Gordon Institute of Business Science
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The role of liquidity and solvency in the probability of DFI loan defaults by private firms

Tokelo Kosana

Student number: 17386579

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ABSTRACT

The aim of this research was to investigate the role of liquidity and solvency in the prediction of DFI ("Development finance institution") loan defaults held by private firms. The research further considered the contribution of firm size and industry group in the prediction of DFI loan defaults. The study made use of firm-level and industry–level data maintained by the Industrial Development Corporation consisting of 566 accounts of privately-held firms for a period between 2008 and 2014.

Through using a binary logistic regression technique, the empirical results showed that solvency is statistically significant in explaining DFI loan defaults such that when solvency improves, the likelihood of default reduces. The study further showed that, even though firms at default are illiquid, liquidity is not a significant variable in the prediction of DFI loan defaults. Firm size did not influence the role of solvency and liquidity in DFI loan defaults. However, Industry group was found to have a significant influence in the DFI loan default prediction models.

The inclusion of solvency and industry group variables is expected to improve the predictive power of default prediction models on DFI loans. This research only focused on private firms default behaviour towards DFI loans which limits its generalizability to other population groups. The study contributes to the literature of corporate failure prediction and represents one of very few sets of results on the determinants of default in private firms' DFI lending. This research can assist DFIs and managers in understanding the factors that impact the credit risk of privately held firms.

KEYWORDS

Liquidity, Solvency, Default, DFIs, private firms

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Tokelo Kosana

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CHAPTER 1: INTRODUCTION TO RESEARCH PROBLEM

1.1. Background to Research Problem

“Default is amongst the most abrasive events in the life of a corporation” (Brogaard, Li, & Xia, 2017, p. 1). It often signals the possibility of corporate bankruptcy which implies substantial financial and social costs (Bhaskar, Krishnan, & Yu, 2017). In the episode of a default, lenders typically suffer considerable losses because of diminished payment collections. For instance, the Moody’s global risk report on the corporate defaults and recovery rates reported that the typical loss rates to debt providers in the event of firm defaults are 49% and 81% for senior secured loan and subordinated loans respectively (Emery, Ou, Tennant, Matos, & Cantor, 2009).

Companies in possession of loans also want to avoid loan defaults because these will affect their credit report negatively, reducing their chances of obtaining credit in the future. Poor credit score may cause difficulty for any business to undertake future expansions or may increase their cost of debt. If the lender has a secured debt, they may perfect their securities which may severely disrupt the business of the borrower or even drive it to closure. It is therefore important to understand firm defaults in order to assist in limiting the default rates. It is also imperative to predict defaults before they happen in order to assist affected parties in taking mitigating actions. This research seeks to improve the understanding of firm defaults by examining the role of liquidity and solvency in default probabilities of firms holding loans from development finance institutions (“DFIs”).

In this study, the Basel Capital Accord description of default was used which is: the missing of a scheduled loan payment for ninety days or more (Basel Committee, 2010). This definition is also used in many studies in the field of corporate failure prediction (Altman, Sabato, & Wilson, 2010; Brogaard et al., 2017; Davydenko, 2013; Lawless & McCann, 2013). Unlike the definitions of insolvency and bankruptcy which differ from one jurisdiction to another, default definition is generally accepted and operationalised by many lenders and financial institutions (Altman et al., 2010). The default definition used in this research does not include technical defaults such as covenant violations and any breach of the loan agreement which does not arise from failing to make a payment.

There have been conflicting views in existing literature as to the role of liquidity and solvency in predicting defaults. Differing results have been obtained depending on the context. For instance, Koh, Durand, Dai, & Chang (2015) claim that financial distress and cash shortages are the main drivers behind firms' probability of default. However, Jessen & Lando (2015) argue that when dealing with default prediction, less significance should be placed on liquidity since a company can raise cash against its free assets. "Different theories about what causes firms to default may result in dramatically different predictions regarding default probabilities" (Davydenko, 2013, p. 2). Hence it is essential to study and understand factors that lead to default.

There is no existing literature which claims to have uncovered all factors that cause or fully predict default events. However, liquidity and solvency are commonly applied as part of factors signalling loan defaults. A more comparable study was done by Davydenko (2013) who studied the role of insolvency and illiquidity on the risk of defaults. This study was done on a sample of Moody's default and recovery database which consists of defaults on public bonds in the United States of America ("U.S.").

The study found that "the market value of assets over the face value of debt to be the only most important variable affecting the timing of default" (Davydenko, 2013, p. 32). Even though the study can be applied in many contexts, it cannot be generalizable to private firms defaulting on the DFI loans. Firstly, it is impractical to obtain the market value of assets for privately held firms because observed market prices of equity, bonds, and bank loans are needed to calculate this factors (Davydenko, Strebulaev, & Zhao, 2012).

Secondly, Davydenko (2013) study may lack the ability to evaluate the population of this research accurately due to differences between listed firms in the U.S and private firms in the South African DFI books. The differences may mostly be caused by dissimilarities in corporate governance practices between the two types of firms which result in differences in the way firms may behave when deciding to default (Altman et al., 2010). Moreover, the firm sizes may also cause the difference, Amendola, Restaino, & Sensini (2015) argue that firm size changes the predictive power of default models as well as the interaction of financial ratios input in the model. The firms listed in the U.S. are expected to be generally larger compared to South African privately held firms funded by the DFIs.

This research forms part of the literature of corporate failure and credit risk. Balcaen & Ooghe (2006) did a review of thirty-five years of the corporate failure prediction studies and found that research in this area is extensive and recommended that the impact of various factors on defaults might differ depending on the context and should, therefore, be tested before applying the models. Following that study, Bellovary, Giacomino, &

Akers (2007) did a review of bankruptcy prediction studies from 1930 to 2007 and suggested that future research should consider understanding and refining existing models instead of building new ones.

More recently, Appiah, Chizema, & Arthur (2015) presented "a systematic review of eighty-three articles reporting 137 prediction failure models published within 1966-2012 in scholarly reviewed journals throughout eleven countries" (p. 461). This study concluded that even though there is a significant body of previous literature on corporate failure prediction, a simple and theoretically sound prediction model has never been developed. The lack of theoretical grounding of corporate failure prediction models presents an opportunity for researchers to seek to fully understand the individual determinants of corporate failure (Appiah et al., 2015).

The firms funded by the DFIs provide a unique library since they are generally risky. According to Calice (2013), the firms funded by DFIs are generally outside the risk appetite of the commercial banks, either because the industry is not of commercial interest to banks or the incumbent does not have sufficient personal security to cover the exposure.

1.2. Purpose of the Study

This research deals with the role of liquidity and solvency on default probabilities of private firms on DFI loans. The business and the theoretical purpose of the study will be explored below.

1.2.1. Business purpose of the study

The business necessity of this study can be seen in the context of both the private companies and DFIs. The study will assist private companies to make better liquidity and financial structure decisions in order to avoid defaults and manage their credit risk profiles. The study will also contribute to DFIs' credit risk assessments by assisting DFIs to understand the impact that liquidity and solvency have on a firm's probability to default on their loan commitments. They will also manage existing clients better by being able to detect loan defaults of private firms before they occur and pro-actively take corrective actions.

The propensity of a firm to default is often exacerbated by a severe economic climate as was seen in the 2009 economic meltdown (Almamy, Aston, & Ngwa, 2016). According to StatsSA (2018), the South African economy grew 0.3% in 2016, 1.3% in 2017 and contracted 2.2% in the first quarter of 2018. The South African economy is thus underperforming compared to the other emerging markets and the global economy as a whole. The 2017 average real growth of emerging markets and the global economy were 4.8% and 3.8% respectively (IMF, 2018).

In the midst of this slow economic growth, DFIs are often expected to play a counter-cyclical role by supporting credit growth and funding businesses that are too risky to the banking sector (Derban, Binner, & Mullineux, 2005). The impact of the weak economic growth on firm defaults is therefore magnified when attention is placed on the DFIs. It is therefore crucial for DFIs to understand credit risk of firms they are about to fund and firms that are already in their books.

Khadiagala (2011), researched the role of DFIs in building South Africa's democratic developmental state and cited that in a poor performing economy, the DFIs are faced with limited credit and increasing costs of raising finance in the risk-averse markets. They are, however, expected to shoulder the increasing burden of injecting funds in the economy. The reason being, DFIs have a broader mandate, stretching beyond the commercial rationale, which is mainly to facilitate empowerment and socio-economic development. Furthermore, some of the South African DFIs are usually tasked to provide finance to small and medium-sized enterprises as well as industries in geographical areas risky to the private sector (Dickinson, 2008). Nevertheless, the DFIs are expected to operate sustainably in a long-term which means understanding and managing the credit risks of firms they fund (Derban et al., 2005).

According to Psillaki, Tsolas, & Margaritis (2010) credit risk is the most significant threat to financial institutions. The non-performing loans of the DFIs pose a risk to the financial well-being of these institutions and thus threatens their long-term sustainability. The responsibility lies on the DFIs to adopt sound internal credit risk practices to assess the businesses they finance. Deeper understating of the credit risk by the DFIs will not only support the sustainability of these institutions but also contribute to an efficient allocation of capital in the economy (Psillaki et al., 2010).

South Africa has three main DFIs which consist of the Land Bank, Development Bank of Southern Africa (DBSA) and Industrial Development Corporation (IDC). These DFIs are mainly mandated to promote economic development through the provision of financial services in the form of loans, deposits, and guarantees (Calice, 2013). These DFIs are meant to support inclusive growth in the economy and are very important to the functioning of the country's democracy (Khadiagala, 2011). However, the South African DFIs are unfortunately burdened by high levels of non-performing loans and impairments. The 2017 non-performing loan book of DBSA and the Land Bank was 4% and 7% respectively compared to the average of 2.5% achieved by the South African commercial lenders (Fin24, 2017). The IDC recorded impairments of 17% in 2017 mainly due to the distressed clients in their books (IDC, 2017). The high impairments are not unique to the IDC. According to de Luna-Martínez & Vicente (2012), the DFIs are prone to taking low-quality assets into their books which results in a high amount of non-performing loans.

The cost of corporate failure of firms or more so the collapse of the DFIs due to corporates not honouring their obligations can have far-reaching effects on the economy as a whole. Ahmad et al. (2016) researched the impact of non-performing loans on economic growth and concluded that non-performing loans endanger the economy and compromise economic growth. The fact that DFIs are prone to provide finance to riskier clients relative to the commercial banks makes the contribution of this research profound since there is no evidence of this population of firms being studied previously.

1.2.2. Theoretical purpose of the study

The literature on default and bankruptcy prediction dates back to the 1930s. Bellovary et al. (2007) did a review of these studies and stated that the bulk of the work had been done on publicly-traded companies which make this population well understood. There has been limited attention to privately held firms. Bauweraerts (2016) attributes this to the lack of publicly available data and the absence of market data relating to private firms. Furthermore, there has not been any cited literature on private firms defaulting on the DFI loans which makes the contribution of this research valuable to the field of credit risk and default prediction.

The asset book of the DFIs is different from that of commercial banks. According to Luna-Martínez & Vicente (2012), the developmental mandate of the DFIs which makes them focus on industry capacitation and employment creation rather than profitability makes them acquire clients with a higher credit risk grading. The commercial banks, on the other hand, take a collateral approach and avoid taking risky firms to their books (Blazy, Martel, & Nigam, 2014). According to Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2017) default prediction models must be adapted to each economic setting in order to increase their relevance and predictive power.

The study (Sayari & Mugan, 2017) also found that financial ratios in default prediction echo characteristics of the external environment and that the material content of each ratio varies among different environments. In fact, it is a consensus among scholars that default models should be developed for different types of failure and specific country contexts (Balcaen & Ooghe, 2006). The population funded by commercial banks in different countries has been well studied. However, for this study, the researcher could find no studies on firms funded by the DFIs which makes the contribution of this study imperative to literature.

Furthermore, the factors which trigger loan default are generally not precisely defined (Kruschwitz, Löffler, Lorenz, & Scholze, 2015). Notions regarding what should be looked at to predict loan default result in radically different default probabilities (Leland & Toft, 1996). Therefore, it is essential to understand the role of factors used in credit risk based on the context. However, even though many default factors have been used in the past, there is a general consensus that the most critical default triggers are liquidity and solvency (Hsu, Lee, Liu, & Zhang, 2015). Therefore, this research seeks to contribute to the literature by examining the role of liquidity and solvency on default probabilities of private firms funded by the DFIs.

1.3. Research Scope

The scope of this research is restricted to investigating the characteristics of defaults in the context of private firms in possession of DFI loans. The study is only limited to privately held firms and cannot apply to other types of firms such as listed companies and state-owned companies. Private firm defaults are less understood by commercial institutions and academic research in this subject is limited (Duan, Kim, Kim, & Shin, 2017).

Furthermore, the privately owned firms to be studied are those in possession of DFI loans. The firms in the DFI books provide a unique library to study since they are riskier and have a higher propensity to default (Luna-Martínez & Vicente, 2012). This study can therefore not be generalizable to firms that do not have DFI loans. Unlike many studies in the field of corporate failure prediction, this research does not attempt to build a better prediction model but focuses on the role of solvency and liquidity on loan default prediction.

1.4. Research Aim

This research aims, through a descriptive study, to investigate the role of liquidity and solvency in default probabilities of private firms in possession of DFI loans. Unlike many studies in the field of default prediction (Almamy et al., 2016; Altman et al., 2017; Ciampi, 2015) the primary objective of this research is not to build a better prediction model but to assess the role of the two specific factors (liquidity and solvency) in signalling DFI loan defaults. By using binary logistic regression as an analysis tool, the study will determine the extent to which each factor empirically explain observed defaults. It will also determine how these factors interact in explaining defaults.

This research will thus seek to answer the following research questions:

1. What is the role of liquidity on the likelihood of default in DFI loans by private firms?
2. What is the role of solvency on the likelihood of default in DFI loans by private firms?
3. What is the role of firm size in the prediction of DFI loan defaults?
4. What is the role of industry group variable in the prediction DFI loan defaults?

The remainder of this research is organised as follows: Chapter 2 presents a literature review to examine the previous literature within the field of the study and develop the research questions. Chapter 3 crystallises the hypotheses. Chapter 4 describes the data set and methodology of the study. Chapter 5 presents the results obtained from the study. Chapter 6 provides a critical account and discussion of the results and chapter 7 makes concluding remarks.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction to Literature Review

This chapter reviews the relevant literature on factors leading to loan default and their impact of private firms funded by development finance institutions (DFIs). The chapter starts by presenting literature on the significance of credit risk on DFIs in order to offer insights into the characteristics of the sample used in the study. It then presents the numerous perspectives that exist in the literature on credit risk and corporate failure. This particular focus is because loan default is central to both credit risk and corporate failure (Davydenko, 2013; Muscettola, 2014).

The chapter then reviews the literature regarding the contributing factors to loan defaults and the assumptions underpinning the selection of independent variables in the corporate failure prediction models. The chapter then examines the two distinct views associated with liquidity and solvency as components signalling defaults. It then explores literature based on the effects of size and industry groups on defaulting firms. It then scrutinises the literature of widely used default prediction models and the specific default prediction model that will be utilised in this research. The chapter closes with a discussion of some of the key concepts developed.

2.2. Development Finance Institutions and Credit Risk

Credit risk and default concept are closely related to the new Basel III framework (Bhimani, Gulamhussen, & Lopes, 2010). In response to the 2009 financial crisis and the collapse of many financial institutions, the Basel Committee on Banking and Supervision published its reforms in the form of Basel III framework (Basel Committee, 2010). This framework consists of three pillars: minimum capital requirements, capital adequacy and the level of risk assessment. Fundamental to the framework is the level of risk assessment that should be undertaken by the financial institution (Bhimani, Gulamhussen, & Lopes, 2014).

“This capital regulation has attempted to measure the riskiness of a bank’s on- and off-balance sheet exposure and to fix the amount of capital needed to limit the probability of default to a desired level of confidence” (Dermine, 2014, p. 1). Under the Basel Framework, the banks are required to have comprehensive risk management for all material risks and appropriate risk-modelling techniques to assess the creditworthiness of clients and determine appropriate interest rates (Bhimani et al., 2014). “A significant innovation of the Basel regulatory framework is the greater use of risk assessments developed internally by the financial institutions as inputs to capital calculations" (Calabrese & Osmetti, 2013, p. 2).

Therefore, the financial institutions are obliged to develop their internal assessment models to measure the credit risk of companies they fund and use them as input for their minimum regulatory capital calculations (Bhimani et al., 2010). The primary input for these credit risk models is the probability of default forecasted one year for clients funded by the financial institutions (Calabrese & Osmetti, 2013). The financial institutions also need to test their default prediction models and document their accuracies (Dermine, 2014).

The South African development finance institutions mostly align themselves to principles of Basel Framework in order to attract funds in the international markets (DBSA, 2018; IDC, 2018). This is to ensure risk transparency and to have access to the capital in the financial markets while maintaining proper risk grading (Kwakkenbos & Romero, 2013). It is indeed even more challenging for DFIs to comply with the framework due to the unique characteristics of risk profile that require them to balance between risk, return, and development focus area (Adesoye & Atanda, 2012). Since the accord recognises that it is credit risk that matters the most, it is highly imperative for DFIs to understand the credit risk models they put in place.

Traditionally, DFIs were meant to provide development finance to address market failures in order to complement both the private sector and the government (Kwakkenbos & Romero, 2013). However, in the South African context, the government has given DFIs a mandate to not only address market failures but to also play a pivotal role in addressing the socio-economic challenges faced by the country (Khadiagala, 2011).

The broader development policy objectives include employment creation, the development of poor groups or regions and promote the socio-economic transition of the black people (Thorne, 2011). This mandate implies that DFIs would place more emphasis on the developmental impact at the expense of financial returns (Adesoye & Atanda, 2012). The promotion of socio-economic transition of the black people has seen BBBEE consortia that lacked capital seeking finance at highly-geared financing structures (Khadiagala, 2011). This behaviour then perpetuates the riskiness of firms in the DFI portfolio.

