Financial Cash Flow Determinants of Company Failure in the Construction Industry

by

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Table of Contents

List of Tables

List of Figures

List of Appendices

Abstract

Construction is a risky business with only 47% of startup businesses in construction operating after four years. The indirect costs of failed companies far exceed the direct costs of their failure.

Cash is often seen as the most important element of construction companies and their operation. Adequate sources of capital, and a reasonable liabilities-to-assets ratio, are critical for business continuity and success. A lack of cash can mean no payments to subcontractors, laborers, and crews, and no purchases of needed materials. It can lead to limited ability to complete tasks on site, cutting corners in work, or slower pace to match the amount of cash available. Negative outcomes can include delayed or incomplete work or increased financing costs and project risks.

Ultimately, construction companies risk failure if they sustain cash flow limitations for some time despite the fact they could be profitable.

In this research, we developed a cash flow model for the assessment of construction companies' operations and their potential for failure. The cash flow model describes a company's operational strength using a cash flow cycle with three measures: 1) cash flow cycle profitability, 2) cash flow cycle duration, and 3) access to additional access. We theoretically establish the importance and justification for each measure.

Using a dataset comprised of full quarterly financial records for construction companies tracked over 20 years, we validate the suitability of the cash flow model in predicting construction company failure 6 months, 1 year, and 2 years in advance of failure event at a statistically significant level.

Chapter 1

Introduction

Construction is a risky business. Only 47% of startup businesses in construction are still operating after four years (University of Tennessee Research, 2014). The indirect costs of failed companies far exceed the direct costs of their failure (Mason & Harris, 1979) (Wong & NG, 2010) (Singh & Lakanathan, 1992). Surveys of construction practitioners point to financial and budgetary factors as the leading causes of failures (Arditi, Koksal, & Kale, 2000) (Kangari R. , 1988) (Davidson & Maguire, 2003) (Kivrak

& Arslan, 2008). Arditi (2000) concluded that budgetary and macroeconomic issues cause more than 80% of company failures within the construction industry. Considerable literature exists on the prediction of company failure; this literature dates back to as early as 1968 (Altman, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, 1968) (Balcaen & Ooghe, 2006) (Beaver W. , 1966). Mason and Harris (1979) recognized that industry factors affect prediction models and that the earlier generic failure models developed primarily based on retail and financial sectors company failure data might not be suitable for application to construction companies. Mason and Harris (1979) developed the first model predicting the failure of construction companies. Several models followed with limited changes in adopted methodology or approach to model development. Variations focused on changing the geographical focus of the data sample, and using Logit statistical analysis instead of multivariate discriminant analysis (Balcaen & Ooghe, 2006) (Wong & NG, 2010). Few of those studies focused on analyzing the effect of specific factors on the probability of construction company failure. For example, (Kale & Arditi, 1999) analyzed the effect of a company's age on its probability of failure, and (Huang, 2009) investigated the effect of using credit risk models to evaluate and predict contract default probabilities.

A separate body of knowledge exists that discusses the proper means of managing and controlling cash flow for construction companies (Jarrah & Kulkarni, 2007) (Lucko & Cooper, 2010) (Park, Han, & Russell, 2005). Most of these models investigate cash flow at the project level, but few attempt to model cash flow at an aggregated company level (Navon R. , 1996). The underlying motivation for this body of knowledge on cash flow modeling stemmed primarily from the industry's need to establish better ways to predict and manage cash flow (Navon R. , 1996). Navon (1996) and Singh (1992) further explained that construction companies often fail due to liquidity constraints, and construction companies could temporarily survive slow profits or even a loss, but can fail because of cash flow constraints despite showing profits on paper.

Despite the independently established importance of the two research areas in the construction management literature, there is little research linking both areas in a unified manner. Failure prediction models, as will be discussed in more detail later, often start with a generic assessment of all financial ratios, or through statistically developed models that rely on values or ratios obtained from the financial statements of companies. The common model development methodology focused more on the review and selection of the appropriate statistical technique to be used, followed by a trial-and-error approach using the more commonly used financial ratios and values from companies' financial statements until a significant statistical correlation between the predicting variables and company failure is obtained.

This research relied on a large data set compiled from the official records of public construction companies. The compiled data set is comprised of more than 1300 observations, with each observation including more than 400 primary and secondary data points. The data set represented 35 companies followed for over 20 years. The companies were divided into four groups: Operational, Failed, Acquired, and Privatized, as will be discussed in more detail later. Unique to this research is that the primary data points were obtained from the quarterly filed balance sheet, income statement, and cash flow statement. Earlier studies relied on annual financial information (Balcaen & Ooghe, 2006). Secondary data points included multiples and ratios calculated using the primary data points as input factors.

Using this data set, we hypothesize that *it is both empirically feasible and theoretically explainable to predict company failure at a statistically significant level using cash flow metrics*. Previous models utilized either a long list of financial metrics or a complex list of financial metrics alongside managerial assessment metrics that might not be readily available. A small percentage of construction companies are public. Private companies are not required to publish financial statements, let alone publish a detailed list of financials as required by some of the existing failure prediction models. In addition, for those companies where financial information exists, the management metrics may prove even harder to obtain. If obtained, they are often based on an internal assessment conducted by managers within the company. Internal management could be biased, or be unaware of the proper relative performance of other companies using the same assessment, thus being unsure that the results are benchmarked properly. In contrast, Cash flow and profitability numbers are readily accessible by the senior management of construction companies. A study by Navon (1996) showed that all of the companies contacted prepare cash flow at the company level even if they do not prepare cash flow on the project level for each of the ongoing projects. We will use statistical methods as discussed later to investigate and validate our hypothesis.

In the rest of this chapter, we provide an overview of the current failure rate for construction companies in the United States construction industry as well as an overview of the typical cash flow cycle of a construction contractor. We follow with an enumerated list of the primary and secondary objectives for this research, and conclude the chapter by offering an overview of the dissertation's structure.

1.1 Construction Company Failure Statistics

The United States Census tracks the start and exit of construction firms. It identifies four measurables in its business survey for construction companies:

1. "Estabs" is defined as an "a single physical location where business is conducted or where services or industrial operations are performed."
2. "Firms" is defined as "a business organization consisting of one or more domestic establishments that were specified under common ownership or control. The firm and the establishment are the same for single-establishment firms."
3. "Firmdeath_Firms" is defined as the "Count of firms that have exited in their entirety during the period. All establishments owned by the firm must exit to be

considered a firm death. This definition of firm death is narrow and strictly applied, so that a firm with 100 establishments would not qualify as a firm death if 99 exited while 1 continued under different ownership."

4. "Firmdeath_Estabs" is defined as the "Count of establishments associated with firm deaths."

The following table summarizes the US Census survey results for the 20-year period ending in 2011 (United States Census Bureau, 2013). It is noticeable that, during that period, 1,016,258 construction companies completely exited the business.

Year	Firms	Firmdeath (Firms)	Percentage Firmdeath (Firms)	Estabs	Firmdeath (Estabs)	Percentage Firmdeath (Estabs)
1991	492,021	50,359	10.24%	498,018	50,400	10.12%
1992	487,453	51,075	10.48%	493,493	51,109	10.36%
1993	496,514	48,317	9.73%	502,344	48,336	9.62%
1994	511,471	47,472	9.28%	517,462	47,479	9.18%
1995	531,258	48,097	9.05%	537,337	48,107	8.95%
1996	541,222	50,638	9.36%	547,303	50,638	9.25%
1997	554,808	49,971	9.01%	560,817	49,971	8.91%
1998	561,604	51,869	9.24%	567,888	51,869	9.13%
1999	572,349	49,204	8.60%	578,912	49,204	8.50%
2000	576,422	49,770	8.63%	583,377	49,770	8.53%
2001	574,944	49,918	8.68%	582,287	49,920	8.57%
2002	571,664	48,153	8.42%	579,554	48,168	8.31%
2003	556,361	49,153	8.83%	564,256	49,155	8.71%
2004	545,091	48,243	8.85%	552,648	48,248	8.73%
2005	531,037	49,808	9.38%	538,665	49,813	9.25%
2006	524,603	43,855	8.36%	532,521	43,920	8.25%
2007	512,969	43,519	8.48%	520,639	43,557	8.37%

Year	Firms	Firmdeath (Firms)	Percentage Firmdeath (Firms)	Estabs	Firmdeath (Estabs)	Percentage Firmdeath (Estabs)
2008	486,574	47,893	9.84%	494,322	47,899	9.69%
2009	435,194	53,785	12.36%	442,748	53,794	12.15%
2010	401,412	43,532	10.84%	408,863	43,538	10.65%
2011	378,967	41,627	10.98%	386,662	41,653	10.77%
		1,016,258	**9.46%**		**1,016,548**	**9.33%**

Table 1: US Census for Firm and Establishments (1991–2011)

In summary, between 10%–15% of the construction companies by count exit the business each year. As cited earlier, most of these exits are due to a lack of operating cash or a closely related issue.

1.2 Overview of the Cash Flow Cycle

Cash Flow is the bloodline of construction companies. The construction lifecycle could take as long as 60 days or more for full cash-to-cash conversion. The full cash flow cycle will be discussed in more detail later. The objective of this section is to provide an overview of the cash-to-cash conversion cycle.

Initially construction operations start with cash provided from one of two sources—equity or debt—and oftentimes it is provided through a mixture of the two. The construction contractor uses its cash to a) purchase fixed assets, b) purchase raw materials, c) pay for its labor, d) pay for its overheads, e) pay for its subcontractor suppliers and vendors, f) pay for its lenders, or g) pay taxes. The combination of the raw material, labor, overheads, and subcontractors' work is transformed into a finished product. This finished product is typically in the form of a completed or partially completed (progress) construction of some sort. Based on a certain agreed upon valuation method (fixed price, cost plus, etc.), the completed or partially completed construction (the finished good) is valued by the client, and the client pays a certain amount of cash to compensate the contractor for the finished goods (Jury, 2012).

There are some inherent challenges in the cash-to-cash conversion cycle for construction companies. The valuation of "finished goods" is a complex process. The finished good is generally valued based on the partial completion of construction, which implicitly assumes some subjectivity in the assessment of the progress completion and corresponding cash payment due.

On a typical construction project, the subcontractors' cash-to-cash conversion cycle may be as long as 60 days. Typically, subcontractors pay their labor workforce on a weekly basis, and pay for suppliers and materials on a bi-weekly basis. Hence, by the end of each month, it is funded the labor expenses for the month for 0–21 days, and funded its materials, suppliers, and all other expenses for 0–15 days. At the end of the each month, the contractor submits its estimation of progress (finished good) to the general contractor or construction manager. Assuming an agreement on the valuation of the completed percentage is easy to obtain, the general contractor combines this valuation along with all other contractors, and submits to the owner for payment. The owner's review of the pay application and payment can take anywhere between 7–30 days depending on contract terms. After the contractor receives its payment, it will generally pay the contractor in 7–14 days. For example, the AIA-A401 Agreement between Contractor and Subcontractor stipulates that the Subcontractor shall receive payment no later than 7 days after the Contractor receives payment from the Owner. In total, the contractor is funding its costs for 14–65 days, with the average closer to the higher end than the lower end.

Two factors make this long cash-to-cash conversion cycle even worse. First, construction projects are plagued with changes. The timely assessment and approval of the cash value for these changes often lag behind the physical construction, further extending the cash-to-cash conversion cycle for these changes. Contractors often find themselves in a position where they have to pay for the labor, material, and suppliers for a change in the scope of work; this happens month(s) before it can be included in the pay application. Second, the payment amount is reduced by a retainage (10% or more) that has the effect of keeping a contractor in a negative cash flow for a longer duration, and in many cases for the total duration of the project.

A construction contractor may very well be profitable and show a positive income on its financial statement, yet suddenly go bankrupt due to a lack of cash. As outlined by Navon (1996), a company may survive for some time with low profitability or even with a loss, but often fails rapidly if it lacks cash to operate. It is no surprise that the working capital and inadequate capitalization of construction contractors are continuously cited as leading reasons for failure (Singh & Lakanathan, 1992) (Navon R. , 1996).

1.3 Research Objectives and Contribution

The objectives of this research can be summarized as follows:

Review the existing prediction models and evaluate the accuracy of the existing prediction models, specifically Z-Score, in predicting construction company failure.

Evaluate the effect of cash flow on construction company operations, in particular the failure to operate.

Develop a cash flow model suitable for assessing the operational strength of construction companies, in particular their failure potential.

Using a data set comprised of quarterly financial information, validate the cash flow model capability for predicting construction company failure.

Provide a prediction model for construction companies based on the cash flow model that allows company management, bonding companies, insurance companies, construction owners, and banks to assess the probability of failure for construction companies.

Establish a direct link between existing literature on cash flow management and construction company failure using quantitative and qualitative analysis.

1.4 Dissertation Outline

The rest of this dissertation is divided into four chapters and a conclusion, as follows:

- Chapter 2 sets the theoretical foundation for the research. It presents a detailed literature review focusing on published work on failure prediction models, in particular those specifically created for the prediction of construction company failure.

- Chapter 3 starts with a review of the importance of cash flow management for construction operations and a review of some of the existing literature on cash flow management for construction companies. It concludes by setting up a cash flow model with parameters for assessing construction company failure potential.

- Chapter 4 provides a short background on the statistical methods utilized in this research, such as Probit, Logit, and Multivariate Discriminant Analysis. It also presents reasons for the selection of Logit as the statistical method of choice, and discusses in detail the Logit statistical analysis method and equations.

- Chapter 5 examines the data set and discusses the scope of the collected data, exclusion and inclusion criteria, and data pre-processing.

- Chapter 6 discusses the data preparation, data grouping, and variable development.

- Chapter 7 is focused on the development of a prediction model for construction company failure to validate the adequacy of using the cash flow model developed in Chapter 3 for assessing the failure potential of construction companies.

- Chapter 8 contains the tabulation of results, and the interpretation of results.

- Chapter 9 summarizes the research and provides conclusions. It also discusses recommendations for future work.

Chapter 2

Theoretical Foundation and Literature Review

The work of Beaver (1966) (1967) is perhaps the first published research about the prediction of company failure. Prior to Beaver's work, there are multiple documented uses of financial analysis and ratio analysis for investigating the health of an operational company. However, the pre-Beaver analysis lacked a prediction capability for predicting the failure of future companies based on statistical prediction models.

The theoretical foundation for this research is voluminous, hence the organization and grouping of previous research contributions is critical. This chapter will be divided into the following sections:

1. <u>Section 2.1 – Definition of Failure</u>
2. <u>Section 2.2 – Ratio and Multiples Analysis:</u> methods for review and analysis of companies using ratio and financial metrics. The review will focus on ratio analysis methods utilized up to 1966.
3. <u>Section 2.3 – Statistical Failure Prediction Models:</u> this section will provide a review of general developments in the field of failure prediction with more emphasis on particular models because of their importance. The models discussed in this section were developed without discriminating between industries, or focused on industries other than the construction industry.
4. <u>Section 2.4 – Predicting Failure of Construction Firms:</u> this section will provide a review of the statistical models focusing on predicting the failure of construction companies. A general review of contributions in this area will be

provided with more focus on particular studies because of their relative importance.

5. Section 2.5 – Problems related to Statistical Failure Prediction Models: this section discusses some of the known deficiencies in statistical models discussed in sections 2.2 and 2.3.

2.1. Definition of Failure

There are several definitions for failure used across the literature discussed in this Chapter. As summarized in Arditi (2000), Frederikslust defines the failure of a company as an inability to pay its obligations when they are due (Frederikslust, 1978). Altman (1993), in turn, explains company failure through an economic lens (Altman, 1993). According to Altman, failure occurs when the "realized rate of return on invested capital, with allowances for risk considerations, is significantly and continually lower than prevailing rates on similar investments" (Arditi, Koksal, & Kale, 2000) (Altman, Corporate Financial Distress and Bankruptcy, 1993). Storey (1994) and Baden-Fuller (1989), meanwhile, express failure as a function of future events: $y = rC - C'$; where "y = present value of anticipated profit in the coming period, C = residual value of the plant if scrapped now, r = rate of interest, and C′ = present value of anticipated capital gain in scrap value from deferring the closure" (Arditi, Koksal, & Kale, 2000) (Baden-Fuller, 1989) (Storey, 1994).

Watson and Everett (1993) highlight four situations in which a company fails: a) discontinuance for any reason, b) ceasing to trade and creditor loss, c) sale to prevent further loss, and d) failure to make a go of it.

2.2. Ratio and Multiples Analysis

A financial ratio is an assessment of one or more numerical values taken from the financial statements relative to one or more numerical values taken from another part of the financial statements. For example, the "Debt Ratio" is a financial ratio that represents the extent of a company's capital leverage. Stated differently, it represents how much money the company owes compared to how many assets it has. The higher the Debt Ratio, the more at risk the company is (Investopedia, 2013). The Debt Ratio is calculated as follows:

$$\text{Debt Ratio} = \text{Total Debt} / \text{Total Assets}$$

Both Total Debt and Total Assets are values obtained from the company's balance sheet.

It is unclear when the first time ratio and multiples analysis were developed and used. It is clear, however, that ratio analysis has been widely used for a long time to analyze and compare companies in general. For example, the use of ratio analysis to determine the credit worthiness of companies was utilized as early as the 1840's by the founders of what is now called Dun and Bradstreet (Dun & Bradstreet , 2013). The first documented academic research attempting to use financial ratio analysis to investigate company failure dates back to the 1930's (Beaver W. , 1967) (Altman, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, 1968). It is highly likely that the great depression of the 1930's triggered researchers to investigate company failure, where they utilized the common company analysis tool available at the time—financial ratio analysis.

Several studies performed in the 1930's over a period of five years concluded that there is evidence that failing companies exhibit different financial ratios than non-failing companies (Smith & Winakor, 1935) (Merwin, 1942). Although these studies concluded that financial ratios could be used to predict company failure, they differed in citing which ratios are more significant indicators for predicting the failure of companies.

The use of financial ratios for company analysis and sometimes company failure predicting became widespread until several academic researcher voiced concerns with the statistical accuracy of financial ratios when used in a predicative capacity (Beaver W. , 1966). The concern about data normality is discussed in more detail later. It has been concluded that the use of financial ratios for company to industry benchmarking may not be statistically accurate since financial ratios do not tend to follow a normal distribution pattern (Barnes P. , 1982). In contrast, the use of financial ratios in a single industry for predictive models such as multiple Discriminant Analysis can be statistically valid (Barnes P. , 1982).

2.3. Statistical Failure Prediction Models

2.3.1. Overview of the Statistical Failure Prediction Models

Balcaena and Ooghe (2006) conducted a thorough literature review, scanning the field of business failure prediction in corporate finance. Their study explored the classic statistical methods for failure prediction, including univariate analysis, risk index models, multivariate discriminant analysis, and conditional probability models. We present an adapted and updated summary of Balcaena’s review. We also provide added detail and focus on particular models of importance, such as Altman’s Z-Score.

The first predictive model was developed as early as 1966. Beaver (1967) originally introduced this model to predict corporate failure using financial ratios selected by a dichotomous classification test. The model indicates an optimal cut-off point for each measure/ratio, followed by a classification procedure based on the firm’s value for each measure and the corresponding optimal cut-off point. The model is very simple, and requires no statistical knowledge. A primary challenge with the model is that it assumes a linear relationship between all measures and the failure status.

The next development was in the form of a risk index model. The risk index models were based on simple, intuitive point systems. Tamari’s (1966) version applies a point system from 0–100, where ratios are weighted, and higher points indicate a better financial position. The weighting of the ratios, however, is subjective. In 1987, Moses and Liao developed an alternative version that determines optimal cut-off points for each ratio, based on a univariate analysis (Moses & Liao, 1987). A dichotomous variable is then developed for each set of ratios, with a score of one assigned when the firm's ratio value exceeds the optimal cut-off point. Values are added, and again a higher score indicates better financial health.

The statistical multivariate discriminant analysis (MDA) technique was brought forth in 1968 by Altman (Altman, 1968). Until the 1980s, MDA then dominated the literature, with the majority of researchers using a linear rather than quadratic MDA. This is likely due to the quadratic MDA's higher level of complexity and requirement for small variables among large samples. The linear model combines variables in a discriminant function to create a single multivariate discriminate score (Lachenbruch, 1975). A lower score usually indicates poor financial health. MDA is based on a continuous scoring system, and the discriminate score allows for the ranking of firms. While variables in this system may not be significant on a univariate basis, they can be in a multivariate MDA model (Altman, 1968).

While MDA dominated the literature until the 1980s, it has since decreased (Dimitras, S., & Zopoudinis, 1996) and has been replaced by less demanding statistical techniques, such as the logit analysis (LA), probit analysis (PA), and linear probability modeling (LPM). These conditional probability models use the non-linear maximum likelihood method to estimate corporate failure.

LA, originally pioneered by Ohlson (1980), has been the most prominently used model of late. The model obtains parameter estimates by combining several firm characteristics into a multivariate probability score. The output determines the firm's probability of failure or vulnerability to failure. The model assigns firms the status of failing or non-failing based on their logit score and cut-off score, and the firms are assigned to the groups they most resemble. Considered less demanding than MDA, the model also allows for the use of qualitative variables (Ohlson, 1980) (Keassey & Watson, 1987). LA has several drawbacks, however. First, there is a cost of type I and type II error rates, though most are minimized and assume equal misclassification costs (Zavgren, 1985) (Koh, 1992) (Hsieh, 1993), and the choice of a cut-off point is seen as robust (Koh, 1992). Second, there is sensitivity to multicollinearity (Ooghe, Joos, D., & De Bourdeaudhuij, 1994) (Doumpos & Zopoudinis, 1999), as well as outliers and missing values (Joos, Vanhoof, Ooghe, & Sierens, 1998).

2.3.2. Altman's Z-Score

Altman (1968) sought to assess the quality of ratio analysis as an analytical technique to predict corporate bankruptcy. Using financial and economic ratios from manufacturing corporations, he employed a multivariate discriminate analysis technique.

Following Beaver's (1967) research, which at that time had begun to suggest abandoning the traditional ratio analysis, Altman instead proposed adapting of model into a multi discriminate analysis technique (MDA). The traditional ratio technique, as Altman affirmed, may not be appropriate for assessing bankruptcy. Nearly always univariate, the methodology emphasizes individual signals, which can lead to a faulty interpretation. MDA, however, has the benefits of considering the entire profile of characteristics common to relevant firms and the interaction of those properties, reducing the analyst's space dimensionality, and analyzing the entire variable profile of objects simultaneously. At that time, a few researchers had previously employed MDA (Fisher, 1936) (Durand, 1941) (Myers & Forgy, 1963) (Walter J. , 1959).

