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default, cash flow, captial structure, short-term debt

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Default probability for the Jordanian Companies: A Test of Cash Flow Theory

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Abstract
This paper aims to investigate the effect of cash flow and free cash flow on corporate failure in the emerging market in particular Jordan using two samples; matched sample and a cross-sectional time-series (panel data) sample representative of 167 Jordanian companies in 1989-2003. LOGIT models are used to outline the relationship between firms' financial health and the probability of default. Our results show that there is firm's free cash flow increases corporate failure. The result also shows that the firm's cash flow decreases corporate failure. Firms' capital structures are fundamental in predicting default. Capital structure is seen as the main factor affecting the probability of default as it affects a firm's ability to access external sources of funds. Jordanian firms depend on short-term debt for both short and long term financing

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1. Introduction

The modern concept of risk has emerged as a central issue in finance over the last three decades. Gallati (2003) defines risk as a condition with potential exposure to adversity. Risk here is defined as a condition in which there is a possibility that the actual outcome will deviate from the expected. Credit risk or default risk is the oldest form of risk associated with financial markets. Various studies have attempted to formulate theories and developed models which help to explain and measure risk (BIS, 1999). Risk is considered as a fundamental factor that influences financial behaviour. Therefore a vast effort to allocate and manage resources in a way to decrease risk is required. Credit risk (default risk) is defined by Lopez and Saidenberg (2000) as "the degree of value fluctuations in debt instruments and derivatives due to changes in the underlying credit quality of borrowers and counterparties"

This paper specifies and tests the hypotheses about cash flow theory and default risk. Cash flow plays an important role in determining a firm's ability to access external sources of funds. Firms with a positive cash flow are able to raise their capital and borrow from the capital market, while firms with a negative, or insufficient, cash flow are unable to borrow and, therefore, face the risk of default.

It was argued that if current cash flows are able to predict corporate financial status, then past and present cash flows should be able to determine and predict corporate default (see, for example, Scott, 1981). A firm's free cash flow has a negative impact on corporate value as a result of a conflict of interest between shareholders and managers (see, for example, Jensen, 1986). Jensen (1986) argued that increased leverage, or increased dividends, can help to lower the cost of asymmetric information between managers and shareholders[1]. Jordan is a bank-based system, bank credit is typically short-term, and the cost of borrowing is quite high, which makes retained earnings an important source of funds. According to Creane et al. (2003) financial intermediation through the banking system in Jordan is mostly short-term[2].

A variety of models have been used to predict PD, including models using accounting data[3] and market prices[4] (BIS, 2000). Since the 1960s, most default (bankruptcy) studies have been conducted in the US and some other developed countries such as England, France, Japan, Australia and Canada (e.g. Beaver (1967), Altman (1968), Marais (1979), Altman and Lavallee (1981), Izan (1984), and Takahashi, Kurokawa and Watase (1984), among others). The applicability of these empirical models to developing countries could be questioned as firms' characteristics differ.

A substantial amount of research has been directed toward analysing the relationship between cash flow and default risk and bankruptcy but, to the best of the author's knowledge, there is no single study that has addressed the issue of free cash flow and default risk in the Jordanian context. It is the objective of this paper to examine

[1] Increases the use of debt, moves ownership from equityholders to debtholders and increases the firm's probability of default. Regarding the dividends, it has been documented in many studies that Jordanian companies have a low dividend ratio (see Al-Malkawi, 2005) which raises important questions about the firm's free cash flow.
[2] Al-Malkawi (2005) and Omet and Mashharawe (2004) also reported that credit facilities in Jordan are mostly short-term.
[3] Using univariate analysis, discriminant analysis, Logit and Probit models; for more details, see Beaver (1967), Altman (1968), Martin (1977), Ohlson (1980), and Zmijewski (1984).
[4] Such as the structural approach model introduced by Merton (1974), and reduced approach model introduced by Jarrow and Turnbull (1992, 1995). For more details, see Crouhy, Galai and Mark (2000, 2001).

whether firms' free cash flow increases the risk of corporate failure in Jordan. This is done by using a Logit model of corporate default. The study also examines the impact of financial variables as well as other firm characteristics, such as firm size and age, on the probability of default. The remainder of the chapter is organized as follows. Section 2 reviews the literature. Section 3 discusses the data used in the analysis and sample selection procedure. Section 4 discusses the estimated model used in the study. Section 5 presents the results of the empirical models. Section 6 summaries the paper.

2. Brief Review of Cash Flow and Default Risk and Literature

It was argued that firms with a positive cash flow are able to raise their capital and borrow from the capital market, while firms with a negative or insufficient cash inflow are unable to borrow and therefore facing the risk of default. According to this argument, a firm is assumed to go bankrupt (default) whenever the current year profit or cash flow is negative or less than the debt obligations or whenever the sum of its current year profit and the expected value of equity (without current income) is negative (less than zero) (Scott, 1981). Following this, Wilcox (1971) used the gambler's ruin to develop his framework to predict default risk. The model assumed that the firm's financial state could be defined as its adjusted cash position or net liquidation at any time. According to the gambler's ruin model the time of bankruptcy is based on the inflows and outflows of liquid resources. Scott (1981) argued that if the current cash flows are able to predict the corporate financial position, then past and present cash flows should be able to determine and predict corporate default.

