlation is higher. Moreover, the longer the time horizon, the more business cycles are triggered by the cyclical correlation (Lucas, 1995), which is one of the main reasons for default correlation. Based on that, the study developed the second hypothesis of the study as,

H_2: *Short (long) time horizons are associated with low (high) default correlations.*

Third, Systematic risk, also known as market risk, is the risk the firms cannot avoid. It affected a large number of firms, and changes can inspire it in GDP, interest rates, inflation, and other macroeconomic factors. The study measures the systematic risk by the beta coefficient of the firms. Firms with high beta are generally more sensitive to the market movements of the general economy. In contrast, firms with a low beta are less sensitive to market movements. Therefore, the high-beta firms more strongly react to the cyclical changes of the economy, so during the recession period, they have a higher default correlation than those with low-beta. This result is in line with the studies done by Li and Chen (2018), Crouhy, Galai, and Mark (2000), and Gersbach and Lipponer (2003). Based on that, this study developed the third hypothesis as follows,

H_3: *Firms with a low (high) beta are associated with low (high) default correlations.*

According to Wu (2007), the market is less efficient for stocks held by small firms due to the difficulty of borrowing stocks for short-selling purposes. As Li and Chen (2018) suggested, individual investors generally hold small firms' stocks. Hence, purchasing stocks for short-selling purposes is more challenging, and market inefficiency occurs. On the other hand, large firms' stocks are generally held by institutions in large quantities; therefore, it is easier to purchase stocks for short-selling purposes. They also argue that possible mispricing due to market inefficiencies could enhance the contagion effect and learn from default-on-default correlation. Based on that, this study developed the fourth hypothesis as follows,

***H*$_4$*:* *Small (large) firms are associated with high (low) default correlations.*

Finally, the firms' liquidity is measured by the annual trading volumes of the stocks. Higher trading volume means the stocks have efficient market pricing. On the other hand, if a market is inefficient due to the mispricing of the stocks, it indicates lower trading volumes. The extant literature has heavily tested the relationship between liquidity and market efficiency. According to Roll, Schwartz, and Subrahmanyam (2007), Boehmer and Kelley (2009), Chordia, Roll, and Subrahmanyam (2011) Chordia, Subrahmanyam, and Tong (2014), increase in liquidity and trading activity are associated with the more significant market efficiency. Li and Chen (2018) also argued that in an inefficient market pricing, the impact of contagion and learning from default-on-default correlations would be magnified. Based on that, this study developed a fifth hypothesis as follows,

***H*$_5$*:* *Illiquid (liquid) firms are associated with high (low) default correlations.*

3. RESEARCH METHODOLOGY

3.1. Population, Sample, and Data

The study population comprises all the companies listed in the Colombo Stock Exchange (CSE). According to the CSE database, there are 295 listed companies representing 20 GICS industry groups as of 30th June 2022.

The sample of this study consists of both Default and Non-Default firms. The study uses four industry sectors that have been negatively affected by the Covid-19 outbreak and Easter attack in the period of 2019, 2020, and 2021 to select the sample. Capital goods, consumer services, food and staples retailing, and consumer durables and apparel. When compared with non-financial firms, financial firms belonging to Banking, Finance, and Insurance sectors were excluded from the sample due to different capital structure and operating activities.

Since measuring default firms is a difficult task due to its infrequent nature, the study follows the three criteria proposed by Parker, Peters, and Turetsky (2002), Gilson (1989), and Ross et al. (2011) to recognize the default events. That is, if a company, during the selection period, suffers from losses, has a negative net worth, or suffers from negative operating cash flows for more than three consecutive years considered a default firm (Fernando et al., 2019)

In order to reduce bias in the results caused by having a relatively small number of default firms, it is required to control the number of non-default firms due to the infrequent nature of default events. Hence, the researcher couples the default firms with non-default firms by matching the basis of the same industry and the highest market value of equity. A default firm of capital goods and consumer durables & apparel industry sectors couple with the two non-default firms using those criteria but a defaulting firm of consumer services and food and staples retailing industry sectors couple with only one non-default firm due to the unavailability of non-default firms to select two firms for a default firm. The sample period of the study spans from 2012 to 2021. Accordingly, the study's final sample consists of 550 firm-year observations (240 for default firms and 310 for non-default firms) consisting of 55 non-financial listed companies from the selected four industry sectors from 2012 to 2021.