Using a sample of 66 manufacturing corporations (33 bankrupt, 33 non-bankrupt), Altman sought to determine which ratios would be most significant for bankruptcy detection, what weights should be attached, and how those weights should be objectively established. The non-bankrupt sample was stratified randomly by industry and size, and small and large firms were eliminated in order to not deflate the statistics. Twenty-two potential financial variables were initially selected based on their popularity in the literature (Beaver W. , 1966), taken from balance sheet and income statement data, under five categories: liquidation, profitability, leverage, solvency, and activity ratios. Five variables were ultimately selected as doing the "best overall job together in the prediction of corporate bankruptcy" (Altman, 1968): a) working capital/total assets, b) retained earnings/total assets, c) earnings before interest and taxes/total assets, d) market value of equity/book value of total debt, and e) sales/total assets. The resulting formula was:

$$\boldsymbol{z = 0.012\, x_1 + 0.014\, x_2 + 0.033\, x_3 + 0.006\, x_4 + 0.999\, x_5} \qquad \textbf{Equation 1}$$

where $X1$ = *Working capital / Total assets*

$X2$ = *Retained earnings / Total assets*

$X3$ = *Earnings before interest and taxes / Total assets*

$X4$ = *Market value equity / Book value of total debt*

$X5$ = *Sales / Total assets*

Z = *Overall Index*

Altman calculated the accuracy model using a matrix summarizing the "Hits" and "Misses," as follows:

Actual Group Membership	**Bankrupt**	**Non-Bankrupt**
Bankrupt	H	M_1
Non-Bankrupt	M_2	H

Table 2: Altman's Classification of Hits and Misses for Model Accuracy Calculations

where H stands for Correct Classifications, M_1 for Type I error misclassification, and M_2 for Type 2 error misclassification. The total model accuracy was computed as the Total Number of Hits divided by the Total Number of Companies ($H/(M_1+M_2)$).

The results of the model predicted a highly significant level of accuracy. Of the initial sample, the model yielded 95% accuracy one financial statement prior to bankruptcy, and 72% accuracy two years prior. To validate further, Altman isolated two new sample groups of 25 bankrupt and 66 non-bankrupt companies. These groups yielded accuracies of 96% and 79%, respectively.

2.3.3. Taffler and Tisshaw prediction model

The use of MDA continued to dominate the field of failure prediction. In 1982, Taffler (1982) developed a similar model to Altman's z-score, also using MDA but focusing on UK companies.

Taffler's discriminant model is also based on a linear formulation. Due to the nature of the model—classification based on samples of failed and solvent firms, as well as variables based on financial statement ratios—he determined the linear approach to be more appropriate than quadratic techniques. In particular, Taffler criticized quadratic techniques as an “incorrect approach where data samples depart from the assumptions of multivariate normality and are small in size relative to the number of constituent variables” (Taffler, Forecasting COmpany Failure in the UK Using Discriminant Analysis and Financial Ratio Data, 1982).

Taffler’s research examined failed and non-failed firms from the London Stock Exchange during the period of 1968–1973. Twenty-three failed firms were selected on the basis of a definition of failure due to receivership, voluntary liquidation (creditors), winding up by court order, or the equivalent. The methodology for selecting non-failed firms was a bit more intricate. Non-failed firms were not matched with failed firms by industry, size, or year due to the fact that such matching reduces the randomness, total size, and degrees of freedom for sampling. The biggest difference, however, in selecting non-failed companies was the “explicit recognition that a continuing firm is not necessarily financially healthy” (Taffler, Forecasting COmpany Failure in the UK Using Discriminant Analysis and Financial Ratio Data, 1982). In other words, the characteristics of some non-failed firms closely resemble those of failed firms. Thus, he deemed it important to remove from the original sample firms that were classified as not financially healthy. In the end, out of an original sample of 61, 45 firms were selected as non-failing and financially healthy.

For the variables in the model, a 50-ratio set was “selected on the basis of effectiveness in previous and related studies, popularity in the literature, theoretical arguments based on the liquid asset model of firm (Blum, 1974) (Walter J. E., 1957), and suggestions by financial analysts based on their experience” (Taffler, Forecasting COmpany Failure in the UK Using Discriminant Analysis and Financial Ratio Data, 1982). Data was public, drawn from the stock exchange, and only accounting statement–based financial ratios were used.

Taffler contended that the model outperformed current and existing US-based models such as that of Altman. In particular, he claimed it demonstrated true *ex ante* predictive ability for a 3-year period. He argued that the primary reasons for the model’s success over others is the financially sound sample of non-failed companies and the non-collinear constituent variables.

One of Taffler's main contributions is his conclusion that models should be monitored over time, due to the changing nature of the economy, policies, and business trends, which when altered or shifted may affect the effectiveness of the model (Taffler, Forecasting COmpany Failure in the UK Using Discriminant Analysis and Financial Ratio Data, 1982).

2.4 – Predicting the Failure of Construction Companies

2.4.1. Business Failure in the Construction Industry

As mentioned earlier, literature focusing on the development of failure prediction models did not delve into assessing the reasons for failure. Instead, it relied more on taking a statistical development approach to creating a best fitting model for the selected sample. One has to look outside of failure prediction model literature to understand industry-specific reasons for company failure. One of the notable studies in this regard is Arditi's: Business failures in the construction industry (Arditi, Koksal, & Kale, 2000).

Arditi concluded that company failure can result from a mixture of environment-dependent and strategic leadership-dependent factors. Drawing on a 1991 study by Boyle and Desai (1991), they developed a model explaining the causes of construction company failure. Boyle and Desai's (1991) environment/response matrix distribution includes four cells: internal-administrative, internal-strategic, external-administrative, and external-strategic. Using data from Dun and Bradstreet's annual *Business Failure Records*, compiled over the years 1989–1993, they adapt the matrix to the construction industry. Budgetary and human capital issues populate the first cell, while issues of adaptation to market conditions populate the second. The third cell includes characteristics of managers and business conflicts, and the fourth covers natural forces and macroeconomic conditions.

Upon inserting data into the model, Arditi isolate five factors as most prevalent to failure in the construction industry. Together accounting for over 80% of failures, these include insufficient profits (26.71%), industry weakness (22.73%), heavy operating expenses (17.80%), insufficient capital (8.29%), and burdensome institutional debt (5.93%). Four of these factors are budgetary, classified as "internal-administrative," and thus can be dealt with internally in the short term. The fifth factor, “industry weakness,” is an environmental factor and thus beyond the company’s scope of immediate action. This, together with other environmental factors, accounts for 25.73% of all reasons for failure (Arditi, Koksal, & Kale, 2000).

Other studies on the reasons for failure are also summarized in the extensive literature review done by (Wong & NG, 2010). They found that the failure of construction companies is usually the result of a complex process, rather than one single factor. The construction industry is particularly vulnerable to failure due to the fragmented nature of the industry, excessive competition, a relatively low barrier to entry, the high uncertainty and risk involved, and the unpredictable fluctuations in construction volume (Kale & Arditi, 1999) (Kangari R. , 1988). Arditi et al. (2000) found budgetary and macroeconomic issues to be the main reason US construction companies fail, while Kivrak and Arslan (2008) observed a lack of business experience and the country’s economic conditions to be the biggest factors for Turkish companies. Other studies around the world place an emphasis on the following fators: high competition, which causes companies to reduce profit margins to win bids (Kangari R. , 1988) (Osama, 1997); lack of managerial experience/maturity (Osama, 1997) (Schaufelberger, 2003); poor accounting, estimating, and early warning systems (Schaufelberger, 2003) (Davidson & Maguire, 2003); and inadequate capital and poor cash flow (Schaufelberger, 2003) (Davidson & Maguire, 2003) (Osama, 1997).

2.4.2. Overview of Statistical Models for Predicting Business Failure

Table 3 is adapted from (Wong & NG, 2010). It summarizes the developments in predicting failure in construction. We follow the table with a detailed discussion of the critical milestones in these developments providing more details about each study. The "Sec Ref." column in the table refers to the section number where detailed discussions of the listed research are presented.

Author(s)	Cou-ntry	Achievements	Source of data	Modeling technique	Sec. Ref.
Mason and Harris (1979)	UK	Developed a Z-model in construction comprising 6 financial ratios	Extel Services cards; 20 failing plus 20 sound civil contractors	MDA	
Kangari (1988)	US	Modeling construction business failure using macroeconomic factors	Macroeconomic data (1977-1986)	Multiple Regression	2.3.3
Kangari et al (1988)	US	Developed a performance index to grade a company by regressing 6 financial ratios	Dun and Bradstreet; 126 construction companies (6 Groups)	Multiple Regression	2.3.4

Author(s)	Cou-ntry	Achievements	Source of data	Modeling technique	Sec. Ref.
Russell and Jaselskis (1992)	US	Developed a model to predict the probability of contractor failure at the project level	20 public plus 28 private projects survey; 23 out of 48 companies involved failure	Logit Regression	
Hall (1994)	UK	Identified factors distinguishing survivors from failures	Survey of 58 small construction companies	Logit Regression	
Abidali and Harris (1995)	UK	Developed a model to predict construction company failure using 7 financial ratio and 13 managerial factors	Extel Services cards; 11 failed companies; 20 non-failed companies	MDA	
Russel and Zhai (1996)	US	Examined the pattern of stochastic dynamics; percentage changes, trends and volatility for economic and financial variables to predict contractor failure	Dun and Bradstreet; 49 failed and 71 non-failed contractors	Multiple Regression	
Kale and Arditi (1999)	US	Explored age-dependent business failure pattern in US Construction industry	Dun and Bradstreet; 1973–1994; 7608 failed companies		
Koksal and Arditi (2004)	US	Explored a model to determine a company's healthiness comprising 11 organizational factors	Westlaw, LexisNexis, and surveys; 11 failing and 41 sound companies	Factor Analysis and Logit Regression	2.3.5.
Chan et al (2005)	HK	Assessed the financial performance of the construction firms in Hong Kong	Annual reports of 8 large contractors; 1997–2002	Ratio Analysis	2.3.6.

Author(s)	Cou-ntry	Achievements	Source of data	Modeling technique	Sec. Ref.
Huang (2009)	Taiwan	Investigated the viability of using structural models of credit risk for predicting contractor default probabilities	19 defaulting and 30 non-defaulting companies; 1999–2006	Ratio Analysis and Logit Regression	2.3.7.

Table 3: Summary of Previous Studies on Predicting Failure in Construction

2.4.3. Review of "Business Failure in the Construction Industry" by Kangari

Kangari (1988) begins by exploring the failure rates within the construction industry and correlating macroeconomic trends. He cites Dun and Bradstreet's ten primary causes of business failure, highlighting specifically "economic factors," which account for the largest chunk of failures at 59.8%. Of the five subcategories under economic factors (bad profits, high interest rates, loss of market, no customer spending, and no future), bad profits alone accounts for 74.2% of all economic factors, or slightly over half of all business failures in total.

Data from the Dun and Bradstreet Corp. over a ten-year period spanning from 1978–1987 shows the number of construction firm failures rising 484%, and the rate of failure increasing 386%. Kangari accounts this rise in part to a change in bankruptcy laws, but more broadly to industry forces, namely the amount of construction activity, interest rates, inflation, and new business activity. Between the years of 1979–1982, the author attributes this rise to both lower construction activity and higher interest rates. Kangari posits that when construction activity declines, construction failure increases. Looking specifically at the contract value index from the Department of Commerce, he finds that changes in the index are less substantial than corresponding changes in failure rates. As such, he postulates that small variations lead to more dramatic and substantial failure rate effects. In addition, higher interest rates are shown to be correlated with higher failure rates. Construction is affected by cash flow, and the ability to borrow cheaply and pay lower loans reduces the risk of negative profits.

Looking at the years 1982–1986 however, Kangari notes that the industry continues to witness a rise in failures despite a reverse in constructive activity. He interprets this as linked to a higher number of new construction businesses. With higher activity and lower interest rates, more early-stage construction firms may have been incentivized to enter the field during that time. New businesses suffer from higher failure rates due to a lack of experience, financial reserves, established reputation, and standard customers. He posits that because the chance of failure is significantly higher during a construction firm's first 3 years of existence, an increased number of new businesses entering the field increases the overall failure rate.

From this analysis, using data from the Business failure record (1977–1986), Dun's census (1978–1986), and the Quarterly business start (1978–1986), Kangari isolated five factors most relevant to failure in the construction industry: bad profits, management incompetence and lack of experience, inadequate sales, loss of market and economic decline, and difficulty collecting from customers. From here, he developed a macroeconomic model to predict business failure in the construction industry. The model is based on external factors and statistics, including: "(1) The federal intermediate credit bank loan rate as a measure of interest rates; (2) the construction-contract valuation index by F. W. Dodge as a measure of construction activity; (3) the new-home, conventional fixed long-term mortgage rate as a measure of interest rates and residential construction activity; (4) the Department of Commerce's construction cost index as a measure of inflation; and (5) the number of yearly business starts as a measure of new business activity" (Kangari R. , 1988, p.

183). The model assumes that most causes of construction business failure are financial, due to the reliance on cash flow and the high level of competition within the industry.

The objective of the model is to determine which variables contribute to a change in failure rate, and to what degree. It presents a mathematical multiple linear regression to determine when construction failure rates are likely to be higher, with the aim of assisting managers in making preemptive decisions to reduce the chance of failure. The model also demonstrates the impact of new businesses entering the market on the rate of failure, thus providing guidance to prospective owners regarding the chance of failure.

2.4.4. Review of "Financial Performance Analysis for Construction Industry" by Kangari et al.

Authors (Kangari, Farid, & Elgharib, 1992) developed a quantitative model to assess the financial performance and grade of a construction company, as well as its chances of business survival.

The model is based on 6 financial variables: current ratio, total liabilities to net worth, total assets to revenues, revenues to net working capital, return on total assets, and return on net worth. Based on data from the years 1982–1988 from Dun & Bradstreet, Inc. *(Industry Norms* 1982-1988), Robert Morris Associates *(RMA Annual* 1985), Department of Treasury's annual publications ("Source Book" 1983-1988), Troy *(Almanac* 1987), Value Line publications *(Investment* 1988), and Standard & Poor *(Corporate Records* 1989), the model combines these variables into one single performance index, *I*, to evaluate the firm's financial performance. Because average industry financial ratios include companies of all sizes (Kangari R. F., 1992) (and are thus unsuitable for cross-company comparison), a "size factor" is also considered to compare firms of varying sizes. The factor essentially compares companies of the same size through a "ratio of the 'financial ratio *i* of overall, average-size construction company in each group' over the 'same ratio *i* of an average-size company in the same size-class as the company under consideration' (Kangari R. F., 1992).

2.4.5. Review of "Predicting Construction Company Decline" By Koksal and Arditi

Koksal and Arditi (2004) propose a model for predicting the decline of a construction company using non-financial indicators. The proposed model, comprised of 11 organizational, human resource, and strategic characteristics, aims to act as an early warning system that can prevent the approach of financial crises.

Unique to this study is that Koksal and Arditi utilize a definition to what it means for an organization to "decline," instead of the more commonly utilized failure definitions. They note that primary issues for decline include a "lack of awareness of environmental threats, internal weaknesses, and [a] lack of corrective action under such conditions" (Levy, 1986). Weitzel and Jonsson (1989) find that organizations begin to decline when they fail to "anticipate, recognize, avoid, neutralize, or adapt to external and internal pressures threatening long-term survival." Finally, Rozanski (1994) states that decline is a "condition in which substantial or absolute decrease in a resource base occurs over a period of time."

Based on this definition, Koksal and Arditi develop a model that assesses an organization's health based on three factors: organizational, human capital, and strategic. To define a "healthy firm," they use Barker's definition: a healthy firm is one that earns at least a risk-adjusted minimum rate of return (Barker, 1992). The factors presented are non-financial, in the sense that they are variables that may *lead* to financial crises, and thus are part of what they call the stage of "initial decline." The first variable—operational factors—assesses the strengths and weaknesses of the hierarchical authority in an organization's structure. Second, the human capital factor explores issues such as the education, knowledge, experience, and cognitive style of executives and managers. Finally, strategic factors look at competitive advantages, synergy, resource utilization, and customer elements. Environmental factors such as industry conditions, economics, and politics are considered "out of control" of the organization, and thus are excluded from the model.

A timely analysis of these factors, Koksal and Arditi argue, can present possible opportunities for response that benefits the firm. However, when the issues are not detected early enough, companies can enter the second stage: "decline recognition." In this stage, a company enters financial difficulty, and management begins to respond to the challenges. Koksal and Arditi question why top managers may not detect such a decline early on, instead detecting the decline only after financial issues become prevalent. Their answer: the symptoms described above in the initial decline stage are mostly equivocal, and much of top management does not see these signs as highly important until it begins to affect financial performance (Koskal & Arditi, 2004).

The third stage outlined in this study, "response to decline," occurs when executives attempt a turnaround of the company. Responses can include "diversifying the product line, forging new alliances with other parties through partnering or joint ventures, taking measures at the business level such as increasing relative market share and firm sales, downsizing the production line, and liquidating some assets to generate cash flow" (Barker, 1992). These responses can have one of two effects: a) the company continues carrying on its activities, or b) the company declares Chapter 11 bankruptcy.

In an attempt to help construction companies avoid reaching stages two and three, Koksal and Arditi developed a statistical model that analyzes company health. To begin, they produced a questionnaire surveying two parallel groups: a) construction companies that previously filed Chapter 11 bankruptcy, and b) companies that have not. Using 21 organizational, human capital, and strategic posture characteristics, they sought to determine whether the presence and/or absence of these characteristics accurately predicted financial crises. From the surveys distributed, they chose 11 indicators to use in the model. To validate the model, they tested it with three randomly selected construction firms: one bankrupt and two non-bankrupt.

From the research, Koksal and Arditi conclude that the non-financial aspects of a construction company are important in assessing the company's decline/failure position. This can be accurately detected using as few as 11 variables. They did note one limitation in the study: obtaining accurate data from bankrupt companies can be extremely challenging, because these companies are either no longer existent or are reluctant to broach the issue. In the future, Koksal and Arditi suggest their model be further validated through the collection of more bankruptcy-related data.

2.4.6. Review of "Model for Predicting Financial Performance of Development and Construction Corporations" By Chen

In this study, Chen (2009) develops a model for predicting the financial performance of construction corporations. The unique characteristic of this research is that it focuses on predicting performance rather than on predicting failure.

Performance is defined by how successfully an organization attains its objectives, and how effectively it implements an appropriate strategy (Otley, 1999). Financial position is shown to affect a firm's performance (Altman, 1968) (Beaver W. , 1966) (Deakin D. , 1972), and many studies focus on performance in the construction industry (Chang, 2001) (Cheung, Wong, Fung, & Coffey, 2006); (Dai & Wells, 2004) (Navon R. , Automated Project Performance Control of Construction Projects, 2005) (Navon R. , 2007) (Odusami, Iyagba, & Omirin, 2003) (Parket & Skitmore, 2005) (Russell & Jaseskis, Predicting construction contractor failure prior to contract award, 1992). However, most of these concentrate on the project-level, while few explore the organizational level (Bassioni, Price, & Hassan, Performance measurement in Construction, 2004) (Bassioni, Price, & Hassan, 2005).

To predict financial performance in the construction industry, the sector variable is important. In fact, since each project has a large influence on a firm's financial performance, the project-based nature of the construction industry amplifies the effect of the sector variable as compared to typical organizational-performance studies (Kaka & Lewis, 2003).

The study sought to develop firm-specific performance-forecasting models for the construction industry. Using Pearson's correlation tests, the author conducted a cross-sectional longitudinal analysis of relationships between firm financial performance and financial and economic variables. Public data was employed (income statements, balance sheets, and economic data) from 42 firms listed on the Taiwan Stock Exchange over a 10-year period (1997-2004), with rate of return on common shareholders' equity as the primary financial performance variable. From relationships found in the Pearson tests, a 3-stage mathematical modeling procedure was developed based on combined time series and regression analysis using ordinary least-squares (OLSs).

The results of the model explained a 78.9% variation in the cross-sectional performance data, with MAPE values in the forecasting model ranging from 9.54% to 19.69%. The author suggests that the results demonstrate that positive and negative correlations exist between change ratios in current time periods, and those in immediately previous time periods. As the author states, when financial/economic variables increase or decrease in the current season, a firm might improve its financial performance in the immediately following corresponding season.

2.4.7. Review of "Predicting Loss for Large Construction Companies" by Adeleye et al.

This research (Adeleye, Huang, Huang, & Sun, 2013) also did not focus on failure in the form of being out of business, but more specifically on predicting "distress," a broad concept ranging in severity from loss to bankruptcy. While a number of previous models have focused on "distress" (Ohlson, 1980) (Zmijewski, 1984) (Shumway, Forecasting bankruptcy more accurately: A simple hazard model, 2001) (Jones & Hensher, 2004), those focusing specifically on construction companies are scarce. Two United Kingdom based models predicted a) failure in the civil engineering sector through 6 variables (Mason & Harris, 1979) and b) construction company insolvency through a ratio analysis technique and Altman Z-score (Langford, 1993). In the US, Koksal and Arditi (2004) developed a statistical model that determines the health of construction companies.

Based on the lack of distress-based models for the construction industry, Adeleye et al. (2013) sought to construct a model that would predict future loss occurrence for large construction companies.

Their model used publicly available financial variables from the North American Compustat database, with a sample of 959 loss firm-years and 2,313 non-loss firm-years between the years of 1976 and 2010. Adeleye et al. chose variables based on self-analysis and reviews of past research on financial distress (Altman, 1968) (Ohlson, 1980) (Shumway, Forecasting bankruptcy more accurately: A simple hazard model, 2001) (Emery & Cogger, 1982) (Hopwood, Mckeown, & Mutchler, 1989). The final models, employing a statistical logistic regression, predicted next-year loss occurrence in two forms: a full model (with 17 predictor variables) and a reduced model (with 11 predictors).

In validating the models, they had 74% accuracy for predicting loss, and a 70% accuracy for predicting non-loss. Both models —full and reduced — demonstrated comparable accuracy. Accordingly, they noted that the reduced model is likely to be more appealing to stakeholders due to its increased simplicity. From the validation, the following characteristics were found most useful for prediction: "the firms' ability to generate sales or net worth, operating expenses, leverage, the presence of special items or foreign transactions, and the type of stock exchange" (Adeleye, Huang, Huang, & Sun, 2013). Results also indicated specific trades within the construction industry demonstrating a higher likelihood of loss; specifically, manufacturing and fabrication, design, and consulting.

Two alternative prediction models were also developed and tested. The first attempts to predict loss in a 2-year span. Previous research indicates that 1- and 2-year prediction models can have similar prediction power (Ohlson, 1980), but that they are generally unreliable after 2 years (Altman, 1968). The model, using an 8-variable stepwise logistic regression, predicted loss occurrence with 64% accuracy for loss, and 62% accuracy for non-loss.

The second alternative model assessed the degree of a predicted loss. Because large losses are usually more severe and difficult to reverse, knowing the size and extent of an upcoming loss can prove useful. This 10-variable stepwise logistic regression model predicted high levels of loss with 73% accuracy, and non-high-levels with 85% accuracy.

2.5. Problems related to the classic statistical methods

There are a number of problems relating to the use of statistical models in predicting business failure such as neglecting the time dimension of failure, over-fitting, and relying only on annual account information. We discuss these problems in this section.