Firm future cash flows affect its ability to enter the equity market to raise capital, as these cash flows are not directly paid out in a form of dividend they are retained and could be reinvested in profitable projects. While, shareholders allow managers to retain cash, the mangers may misuse the retained cash, i.e., invest in unprofitable or negative projects[5]. Therefore, the potential agency problems exist as a result of a conflict interest between shareholders (principals) and managers (agents) (see Jensen and Meckling, 1976).

Jensen (1986) argued that increased leverage or increased dividends can help to lower the cost of asymmetric information between managers and shareholders, so the free cash flow should be distributed to shareholders as dividends in order to maximise firm value. However, increases the use of debt, moves ownership from equity to debt holders and increasing the firm's probability of default. A high proportion of Jordanian companies' capital structure is short-term debt, which could be affected by the banks credits facilities. Regarding the dividends, it has been documented in many studies that Jordanian companies have low dividend ratios (see Al-Malkawi, 2005).

Nevertheless, the retained earnings or cash flows provide the internal source of finance which can be less costly compared with external sources of finance. The trade off between the benefits of free cash flow's as internal finance and the cost of the free cash flow is the main focus of the free cash flow theory. Furthermore, the main

[5] Projects with a negative net present value (NPV).

objective of the free cash flow theory is to balance the benefits and costs of investing earning (Dhumale, 1998).

Recall that according to the pecking order theory due to the presence of asymmetric information between insiders and outsiders, firm's first relay on its internal sources of funds, then on debt, and on issuing equity (Myers and Majluf, 1984). Therefore, firms' internal sources of funds could have an impact on firms investing decisions and on its probability of default.

Several studies incorporated these theoretically determined issues in order to explain the determinants of corporate failure. Gentry, Newbold and Whitford (1985) used a cash-based funds flow model developed in 1972 by Helfert (1982) to classify the failed and non failed companies. They find that cash-flow components offer a viable alternative for classifying failed and no-failed firms. However, their finding substantiate Casey and Bartczak (1985) findings that cash flow from operations does not improve the classification result of failed and non-failed firms. On the other hand, Aziz, Emanuel and Lawson (1988) used the cash flow model to explain and predict default. They found that cash flow is a fundamental factor signaling the possibility of corporate default. Therefore, it could be concluded that the probability of default or failure is a function of cash flow. The higher positive cash flow, the lower the probability of default risk will be.

Different empirical models have been used to predict the business default in spite of the absence of a unifying theory. The first approach to predict default probability applies a statistical classification technique called multi descriminant analysis (MDA). One of the first works in this area of financial ratio analysis and bankruptcy classification was Beaver (1967), followed by Altman in (1968) who pioneered MDA. New analytical techniques like Logit and probit models have been introduced into this field. Martin (1977), Ohlson (1980) and Zmijewski (1984) were the first to apply probit and logit models in predicting default risk.

Although these and many other empirical studies have been successful in different and many respects, still is a lack of evidence from emerging market, particularly from Middle Eastern countries more specifically from Jordan, which could be as a result of data availability. Also there is a lack of evidence about the effect of cash flow and the free cash flow on corporate failure from the emerging markets.

A substantial a mount of research has been directed to ward analysing the relationship between cash flow and default risk and bankruptcy. However, to the best of the author knowledge, there is no single study that that has addressed the issue of free cash flow and default risk in the Jordanian context. This motivates the present study to examine whether cash flow variable and free cash flow variable can affect the default risk of the Jordanian companies.

The discussion above shows that cash flow and free cash flow may play a significant role in determining the corporate default risk. To further investing the effect of cash flow on firm's probability of default for the Jordanian companies the selected variables should be related to the cash flow and debt obligations of the company and the firm value after current period of time.

3. Data and Methodology

3.1. Data Sources and Default Definition

The data used in this study is derived from publicly traded companies quoted on the Amman Stock Exchange (ASE), over the period 1989-2003. The number of publicly traded companies on the Amman Stock Exchange from 1989 to 2003 was 239[6]. The available data does not extend prior to 1989 so data collection is limited to this period. For data analysis, a clear and consistent definition of failure or default is required[7]. While default is usually defined as a corporation not being able to meet its obligations on a due date, different researchers have used different criteria to define default. For example, Beaver (1968) used a wider definition of default, which includes default on a loan, an overdrawn bank account, and non-payment of a preferred stock dividend. Alternatively, default may be defined in a stricter legal sense as in Deakin (1972), who defined default to include only those firms which experienced bankruptcy or liquidation and faced legal action. In the case of Jordan, we define default as a firm that had a receiver or liquidator appointed, was delisted from the Amman Stock Exchange (ASE) in the period 1989 to 2003[8], or that stopped issuing financial statements for two years or more, since firms are obliged by law to submit their annual financial statements or had restructured their capital. The date of failure is either the date the liquidator was appointed, the date of delisting from the formal market[9], or the date of the first failure to submit returns.

3.2. Sample Size

The initial sample in this study consisted of 59 industrial and services firms with 29 failed and 30 non-failed firms. The 29 failed firms ranged in size from 116338 JD ($163856 US dollars) to 415 million JD ($584 million US dollars) in total assets. The non-failed sample was matched to the failed sample from the same industry and by the same size and the same year in the first sample. The second sample included pooled cross-sectional and time-series data for 167 firms (47 defaulted firms and 120 non-defaulted firms) over the period 1989-2003. It is well documented that financial ratios methodically vary from one industry to another, which is the main reason that most researchers have focused on one industry[10]. To control for the effect of the industrial sector, dummy variables were used in this study for each industry.