Moreover, the DFIs are meant to initiate greenfield projects where the commercial banks are not willing to take the risk without collateral (Yitaferu, 2013). DFIs are also active in financing private firms and start-ups, often viewed as too risky by the banks. The firms in these categories do not have a huge asset base and personal contribution to put as equity. For instance, the IDC has reduced the minimum contribution required to receive start-up capital from 10% to 2.5% (IDC, 2017). Consequently, the development of financial institutions ought to have clients that are highly geared and risky (Romero & Van de Poel, 2014).

On the other hand, the socio-economic outcomes and government development needs do not form part of the primary strategic focus of the Basel framework and the commercial banks (Yitaferu, 2013). The commercial banks also tend to fail in providing sufficient long-term finance to the high-risk sectors of the economy (Adesoye & Atanda, 2012). Hence, the characteristics of the clients in their portfolio would differ from the firms funded by the DFIs. Furthermore, the banks have better monitoring on their clients and can react quickly if the client shows patterns leading to default.

The distinct differences between DFIs and commercial banks are likely to affect the behaviour of firms when it comes to loan repayments (Nyumba, Muganda, Musiega, & Masinde, 2015). Altman et al. (2017) also maintain that the economic environment, monitoring and contractual arrangements by institutions can impact the boundary between defaulting and non-defaulting firms. Since DFIs provide a different engagement structure compared to commercial banks, it is essential to understand what signals default specifically for firms funded by DFIs.

Furthermore, “developing effective internal systems for corporate risk management requires building default prediction models geared to the specific characteristics of corporate sub-populations (i.e., private companies, listed companies, SME’s), tuned to changes in the macro environment and tailored to the availability of data” (Hernandez Tinoco & Wilson, 2013, p. 394). Hence, this research study focuses explicitly on the private firms defaulting on DFI loans.

2.3. Corporate Failure Prediction

The literature on corporate failure has been studied for more than eight decades and remains investigated in current times (Mselmi, Lahiani, & Hamza, 2017). Starting with the ratio analysis pioneered by FitzPatrick (1932), there has been a continuous effort and a large amount of research contemplating prediction of corporate failure from the different perspective of finance, accounting, and economics (Vinh, 2015). There is, however, a general agreement that corporate failure negatively affects various stakeholders such as employees, creditors, government and shareholders (Mselmi et al., 2017). Yeen Lai, Sin Yee, Suet Cheng, Peck Ling, & Wan Leng (2015) precisely describe corporate failure as a phenomenon that breaks up a corporation's social and commercial interface. Encompassed in the literature on corporate failure prediction are financial distress, bankruptcy, insolvency, and default prediction (Bellovary et al., 2007).

A continuing large number of bankruptcies around the globe has increased the importance of developing early warning signs to detect and allow preventive measures to be taken in order to avert corporate failures (Vinh, 2015). Similarly, financial institutions need to recognise problematic loans early in order to quickly take mitigating actions (Bhimani et al., 2014). "The delay of recognising the problem may result in the liquidation of the firms and the loss of the financial institution's investment" (Yeen Lai et al., 2015, p. 343).

To date, corporate failure literature has mainly been dedicated to the development of new failure prediction models and testing of the old ones in different contexts (Sun, Li, Huang, & He, 2014). However, research of corporate failure prediction is fragmented and mainly empirical (Altman et al., 2017). According to Laitinen & Suvas (2013), corporate failure investigations suffer from lack of theoretical grounding which weakens the interpretation of results and conceptualisation of the event of interest. Moreover, no prevailing theory is currently used to guide the selection of independent variables for corporate failure prediction models (Altman et al., 2017).

du Jardin (2009) did a critical review of the variable selection methods used to build empirical bankruptcy prediction models; it was concluded that there is no prevailing theory on variables choice used in prediction models. Hence, many researchers use popular variables and statistics to find empirical predictors. This very fact is the cause of models with different predictors and the lack of generalizability of corporate failure models (Appiah et al., 2015). Therefore, "the corporate failure models are strongly associated with original estimation data and cannot be generalised for different kinds of context" (Laitinen & Suvas, 2013, p. 3). It is also where the term 'brute empiricism' is evident, where statistical significance of variables is emphasised and the economic considerations or theories are disregarded (Appiah et al., 2015; Balcaen & Ooghe, 2006).

Therefore, there is no strong theoretical evidence demonstrating the importance of one financial ratio over another in the prediction of defaults (Foster & Zurada, 2013). Although, the corporate failure literature suggests that some measures should be more critical than others in the prediction of defaults (Jones, 2017). In the review of bankruptcy prediction studies done from 1930 to 2006, Bellovary et al. (2007) found that factors measuring liquidity and solvency are mostly used in the corporate distress prediction literature which supports the focus of this research.

2.3.1. Bankruptcy prediction and loan defaults

Corporate bankruptcy is a legal process by which a firm declares that it is unable to honour its debt obligations and requires exoneration (du Jardin, 2017). Some corporate failure prediction models apply a connotation that is contingent upon its ultimate legal consequence such as bankruptcy or insolvency (Subrahmanyam et al., 2017). The reason being, "these events are highly visible legal events that can be objectively and accurately dated for use as an outcome variable" (Hernandez Tinoco & Wilson, 2013, p. 395). Bankruptcy definitions are specific to the country's legislation (du Jardin, 2017). That makes "the determinants of bankruptcy not to be generalised across other forms of failure and context" (Bhimani et al., 2010, p. 519). Default, on the other hand, is defined in the Basel III framework as the omission of payment for three consecutive months or more and this has been adopted by many financial institutions across jurisdictions (Altman et al., 2017).

Bauer & Agarwal (2014) claims that the prediction of bankruptcy and default are similar since the two concepts are related. Other related views report that default is an early warning sign for bankruptcy since in many cases formal supervision is enforced mainly by creditors (Bhimani et al., 2010; du Jardin, 2017). Furthermore, the likelihood of bankruptcy and default are modelled in the same way using binary choice models which discriminate between failing and non-failing firms (Hernandez Tinoco & Wilson, 2013). Even though the loan default and corporate bankruptcy are defined differently, in this research, it is recognised that they share similar determinants and prediction models.

2.3.2. Financial distress prediction

The definition of financial distress differs from one author to the next. Rodano, Serrano-Velarde, & Tarantino (2016) argue that financial distress is synonymous with insolvency which is indicated by negative net asset value. Geng et al. (2015) posit that financial distress explains both a failure to pay outstanding obligations and negative net-worth. According to the study (Hernandez Tinoco & Wilson, 2013), the process of financial distress starts with a company not being able to pay short-term obligations, as and when they fall due which precisely means when a firm defaults.

Sun, Huang & He (2014) define financial distress as a state where a firm's cash flow is unable to meet debts or preferred dividend or any contractually required payment as they come due. The definition by Sun et al. (2014) is very similar to the South African

Companies Act definition of financial distress. The definition is stated in section 128(f), chapter 6, of the South African New Companies Act as a firm that meets either of the two criteria. Firstly, it must “be reasonably unlikely that the company will be able to pay all of its debts as they fall due and payable within the next six months.” Secondly, “it must be reasonably likely that the company will become insolvent within the immediate ensuing six months” (RSA, 2008).

The first part of the legislation relates to reasonably predicting the probability of default before it happens. The second part refers to technical insolvency as can be tested in the balance sheet. A company is regarded as technically insolvent if the liabilities of the company exceeds its assets (Rodano et al., 2016). Davydenko (2013) claims that firms default when the market value of assets falls below a particular threshold relative to the face value of debt. These assertions show that default prediction is embedded in the South African legislature emphasising the importance of this study in the South African context.

2.4. Default Indicators of Private Firms

The previous studies have focused on publicly listed firms because of the availability of financial information for these companies (Cultrera & Brédart, 2016). To date, there has been limited work on the privately held firms. Hence, default prediction on privately held firms has been a subject of recent debates in various emerging markets (Ciampi, 2018).

Mselmi et al. (2017) did a financial distress prediction study on French SMEs and found that the financial ratios that have a reliable prediction power are those representing liquidity, solvency, and profitability, mainly because they have lower repayment capacity. Bauweraerts (2016) and Cultrera & Brédart (2016) investigated the default behaviour of Belgian private firms on separate occasions. By using variable selection in a binary logistic regression on more than 30 financial ratios, they found that reduced levels of liquidity, solvency, and profitability increase the probability of default.

Muscettola (2014) studied the determinants of default risk for Italian private firms using the logit model and concluded that leverage, liquidity and interest coverage are the significant predictors of default risk. Duan, Kim, Kim, & Shin (2017) examined the credit risk of Korean privately held firms and found that gross profit over the current asset, earnings before interest, taxes, depreciation, and amortization over interest expense, cash over the current asset and the change in interest rate to be the significant indicators of whether Korean private firms would default or not.

Since the studies were contextualised to provide a relevant and accurate forecast of a particular setting, it does not hold to other legal, country, and institutional contexts (Bauweraerts, 2016). It is therefore warranted to understand private firms default in the context of South African Development finance institutions.

In the quoted previous studies, the variable selection of the private firms was based on the statistical significance of variables in the prediction of default; no theory has been relied upon. However, views about the conditions that best signals the likelihood of default have always been present in the structural models of credit risk (Davydenko, 2012). There are two distinct conditions applied in the structural models of credit risk which result in radically different predictions regarding default probabilities.

These models either assume that the default is driven by insufficient liquidity (cash-based) or low asset values relative to debt (value-based) (Sundaresan, Wang, & Yang, 2014). The cash-based structural models posit that a firm can only be in default due to insufficient balance sheet liquidity even when a business is fundamentally sound (Davydenko, 2013). This means financial distress is a single most important signal of default. On the contrary, the value-based structural models assume that economic distress should trigger a default. Meaning, firms only default when the asset value relative to debt falls below a certain threshold (Leland & Toft, 1996). In private firms, the market value of assets can be represented by the book value of total tangible assets (Fairhurst, 2017). The relationship between total tangible assets and debt endogenously refers to the solvency of a firm (Davydenko, 2013).

2.5. Role of Liquidity on Defaults

There are some studies that raise liquidity as being central to the prediction of default. Liu, Xu, Yang, & Zhang (2017) investigated the significance of financing constraints on Chinese listed firms and emphasised the importance of liquidity and liquidity management in reducing default risk. They further found that attention to a firm's liquidity default risk can change a firm's attitude towards investment, optimal capital structure decision and dividend policy. Brogaard, Li, & Xia (2017) researched the relationship between default probability and stock liquidity across various liquidity measures using expected default frequency model on the listed firms in the U.S. They established a significant negative association between stock liquidity and firm's default probability mainly because of increased shareholder activism and ease of access to cash.

Kruschwitz et al. (2015) studied the role of illiquidity and over-indebtedness on triggering defaults within the theory of discounted cash flow. They found that under the occurrence of both, illiquidity and over-indebtedness, “illiquidity is the stricter default trigger which indicates that illiquidity necessarily implies over-indebtedness at the same time, whereas over-indebted firms may at the same time still be able to pay off their debt obligations in full” (Kruschwitz, Löffler, Lorenz, & Scholze, 2015, p. 218).

Koh, Durand, Dai, & Chang (2015) also claim that financial distress and cash shortages are the main drivers behind firms’ default and subsequent bankruptcy. du Jardin (2017) maintains that an insufficient balance sheet liquidity and the existence of short-term financial obligations may trigger a default, despite a firm having a healthy solvency level. Duarte et al. (2018) propound that working capital management is a significant role player in firms falling into default. Good working capital management means management finds proficient ways to ensure that cash is available for everyday operations which leads to increased cash flows and lowers the probability of default (Kieschnick, Laplante, & Moussawi, 2013).

Some structural models of credit risk such as contingent claims model assume that default occurs when a firm’s instantaneous cash flow becomes insufficient to service its immediate debt obligations (Sundaresan et al., 2014). In these models, default risk is mainly affected by the variation in available cash which substantiates the use of liquidity measures as a central default predictor (Detering & Packham, 2016). “In such models, external financing is typically prohibited which then means temporary cash shortages may result in the firm’s inability to meet its current financial obligations, despite the fundamentally sound nature of its business” (Davydenko, 2013, p. 11).

The view that supports liquidity as a critical default indicator is not unreasonable because distressed firms may struggle to raise necessary external financing due to various market frictions such as legislative hurdles (Shin & Kim, 2015). This view is also consistent with the debt service coverage covenant which is generally imposed by loan providers which implies that default risk increases when cash available for debt service drops below a certain level (Demerjian & Owens, 2016).

On the contrary, other literature argues that liquidity is insignificant to default as long as a firm has free assets to raise cash against. In the seminal work of Fitzpatrick (1932) was amongst the first to report that when dealing with default predictions, less reliance should be placed on liquidity ratios to firms having long-term liabilities. It is probably because short-term cash flow problems have less effect on the firm if the balance sheet is well managed (Almamy et al., 2016).

In recent literature, Jessen & Lando (2015) argue that falling cash flow will not cause immediate default because a firm can easily convert available assets into cash. The argument seems to render liquidity less necessary as an indicator of whether the firm will default or not. Firms have mechanisms such as using credit lines and equity issuances to replenish cash balances in case of cash constraints (Bazdresch, Jay Kahn, & Whited, 2018). Davydenko (2013) postulates that default can only be triggered by liquidity if the external debt is unavailable.

There seems to be no general agreement as to what extent liquidity explains the likelihood of defaults. This research will thus seek to understand the role of liquidity in private firms defaulting on DFI loans thus contributing to the body of existing research.

2.6. Role of Solvency on Defaults

Solvency refers to a measure of a company's assets in excess of its liabilities (Khoja, Chipulu, & Jayasekera, 2016). It measures the firms' capacity to meet all of its financial commitments. Unlike liquidity, solvency indicates a more serious underlying problem that is generally much lengthier to correct (Bhaskar et al., 2017). Liquidity problem can be solved by cash injection mostly by raising cash against available assets as long as the firm is solvent (Almamy et al., 2016). However, insolvency generally requires radical change, such as selling off some assets or laying off employees (Khoja et al., 2016).

The link between solvency and default has been debated for many years. An earlier study on capital structure theory done by Leland (1994) on the corporate debt values and capital structure found that "a firm's optimal leverage and debt values are explicitly linked to firm's default risk and bankruptcy probabilities" (p. 38). Following that, Leland & Toft (1996) also argued that an increase in capital gearing (debt/assets) raises the probability of corporate failure as a firm is likely to default on its obligations.

The theory of accounting and finance deliberates that "limited liability conventions lower the downside risk while retaining the upside potential and creating options like payoff structure with associated incentives for taking risks" (Bhimani et al., 2010, p. 519). Therefore, it can be inferred that the default is directly related to capital structure.

The more recent literature on the review of Merton's Model points out that structural models in capital structure take solvency constraints as a course of default and assumes that firms do not default at the optimal capital structure (Sundaresan, 2013). Therefore, it can be argued that there is a link between default risk and leverage such that when a firm has low leverage its default risk decreases and when a firm has high leverage its default risk increases (Glover, 2016). Kim, Patro, & Pereira (2017) also maintain that in order for a firm to control its default risk, it must control its leverage because the two are intimately connected.

Succurro (2017) did a research to describe financial bankruptcy across Western European countries and concluded that an increase in a firm's debt level significantly increases its likelihood of default. Altman et al. (2017) also cite that the theoretical models of bankruptcy and financial distress prediction generally relate distress to low debt service cover ratio. Demerjian & Owens (2016) report that growing capital gearing (debt/assets) raises the probability of firm failure. They also argue that high debt coupled with low profitability have a stronger effect on the default prediction compared to a situation where the two happen in isolation.

The traditional structural models of risky debt (Choi & Richardson, 2016) undertake that a company "defaults when the market value of assets falls below a certain solvency boundary, which may be exogenously specified or endogenously determined by stakeholders" (Davydenko, 2013, p. 2). In the event that a cash shortfall results in a liquidity problem, equity holders will step in by raising the outside funding to honour the current debt obligations, as long as the company assets still exceed the total liabilities (Leland, 1994). This view renders pure liquidity irrelevant in the prediction of default. Furthermore, the literature in bankruptcy and reorganisation identifies net worth as a critical factor that affects the ability of a firm to raise external finance (Shibata & Nishihara, 2018).

In his study of, "When do firms default?" Davydenko (2012) measures the boundary at which firms default based on market values of listed firms. He finds that, on average, firms default when market values of assets are 66% of the face value of debt. This point is said to be the default boundary, and it occurs when firms are already insolvent (Davydenko, 2012). This article supports the assertion by Leland (1994) that firms default when the market value of assets passes below a threshold named default boundary.

The findings by Davydenko (2012) are based on market values which limit their usefulness to the privately held firms. In the case of private firms, it would be more practical to look at the solvency measures based on book values obtained from the companies' balance sheets (Ciampi, 2017).

The usage of the book values is supported by various authors. Tian, Yu, & Guo (2015) in the study of variable selection and bankruptcy forecasts report that in the corporate failure prediction; book solvency ratios are more reliable indicators than market solvency values because "firms rarely counteract to changes in their capital structure caused by fluctuations in their stock prices" (p. 90). Therefore, solvency calculated from book values is more likely to signal the default risk better.

The study (Duarte et al., 2018) reiterates the relevance of accounting-based variables by showing that their predictive power is high and steady over time. Similarly, Ciampi (2017) emphasises the relative importance of accounting information compared to market data in default prediction. Therefore, this research will utilise book values as a proxy for solvency measures of private firms defaulting on DFI loans.

2.7. Role of Firm Size on Defaults

The non-financial information that represents the dimensions of a firm which cannot be captured by financial ratios is vital for signalling loan defaults (Ciampi, 2015). du Jardin (2017) highlights that even though "financial ratios are by far the best default predictors, they do not embody all causes or symptoms of financial failure" (p. 2). The addition of the non-financial information in the default prediction models has been proven in to improve the accuracy of prediction models because the impact of factors not detectable by financial information is also represented (Bauweraerts, 2016).

Qi, Zhang, & Zhao (2014) point "that not all relevant risk factors are known and quantifiable for modelling and prediction purposes" (p. 216), however, the marginal contribution of non-accounting data and information on firm characteristics have been proven to be very valuable to the prediction of defaults (Kuvek & Generale, 2013).