2.5.1. Limitations of the MDA Prediction Models

Strictly speaking, MDA is not so much considered predictive as classifying. By grouping firms into failing and non-failing based on other firms with similar characteristics, instead of predicting future failure it indicates the current state of affairs of a company's financial health (Balcaen & Ooghe, 2006) (Lennox, 1999).

There are also several assumptions that restrict the predictive power of MDA. Most failure predictions using MDA do not check data against these satisfying assumptions, leading to inappropriate applications that are often not suited for generalization (Joy & Tollefson, 1975) (Eisenbeis, 1977) (Richardson & Davidson, On linear discrimination with accounting ratios, 1974) (Zavgren, 1985). The assumption of multivariate normally distributed independent variables is often violated (Deakin E. B., 1976) (Taffler & Tisshaw, 1977) (Barnes P. , 1987), which has been said to cause biased significance tests and error rates (Eisenbeis, 1977) (Richardson & Davidson, 1984) (McLeay & Omar, 2000).

Researchers have attempted to compensate the problem by approximating univariate normality through transforming variables or trimming outliers, but "they ignore the following facts: (1) univariate normality is not a sufficient condition for multivariate normality; (2) transformation may change the interrelations among the variables (Eisenbeis, 1977) (Ezzamel & Mar-Molinero, 1990), thus distorting the MDA model; and (3) outlier trimming may cause a significant loss of information (Ezzamel & Mar-Molinero, 1990)" (Balcaen & Ooghe, 2006).

The second problem lies in the fact that the "data rarely satisfies the assumption of equal variance-covariance matrices across the failing and non-failing group" (Balcaen & Ooghe, 2006). This can produce biased significance tests. Although the quadratic MDA model addresses the challenge of unequal matrices (Joy & Tollefson, 1975) (Eisenbeis, 1977) (Zavgren, 1985), its complexity impedes its application, and instead researchers approximate equal dispersion matrices through the linear MDA (Taffler, 1982).

When using MDA, researchers also often ignore prior probabilities of failure and costs of misclassification. This can have the effect of misleading the accuracy of the model (Edmister, 1972) (Eisenbeis, 1977) (Zavgren, 1985) (Hsieh, 1993). Finally, while multi-collinearity is irrelevant in MDA models (Eisenbeis, 1977), correlation among variables can produce unstable, difficult-to-explain parameter estimates (Edmister, 1972) (Joy & Tollefson, 1975) (Doumpos & Zopoudinis, 1999).

2.5.2. Problems with Classification, Categorization and Data Preparation

There is a wide host of problems related to the use of statistical methods in predicting company failures. Unless addressed in data classification, categorization and preparation, statistical methods may fail to address certain sources of uncertainty in classification, such as the arbitrary definition of failure, non-stationary and data instability, sampling selectivity, and the arbitrary choice of optimization criteria. Due to these problems, Moses and Liao (1987) argue that many models can be misleading in their reliability. Some are subject to "over-modeling", and corporate failure prediction studies are often optimized to fit the presented issue (Balcaen & Ooghe, 2006).

In addition, a common confusion between ex-post classification results and ex ante predictive abilities has tended to exaggerate the models' predictive abilities (Joy & Tollefson, 1975). To ensure their viability, these models should be tested on data after their creation (Joy & Tollefson, 1975) (Moyer, 1977), especially on new samples (Taffler, 1983).

While MDA and conditional probability models categorize failing and non-failing firms in a well-defined, clear manner, their separation tends to be arbitrary. Definition of failure is inconsistent, and often fraught with errors. Many use the juridical definition, usually bankruptcy (Dirickx & Van Landdeghem, 1994) (Ward & Foster, 1997) (Van Caillie, 1999) (Charitou, Neophytou, & Charalambous, 2004), but bankruptcy as a single defining factor of failure presents multiple dilemmas. First, because bankruptcy figures primarily concern liquidity and solvency, such companies may not exhibit other important signs of failure.

This especially includes companies that choose bankruptcy more strategically (e.g. to get rid of debts) or are forced into bankruptcy due to unexpected external events. It is useful here to distinguish between "sudden bankruptcies" (Hill, Perry, & Andes, 1996) and "accidental bankruptcy" (Davis & Huang, 2004). In addition to this challenge, bankruptcies should be recognized as only one of many possible endings. Other forms of exits occur, such as mergers, absorptions, dissolution, and liquidation. Finally, focusing on the moment of bankruptcy may ignore the often long time lag between a firm's initial problems and final bankruptcy (Theodossiou, 1993).

This bankruptcy definition of failure is only one of many, however. Others include "'financial distress' (Keasey & Watson, 1987) (Hill, Perry, & Andes, 1996) (Doumpos & Zopoudinis, 1999) (Platt & PLatt, Predicting corporate financial distress: reflections on choice-based sample bias, 2002) (Kahya & Theodossiou, 1996) or on failure-related events such as cash insolvency (Laitinen E. , Traditional versus operating cash flow in failure prediction, 1994), loan default (Ward & Foster, 1997), capital reconstructions, major closures, forced disposals of large parts of the firm, informal government support, and loan covenant renegotiations with bankers" (Taffler & Agarwal, 2003). Indeed, corporate failure is not a well-defined dichotomy, and as a result the definitions of failure may not match real interest, i.e. ex-post classifications may differ from ex-ante. Additionally, the arbitrary selection of a time period can create selection bias (Shumway, 1999) or contaminated populations (Taffler, 1982) (Taffler, 1983).

Due to the nature of these models, data relationships are assumed to remain stable over time, between independent and dependent variables (Edmister, 1972) (Zavgren, 1985) (Mensah, 1984) (Jones F. , 1987) and inter-correlations between independent variables (Edmister, 1972) (Zavgren, 1985). However, several authors demonstrate evidence of data instability (Barnes P. , 1982) (Richardson & Davidson, 1984) (Zmijewski, 1984). This can be caused by external factors (e.g. inflation/interest rate changes, or shifts in business cycle) (Mensah, 1984) or changes in the competitive nature of the market, corporate strategy, or technology (Wood & Piesse, 1987). In fact, data instability generally occurs most when firms are about to fail (Dambolena & Khoury, 1980).

The time factor plays into the equation here: as data is pooled across a range of years, variables should be stable over time (Altman & Eisenbeis, 1978) (Zmijewski, 1984), including for future samples. As a result, there are severe consequences for prediction. With data instability, future-dated samples have been shown to have poor predictive ability (Mensah, 1984). Because much data is fundamentally unstable, and not robust, over time, models should be re-estimated, re-developed, and updated with new coefficients (Joy & Tollefson, 1975) (Taffler, 1982) (Taffler, 1982) (Mensah, 1984) (Keasey & Watson, 1987) (Dirickx & Van Landdeghem, 1994). This, however, is rarely done. As a result, data may be temporarily distorted, which can result in inconsistent coefficient estimates (Platt, Platt, & Pederson, 1994) and low accuracy (Back, Laitinen, Hekanaho, & Sere, 1997).

Another issue is related to sampling selectivity. Although classic statistical methods assume that samples are random, many prediction models in fact use non-random samples (Altman, 1968) (Deakin D. , 1972) (Blum, 1974) (Taffler & Tisshaw, 1977) (Dambolena & Khoury, 1980) (Frederikslust, 1978) (Ohlson, 1980) (Zavgren, 1985) (Keasey & Watson, 1987). This can result from a) over-sampling of failing companies due to the much lower number of failed firms (Zmijewski, 1984) (Platt & PLatt, 2002), b) applying "complete data" sample selection criteria (Taffler, 1982) (Ooghe & Verbaera, 1985) despite failing firms' tendencies to be younger and smaller, and c) matching pairs of failing and non-failing firms (Ohlson, 1980) (Platt & PLatt, 2002). Ooghe and Joos (1990) state that to be predictive, samples should represent the entire population of firms. When sampling fails to accomplish this, consequences include biasing the parameter estimates (Zmijewski, 1984), an overstatement of ex-post accuracy and an understatement of the misclassification error rate for the over-sampled failing group (Zavgren, 1985) (Zmijewski, 1984) (Platt & PLatt, 2002) (Piesse & Wood, 1992), biased model coefficients (Zmijewski, 1984), and a sample-specific model (Zavgren, 1985). The result can include misleading predictive accuracy (Keasey & Watson, 1987).

The second primary problem outlined by the authors regards models' neglect of the time dimension failure. Essentially, many models ignore the changing nature of companies over time. Nearly all classic statistical failure prediction models use only one single observation—the annual account— based on the assumption that consecutive annual accounts are independent. However, Dirickx and Van Landeghem (1994) find that these observations are not entirely independent. Considering that, choosing to observe annual accounts over only one specific period can create selection bias (Mensah, 1984) (Shumway, 1999). In addition, models do not account for the time-series behavior. Although failure prediction should depend on more than one annual account or change in financial health (Shumway, 1999), past information regarding corporate performance is sometimes ignored (Dirickx & Van Landdeghem, 1994) (Kahya & Theodossiou, 1996) (Theodossiou, 1993). A signal inconsistency problem can also occur, through repeatedly applying the model to consecutive annual accounts (Dirickx & Van Landdeghem, 1994) (Keasey & Watson, 1987).

An additional time dimension issue regards the contradiction of the fixed score output. Static models, such as the MDA and LA, are not suited to failure prediction due to the fact that their summarization of issues without a real time dimension renders predictions not applicable to the standard discriminant analysis (Altman & Eisenbeis, 1978). At the same time, the retrospective character of these models demonstrates the dissimilarities of failing and non-failing firms, rather than being predictive (Ooghe & Joos, 1990).

A potential solution to this issue is to develop short-term estimations that are one, two, and three years prior to failure (Deakin D. , 1972), although for the model to be effective in the long-term it would need to be re-estimated and re-developed to consider other coefficients and variables in later years. The models also face the problem of examining company failure as a discrete event (Altman, 1984), paying less attention to the longer-term progress and dynamics of the failure process. Models assume failure is a steady state (Luoma & Laitinen, 1991) (Laitinen E. , 1993) (Laitinen & Kankaanpaa, 1999), but in reality failure is not sudden or unexpected (Luoma &

Laitinen, 1991). The failure process, in addition, is not uniform as often is assumed but may take many paths (Laitinen E. , 1991).

The third category of problems relates to the application focus. Many models have been developed without a complete understanding of the nature of company failure, often employed from an outsider's viewpoint. Due to the models' statistical nature, they are heavily dependent on variables. Variables are initially selected arbitrarily; there is a lack of theoretical basis for this selection (Dirickx & Van Landdeghem, 1994) (Karels & Prakash, 1987). Although variables are tested for reliability, there is no consensus or theory as to which are superior in their predictability (Scott, 1981), which removes any real scientific approach to failure prediction (Zavgren, 1985).

Other drawbacks to empirical selection include a limited ability for generalization (Edmister, 1972) (Gentry, Newbold, & Whitford, 1987) state that variables should be selected carefully for each industry (Karels & Prakash, 1987) because the choice of variables is often sample specific, which implies models can also be sample specific (Edmister, 1972) (Zavgren, 1985). Additionally, most models are based on multiple variables (Beaver W. , 1967) (Blum, 1974) (Gentry, Newbold, & Whitford, 1987), which limits availability of data and adds complexity. Interestingly, the models with the best accuracy for failure classification tend to be simpler models, with a small number of predictors. Marginal improvement in accuracy decreases as complexity increases (Balcaen & Ooghe, 2006).

Chapter 3

The Cash Flow Model

3.1. Introduction to Cash Flow Management

3.1.1. Introduction

“Cash flow management and liquidity are key elements in the survival of contractors” (Navon R. , 1996). Hegazy and Kassab (2003) suggest that the efficient utilization of resources increases the chance of success for project managers. Along these lines, prediction of cash flows in particular have been shown to help anticipate resources needed during various project intervals in upcoming months (Touran, Discussion of current float techniques for resources scheduling, 1991) (Touran, Atgun, & Bhurisith, 2004).

The simplest cash flow project model is the S-curve (Touran, Atgun, & Bhurisith, 2004), and the most popular models are third-, fourth-, and fifth-degree polynomials (Navon R. , 1996). While project cost, duration, and other characteristics are the most common inputs (Touran, Atgun, & Bhurisith, 2004), additional details can produce cash flow management tools applicable on company levels (Navon R. , 1996).

3.1.2. Cash Flow: Terms and Introduction

Cash flow is the summation of all payment receipts collected by a firm during a specific time period, less all payments paid out during the same period. Distinguishing this from cost flow—the projection of a project's costs over a period of time—cash flow is instead a function of expenses and incomes. It encompasses the flow of costs, payments, and earnings over a time lag, and can be represented mathematically as income flow—expense flow—overheads. Notably, cash flow considers only amounts that have “exchanged hands” (not those merely listed as payable).

Cash flow can be measured weekly, monthly, and/or cumulatively. Period cash flow examines variables month-by-month, producing a regular monthly analysis of incomes and expenses over that period. Cumulative cash flow, meanwhile, involves the continuous addition of period cash flow from the beginning of a given milestone to the end of another. In other words, it is the summation of period cash flow over the duration of a project, from the Project Start Milestone to the Project Finish Milestone.

Typically, within a cash flow, the cash out includes bid costs, preconstruction costs (engineering, design, mobilization, etc.), materials and supplies, equipment and equipment rentals, payments of subcontractors, labor, and overhead (Park, Han, & Russell, 2005). Cash in, meanwhile, considers items such as billings (less retentions), retentions, claims, and change orders (Park, Han, & Russell, 2005). Within a construction company, cash flow can be measured on the project-specific level, where specific activity costs and client payments are measured, as well as on the more comprehensive company-wide level.

Cash flow is a dynamic, ever-changing process. The complex interplay of transactions dependent on time, events, and prior costs (Lucko & Cooper, Modeling Cash Flow Profiles with Singularity Functions, 2010) is continually affected by changes in costs or deviations in progress (Navon R. , 1996). Major elements affecting cash flow include time delays, cost overruns, unconfirmed earned values, change orders, and changes of cost plan elements (Bennett & Ormerod, 1984).

3.1.3. The Importance of Cash Flow to the Construction Industry

Cash is often seen as the most important element of construction companies and their projects (Hwee & Tion, 2001). Adequate sources of capital, and a reasonable debt-to-income ratio, are critical for a business's profitability (Chen, O'Brien, & Herbsman, 2005). Conversely, lacking this capital can lead to default or bankruptcy (Lucko & Cooper, 2010).

Cash flow in particular is the bloodline of construction companies. A lack of cash can mean no payments to subcontractors, laborers, and crews, and no purchases of needed materials. It can lead to a limited ability to complete tasks on a site, a need to cut corners in the work, or a slower pace to match the amount of cash available. Negative outcomes can include delayed or incomplete work, increased financing costs and project risks, or the reduction of payments from owners and project funders.

Cash flow is particularly important during the project implementation period for a construction contractor. This period is most often the highest-risk compared to planning and operation periods (Martinez, Halpin, & Rodriguez). During this time, if revenues are not available, supporting expenses through loans can lead to an accumulation of interest that becomes a significant part of the project's overall costs (Martinez, Halpin, & Rodriguez) . Because the overall balance of profits and losses only appears at the finish of a project, a scarcity of physical cash during the project's implementation can lead to disruptions, and even bankruptcy (Lucko & Cooper, Modeling Cash Flow Profiles with Singularity Functions, 2010).

Cash is distinguished from profitability in that a company can survive for a transitional period without demonstrating a profit, or even while holding a loss (Navon R. , 1996). But a lack of cash can cause a company to collapse, even if it has a positive balance (Navon R. , 1996). Indeed, globally most construction companies that failed did so because of lack of working capital, and in spite of profitability (Navon R. , 1996).

The management of cash flow is claimed to be key for a construction business's financial viability and survival (Navon R. , 1996) (Kenley, 2003). Because liquidity problems for a construction company can often arise without prior warning (Navon R. , 1996), effective planning and the use of available resources plays an important role in the success of project management (Hegazy & Kassab, 2003). The prediction of cash flow in particular can anticipate the resources a company needs during current and upcoming projects and periods (Touran, Discussion of current float techniques for resources scheduling, 1991) (Touran, Atgun, & Bhurisith, 2004).

One significant outcome of cash flow management regards the cost and availability of investments and loans for construction projects. Obtaining loans can present a challenging process for the high-risk construction industry (Lucko & Cooper, Modeling Cash Flow Profiles with Singularity Functions, 2010). The ability of a construction company to secure a loan is strengthened by a convincing demonstration that any lack of liquidity is both temporary and expected (Navon R. , 1996). Because investors often provide funds based on a project's estimated revenues, cash flow projections can determine the level of loan servicing or the return on invested equity (Finnerty, 1996). Financial viability and adequate liquidity are central to a construction company (Navon R. , 1996), and adequate cash flow management can be the make-or-break factor for bank financing.

3.1.4. Cash Flow and Construction Company Failure

Construction companies are generally viewed as high-risk businesses, particularly vulnerable due to both internal and external challenges. These challenges include the fragmented nature of the industry, excessive competition due to a relatively low barrier to entry, high uncertainty in planning and implementation, and unpredictable fluctuations in construction volume (Kangari R. , 1988) (Kale & Arditi, 1999). As a result, failure in construction is more common than in other industries. Within the United States, census data from 1989–2002 cites an average failure rate for construction companies at 14%, consistently higher than the industry-wide rate below 12% (McIntyre, 2007).

There are many reasons why a construction company may fail, including but not limited to onerous contracts, issues in project scope, low profit margins, inadequate capitalization, unrealistic growth, improper accounting, bad judgment, and environmental effects. Among these, financial challenges rank at the top of the list. Multiple studies support this statement: Russell (1991) found more than 60% of construction company failures to be related to economic factors, while Kangari (1988) observed half of all construction business failures to be related to unrealistic profit margins. Further, Arditi et al. (2000) demonstrated budgetary and macroeconomic issues to be the main reasons US construction companies fail, with 80% of those failures from 5 factors: insufficient profits, industry weakness, heavy operating expenses, insufficient capital, and burdensome institutional debt (Arditi, Koksal, & Kale, 2000).

Among these issues, inadequate cash flow is a consistent cause of failure. Singh and Lakanathan (1992) confirm that more construction companies fail due to a lack of liquidity for day-to-day activities than because of inadequate management of other resources.

3.2. Previous Work on Cash Flow Management

Cash flow management has received considerable attention from both practitioners and academicians alike. A large collection of scholarly work exists on the topic. Previous work can be subdivided into two different, but related categories: project-level cash flow management, and company-level cash flow management. Project-level cash flow is concerned with managing the cash inflow and outflow on a single project. Company cash flow management is concerned with the aggregation of the project cash flow information in addition to cash inflows and outflows at the company level, such as interest paid, corporate salaries, corporate office overheads, investment revenues, and other similar income or expense items.

At the project level, there are numerous models developed to track and manage cash flow of construction operations at the project level. Models are sometimes approximate such as in the S-curve, or detailed such as in the cost/schedule integration models developed at the activity level.

The approximate mathematical models are most used when access to project data is limited. These most common cash-flow forecasting models are based first on cost flow, then later on cash flow, with the third-, fourth-, and fifth-level polynomials being the most popular (Ashley & Teicholz, 1977) (Gates & Scarpa, 1979). These models divide direct costs into elements (e.g., labor, materials, etc.), as a percentage of total costs, and are determined individually by typical time lag. From this, a simple formula forecasts cash flow. The main issue with these mathematical models, however, is that they are inaccurate and based on generic data, without reaching down to the resource level. Most don't take time lags into account, and income flows ignore the billing period. That said, Bathurst and Buttler (1980) demonstrate that some of these models have been used successfully.

The second types of model involve cost/schedule integration. Developed for projects with detailed data, this method considers both cost and schedule as factors to the cash flow. (Navon R. , 1996) summarizes the problems involved with these types of cash flow models. The main challenge being that compiling lists of resources with activities can be very time consuming. Additionally, computerization attempts fail due to issues of compatibility; the relationship between cost items (in terms of building elements) and scheduling (in terms of activities) is complex. Three methods solve the incompatibility problem: a) manual integration—an accurate but manually exhaustive process; b) approximate models—an automated but less accurate solution; and c) automatic cost/schedule integration models—an accurate method based on integration with an embedded database, requiring no human involvement.

As examples of cost/schedule integration models, some of the authors such as Lucko and Cooper (2010) advocate for the use of singularity functions as "an elegant way to model and analyze complex phenomena". The use of singularity functions builds on previous work by Lucko (2009) on analyzing linear schedules. Additionally, some models advocate the use of neuro-fuzzy networks and Monte Carlo simulation for obtaining more accurate cash flow estimates (Martinez, Halpin, & Rodriguez). Jian, Issa and Malek (2011) propose a multiple-objective cash flow planning model that considers typical banking instruments, constraints of the financial market, budget constraints, and the retention of money. Using the Pareto optimality efficiency network model, it applies cash flow management at the project level, during the tendering and construction stages. Other authors argued that mathematically complex models are difficult to implement on site, and proposed simpler alternatives. For example, Park, Han, and Russell (Park, Han, & Russell, 2005) proposed a project-level cash flow forecasting model that can be implemented on the jobsite level from a general contractor's viewpoint.

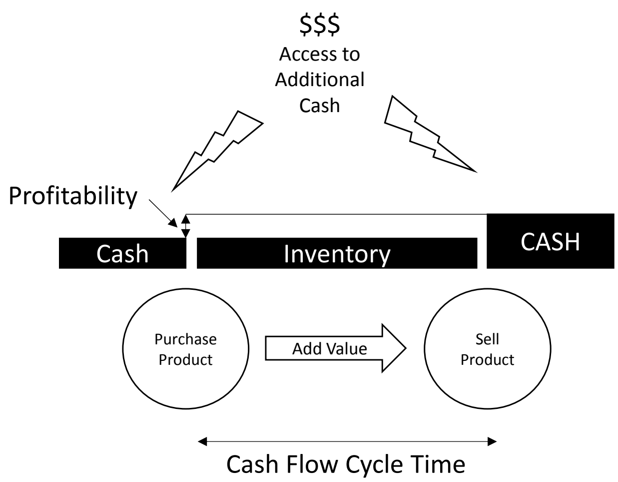
In contrast to the project-level cash flow management, company-level cash flow management did not receive the same level of attention from researchers. (Navon R. , 1996) developed a list of guidelines for use in developing cash flow models at the company level:

- The model has to cover all projects of the company, and should, for comprehensive cash flow forecasts, include company overheads and other general expenses and cost centers of the company.
- The model has to be flexible enough to accept data at all levels of detailing (from detailed data down to limited data). Evidently, the accuracy of the forecast will increase with the level of detail.
- The model has to be linked to all of the company's databases (bill of quantities, estimate, schedule, etc.) so that the forecasts are based on the most up-to-date data.

- Construction projects undergo constant changes due to shifting environmental conditions. Therefore, the model has to make provisions for constant updating.
- The model must be simple and require minimal human involvement and time investment, so as to permit frequent usage.
- The model has to allow for adjustments to inflation, so as to bring the costs of different projects to a common denominator.
- In view of the variability of the number of working days per month according to the season, site location, holidays, and type of work, the model must provide alternative calendars, permitting each project to be linked to the most suitable calendar.
- The model has to accommodate logical and integrity tests for reliability.