3.3. Hypothesis Development and Variable Identification

Financial literature identifies a number of variables as significant indicators of corporate failure. The choice of factors and hypothesis formulation is motivated by both theoretical and empirical considerations. The selected variable should be related to the properties of the cash flow in combination with the debt obligations and the value of the firm to make use of cash flow theory and distress theory. To test whether the sign and significance of the coefficients reject the hypothesis or not, a suitable

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[6] See www.ammanstockex.com.

[7] A summary of the definitions of failure adopted by major empirical studies on company failure can be found in Castagna and Matolcsy (1981).

[8] This definition is very similar to the one by Izan (1984).

[9] According to Ohlson (1980), the timing issue is a crucial problem in data collection. It arises as firms' financial statements are not always released to the public on a timely basis.

[10] See, for example, Altman (1973) and Altman et al. (1977), who focused on the railroads in the first study and on the saving and loan associations in the second study. All industries are considered in this study except financial companies, such as financial or insurance firms, since the characteristics of these firms are so different (for more detail see, for example, Lincoln (1984)).

statistical model should be selected, taking into account that the transition from theoretical concept to empirical could be large.

The more sensitive a measure is to default risk or bankruptcy risk, the more quickly it can reflect changes in a firm's health and, therefore, the more effective that factor will be as an early warning factor. The following variables were adopted for the analysis: net income plus depreciation (cash flow) over the total debt (CSDT), current assets minus current liabilities over total assets (WCTA), net income to total equity (NITE), sales over total assets (SATA), returned earnings to total assets (RETA) and total debt to total equity (TDTE).

The cash flow over total liabilities (CSDT) gives a direct measure of firm cash inflows in relation to the total debt outstanding. It measures the extent to which cash flow can service debtholders. Firms with a high positive cash flow have more capacity to pay their debt obligations and to raise funds from external sources. The CSDT is hypothesised to be negatively related to the probability of default (PD). Thus, the first hypothesis can be stated as:

Hypothesis 1*: Firms with high cash flow have a lower probability of default.*

Another important variable is the free cash flow proxied by the retained earnings to total assets. Free cash flow theory suggests that a high free cash flow have a negative impact on corporate value as managers could misuse the free cash (e.g. invest in a negative NPV project). Therefore, free cash flow ought to be more positively and more significantly related to the probability of default. Thus, the second hypothesis can be stated as:

Hypothesis 2: *The firm's probability of default increases as the firm's free cash flow increases*.

Following previous research, free cash flow is proxied by retained earning to total assets RETA (see Dhumale, 1998, Kholdy and Sohrabian, 2001). RETA shows explanatory power in many empirical works (see e.g. Altman, (1968), Lincoln, (1984), and Bhargava, Dubelaar and Scott (1998)). Sales to total assets (SATA) is used to measure management risk. If a company is able to generate cash from its own sources, PD will be decreased. This factor has been used in many empirical models including Altman (1968), among others.

A firm's liquidity affects the probability of default as the unavailability of liquidity affects the firm's ability to meet its obligations. Liquidity risk in this study is measured by WCTA[11]. It is hypothesised that a firm's liquidity is negatively related to the probability of default (PD). A firm's ability to pay its debt obligations is positively related to its profitability measured in terms of NITE[12]. It is hypothesised that the PD is negatively related to NITE. A firm's leverage is considered a key factor in determining default risk[13]. To control for the effect of a firm's capital structure, the

[11] Other measures of liquidity could be used to investigate the effect of liquidity risk on PD such as current assets to current liabilities (CACL) and current assets to total assets (CATA). However, both variables did not show any significant difference between default and non-default. Chaudhury (1999) and Becchetti and Sierra (2003), among others used the WCTA in predicting default risk.

[12] There are other measures of profitability such as net income to total assets (NITA). NITA is also used in the analysis.

[13] In this study the terms credit risk, default risk, and bankruptcy are used to give the same meaning.

total debt over total equity (TDTE)[14] is used to measure and investigate the effect of capital structure on the firm's PD. It is hypothesised that firms with high TDTE ratios have a higher probability of default. Therefore, a positive relationship between a firm's leverage and PD is expected.

Two variables are intended to capture, in an indirect way, some of the distributional properties of cash flow: size and age. Both are considered to have an effect on a firm's cash flow and its ability to borrow. It is argued that small companies are more prone to go bankrupt because their access to the credit markets is more limited than for large companies (see for example, Altman, 1973, Bernnake and Gertler, 1995). A firm's size[15] is expected to have a negative effect on the probability of default. Firm size is measured by the logarithm of firm's total assets (SIZE)[16]. This is supported by the argument that large firms tend to have easier access to a wider variety of capital markets and can diversify their investments. According to trade-off theory, expected bankruptcy costs for large firms will be low; also the cost of debt, according to agency theory, will be low. Thus the third hypothesis can be stated as:

Hypothesis 3: *A firm's probability of default is negatively related to the firm's size.*

It is argued that young companies are more likely to fail than experienced companies (see Altman, 1993). A firm's age (AGE) is therefore also used to predict the PD. It is argued that young firms have a higher PD than older ones; the variable is expected to have a negative impact on corporate failure. The firm's age has been used by previous studies such as Westgaard and Wijst (2001). 16 dummy variables are used in this study. To give an impression of the differences between default and non-default firms with respect to these variables, Table 1 presents the average ratios for the default and non-default firms for four years before default. Furthermore, Table 2 describes the variables used in this study and the expected sign of their coefficients.