In the study done by Amendola, Restaino, & Sensini (2015) firm size was found to improve the predictive power of default models as well as the interaction of financial ratios input in the model. Firm size has also been found to influence the probability of firm bankruptcy in such a way that small firms are more likely to be bankrupt than larger firms (Balcaen & Ooghe, 2006). Consequently, smaller firms may be expected to be more prone to defaults.

Large firms are expected to exhibit a lower failure probability since they are more likely to benefit from economies of scale and have more power in negotiations with their credit providers (Balcaen & Ooghe, 2006). The more modern study by Duan et al., (2017) claims that the default intensity significantly decreases with the increase in the firm's size measured, ceteris paribus. They cite a reason that larger firms benefit from their experience and learning effects.

In the study (Bauweraerts, 2016) predicting bankruptcy of private firms, it was found that smaller firms have a higher probability of default than bigger firms. In the development of the logit model, Ohlson (1980) finds that firm size is a significant and important variable in the prediction default such that when firm size increases default reduces. Altman et al. (2017), in a review of the Z-score model, concluded that firm size significantly improved the model when it was explicitly taken into account.

The boundary between defaulting and non-defaulting firms is dissimilar for small and large firms (Altman et al., 2017). The socio-economic and developmental mandate of the South African DFIs requires them to fund both small and large firms (Khadiagala, 2011). It is critical to understand and appreciate if the firm size has a significant role in the probability of defaulting on the DFI loans.

2.8. Role of Industry Group on Defaults

Appiah et al. (2015) noted that analysing corporate failure would not be complete without considering the environment within the firm operates. Nguta & Huka (2013) researched the factors that influence loan repayment default in Kenya's micro-finance institutions and provided evidence that industry type significantly influences the non-repayment of loans.

Sayari & Mugan (2017) posits that "financial ratios resonate with industry characteristics and that information of specific ratios varies among different industries" (p. 59). Therefore, "the models developed for the general application may not be as appropriate as industry-specific models" (Bellovary et al., 2007, p. 3). Some authors have advocated for building industry-specific models (Ooghe et al., 2003, Sayari & Mugan, 2017).

"Firms in different industries tend to report different levels of the same financial ratios, which may affect the boundary between defaulting and non-defaulting firms" (Altman et al., 2017, p. 167). Ciampi (2017) focused his study on the small Italian manufacturing firms and observed that sector-specific factors play a crucial role in determining their default behaviour. The firms holding DFI loans also provide an interesting library to see if the industry has, likewise, a significant effect on loan defaults.

In economics, industry effects have a significant impact on financial performance, liquidity, and solvency of the firms (Fuller, Yildiz, & Uymaz, 2018). Therefore, industry class may be a crucial constituent in the prediction of default probabilities. For instance, various industries face different levels of market forces. Thus, the probability of default can vary for firms in different industries with otherwise similar balance sheets (Hernandez Tinoco & Wilson, 2013). Furthermore, the firms frequently encounter different cultural and sectoral dynamics which are crucial in determining their long-run financial stability (Sayari & Mugan, 2017).

A conflicting view is presented in the findings of Altman et al. (2010) who found that industry and country effects have marginal to insignificant contribution in the prediction of financial distress. Since default and financial distress prediction are related, it can be extended that industry effects would have no significant effect in the prediction of default.

Majority of the reviewed articles seem to suggest that industry group is an essential variable in the prediction of default and might improve the predictive abilities of other variables in the logistic regression (Balcaen & Ooghe, 2006). This research will test the role of an industry group in improving the predictive power of liquidity and solvency variables in the context of private firms holding DFI loans.

2.9. Review of Prediction Models

This research will test the role of liquidity and solvency on the default probability of firms funded by DFIs. This will be achieved by utilising the logit model to aid in testing the hypothesis. The literature review of default prediction models is therefore presented.

The models of default in corporate lending can broadly be placed into two groups, namely: market outcome-based models and accounting based models (Foster & Zurada, 2013). The market outcome-based models are based mainly on market data, the example being Merton (1974) Distance to Default and Black & Scholes (1973) option pricing model.

Research on the predictors of default of privately held firms generally takes an accounting-based model which uses firm-level information due to lack of market value information (Gupta, Gregoriou, & Ebrahimi, 2018). Altman et al. (2017) did a review of 31 articles on bankruptcy prediction and found that accounting based models under-performs compared to the market-based models in long-term prediction but performs at the same level for short-term default prediction. du Jardin (2009) posits that "accounting-based models perform comparably to the market-based models for credit default spread estimation" (p. 10). The study also points out that the use of accounting-based models is advantageous because they allow for a higher level of risk-adjusted return on credit activity.

Balcaen & Ooghe (2006) reviewed accounting-based models of business failure prediction which they "classified into four categories: univariate models; risk index models; MDA models; and conditional probability models" (p. 3). In the more recent review, Jackson & Wood (2013) presented the performance of insolvency prediction and credit risk models in the U.K. They found that most popular methods of corporate failure prediction were multiple discriminant analysis (MDA) and logit models.

The MDA rests on the fact that failing and non-failing firms manifest dissimilar financial ratios and this then makes it possible to discriminate between the two groups (Mselmi et al., 2017). "This statistical technique is used to classify an observation into one of several groups dependent upon observations of individual characteristics" (Balcaen & Ooghe, 2006, p. 11). The MDA presents significant limitations as it imposes some requirements regarding the distribution of predictors.

Firstly, it requires that the independent variables used in the model to be normally distributed, which is rarely achieved and also means that dummy variables cannot be used (Jackson & Wood, 2013). Secondly, it requires that both defaulting and non-defaulting groups have equal dispersion matrices of the predictors. Balcaen & Ooghe (2006) indicate that most corporate failure studies do not attempt to analyse whether the data satisfies these restrictive assumptions. Therefore the results of these studies may be suspicious and have questionable generalizability (Bauer & Agarwal, 2014).

MDA is very similar to the multiple regression technique. However, it is computationally not the same (Balcaen & Ooghe, 2006). The estimation procedure of the least square is not suitable for estimation of relation with a binary dependent variable (Balcaen & Ooghe, 2006). Therefore, MDA is not suitable for estimating default probabilities since the dependent variable is binary. In an attempt to address limitations brought by MDA, researchers developed conditional probability models.

The first conditional probability model was pioneered in the seminal work of Ohlson (1980). The study made use of logit analysis of financial ratios and company characteristics in order to predict corporate failure. The conditional probability model estimates the probability of default on a range of selected firm characteristics by a non-linear maximum likelihood (Balcaen & Ooghe, 2006). The model makes use of the logit function to transform the dependent variable of default probability into a continuous parameter that is then suitable for linear regression interpretation (Sun et al., 2014).

The popularly used conditional probability model is the logit model which assumes the logistic distribution of variables (Bauweraerts, 2016). The logit model does not require the predictors to be normally distributed and it makes no assumptions regarding the distribution of the independent variable (Ohlson, 1980). Furthermore, it does not make any assumption of multivariate normality and equal covariance matrices (Appiah et al., 2015). It is also highly suitable for the prediction of loan defaults because it requires the dependent variable to be dichotomous. The shortfall of the logit model is its extreme sensitivity to multicollinearity, missing values, and outliers (Balcaen & Ooghe, 2006).

A number of papers show that logit models outperform the MDA model in default prediction. Pervan & Kuvek (2013) developed a model for bankruptcy prediction based on the data of Croatian firms. The study was conducted on a sample of 78 failed and 78 healthy firms from Croatian manufacturing Industry. “Logit model had higher classification accuracy (86%) in comparison with MDA with an 80% accuracy” (Pervan & Kuvek, 2013, p 166). The use of MDA had significant limitations since the two principal “assumptions were violated: data normality and equality of covariance matrices” (Pervan & Kuvek, 2013, p. 163).

Tserng, Chen, Huang, Cheng, & Hung (2014) performed a default prediction study on U.S construction firms using Logit model and MDA. Logit model outperformed MDA in the prediction of defaults for this population. Mousavi, Ouenniche, & Xu (2015) did a performance evaluation of bankruptcy prediction models, using Uni-dimensional rankings of bankruptcy prediction models, they found that logit model outperforms MDA in discriminatory power and accuracy and MDA performs better in misclassification rate.

The logit model has been chosen for this research because of its robustness in the prediction of defaults and its suitability in the testing of hypothesis. According to Bhimani et al. (2010), the MDA is more appropriate when the study is about discrimination of failed and non-failed firms whereas the binary logistic regression models are better suited when the objective is to test the hypotheses.

2.10. Conclusion to Literature Review

In summary, prior studies have advised that liquidity and solvency are the major factors in the prediction default. The structural models of credit risk hinge on two distinct assumptions which result in entirely different default probabilities (Davydenko, 2013). One view states that liquidity is the most significant and essential driver of default risk. It further stresses the irrelevance of solvency in the prediction of default.

On the contrary, other structural models posit that firms default when the market value of assets drops below the face value of debt. It explicitly implies that solvency measure is the most critical variable in the prediction of loan default. These conflicting views regarding the role of these two factors will be tested in the context of private firms funded by the DFIs.

The role of firm size and industry groups have previously been found to be critical in the prediction of default probabilities in the past. These factors were also found to have a profound effect on the interaction and the prediction power of other accounting variables. It is therefore critical to test these factors in the context of private firms in possession of DFI loans.

Even though the MDA model is popularly used in the literature, it was found to have severe limitation restricting its usefulness for this study. The logit model was found to be the most suitable model for this study. The research will thus test the extent to which the factors above impact the probability of default for firms funded by DFIs using a logit model as an analysis tool.

CHAPTER 3: HYPOTHESES

The study examines the South African private firms in possession of DFI loans between the year 2008 and 2014 in order to test the role of liquidity and solvency on DFI loan default probabilities. Based on the research questions outlined in chapter one and the literature review in chapter two a set of hypotheses were formulated.

3.1. Hypothesis One – Liquidity

The first research question was*: What is the role of liquidity on the likelihood of default in DFI loans by private firms?*

In this research, liquidity is represented by the quick ratio and the current ratio. The quick ratio is the sum of cash and account receivable divided by current liabilities. It only takes into account the most liquid assets which are either already cash or can be turned into cash quickly.

- Hypothesis 1A refers to the quick ratio as a proxy of liquidity.

Null Hypothesis ($H1A_0$): Quick ratio is not a significant variable in the prediction of DFI loans' defaults.

Alternate Hypothesis ($H1A_{Alt}$): Quick ratio is a significant variable in the prediction of DFI loans' defaults such that when quick ratio increases default probability reduces.

- Hypothesis 1B refers to the current ratio as a proxy of liquidity. The current ratio is the ratio of the total current assets to the total current liabilities.

Null Hypothesis ($H1B_0$): Current ratio is not a significant variable in the prediction of DFI loans' defaults.

Alternate Hypothesis ($H1B_{Alt}$): Current ratio is a significant variable in the prediction of DFI loans' defaults such that when current ratio increases default probability reduces.

3.2. Hypothesis Two – Solvency

The second research question was*: What is the role of solvency on the likelihood of default in DFI loans by private firms?*

In this research, solvency is represented by the ratio of total liability to total assets (TL/TA) and the ratio of long-term debt to total assets (LTD/TA).

- The hypothesis 2A refers to TL/TA as a proxy for solvency

Null Hypothesis ($H2A_0$): TL/TA is not a significant variable in the prediction of DFI loans' defaults.

Alternate Hypothesis ($H2A_{Alt}$): TL/TA is a significant variable in the prediction of DFI loans' defaults such that when TL/TA increases default probability rises.

- The hypothesis 2B refers to LTD/TA as a proxy for solvency

Null Hypothesis ($H2B_0$): LTD/TA is not a significant variable in the prediction of DFI loans' defaults.

Alternate Hypothesis ($H2B_{Alt}$): LTD/TA is a significant variable in the prediction of DFI loans' defaults such that when LTD/TA increases default probability also increases.

3.3. Hypothesis Three – Firm Size

The third research question was: *What is the role of firm size in the prediction of DFI loan defaults?*

Null Hypothesis ($H3_0$): Firm size is not a significant variable in the prediction of DFI loans' default

Alternate Hypothesis ($H3_{Alt}$): Firm size is a significant variable in the prediction of DFI loans' default such that when firm size increases default probability reduces.

The proxy of firm size will be logarithm to the base of 10 of total assets – log(TA).

3.4. Hypothesis Four – Industry Group

The last research question was*: What is the role of industry group variable in the prediction DFI loan defaults?*

Null Hypothesis ($H4_0$): Industry group is not a significant variable in the prediction of DFI loans' defaults.

Alternate Hypothesis ($H4_{Alt}$): Industry group is a significant variable in the prediction of DFI loans' defaults.

CHAPTER 4: RESEARCH METHODOLOGY

1.1. Research Design

Within a positivist paradigm, this research was a deductive study making use of the secondary data in a cross-sectional design. This research required an application of statistical regression in order to explain the default events of firms. Hence a positivism philosophy was chosen. A deductive approach can be seen in the testing of existing theoretical propositions to specific observations.

This research had a cross-sectional design because it used data between the year 2008 and 2014 to compare multiple observations at that single timeframe. The cross-sectional design is consistent with studies in the field of corporate failure (Balcaen & Ooghe, 2006). This study used archival information consisting of financial records of private firms funded by a DFI. Data collected was therefore secondary since it was not collected for research purposes, but for the internal administration of a financial institution.

The analysis followed a prediction study approach in order to test the set hypotheses. Previous literature of default and corporate failure prediction adopted a similar approach (Bellovary et al., 2007). A prediction study uses multiple regression to develop a formula or to test the significance of observed values of independent variables in the prediction of a dependent variable (Spirtes et al., 2000). The possibility of this study being causal was ruled out because this study cannot prove that the chosen independent variables always cause the occurrence of a dependent variable (defaults). Causality is deterministic in nature, but Imbens & Rubin (2015) define default studies as being probabilistic. The study was meant to check whether the variability in the selected independent variables affected the occurrence probability of a dependent variable.

1.2. Population

In line with the definition of a population by Saunders & Lewis (2012), the population of this study comprises all South African private firms, both Proprietary Limited “Pty Ltd” and Close Corporation “CC,” that held DFI loans cumulatively from 2008 to 2014. The study is designed to allow inferences on the South African privately held firms holding DFI loans. The study also requires a dichotomous dependent variable. Therefore, the population consists of firms that have defaulted and those that have not defaulted on the DFI loans. The availability of data dictated the boundaries of this population. Data were available from 2008 to 2014.

This study may be prone to survivorship bias as companies that did not have enough information during the study period were eliminated from the research. Furthermore, data used in this study were collected for administrative use and not for research purpose. However, data was collected from a reputable DFI with a robust record-keeping function.

1.3. Sampling Frame

The sampling frame of this study was the database of the Industrial Development Corporation ("IDC") consisting of the detailed company level, industry, and default status data. The database contains a yearly balance sheet and income statements from corporate firms, both listed and private, from 2008 to 2014, which is the most recent year available. The sample frame consisted of a complete list of all firms in the IDC data between 2008 and 2014 which then provided a pool to draw a final sample (Saunders & Lewis, 2012).

The IDC is a South African self-financing, state-owned DFI that has funded many entrepreneurs and private businesses engaged in different industries (IDC, 2018). The IDC provides an appropriate sample frame since it is one of the few DFIs in South Africa that focuses on providing loans to firms across different sectoral areas including manufacturing, retail, infrastructure, automotive, tourism, mining, and agro-processing. It also consists of a comprehensive financial and non-financial information needed to perform analysis at a micro-level.

1.4. Unit of analysis

The unit of analysis is the privately held firm in receipt of a DFI loan.

1.5. Sampling Method and Size

In order to get the final sample to be used in the analysis, a non-probability, judgemental sampling technique which excludes non-conforming data was employed (Sayari & Mugan, 2017). In this research, only private South African firms in possession of an IDC loan were considered. Furthermore, only information regarding default on IDC loans was taken into account. Other credit lines, grants, equity instruments, and renegotiated credits were disregarded (Antunes, Gonçalves, & Prego, 2016). The main reason for the exclusion of firms with no IDC loan is that the aim of this research hinges on firms defaulting on DFI loans.

The firms with traded stocks were excluded since the research is focusing on private firms. Also, the firms that were registered outside of South Africa were also excluded in order to have a final sample of South African firms. Lastly, firms that reported inadequate or illogical data, such as financials with total negative assets or negative revenue, were excluded.

The sample, therefore, consisted of the privately held firms with existing IDC loans between 2008 and 2014 minus the excluded firms. Left were the 566 data points which were considered for inclusion in the final sample, 88 of which defaulted at least once between 2008 and 2014. Furthermore, the study relates the accounting data for the year before “t-1” to the default status of the firm in a year “t” (Davydenko, 2013).

1.6. Data Gathering Process

1.6.1. Ethical Clearance

Before data could be collected, an ethical clearance as required by the Gordon Institute of Business Science was obtained. An approval from the IDC was also obtained on condition that strict confidentiality is applied when dealing with the data. Confidentiality meant that none of the IDC clients would be mentioned by name in the research or talked about in any public platform as a result of the study. As a result, this research only made use of aggregate data to understand patterns and perform statistical analysis; it did not single out any particular IDC client for discussion. This conforms to the previous work done in the space of corporate failure prediction (Balcaen & Ooghe, 2006; Mselmi et al., 2017).

1.6.2. Data collection

Data were collected from the three IDC source systems which contained relevant information. The source systems used were SAP, risk analyst database and ZPR tables. Table 1 shows the kind of data obtained in each database.

Table 1: Database and the type of information received

Data Base System	Data Type
SAP	Business Partner numbers, contract numbers, Facility type
Risk Analyst	Financial data, default status
ZPR tables	Industry, exposure information, arrears, country, province

All databases were available in the software that can be read directly into excel based spreadsheet. This allowed the data to be collated in one dataset to be cleaned and analysed. All relevant data were mapped to contract numbers and BP number.

1.6.3. Data filtering

Once the data have been collated, unsubtle and irrelevant entries were filtered in order to get to the data that can be analyzed. Table 2 shows the data issues encountered with the combined dataset and the mitigating action that was taken to come to the final dataset.