3.3. The Cash Flow Failure Prediction Framework

Our concern with cash flow stems is focused only on the assessment of cash flow variables as an indicator of business strengths, and in particular its potential for predicting company failure. We start with defining the objective of a for-profit business[1]. The main objective of a business is to generate more cash (Jury, 2012). Jury (2012) describes the most basic form of business as a trading business where a buyer buys a product from an entity, and sells it to another entity for more than he paid. We identify three critical elements in this trading cycle as depicted in the picture below:



1. *The profitability of the cash flow cycle*. In this simple trading example, the profitability can be measured by the difference between the purchase price and the selling price. Without any external influence (e.g., loans), the

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[1] For brevity's sake, we will drop the term "for-profit" and use only "business" to describe a for-profit business in this chapter.

profitability determines the rate of organic growth. In the same example, if the initial investment to purchase the goods was $100, and the goods were then resold for $120, then the cash available to purchase goods for the new cash flow cycle is now $120.

2. *The cash cycle time*. This is simply a measure of how much time it takes to go through a complete cash flow cycle. The cycle in the trading example is simple. It starts with the purchase of the goods (i.e., conversion of cash into a non-cash item), and ends with the sale of the goods (i.e., conversion of non-cash item back into cash).
3. *Access to additional cash*. This is a measure of how much additional cash the business can access when and if needed. There are many scenarios when access to additional cash becomes critical. In the trading example, suppose the trader purchased product A for $100, and sold it to a buyer for $120. However, the buyer did not pay the trader in immediate cash, but promised to pay in 30 days. The trader can now wait for 30 days until he gets his cash back to restock his product in the hopes of starting another cash flow cycle. Or, if he has access to additional cash on commercially feasible terms, he can inject this cash into his business on a temporary basis for 30 days until he

gets his cash back from the first buyer. Note that even though the trader now gets an opportunity to start the new cash cycle earlier, the first cash cycle time is still the same. The first cash cycle time is not over until he receives the sale price from the first buyer.

3.3.1. Applying the Cash Flow Framework to Construction Operations

The construction operation is not as simple as a direct buy and sell trade operation. Surprisingly, however, it still shares in the same cash flow cycle attributes outlined earlier. Figure 1 summarizes the application of this cash flow model on a construction operation in a simplified manner. In the following section we will describe how the construction cash flow cycle can still be described using those three cash flow variables.

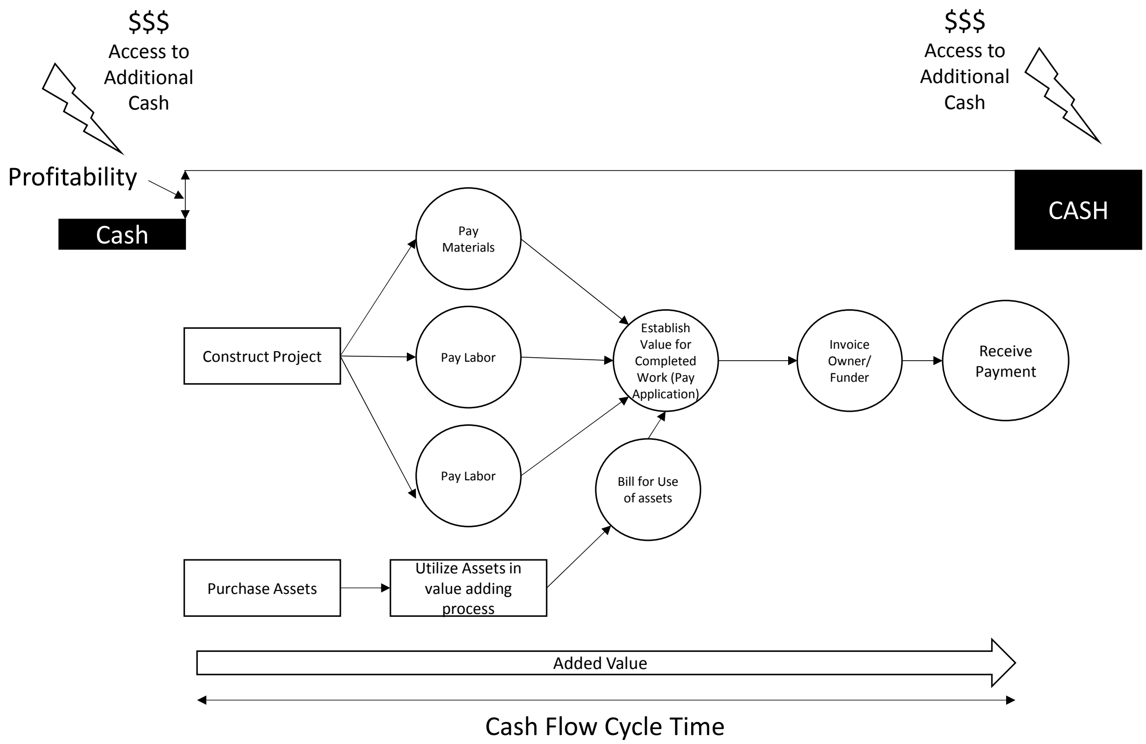

Figure 1: Construction Cash Flow Cycle

3.3.2. The profitability measure of the cash flow cycle

In the simple trading example, the profitability was simply a measure of the difference between the sales price and the purchase price of the goods sold. In the construction operations model, the profitability still reflects the difference between the cash at the end of the cycle and the cash at the beginning of the cycle. This difference, however, is not as easy to obtain for many reasons. First, it is not easy to distinguish the exact cash spent on the different components included in the work in progress upon which the cash receipt at the end of the cycle is based. Second, the retainage process—wherein the owner retains 5%–10% of the value of the work on each payment cycle until the end of the project—complicates the calculation on a cycle-by-cycle basis. A third complication is caused by the introduction of assets and asset utilization. Depending on the method of purchasing for assets, the cash payment for the asset may not coincide within the same cash cycle where the asset it utilized and cash is collected for its utilization. Many of those challenges could be resolved from a cash accounting perspective, albeit by adding more complexity to the framework. Since accounting for each independent cash flow cycle may prove difficult, and the reliability of a single cycle information for use in decision making is low, we opted to consider the averages over a period of three month. In other words, we will look at the measure of profitability taking into consideration the cash flow information at the end of a three-month period, and compare it to the cash flow information at the beginning of the three-month period.

To further assess the profitability, we will test the use of four measures for profitability: Return on Assets %, Return on Capital %, EBIDTA %, and Gross Margin Percentage as defined below:

- Return on Assets (ROA) gives an indication as to how profitable a company is relative to its total assets. It is calculated by dividing the company's annual earnings by its total assets. ROA = Net Income/Total Assets (Investopedia, 2013).
- Return on Capital (ROC) is a ratio that measures a company's profitability and the efficiency with which its capital is employed. ROC is calculated by dividing the Earnings Before Interest and Tax (EBIT) by the company's Capital Employed (Investopedia, 2013).
- Earnings Before Interest, Tax, Deprecation and Amortization margin (EBIDTA Margin) is another measurement of a company's profitability calculated by dividing the company's EBITDA by its total revenues (Investopedia, 2013).
- Gross Margin is also another form of profitability measure that looks at the difference between the revenue and cost before accounting for other costs. Gross Margin is calculated as (Revenue-Cost of Goods Sold)/Revenue (Investopedia, 2013).

3.3.3. The cash flow cycle time

The definition of cash flow cycle time in a construction operation does not differ much from its definition in the simple trading example mentioned earlier. The cycle time is the number of days starting from conversion of cash into a non-cash item, until the conversion back of the non-cash items, or its derivatives (e.g., completed construction), into cash. The calculation of the cash flow cycle time in its purest sense is not always readily available in publicly available financial statements. However, few readily available financial measures give an indication of the overall duration of the cash flow cycle. These measures include Average Days Sales Outstanding and Average Days Payables Outstanding. These measures are defined as follows:

- Average Days Sales Outstanding (ADSO) is a measure of the average number of days a company takes to collect revenue after a sale has been made. ADSO is calculated as follows: (Account Receivable/Total Credit Sales) X Number of Days (Investopedia, 2013).
- Average Days Payable Outstanding (ADPO) is a measure of how long it takes a company to pay its invoices. ADPO is calculated as follows: Ending Accounts Payable / (Cost of Sales/ Number of Days) (Investopedia, 2013).

3.3.4. The Access to Cash

In simple terms, access to cash is an indicator of the ability of current owners' to bring in more cash to the business whether through equity or debt; not necessarily in short term. This could be considered as a solvency measure, or long term credit worthiness measure. There are many ways to evaluate both perspectives, however, for the purpose of our cash flow model, we propose the use of Total Liabilities to Total Assets ratio for this purpose. Total Liabilities to Total Assets is a company's solvency ratio that is commonly used in construction operations, and provides a good assessment for a company's medium- to long-term solvency risk (Huang, 2009). Several alternative measures could be utilized to assess the company's access to cash, such as current ratio and possibly other leverage ratios as well.

3.4. Cash Flow Cycle Framework for Assessing Company Failure

Our hypothesis as explained earlier is that we can utilize this cash flow model that describes the company's cash flow cycle in terms of three variables—profitability variable, time variable, and access to cash variable—to statistically assess the performance of construction companies and predict their failure. To test and validate this hypothesis, the next chapters discuss the utilization of a data set comprised of quarterly financial information for construction companies, to quantitatively test our hypothesis. The testing will be conducted by selecting one variable from each category in a logistic regression test and comparing the result to a benchmark. The benchmark selected is the commonly utilized Altman Z-Score test for company failure prediction.

Chapter 4

Statistical Analysis Approach

4.1. Selection of Statistical Analysis Approach

The primary factor that determines the statistical technique to be used is the variables being analyzed—specifically the type or scale of variables and the number of independent and dependent variables (Mertler & Vannatta, 2002). For research questions requiring the prediction of group membership with two or more independent variables, and one dependent variable, Discriminant Analysis and Logit or Probit Regression are the most suitable methods (Mertler & Vannatta, 2002).

Discriminant Analysis is a method to classify a dependent variable into one of several groups based on the independent variables. Discriminant Analysis is computationally simpler than logistic regression. However, Discriminant Analysis assumes the independent variables (predictor variables) to be normally distributed, and assumes that the variables jointly follow a multivariate normal distribution (Hailpern & Visintainer, 2003). In terms of statistical preference, if the populations are normally distributed, then discriminant analysis is preferred. In contrast, under conditions of non-normality, logistic regression is preferred (Press & Wilson, 1978).

4.2. Statistical Assumptions and Data Normality

Historically, financial ratios have been used for company analysis (Altman, 1968), company-to-company and company-to-industry benchmarking (Beaver W. , 1967), and as inputs to financial prediction models (Beaver W. , 1967). Most of these comparative and predictive models have employed statistical techniques utilizing financial ratios as inputs. Hence, the validity of the resultant models hinges on the validity of certain assumptions made about the input variables. Since an empirical distribution of financial accounting ratios is not known, most of the existing models assumed that financial ratios fit a normal distribution as an approximation. Earlier tests of the normality of financial ratios assumption were shown to be inaccurate (Deakin E. B., 1976).

(Deakin E. B., 1976) investigated the normality of distributions of eleven commonly used financial ratios, referenced in the following table:

Ratio
Asset Turnover Ratios
$\frac{Current\ assets}{Sales}$
$\frac{Quick\ assets}{Sales}$
$\frac{Working\ capital}{Sales}$
Liquid Asset Ratios
$\frac{Current\ assets}{Current\ liabilities}$
$\frac{Quick\ assets}{Current\ liabilities}$
$\frac{Current\ assets}{Total\ assets}$
$\frac{Quick\ assets}{Total\ assets}$
$\frac{Working\ capital}{Total\ assets}$
Profitability Ratios
$\frac{Cash\ flow}{Total\ debt}$

$\frac{Net\ income}{Total\ assets}$
Debt/Equity Ratio
$\frac{Total\ debt}{Total\ assets}$

The result asserted by (Deakin E. B., 1976) is that the "eleven financial accounting ratios were distributed significantly different from a normal distribution." And a test of stability indicated unstable variances for all ratios except for the Debt/Equity Ratio. Several other studies confirmed the non-normality of financial ratios (Karels & Prakash, 1987) (Barnes P. , 1982) (McLeay & Omar, 2000). Barnes went on to successfully investigate the source of the non-normality in financial ratios (Barnes P. , 1982).

Based on the non-normality findings, the transformation of non-normally distributed financial ratios was recommended by several authors (Deakin E. B., 1976). Deakin (1976) further suggested that the transformation of the data into square roots could possibly improve the data normality, though not to the extent of being considered normally distributed. The study results state that "it does appear that normality can be achieved in certain cases by transforming the data. Although there are no guidelines possible from this study as to which transformation would be appropriate in a given situation, there appear to be cases in which both the square roots of the data and the natural logs of the data were normally distributed" (Deakin E. B., 1976).

This view about requiring transformation was later challenged. Several authors rejected the idea of transformation. For example, Barnes (1982) stated that "the usual transformation methods such as square roots or natural logarithms as suggested by Deakin merely confuses the data further. Transformation in fact may change the interrelationships among the variables and may also affect the relative positions of the observations of the group." Barnes's research distinguished between two uses of financial ratios: (1) use of financial ratios in statistical models, and (2) use of financial ratios for comparison of company to industry average or other norm derived from the ratios (Barnes P. , 1982). He proved that "non normality is not a vital condition of regression analysis and multiple discriminant analysis and where these techniques are used there is no necessity to transform non-normal distributions" (Barnes P. , 1982). Whittington (1980) also concurred with the non-necessity of transformation of non-normally distributed financial rations when used as input to statistical models. Additionally, Deakin also found an indication that financial ratios "might be normally distributed within a specific industry group" (Deakin E. B., 1976) (Deakin D. , 1972).

The data set collected for this research theoretically fits Deakin's conclusion that the financial ratios "might be normally distributed" given they are all members of the same industry group. Indeed, all prediction models developed earlier than the mid 1980's adopted this position and accordingly used the discriminant analysis as the statistical method of choice. As summarized earlier in Chapter 2, some of the construction prediction models developed as of today, assumed data normality (Wong & NG, 2010). Deakin's conclusion however is uncertain. His statement is that even in the same industry group, the data "might" be normally distributed. For this reason, and several other reasons related to the interpretation strengths of logistic regression that will be discussed later, we opted to use logistic regression as the preferred statistical analysis technique in lieu of the discriminant analysis technique.

4.3. The Logit Regression Model

There are multiple ways to introduce the Logit Regression Model. We will introduce the model starting with a generalized linear regression model following Dobson (1990) and McCullah and Nelder (1989) derivation as illustrated in Liao (1994).

In the linear regression model, the dependent variable Y_i expected value is given by the equation:

$$\boldsymbol{E\ (Y_i) = \mu_i} \qquad \textbf{Equation 2}$$

For ease of presentation, we drop the subscript *i* because the vector of the dependent variable is understood. When a linear model is specific, the estimate of Y is predicted based on a combination of K explanatory or independent variables and covariates, as follows:

$$\boldsymbol{E\ (y) = \mu = \sum_{K=1}^{k} \beta_k x_k} \qquad \textbf{Equation 3}$$

The last equation is that of an ordinary linear regression model. To generalize the model, we introduce the variable n, where n is always linearly produced by the independent variables $x_1, x_{2,} \ldots, x_k$ and their covariates. The relationship between n and the independent variables is given by the following equation:

$$\boldsymbol{n} = \sum_{K=1}^{k} \boldsymbol{\beta_k x_k} \quad \textbf{Equation 4}$$

n is also a predictor of μ , however the function between n and μ must be specified. The link between n and μ is determined according to the regression model to be selected. In the case of linear regression, the link between n an μ is straightforward where $n = \mu$. In Logit regression, which is our statistical analysis method of choice, the link is determined as follows:

$$\boldsymbol{n} = \log\left[\frac{\boldsymbol{\mu}}{1-\boldsymbol{\mu}}\right] \quad \textbf{Equation 5}$$

The choice of this link function limits the outcome to a binary outcome variable. The resulting generalized model equation when combining both parts takes the following form:

$$\mathbf{E(y)} = \log\frac{\boldsymbol{\mu}}{1-\boldsymbol{\mu}} = \sum_{K=1}^{k} \boldsymbol{\beta_k x_k} \qquad \textbf{Equation 6}$$

where

$$E\,(y) = 1 \;\; if \; E\,(Y\;\;) \geq 0$$

$$E\,(y) = 0 \;\; otherwise$$

4.4. Logit in Stata Software

In stata, two commands can be used interchangeably: *logit* and *logistic*. The logit command produces results in terms of coefficients scales in log odds, while the logistic command produces results in terms of odds ratios (Abdon, 2010). The direct relationship between the two outputs—coefficients and odds ratios—are explainable by the following series of equations (UCLA: Institute for Digital Research and Education, 2014):

$$\boldsymbol{logit(p)} = \mathbf{log}(\boldsymbol{odds}) = \mathbf{log}\frac{\boldsymbol{p}}{\boldsymbol{q}} = \mathbf{log}\frac{\boldsymbol{p}}{\mathbf{1}-\boldsymbol{p}} \quad \textbf{Equation 7}$$

Combining $\mathbf{E}(\mathbf{y}) = \mathbf{log}\frac{\boldsymbol{\mu}}{\mathbf{1}-\boldsymbol{\mu}} = \sum_{K=1}^{k} \boldsymbol{\beta_k x_k}$ Equation 6 and Equation 7 gives us:

$$\boldsymbol{logit(p)} = \mathbf{log}(\boldsymbol{odds}) = \mathbf{log}\frac{\boldsymbol{p}}{\boldsymbol{q}} = \mathbf{log}\frac{\boldsymbol{p}}{\mathbf{1}-\boldsymbol{p}} = \sum_{K=1}^{k} \boldsymbol{\beta_k x_k} \quad \textbf{Equation 8}$$

This can be expressed in odds by getting rid of the log by taking **e** to the power of both sides of the equation.

$$\boldsymbol{e}^{\mathbf{log}\frac{\boldsymbol{p}}{\mathbf{1}-\boldsymbol{p}}} = \boldsymbol{e}^{\sum_{K=1}^{k} \boldsymbol{\beta_k x_k}} \quad \textbf{Equation 9}$$

$$\frac{\boldsymbol{p}}{\mathbf{1}-\boldsymbol{p}} = \boldsymbol{e}^{\sum_{K=1}^{k} \boldsymbol{\beta_k x_k}} \quad \textbf{Equation 10}$$

4.5. Summary and Conclusion

In this chapter, we discussed the different statistical models historically utilized for failure prediction modeling and analysis. In particular we discussed Multivariate Discriminant Analysis, and Logit and Probit regression models. We presented our reasons for selecting the Logit regression model as the statistical method of choice, and discussed in more detail the mathematical background behind the Logit model, as well as the representation of the model in the statistical software (Stata). Further discussion regarding the interpretation of Logit model results in general, and the developed model results in specific, is offered in Chapter 8.

Chapter 5

Data Collection

This chapter is concerned with the data collected for this research. It discusses the data sources, data collection methodology, company inclusion and exclusion criteria, frequency of measurement and data intervals, and other important aspects of the data used in this research. In summary, the data collected for this research is comprised of financial statements of publicly listed construction companies. The list of companies researched includes all of the companies listed publicly at any point in time between

1992 and 2012. The quarterly financial statements are submitted as part of the required U.S. Securities and Exchange Commission (SEC) filing requirements for publicly listed companies.

5.1. Data Collection Overview

This research relied on several sources of information to arrive at the dataset used in the analysis and hypotheses testing. Initially a basic set of criteria was employed to guide the selection of the company list. To compile the final dataset, three different categories of data and information were required:

1. Data and information used for the identification of the target company list.
2. Financial data and information collected from the selected companies' financial statements and official financial records.
3. Additional background information about each of the selected companies used.

The following figure summarizes the data collection approach and sources:

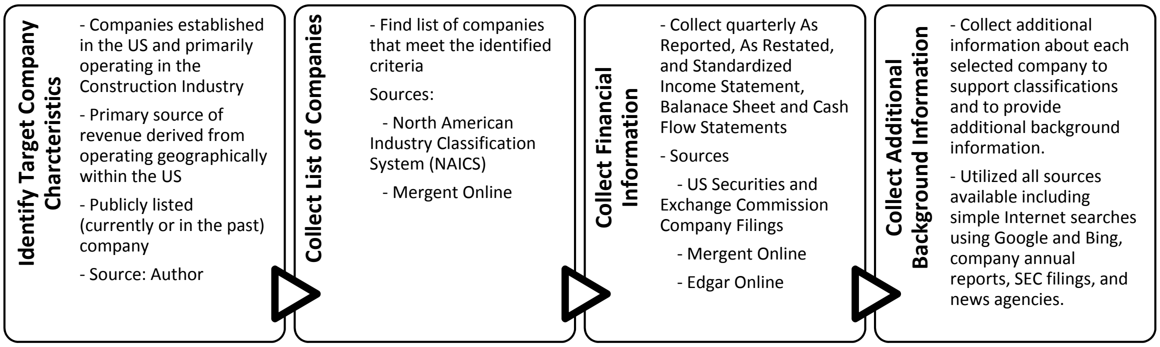

Figure 2: Data Collection Overview

5.2. Data Sources

Several sources were used to collect the data utilized in this research. Some of the sources reflect the same data and information organized differently, or provide better ease of access to the data. In this section, each one of those sources is discussed in detail.

5.2.1. North American Industry Classification System (NAICS)

The NAICS "is the standard used by the United States Federal statistical agency in classifying establishments for the purpose of collecting, analyzing and publishing statistical data related to the U.S. business economy" (United States Census Bureau, 2013). This research relied on the 2012 NAICS Structure, which groups business establishments into seventeen categories, as summarized in Appendix 1.

5.2.2. US Securities and Exchange Commission

The U.S. Securities and Exchange Commission (SEC) is part of the United States Federal Government and has the responsibility of enforcing federal securities law. Of particular interest is the role SEC plays in the collection and dissemination of financial information about public companies listed in the US stock market. Each publicly listed company is required to maintain its good status by complying with multiple securities law provisions, amongst those companies are required to file information about their financial performance along with other relevant information for investors. Most important for this research are forms required from all publicly listed companies:

- Form Number 10-K: Annual report pursuant to Section 13 or 15, and
- Form 10-Q: General form for quarterly reports under Section 13 or 15 (d)

Each company listed in the US stock market files form 10-K, annually. Attached to the form, the company must provide its three audited financial statements: Balance

Sheet, Income Statement, and Cash Flow Statement. Similarly, the same companies are required to file Form 10-Q on a quarterly basis only on the first three quarters of the fiscal year. Filing of the 10-Q is not required for the fourth quarter of any fiscal year.

As the instructions for both forms explain, the filing companies are not required to adopt a standardized account structure, sometimes called Chart of Accounts or Accounting Codes, for reporting their financial statements. This creates a challenge when comparing several companies, as their financial numbers will be reported under different account names and titles. This challenge is usually resolved if the accounts are summarized up to a generic standardized list of accounts that is suitable for the industry being analyzed. The standardization process is discussed in more detail later in this chapter.