Table 1: Average Ratio for Defaulted and Non-Defaulted Firms

Variables	Defaulted				Non-defaulted			
	One year	Two year	Three year	Four year	One year	Two year	Three year	Four year
NITL	-1.8688	-0.2919	-0.6439	-0.2203	0.2148	-0.0776	0.0921	0.1113
ROE	-1.7968	-0.4988	-4.9052	-0.0666	0.0339	0.0273	0.0202	0.0700
SATA	0.3699	0.2986	0.3085	0.3138	0.5738	0.5371	0.4558	0.5785
WCTA	-0.1813	-0.1277	-0.0164	0.0530	0.2216	0.1961	0.1934	0.2164
CACL	3.2708	3.3577	13.7251	2.7915	3.7712	17.4925	11.0260	8.3291
CLTA	0.5797	0.5255	0.4320	0.4185	0.2089	0.2322	0.2560	0.2473
LTDTA	0.0877	0.0816	0.1007	0.0626	0.0603	0.0629	0.0531	0.0609
CATA	0.3983	0.3977	0.4156	0.4714	0.4305	0.4283	0.4494	0.4637
TDTA	0.6774	0.6238	0.5534	0.5129	0.2766	0.3035	0.3155	0.3254
TDTE	5.9044	2.9106	43.9548	0.8295	0.4910	0.5504	0.5323	0.5923
RETA	-0.6500	-0.5069	-0.3286	-0.3262	-0.0550	-0.0596	-0.0484	-0.0385

[14] Several variables are used to measure the leverage. The variables of long-term debt to total assets (LTDTA), short-term debt to total assets (CLTA), and the total debt to total assets (TDTA) are used to capture the effect of debt's maturity on PD. Another measure is the total debt to total equity (TDTE).

[15] Firm size is found to have a significant impact for example Altman (1984).

[16] In this study the author has used the logarithm of capitalisation and the logarithm of the total sales. The base 10 logarithm of the firm's total assets appears to be the most satisfactory size measure in this study.

Table 2: Variables Used in the Study

Variables	Description	Expected relation to Default risk
NITL	Net Income to Total Liabilities	-
ROE	Return on Equity (Net income to Total Equity)	-
SATA	Sales to Total Assets	-
WCTA	Current Assets minus Current Liabilities to Total Assets	-
CACL	Current Assets to Current Liabilities	-
CLTA	Current Liabilities to Total Assets	+
LTDTA	Long-Term Liabilities to Total assets	-
TDTA	Total Liabilities to Total Assets	+
TDTE	Total Debt to Total Equity	+
AGE	Firms Age in years	-
SIZE	Log the Assets of the firm	-
RETA	Return Earning to Total Assets	-

4. Econometrics Models

To investigate the effect of the selected variables on the probability of default for Jordanian companies, and to estimate the probability of default, a suitable statistical technique must be used. A large number of bankruptcy studies based on financial ratios used the MDA method to predict default (see e.g. Altman (1968), Altman, Haldeman and Narayanan (1977), and Ginoglou, Agorastos and Hatzigagios (2002)). However, empirical models based on MDA failed to give a clear picture of the indicators of corporate failure (Westgaard and Wijst, 2001). Furthermore, MDA requires the assumption that independent variables have identical normal distributions. It also does not provide convenient tests of the significance of the coefficients (see e.g. Altman,(1993) and Altman, (2002)). MDA does not produce probabilities (Eisenbeis, 1977). So, MDA is not suitable for the purpose of this research.

Regression analysis in the form of the linear probability model (LPM) has been used in default risk studies. The major problem with the linear probability model is that the linear functions are inherently unbounded, while the actual probability is bounded between 0 and 1 (Greene, 2003). Using the Logit model solves the problem of bounded dependent variables by transforming the probability so that it is no longer bounded, which makes the Logit model the most suitable regression analysis for this research (Greene, 2003). Studies using Logit models are Martin (1977), and Ohlson (1980) as well as Zavgren (1985), Johnsen and Melicher (1994) Lennox (1999), Westgaard and Wijst (2001), and Ginoglou, Agorastos and Hatzigagios (2002), among others[17]. For the matched sample, the estimation is carried out using the Logit model[18]. The model can be written as:

$$y_i^* = \beta' X_i + u_i \qquad \forall i = 1(1)n \tag{1}$$

where n is the number of observations, X_i is the vector of relevant regressors for the i^{th} observation, β is the vector of parameters, and u_i is the stochastic disturbance

[17] Studies using the Probit model in default studies are Zmijewski (1984), Acharya, Chatterjee and Pal (2003) and Ginoglou, Agorastos and Hatzigagios (2002), among others. Appendix 2-2 provides a survey of the defaulted studies using MDA, Logit, and Probit models.

[18] For further details on Logit, see Maddala (1983) and Gujarati (1998).

term corresponding to the i^{th} observation. However we observe a proxy for the latent variable y_i with the following rule:

$$y_i \begin{cases} =1 & \text{if } y_i^* > 0 \\ =0 & \text{if } y_i^* \le 0 \end{cases}$$ with y_i =1 if the firm *i* defaults, y_i =0 otherwise.