Table 2: Data issues experienced and action taken to clean the data

Data Issues	Mitigating Action
Financial data does not have a corresponding BP number on SAP	Drop observations were BP cannot be found on SAP database
Incomplete mapping of financials to business partner list from SAP	Drop from the dataset
Some individual financial items missing	Drop the observation where there are required missing factors
Account switch from default to non-default	If the client defaults- omit data beyond the year of default
BP has zero exposure in the period between 2008 and 2014	Drop from the dataset

1.6.4. Definition of default

In the IDC's database, a number of days in arrears are given for each firm. Ninety days' payment overdue was used as a cut-off for default in this research. This is in line with literature which defines default as payment omissions for three months or more (Altman et al., 2017).

1.7. Analysis Approach

On conclusion of the data gathering process, the collected data were tabulated in Microsoft Excel for analysis. The software called Statistical Package for Social Sciences (SPSS) version 25.0.0.0 was utilised to conduct the statistical analysis and hypotheses testing.

The dependent variable is the DFI loan default status of a private firm. The independent variables of the study are solvency variables, liquidity variables, firm size, and industry group.

1.7.1. Descriptive statistics

SPSS was used to do basic descriptive statistics in order to condense and describe the population parameters into the mean, median, and standard deviation. This was done to describe the data, checking it for sanity and ensuring that the underlying statistics are not violated (Pallant, 2016). The descriptive statistics also formed a basis for inferential analysis and expedited the process of writing about the results.

1.7.2. Data classification

Data were grouped into different categories in order to start seeing the default frequency patterns. It was grouped into the industries, as well as provinces and years. The following industry groups were used: clothing & textiles, agro-processing, Mining & Metals, Chemical products, food & retail, automotive equipment, manufacturing, and "other" industries. The "other" industry class incorporates firms that were too few to be classified in their individual industries. The industry and their corresponding observations (number of accounts) are shown in Table 3.

Table 3: Industry classes and their respective dummy variables

#	Industry Classes	# Observations
1	Clothing & Textiles	69
2	Agro-processing,	106
3	Mining & Metals	25
4	Chemical products	85
5	Food & Retail	135
6	automotive equipment	63
7	Manufacturing	86
8	other	27
Total		**596**

It must be noted that there were no financial firms, such as private equity firms, in the sample since these are a unique set of firms which cannot be included with non-financial firms in failure prediction studies (Balcaen & Ooghe, 2006). The provinces and year of default status together with their respective observations are shown in Table 4 and Table 5.

Table 4: Provinces and their representative numbers

#	Province	# Observations
1	Gauteng	246
2	Western Cape	93
3	KwaZulu Natal	79
4	Eastern Cape	81
5	Limpopo	32
6	Mpumalanga	24
7	North West	14
8	Free State	16
9	Northern Cape	11
	Total	**596**

Table 5: Year of account

Year	#Accounts
2008	64
2009	107
2010	105
2011	108
2012	97
2013	69
2014	46
Total	**596**

1.7.3. Binary Logistic Regression

The purpose of this research is to assess the role of liquidity and solvency in privately-held firms in receipt of DFI loans. The analytical technique needs to allow for a binary dependent variable (default or non-default) and the input of independent variables in the prediction of default probabilities. It also needs to permit for a categorical independent variable in order to allow the industry group variable to be included. A binary regression model (logit model) becomes an obvious candidate as compared to techniques that are used in the failure prediction studies. The advantages of using a logit model were discussed in details in the literature review section 2.9.

A logit model allows for the estimation of the probability of the binary outcome, based on the values of the explanatory variables. The technique makes use of the logit function, which is presented as logit(p) = ln(p/(1-p)), where p is the probability of default to occur. The p/(1-p) is the odds of the default happening. The ln (p/(1-p)) known as log(odds) lets explanatory variables to be set in a linear equation. The linear structure enables the modelling of coefficients in order to understand the strength and direction of the relationships between the independent variables and the dependent variable.

"The logit model also enables the estimation of how much the event probability changes when a given predictor is changed by one unit, i.e., the marginal effect" (Bhimani et al., 2010, p. 525). The coefficient of the logit model can be interpreted separately, looking at magnitude and signs, in the explanation of default probability (Ohlson, 1980). The model allowed for the use of categorical data, meaning that the qualitative variables represented by dummies could be incorporated.

The Logit model can be transformed into Equation 1

Equation 1: Logit Model

$$\ln\left(\frac{p}{1-p}\right) = \beta o + \sum \beta i X i$$

- P represents the default probability.
- P/(1-P) represents the odds of default
- βo is a constant parameter to be estimated by SPSS.
- βi are coefficient parameters to be estimated by SPSS.
- Xi is the vector of financial characteristics of firm i. It denotes financial ratios on firms' solvency and liquidity, and additional variables (firm size and industry type).

1.7.4. Dependent Variable

In this study, the dependent variable is the default status of a firm. Since default and non-default events are categorical in nature - a firm that has defaulted is given a dummy number of 1 and a firm that has never defaulted during a period of interest is given a dummy number of 0. A binary regression model requires that a dependent variable should be measured on a dichotomous scale which means it should only have two different category levels which work in this research because defaulting or non-defaulting firms are classified (Kruschwitz et al., 2015).

1.7.5. Independent Variables

The selected independent variables have four dimensions, namely: liquidity, solvency, firm size, and industry group. The variables are shown in Table 6.

Table 6: Representation of independent variables used in the study

Variables	**Comments**
Liquidity	
Quick ratio Current ratio	(current assets - inventory)/current liabilities current assets/current liabilities
Solvency	
TL/TA LTD/TA	Total Liabilities/Total Assets Long term debt/Total Assets
Firm Size	
Log (TA)	Logarithm base 10 of total assets
Industry group	
Dummies	number 1 to 8 (Table 3)

1.8. Reliability and validity

Reliability is realized when a test can be used by a number of different researchers under stable conditions and obtain consistent results (Antunes et al., 2016). Therefore, reliability ensures replicability and consistency over a period of time. In this research, a clear research design, sampling method, and the data analysis approach ensure reliability.

Validity refers to the accuracy of an assessment (Soderstrom & Sun, 2007). There are two main types of validity, namely: Internal and External validity (Saunders & Lewis, 2012). The internal validity is concerned with the degree of certainty that the findings are actually as a result of the experiment rather than extraneous variables. In this research, the period of time of the selected data is a potential concern for internal validity.

In the period between 2008 and 2009, there was a global financial meltdown which resulted in an adverse operating condition for many firms (Sikorski, 2011). This might influence the default behaviour and distort the role of the selected independent variables. The impact of this period was tested, and it found that it did not have a visible impact on the data used. The results are presented in section 5.2.

External validity exists when a study's findings can be generalized beyond the controlled setting of the research (Adcock & Collier, 2001). In this research, the quality of secondary data obtained was identified as a possible risk to external validity. Fairhurst (2017) points out that when dealing with secondary data, a researcher has no real control over the quality of the data and an assessment of data quality is based on the credibility of the data source. Therefore, to ensure the external validity of this research, the data source was assessed for credibility.

Data used in this research was sourced from a reputable organization – the IDC. It is a registered financial institution with a regulatory oversight conducted by the Financial Services Board. It also needs to comply with the Financial Intelligence Centre Act 38 of 2001 (Financial Intelligence Centre Act 38 of 2001, 2002) and the Financial Advisory and Intermediary Services Act (Financial Advisory and Intermediary Services Act 37 of 2002, 2002) (Fairhurst, 2017). The IDC uses the information used in this research for their internal assessment of companies for creditworthiness and the provision of credit.

Furthermore, the financial information in this research is only from audited financial statements despite belonging to private firms. The private firms funded by the IDC are contractually obligated to audit their financials by following the audit procedure as required by the International Financial Reporting Standards (IFRS) and the South African Companies Act (*Companies Act No. 71 of 2008, 2009*). This fact increases the credibility of the annual financial information used. According to Christensen, Lee, Walker, & Zeng (2015) , an IFRS audit provides the highest level of assurance that a firm's financial statements are fairly stated in all material respect.

CHAPTER 5: RESULTS

5.1. Introduction to the Results Section

The purpose of this research was to investigate the role of liquidity and solvency on default probabilities of private firms in possession of DFI loans. It was achieved by identifying four research questions as outlined in chapter one. Through a comprehensive literature review and analysis of sampled data, this research identified key evidence to answer the hypotheses of this research.

The objective of chapter five is to present the results obtained from data analysis. This chapter is structured as follows: Firstly, the results describing the data will be presented to show the characteristics of the sample. It is then followed by a presentation of empirical evidence in line with the hypotheses posed in chapter three.

5.2. Sample Description

The sample consists of comprehensive accounting and non-accounting data of a sample of the privately held South African firms compiled from the Industrial Development Corporation (IDC). The IDC has a compilation of usable loan default data, and it is a credible source for answering the research questions arising from this thesis. The IDC has given access to not only the default status but to the dates, geographical areas and the industries which the firms belong.

5.2.1. Total accounts and default observations per period

Data consisting of a number of total accounts and defaults were grouped according to the year of credit status. The period of the sample was between 2008 and 2014. The results are presented in Table 7.

Table 7: Accounts and Defaults 2008 - 2014

Status year	Number of Accounts	Number of Defaults	Default rate
2008	52	6	11.54%
2009	101	14	13.86%
2010	103	14	13.59%
2011	106	22	20.75%
2012	95	18	18.95%
2013	65	7	10.77%
2014	44	7	15.91%
Total	566	88	15.55%

The total accounts in the final sample were 566. Of the 566 observations 88 related to firms that entered into loan default between the year 2008 and 2014, representing 15.55% of the total sample. The highest default rate (Defaults in year t / total accounts in year t) of 20.75% was in 2011. It was followed by a default rate of 19%, 17% and 16% in 2012, 2014 and 2009 respectively. The lowest default observations of 12% and 13% were seen in 2013 and 2010 respectively.

5.2.2. Non-defaults and defaults per province

Data were split into defaults and non-defaults observations and then grouped according to the regions in order to see the data characteristics. Figure 1 shows the distribution of non-defaults and defaults accounts by province.

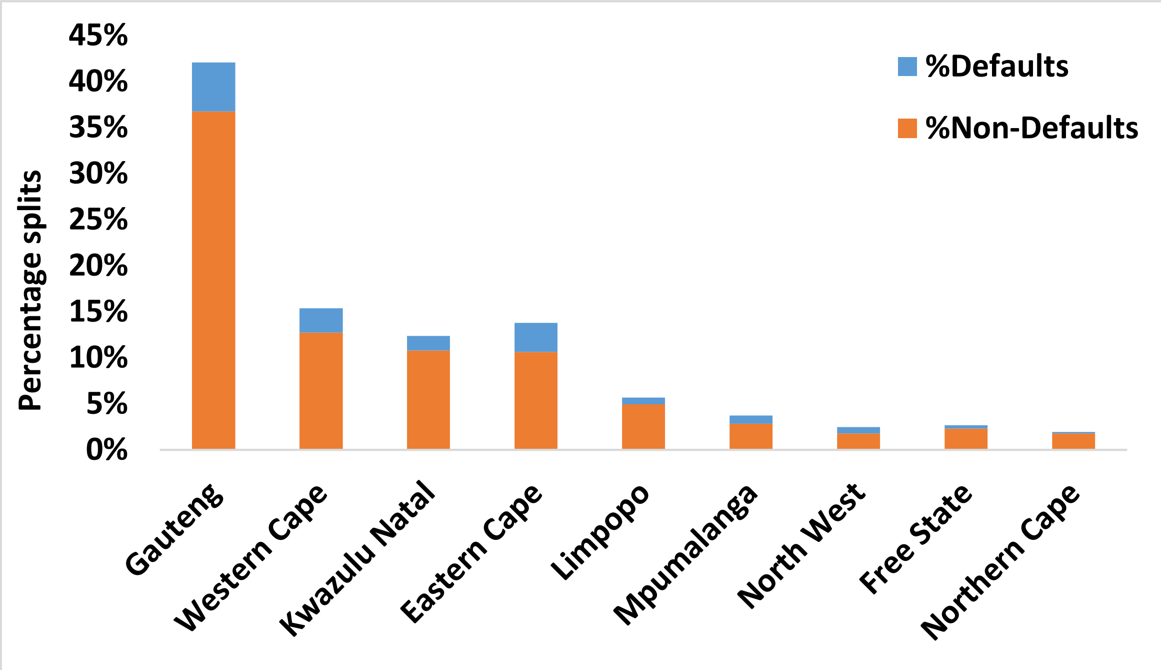

Figure 1: Percentage distribution of default and non-default observations by province

The overall data distribution is biased towards Gauteng province which accounts for 41% of the observations. About 84% of the firms are in the four provinces. Namely, Gauteng, Western Cape, KwaZulu Natal, and the Eastern Cape. The highest default rates were in the North West (29%) and the Eastern Cape (25%). However, North West only accounted for 4% of the overall defaults. Gauteng has a default rate of 13% but accounts for 33% of the total defaults.

5.2.3. Non-defaults and defaults per industry

Data were separated into defaults and non-defaults observations and then grouped based on the industry they belong. The variation of defaults and non-defaults across different industries was then plotted in Figure 2.

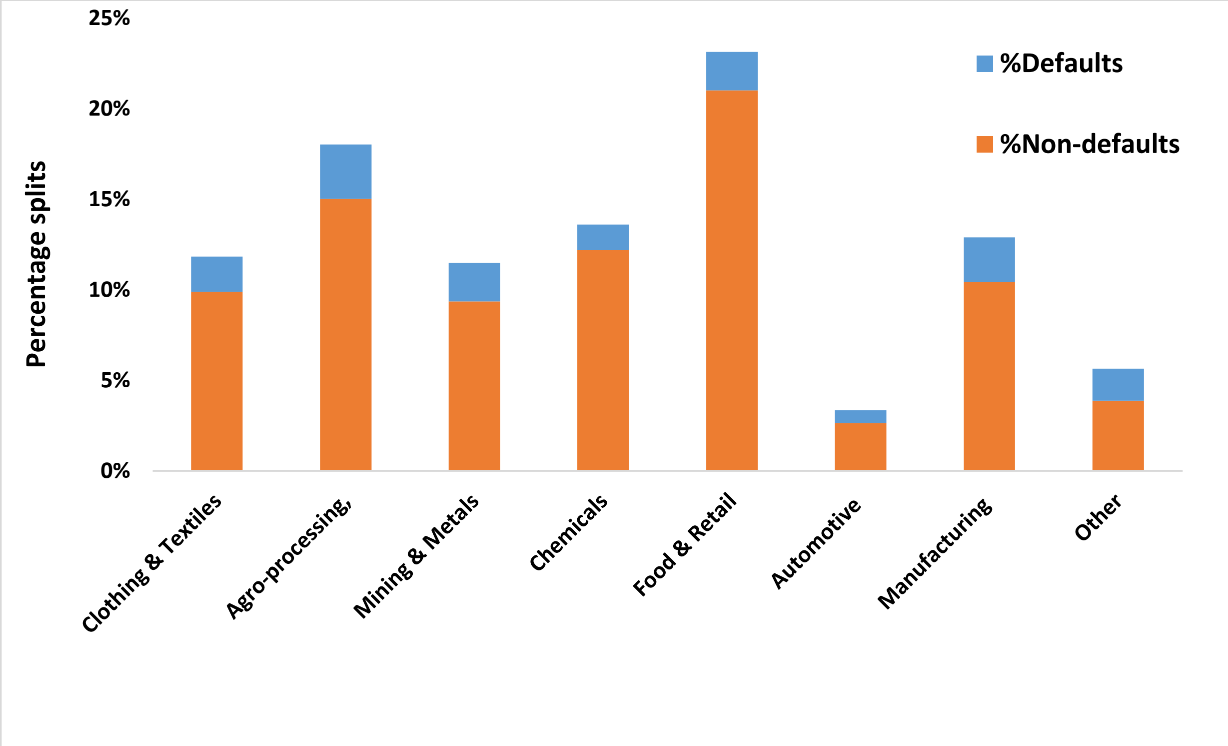

Figure 2: Percentage distribution of default and non-default observations per Industry type

The firms in the Food & Retail industry accounted for 23% of the observations which is the highest in the sample. This was then followed by agro-processing and chemicals industry at 18% and 14% respectively. The highest default rate was in "Other" industry (31%) followed by Automotive (21%) and Manufacturing (19%). Carving out defaulting firms only saw most defaulting firms being in agro-processing which account for 19% of the total defaults. It was followed by manufacturing contributing 16% to the global defaults.

5.2.4. Defaults per firm size

Based on previous work on default and bankruptcy prediction such as (Altman et al., 2010; Bhimani et al., 2010; Cultrera & Brédart, 2016) the firm size is represented by the logarithm to the base ten of total assets [log(TA)]. Data were separated into default and non-default events, then the log(TA) was computed for each firm. The percentage frequency was computed for each bin to normalize the data. The histograms of defaulting and non-defaulting firms were made separately and later merged into one diagram to see the contrasts in size distribution for the two groups. The results are depicted in Figure 3.