The SEC filings for public companies are available to the public and can be accessed and downloaded online (U.S. Securities and Exchange Commission, 2013). However, the forms are only available in a text-based format that is not particularly suitable for extensive data mining. Several companies provide access to the same public information in formats that are more readily accessible and can be downloaded into Excel Spreadsheets. For ease of reference, we refer to those services as Consolidated SEC Filings Databases.

5.2.3. Consolidated SEC Filings Databases

Many service companies act as a data consolidator with heavy reliance on the SEC public company filings as their primary source of information. These service companies primarily get the text-based information for companies of interest from the SEC filing database, convert it into database-friendly formats (e.g., Excel, XML datasheets, etc.), and sometimes standardize the financial statements into a standard format for ease of company to company comparison. As part of this research, we accessed the SEC filing data through the following four service providers in addition to the primary SEC database access: Mergent Online, Edgar Online, Bloomberg Financials, and Capital IQ. Essentially all of them use the same source of information—company filings as required by the SEC—however, they differ in coverage and standardization.

The coverage issue comes into play when the financial data consolidator decides it will not include the company, or companies, selected for this research in its list of companies for which it processes the text-based filed financial information into a standardized spreadsheet data. This issue was very common with the list of companies selected for this research. Unlike companies like Microsoft, Apple, or Google, which were covered by all of the financial data consolidators, the coverage for construction companies was very limited. Accordingly, we had to rely on multiple sources in an attempt to get full coverage for all companies selected for this research.

The second issue is the standardization of the financial data. Each company publishes its financial statements using its unique Chart of Accounts. For example, one company that operates nationally may be operating with five subsidiary companies, each having a different geographic market focus (e.g., Northeast US, Western US, etc.). This company may break its revenues across multiple lines, where each line lists the revenue for one of its subsidiary companies. The division of the revenue into multiple sources varies from one company to the next. To compare all of the companies' financial information, one must first create a standard set of accounts, then summarize each one of the financial statements to this standard account list, then compare all companies based on this standardized account list. This process is called Data Standardization and is generally performed by the data consolidator companies.

With the standardization of financial data, there are three types of financial information collected:

- As Reported Information: “As reported” refers to the filing of the required form with required financial statements and additional information on the initial due date. The due date for the annual filing (10-K) ranges from 60–90 days from the end of the fiscal year depending on the method of filing and the status of the filing company. The due date for the 10Q quarterly filing ranges between 40–45 days depending on the status of the filing company.
- As Restated. Companies are allowed to correct their initial “As Reported” filings or adjust it within 30 days of the initial filing due date for any material change in its financial standing. The adjusted financial statements are titled “As Restated.”
- Standardized. The “Standardized” financial statements are not part of the standard SEC filing requirements. As described earlier, the standardized

financial statements use a standard list of financial accounts to summarize each company's financial statements for ease of company-to-company and industry-wide comparisons.

5.3. Identifying Target Company List

A. *Limit to Publicly Listed Companies subject to SEC filing requirements.* Data availability in construction company research is a key challenge. The majority of construction companies are private companies (United States Census Bureau, 2013). Accordingly, they are not required to publish financial records. Several financial data consolidators claim they have compiled financial information for private companies. However, checking with the four financial data consolidation services utilized in this research, there the financial data for private construction companies were sparse and did not make for a complete or a partially complete dataset that could be adequately analyzed. Based on this data availability limitation, and to make the dataset consistent, we opted to analyze only publicly listed construction companies subject to SEC filing requirements.

B. Primary source of revenue derived from operating geographically within the US. Construction companies are very sensitive to the economic environments they operate within. The majority of companies fitting the first criterion (public companies in the US) derived the bulk of their operating revenue from US-based operations. However, there were few companies that were listed in the US stock market but operated entirely internationally. Since those companies are operating in an entirely different economic environment(s), data consistency would have been sacrificed if they were to be included in the dataset. Also, doing multiple manipulations of the data to adjust for the varying economic impact based on the geographical market they operate within will impact the reliability and accuracy of the statistical analysis and the conclusions drawn from such analysis. Accordingly, we opted to limit the dataset to companies that derive the majority of their revenue from operating in the US.

The US market is still large enough with varying local economies from state to state and sometimes even city to city. Smaller companies with very focused geographical operations could be significantly affected by the local economy and, to a much lesser extent, by the overall US economy. Originally, we anticipated the need for some adjustments for the local economies. However, after the initial data collection has been performed and the companies meeting the outlined criteria identified, we realized they were all large corporations with office representation and operations across the US. In essence, they were not subject to the variations in local economies and were more directly tied to the US economy in general.

C. Primary source of revenue derived from construction operations. Going through the initial list of candidate companies based on the NAICS classifications, it was noticeable that some companies were listed as construction companies; however, they derived most of their revenue from non-construction operations. By non-construction, we specifically mean manufacturing operations and/or mining, oil, and gas exploration operations.

The operations of a manufacturing company are different from that of a construction company. The construction company is a more project-based operation. Cash flow projections and management are different for project-based operations from manufacturing management, and financial considerations are quite different for each type of operation. Some of the companies listed as construction companies derived the majority of their revenue from non-construction–related activities (e.g., oil and gas exploration, and real estate development). To ensure the consistency of the type of operations amongst the selected companies within our dataset, we opted to exclude companies that do not derive a considerable portion of their revenue from construction-related operations.

D. Timeframe. The dataset collected included financial statements dating back to 1992 and as recent as the last quarter of 2012. This 20-year time limit was primarily set because of data availability, as many of the financial data consolidators employ a 20-year backward limit on the availability of standardized data.

5.4. Collect List of Companies

A. Initial List of Companies under target NAICS codes. The first step in developing the actual list of companies to be included in this research was conducting a review of the companies listed under each NAICS code. The initial list of codes reviewed were the ones listed under Section 23: Construction. Those were:

- 236 Construction of Buildings
- 237 Heavy and Civil Engineering Construction

- 238 Specialty Trade Contractors

There were 79 companies in total listed under those three NAICS codes. Nineteen (19) companies were listed under NAICS Code 236, forty six (46) under NAICS code 237, and fourteen (14) under NAICS code 238.

As part of the initial review of this company list, we realized that a large percentage of those companies either were manufacturers of construction material or were solely established as a holding company to carry a license for oil and gas exploration or nuclear power generation facilities. It seemed also that the historical development of the company played a role in the NAICS code under which it was listed. Several companies originally started in the construction business and were accordingly listed under the right code, then later diversified into real estate operations, for example. However, they remained listed under the same NAICS code. This observation warranted a review of how the NAICS codes were assigned to each company.

Information obtained from the US Census Bureau confirmed this observation. According to the US Census Bureau (United States Census Bureau, 2013):

- “There is no central government agency with the role of assigning, monitoring, or approving NAICS codes for establishments. Individual establishments are assigned NAICS codes by various agencies for various purposes using a variety of methods. The U.S. Census Bureau has no formal role as an arbitrator of NAICS classification. The U.S. Census Bureau assigns one NAICS code to each establishment based on its primary activity (generally the activity that generates the most revenue for the establishment) to collect, tabulate, analyze, and disseminate statistical data describing the economy of the United States. Generally, the U.S. Census Bureau's NAICS classification codes are derived from information that the business establishment provided on surveys, census forms, or administrative records,” and
- “There is no "official" way to have a company's NAICS code changed and there is no central register that represents the "official" NAICS classification for business establishments. Various Federal government agencies maintain their own directories of business establishments, and assign classification codes based on their own needs. Generally, the classification codes are derived from information that the business establishment has provided on surveys, forms, or administrative records.”

Based on this observation, it was prudent to review all of the companies under each one of the selected NAICS codes to ascertain that they are indeed representative of the NAICS operation. It was also important to evaluate what other non-construction NAICS codes could have companies that matched our search criteria. Those would be companies that are closely related to construction operations where a company could have been initially established as an Engineering company, for example, and later expanded into Construction.

B. Inclusion of companies in NAICS code 541330. As per the discussion above, we revised other NAICS codes for businesses that are closely correlated with construction. As a result we added NAICS code 541330 for Engineering Services to our list of NAICS codes to review. Several of the companies that started as engineering service companies later moved into construction management and construction operations, such as the URS Corporation after its acquisition of Washington Group International.

C. Exclusion of companies not meeting criteria. The initial list of companies was comprised of 156 companies. The initial list was then subjected to the company selection criteria identified in Section 5.3. Identifying Target Company List. A large percentage of companies did not fit the criteria identified, and the total count of companies in the final selection was only 35 companies.

An example of companies that were excluded and did not fit the criteria is Anthony & Sylvan Pools Corp. The company was listed under NAICS 2362 for Nonresidential Building Construction. However, upon review of the scope of services the company performed via its annual reports and website, it was discovered that the company operations can be summarized as follows:

- "Anthony & Sylvan Pools Corporation, a swimming pool company, engages in designing and building ground swimming pools and spas. It provides pool modernization services, such as new swimming pool and spa installations, equipment repairs, new equipment sale and upgrades, and pool safety covers installations, as well as existing commercial pools renovations, including community, hotel/motel, country club, and school pools. The company also operates retail supply centers that provide pool equipment

> and maintenance supplies, such as heaters, filters, pumps, replacement parts, accessories, and chemicals for water maintenance, as well as backyard extras, including floatation devices, pool games and water toys, outside speakers, and other backyard fun items. The company serves families, couples, groups of friends, athletes, and people with physical ailments. It has pool service centers in Annapolis Junction, Maryland; Mays Landing, New Jersey; Chantily, Virginia; and Lititz, Doylestown, West Chester, and Montgomeryville, Pennsylvania" (Anthony & Sylvan Pools, 2013).

The company derives a considerable part of its revenue stream from operating "pool supply stores and service centers," where it provides maintenance services for existing pools and sells a variety of pool chemicals, suppliers, equipment and accessories. Accordingly, it does not meet criterion 4.3.C for company selection, and thus was excluded. The final list of selected companies is summarized in the following section.

The following table also summarizes the count of companies in the initial list and the final count of selected companies.

NAICS Code	NAICS Description	Total Companies Listed	Companies Not Meeting Criteria	Selected Companies	Percentage of Companies Included
2362	Non Residential Building Construction	19	12	7	36.84%
237	Heavy & Civil Engineering Construction	46	33	13	28.26%
238	Specialty Trade Contractors	14	11	3	21.43%
541330	Engineering Services	77	65	12	15.58%
		156	121	35	22.43%

Table 4: Count of Selected Companies by NAICS Code

The final list of selected companies is summarized in the following table:

ID	Ticker	Company Name
1	ATKQ	Atkinson (Guy F.) Co. of California
2	DAWK Q	DAW Technologies Inc.
3	JEC	Jacobs Engineering Group, Inc.
4	MTRX	Matrix Service Co.
5	TXGE	Texas Gulf Energy Inc
6	TPC	Tutor Perini Corp
7	USBR	USA Bridge Construction of New York Inc.
8	ALAN	Alanco Technologies Inc
9	ACX	Arguss Communications Inc
10	DY	Dycom Industries, Inc.
11	ESOA	Energy Services of America Corp.
12	IFS	InfraSource Services Inc
13	KBR	KBR Inc
14	MTZ	MasTec Inc. (FL)
15	MVCO	Meadow Valley Corp.
16	MYRG	MYR Group Inc
17	XMIT	OmniAmerica Inc.
18	DMO U	Dominion Bridge Corp.
19	ORN	Orion Marine Group Inc
20	USBG	USABG Corp.
21	FCIN	Flour City International Inc.
22	IREX	Irex Corp.

ID	Ticker	Company Name
23	SHFK	Schuff International, Inc.
24	ACM	Aecom Technology Corp (DE)
25	BKR	Baker (Michael) Corp.
26	CRRP	Corrpro Cos., Inc.
27	MCON	EMCON
28	ENG	ENGlobal Corp.
29	FLR	Fluor Corp.
30	TKCI	Keith Companies Inc
31	SWBI Q	Stone & Webster Inc.
32	STVI	STV Group, Inc.
33	TTEK	Tetra Tech, Inc.
34	URS	URS Corp
35	VSR	Versar Inc.

Table 5: Final List of Selected Companies

5.5. Collection of Financial Statements

For each one of the final selected companies, all existing SEC files and reports have been collected and reviewed. In particular, the collected information consisted of the 10-K Annual Filing and the 10-Q quarterly filing (for the first three quarters of each year). Those documents contained the three financial statements: Balance Sheet, Income Statement, and Cash Flow Statement. The statements were collected directly via the data consolidation services outlined earlier. If a company had a "Restated" filing, the Restated financial statements were used instead of the "As Reported." In all cases, the Standardized version of all statements were used to allow for company-to-company comparison.

For a company that is established and registered in the US stock market on or before 1992, and is in continuous operation until the end of 2012, a complete 20 years of financial information was collected. For each company, the financial statements were collected on a quarterly basis resulting in 80 different and distinct periods for a company that spanned the whole study duration. Some companies however were either established or listed in the stock market later than 1992, and/or were delisted or failed before 2012. For those companies the complete set of their financial statements that exists within the span of 1992–2012 were also collected on a quarterly basis.

Some of the companies followed a fiscal year starting in January and ending in December, and others followed a fiscal year starting with July and ending in June. Accordingly the Fiscal Year Quarter, names were inconsistent for comparison purposes. To eliminate this inconsistency, a calendar year quarter naming convention was utilized for all quarters. This standardized quarter naming was adopted for all companies. According to the standardized naming convention, the period 2012 Q1 means the timeframe covering January 1, 2012 to March 31, 2012 for all companies regardless of their fiscal year start and finish dates.

Chapter 6

Data Preparation

This chapter describes the data preparation for this research. In particular, it discusses all data formatting, cleanup, the calculation of derivative financial ratios, and trends. It also discusses in detail all of the steps taken to transform the raw data collected and described in the previous chapter into data suitable for feeding into the statistical analysis package. It also briefly discusses the statistical analysis package of choice.

6.1. Formation of Data Groups

In this research, the list of companies selected was assigned attributes that allow for the formation of data groups. These attributes were: a) NAICS Code and Description, and b) Company Status. Additional information was collected to identify the company status, as described in more detail below. Companies were then assigned to one, and only one, of the groups based on these attributes.

6.1.1. Formation of Data Groups by Company Status

The Company Status attribute described the status of the company as of the last financial statement quarter collected. The last financial statement quarter was the last one issued by the company before it went out of business, was acquired or merged with another company, or went private, except for operational companies. For companies still in operation, the last period was Q4 of 2012. Accordingly, four attributes were used to form the Company Status Data Groups:

1. Active. The Active data group includes companies that remained in full operation as of the last quarter in 2012. A company that is still active with a published financial statement was considered operational. It is important to

note however that being operational does not mean that the company is in good standing or profitable. This distinction will be discussed in more detail in the data analysis chapter.

2. Private. The Private data group includes companies that converted from being a publicly operating company that is subject to the SEC filing requirements to a privately held company. We did not have access to the financial statements of privately held companies, and private companies are under no obligation to publish their financial statements. Accordingly, the last financial statements for these companies were the last statements published before they converted from being publicly held to privately held.
3. Inactive. The Inactive data group includes companies that are no longer in operation. Companies were not distinguished based on how they failed. These businesses are not doing business any more independently or as part of another company or under any other form.
4. Acquired. The Acquired data group includes companies that either merged with or were acquired by other companies. We did not distinguish between merger or acquisition transactions.

The count of companies in each one of the data groups identified above is summarized in the following table:

Company Status Group Names	Company Count
Active	19
Private	3
Inactive	6
Acquired	7
Total	**35**

Table 6: Summary Data Group Company Count by Operational Status

The companies in each one of the groups is summarized below in the following table:

ID	Ticker	Company Name	Data Group
1	ATKQ	Atkinson (Guy F.) Co. of California	Failed
2	DAWK Q	DAW Technologies Inc.	Failed
3	JEC	Jacobs Engineering Group, Inc.	Operational
4	MTRX	Matrix Service Co.	Operational
5	TXGE	Texas Gulf Energy Inc	Operational
6	TPC	Tutor Perini Corp	Operational
7	USBR	USA Bridge Construction of New York Inc.	Failed
8	ALAN	Alanco Technologies Inc	Operational
9	ACX	Arguss Communications Inc	Acquired
10	DY	Dycom Industries, Inc.	Operational
11	ESOA	Energy Services of America Corp.	Operational
12	IFS	InfraSource Services Inc	Acquired
13	KBR	KBR Inc	Operational
14	MTZ	MasTec Inc. (FL)	Operational
15	MVCO	Meadow Valley Corp.	Private
16	MYRG	MYR Group Inc	Operational
17	XMIT	OmniAmerica Inc.	Acquired
18	DMO U	Dominion Bridge Corp.	Failed
19	ORN	Orion Marine Group Inc	Operational
20	USBG	USABG Corp.	Failed
21	FCIN	Flour City International Inc.	Failed
22	IREX	Irex Corp.	Private
23	SHFK	Schuff International, Inc.	Operational

ID	Ticker	Company Name	Data Group
24	ACM	Aecom Technology Corp (DE)	Operational
25	BKR	Baker (Michael) Corp.	Operational
26	CRRP	Corrpro Cos., Inc.	Acquired
27	MCON	EMCON	Acquired
28	ENG	ENGlobal Corp.	Operational
29	FLR	Fluor Corp.	Operational
30	TKCI	Keith Companies Inc	Acquired
31	SWBI Q	Stone & Webster Inc.	Acquired
32	STVI	STV Group, Inc.	Private
33	TTEK	Tetra Tech, Inc.	Operational
34	URS	URS Corp	Operational
35	VSR	Versar Inc.	Operational

Table 7: List of Selected Companies

6.1.2. Formation of Data Groups by NAICS Codes

The second attribute that was used to for grouping data is the NAICS code. The count of companies in each one of the selected NAICS codes is summarized in the table below:

NAICS Code	NAICS Description	Company Count
2362	Nonresidential Building Construction	7
2371	Utility System Construction	10
2373	Highway, Street, and Bridge Construction	3
2381	Foundation, Structure, and Building Exterior Contractors	3
541330	Engineering Services	12
Grand Total		**35**

Table 8: Summary of Data Group Company Count by NAICS Codes

The detailed description of each one of the selected NAICS code categories is provided in appendix 3. And the assignment of each company to the NAICS code group is summarized in the following table:

ID	Ticker	Company Name	NAICS Code	NAICS Description
1	ATKQ	Atkinson (Guy F.) Co. of California	2362	Nonresidential Building Construction
2	DAWK Q	DAW Technologies Inc.	2362	Nonresidential Building Construction
3	JEC	Jacobs Engineering Group, Inc.	2362	Nonresidential Building Construction
4	MTRX	Matrix Service Co.	2362	Nonresidential Building Construction
5	TXGE	Texas Gulf Energy Inc	2362	Nonresidential Building Construction
6	TPC	Tutor Perini Corp	2362	Nonresidential Building Construction
7	USBR	USA Bridge Construction of New York Inc.	2362	Nonresidential Building Construction
8	ALAN	Alanco Technologies Inc	2371	Utility System Construction
9	ACX	Arguss Communications Inc	2371	Utility System Construction
10	DY	Dycom Industries, Inc.	2371	Utility System Construction
11	ESOA	Energy Services of America Corp.	2371	Utility System Construction
12	IFS	InfraSource Services Inc	2371	Utility System Construction
13	KBR	KBR Inc	2371	Utility System Construction
14	MTZ	MasTec Inc. (FL)	2371	Utility System Construction
15	MVCO	Meadow Valley Corp.	2371	Utility System Construction
16	MYRG	MYR Group Inc	2371	Utility System Construction
17	XMIT	OmniAmerica Inc.	2371	Utility System Construction
18	DMO U	Dominion Bridge Corp.	2373	Highway, Street, and Bridge Construction
19	ORN	Orion Marine Group Inc	2373	Highway, Street, and Bridge Construction

ID	Ticker	Company Name	NAICS Code	NAICS Description
20	USBG	USABG Corp.	2373	Highway, Street, and Bridge Construction
21	FCIN	Flour City International Inc.	2381	Foundation, Structure, and Building Exterior Contractors
22	IREX	Irex Corp.	2381	Foundation, Structure, and Building Exterior Contractors
23	SHFK	Schuff International, Inc.	2381	Foundation, Structure, and Building Exterior Contractors
24	ACM	Aecom Technology Corp (DE)	541330	Engineering Services
25	BKR	Baker (Michael) Corp.	541330	Engineering Services
26	CRRP	Corrpro Cos., Inc.	541330	Engineering Services
27	MCON	EMCON	541330	Engineering Services
28	ENG	ENGlobal Corp.	541330	Engineering Services
29	FLR	Fluor Corp.	541330	Engineering Services
30	TKCI	Keith Companies Inc	541330	Engineering Services
31	SWBI Q	Stone & Webster Inc.	541330	Engineering Services
32	STVI	STV Group, Inc.	541330	Engineering Services
33	TTEK	Tetra Tech, Inc.	541330	Engineering Services
34	URS	URS Corp	541330	Engineering Services
35	VSR	Versar Inc.	541330	Engineering Services

Table 9: Companies Listed by NAICS Cateogires

6.2. Data Formatting and Manipulation

6.2.1. Preparation of Input Files

One of the major difficulties in the research was the preparation of the data for input into the statistical package. A good portion of the retrieved data was in text formats that are not readable by statistical packages. Multiple computer programs were developed in Visual Basic for Applications (VBA) to automate the conversion of raw data into properly formatted Excel spreadsheets that can be easily fed into the statistical package of choice. Appendix 4 lists the VBA code utilized for this purpose.

6.2.2. Statistical Computer Package

All statistical analyses conducted as part of this research were done utilizing Stata. Stata is a general purpose statistical software packaged created in 1985 by StataCorp. The version used in the research is Stata 13 IC.