In the Logit model

$$P_i = F_{LOG}\left(X_i^{'}\beta\right) = \Lambda\left(X_i^{'}\beta\right) = \frac{\exp\left(X_i^{'}\beta\right)}{1+\exp\left(X_i^{'}\beta\right)} = \left(1+e^{-X_i^{'}\beta}\right)^{-1} \qquad (2)$$

$F(\cdot)$ is the logistic function, and $(\cdot)$ is the cumulative density function for the Logit distribution. The model's parameters are estimated by maximum likelihood, and the likelihood function for the whole sample is:

$$f_{Y_1,Y_2,\ldots\ldots,Y_N}\left(y_1, y_1, \ldots\ldots, y_N\right) = \prod_{i=1}^{n} P_i^{y_i}\left(1-P_i\right)^{1-y_i} \qquad (3)$$

Taking the log-likelihood function, the model will be as follows:

$$\ell(\beta) = \sum_{i=1}^{N} y_i \ln F\left(X_i^{'}\beta\right) + \sum_{i=1}^{N}\left(1-y_i\right)\ln\left(1-F\left(X_i^{'}\beta\right)\right) \qquad (4)$$

Hence, our estimation for the Logit model, the log-likelihood function, will take the following form:

$$\ell(\beta) = \sum_{i=1}^{N} y_i \ln\left(\frac{e^{X_i^{'}\beta}}{1+e^{X_i^{'}\beta}}\right) + \sum_{i=1}^{N}\left(1-y_i\right)\ln\left(\frac{1}{1+e^{X_i^{'}\beta}}\right) \qquad (5)$$

To estimate the goodness of fit for the Logit model, the McFadden R^2 and likelihood ratio statistic $LR_{(df)}$ are computed. The empirical model to be estimated using the Logit model can be written as:

$$\begin{aligned} Y_i^* &= \beta_0 - \beta_1 CSDT_i - \beta_2 NITE_i - \beta_3 SATA_i - \beta_4 WCTA_i \\ &+ \beta_5 RETA_i + \beta_6 TDTE_i - \beta_7 AGE_i - \beta_8 SIZE_i + u_i \end{aligned} \qquad (6)$$

where the variables are defined in Section 2.3. The hypotheses to be tested in this study are that variables are significant in predicting the probability of default (the signs indicate the hypothesised impact on the probability of default). This model's also estimated using the Random Effects Logit model on panel data[19]. The models are estimated by using the SHAZAM software package (see Whistler, White, Donna Wong and Bates, 2001) and the STATA 8 software package. Both programs use a procedure that estimates binary models via maximum likelihood for the Logit model.

5 Empirical Results

5.1 Preliminary Statistics

The summary statistics for the variables used in this study are displayed in Table 3 for both the default and non-default groups. Table 3 shows that the mean of CSDT for defaulted firms is negative (-2.4), while it is positive for non-defaulted firms (0.26). Furthermore, the means of the variables ROE and WCTA have a negative mean in the

[19] The Random effects model is the suitable model as the dummy variables of industrial sectors (all time-invariant variables) are dropped out in the fixed effects model.

defaulted firms, compared with a positive mean in the non-defaulted firms. Table 4 shows the correlation matrix of the variables in both default and non-default firms. The low intercorrelations among the explanatory variables (between defaulted and non-defaulted) used in the regressions indicate no reason to suspect serious. In attempting to test for heteroskedasticity, a Lagrange Multiplier test devised by Breusch-Pagan (1979) was formulated. The results show that our models do not suffer from heteroskedasticity. For example, in the first estimation, the observed Chi-square value of 0.38 (P= 0.5376) is not significant at any level of significance.

Table 3: Summary Statistics for both Default and Non-Default Firms

	Default						Non-Default					
	Mean	**Variance**	**Median**	**Max**	**Min**	**STDV**	**Mean**	**Variance**	**Median**	**Max**	**Min**	**STDV**
CSDT	-2.04	40.64	-0.18	0.05	-30.75	6.38	0.26	0.33	0.15	1.72	-1.24	0.57
TDTE	0.98	6.39	0.66	7.02	-5.84	2.53	0.51	0.23	0.40	1.88	0.026	0.48
ROE	-0.28	0.26	-0.125	1.07	-1.30	0.51	0.04	0.016	0.05	0.34	-0.29	0.128
WCTA	-0.17	0.46	-0.145	0.92	-2.07	0.68	0.22	0.08	0.19	0.7	-0.38	0.29
SATA	0.37	0.13	0.25	1.39	0	0.36	0.59	0.241	0.47	1.93	0	0.49
RETA	-0.64	1.04	-0.195	0.05	-3.60	1.02	-0.06	0.019	0.0036	0.12	-0.41	0.14
AGE	15.45	145.68	14	66	2	12.07	19.37	162.79	16	47	5	12.76
SIZE	6.497	0.31	6.58	7.38	5.07	0.56	6.94	0.22	6.89	8.62	6.09	0.47