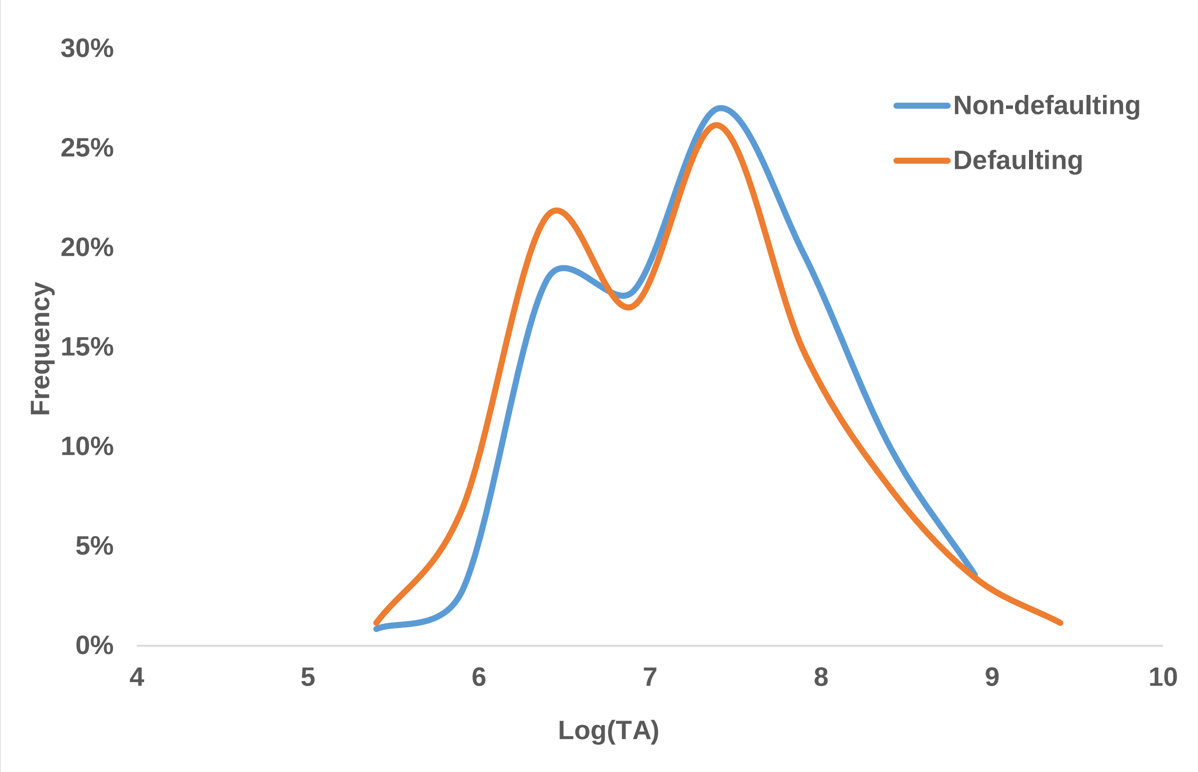

Figure 3: Normalized histogram: Log (TA) vs percentage frequency

Overall above 85% of the firms had firm size ranging from log(TA) of 6 to 8 which translate to firms having total assets between R1m to R100m. The defaulting firms have their size skewed towards smaller firms with about 50% below log(TA) of 7 as compared to 40% of non-defaulting firm size below the same point. The non-defaulting firms appear to be more prominent in size with about 35% above log(TA) of 7.5 compared to 25% of defaulting firms above the same value. There are two defaulting firms with sizeable total asset values above R700 million, hence a long tail of the plot of defaulting firms. These potential outliers might skew the descriptive statics of defaulting firms.

5.3. Descriptive Statistics – Performance Measures

The financial statements data was grouped according to defaulting and non-defaulting firms. The results of the descriptive results are shown in **Error! Reference source not found.** and Table 9 respectively.

Table 8: General Descriptive Statistics of defaulting firms

	Mean	**median**	**SD**
Total Assets	R 48 324 349	R 8 630 406	R 139 168 131
Revenue	R 33 480 105	R 7 978 384	R 72 943 150
Sales/Total Assets	0,69	0,99	2,60
EBIT/Total Assets	-0,01	0,01	0,27
Profit margin	-142,42%	-0,36%	746,64%
%Making losses	52,27%		
%negative equity	21,50%		

Table 9: General Descriptive Statistics of Non-defaulting firms

	Mean	**median**	**SD**
Total Assets	R 42 136 719	R 1 030 956	R 89 701 566
Revenue	R 50 077 164	R 16 671 624	R 91 014 092
Sales/Total Assets	1,19	1,26	2,35
EBIT/Total Assets	0,04	0,07	0,24
Profit margin	-160,03%	1,74%	1877,30%
%Making losses	36,27%		
%negative equity	12,30%		

According to the descriptive statistics results, the defaulting firms appeared to be slightly larger than the non-defaulting firms on average (*M* = R 48 324 349, *SD* = R 139 168 131 versus *M* = R 42 136 719, *SD* = R 89 701 566). The asset turnover ratio (sales / total assets) appeared to be higher for non-defaulting firms (*M* =1.19, *SD* = 2.35) compare to defaulting firms (*M* = 0.69, *SD* = 2.60). The profitability measures seem to suggest that non-defaulting firms were more profitable than the defaulting firms.

More than half of the defaulting firms in the sample (52.27%) were loss-making compared to 36.27% for the non-defaulting sample. Up to 21.50% of the defaulting firms in the sample had a negative net worth compared to 15.30% of the non-defaulting sample. It was interesting to see that the average profit margin of non-defaulting firms was more adverse than the defaulting firms (*M* = -160.03%, *SD* = 1877.30% versus *M* = -142.42%, *SD* = 746.64%).

Overall the firm performance measures revealed that defaulting firms performed poorly compared to non-defaulting firms. However, there was still a significant number of non-defaulting firms with adverse performance. This supported a view that although profitability is an obvious firm performance measure, it might not be the best or only relevant default measure (Balcaen & Ooghe, 2006).

5.4. Univariate Analysis

This section reports various measures of solvency and liquidity for defaulting and non-defaulting firms. Data were split into default and non-default firms, and then the financial ratios representing solvency and liquidity were calculated separately for each firm. A descriptive statistic was then run on the two groups to get the mean, median, and standard deviation. The terms that were used to carry the analysis and their meaning are presented in Table 10.

Table 10: Terms used in the analysis and their respective definitions

Terms	**Definition**
Quick Ratio	the sum of cash and accounts receivable divided by current liabilities
Current ratio	the fraction of current assets and current liabilities
EBITDA	the sum of pre-tax income, interest expense, and depreciation
Interest cover ratio	the ratio to EBITDA to interest expense
%Quick ratio below 1	the proportion of firms with a quick ratio below the value of one

The descriptive statistics of liquidity and solvency measures for defaulting and non-defaulting firms are shown in Table 11 and Table 12 respectively.

Table 11: Liquidity and solvency measures of defaulting firms

	Mean	**median**	**SD**
Liquidity Measures			
Quick Ratio	1,45	0,63	4,61
Current ratio	1,85	0,94	4,71
Interest cover ratio	2,45	1,25	6,48
%Quick ratio below 1	75%		
Solvency measures			
Total Liabilities/Total Assets	0,77	0,66	0,68
Long term debt/Total Assets	0,42	0,29	0,58

Table 12: Liquidity and solvency measures of non-defaulting firms

	Mean	**median**	**SD**
Liquidity Measures			
Quick Ratio	4,08	0,69	35,64
Current ratio	4,73	1,19	35,65
Interest cover ratio	5,45	2,96	56,00
%Quick ratio below 1	66%		
Solvency measures			
Total Liabilities/Total Assets	0,62	0,54	0,43
Long term debt/Total Assets	0,27	0,17	0,31

The average quick ratio of defaulting firms appeared to be lower than that of non-defaulting firms (*M* = 1.45, *SD* = 4.61 in Table 11 versus *M* = 4.08, *SD* = 35.64 in Table 12). About 75% of defaulting firms had a quick ratio below one compared to 66% of non-defaulting firms. The current ratio supported the results of the quick ratio with defaulting firms (median = 0.94) displaying lower values lower than non-defaulting firms (median=

1.19). The interest cover ratio shows the number of times the interest expense gets covered by cash generated from operations (EBITDA). This ratio was found to be on average lower for defaulting firms compared to non-defaulting firms (M= 2.45, SD= 6.48 versus M= 5.45, SD = 56.00).

The variables used for the indication of solvency in this research are a total liability and total assets (TL/TA) and the ratio of long-term debt and total assets (LTD/TA). The defaulting firms appear to have higher liabilities relative to total assets when compared to non-defaulting firms; this was shown by the respective TL/TA (*M* = 0.77, *SD* = 0.68 versus *M* = 0.62, *SD* = 0.43). The LTD/TA also showed the same results, with a mean and median of 0.42 and 0.29 respectively for defaulting firms; compared to mean and median of 0.27 and 0.17 for non-defaulting firms.

The quick ratio and the solvency measure of all dataset were plotted to have a clear view of the difference between the defaulting and non-defaulting firms. This is shown in Figure 4 below.

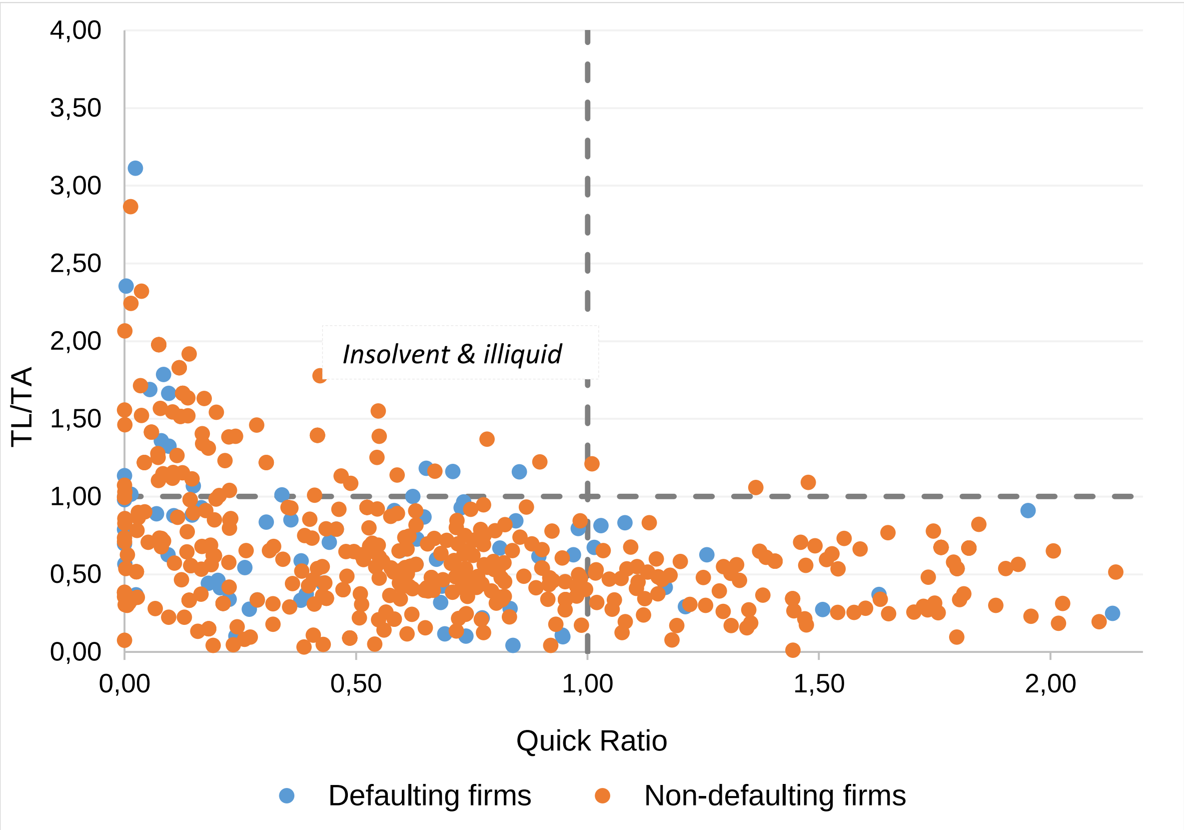

Figure 4: Solvency vs quick ratio for defaulting and non-defaulting firms

The graph shows the combination of solvency (measured by TL/TA) and balance liquidity (measured by quick ratio) for defaulting and non-defaulting firms. Moving upwards in the plot corresponds to increasing insolvency, and all firms above the value of one are considered insolvent and have negative equity in their balance sheet.

Moving to the right in the plot corresponds to the increase in liquidity. All firms with a quick ratio below the value of one indicate illiquidity as a firm will have an insufficient liquid asset to cover current liabilities. Approximately 22% of defaulting firms were insolvent compared to 13% of non-defaulting firms in the same situation. About 20% of the defaulting firms were both insolvent and illiquid at the same time as compared with the non-defaulting firms of whom 12% were both insolvent and illiquid. About 11% of the defaulting firms had liquidity above one and TL/TA below one indicating that they default under no financial distress.

5.5. Empirical Findings

This section is specific to directly answering the hypotheses as set out in chapter three. Since the analytical method needs to permit for a binary dependent variable, the binary logistic regression (logit model) was employed to test the hypotheses. The logit model seeks to model a probability of a default event happening depending on the values of independent variables, which are either numerical or categorical.

The results of the logit model are logarithm of odds ratio: logit(p)= ln(p/(1-p)) = log (odds). Equation 1 shows the logit model in its linear form. A separate logit model will be run to test each hypothesis. The results table in SPSS gives a constant βo, βi and Exp(βi). For a change of one unit in Xi; βi and Exp(βi) represents log (odds) and odds ratio respectively. The odds ratio represents the ratio of the probability of a default event occurring and a default event not occurring. The odds ratio for a variable in the logit model represents how the odds change for a 1 unit increase in that explanatory variable, all other variables remaining constant (Bhimani et al., 2010).

Equation 1: Logit Model

$$\ln\left(\frac{p}{1-p}\right) = \beta o + \sum \beta i X i$$

The SPSS results also consist of the p-value which can be read to check if the explanatory variable is significant or not. The statistics are run at a significant level of 95% (p-value of 0.05). Any p-value less than 0.05 is deemed as significant.

The output also gives the confidence interval for Exp(β) at 95% level. The interval is relevant because it shows the range of values which can potentially be the correct odds ratio. For the measured variable to have any explanatory power, the interval should not contain the value 1.00 because ln (1.00) is zero which means the coefficient for the variable in question would not have any impact of defaults.

The pseudo R^2 is the Nagelkerke R^2 which must be interpreted with caution since it is not the same as the goodness of fit R^2. However, the Pseudo R^2 does indicate the relative importance of the explanatory variables in the prediction of a dependent variable.

In contrast to other predictive studies, this analysis is aiming to investigate the role of liquidity and solvency variables on default, rather than build a better forecasting model. So, the emphasis was on the contribution of the individual variables rather the performance of the model.

The influence of the outliers was considered. There were two defaulting firms with large asset values as depicted in Figure 3 which could have potentially influenced the results. All the statistics were run with and without the outliers, and the outcomes of the hypotheses did not materially change. Therefore, a decision was taken to only show the results of the total sample size (including outliers).

5.5.1. Hypothesis 1: Liquidity tests

Null Hypothesis ($H1A_0$): Quick ratio is not a significant variable in the prediction of defaults of private firms on DFI loans.

Alternate Hypothesis ($H1A_{Alt}$): Quick ratio is a significant variable in the prediction of default of private firms on DFI loans such that when quick ratio increases default probability reduces.

Table 13: Logistic regression results – Quick Ratio variable

	B	P-Value	Exp(β)	95% C.I.for EXP(β)	
				Lower	Upper
Quick Ratio	0,001	0,713	1,00	1,00	1,01
constant	-1,70	0,000	0,18		
Pseudo R^2	*0.00*				

It can be seen in Table 13 that quick ratio is not a significant variable in the prediction of DFI loan defaults of private firms, *p* = 0,713. The null hypothesis was accepted. Furthermore, the odds ratio or Exp(β) = 1.00 which indicates that any change in quick ratio would not have an impact on the odds of default. The pseudo $R^2 < 0.001$ also indicates that the quick ratio had no explanatory power on defaults on DFI loans.

Hypothesis 1B seeks to test the impact of the current ratio on defaults.

Null Hypothesis ($H1B_0$): Current ratio is not a significant variable in the prediction of defaults of private firms on DFI loans.

Alternate Hypothesis ($H1B_{Alt}$): Current ratio is a significant variable in the prediction of default of private firms on DFI loans such that when current ratio increases default probability reduces.

The results are shown in Table 14 below.

Table 14: Logistic regression results – current ratio variable

	B	P-Value	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
Current ratio	0,001	0,757	1,001	0,995	1,006
constant	-1,70	0,000	0,18		
Pseudo R2	*0.00*				

The current ratio is also not a significant variable in the in the prediction of defaults of private firms on DFI loans, *p* = 0,757. The null hypothesis was accepted. Furthermore, the odds ratio or Exp(β)= 1.00 which indicates that any change in quick ratio would not have an impact on the odds of default. The pseudo R^2 is less than 0.001 which also indicated that the quick ratio had no explanatory power on private firms' defaults on DFI loans.

Both the quick ratio and the current ratio were not significant variables in the prediction of DFI loan defaults. The pseudo R^2 was also very close to 0 for both the variables indicating the variables had no explanatory power in the logit model. The odds ratio for one-point increase EXP(β) was 1.00 indicating that any marginal increase in liquidity did not have any impact on default probability. The analysis provided sufficient evidence to accept the null hypothesis that liquidity is not a significant variable in the prediction of default of private firms on DFI loans.

5.5.2. Hypothesis 2 - Solvency

Null Hypothesis ($H2A_0$): TL/TA is not a significant variable in the prediction of defaults of private firms on DFI loans.

Alternate Hypothesis ($H2A_{Alt}$): TL/TA is a significant variable in the prediction of default of private firms on DFI loans such that when TL/TA increases default probability rises.

The SPSS results are presented below:

Table 15: Logistic regression results – TL/TA variable

	B	P-Value	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
TL/TA	0,56	0,01	1,74	1,15	2,64
constant	-2,07	0,00	0,13		
Pseudo R^2	*0,020*				

TL/TA is a significant variable in the prediction of firms defaulting on DFI loans, $p = 0.001$. The odds of defaulting increase with any unit increase in TL/TA (β = 0.56; Exp(β)= 1.74). The pseudo R^2 of 0.02 shows that TL/TA has some explanatory power to whether a firm defaults or not. Reject the null hypothesis, TL/TA is a significant variable in the prediction of default of private firms on DFI loans such that when TL/TA increases default probability rises. There is 95% confidence that the true value of Exp(β) lies in the interval CI = [1.15;

2.64]. This interval does not consist of the value of 1.00 which means the variable is meaningful in the range.

The hypothesis 2B was as follows:

Null Hypothesis ($H2B_0$): LTD/TA is not a significant variable in the prediction of DFI loans' defaults of private firms on DFI loans.