6.3. Calculation of Ratios

In this research we tested the existing models developed for the prediction of company failure on the collected dataset. This testing scheme required the computation of a large number of financial ratios. Each one of the tested models used different types, numbers, and variables in computation of the financial ratios that were ultimately utilized in the prediction model. Thirty-eight financial ratios were computed for each quarter for each of the 35 companies in the dataset. Not all the ratios computer were utilized in the final model developed and preparation. However, they provided additional information for each company that helped in understanding the modality of failure and initial non-statistical testing of our hypothesis. The list of all 38 ratios is offered in the following table:

Ratio ID	Ratio Group	Ratio Title
P1	Profitability	Return on Assets %
P2	Profitability	Return on Capital %
P3	Profitability	Return on Equity %
P4	Profitability	Return on Common Equity %
MR1	Margin Analysis	Gross Margin %
MR2	Margin Analysis	SG&A Margin %
MR3	Margin Analysis	EBITDA Margin %
MR4	Margin Analysis	EBITA Margin %
MR5	Margin Analysis	EBIT Margin %
MR6	Margin Analysis	Earnings from Cont. Ops Margin %
MR7	Margin Analysis	Net Income Margin %
MR8	Margin Analysis	Net Income Avail. for Common Margin %
MR9	Margin Analysis	Normalized Net Income Margin %
MR10	Margin Analysis	Levered Free Cash Flow Margin %
MR11	Margin Analysis	Unlevered Free Cash Flow Margin %
AT1	Asset Turnover	Total Asset Turnover
AT2	Asset Turnover	Fixed Asset Turnover
AT3	Asset Turnover	Accounts Receivable Turnover
AT4	Asset Turnover	Inventory Turnover
STL1	Short Term Liquidity	Current Ratio
STL2	Short Term Liquidity	Quick Ratio
STL3	Short Term Liquidity	Cash from Ops. to Curr. Liab.
STL4	Short Term Liquidity	Avg. Days Sales Out.
STL5	Short Term Liquidity	Avg. Days Inventory Out.
STL6	Short Term Liquidity	Avg. Days Payable Out.
STL7	Short Term Liquidity	Avg. Cash Conversion Cycle

Ratio ID	Ratio Group	Ratio Title
LTL1	Long Term Solvency	Total Debt/Equity
LTL2	Long Term Solvency	Total Debt/Capital
LTL3	Long Term Solvency	LT Debt/Equity
LTL4	Long Term Solvency	LT Debt/Capital
LTL5	Long Term Solvency	Total Liabilities/Total Assets
LTL6	Long Term Solvency	EBIT / Interest Exp.
LTL7	Long Term Solvency	EBITDA / Interest Exp.
LTL8	Long Term Solvency	(EBITDA-CAPEX) / Interest Exp.
LTL9	Long Term Solvency	Total Debt/EBITDA
LTL10	Long Term Solvency	Net Debt/EBITDA
LTL11	Long Term Solvency	Total Debt/(EBITDA-CAPEX)
LTL12	Long Term Solvency	Net Debt/(EBITDA-CAPEX)

Table 10: Financial Ratios Calculations

Appendix 5 provides additional information about the calculation of each one of the ratios used as well as a list of abbreviations.

Chapter 7

Model Development

7.1. Introduction

This chapter discusses in detail the development of the financial prediction model. The model was developed using binary outcome regression models: Logit and Probit. All aspects of the model development are described in this chapter. To ease the description and avoid redundancy, Section 7.2. provides the statistical software and the overall initial setup. It also includes the method of model accuracy calculation.

Section 7.3. describes the general algorithm used for each iteration testing different input variables. Section 7.4. contains a detailed description, input syntax, and output for one sample run. Chapter 8 contains the tabulated results for all runs.

7.2. Binary Regression Model Development Setup

7.2.1. General Setup and Dependent Variables

As mentioned earlier, the statistical software utilized is Stata/IC 13. The data was prepared as discussed in the previous chapter and loaded into the software. Four variables were set up to identify and track failure:

- Failed 1Q: this is a binary 0/1 variable. The value of Failed 1Q was set to 1 for the last quarter before a failed company is known to have failed. All other observations for the same variable had a 0 variable. This variable was utilized as an output (dependent) for testing the accuracy of the model in predicting company failure one quarter before failure date.
- Failed 2Q: this is a binary 0/1 variable. The value of Failed 1Q was set to 1 for the last two quarters before a failed company is known to have failed. All other observations for the same variable had a 0 variable. This variable was

utilized as an output (dependent) for testing the accuracy of the model in predicting company failure two quarters before failure date.

- Failed 4Q: this is a binary 0/1 variable. The value of Failed 1Q was set to 1 for the last four quarters before a failed company is known to have failed. All other observations for the same variable had a 0 variable. This variable was utilized as an output (dependent) for testing the accuracy of the model in predicting company failure one year before failure date.
- Failed 8Q: this is a binary 0/1 variable. The value of Failed 1Q was set to 1 for the last eight quarters before a failed company is known to have failed. All other observations for the same variable had a 0 variable. This variable was utilized as an output (dependent) for testing the accuracy of the model in predicting company failure two years before failure date.
- DataGroup: is a byte variable that divides observations into 4 groups. For all observations where the company is operational, the DataGroup variable is set to 1. For all observations where the company has failed, the DataGroup variable is set to 2. For all observations where the company has been Acquired, the DataGroupVariable is set to 3. For all observations where the company has turned from a public into a private company, the DataGroup

variable is set to 4. The DataGroup variable was used for filtering and testing within a particular group of companies sharing the same final fate.

7.3. Model Development Algorithm

The model development process is iterative in general. The standard methodology used in the development of prior models was mechanically iterative. It starts with using independent variables and running the regression model, and then calculating a measure of fit and error. One after one, other variables are tried in the same fashion. The researcher then takes the variable with the highest fit and the least error, and adds another variable. The regression is repeated with both variables, and the same metrics for fit and error are calculated. This process is repeated iteratively until a satisfactory model is achieved. While a statistical relationship is developed, it may prove very difficult to explain the developed statistical model using general management or financial management theories.

Our efforts are similar with one exception: the model development process starts with a specific hypothesis based on a strong theoretical foundation and supported by industry surveys, as explained earlier. We hypothesize that a statistically significant model predicting the failure of construction companies can be developed using the Cash Flow Input/Output Model described earlier. The Cash Flow model can be represented by three variables:

- Cycle Time Measure: these are variables indicating how long a company takes to convert its cash into raw material, labor effort, and other expenses that go into the progress of current work (Work In Progress) that is later completed, sold, and converted again into cash. Examples for Cycle Time variables include: Average Days Sales Out, Average Days Payable Out, and Average Cash Conversion Cycle.
- Cycle Profitability Measure: the cycle profitability measure is an indicator of the amount of disposable cash generated in each cash-to-cash cycle. Profitability measures include Return on Assets, Return on Capital, and Return on Equity. They could also include some of the margin ratio such as Gross Margin, or EBIDTA Margin.

- Access to Cash Measures: this group of measures indicates the power of a company to access additional cash when and if needed. They include measures such as Total Debt/Total Equity, or Total Liability/Total Assets.

Our model development algorithm relies on the Cash Flow model to establish its starting variables for iteration, and also a constraint variable selection based on these three distinct groups: Cycle Time, Cycle Profitability, and Access to Cash.

Each iteration can be summarized as follows:

1. Selection of Variables. Discussed in Section 7.4.1.
    a. Select one variable to represent each one of the three Cash Flow Model groups.
    b. Plug the three variables into the binary regression model.
2. Run the Model and Review Output. Discussed in Section 7.4.2.
    a. Run the Model and review overall Prob > chi2 value in comparison to alpha.
    b. Review individual parameters' coefficients, Z-Value, and P>|Z| values to reject null hypothesis.
3. Calculate model accuracy. Discussed in Section 7.4.3.

4. Tabulate model accuracy in summary results sheet, and repeat steps with new set of independent variables.
5. After steps 1–4 are completed for the sets of independent variables selected, compare all test results and discuss final model selection.

7.4. Detailed Example of Single Model Development Iteration

7.4.1. Selection of Variables

Three variables where selected, one representing each one of the Cash Flow Model groups, as discuss earlier. The variables selected in this iteration were as follows:

- Cycle Time Measure: the Average Days Pay Out was selected as the Cycle Time Measure.
- Cycle Profitability Measure: the Return on Assets was selected as the Cycle Profitability measure.
- Access to Cash Measure: the Total Liabilities/Total Assets was selected as the Access to cash measure.

7.4.2. Estimation Using Logit

The selected variables were run in Stata using the following command:

```
logit Failed8Q  Avg_Days_Pay_Out Rtrn_Ast Liab_Asts  if DataGroup==1 | DataGroup==2
```

The output for the command resembles the following.

```
Iteration 0:   log likelihood = -191.97851
Iteration 1:   log likelihood = -152.88999
Iteration 2:   log likelihood = -143.70725
Iteration 3:   log likelihood = -143.59033
Iteration 4:   log likelihood = -143.59012
Iteration 5:   log likelihood = -143.59012

Logistic regression                    Number of obs    =     1251
                                       LR chi2(3)       =    96.78
                                       Prob > chi2      =   0.0000
Log likelihood = -143.59012            Pseudo R2        =   0.2521

------------------------------------------------------------------------------
       Failed8Q    |   Coef.      Std. Err.     z     P>|z|   [95% Conf. Interval]
-----------------+------------------------------------------------------------
Avg_Days_Pay_Out |   .0201073   .0038597    5.21   0.000    .0125423    .0276722
      Rtrn_Ast   |  -5.511513   1.488716   -3.70   0.000   -8.429343   -2.593682
     Liab_Asts   |   4.969061   1.01616     4.89   0.000    2.977424    6.960699
        _cons    |  -7.01978    .7773755   -9.03   0.000   -8.543408   -5.496152
------------------------------------------------------------------------------
```

Below is an explanation of each section in the model estimation output.

1. *Iteration 0 to Iteration y*. The listing for Iteration 0 to Iteration y (in above example y=5) is a listing of the log likelihood for each iteration. Stata uses maximum likelihood iterative procedure to calculate the logistic regression.

The first iteration (Iteration 0) is the null model where the model is run with no predictors. The objective is to increase the log likelihood until the model converges, i.e., the difference between each two iteration is minimal or none.

2. *Log Likelihood.* This is the log likelihood of the final model. It has no meaning in and of itself; however, it will be used, as explained later, for the calculation of chi2.
3. *Number of obs.* This number denotes the exact number of observations used in this particular run. This number is always equal to or less than the total number of observations in the data set. The reason for any discrepancy is missing values in one of the variables selected. We are using the default setting that eliminates the complete observation from the regression modeling if one or more of the used values in the model is missing.
4. *LR chi2(3).* This is the likelihood ratio (LR) chi-square test. The number between the parentheses is the degree of freedom. In this case, the degree of freedom is 3 for the three independent variables used in the model—Avg_Days_Pay_Out, Rtrn_Ast, and Liab_Asts. The LR chi2 can be calculated as twice the difference between the first log likelihood and the final log likelihood.

5. Prob > chi2. This is the test for the null hypothesis. It is the probability of obtaining the same chi-square if there is no effect of the independent variables (predictor variables) together on the dependent variable. This is the p-value that determines if the model is statistically significant or not. In this case, the model is statistically significant because the p-value is less than “0.0000”.
6. Pseudo R2. Logistic regression does not have an equivalent to the R-squared that is found in linear regression. Since the Pseudo R2 does not have the same significance as in linear regression, we will not use it for comparing model outputs.
7. Parameter Estimation Table. Below the general estimate information, a table summarizing the parameters’ estimation results. The following is an explanation of the table values:
   - Failed8Q. This is the dependent variable. It was described in full earlier in the data preparation discussion.
   - Coef. These are the values for the logistic regression equation for predicting the dependent variable from the independent variables. The prediction equation for this particular run takes the following form:

$$\log(\text{odds of Failed8Q}) = -7.01978 + (4.969061 \times \text{Liab}_{\text{Asts}}) + (-5.511513 \times \text{Rtrn\_Asts}) + (.0201073 \times \text{Avg\_Days\_Pay\_out}).$$

- *Std. Err.* These are the standard errors associated with each coefficient. The standard error are used for calculation of the Z-value and the confidence interval.
- *Z and P*>|Z|. These columns provide the z-value and 2-tailed p-value used in testing the null hypothesis to see whether the coefficient, and accordingly the independent variable, is 0. At an alpha value of 0.05, we can reject the null hypothesis if the p-value is less than the 0.05. For example, the Liab_Asts coefficient is significantly different from 0 using an alpha of 0.05 because its p-value is 0.000, which is smaller than 0.05. Accordingly, we reject the null hypothesis and conclude that the Liab_Asts is of statistical significance at an alpha of 0.05.
- *[95% Conf. Interval]*. This indicates the lower and upper limit value for the 95% confidence interval for each coefficient.

7.4.3. Model Accuracy Calculations

The accuracy of the model is calculated based on a simple 2x2 matrix similar to that in Table 11.

Actual Group Membership	Predicted Group Membership	
	Not-Failed	**Failed**
Not-Failed	Correct (C1)	Error 1 (E1)
Failed	Error 2 (E2)	Correct (C2)

Table 11: Model Accuracy Matrix

The "Actual Group Membership" represents the correct classification of companies based on our knowledge of their failure status. The "Predicted Group Membership" represents the classification based on the model prediction. The resulting values in the matrix are divided into four categories:

- Non-Failed-Non-Failed (C1): This is an observation for a company that is operational where the model had predicted it is operational. This is the first type of correct predictions.
- Non-Failed-Failed (E1): This is an observation for a company that is operational where the model had predicted it is failed. This corresponds to the second type of error where the model over-predicts failure.
- Failed-Non Failed (E2): This is an observation for a company that failed where the model had predicted it is operational. This corresponds to one type of error where the model under-predicts failure.

- Failed-Failed (C2): represents an observation for a company that failed where the model had predicted that it failed. The Failed-Failed is a correct prediction. This is the second type of correct predictions.

Based on these variables, we compute the following percentages to compare model accuracy:

- Overall Model Accuracy = $\frac{(c1+c2)}{Total\ Number\ of\ Observations}\ X\ 100$
- Correct Failed Prediction Accuracy = $\frac{c2}{C2+E2}\ X\ 100$
- % False Negatives = $\frac{E2}{Total\ Number\ of\ Observations}\ X\ 100$
- % False Positives = $\frac{E1}{Total\ Number\ of\ Observations}\ X\ 100$

Chapter 8

Resultant Models

8.1. Logit Regression Results

In this chapter we discuss the results of the statistical analysis. The statistical analysis was primarily structured to test our initial hypothesis amongst other objectives. Our initial hypothesis is that *it is both empirically feasible and theoretically explainable to predict company failure at a statistically significant level using cash flow metrics*. We defined cash flow metrics in Chapter 3. In summary, cash flow metrics are three metrics describing the following attributes of a company's cash flow cycle:

1. The profitability of the cash flow cycle, and
2. The duration of the cash cycle, and
3. Access to additional cash throughout the cash cycle.

Each of those attributes was detailed in Chapter 3. We also proposed the use of different financial metrics to measure each one of the three attributes. Return on Assets, Return on Capital, EBITDA margin, and Gross margin were selected as suitable measures for the profitability of the cash cycle. Average Days Sales Outstanding and Average Days Payable Outstanding were selected as suitable measures for the cash cycle duration. Total Liabilities to Total Assets was selected as a suitable measure for the access to additional cash attribute.

To test our hypothesis, we used Logit regression to evaluate if the cash flow cycle parameters can be used to predict company failure at a statistically significant level. We created sets of three independent variables—one from each attribute category as input to the logit regression estimating. For example in run 01, we used Return on Assets (Profitability), Average Days Sales Out (Duration), and Total Liabilities to

Total Assets (Access to Cash). We continued to test each possible combination of the independent variables with the only constraint being that there is always a single measure for profitability, a single measure for cycle duration, and a single measure for access to cash.

The models including the coefficients are summarized in the table below.

		Profitability Measure				**Cycle Time**		**Access to Cash**
Model Name	Constant	Return on Assets %	Return on Capital %	EBITDA Margin %	Gross Margin %	Avg. Days Sales Out.	Avg. Days Payable Out.	Total Liabilities/Total Assets
Z-Score								
Model 01	-4.62419	-7.32728				0.02204		3.63088
Model 02	-3.40774	-5.57034					0.02027	4.43717
Model 03	-4.34753		-4.47484			0.02188		3.38579
Model 04	-3.41189		-3.81308				0.02028	4.36891
Model 05	-5.20575			-2.54817		0.02415		4.35609
Model 06	-4.24077			-0.12486			0.02925	4.47499
Model 07	-4.38841				-3.52611	0.02669		4.24288
Model 08	-4.08575				-0.19773		0.02680	4.54476

Table 12: Resulting Models with Logit Coefficients

Recall from the statistical model discussion in Chapter 4 the generalized Logit equation:

$$\mathbf{E(y) = \log\frac{\mu}{1-\mu} = \sum_{K=1}^{k} \beta_k x_k} \qquad \textbf{Equation 11}$$

This equation can be specified for these runs as follows:

$$\mathbf{E(y) = \log\frac{\mu}{1-\mu} = \epsilon + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3} \qquad \textbf{Equation 12}$$

Substituting the model 1 variable in this equation, for example, yields the following:

$$\mathrm{E(y)} = \log\frac{\mu}{1-\mu} = -4.62419 - 7.32728\, X\ Return\ on\ Assets\,\% + 0.02204\, X\ Average\ Days\ Sales\ Out + 3.63088\, X\ (Total\ Liabilities/\ Total\ Assets)$$

Where

$$E\ (y) = 1\ \ if\ E\ (y)\ \geq 0$$

$$E\ (y) = 0\ \ \ otherwise$$

The same substitution could be equally applied for the other seven models. The detailed results including their associated log likelihood and chi2 values are included in Appendix 6. All eight models were statistically significant at a 95% confidence level.

8.2. Evaluation of Models' Accuracy

To evaluate the accuracy of each model, we calculated the E(y) after substituting the correct set of coefficients and variables. The failure estimate produced by the model was then compared to actual failure information at three different intervals:

- Comparison of predicted failure with actual failure at 8 quarters before failure event (Failed8Q),
- Comparison of predicted failure with actual failure at 4 quarters before failure event (Failed4Q)
- Comparison of predicted failure with actual failure at 2 quarters before failure event (Failed2Q)

Based on these comparisons, we computed four values, as described in more detail in Chapter 7:

Actual Group Membership	**Predicted Group Membership**	
	Not-Failed	**Failed**
Not-Failed	Correct (C1)	Error 1 (E1)
Failed	Error 2 (E2)	Correct (C2)

Based on the computed values (C1, C2, E1, and E2), we calculated the following four percentages, also described in more detail in Chapter 7.

- Overall Model Accuracy = $\frac{(c1+c2)}{Total\ Number\ of\ Observations}\ X\ 100$

- Correct Failed Prediction Accuracy = $\frac{c2}{C2+E2}\ X\ 100$

- % False Negatives = $\frac{E2}{Total\ Number\ of\ Observations}\ X\ 100$

- % False Positives = $\frac{E1}{Total\ Number\ of\ Observations}\ X\ 100$

To establish a benchmark to which to compare results, we also computed the values for Altman's Z-Score for each observation, and calculated the same model accuracy metrics using the same methodology.

The summary of all results for predicting the failure of companies 2 years (8 quarters), 1 year (4 quarters), and 6 months before the actual failure event is presented in the following Section.

8.2.1. Accuracy Evaluation for predicting failure 2 years in advance

Predicting the failure of construction companies early enough allows management an opportunity to make corrective actions and possibly avert the failure event. In our analysis, we relied on Altman's Z-score as the benchmark for failure prediction. The Z-score predicted approximately 70% of the failed events 2 years in advance with an overall prediction accuracy around 77%. Although the false negatives were minimal at around only 1%, the false positives were higher at around 22%.

	Profitability Measure				Cycle Time		Access to Cash	Failure Predition 8 Quarters									
Model Name	Return on Assets %	Return on Capital %	EBITDA Margin %	Gross Margin %	Avg. Days Sales Out.	Avg. Days Payable Out.	Total Liabilities/Total Assets	Top Left Corner (0-0)	Top Right Corner (0-1)	Bottom Left Corner (1-0)	Bottom Right Corner (1-1)	Total Observations	Overall Model Accuracy - Percentage Correct	Percentage Misclassified	Percentage False Positives	Percentage False Negatives	Correct Failed Prediction Percentage
Z-Score								969	14	285	33	1301	77.02%	22.98%	21.91%	1.08%	70.21%
Model 01	X				X		X	1088	15	166	32	1301	86.09%	13.91%	12.76%	1.15%	68.09%
Model 02	X					X	X	952	7	302	40	1301	76.25%	23.75%	23.21%	0.54%	85.11%
Model 03		X			X		X	1072	13	182	34	1301	85.01%	14.99%	13.99%	1.00%	72.34%
Model 04		X				X	X	970	7	284	40	1301	77.63%	22.37%	21.83%	0.54%	85.11%
Model 05			X		X		X	1015	14	239	33	1301	80.55%	19.45%	18.37%	1.08%	70.21%
Model 06			X			X	X	1012	9	242	38	1301	80.71%	19.29%	18.60%	0.69%	80.85%
Model 07				X	X		X	833	4	421	43	1301	67.33%	32.67%	32.36%	0.31%	91.49%
Model 08				X		X	X	995	9	259	38	1301	79.40%	20.60%	19.91%	0.69%	80.85%

Table 13: Failure Prediction Accuracy at 8 Quarters Ahead of Failure Event

In comparison, seven of the eight models developed based on the cash flow framework we developed had a better prediction rate than the Z-score. Five of the models had the capability of predicting 80% of the time 2 years in advance. In particular, all models utilizing the Average Days Payable Outstanding predicted failure at a rate of 80% or higher.

The accuracy of all models however indicate that there is a tradeoff between prediction accuracy and overall model accuracy. If the model is sensitive to predicting failure with an increase rate of failure prediction, it produces a higher level of false positives, hence a lower overall model accuracy rate. This inverse relationship between the failure prediction accuracy and the overall model accuracy is evident. In terms of classifications, there are certain observations that are easy to classify one way or another (failed or not). However, there is a certain percentage of observations that fits in a "gray" area. Regardless of the model fit, classifying companies within this area will cause the highest percentage of errors. If the model is more sensitive in identifying failed companies, it tends to classify more of the companies within this gray area as failed, which in turn will yield a higher percentage of misclassified companies.

Overall, we can conclude that all of the models developed based on the theoretical background about the cash flow framework produced results that are equal to or superior to the Z-score prediction rates at 2 years ahead of failure events.

8.2.2. Accuracy Evaluation for predicting failure 1 year in advance

	Profitability Measure				Cycle Time		Access to Cash		Failure Predition 4 Quarters									
Model Name	Return on Assets %	Return on Capital %	EBITDA Margin %	Gross Margin %	Avg. Days Sales Out.	Avg. Days Payable Out.	Total Liabilities/Total Assets		Top Left Corner (0-0)	Top Right Corner (0-1)	Bottom Left Corner (1-0)	Bottom Right Corner (1-1)	Total Observations	Overall Model Accuracy - Percentage Correct	Percentage Misclassified	Percentage False Positives	Percentage False Negatives	Correct Failed Prediction Percentage
Z-Score									981	2	296	22	1301	77.09%	22.91%	22.75%	0.15%	91.67%
Model 01	X				X		X		1102	1	175	23	1301	86.47%	13.53%	13.45%	0.08%	95.83%
Model 02	X					X	X		959	0	318	24	1301	75.56%	24.44%	24.44%	0.00%	100.00%
Model 03		X			X		X		1084	1	193	23	1301	85.09%	14.91%	14.83%	0.08%	95.83%
Model 04		X				X	X		977	0	300	24	1301	76.94%	23.06%	23.06%	0.00%	100.00%
Model 05			X		X		X		1027	2	250	22	1301	80.63%	19.37%	19.22%	0.15%	91.67%
Model 06			X			X	X		1020	1	257	23	1301	80.17%	19.83%	19.75%	0.08%	95.83%
Model 07				X	X		X		837	0	440	24	1301	66.18%	33.82%	33.82%	0.00%	100.00%
Model 08				X		X	X		1003	1	274	23	1301	78.86%	21.14%	21.06%	0.08%	95.83%

Table 14: Failure Prediction at 1 Year in Advance of Failure Event

The same assessment is performed to evaluate the accuracy of the produced models in general and in comparison to the Z-score as a benchmark. As expected, all of the models including the Z-score were more accurate in predicting failure at one year ahead of the failure event compared to two years ahead of the failure event. However, it is particularly interesting that the rates of improvement amongst our eight models were higher than the rates of improvement for the Z-score. At 2 years, seven out of the eight models had failure prediction power equal to or better than the Z-score. The eighth model produced slightly lower results than the Z-score (68% compared to 70%). At the one-year prediction horizon, all eight of the models produced equal or more superior results than the Z-Score. All of the models were able to predict the failure of 95% or more of the failed observations, except for only one model-producing results equal to the Z-score at around 92%.