All the data used for this study is quantitative and collected from secondary sources. To calculate the credit quality of each firm and define the firm size, the researcher collects financial information from the annual reports of each company and the CSE database. Then the study identifies time horizons as one-year and five-year based on the literature (Li & Chen, 2018). The study collects data from the CSE database to identify the firms' beta coefficient and liquidity.

3.2. Operationalization

Table 1: Operationalization

Variable	Measurement Method	Evidence
Default Correlation	Lucas's (1995) Method: $Corr(A,B) = \frac{P(A,B) - P(A) \times P(B)}{\sqrt{P(A) \times [1 - P(A)]} \times \sqrt{P(B) \times [1 - P(B)]}}$	Lucas, (1995); Li & Chen, (2018); Fernando et al, (2019).
Credit Quality	Altman's (1968) Z-score model: $\zeta = 1.2\left(\frac{WC}{TA}\right) + 1.4\left(\frac{RE}{TA}\right) + 3.3\left(\frac{EBIT}{TA}\right) + 0.6\left(\frac{MVE}{TL}\right) + 1.0\left(\frac{SALES}{TA}\right)$	Li & Chen, (2018); Fernando et al, (2019); Samarakoon & Hasan, (2003); Gunathilaka, (2014).
Time Horizon	One Year, Five Year, Ten Year	Li & Chen, (2018); Fernando et al, (2019).
Systematic Risk	Beta Coefficient	Li & Chen, (2018).
Firm Size	Book value of assets	Li & Chen, (2018).
Liquidity	Annual trading volume of stocks	Li & Chen, (2018).

3.3. Formation of Research Design for Testing Default Correlation

To measure default correlation among firms, as a first step, different credit qualities of companies need to be recognized. The steps are applied to find the default correlation among the firms.

1. Following past studies, the study employs Altman's (1968) Z-score model to measure a firm's credit quality (Li & Chen. 2018; Fernando et al., 2019). The

study chose Altman's Z-score model. Sales to total assets, working capital to total assets, earnings before interest and tax to total assets, retained earnings to total assets, and market value of total assets to book value of total liabilities are used with the weights in the original Altman's model to determine the Z-score values.

Altman's (1968) Z-score model:

$$\zeta = 1.2\left(\frac{WC}{TA}\right) + 1.4\left(\frac{RE}{TA}\right) + 3.3\left(\frac{EBIT}{TA}\right) + 0.6\left(\frac{MVE}{TL}\right) + 1.0\left(\frac{SALES}{TA}\right)$$

Moreover, according to the literature, high credit ratings generally imply by a high Z-score value (Gunathilake, 2014; Samarakoon & Hasan. 2003). According to the original cut-off points given in Altman's model, a Z-score value above 2.99 indicates a non-bankrupt firm, whereas Z-score values below 1.81 indicate a bankrupt firm. The range between 1.81 and 2.99 is called the gray area regarding bankruptcy. Using the same criteria, this study also defined three credit ranges after calculating the Z-score values: high grade (Z-score ≥ 2.99), medium grade (2.99> Z-score ≥ 1.81), and Low grade (1.81 > Z-score).

2. Using the different credit qualities measured from Altman's Z-score model, the default correlations across the firms with different credit qualities addressed in Section 3.4 (H1) can be examined.
3. To find the default correlations across the firms over short and long-time horizons, estimate the default correlations over one year and cumulative default correlations over five-year period and conduct the comparative analysis between the two-time horizons.
4. To find out the default correlation of firms with the high versus low systematic risk addressed in hypothesis 3. The study collects the beta coefficient of all the firms and then uses the average of all the beta coefficients to divide the sample into two subgroups: high-beta firms and low-beta firms. The default correlations are then estimated separately for each subgroup with different credit qualities and conduct a comparative analysis between the two subgroups.
5. Finally, to test the default correlation of firms with the large versus small firms and the liquid versus illiquid firms addressed in hypotheses four and five. The study used the book value of assets and annual trading volume of stocks to divide the sample into two subgroups, large and small firms; and liquid and illiquid firms. Then the default correlations are estimated separately for each pair of subgroups, and a comparative analysis between them is conducted.