Alternate Hypothesis ($H2B_{Alt}$): LTD/TA is a significant variable in the prediction of DFI loans' defaults of private firms such that when LTD/TA increases default probability also increases.

Table 16: Logistic regression results – LTD/TA variable

	B	P-Value	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
LTD/TA	0,93	0,001	2,53	1,46	4,39
constant	-2,00	0,000	0,14		
Pseudo R2	*0,034*				

The LTD/TA is a significant variable in the logit model, p = 0.001. The 95% confidence interval CI = [1.46; 4.39] does not consist of the value of 1.00 which means the variable is meaningful in the confidence interval range. The pseudo R^2 of 0.034 shows that the variable has significant explanatory power in the logit model. The log (odds) of defaulting are higher for increase in LTD/TA, β = 0.93. Also for an additional unit of LTD/TA, the odds of defaulting increase by a factor of 2.53, Exp(β) = 2.53.

The null hypothesis is rejected; LTD/TA is a significant variable in the prediction of default of private firms on DFI loans such that when LTD/TA increases default probability rises. It should be noted that the increase in this ratios signifies a reduction in solvency and decrease equates to increase in solvency.

Both solvency ratios are significant variables in the prediction of DFI loans default. Therefore, the null hypothesis is rejected, and the alternate hypothesis is accepted. Solvency is indeed a significant variable in the prediction of default of private firms on DFI loans. The direction is that when solvency increases default probability reduces.

5.5.3. Hypothesis 3 – Firm Size

Null Hypothesis ($H3_0$): Firm size is not a significant variable in the prediction of defaults on DFI loans by private firms.

Alternate Hypothesis ($H3_{Alt}$): Firm size is a significant variable in the prediction of defaults on DFI loans by private firms such that when firm size increases default probability reduces.

The firm size is represented by a logarithm of total assets for each observation. Table 17 shows the results of the logit model which included liquidity, solvency and firm size as independent variables. It was to test if firms size has a marginal impact and improves the explanatory power of key variables.

Table 17: Binary logistic regression results – Firm size variable

	B	P-Value	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
LTD/TA	0,87	0,004	2,39	1,31	4,36
Current ratio	0,00	0,98	1,00	0,99	1,01
Size	-0,08	0,65	0,92	0,66	1,30
constant	-1,43	0,26	0,24		
Pseudo R2	*0,034*				

Firm size is not a significant variable in the prediction of loan defaults, p = 0.65. Furthermore, there is no improvement in pseudo R^2 in comparison with the results in Table 16. This shows that firm size has no significant influence on the defaulting behaviour of private firms on DFI loans. Therefore the null hypothesis **($H3_0$)** is accepted. Firm size is not a significant variable in the prediction of defaults of private firms on DFI loans.

5.5.4. *Hypothesis 4 – Industry group*

The fourth hypothesis seeks to address another critical objective of this research which is to check if industry type has any significant bearing on the prediction of defaults on DFI loans. The following hypothesis was formulated:

Null Hypothesis ($H4_0$): Industry type is not a significant variable in the prediction of private firm's defaults on DFI loans.

Alternate Hypothesis ($H4_A$): Industry type is a significant variable in the prediction of private firm's defaults on DFI loans.

Industry type is the only categorical independent variable in this study. There is a slight difference in how categorical variable is treated in SPSS logistic regression tool. It uses the comparison of odds ratios to the base case. SPSS selects the last industry in the list as the base case and does not allocate a dummy variable to it since all other industries will be referenced to this industry. The "Other" industry was selected as the base case. The rest of the industry groups are allocated dummy variable (1) to (7) in the matrices form.

Table 18: SPSS categorical variable coding

	Frequency	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Clothing & Textile	67	1	0	0	0	0	0	0
Agro-Processing	102	0	1	0	0	0	0	0
Mining & Metals	65	0	0	1	0	0	0	0
Chemicals	77	0	0	0	1	0	0	0
Food & Retail	131	0	0	0	0	1	0	0
Automotive	19	0	0	0	0	0	1	0
Manufacturing	73	0	0	0	0	0	0	1
Other	32	0	0	0	0	0	0	0

Table 18 presents the results of SPSS dummy variable allocation. The "Other" industry group is not allocated a 1 in its row because it is a reference industry group. The matrices in Table 18 shows that there is a 1 unit allocated for all other industries corresponding to dummy variable (1) to (7). For instance industry#(1) corresponds to clothing & textiles industry and industry#(3) corresponds to mining and Metals industry.

The industry influence is tested using a logit model which includes liquidity, solvency, size, and industry group variables. The output of SPSS is presented in Table 19. Since the industry group variable was multi-categorical, SPSS gave results for the overall contribution of the industry groups parameters as well as the contribution of each industry group.

Table 19: Binary logistic regression results – Industry variable

	B	P-Value	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
LTD/TA	1,12	0,001	3,08	1,57	6,05
CA/CL	0,00	0,934	1,00	0,99	1,01
Size	-0,26	0,169	0,77	0,53	1,12
Industry #		0,008			
Industry #(1)	-0,49	0,337	0,61	0,22	1,68
Industry #(2)	-1,14	0,021	0,32	0,12	0,84
Industry #(3)	-0,42	0,410	0,66	0,24	1,78
Industry #(4)	-1,34	0,016	0,26	0,09	0,78
Industry #(5)	-1,81	0,000	0,16	0,06	0,44
Industry #(6)	-0,43	0,528	0,65	0,17	2,50
Industry #(7)	-0,57	0,246	0,57	0,22	1,48
Constant	0,69	0,625	1,99	0,00	0,00
Pseudo R^2	*0,094*				

The industry group is a significant variable in the prediction of default probability of private firms on DFI loans, $p = 0.008$. Furthermore, the industry variable also increases the explanatory power of the logit model as evident by pseudo R^2 of 0.089 which is higher than pseudo R^2 of 0.034 in Table 16. Therefore, **$H4_0$** is rejected.

Regarding the individual contribution. The agro-processing industry had a significant impact to DFI loan default such that there was a lower likelihood of default when a firm belonged to Agro-Processing compared to "other industry," $p = 0.021$, EXP(β)= 0.26. Similarly, p-values for Chemicals and Food & Retail industries were less than 0.05 each, and their 95% C.I. did not include the value of 1. The likelihood of default reduced when a firm was in these industries compared to the "other" industry.

The p-values of other industries are higher than 0.05. That means it makes no significant difference in default probabilities for a firm belonging to these industries as opposed to "other" industry.

CHAPTER 6: DISCUSSION

This chapter presents an in-depth discussion of the results laid out in Chapter five. The objective of this chapter is to answer the four research questions posed in chapter one by the hypotheses formulated following the extensive literature review in chapter two. This chapter seeks to highlight the connections and contrasts of the results found in this study with those presented in literature, with the aim of contributing to the field of corporate failure and default prediction.

6.1. Data Evaluation

The total sample drawn from the databases of the Industrial Development Corporation consisted of 566 accounts, of which 88 accounts related to firms that entered into loan default between the year 2008 and 2014. The overall default rate over the entire period was therefore 15.55%. This was in a range of the average impairments of the South African DFIs (IDC, 2017; DBSA, 2017).

The sample period included recession period of 2008 - 2009 for South Africa which made it imperative to check if there was a visible impact of the recession on the sample obtained. The adverse operating condition might have influenced the default behaviour and distorted the role of the selected independent variables (Sikorski, 2011). The default rate trends varied between 11% and 21% in the sample period, see Table 7 in section 5.2.1.

The highest default rate of 21% was seen in 2011. Which was followed by a default rate of 19% and 17% in 2012 and 2014 respectively. The default rate around the recession period was about 14% which was below the overall average of the entire sample. The significant adverse events in the economy are generally expected to increase the default rates (Almamy et al., 2016). However, there seemed to be no evidence that the recession increased the default rate in this research. This finding alleviates fears that the sample period could have negatively impacted the internal validity of the study.

The sample consisted of South African private firms from different provinces. Since, each province might provide a different operating environment in terms of by-laws and market forces (Yitaferu, 2013). The default rates were also compared per geographical area within South Africa. Most of the accounts in the sample (41%) were firms based in Gauteng province, followed by Western Cape (16%). The trend was expected since Gauteng and the Western Cape have substantial economic activities in South Africa that firms from these provinces would form the majority of the DFI loan book. The highest default frequencies were in the North West (29%) and the Eastern Cape (25%). However, North West accounted for 4% of the overall defaults. Gauteng had a default rate of only 13% but accounted for 33% of the overall defaults. There seems to be a variation in default rates between different geographical areas; it might provide an exciting research topic in the future to see if default models should be controlled for this variable.

6.2. Characteristics of Defaulting Vs Non-Defaulting Firms

In order to further explore the characteristics of defaulting and non-defaulting firms, key performance ratios were computed based on the audited financial records of the firms in the sample. The results of the descriptive statistics are shown in **Error! Reference source not found.** and Table 9 in section 5.3.

On average, the non-defaulting firms were seen to be more efficient in deploying their assets to generate revenue compared to the defaulting firms. This observation was based on the asset turnover ratio which was higher for non-defaulting firms (*M* = 1.19, *SD* = 2.35) compared to defaulting firms (*M* = 0.69, *SD* = 2.60). These results were expected since defaulting firms are generally not well managed relative to non-defaulting firms (Bellovary et al., 2007).

The profitability measures also seem to suggest that non-defaulting firms were more profitable than the defaulting firms. The EBIT/total asset was higher for non-defaulting firms (*M* = 0.04, *SD* = 0.07) relative to defaulting firms (*M* = -0.01, *SD* = 0.01). More than half of the defaulting firms in the sample (52.27%) were loss-making compared to 36.27% of the non-defaulting sample. Up to 21.50% of the defaulting firms in the sample had a negative net worth compared to 15.30% of the non-defaulting sample. According to Bhimani et al. (2014), profitability could be a good indicator of how the firm was managed and consequently a good signal of the likelihood of default.

However, there was still a significant number of non-defaulting firms with adverse performance. For instance, 36.27% for the non-defaulting firms were in a loss-making position. Furthermore, the average profit margin of non-defaulting firms was more adverse than the defaulting firms (*M* = -160.03%, *SD* = 1877.30% versus *M* = -142.42%, *SD* = 746.64%). This supports a view that although profitability is an obvious firm performance measure, it might not be the best or only relevant default measure (Balcaen & Ooghe, 2006).

The liquidity and solvency measures were also studied carefully. Figure 4 depicts the liquidity and solvency levels of the sample.

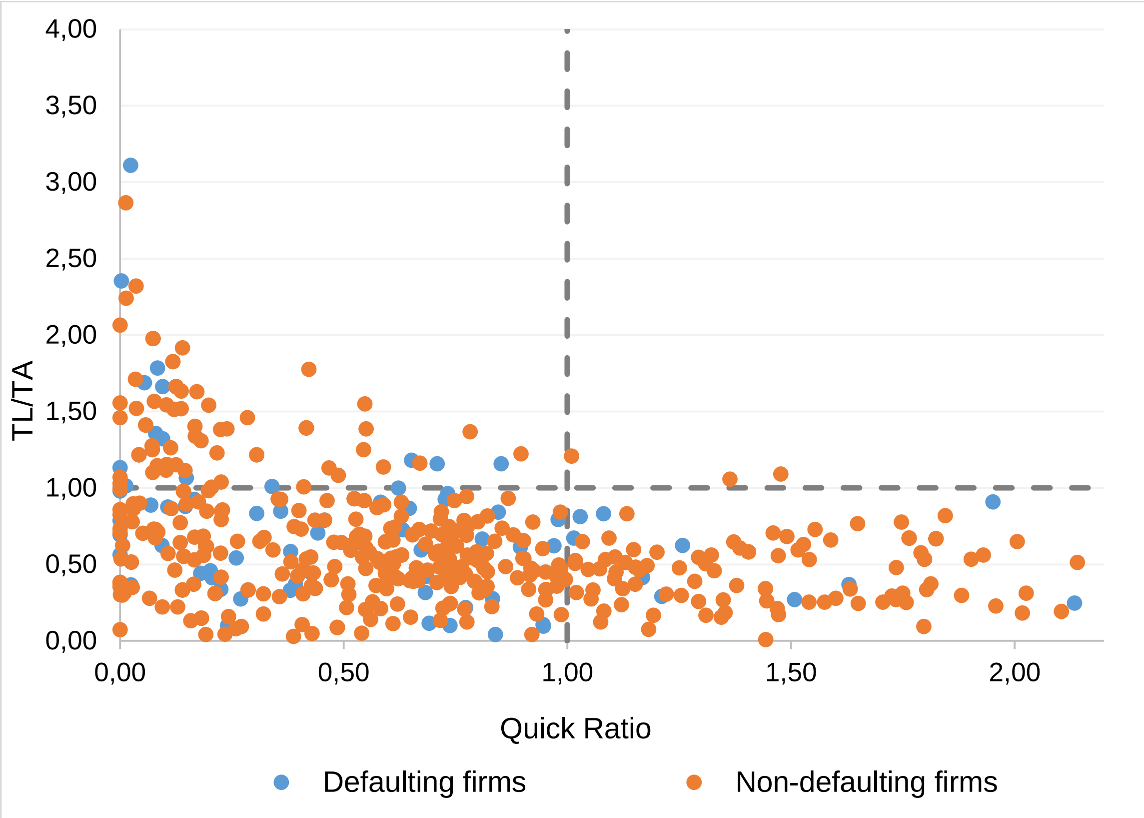

Figure 4: Solvency vs quick ratio for defaulting and non-defaulting firms

About 89% of the defaulting firms were either facing liquidity problem or under solvency strain. It might have been an indication that solvency and liquidity measures played an important role in influencing DFI loan defaults. It could also be a systematic bias that related to the profiles of firms that are funded by the DFIs. According to Yitaferu (2013), DFIs are more prone to fund firms that are risky in nature due to their developmental mandate.

Approximately 22% of defaulting firms were insolvent compared to 13% of non-defaulting firms in the same situation. About 20% of the defaulting borrowers were both illiquid and insolvent at the same time as compared to 12% of non-defaulting firms in a similar situation. Data in Table 11 showed that 75% of defaulting firms had a quick ratio below one, while only 22% of firms defaulting on DFI loans were insolvent. Therefore, firms that were insolvent were also mostly illiquid, but firms that were illiquid were not necessarily insolvent. This is consistent with the notion that firms with high leverage and low solvency can eventually become financially distressed (Davydenko, 2012). It was also interesting to see that firms could be financially distressed and not default on the DFI loans. Nonetheless, this could have been at a detriment of other creditors because Ciampi (2018) pointed out that firms would tend to default on other small creditors before defaulting on the main creditor. Furthermore, about 11% of the defaulting firms were in a healthy liquidity and solvency position. Even though liquidity and solvency appeared to play some role in the selected sample; other firms seemed to be driven by other factors to default on DFI loans.

6.3. Research Question 1 - Liquidity

Various studies advocate for liquidity as being a central variable in the prediction of default probabilities (Brogaard et al., 2017). Some structural models of credit risk assume that default occurs when a firm's instantaneous cash flow becomes insufficient to service its immediate debt obligations (Sundaresan et al., 2014). Meaning "cash flow distress or insufficient balance sheet liquidity may result in payment default despite the absence of economic distress" (Davydenko, 2013, p. 1). It essentially elevates the importance of liquidity measures as default indicators.

However, "in such models, external financing is typically prohibited, and firms do not maintain a cash reserve which means temporary cash shortages may result in the firm's inability to meet its current financial obligations" (Davydenko, 2012, p. 6). The view that supports liquidity as a critical default indicator is not unreasonable because distressed firms may struggle to raise necessary external financing due to various market frictions such as legislative hurdles (Shin & Kim, 2015). Firms in possession of DFI loans are not immune to this fact, in times of distress they would struggle to raise external finance from their shareholders, commercial banks or DFIs themselves.

This study found that defaulting firms had lower liquidity than the non-defaulting firms. The liquidity measures showed that the defaulting firms had an average quick ratio of (M = 1.45, SD = 4.61) compared to an average of non-defaulting firms (M = 4.08, SD = 35.64). Furthermore, about 75% of defaulting firms have a quick ratio below one, indicating that the majority of firms at default were illiquid. On the other hand, about 66% of the non-defaulting firms were also found to be illiquid.

The quick ratio represents a much more robust measure of liquidity since it looks at cash and items with a high probability of being converted to cash relative to current liability. The other measure of liquidity reported was the current ratio. Current ratio means a company's ability to pay off short-term liabilities with its short-term assets. However, it includes inventory in the current assets which can sometimes be an illiquid form of assets. Davydenko (2012) reports that “firms in decline often cannot convert their inventory into cash quickly, which makes current ratio less informative about the firm’s liquidity in distress than the quick ratio” (p. 14). However, the results show that according to the current ratio, the defaulting firms were still less liquid compared to non-defaulting firms.

This apparent association of defaulting firms with illiquidity must be interpreted carefully. If a firm has an inadequate liquid asset, it means that they have to rely on external funding or cash from operations to meet its current obligations (Davydenko, 2013). Therefore it can be deduced that if either of these two sources of funds become unavailable, a firm would default.

The results in Table 11 and Table 12 also showed that defaulting firms appeared to have lower interest cover ratio (mean = 2.45, median = 1.25, *SD* = 6.48) compared to (mean = 5.45 and median = 2.96, *SD* = 56.00) of non-defaulting firms. It shows that defaulting firms produced relatively low cash from operations to even cover for their interest expense compared to non-defaulting firms. It made an argument that variation in liquidity for these firms might affect their decision to default on DFI loans plausible.

The interest cover of non-defaulting firms was higher which meant they generated higher EBITDA to cover for their loan obligations. Even though 66% of the non-defaulting firms had a quick ratio below one, they seemed to generate enough cash from operation for them not default on DFI loans. This was in line with the view that interest cover ratio is a critical measure of whether a firm would honour its debt obligations or not (Muscettola, 2014).

There seemed to be sufficient evidence that defaulting firms in the sample were illiquid, but did liquidity play a part in influencing firms to default on DFI loans? This led to research question 1.

What is the role of liquidity on the likelihood of default in DFI loans by private firms?