The same inverse relationship between the model failure prediction rate and the overall accuracy was also noticeable, albeit with a smaller gap between the two accuracy measures.

Overall, we can conclude that all of the models developed based on the theoretical background about the cash flow framework produced results that are equal to or superior to the Z-score prediction rates at 1 year ahead of failure events.

8.2.3. Accuracy Evaluation for predicting failure 6 months in advance

We performed the same assessment for a third time with a comparison of results at 6 months in advance of the failure events. It was noticeable this time that all of the models, including the Z-score, managed to predict all of the failure events six months in advance. The main difference was in the level of false positives associated with the model application.

	Profitability Measure				Cycle Time		Access to Cash		Failure Predition 2 Quarters									
Model Name	Return on Assets %	Return on Capital %	EBITDA Margin %	Gross Margin %	Avg. Days Sales Out.	Avg. Days Payable Out.	Total Liabilities/Total Assets		Top Left Corner (0-0)	Top Right Corner (0-1)	Bottom Left Corner (1-0)	Bottom Right Corner (1-1)	Total Observations	Overall Model Accuracy - Percentage Correct	Percentage Misclassified	Percentage False Positives	Percentage False Negatives	Correct Failed Prediction Percentage
Z-Score									983	0	306	12	1301	76.48%	23.52%	23.52%	0.00%	100.00%
Model 01	X				X		X		1103	0	186	12	1301	85.70%	14.30%	14.30%	0.00%	100.00%
Model 02	X					X	X		959	0	330	12	1301	74.63%	25.37%	25.37%	0.00%	100.00%
Model 03		X			X		X		1085	0	204	12	1301	84.32%	15.68%	15.68%	0.00%	100.00%
Model 04		X				X	X		977	0	312	12	1301	76.02%	23.98%	23.98%	0.00%	100.00%
Model 05			X		X		X		1029	0	260	12	1301	80.02%	19.98%	19.98%	0.00%	100.00%
Model 06			X			X	X		1021	0	268	12	1301	79.40%	20.60%	20.60%	0.00%	100.00%
Model 07				X	X		X		837	0	452	12	1301	65.26%	34.74%	34.74%	0.00%	100.00%
Model 08				X		X	X		1004	0	285	12	1301	78.09%	21.91%	21.91%	0.00%	100.00%

Table 15: Failure Prediction at Six Months in Advance of Failure Event

Seven out of eight of our models produced results that are equal to or superior to the Z-score in terms of false positives.

8.2.4. Overall Accuracy Evaluation Comments

Many critical observations can be made based on the accuracy results displayed:

- As expected, the accuracy of predicting failing companies increases as we near the failure event. All eight models, as well as the Z-Score, were able to predict 100% of the failed companies six months before they failed. Although all failures at 2Q were predicted, there were still a good percentage of false positives predicted by all models. At 2Q, all eight models produced comparable results to the Z-score. Some fared better than others. For example, Models 01 and Model 03 had lower rates of false positives than the Z score did (14.30% and 15.68%, respectively, compared to 23.52% for the Z-score.)
- As discussed earlier, there is an inverse relationship between the model overall accuracy and its ability to predict failures. The gap, however, between the two values decreases as the prediction horizon decreases.

- Even though all of the models developed based on the theoretical foundation described in the cash flow model in Chapter 3 have acceptable to superior prediction accuracy, Model 03 seems to offer the most balanced results for all prediction horizons. Model 03 utilizes Return on Capita %, Average Days Sales Outstanding, and Total Liabilities/Total Assets. This particular model was able to predict failure at 72.34% 2 years in advance, 95.83% 1 year in advance, and 100% six months in advance, while maintaining an overall model accuracy rate of around 85%.
- While the 100% prediction success for failure events at the six-month prediction horizon seems high, it is explainable. Failure could be caused by a multitude of reasons including, for example, cash flow constraints, large loss on a single project, and the inability to secure more work. Regardless of the reason for failure, the symptoms noticeable on all failing companies just before they fail are very similar. Failing companies will usually not be able to pay their vendors and contractors on time. Accordingly, their Average Days Payables Outstanding is much higher than for an otherwise healthy company. In the construction industry, it is all too common for Owners to notice if contractors or subcontractors are at risk of failure, which typically prompts

them to increase their retainage on projects or to request the joint signature of subcontractors and suppliers on checks to avoid liens on their projects. These actions are directly noticeable on the Average Days Sales Outstanding where payments are delayed as a symptom of failure, not as a cause of failure. In addition, failing contractors will usually incur additional liabilities with a fixed or eroding asset base, resulting in an increase in the Total Liabilities to Total Assets ratio. A long payment cycle and higher liabilities eventually erode profitability, and the profitability rates start dropping significantly. In summary, even if the cash flow constraints are not some of the leading causes of failure, they will be one of the symptoms of an impending failure event.

8.3. Discussion of Variables

From our earlier discussion on Logit models, we know that the effect of each independent variable on n is always linear. Interpreting a variable effect linearly on the predictor n is straightforward. However, the relationship between n and μ will only suggest the effect on the logit or log odds that is not easy to interpret. Some interpretations however do not require the quantitative values, such as interpretations of the signs for each independent variable. Additionally, we can exponentiate both sides to calculate the odds, instead of the log odds, and evaluate the coefficients of the independent variables' effect on the odds of failure.

Throughout the analysis and interpretation of variables, we abide by the ceteris paribus rule, or, *all other things being equal* (Liao, 1994). Our general assumption when interpreting the sign, value, or other attribute related to Independent variables is that such interpretation is valid only while all other independent variables remain unchanged. We will not reiterate this constraint for each interpretation throughout this discussion.

		Profitability Measure				Cycle Time		Access to Cash
Model Name	Constant	Return on Assets %	Return on Capital %	EBITDA Margin %	Gross Margin %	Avg. Days Sales Out.	Avg. Days Payable Out.	Total Liabilities/Total Assets
Z-Score								
Model 01	-4.62419	-7.32728				0.02204		3.63088
Model 02	-3.40774	-5.57034					0.02027	4.43717
Model 03	-4.34753		-4.47484			0.02188		3.38579
Model 04	-3.41189		-3.81308				0.02028	4.36891
Model 05	-5.20575			-2.54817		0.02415		4.35609
Model 06	-4.24077			-0.12486			0.02925	4.47499
Model 07	-4.38841				-3.52611	0.02669		4.24288
Model 08	-4.08575				-0.19773		0.02680	4.54476

Table 16: Models' Variables and Coefficients

8.3.1. Analysis of the Sign of the Independent Variables

In all the models developed, the signs of the independent variables were consistent in each one of the three cash flow cycle groups regardless of the specific independent variables used. The sign for all profitability variables were negative. The sign of profitability variables is theoretically explainable. The increase in the profitability of the company reduces the likelihood of a company's failure. In contrast, the sign of the cycle time variables and the access to cash variables are both positive. This is also theoretically explainable. The longer a company takes to either pay its liabilities or get paid for its revenues, the more prone it is to failure. Similarly, a company's high liabilities to assets ratio signifies that it has limitations in terms of accessing additional cash for its operating cash flow cycle, which increases the likelihood of failure.

8.3.2. Estimating the Probability of Failure

Solving the Logit equation for the probability of failure yields the following equation:

$$\boldsymbol{Prob}\ (\boldsymbol{y}=\mathbf{1}) = \frac{e^{\sum_{k=1}^{k} \beta_k x_k}}{1+e^{\sum_{k=1}^{k} \beta_k x_k}} \quad \textbf{Equation 13}$$

Interpreting the failure rate using a probability function provides an easier way for management to utilize the resulting models. For example, using Model 03, a Return on Capital of 0.2, an Average Days Sales Outstanding of 60 days, and a Total Assets to Total Liabilities of 0.4, corresponds to a probability of failure of approximately only 7%.

8.4. Hypothesis Validation and Conclusion

The detailed results of the each model are presented in Appendix 6. All models were statistically significant at an α of 0.05 (95% confidence level). Since all models were statistically significant, and all models established acceptable or superior failure prediction and accuracy as described earlier in this chapter, we accept our hypothesis. We conclude that it is both empirically feasible and theoretically explainable to predict company failure at a statistically significant level using cash flow metrics.

Chapter 9

Discussion and Conclusion

9.1. Introduction

As noted at the onset, construction is a risky business with only 47% of startup businesses in construction still operating after four years. The indirect costs of failed companies far exceed the direct costs of their failure. Cash is often seen as the most important element of construction companies and their operation. Adequate sources of capital, and a reasonable liabilities-to-assets ratio, are critical for business continuity and success. A lack of cash can mean no payments to subcontractors, laborers, and crews, and no purchases of needed materials. It can lead to a limited ability to complete tasks on site, to cutting corners in work, or to a slower pace to match the amount of cash available. Negative outcomes can include delayed or incomplete work, or increased financing costs and project risks. Ultimately, construction companies risk failure if they sustain cash flow limitations for some time even if they are profitable. Even though cash flow and capitalization constraints have been referenced as the leading cause of company failure, and despite the fact that there have been numerous models developed for the prediction of construction company failure, there has been no study that focused on researching the utilization of cash flow information to predict construction company failure.

9.2. Research Summary

In this research, we highlight the importance of two distinct but related topics: the failure of construction companies, and cash flow management for construction companies. Both fields are of great importance. On one end, the percentage of construction companies failing is consistently high. On the other end, cash flow is the bloodline of construction companies. Each topics has received wide attention in the academic and professional literature. Cash flow has been mentioned as one of the leading causes of construction company failure. However, there was no previous research looking into the use of cash flow metrics as a predictor of failure. Additionally, there was no clear definition or understanding of how to describe a company in terms of its cash flow.

This research developed a cash flow framework that could be used for describing a company in terms of its cash flow position. The cash flow framework describes a company's operational strength using a cash flow cycle with three measures: 1) cash flow cycle profitability, 2) cash flow cycle duration, and 3) access to additional cash. The research established the importance and justification for each measure.

The research further hypothesized that this cash flow framework can be used to assess the potential of failure for construction companies. To test and validate this hypothesis, we used a dataset comprised of full quarterly financial records for construction companies tracked over 20 years, and evaluated the suitability of the cash flow model in predicting construction company failure 6 months, 1 year, and 2 years in advance of the failure event at a statistically significant level.

9.3. Research Findings and Contributions

The findings of this research presents a major contribution to research in construction company cash flow management and failure prediction. There are several aspects of the contribution that will be discussed in more detail in the following paragraphs. Perhaps of utmost importance is that failure of construction companies is predictable with high level of accuracy based on a theoretically explainable cash flow framework. Furthermore, the prediction model utilized is a simple model utilizing a small number of predictor variables. Prediction models are much more powerful when they are theoretically explainable, and simple. The outcome of this research produced not only a single model, but several models that are simple to construct, easy to use, theoretically explainable and provide high prediction reliability. Of equal importance, is the methodology developed and utilized in the research. The focus on the development of a theoretical foundation for understanding modality of failure in construction companies before proceeding with statistical validation provides researches and industry professionals a repeatable model for development and testing of hypothesis relating to construction management operations.

Other than the research's contribution to the prediction of failure knowledge area, it also equally contributed to the cash flow theory and its application in construction management. The research adapted a cash flow framework to the construction industry and outlined simple, yet descriptive and effective measures capable of measuring and comparing the strength and efficiency of cash flow cycles across companies. The cash flow framework and research methodology can be used to learn about the effect of cash flow on other aspects of construction operations such as safety, claim records, or even employee morale.

The findings of this research can be summarized in the following points:

1. There are a variety of failure prediction models in existence, starting with Altman's Z-score and branching into other industry-specific models such as the one developed by Mason and Harris in 1979. The development of these models relied on a trial and error approach of using a combination of financial ratios in a statistical model. The model was estimated to fit a

particular sample, and then validated with another data sample. After the model was developed, an effort was made to explain the variables selected as predictor variables.

2. As the industry and economy changes, there is a need to re-evaluate existing prediction models, and then to modify them. Industry and economy changes lead to different operational levels for all companies within that industry. For example, the model parameters for some of the earlier prediction models may need to be changed to reflect how the interest rate is much lower today than when the Z-Scores were first developed.

3. Earlier attempts to use statistical techniques for predicting company failure relied on Multivariate Discriminant Analysis as the tool of choice. However, in the last twenty years, researchers focused on using Logit and Probit statistical models to evaluate and estimate company failure. Logit and Probit are more suitable for failure prediction because they do not require predictor variables to be normally distributed.

4. While Z-scores may have proved useful for lending institutions and banks to assess the failure potential of companies, they pose more challenges for use by practitioners and the senior management of construction companies.

5. A company's cash flow position can be described using three parameters:

    - a parameter that describes its profitability in each cash flow cycle, such as Return on Assets, or Return on Capital;

    - a parameter that describes its total cash flow cycle duration, such as Average Days Sales Outstanding or Average Days Payable Outstanding; and

    - a parameter that describes its ability to access additional cash for infusion into its cash flow cycle, such as total liabilities / total assets.

6. The cash flow framework identified above, including the three parameters describing the cash flow cycle, can be utilized to predict failure risk and the probability of failure for construction companies with a high degree of accuracy at the 95% confidence level.

7. Return on Assets, Return on Capital, EBIDTA Margin, and Gross margin can all be used as measures of profitability in the Cash Flow Framework. However, some (i.e., Return on Assets, Return on Capital, and EBIDTA Margin) are more reliable and more statistically significant than others (i.e., Gross Margin). Gross Margin does not take into consideration many of the variables that affect the net profitability of an operating company such as tax rates, asset depreciation, and capitalization factors.

8. Average Days Sales Outstanding and Average Days Payable Outstanding are both measures that can be used to describe the cash flow cycle duration in the cash flow framework.

9. There is a tradeoff between the sensitivity of a prediction model to highlight failed companies and its percentage of false positives. In each data set, companies fit into one of three categories:

    - Group A: Those exhibiting all signs of failure according to the tested model, or

    - Group B: Those exhibiting none of the signs of failure according to the tested model, or

- Group C: Those exhibiting some signs of failure, and some signs of non-failure according to the tested model.

- Groups A and B are always classified with no errors since they fit the model being tested perfectly well. Group C, on the other hand, is where classification errors are realized.

10. Earlier Prediction models used to come up with an arbitrary value for the failure versus non-failure classification to maximize correct hits in Group C. For example, Altman's Z-score realized that all companies scoring above 2.99 have failed, and all scoring less than 2.3 have not. Companies in between those two scores were a mixed bag. Accordingly, he calculated a cutoff rate of 2.675, which happens to maximize the number of correct hits for companies scoring between 2.3 and 2.99. The problem with this methodology is that the 2.675 is an arbitrary number and does not necessarily yield the same accuracy level when tested with other companies.

11. Logit models are better in predicting failure since the margins for differentiating between failed and non-failed companies are standardized.

If the logit value is equal to or greater than 0, then the company is classified as failed. Otherwise it is classified as non-failed.

12. Selecting a particular cutoff point for classifying failed versus non-failed companies may be necessary for the calculation of accuracy measures to evaluate prediction models. However, in industry implementation and practice it is preferable to use odds ratios or probabilities to refer to chances of failure, instead of using a hard cut-off classification point. Unlike Discriminant Analysis, Logit models allow for the calculation of the odds and probabilities of failure.

13. There are multiple factors that affect and cause companies to fail. Some of these factors appear in a company's financial statement as early as two, or perhaps more, years before the failure event. It is difficult to categorize those factors that show in the financial statement as a cause of failure or a symptom of failure. Regardless of the causes, however, six months before a company fails, there are some clear signs that can be identified by prediction models with a very high level of accuracy. The management of

companies may, after all, have an opportunity to cause a change in their company's operation, and so avoid failure during those six months.

14. Even though all discussed prediction models were able to spot failed companies six months in advance of the failure events, they all produced a percentage of false positives. It is possible that those false positives were for companies destined to fail in six months' time, but then those companies' management teams took actions or measures to save their companies during those six months.

15. Having a single score alone, like the Z-Score, does not give senior managers of a company enough information about the true underlying mechanisms of failure at play. The development of the Cash Flow Framework as an underlying theoretical foundation for the failure prediction models, provide a comprehensive management tool for managers to rely on, and a way for them to understand how the cash flow cycle could be both a cause of failure or a symptom of failure. This can provide management with a tool for risk management.

9.3. Recommendations for Implementation

The results of this research have a wide range of implementation possibilities. We outline a few of these possibilities below:

- Construction insurance and bonding companies can use the developed models to evaluate construction company risk. The use of the models should constitute part of an overall assessment, but decisions should not be made solely on prediction results.
- Owners and senior managers of construction companies can use the Cash Flow Framework to manage the risk of failure. Unlike other models that give owners and senior managers just a number, the Cash Flow Framework offers more depth in understanding the effect of cash flow on the long-term operations of their company and the risk of failure. Understanding and describing company operations in terms of three cash flow metrics gears managers to focus on those metrics. One of the reasons these metrics are powerful when used in sync is that they summarize myriad other operational metrics.

9.4. Contribution to the Construction Industry

This research provides insights into the relationship between failure and cash flow management. It links the literature on failure prediction with that on cash flow management. It also provides several models for the prediction of failure in construction companies as early as two years before the failure event. More importantly, it builds a strong theoretical foundation on using cash flow descriptors as a means of explaining failure risk for construction companies. It also defines three parameters as suitable for describing construction companies' cash flow cycles.

9.5. Further Research

Several research opportunities are triggered by the results of this research:

1. Develop a failure response mechanism: Since prediction models can identify high-risk companies months, and even years, in advance, then failure could be averted if proper action is taken. Study what is the best response mechanism for a company with a high risk of failure. Study all of the observations for companies identified as failing in a six-month duration and

yet remaining operational to evaluate if there were corrective actions applied by management during those six months that averted a failure event.

2. Unlike financial management ratios alone, management of the cash flow cycle of a company is an operational capability: The development of an in-depth understanding of the means and methods for building such capability within construction companies could reduce the percentage of failed companies.
3. Utilize the Cash Flow Framework and the research methodology to evaluate the relationship between cash flow and other operational factors. Some of the operational factors that can be evaluated using this research methodology and the Cash Flow Framework are:
    a. Effect of cash flow constraints on safety records, or
    b. Effect of cash flow constraints on prevalence of claims on projects.

Appendix 1. NAICS Code Detailed Description

The detailed description for the NAICS codes used for company filtering and grouping are provided below as referenced in the **North American Industry Classification System** (**NAICS**) web page (http://www.census.gov/eos/www/naics/).

- 236210 Industrial Building Construction

This industry comprises establishments primarily responsible for the construction (including new work, additions, alterations, maintenance, and repairs) of industrial buildings (except warehouses). The construction of selected additional structures, whose production processes are similar to those for industrial buildings (e.g., incinerators, cement plants, blast furnaces, and similar nonbuilding structures), is included in this industry. Included in this industry are industrial building general contractors, industrial building for-sale builders, industrial building design-build firms, and industrial building construction management firms.

Illustrative Examples:

- Assembly plant construction
- Furnace, industrial plant, construction
- Cannery construction

- Mine loading and discharging station construction
- Cement plant construction
- Paper or pulp mill construction
- Chemical plant (except petrochemical) construction
- Pharmaceutical manufacturing plant construction
- Factory construction
- Steel mill construction
- Food processing plant construction
- Waste disposal plant (except sewage treatment) construction

➢ 236220 Commercial and Institutional Building Construction

This industry comprises establishments primarily responsible for the construction (including new work, additions, alterations, maintenance, and repairs) of commercial and institutional buildings and related structures, such as stadiums, grain elevators, and indoor swimming facilities. This industry includes establishments responsible for the on-site assembly of modular or prefabricated commercial and institutional buildings. Included in this industry are commercial and institutional building general contractors, commercial and institutional building for-sale builders, commercial and institutional building design-build firms, and commercial and institutional building project construction management firms.

Illustrative Examples:

- Airport building construction
- Office building construction
- Arena construction

- Parking garage construction
- Barrack construction
- Prison construction
- Farm building construction
- Radio and television broadcast studio construction
- Fire station construction
- Religious building (e.g., church, synagogue, mosque, temple) construction
- Grain elevator construction
- Restaurant construction
- Hospital construction
- School building construction
- Hotel construction
- Shopping mall construction
- Indoor swimming facility construction
- Warehouse construction (e.g., commercial, industrial, manufacturing, private)

- 237110 Water and Sewer Line and Related Structures Construction

This industry comprises establishments primarily engaged in the construction of water and sewer lines, mains, pumping stations, treatment plants, and storage tanks. The work performed may include new work, reconstruction, rehabilitation, and repairs. Specialty trade contractors are included in this group if they are engaged in activities primarily related to water, sewer line, and related structures construction. All structures (including buildings) that are integral parts of water and sewer networks (e.g., storage tanks, pumping stations, water treatment plants, and sewage treatment plants) are included in this industry.

Illustrative Examples:

- o Distribution line, sewer and water, construction
- o Sewer main, pipe, and connection, construction
- o Fire hydrant installation
- o Storm sewer construction
- o Irrigation systems construction
- o Water main and line construction
- o Pumping station, water and sewage system, construction
- o Water system storage tank and tower construction
- o Reservoir construction
- o Water treatment plant construction
- o Sewage disposal plant construction
- o Water well drilling, digging, boring, or sinking (except water intake wells in oil and gas fields)

- ➢ 237130 Power and Communication Line and Related Structures Construction

This industry comprises establishments primarily engaged in the construction of power lines and towers, power plants, and radio, television, and telecommunications transmitting/receiving towers. The work performed may include new work, reconstruction, rehabilitation, and repairs. Specialty trade contractors are included in this group if they are engaged in activities primarily related to power and communication line and related structures construction. All structures (including buildings) that are integral parts of power and communication networks (e.g., transmitting towers, substations, and power plants) are included.