3.4. Method of Estimating Default Correlation

In order to estimate default correlation, the study uses a method proposed by Lucas (1995). To describe how it works, assume that there are two companies: a high-rating company (A) and a low-rating (B). Then the default correlation between A and B can be computed as follows.

$$Corr(A,B) = \frac{P(A,B) - P(A) \times P(B)}{\sqrt{P(A) \times [1 - P(A)]} \times \sqrt{P(B) \times [1 - P(B)]}} \rightarrow \quad (1)$$

Where *P(A)* and *P(B)* represent the default probabilities of A and B-companies separately, *P(A, B)* represents the joint default probability of both A-rated and B-rated companies.

To estimate the individual and joint probability of default, Lucas (1995) suggested a standard binomial approach based on the historical default data. According to that method, we develop our estimation process as follows. First, we define A_i (t) = 1 if A-rated firm *i* default at time t; otherwise, 0. B_i (t) = 1 if B-rated firm *i* default at time t, otherwise 0. Then we identify N_A and N_B as the number of A-rated and B-rated firms, respectively in a year. Therefore, $N_{A,1}$ and $N_{A,0}$ represent the A- rated default firms and non-default firm, respectively. Accordingly, $N_{B,1}$ and $N_{B,0}$ represent the B-rated default firms and non-default firms, respectively. The total A-rated group consists of both default and non-default companies. So, $N_{A,1} + N_{A,0} = N_A$. Similarly, for the B-rated group, $N_{B,1} + N_{B,0} = N_B$.

As well as the number of all possible pairs of A-rated and B-rated companies could be calculated as $N_A \times N_B$. In the same way, the number of all possible pairs of A-rated and B-rated defaulting companies could be computed as $N_{A,1} \times N_{B,1}$. Therefore, the following equation could be used to present the joint default probability:

$$P(A,B) = \frac{N_{A,1} \times N_{B,1}}{N_A \times N_B} \rightarrow \quad (2)$$

The individual default probabilities for A-rated and B-rated companies can be calculated using the same principle, respectively, as follows:

$$P(A) = \frac{\frac{N_{A,1}(N_{A,1}-1)}{2}}{\frac{N_A(N_A-1)}{2}} \rightarrow \quad (3)$$

$$P(B) = \frac{N_{B,1}(N_{B,1}-1)/2}{N_B(N_B-1)/2} \rightarrow \quad (4)$$

4. FINDINGS AND DISCUSSION

4.1. Descriptive Statistics

The descriptive statistics and correlation coefficients of Z-score components are given in Table 2. Panel A of table 2 presents comparative analysis between default and non-default firms. The mean values of all the Z-score component variables of non-default firms are higher than the default firms, except for the sales to total assets (SALES/TA), indicating that default firms have lower value of working capital, retained earnings, earnings before interest and taxes, and market value of equity than the non-default firms. However, when it comes to sales revenue, default firms have higher mean values than the non-default firms. The standard deviations of the variables of default firms have higher values than the non-default firms, except for the market value of equity to total liabilities (MVE/TL). This indicates that data of the variables of default firms are more spread out from the mean value than the non-default firms' data except for the MVE/TL. The MVE of non-default firms has higher dispersion of data than the default firms. The t-values and p-values show that t-test of equal means of all these variables between default firms and non-default firms are insignificant at the 5% level.

The panel B of Table 2 presents the correlation coefficient of each pair of Z-score component variables. WC/TA (working capital over total assets) and RE/TA (retained earnings over total assets) are highly correlated positively, In contrast, SALES/TA (sales over total assets) and WC/TA, and SALES/TA and RE/TA are highly correlated with a negative coefficient. In other pairs of variables, high correlation coefficient is not observed.