Using both quick and current ratios as proxies for liquidity in a logit model showed that liquidity was not a significant variable in the prediction of DFI loan defaults. The p-values of the quick ratio and current ratios were both higher than 0.05 indicating that both variables were not significant variables in the prediction of DFI loans defaults. The pseudo R^2 of both prediction models were also less than 0.001 for both the variables indicating the variables had no explanatory power in the logit model. The odds ratio for one-point increase EXP(β) was 1.00 indicating that any marginal increase in liquidity variables did not have any impact on default probability. This indicated that liquidity played no significant role in the firm's run-up to defaulting on the DFI loans.

It was interesting to see that even though firms became illiquid at default, liquidity did not seem to have driven them to the default state. However, this results must be interpreted with caution since the research only focused on DFI loan instrument, not on other forms of credit or even loans from commercial banks. Therefore, it was possible that firms might have been defaulting on other forms of credits before starting to default on DFI loans.

This evidence supported the assumption of value-based models that liquidity shortages were irrelevant in the trigger of default (Davydenko, 2013). "If a temporary reduction in cash flow leads to a liquidity crisis, shareholders could meet the required debt payments by raising external finance, as long as the asset value remains above the boundary" (Davydenko, 2012, p. 2). This assumption typically renders pure liquidity less important.

The findings of this study contrast the conclusions by Koh et al. (2015), who argued that financial distress and cash shortages were the main drivers behind firms' defaults and subsequent bankruptcies. Kruschwitz et al. (2015) also studied the role of illiquidity and over-indebtedness on triggering defaults within the theory of discounted cash flow. They found that illiquidity was a stricter trigger of default. These studies used samples from the U.S listed firms which might be different in character and have a different operating environment which might not apply to firms in possession of DFI loans. This research found that defaulting firms were indeed illiquid, however, using binary logistic regression, liquidity did not signal the likelihood of default.

Other literature on corporate failure prediction supported the findings of this study. The seminal work of Fitzpatrick (1932) was amongst the first to report that when dealing with default predictions, "less significance should be placed on current and quick ratios to firms having long-term liabilities" (Almamy et al., 2016, p. 279). It is because short-term cash flow problems have less effect on the firm if the balance sheet is well managed. Jessen & Lando (2015) argued that falling cash flow would not cause immediate default as long as a firm could convert available assets into cash. This seemed to render liquidity less necessary as an indicator of whether the firm would default or not.

6.4. Research Question 2 - Solvency

Solvency refers to a measure of a company's assets in excess of its liabilities (Khoja et al., 2016). The link between solvency and default has been debated for many years. In capital structure theory, a ratio of firm's debt to asset values is explicitly linked to the risk of default (Leland, 1994). The theory of accounting and finance deliberates that "limited liability conventions lower the downside risk while retaining the upside potential and creating options like payoff structure with associated incentives for taking risks" (Bhimani et al., 2010, p. 519). Therefore, it can be inferred that the default is directly related to capital structure.

In this research, solvency is represented by the ratio of total liabilities to total assets (TL/TA) and the ratio of long-term debt to total assets (LTD/TA). It was found that defaulting firms have, on average, lower solvency values and higher leverage compared to the non-defaulting firms. These were depicted in Table 11 and Table 12 by the ratio of total liabilities to total assets and long-term debt to total assets. The results were expected since firms at default are usually highly indebted (Kruschwitz et al., 2015).

Further analysis showed that up to 21.50% of firms defaulting on DFI loans were insolvent which meant they had a negative net worth. These findings were probably a result of continuing losses which usually erode available equity (Altman et al., 2017). The statement was supported by the fact that the sample of firms defaulting on DFI loans in this study had a negative net profit margin as shown by the median of -0,36% compared to the non-defaulting firms which have the median of 1.74%.

An average of 12.30% of the non-defaulting firms also had negative net worth which suggested that insolvent firms did not necessarily default immediately. This finding might indicate that a lot of the creditor value had been destroyed by the time these firms defaulted on DFI loans. It might also indicate that some of the firms not defaulting on DFI loans might already be defaulting on other forms of credit. These results are in line with Davydenko (2013) who reported that some firms could take up to three years to default after being insolvent.

The research question for this study was: *What is the role of solvency on the likelihood of default in DFI loans by private firms?*

To answer the research question: two hypotheses were proposed to test the standard measure of solvency in default studies. The first hypothesis (2A) was:

Null Hypothesis ($H2A_0$): TL/TA is not a significant variable in the prediction of DFI loan defaults by private firms.

Alternate Hypothesis ($H2A_{Alt}$): TL/TA is a significant variable in the prediction of DFI loan defaults by private firms such that when TL/TA increases default probability also rises.

Table 15 showed TL/TA is a significant variable in the prediction of firms defaulting on DFI loans, $p = 0.001$. The odds of defaulting increase with any unit increase in TL/TA ($\beta = 0.56$; Exp(β)= 1.74). The pseudo R^2 of 0.02 also showed that TL/TA has some explanatory power to whether a firm defaults or not. Based on this, the null hypothesis was rejected, and the alternate hypothesis accepted. TL/TA is a significant variable in the prediction of default of private firms on DFI loans such that when TL/TA increases default probability rises.

The second hypothesis (2B) was as follows:

Null Hypothesis ($H2B_0$): LTD/TA is not a significant variable in the prediction of defaults of private firms on DFI loans.

Alternate Hypothesis ($H2B_{Alt}$): LTD/TA is a significant variable in the prediction of default of private firms on DFI loans such that when LTD/TA increases default probability also increases.

The results in Table 16 showed that LTD/TA was a significant variable in the logit model, $p = 0.001$. The log (odds) of defaulting increased with increase in LTD/TA, $\beta = 0.93$. Also for any additional unit in LTD/TA, the odds of defaulting increase by a factor of 2.53, Exp(β) = 2.53. These indicated that the likelihood of defaulting grew with an increase in LTD/TA – meaning a reduction in solvency. Based on the statements above, the null hypothesis was rejected, and the alternate hypothesis accepted. LTD/TA was found to be a significant variable in the prediction of default of private firms on DFI loans such that when solvency increased default probability reduced. Furthermore, the pseudo R^2 of 0.032 showed that LTD/TA had a relatively high influence on a firm's probability of default.

The results suggested that both solvency ratios were significant variables in the prediction of DFI loans default. Therefore, Solvency was indeed a significant variable in the prediction of DFI loan defaults by private firms. The direction is that when solvency increased default probability reduced. These findings have a reference in the literature. An earlier study on capital structure theory done by Leland (1994) on the corporate debt values and capital structure found that “a firm’s optimal leverage is explicitly linked to firm’s default risk and bankruptcy probabilities” (p. 38). Leland & Toft (1996) also argued that an increase in capital gearing (debt/assets) raises the probability of corporate failure as a firm is likely to default on its obligations. The two studies show that solvency ratios might be useful in signalling loan defaults. This research contributes to the literature by showing that solvency measures are also critical indicators of DFI loan defaults.

Davydenko (2013) found that solvency measured by the market value of assets relative to the face value of debt was the most influential variable in the prediction of defaults of listed firms. This is in line with the traditional structural models of risky debt which assume that firms only default when the market value of assets falls below the face value of debt (Choi & Richardson, 2016). Tian et al. (2015) in the study of variable selection and bankruptcy forecasts reported that in the corporate failure prediction; book solvency ratios are more reliable indicators than market solvency values. By using balance sheet measures of solvency, this research also showed that solvency was essential for firms in possession of DFI loans which adds to the body of existing literature.

According to Bhaskar et al. (2017) solvency indicates a more structural problem that is generally much lengthier to correct which is contrary to liquidity. Illiquidity can be solved by cash injection which can be obtained from raising cash against available assets as long as the firm is solvent (Almamy et al., 2016). However, insolvency generally requires radical change, such as selling off some assets or laying off employees (Khoja et al., 2016). These views show that solvency is highly crucial in the prediction of defaults. However, it indicates that pure liquidity is mostly irrelevant.

The results stress the importance of putting significance on solvency measures when analyzing the credit risk of clients in need of DFI loans. These measures should also be closely monitored at post-investment to see if their client’s probability of default is increasing or not.

6.5. Research Question 3 – Influence of Firm Size

The marginal contribution of firm size has been proven to be very valuable to the prediction of defaults (Pervan & Kuvek, 2013). In the development of the logit model, Ohlson (1980) found that firm size is a significant and vital variable in the prediction of corporate failure. Altman et al. (2017), in a review of the Z-score model, maintained that firm size significantly improved the model when it was explicitly taken into account. This research used the logarithm of total assets [log(TA)] as a proxy for firm size which is in line with the previous studies in the field of default prediction (Bellovary et al., 2007; Bhimani et al., 2010; Ciampi, 2017). Figure 3 presents the normalized histogram of log (TA) to the distribution of firm size for defaulting and non-defaulting firms.

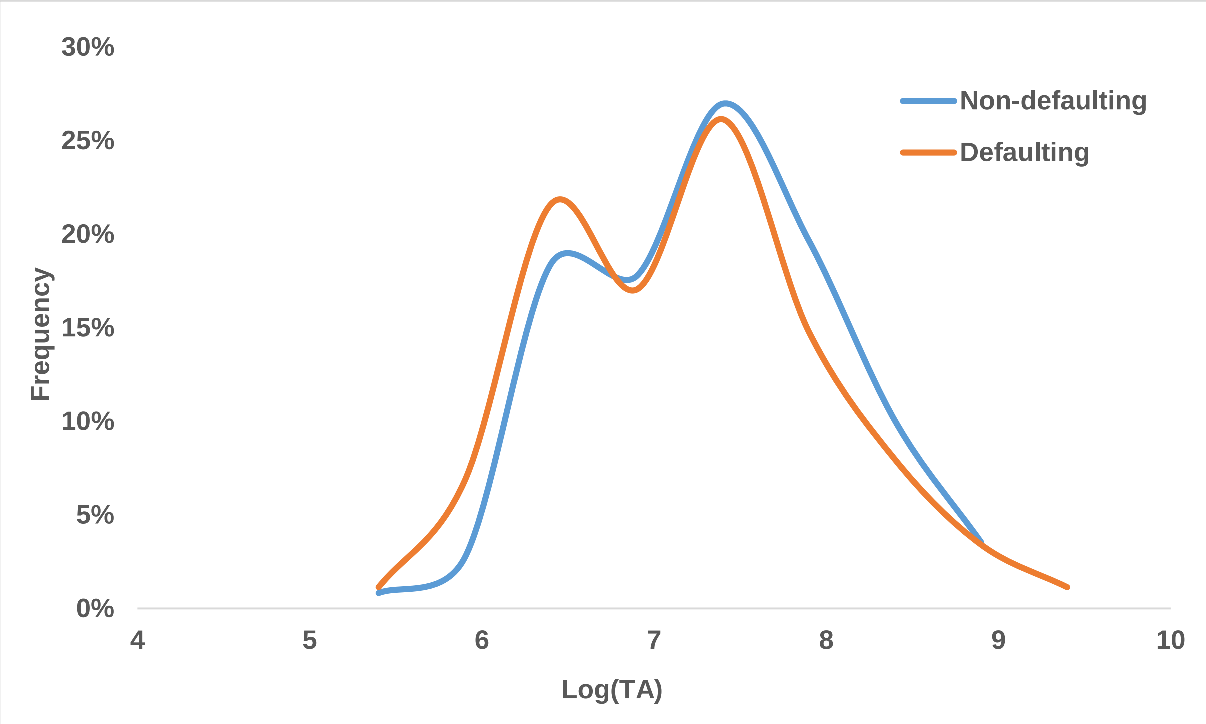

Figure 3: Normalized histogram: Log (TA) vs percentage frequency

The most significant result is that the non-defaulting firms appear to be larger in size compared to defaulting firms, about 35% above log(TA) of 7.5 compared to 25% of defaulting firms above the same value. There are two defaulting firms with sizeable total asset values above R700 million, hence a long tail of the plot of defaulting firms. These potential outliers might skew the descriptive statics of defaulting firms. These firms were obvious outliers to the sample and had the potential to skew the results. The influence of the outliers was considered. In light of this, all the statistics were run with and without the outliers, and the outcomes of the hypotheses did not materially change. Therefore, a decision was taken only to show the results which include the outliers because of their essential contribution to the understanding of firms funded by the DFIs.

The defaulting firms have their size skewed towards smaller firms with about 50% below log(TA) of 7 as compared to 40% of non-defaulting firm size below the same point. These results suggest that default events are more prominent on the smaller firms than larger firms. Yet, the descriptive statistics in Table 8 and Table 9 section 5.3 seemed to suggest that, on average, defaulting firms were larger than the non-defaulting firms in asset base, (*M* = R 48 324 349, *SD* = R 139 168 131 versus *M* = R 42 136 719, *SD* = R 89 701 566), however, there was a considerable variation within each group as shown by the respective standard deviations.

Overall, it appeared that the higher default rate could be associated with smaller firms as compared to larger firms. Various studies have concluded that default probability significantly decreases with the increase in the firm's size (Duan et al., 2017). “Larger firms are expected to exhibit a lower failure probability because they are more likely to benefit from scale-effects, have more power in negotiations with their financial and social partners and are more likely to benefit from their experience or learning effects” (Balcaen & Ooghe, 2006, p.37).

The research question regarding firm size was: “what is the role of firm size in the prediction of firms defaulting on DFI loans.” The following hypothesis was posed to answer the research question.

Null Hypothesis ($H3_0$): Firm size is not a significant variable in the prediction of defaults on DFI loans by private firms.

Alternate Hypothesis ($H3_{Alt}$): Firm size is a significant variable in the prediction of defaults on DFI loans by private firms such that when firm size increases default probability reduces.

The results from the binary logistic regression (Table 17) presented results that are contrary to literature. Firm size was found to not be a significant variable in the prediction of loan defaults, $p = 0.65$. Furthermore, there was no improvement in pseudo R^2 showing that the firm size did not influence the interaction of key variables and did not increase the predictive power of the logit model. Therefore the null hypothesis **($H3_0$)** was accepted. Firm size had no significant influence on the defaulting behaviour of private firms on DFI loans.

The results of this study did not support the findings by Amendola et al. (2015) who found firm size to improve the predictive power of default models as well as the interaction of financial ratios input in the model. The study was on the population of Italian firms that operate in the building sector. This population is specific and might present different characteristics to the South African private firms in possession of DFI loans.

Other articles claim that larger firms should exhibit a lower failure probability since they are more likely to benefit from economies of scale and have more power in negotiations with their credit providers (Balcaen & Ooghe, 2006). Duan et al., (2017) also argued that firm size is a critical variable in default prediction such when firm size increases default probability always reduces. Even though this research found that smaller firms appear to exhibit high default rates, it did not find firm size as a significant variable in signalling the likelihood of DFI loan defaults.

The contradiction of the findings of this research to literature might be because of the characteristics of private firms in possession of DFI loans. These firms tend to be risky, and they tend to be highly geared (Calice, 2013). The massive debt relative to total assets might make firm size an irrelevant factor in the prediction defaults. Furthermore, the various limitations might have made the impact of firm size irrelevant. One of them might be a limited sample obtained from one DFI.

6.6. Research Question 4 – Influence of the Industry Group

In previous literature is was argued that the industry group has a significant bearing on the behaviour of firms with regards to corporate failure (Bellovary et al., 2007). It was further claimed that defaulting firms are often concentrated in specific failing industries (Balcaen & Ooghe, 2006). Since industry groups rarely go through similarly economic cycles, it can be expected that a randomly selected sample would consist of substantially different default rates across different industries. In this research, a sample which consisted of defaulting and non-defaulting firms was split into eight industries, and the results are depicted in Figure 2, Section 5.2.3.

The default rate differs considerably across different industry groups. The Food & Retail industry accounts for most observation in the sample (~23%). Agro-processing accounts for most (19%) of the defaults in the sample. However, the highest default rate is found in the "other" industry (31%) followed by the Automotive industry (21%) and Manufacturing industry (19%). Agro-processing has a 16% default rate. This finding might suggest that the default model might need to be controlled for the industry group variable in order to improve the model performance.

In order to capture the effect of industry, several authors have included industry information –industry-dummies or industry- relative ratios (Balcaen & Ooghe, 2006). In this research, industry dummies were included in the logit model for the objective of seeing if the industry was a significant variable and its effect on the DFI loan defaults. The following hypothesis was formulated:

Null Hypothesis ($H4_0$): Industry type is not a significant variable in the prediction of private firm's defaults on DFI loans.

Alternate Hypothesis ($H4_A$): Industry type is a significant variable in the prediction of private firm's defaults on DFI loans.

The logit model which included liquidity, solvency, size, and industry variables seemed to suggest that industry was a significant variable in the prediction of DFI loan default, $p = 0.008$. Furthermore, the industry also increased the explanatory power of the logit model as evident by pseudo R^2 of 0.089 which was higher than pseudo R^2 of 0.034 in the base logit model consisting of solvency and liquidity variable. Therefore, **$H4_0$** was rejected.

It meant that an industry which a firm belonged to should be included as a control variable when dealing with default prediction of private firms on DFI loans. The finding is in line with the study (Bhimani et al., 2010) which found that industry influences defaults of privately held firms. Sayari & Mugan (2017) attributed the difference to the industry characteristics which have a bearing on the diverging impact of financial ratios on firms' distress. In economics, different industries face different levels of market forces and, therefore, the probability of default can vary for firms in different industries with otherwise similar balance sheets (Hernandez Tinoco & Wilson, 2013).

Similarly, with the DFIs, some industries have concessionary funds such as grants and cheap patient debt in order for firms in that industry to be competitive in the global markets (IDC, 2018). For instance, industries such as clothing & textiles and agro-processing have support and funds available to them that are otherwise not available to firms in other industries (IDC, 2018). It can be argued that the availability of this support might curb default rates in those industries.

However, contrary to Chava & Jarrow (2001), the industry effects did not improve the interaction of solvency and liquidity variables. The liquidity variables remained not a significant variable despite incorporating the industry variables. It is despite Sayari & Mugan (2017) concluding that liquidity ratios were the most divergent and consisted of the most information content across different industry groups. It might indicate that liquidity had no bearing on DFI loan default behaviour, even across different industries.