Illustrative Examples:

- Alternative energy (e.g., geothermal, ocean wave, solar, wind) structure construction
- Power line stringing
- Cellular phone tower construction
- Radio transmitting tower construction
- Co-generation plant construction
- Satellite receiving station construction
- Communication tower construction
- Telephone line stringing
- Electric light and power plant (except hydroelectric) construction
- Transformer station and substation, electric power, construction
- Electric power transmission line and tower construction
- Underground cable (e.g., cable television, electricity, telephone) laying
- Nuclear power plant construction

- 238110 Poured Concrete Foundation and Structure Contractors

This industry comprises establishments primarily engaged in pouring and finishing concrete foundations and structural elements. This industry also includes establishments performing grout and shotcrete work. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Concrete pouring and finishing
- Gunite contractors
- Concrete pumping (i.e., placement)
- Mud-jacking contractors
- Concrete work (except paving)

- Shotcrete contractors
- Footing and foundation concrete contractors

- 238120 Structural Steel and Precast Concrete Contractors

This industry comprises establishments primarily engaged in (1) erecting and assembling structural parts made from steel or precast concrete (e.g., steel beams, structural steel components, and similar products of precast concrete) and/or (2) assembling and installing other steel construction products (e.g., steel rods, bars, rebar, mesh, and cages) to reinforce poured-in-place concrete. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Concrete product (e.g., structural precast, structural prestressed) installation
- Rebar contractors
- Erecting structural steel
- Reinforcing steel contractors
- Placing and tying reinforcing rod at a construction site
- Structural steel contractors
- Precast concrete panel, slab, or form installation

- 238130 Framing Contractors

This industry comprises establishments primarily engaged in structural framing and sheathing using materials other than structural steel or concrete. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Building framing (except structural steel)
- Post frame contractors
- Foundation, building, wood, contractors
- Steel framing contractors
- Framing contractors
- Wood frame component (e.g., truss) fabrication on site

- 238140 Masonry Contractors

This industry comprises establishments primarily engaged in masonry work, stone setting, brick laying, and other stone work. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Block laying
- Marble, granite, and slate, exterior, contractors
- Brick laying
- Masonry pointing, cleaning, or caulking
- Concrete block laying
- Stucco contractors
- Foundation (e.g., brick, block, stone), building, contractors

- 238150 Glass and Glazing Contractors

This industry comprises establishments primarily engaged in installing glass panes in prepared openings (i.e., glazing work) and other glass work for buildings. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Decorative glass and mirror installation
- Glazing contractors
- Glass cladding installation
- Stained glass installation
- Glass coating and tinting (except automotive) contractors
- Window pane or sheet installation
- Glass installation (except automotive) contractors

- 238160 Roofing Contractors

This industry comprises establishments primarily engaged in roofing. This industry also includes establishments treating roofs (i.e., spraying, painting, or coating) and installing skylights. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Painting, spraying, or coating, roof
- Sheet metal roofing installation
- Shake and shingle, roof, installation
- Skylight installation

- 238170 Siding Contractors

This industry comprises establishments primarily engaged in installing siding of wood, aluminum, vinyl, or other exterior finish material (except brick, stone, stucco, or curtain wall). This industry also includes establishments installing gutters and downspouts. The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Downspout, gutter, and gutter guard installation
- Siding (e.g., vinyl, wood, aluminum) installation
- Fascia and soffit installation

- 238190 Other Foundation, Structure, and Building Exterior Contractors

This industry comprises establishments primarily engaged in building foundation and structure trades work (except poured concrete, structural steel, precast concrete, framing, masonry, glass, glazing, roofing, and siding). The work performed may include new work, additions, alterations, maintenance, and repairs.

Illustrative Examples:

- Curtain wall, metal, installation
- Forms for poured concrete, erecting, and dismantling
- Decorative steel and wrought iron work installation
- Ornamental metal work installation
- Fire escape installation

- Welding, on site, contractors

- 541330 Engineering Services

This industry comprises establishments primarily engaged in applying physical laws and principles of engineering in the design, development, and utilization of machines, materials, instruments, structures, processes, and systems. The assignments undertaken by these establishments may involve any of the following activities: provision of advice, preparation of feasibility studies, preparation of preliminary and final plans and designs, provision of technical services during the construction or installation phase, inspection and evaluation of engineering projects, and related services.

Illustrative Examples:

- Civil engineering services
- Environmental engineering services
- Construction engineering services
- Mechanical engineering services
- Engineers' offices

Appendix 2. NAICS 2012 – Main Classification Codes

2012 NAICS Structure	
2012 NAICS Code	2012 NAICS Title
11	Agriculture, Forestry, Fishing and Hunting
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
42	Wholesale Trade
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

Appendix 3. NAICS 2012 Construction Code

23 sub-classification codes

23	**Construction**
236	**Construction of Buildings**
2361	**Residential Building Construction**
23611	Residential Building Construction
236115	New Single-Family Housing Construction (except For-Sale Builders)
236116	New Multifamily Housing Construction (except For-Sale Builders)
236117	New Housing For-Sale Builders
236118	Residential Remodelers
2362	**Nonresidential Building Construction**
23621	Industrial Building Construction
236210	Industrial Building Construction
23622	Commercial and Institutional Building Construction
236220	Commercial and Institutional Building Construction
237	**Heavy and Civil Engineering Construction**
2371	Utility System Construction
23711	Water and Sewer Line and Related Structures Construction
237110	Water and Sewer Line and Related Structures Construction
23712	Oil and Gas Pipeline and Related Structures Construction
237120	Oil and Gas Pipeline and Related Structures Construction
23713	Power and Communication Line and Related Structures Construction
237130	Power and Communication Line and Related Structures Construction
2372	**Land Subdivision**
23721	Land Subdivision
237210	Land Subdivision
2373	**Highway, Street, and Bridge Construction**

23731	Highway, Street, and Bridge Construction
237310	Highway, Street, and Bridge Construction
2379	**Other Heavy and Civil Engineering Construction**
23799	Other Heavy and Civil Engineering Construction
237990	Other Heavy and Civil Engineering Construction
238	**Specialty Trade Contractors**
2381	**Foundation, Structure, and Building Exterior Contractors**
23811	Poured Concrete Foundation and Structure Contractors
238110	Poured Concrete Foundation and Structure Contractors
23812	Structural Steel and Precast Concrete Contractors
238120	Structural Steel and Precast Concrete Contractors
23813	Framing Contractors
238130	Framing Contractors
23814	Masonry Contractors
238140	Masonry Contractors
23815	Glass and Glazing Contractors
238150	Glass and Glazing Contractors
23816	Roofing Contractors
238160	Roofing Contractors
23817	Siding Contractors
238170	Siding Contractors
23819	Other Foundation, Structure, and Building Exterior Contractors
238190	Other Foundation, Structure, and Building Exterior Contractors
2382	**Building Equipment Contractors**
23821	Electrical Contractors and Other Wiring Installation Contractors
238210	Electrical Contractors and Other Wiring Installation Contractors
23822	Plumbing, Heating, and Air-Conditioning Contractors
238220	Plumbing, Heating, and Air-Conditioning Contractors
23829	Other Building Equipment Contractors
238290	Other Building Equipment Contractors
2383	**Building Finishing Contractors**
23831	Drywall and Insulation Contractors

238310	Drywall and Insulation Contractors
23832	Painting and Wall Covering Contractors
238320	Painting and Wall Covering Contractors
23833	Flooring Contractors
238330	Flooring Contractors
23834	Tile and Terrazzo Contractors
238340	Tile and Terrazzo Contractors
23835	Finish Carpentry Contractors
238350	Finish Carpentry Contractors
23839	Other Building Finishing Contractors
238390	Other Building Finishing Contractors
2389	**Other Specialty Trade Contractors**
23891	Site Preparation Contractors
238910	Site Preparation Contractors
23899	All Other Specialty Trade Contractors
238990	All Other Specialty Trade Contractors

Appendix 4. Data Cleanup Macros

```
Sub LoopThroughAllFiles()
        Dim folderPath As String
        Dim filename As String
        Dim wb As Workbook

        Application.ScreenUpdating = False

        folderPath = "C:\data\FinancialData\"

        If Right(folderPath, 1) <> "\" Then folderPath = folderPath + "\"

        filename = Dir(folderPath & "*.xls")

        Do While filename <> ""
          Application.ScreenUpdating = False
           'MsgBox folderPath & filename
           Set wb = Workbooks.Open(folderPath & filename)
           wb.Activate

           ' Sheet Formatting
           'ActiveWorkbook.Select

           WorksheetLoop
           filename = Dir
           wb.Save
           wb.Close
        Loop

      Application.ScreenUpdating = True
End Sub
```

****

```
Sub WorksheetLoop()

    Dim WS_Count As Integer
    Dim I As Integer

    WS_Count = ActiveWorkbook.Worksheets.Count

    For I = 1 To WS_Count

            Sheets(I).Select
            PeriodDates
            Format1
            Format2
            Format3
            Format4
            Format5
            Format6

        Next I

    End Sub

    **************

    Sub Format1()

     Dim rng As Range
     Dim cell As Range
     Set rng = Nothing

     For Each cell In ActiveSheet.UsedRange
       If cell.NumberFormat = "_(* #,##0.0_);_(* (#,##0.0)_) ;_(* 0_)" Then
       If rng Is Nothing Then
       Set rng = cell
```

```
   Else
   Set rng = Union(rng, cell)
   End If
   End If
   Next cell
   If Not rng Is Nothing Then
   rng.Select

   rng.NumberFormat = "0.00"
   rng.Interior.ColorIndex = 10
   End If

End Sub


Sub Format2()

 Dim rng As Range
 Dim cell As Range
 Set rng = Nothing

 For Each cell In ActiveSheet.UsedRange
   If cell.NumberFormat = "_($#,##0.0#_);_(($#,##0.0#)_);_($"" - ""_)" Then
   If rng Is Nothing Then
   Set rng = cell
   Else
   Set rng = Union(rng, cell)
   End If
   End If
   Next cell
   If Not rng Is Nothing Then
   rng.Select

   rng.NumberFormat = "0.00"
   rng.Interior.ColorIndex = 10
```

```
    End If

End Sub


Sub Format 3()

 Dim rng As Range
 Dim cell As Range
 Set rng = Nothing

 For Each cell In ActiveSheet.UsedRange
    If cell.NumberFormat = "mmm-dd-yyyy" Then
    If rng Is Nothing Then
    Set rng = cell
    Else
    Set rng = Union(rng, cell)
    End If
    End If
    Next cell
    If Not rng Is Nothing Then
    rng.Select

    rng.NumberFormat = "m/d/yyyy"
    rng.Interior.ColorIndex = 10
    End If

End Sub

Sub Format 4()

 Dim rng As Range
 Dim cell As Range
 Set rng = Nothing
```

```
 For Each cell In ActiveSheet.UsedRange
   If cell.NumberFormat = "#,##0.00x" Then
   If rng Is Nothing Then
   Set rng = cell
   Else
   Set rng = Union(rng, cell)
   End If
   End If
   Next cell
   If Not rng Is Nothing Then
   rng.Select

   rng.NumberFormat = "0.00"
   rng.Interior.ColorIndex = 10
   End If

End Sub


Sub Format5 ()

 Dim rng As Range
 Dim cell As Range
 Set rng = Nothing

 For Each cell In ActiveSheet.UsedRange
   If cell.NumberFormat = "_(#,##0.0%_);_((#,##0.0%)_);_(#,##0.0%_)" Then
   If rng Is Nothing Then
   Set rng = cell
   Else
   Set rng = Union(rng, cell)
   End If
   End If
   Next cell
   If Not rng Is Nothing Then
```

```
    rng.Select

    rng.NumberFormat = "0.00"
    rng.Interior.ColorIndex = 10
    End If

End Sub

Sub Format 6()

 Dim rng As Range
 Dim cell As Range
 Set rng = Nothing

 For Each cell In ActiveSheet.UsedRange
    If cell.NumberFormat = "#,##0.0x" Then
    If rng Is Nothing Then
    Set rng = cell
    Else
    Set rng = Union(rng, cell)
    End If
    End If
    Next cell
    If Not rng Is Nothing Then
    rng.Select

    rng.NumberFormat = "0.00"
    rng.Interior.ColorIndex = 10
    End If

End Sub


Sub PeriodDates()
'
```

```
    Cells(1, 1).Select
    Cells.Find(What:="", After:=ActiveCell, LookIn:=xlFormulas, LookAt:= _
        xlPart, SearchOrder:=xlByRows, SearchDirection:=xlNext, MatchCase:=False
_
        , SearchFormat:=True).Activate
    X = ActiveCell.Row
    If ActiveSheet.Name = "Multiples" Then GoTo 10
    If ActiveSheet.Name = "Capital Structure Details" Then GoTo 10
    Range("B1").Select
    ActiveCell.FormulaR1C1 = "=right(R[" & X & "]C,11)"

    If ActiveSheet.Name = "Key Stats" Then ActiveCell.FormulaR1C1 =
"=left(right(R[" & X & "]C,12),11)"
    Range("B1").Select
    Selection.Copy
    Range("B1").Select
    Set LastCell = Selection.End(xlToRight)
    Range(Cells(1, 2), LastCell).Select
    ActiveSheet.Paste

    Range(Cells(1, 2), LastCell).Select
    Selection.Copy
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=False
    Application.CutCopyMode = False
    Selection.NumberFormat = "m/d/yyyy"
    Range("A1").Select
    ActiveCell = ""
10 End Sub
```

Appendix 5. Financial Ratios Abbreviations and Computations

Ratio	Computation	Information Provided
Current Ratio	$(Current\ assets)/(Current\ liabilities)$	Measures ability to pay current liabilities with current assets.
Acid-Test (quick) ratio	$(Cash + Short\ term\ investments + Net\ current\ recievables)/(Current\ liabilities)$	Shows ability to pay all current liabilities if they come due immediately.
3. Inventory turnover	$(Cost\ of\ goods\ sold)/(Average\ inventory)$	Indicates sale-ability of inventory the number of times a company sells its average inventory level during a year.
4. Accounts Receivable turnover	$(Net\ credit\ sales)/(Average\ net\ accounts\ recei$	Measures ability to collect cash from credit customers.
5. Days' sales in receivables	$(Average\ net\ accounts\ recei$ $/(One\ day^{\wedge\prime}\ sales)$	Shows how many days' sales remain in Accounts Receivable- how many days it takes to collect the average level of receivables.
6. Debt ratio	$(Total\ Liabilities)/(Total\ Assets)$	Indicates percentage of assets financed with debt.
7. Times-interest-earned ratio	$(Income\ from\ operations)/(Interest\ expense)$	Measures the number of times operating income can cover interest expense.
8. Rate of return on net sales	$(Net\ Income)/(Net\ Sales)$	Shows the percentage of each sales dollar earned as net income.
9. Rate of return on total	$(Net\ income + Interest\ expense)/(Average\ total\ assets)$	Measures how profitably a company uses its assets.

Ratio	Computation	Information Provided
10. Rate of return on common stockholders' equity	$(Net\ Income + Preferred\ Dividends)/(Average\ stock\ holders^{\wedge\prime}\ eq$	Gauges how much income is earned with the money invested by common stockholders.
11. Earnings per share of common stock	$■(Net - Preferred@Income\ \ dividends)/(Number\ of\ shares\ of\ common\ stock\ out$	Gives the amount of net income per one share of the company's common stock.
12. Price/earnings ratio	$(Market\ price\ per@share\ of$ $(Earnings\ per\ share)$	Indicates the market price of \$1 of earnings.
13. Dividend yield	$(Dividend\ per\ share@of\ com$ $(Market\ price\ per\ share@of$	Shows the percentage of a stock's market returned as dividends to stockholders each period.
14. Book value per share of common stock.	$(Total\ stockholders^{\wedge\prime}\ equity$ $Perferred\ equity)/$ $(Number\ of\ shares\ of\ comm$	Indicates the recorded accounting amount for each share of common stock outstanding.

Appendix 6. Statistical Run Results

```
------------------------------------------------------------------------------

name:  PhD_Log

log:  C:\.....\~~Current\Model Runs\RunLods.log

  log type:  text


==============================

Run 01

==============================


. logit Failed8Q  Rtrn_Ast Avg_Days_Sales Liab_Asts  if DataGroup==1 | DataGroup==2 |

DataGr

> oup==3, nolog


Logistic regression                                Number of obs   =       1210

                                                   LR chi2(3)      =     126.88

                                                   Prob > chi2     =     0.0000

Log likelihood = -135.30062                        Pseudo R2       =     0.3192


------------------------------------------------------------------------------

    Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
---------------+----------------------------------------------------------------
      Rtrn_Ast |  -7.327278   1.561447    -4.69   0.000    -10.38766   -4.266899
Avg_Days_Sales |   .0220402   .0036695     6.01   0.000     .0148481    .0292324
     Liab_Asts |   3.630876   1.018345     3.57   0.000     1.634957    5.626795
         _cons |  -4.624188   .8195949    -9.24   0.000    -6.176972   -2.964219
--------------------------------------------------------------------------------
===============================
Run 02
===============================

. logit Failed8Q  Rtrn_Ast Avg_Days_Pay_Out Liab_Asts  if DataGroup==1 | DataGroup==2
| Data
> Group==3, nolog

Logistic regression                               Number of obs   =       1178
                                                  LR chi2(3)      =      97.44
                                                  Prob > chi2     =     0.0000
Log likelihood = -148.73687                       Pseudo R2       =     0.2467

--------------------------------------------------------------------------------
        Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+--------------------------------------------------------------
        Rtrn_Ast |   -5.57034   1.430091    -3.90   0.000    -8.373267   -2.767412
```

```
Avg_Days_Pay_Out |   .0202665   .0038206     5.30   0.000     .0127782    .0277548

       Liab_Asts |   4.437173   .9406665     4.72   0.000       2.5935    6.280845

           _cons |  -3.407740   .7301548    -9.35   0.000    -6.261169   -1.399015

------------------------------------------------------------------------------------


===============================

Run 03

===============================


. logit Failed8Q  Rtrn_Capital Avg_Days_Sales Liab_Asts  if DataGroup==1 | DataGroup==2
| Da
> taGroup==3, nolog


Logistic regression                               Number of obs   =       1210

                                                  LR chi2(3)      =     132.80

                                                  Prob > chi2     =     0.0000

Log likelihood = -132.33985                       Pseudo R2       =     0.3341


----------------------------------------------------------------------------------

      Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

---------------+------------------------------------------------------------------

  Rtrn_Capital |  -4.474839   .9880809    -4.53   0.000    -6.411442   -2.538236

Avg_Days_Sales |    .021875   .0036994     5.91   0.000     .0146242    .0291258
```

```
     Liab_Asts |   3.385785   1.083482     3.12   0.002     1.262198    5.509371
         _cons |  -4.347525   .8420279    -8.77   0.000    -6.035937   -2.735248
------------------------------------------------------------------------------


===============================
Run 04
===============================

.  logit  Failed8Q    Rtrn_Capital  Avg_Days_Pay_Out  Liab_Asts    if  DataGroup==1  |
DataGroup==2 |
> DataGroup==3, nolog

Logistic regression                               Number of obs   =       1178
                                                  LR chi2(3)      =     106.65
                                                  Prob > chi2     =     0.0000
Log likelihood = -144.13254                       Pseudo R2       =     0.2701

----------------------------------------------------------------------------------
        Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
    Rtrn_Capital |  -3.813082   .8577007    -4.45   0.000    -5.494145    -2.13202
Avg_Days_Pay_Out |   .0202809   .0037236     5.45   0.000     .0129827    .0275792
       Liab_Asts |   4.368911   .9923958     4.40   0.000     2.423851    6.313971
```

```
           _cons |  -3.411892   .7547383    -8.94   0.000    -5.228747   -2.270227
------------------------------------------------------------------------------------


================================
Run 05
================================


. logit Failed8Q  EBITDA_Mrgn Avg_Days_Sales Liab_Asts  if DataGroup==1 | DataGroup==2
| Dat
> aGroup==3, nolog

Logistic regression                               Number of obs   =       1209
                                                  LR chi2(3)      =     111.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -143.20222                       Pseudo R2       =     0.2793

------------------------------------------------------------------------------
      Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
   EBITDA_Mrgn |  -2.548173   .6524311    -3.91   0.000    -3.826915   -1.269432
Avg_Days_Sales |   .0241528   .0037437     6.45   0.000     .0168153    .0314904
     Liab_Asts |   4.356085   .9869948     4.41   0.000     2.421611    6.290559
         _cons |  -5.205753   .8283241   -10.00   0.000    -6.905693   -3.658722
```

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Run 06

===============================


. logit Failed8Q  EBITDA_Mrgn Avg_Days_Pay_Out Liab_Asts  if DataGroup==1 | DataGroup==2
| D
> ataGroup==3, nolog


Logistic regression                               Number of obs   =       1176

                                                  LR chi2(3)      =      86.06

                                                  Prob > chi2     =     0.0000

Log likelihood = -154.34417                       Pseudo R2       =     0.2180


------------------------------------------------------------------------------

    Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

 EBITDA_Mrgn |  -.1248598   .7000943    -0.18   0.858     -1.49702      1.2473

Avg_Days_Pay_Out |    .029248   .0042544     6.87   0.000     .0209095    .0375865

   Liab_Asts |   4.474993    .927551     4.82   0.000     2.657026     6.29296

       _cons |  -4.240771   .7217483   -10.20   0.000    -5.779335   -2.950134

------------------------------------------------------------------------------
```

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===============================

Run 07

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. logit Failed8Q  Grs_Mrgn Avg_Days_Sales Liab_Asts  if DataGroup==1 | DataGroup==2 |
DataGr
> oup==3, nolog

Logistic regression                               Number of obs   =       1210
                                                  LR chi2(3)      =     108.93
                                                  Prob > chi2     =     0.0000
Log likelihood = -144.27685                       Pseudo R2       =     0.2740

--------------------------------------------------------------------------------
      Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
      Grs_Mrgn |  -3.526109   1.144125    -3.08   0.002    -5.768552   -1.283666
Avg_Days_Sales |   .0266929   .0036394     7.33   0.000     .0195598    .0338259
     Liab_Asts |    4.24288   1.030063     4.12   0.000     2.223993    6.261766
         _cons |   -4.38840   .8506954    -9.44   0.000    -5.700563   -2.365898
--------------------------------------------------------------------------------
```

```
==============================

Run 08

==============================

. logit Failed8Q  Grs_Mrgn Avg_Days_Pay_Out Liab_Asts  if DataGroup==1 | DataGroup==2
| Data
> Group==3, nolog

Logistic regression                                Number of obs   =       1178
                                                   LR chi2(3)      =      80.10
                                                   Prob > chi2     =     0.0000
Log likelihood = -157.40892                        Pseudo R2       =     0.2028

------------------------------------------------------------------------------------
        Failed8Q |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
        Grs_Mrgn |  -.1977295   1.100215    -0.18   0.857    -2.354112    1.958653
Avg_Days_Pay_Out |   .0268026   .0035018     7.65   0.000     .0199393    .0336659
       Liab_Asts |   4.544759   .9218263     4.93   0.000     2.738012    6.351505
           _cons |  -4.085747    .758464    -9.55   0.000    -4.731733   -1.758609
------------------------------------------------------------------------------------
```

```
. log close
      name:  <unnamed>
       log:  C:\.....\Model Runs\RunLods.log
  log type:  text
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