Table 2: Descriptive statistics

Panel A: Descriptive Statistics

	Default Firms (N = 240)		**Non-Default firms (N = 310)**		**Test of equal means**	
Variable	**Mean**	**S.D**	**Mean**	**S.D**	**t-Value**	**p-Value**
WC/TA	-2.396	23.105	0.094	0.183	1.8981	0.058
RE/TA	-19.75	205.34	0.216	0.276	1.712	0.088
EBIT/TA	-1.98	29.762	0.069	0.077	1.2126	0.226
MVE/TL	22.165	183.84	87.516	502.39	1.9179	0.056
SALES/TA	0.398	2.063	0.274	0.395	-1.033	0.302

Panel B: Correlation matrix

Variable	**WC/TA**	**RE/TA**	**EBIT/TA**	**MVE/TL**	**SALES/TA**
WC/TA	1.0000				
RE/TA	0.9945	1.0000			
EBIT/TA	0.3188	0.2439	1.0000		
MVE/TL	0.0099	0.0086	0.0063	1.0000	
SALES/TA	-0.8308	-0.8768	0.0008	-0.0320	1.0000

4.2. Effect of Credit Quality and Time Horizon

Using the Z-score as mentioned above component variables and calculating Altman's Z-score values, the study divides the sample into three credit qualities: high grade, medium grade, and low grade, respectively. According to the literature, a high Z-score value generally indicate high credit ratings (e.g., Li & Chen, 2018; Gunathilaka, 2014). The study uses those three credit qualities to examine the default correlations across the firms with different credit qualities addressed in H1. Panel A of Table 3, which presents the default correlation matrix based on a one-year time horizon, does not give a supportive result for the H1. However, the results of panel B of Table 3, which shows the default correlation matrix based on the five-year time horizon, give more supportive information for the H1. It clearly shows that default correlations are small and less significant in high credit qualities than the low credit qualities. When it goes to the right-hand side of the matrix, low-credit quality firms have a higher default correlation, which is more significant than the high-grade firms. These results are consistent with the previous findings regarding the relationship between default correlations and different credit qualities.

By doing the comparative analysis between panel A and panel B of Table 3 the study can examine the default correlations among firms over short and long-time horizons addressed in H2. It clearly shows that one-year default correlations are small and not significant. However, five-year default correlations are higher and more significant than one-year ones. These results are consistent with the H2 and the previous findings suggested by Li and Chen (2018).

Table 3: Default correlations of various credit qualities over short and long-time horizon

	High Grade	Medium Grade	Low Grade
Panel A: One-year default correlation			
	High Grade	**Medium Grade**	**Low Grade**
High Grade	1.59% (0.88)		
Medium Grade	2.14% (1.07)	-0.08% (-0.02)	
Low Grade	2.28% (1.51)	0.05% (0.02)	-2.74% (-1.35)
Panel B: Five-year default correlation			
	High Grade	**Medium Grade**	**Low Grade**
High Grade	17.32% (36.41)**		
Medium Grade	21.50% (42.23)**	26.22% (24.05)**	
Low Grade	26.42% (69.48)**	34.76% (62.43)**	48.67% (88.93)**

The t-statistics are in parentheses, and ** and * indicate significance at 1% and 5% levels, respectively.

4.3. Effect of Systematic Risk

To examine the degree of default correlation across the firms in terms of systematic risk addressed in H3, the study divides sample firms into two subgroups: firms with low beta versus those with high beta. The beta coefficients are sorted into two groups using the mean value of all the beta coefficients. Panel A of Table 4 presents the default correlation matrix for low-beta firms, and panel B present the default correlation matrix for high-beta firms. Using the comparison of these two panels, the study can identify high-beta firms are generally associated with higher default correlations than the low-beta firms. For example, the medium grade of low-beta firms has a default correlation of 5.23%, while high-beta firms have 27.86% of default correlation. These findings are consistent with the H3.

Table 4: Default correlations of high versus low beta firms

	High Grade	Medium Grade	Low Grade
High Grade	1.66% (0.53)		
Medium Grade	3.23% (0.96)	5.23% (0.71)	
Low Grade	-1.45% (-0.52)	-4.23% (-1.02)	-11.05% (2.66) **
Panel B: High-beta firms			
	High Grade	**Medium Grade**	**Low Grade**
High Grade	1.89% (0.47)		
Medium Grade	12.93% (2.98) **	27.86% (3.08) **	
Low Grade	3.08% (0.95)	2.05% (0.45)	-7.34% (-1.85)

The t-statistics are in parentheses, and ** and * indicate significance at 1% and 5% levels, respectively.