Table 4: Correlation Matrix of Variables

		RETA		**CSDT**		**SATA**		**WCTA**		**SIZE**		**NITE**		**TDTE**		**AGE**	
		DF	*ND*	*DF*	*ND*	*DF*	*ND*	*DF*	*ND*	*DF*	*ND*	*DF*	*ND*	*DF*	*ND*	*DF*	*ND*
RETA	DF	1															
	ND	0.319	1														
CSDT	DF	0.38	0.38	1													
	ND	0.211	0.29	0.12	1												
SATA	DF	-0.203	-0.3	-0.501	-0.05	1											
	ND	0.29	-0	0.141	0.203	-0.02	1										
WCTA	DF	0.395	0.11	-0.392	0.058	0.39	0.232	1									
	ND	0.18	-0.1	0.119	0.186	-0.11	0.213	0.09	1								
SIZE	DF	0.460	0.13	0.506	0.077	-0.23	0.16	-0.2	0.261	1							
	ND	0.184	0.46	0.224	0.146	-0.21	-0.29	-0.1	-0.08	0.08	1						
NITE	DF	0.038	0.04	0.291	-0.11	-0.17	-0.01	-0.3	-0.01	0.15	0.062	1					
	ND	0.257	0.33	0.063	0.573	-0.01	0.314	0.24	0.211	-0.05	0.155	-0.09	1				
TDTE	DF	0.327	0.05	0.11	0.269	-0.12	0.208	0.21	0.201	0.21	0.042	-0.76	0.25	1			
	ND	-0.306	-0.1	-0.149	-0.36	0.107	-0.52	-0.3	-0.45	-0.19	0.203	0.122	-0.5	-0.3	1		
AGE	DF	0.06	-0.4	0.062	0.331	-0.08	0.325	0.01	0.036	0.22	-0.33	-0.22	-0.2	0.42	-0.1	1	
	ND	0.154	-0	0.003	0.108	0.098	0.248	0.35	0.282	-0.22	0.227	0.182	0.22	-0.1	0.1	-0.09	1

5.2 Parameter Estimation and Hypothesis Test

The results of the Logit models analyses are summarised in Table 5 using a matched sample. Similar to the linear regression, the analysis of Logit gives the estimated coefficient of the variables and the *t* ratios to test the hypothesis that each coefficient is significant in predicting the PD. From Hypothesis 1, the variable representing the firm's cash flow is expected to influence the corporate failure negatively. Table 5 presents the results of the first sample. The coefficient of CSDT, as predicted, is negatively and significantly related to the probability of default. The negative sign indicates that firms with a high CSDT ratio have a decreased probability of default. Firms with a high CSDT have a low debt ratio and a lower probability of default, as corporate cash flow represents the initial sources of funds according to the pecking order theory. Therefore, a positive cash flow decreases the demand for debt and, hence, decreases debt payment. The sign and significance of the coefficient of the CSDT variable warrants acceptance of Hypothesis 1, that firm with a high cash flow have a lower probability of default. The finding of a negative relationship between cash flow and the probability of default is consistent with prior research including Westgaard and Wijst (2001), among others.

Hypothesis 2 predicts that firms with a high free cash flow tend to have a higher probability of default. From the regression results in Table 5, as predicted by the free cash flow theory, the coefficient of RETA is positive and significant at the 5% level of significance. The significance and the positive sign lead to an acceptance of the hypothesis that firms with a high free cash flow proxied by the RETA have a higher probability of default. This result is consistent with the free cash flow theory (Jensen, 1986) and with the empirical findings of Dhumale (1998) that free cash flow could have a negative impact on the firm's value, as a result of a conflict of interests between shareholders and managers. RETA is also found to be significant in predicting default in many empirical studies including Altman (1968) and Altman, Haldeman and Narayanan (1977), among others.

Table 5: Estimated Coefficients for the Participation Model

Variables	Expected sign	Coefficient Estimates
Constant		-41.33 (-2.35)**
CSDT	-	-2.284 (-1.898)*
RETA	+	11.601 (2.091)**
SATA	-	-6.451 (-2.56)***
WCTA	-	-12.279 (-1.6875)*
NITE	-	-7.079 (-2.57)***
TDTE	+	16.578 (1.913)*
SIZE	-	0.151 (0.550)
AGE	-	10.640 (1.641)*
Percent of success		0.915
Log-likelihood		-13.345
Likelihood Ratio statistic *(LR)*		(55.085)***
McFadden R^2		0.67

Notes: *, **, *** Significant at 10, 5, and 1 percent levels, respectively. The estimated sample includes 59 observations from 1989 to 2002. The hypotheses tested depend on the sign and the significance of the estimated parameters (coefficients). *t*-statistics is determined with White (1980) standard errors to correct for heteroskedasticity are in parentheses. Industrial dummy variables are included in the regression and most of them significant at the 1% level. Time dummy variables are included in the regression.

The coefficient of SATA is found to be negative and significant at the 1% level. The negative sign indicates that firms with high sales have a lower probability of default. This finding is consistent with the previous studies such as Altman (1968) and others. Furthermore, the coefficients for both WCTA and NITE are negative and significant, at least at the 10% and 1% level, respectively. This is also consistent with cash flow theory and agency theory, as a firm which is able to generate cash flow and cover its obligation will decrease its PD. So, this leads to acceptance of the hypothesis that firms with low cash flow ratios have higher PDs. The TDTE is found to have a positive and significant impact on the probability of default, as defaulted firms are expected to have greater financial leverage than healthy counterparts, since these high fixed loan interest payments are usually a forerunner to eventual bankruptcy. The coefficient of total debt to total equity TDTE is significant, at least at the 10% level. This result is consistent with the theory of capital structure and trade-off theory that there is a positive relationship between PD and a firm's debt, as the firm's capital structure affects its ability to access external sources of funds. Firm size was found not to have any significant impact on a firm's probability of default in the matched sample. This finding is not consistent with the theory and previous empirical work showing that large firms have a lower probability of default, as they have lower bankruptcy costs. The result is different from studies such as Ohlson (1980) and the later study by Manzoni (2004) that found firm size is a significant factor in predicting PD. The same is true for Age which is also not significant.

This study further reports the estimated results for the matched sample two years before default and three years before default. The results are reported in Table 6. From the regression results in Table 6, the coefficients of SATA and NITE are negative and significant in predicting the probability of default two years before default, whereas, the coefficient of AGE has a positive and significant impact on a firm's probability of default two years before default and three years before default. However, RETA, CSDT, SIZE, and TDTE[20] are found not to be significant in predicting default two and three years before default. Dummy industrial variables were used to control for the effect of the industrial sectors in this study and they were found to have a significant and positive impact on the firm's probability of default. Furthermore, time dummy variables were included to control for the time effect and they were found to have a significant relationship to corporate failure.

In the second sample, using pooled cross-sectional and time-series data, a logistic model is estimated using the random effects model. The empirical results for the panel sample are presented in Table 7, which shows that the probability of default decreases for a firm with higher cash inflow total liabilities (NITL), higher sales to total assets (SATA), and large size (SIZE) ratios, whereas it increases if it has a higher total debt to total assets (TDTA) ratio. The coefficient of RETA is positive and significant at the 10% level. The positive sign is as predicted by the free cash flow theory. This is also consistent with the results in Table 5 for the matched sample. The coefficient of liquidity ratio, current assets to current liabilities (CACL)[21] is negative but insignificant. The coefficient of TDTA became more significant in the panel sample, which shows the important effect of leverage ratio on firms' default risk. From the regression results, contrary to expectations, the coefficient of AGE is positive and insignificant. To the best of the author's knowledge, this thesis provides the first attempt to document that the age of the firms is positively related to corporate failure. Furthermore, the firm's profitability using NITE[22] has no significant impact on a firm's probability of default. The results also show that the industrial dummy variables for 16 sectors have a positive and significant impact on the firm's probability of default.

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[20] The variable total debt to total assets (TDTA) was used in this study and found to have a positive and significant impact on corporate failure.
[21] The WCTA is also used and yield a similar result.
[22] However, using the net income to total assets (NITA) instead of NITE was found to have a negative and significant impact on firms' probability of default.

Table 6: Estimated Coefficients for the Participation Model two and three years before default

Variables	Two years before default	Three years before default
CASDET	-1.1541	-2.7285
	(-1.197)	(-1.2346)
RETA	2.5981	3.7801
	(0.80343)	(1.2579)
SATA	-4.2009	-2.0641
	(-2.2421)**	(-1.479)
WCTA	-3.0894	3.9954
	(-0.76014)	(0.8127)
NITE	-4.2020	-4.3282
	(-2.2018)**	(-2.758)***
TDTE	4.7729	-2.9575
	(1.1171)	(-0.62321)
SIZE	-0.0452	-0.0072
	(-0.265)	(-0.042)
AGE	8.3033	12.644
	(2.155)**	(2.56)***
Constant	25.554	25.962
	(2.1164)**	(2.708)***
Percent of success	0.80	0.81
Log-likelihood	-14.318	-16.928
Likelihood Ratio statistic *(LR)*	(41.14)***	(41.102)**
McFadden R^2	0.50	0.50

Notes: *, **, *** Significant at 10, 5, and 1 percent levels, respectively. The estimated sample includes 59 observations from 1989 to 2002. The hypotheses tested depend on the sign and the significance of the estimated parameters (coefficients). *t*-statistics is determined with White (1980) standard errors to correct for heteroskedasticity. Industrial dummy variables are included in the regression and most of them significant at the 1% level. Time dummy variables are included in the regression.

Table 7: Results from Random Effects Binary Logit for the Unbalanced Panel of the Jordanian Quoted Companies, the Panel Period 1989-2003

Variables	Coefficient Estimates	Marginal Effects
Constant	(15.277)	
	(4.95)***	
CSDT	-0.2690	-0.26903
	(-2.95)***	
RETA	0.8739	0.87390
	(1.74)*	
SATA	-2.1019	-2.10192
	(-3.35)***	
CACL	-0.0104	-0.01039
	(-0.75)	
TDTA	3.7998	3.79984
	(5.04)***	
SIZE	-0.9603	-0.96028
	(-2.25)**	
NITE	-0.0116	-0.01161
	(-0.76)	
AGE	0.0027	0.00271
	(0.14)	
No.of Observations	1557	
Wald test	5584.40	
P-value	(0.00)***	
Rho ρ (1)	0.4635**	
Log likelihood	-164.69	
Adjusted R-square	0.20	

Notes: *, **, *** Significant at 10, 5, and 1 percent levels, respectively. The hypotheses tested depend on the sign and the significance of the estimated parameters (coefficients). *t*-statistics is determined with White (1980) standard errors to correct for heteroskedasticity. (1) The proportion of the total variance contributed by panel-level variance component. 16 dummy variables are included in the regression and most of them significant at the 1% level. Time dummy variables are included in the regression.