4.4. Effect of Firm Size

To examine the impact of firm size on the degree of default correlation addressed in H4, the study first divides the sample into two subgroups: large firms and small firms, using the market value of equity. Panel A of Table 5 presents the default correlation matrix based on the large firms, and the default correlation for small firms is shown in panel B. According to the results shown in this table, large firms' default correlations are insignificant. In the small firms shown in panel B, high grade, medium grade pairs only have significant results. Therefore, when considering the significant results, small firms have a significant default correlation than large firms. So, these results are also in line with the H4 because small firms have a significant default correlation while large firms' results are insignificant.

Table 5: Default correlations of large versus small firms

	Panel A: Large firms		
	High Grade	**Medium Grade**	**Low Grade**
High Grade	-9.85% (-1.90)		
Medium Grade	-7.18% (-1.09)	-28.21% (-1.35)	
Low Grade	-4.95% (-0.55)	-9.86% (-0.46)	-3.45% (-0.12)
	Panel B: Small firms		
	High Grade	**Medium Grade**	**Low Grade**
High Grade	3.20% (1.13)		
Medium Grade	6.44% (2.21)*	4.64% (0.79)	
Low Grade	1.29% (0.63)	2.40% (0.90)	-4.23% (-1.91)

The t-statistics are in parentheses, and ** and * indicate significance at 1% and 5% levels, respectively.

4.5. Effect of Liquidity

Finally, the study divides its sample into two subgroups using the annual stock trading volume with firms with high versus low trading volume to examine the degree of default correlation among firms regarding liquidity address in H5. Panel A of Table 6 shows the default correlation matrix based on the liquid firms and the default correlation matrix based on illiquid firms listed in panel B.

Table 6: Default correlations of liquid versus illiquid firms

	Panel A: Liquid firms		
	High Grade	**Medium Grade**	**Low Grade**
High Grade	13.75% (1.76)		
Medium Grade	7.25% (0.80)	13.42% (0.50)	
Low Grade	-0.88% (-0.16)	14.71% (1.54)	-73.81% (-12.35)**
	Panel B: Illiquid firms		
	High Grade	**Medium Grade**	**Low Grade**
High Grade	-1.43% (-0.62)		
Medium Grade	0.72% (0.29)	-2.68% (-0.52)	
Low Grade	1.07% (0.51)	-0.39% (-0.14)	16.11% (5.55)**

The t-statistics are in parentheses, and ** and * indicate significance at 1% and 5% levels, respectively.

According to this table, high grade and medium grade default correlation values are insignificant. Due to that, the study can only consider the default correlation between low-grade firms. Those are significant at the 1% level. It shows that liquid firms have a higher negative default correlation (-73.81%) than the illiquid firms (16.11%). Therefore, these results are not supported by the H5 that Illiquid (liquid) firms are associated with high (low) default correlations.

4.6. Discussion

The findings of this study are also more in line with the previous researcher's findings (Li & Chen, 2018) and the empirical results suggest several useful implications for portfolio credit risk management and measurement. First, as shown in Table 3, high credit quality firms and short time horizons have relatively small default correlation. Therefore, banks should design credit portfolios with these characteristics to reduce default risk. Lenders can add those kinds of firms to their loan portfolio for the reduction of default risk of their overall credit asset portfolio. However, there is a high default correlation in firms with low credit quality and long-time horizon (5 years). The higher the loan period, the correlation of defaults is also higher. The result is consistent with the findings of Li and Chen (2018). With those firms, the risk reduction in credit portfolio is less effective due to highly correlated default events associated with them. This dynamic nature of default correlation shows that increment in default risk of individual credit assets is engaging with a disproportionate increment in portfolio credit assets. Therefore, results implied that if the default probability of each loan doubles, then joint default probability will more than double. Thus, these results indicate that active credit risk management is essential for banks. To minimize the risk of credit loss due to default clustering, banks must adjust their capital requirement accordingly.