To further investigate the impact of the selected variables on a firm's probability of default, a marginal effect after the logistic estimation is formulated. The TDTA has the highest positive marginal effect on a firm's probability of default followed by RETA, with 3.799% and 0.887% respectively. The marginal effect shows that TDTA and RETA have the greatest impact in determining and increasing the probability of default. On the other hand, SATA followed by SIZE have the highest negative impact on a firm's probability of default, with a marginal effect of -2.10% and -0.96% respectively.

To summarise, the estimations for the two samples suggest an expected positive relationship between retained earnings to total assets (RETA) and failure risk. The positive and significant coefficient of the RETA indicates that firms with a high ratio of RETA have a high probability of default. In the two samples, the liquidity ratio suggests a negative influence of liquidity on the risk of failure[23]. According to the free cash flow theory, under imperfect markets and asymmetric information problems firms with a high opportunity for investment should remain more liquid than firms with less opportunity for diversified investments.

The estimations of the two samples yield the CSDT as a determinant of failure, which is significant at the 10% and 5% level in the matched sample and in the panel sample respectively. Moreover, the strong influence of total debt to total assets (TDTA) is supported in the two estimations, and at a high level of significance. Lastly, the sales to total assets (SATA), that measures management efficiency, plays a significant role in determining the probability of default in both samples.

5.3 Predictive Powers of the Model

The goodness of fit for the Logit model given by the McFadden R^2 and the LR statistic for the matched sample are computed and presented in Table 8. This shows that the McFadden R^2 for the Logit model is about 67%, while the LR is equal to 55.08 and is statistically significant in the corresponding asymptotic Chi-squared distribution at the 1% level. In evaluating the explanatory power of the model, two types of prediction error are defined. A Type I error [24] occurs when the firm is predicted to default but the outcome is non-default. A Type II error occurs when the firm is predicted not to default but the outcome is default. Table 8 shows the predictive success for default and non-default firms and the two types of error, Type I error and Type II error. The cost of error Type II is, however, more than the cost of error Type I.

Table 8: The cost of Type I errors and Type II errors

	Type I error	**Type II error**
	Default	Non-default
Original sample	29	30
Number of right predictions	26	28
Number of wrong predictions	3	2
Percentage of right predictions	0.896	0.93
Overall accuracy of Logit	0.914943	

[23] The liquidity ratio deals with the most liquid assets and is regarded as the best guide to short-term solvency.
[24] Type I error occurs when a failed firm is misclassified as non-failed; on the other hand type II error occurs when a non-failed firm is incorrectly classified as failed.

The correct prediction of default firms is about 90% compared with 93% correct prediction of non-default firms. The overall accuracy of the model is about 93.3%, which is extremely high in predicting default compared with other empirical models. The diagnostics indicate that the panel data model has good overall fit – the Likelihood Ratio test statistics are significant at the 1% per cent level for the random effects binary Logit model. The likelihood ratio (LR) test reported at the bottom of each table of the results shows that the random effect model is significant at least at the 1% level of significance

6 Summary

This chapter has examined the effect of cash flow and free cash flow on corporate failure in Jordan. This chapter has concentrated on predicting default risk for Jordanian companies. In the first sample, a Logit estimation was used to examine the determinants of corporate failure using a cash flow hypothesis. The results for the first sample were obtained using the maximum likelihood estimation of Logit regression. In the second sample, Logit regression was also used to examine the determinants of corporate failure using cash flow variables. The results for the first sample were obtained using the maximum likelihood estimation of the random effects Logit regression. The chapter provided some important descriptive statistics on the defaulted and non-defaulted firms and the variables used in the analysis. In order to ensure that our result is robust, several diagnostic tests were formulated such as correlation matrix, heteroskedasticity test, and the predictive power of the model.

The result shows that the cash flow variable, as measured by CSDT, seems to be related to corporate failure in Jordan, and has a significant effect in predicting the probability of default since it was significant in both samples. That is, it has a negative effect on a firm's probability of default. The free cash flow variable, as measured by RETA, has a positive and significant impact on corporate failure in both samples as it increases the probability of default. These variables are important in determining corporate failure in Jordan. These results are generally consistent with the cash flow theory and free cash flow theory.

The data shows that management efficiency, as measured by SATA, has a significant effect on corporate failure in the two samples, indicating that SATA is an important determinant of corporate failure in Jordan. The liquidity ratio, measured by WCTA and CACL, seems to not be related to corporate failure in Jordan since it was insignificant in both samples. The variable NETE has a negative and significant effect on corporate failure in the matched sample, while it has a negative but insignificant effect in the panel data estimation. The capital structure variable has a positive and significant effect on corporate failure in the two samples.

The firm's age positively but insignificantly affects its failure in both samples. This result is inconsistent with the previous findings. While the data does not provide support for the effect of a firm's size on corporate failure in the matched sample one year before default, it provides strong support for the effect of size in determining corporate failure. Following the discussion above, our principle conclusion is that corporate failure in Jordan can be partly explained by the free cash flow theory and agency theory. These findings are important as they provide evidence about the important role of cash flow variables in determining corporate failure in Jordan. While microeconomic variables that are related to the cash flow have been used in this chapter, the next chapter will expand the analysis of the determinants of corporate failure by introducing macroeconomic variables.

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