According to Tables 4 and 5, the banks also need to consider the firm size and systematic risk for providing loans to corporates. If banks or financers add more small firms and high beta firms to their credit asset portfolio, the default risk of those firms is higher. To reduce the risk level of the credit portfolio, they need to analyze those firms and add larger and lower beta to their credit asset portfolio than the small and high beta firms. Moreover, risky loan portfolios such as small and high beta firms can earn more returns by increasing the loan rate. This study shows liquidity is not a good measurement for default correlation analysis in Sri Lankan context. There are no significant values in the correlation matrix (table 6). However, previous studies relevant to the USA context prove that liquidity is also a good measurement for credit risk analysis (e.g., Li & Chen, 2018).

5. CONCLUSION

This study addresses the impact of various credit qualities, time horizons, firm size, systematic risk, and firms' liquidity on the degree of default correlation. Default correlation is the extent to which one company's default causes another's default. It measures the relationship between a firm's individual default probability and the joint default probability among firms. This study contributes to the literature by extending the same study related to the Sri Lankan context. The study employs Lucas's (1995) method for testing default correlation using the historical data of default events rather than using a structural model of default correlation based on asset correlation or CDSs, and bond spread data.

The study employed 550 firm-year observations for the sample consisting of 240 default and 310 non-default firm-year observations from 2012 to 2021 for the analysis. The sample comprises four industry sectors: capital goods, consumer services, food, and staples retailing, and consumer durables and apparel. The study's objective is to examine the degree of default correlation among firms in terms of credit quality, time horizon, systematic risk, firm size, and liquidity. To measure the credit qualities of the study, employ Altman's (1968) Z-score model and weights of the original Altman's model used to determine the Z-score values. According to the original cut-off points given in Altman's model, this study also defined three credit ranges after calculating the Z-score values: high grade (Z-score ≥ 2.99), medium grade (2.99> Z-score ≥ 1.81), and Low grade (1.81 > Z-score). Regarding the time horizon, the study uses two-time horizons as one-year and five-year. To examine the degree of default correlation among firms in terms of systematic risk, the sample was divided into two subgroups: high and low beta firms. The market value of equity is used to divide the sample into small and large firms. Annual stock trading volumes are used to divide the sample into liquid firms and illiquid firms. Then the default correlations of each pair of credit qualities are calculated for each subcategory using Lucas's (1995) method and comparative analysis using the results.

The study found that the degree of default correlations is higher the firms with poor credit quality, long time horizon, small firms, and high beta are more supportive of the hypothesis developed and the previous findings.

The study analysis gives more supportive results to the hypotheses developed in section 2.5, except for the H5 that Illiquid (liquid) firms are associated with high (low) default correlations. As presented in the findings, first, the study found that firms with poor credit quality are associated with high default correlation, and firms with good credit quality are associated with low default correlation. Second, the study found that short-time horizons are associated with low and insignificant default correlation, while long time horizons are associated with high and very significant default correlation. Third, the firms with high beta are associated with high default correlation, and firms with low beta are associated with low default correlation. Fourth, small firms are associated with high default correlation and conversely, large firms are associated with low default correlation. Finally, the study found that liquidity is not a good measurement for default correlation analysis in Sri Lankan context due to insignificant results. With these results the study can conclude that the degree of default correlation could increase disproportionally for firms with poor credit quality, long time horizon, small size, and high beta.

The banks generally hold a portfolio of credit assets to reduce the risk level of individual credit facilities alone. However, they have to consider the joint default probabilities of each pair of credit assets. Therefore, default correlation is crucial in credit risk management. This study does not consider financial firms and private companies.

Lucas's (1995) method for default correlation estimation, which this study adopted to estimate default correlation; however, there are different ways of measuring the default correlation. It might be interesting to see which method is more suitable because each method has its advantages and disadvantages. Due to the time constraint, this study uses only four industry sectors when selecting the sample. The result might be more accurate if future researchers could use all the non-financial industry sectors for the sample selection. This study uses Altman's (1968) Z-score model for credit rating, beta coefficient for systematic risk, market value of equity to determine firm size, and annual stock trading volume to determine liquidity. Future researchers could consider alternative measurements for those measurements.

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