CHAPTER 7: CONCLUSION

This chapter reflects on the research findings which were drawn from the discussions and insights in chapter six. The study has implications for both management and development finance institutions. Therefore, the recommendations to these stakeholders will be presented. The research limitations will then be summarized. Lastly, in light of this study, the suggestions for future research will be presented.

The primary aim of this research study was to examine the relative importance of liquidity and solvency in default probabilities of firms holding loans from development finance institutions ("DFIs"). By using a firm level and default data from the database of the Industrial Development Corporation, the study found four principal findings in line with the research questions posed in section 1.4.

- Liquidity is not a significant variable in the prediction of DFI loan defaults of private firms. There is, however, evidence that firms at default are mostly illiquid.
- Solvency is a significant variable in the prediction of DFI loan defaults of private firms.
- Firm size has no significant influence in the prediction of DFI loan defaults of private firms.
- Industry group is a significant predictor of DFI loan default and should be included as a control variable. However, it does not influence the role of liquidity and solvency in the logit model.

These findings are discussed in detail below:

7.1. Principal Findings and Contribution to Literature

7.1.1. Liquidity findings

The principal findings from the first research question revealed that liquidity was not a significant variable in the prediction of DFI loan defaults in private firms. Quick and current ratios were applied separately as proxies for liquidity in a logit model. Both these ratios were not significant in the prediction model at 5% significant level. These ratios also proved to have no explanatory power in the logit model. This conclusion was based on the observations that both the quick ratio and the current ratio did not improve the pseudo R^2 of the logit model.

Most of the firms defaulting on DFI loans are illiquid. The study showed that 75% of defaulting firms had a quick ratio below 1. Therefore, even though firms become illiquid at default, liquidity did not seem to have driven them to a default state. However, this research only focused on DFI loan instrument, not on other forms of credit or even loans from commercial banks. Therefore, it is possible that firms might have been defaulting on other forms of credits before starting to default on DFI loans.

The findings seem to support the view of the value-based models that assume that liquidity is not involved in the triggering of default (Davydenko, 2013). "If a temporary reduction in cash flow leads to a liquidity crisis, shareholders meet the required debt payments by raising external finance, as long as the asset value remains above the boundary" (Davydenko, 2012, p. 2). Jessen & Lando (2015) also argued that falling cash flow will not cause immediate default because a firm can convert available assets into cash. Similar conclusions were found in this study, that variation in liquidity is not necessarily a good measure for whether a private firm is going to default on DFI loans or not.

7.1.2. Solvency findings

The second principal finding was that solvency is a significant variable in the prediction of DFI loan defaults. The contribution of solvency was tested using two variables separately in the logit model. Namely, the ratio of total liability to total assets (TL/TA) and ratio to long-term debt to total assets (LTD/TA). TL/TA was found to be a significant variable in the prediction of default of private firms on DFI loans such that when TL/TA increases default probability reduces. Furthermore, the pseudo R^2 showed that TL/TA had an explanatory power to whether a firm default on DFI loans or not.

In the similar vein, LTD/TA was found to be a significant variable in the prediction of default of private firms on DFI loans such that when solvency increased default probability reduced. The pseudo R^2 indicated that LTD/TA had a higher influence on a firm's probability of defaults on DFI loans.

Solvency ratios proved to have a significant role in signalling DFI loans defaults. Further results showed that about 22% of firms defaulting on DFI loans were insolvent which means they had a negative net worth. Altman et al. (2017) attribute the negative net worth of failing firms to continuing losses which usually erode available equity. The statement is supported by the fact that the sample of firms defaulting on DFI loans in this study had on average poor profitability measures. An average of 12.30% of the non-defaulting firms were also insolvent which meant that insolvent firms did not necessarily default immediately. This finding might indicate that a lot of the creditor value had been destroyed by the time these firms defaulted on DFI loans. It might also indicate that some of the firms not defaulting on DFI loans might already be defaulting on other forms of credit. These results are in line with Davydenko (2012) who reported that some firms could take up to three years to default after being insolvent.

These principal findings regarding solvency are consistent with the study (Davydenko, 2013) which found that solvency was a single most influential variable in the prediction of loans and bond defaults of listed firms in the U.S. Furthermore, the structural models of credit risk assume that solvency is the only predictor that matters instead of liquidity (Leland, 1994). The study by Davydenko (2013) was based on the market value of assets which could not be obtained for this study since the research focused on private firms. However, Tian et al. (2015) in the study of variable selection and bankruptcy forecasts reported that in the corporate failure prediction; book values of solvency are more reliable indicators than market values of solvency. By using the solvency measures obtained from the balance sheets of private firms in possession of DFI loans, this research found that solvency ratios are critical in the prediction of DFI loan defaults which adds to the body of existing literature.

7.1.3. Firm size findings

The main finding related to the third research question is that firm size does not have any significant impact on the prediction of DFI loan defaults. Furthermore, it did not improve the explanatory power of liquidity and solvency in the logit model. This is contrary to previous research which found firm size as a significant predictor of defaults and bankruptcy (Altman et al., 2017; Balcaen & Ooghe, 2006; Bhimani et al., 2010). The contradiction of the findings of this research to literature might be because of the characteristics of private firms in possession of DFI loans. These firms tend to be risky, and highly geared (Calice, 2013). The substantial debt relative to total assets of this firms might make firm size an irrelevant factor in the prediction defaults. This research used the logarithm of total assets [log(TA)] as a proxy for firm size, perhaps other measures of firm size such as turnover or number of employees (Balcaen & Ooghe, 2006) could be explored.

7.1.4. Industry group findings

The principal findings from the fourth research question revealed that industry group is a significant variable in the prediction of DFI loan defaults. A sample which consisted of defaulting and non-defaulting firms was split into eight industries. The significance test was applied using the logit model which included liquidity, solvency, size, and industry group as independent variables. The industry group variable also increased the explanatory power of the logit model.

The finding is consistent with Bhimani et al. (2010) who found that industry group influences defaults of privately held firms. Sayari & Mugan (2017) attributed the difference to the industry characteristics which have a bearing on the diverging impact of financial ratios on firms' distress. Various industries usually face different levels of market forces which could impact on the probability of default for firms in different industries with otherwise similar balance sheets (Hernandez Tinoco & Wilson, 2013).

About the DFIs, some industries have concessionary funds such as grants and cheap patient debt to enable firms in that industry to be competitive in the global markets or for socio-economic redress (IDC, 2018). For instance, industries such as clothing & textiles and agro-processing have support and funds available to them that are otherwise not available to firms in other industries (IDC, 2018). It can be argued that the availability of this support might curb default rates in those industries.

Even though the industry group had a significant impact on the DFI loan prediction, it did not improve the influence of solvency and liquidity variables. This finding is contrary to Chava & Jarrow (2001) who argued that the industry group variable improves the interaction of financial ratios in the logit model. However, the finding indicates that industry group should be included as a control variable when dealing with default prediction of DFI loans by private firms.

7.1.5. Concluding remarks

Since there is no overarching theory in the selection of variables used in the prediction of loan defaults (Appiah et al., 2015; Balcaen & Ooghe, 2006). It is, therefore, critical to understand the contribution of the important variables in loan default predictions and credit risk assessment based on the context. Consistent with the core assumption of value-based models, this research found that solvency ratios are pivotal inclusions to the prediction models of default of private firms on DFI loans. It further found that liquidity is not a significant variable in the prediction of DFI loan defaults. The study also revealed that industry group should be included as a control variable in the DFI loan default prediction models. The inclusion of both the solvency and industry group variables is expected to improve the accuracy and the predictive power of DFI loan default prediction models.

7.2. Implications for Managers and DFIs

This research study has an implication on managers because they have a responsibility to understand the credit risk of their companies. This is to avoid and mitigate loan defaults and poor credit scores on the companies they manage. Poor credit score may cause difficulty for any business to undertake future expansions by reducing their chances of obtaining credit and may increase their cost of debt. The risk is magnified by the fact that it is not easy for private firms to raise funding in the open market. This research helps managers to understand significant factors that affect the probability of default on DFI loans.

The study will also contribute to DFIs' credit risk assessments by assisting DFIs to understand the impact that liquidity and solvency have on a firm's probability to default on the loan commitments. The study found that solvency ratios are better indicators of the default behaviour of private firms holding DFI loans. It is further shown that, even though firms at default are illiquid, liquidity is not a good indicator of DFI loan default. Firm size was also found not to be an influential factor in the prediction of DFI loan defaults. However, the DFIs' default prediction models should incorporate the industry group of a firm in order to improve the predictive abilities of their credit assessment models.

7.3. Research Limitations

The sample chosen from one organization due to convenience might have introduced sample bias and may limit the generalizability of this study. The firms contained in the IDC database might have characteristics which are not necessarily a norm to the entire DFI firms' population. Furthermore, secondary data being sourced from this financial institution was seen as a threat to external validity. However, comfort could be gained from the fact that the IDC is a reputable organization. It has a regulatory oversight conducted by the Financial Services Board (FSB). It is also obliged to comply with the Financial Intelligence Centre Act 38 of 2001 (Financial Intelligence Centre Act 38 of 2001, 2002) and the Financial Advisory and Intermediary Services Act (Financial Advisory and Intermediary Services Act 37 of 2002, 2002).

The time period in which the data was chosen is a potential concern for internal validity. The time period is between 2008 and 2014. Around 2008 and 2009 there was a global financial meltdown which resulted in an adverse operating condition for many firms (Sikorski, 2011). This might influence the default behaviour and distort the role of the selected independent variables. However, the impact of this period was tested, and it was found that it did not have any visible impact on the data used.

7.4. Suggestions for Future Research

The suggestions for future research are as follows:

- This research highlighted that the non-financial information which represents the dimensions of a firm which cannot be captured by financial ratios is crucial for signalling loan defaults (Ciampi, 2015). The addition of the non-financial information in the default prediction models has been proven to improve the accuracy of prediction models because the impact of factors not detectable by financial information is also represented (Bauweraerts, 2016). The private firms funded by DFIs provide an interesting library since these firms are less studied. Future research should look at the impact of corporate governance variables (such as the proportion of non-executive directors, size of a board and ownership concentration), covenant violations, and personal risk on DFI loan defaults of private firms.

- This research found a significant variation in default rates between different geographical areas. This might provide an exciting research topic in the future to see if default models should be controlled for geographical area variable.

- Government and the DFIs provide specific industries with concessionary funds such as grants and cheap patient debt in order to increase their competitiveness. For instance, industries such as clothing and textiles and agro-processing have support and funds available to them that are otherwise not available to firms in other industries. Future research can look into the effectiveness of this support and its impact in curbing defaults rates.

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APPENDICES

Appendix A: Raw Data

Table 20: Raw Data - Region, year of credit status, and default status

Firm Identifier	Country	Province	Year	default status
1000	South Africa	Gauteng	2013	0
1001	South Africa	Gauteng	2008	0
1002	South Africa	Gauteng	2009	0
1003	South Africa	Gauteng	2010	0
1004	South Africa	Gauteng	2012	0
1005	South Africa	Gauteng	2011	0
1006	South Africa	Gauteng	2008	0
1007	South Africa	Gauteng	2009	0
1008	South Africa	Eastern Cape	2009	0
1009	South Africa	Eastern Cape	2010	0
1010	South Africa	Eastern Cape	2011	0
1011	South Africa	Free State	2009	0
1012	South Africa	Free State	2010	1
1013	South Africa	Western Cape	2008	0
1014	South Africa	Gauteng	2008	0
1015	South Africa	Gauteng	2009	0
1016	South Africa	Gauteng	2010	0
1017	South Africa	Gauteng	2011	0
1018	South Africa	Gauteng	2014	0
1019	South Africa	Gauteng	2010	0
1020	South Africa	Gauteng	2009	0
1021	South Africa	Gauteng	2008	0
1022	South Africa	KwaZulu Natal	2013	0
1023	South Africa	KwaZulu Natal	2014	0
1024	South Africa	KwaZulu Natal	2012	0
1025	South Africa	KwaZulu Natal	2009	0
1026	South Africa	KwaZulu Natal	2011	0
1027	South Africa	Eastern Cape	2009	0
1028	South Africa	Gauteng	2011	0
1029	South Africa	Gauteng	2010	0
1030	South Africa	Western Cape	2012	0
1031	South Africa	Western Cape	2013	0
1032	South Africa	Eastern Cape	2012	0
1033	South Africa	Eastern Cape	2013	0
1034	South Africa	Eastern Cape	2011	0
1035	South Africa	Eastern Cape	2010	0
1036	South Africa	Eastern Cape	2014	0
1037	South Africa	KwaZulu Natal	2010	0
1038	South Africa	Limpopo	2009	0
1039	South Africa	Western Cape	2009	0
1040	South Africa	Gauteng	2008	0

Firm Identifier	Country	Province	Year	default status
1041	South Africa	Western Cape	2012	1
1042	South Africa	Western Cape	2011	0
1043	South Africa	Western Cape	2009	0
1044	South Africa	Western Cape	2014	0
1045	South Africa	Western Cape	2010	0
1046	South Africa	Western Cape	2012	0
1047	South Africa	Western Cape	2011	0
1048	South Africa	Western Cape	2013	0
1049	South Africa	Western Cape	2008	0
1050	South Africa	Mpumalanga	2008	0
1051	South Africa	Western Cape	2012	0
1052	South Africa	Western Cape	2011	0
1053	South Africa	Gauteng	2008	0
1054	South Africa	Gauteng	2009	0
1055	South Africa	Limpopo	2008	0
1056	South Africa	Gauteng	2011	1
1057	South Africa	Limpopo	2011	0
1058	South Africa	Limpopo	2012	0
1059	South Africa	Limpopo	2013	0
1060	South Africa	Limpopo	2009	0
1061	South Africa	Limpopo	2010	0
1062	South Africa	Limpopo	2008	0
1063	South Africa	Gauteng	2009	0
1064	South Africa	Gauteng	2008	0
1065	South Africa	Western Cape	2008	1
1066	South Africa	North West	2008	0
1067	South Africa	North West	2009	0
1068	South Africa	Gauteng	2008	0
1069	South Africa	Gauteng	2009	1
1070	South Africa	KwaZulu Natal	2012	0
1071	South Africa	KwaZulu Natal	2010	0
1072	South Africa	KwaZulu Natal	2011	0
1073	South Africa	Gauteng	2010	1
1074	South Africa	Gauteng	2009	0
1075	South Africa	Gauteng	2008	0
1076	South Africa	Gauteng	2009	0
1077	South Africa	Gauteng	2010	0
1078	South Africa	Gauteng	2013	0
1079	South Africa	Gauteng	2011	0
1080	South Africa	Gauteng	2012	0

Firm Identifier	Country	Province	Year	default status
1081	South Africa	Limpopo	2008	0
1082	South Africa	Limpopo	2011	0
1083	South Africa	Limpopo	2012	0
1084	South Africa	Limpopo	2013	0
1085	South Africa	Limpopo	2014	0
1086	South Africa	Limpopo	2009	0
1087	South Africa	Western Cape	2011	1
1088	South Africa	KwaZulu Natal	2012	0
1089	South Africa	KwaZulu Natal	2011	0
1090	South Africa	Gauteng	2010	0
1091	South Africa	Gauteng	2010	0
1092	South Africa	Gauteng	2009	0
1093	South Africa	Limpopo	2008	0
1094	South Africa	Limpopo	2009	0
1095	South Africa	Limpopo	2011	1
1096	South Africa	Limpopo	2008	0
1097	South Africa	Limpopo	2009	0
1098	South Africa	Limpopo	2010	0
1099	South Africa	Eastern Cape	2008	0
1100	South Africa	Gauteng	2009	0
1101	South Africa	Gauteng	2010	0
1102	South Africa	Eastern Cape	2009	0
1103	South Africa	Eastern Cape	2010	0
1104	South Africa	Gauteng	2011	0
1105	South Africa	Gauteng	2010	0
1106	South Africa	Gauteng	2009	0
1107	South Africa	North West	2013	0
1108	South Africa	North West	2010	0
1109	South Africa	North West	2009	0
1110	South Africa	North West	2012	0
1111	South Africa	Gauteng	2009	0
1112	South Africa	Gauteng	2010	0
1113	South Africa	KwaZulu Natal	2008	1
1114	South Africa	Western Cape	2012	0
1115	South Africa	Western Cape	2011	0
1116	South Africa	KwaZulu Natal	2008	0
1117	South Africa	KwaZulu Natal	2009	0
1118	South Africa	KwaZulu Natal	2012	0
1119	South Africa	KwaZulu Natal	2011	0
1120	South Africa	KwaZulu Natal	2013	0

Firm Identifier	Country	Province	Year	default status
1121	South Africa	KwaZulu Natal	2014	0
1122	South Africa	Limpopo	2009	0
1123	South Africa	Limpopo	2008	0
1124	South Africa	Limpopo	2010	0
1125	South Africa	Limpopo	2009	0
1126	South Africa	Gauteng	2011	1
1127	South Africa	Western Cape	2010	0
1128	South Africa	Western Cape	2008	0
1129	South Africa	Western Cape	2011	1
1130	South Africa	Gauteng	2014	0
1131	South Africa	Gauteng	2013	0
1132	South Africa	Gauteng	2012	0
1133	South Africa	Gauteng	2011	0
1134	South Africa	Northern Cape	2010	1
1135	South Africa	Western Cape	2010	0
1136	South Africa	Western Cape	2012	0
1137	South Africa	Western Cape	2013	0
1138	South Africa	North West	2010	0
1139	South Africa	North West	2009	0
1140	South Africa	Free State	2012	0
1141	South Africa	KwaZulu Natal	2008	0
1142	South Africa	KwaZulu Natal	2010	0
1143	South Africa	KwaZulu Natal	2012	0
1144	South Africa	KwaZulu Natal	2009	0
1145	South Africa	KwaZulu Natal	2011	0
1146	South Africa	Western Cape	2008	1
1147	South Africa	Gauteng	2008	1
1148	South Africa	Western Cape	2009	0
1149	South Africa	Western Cape	2008	0
1150	South Africa	Gauteng	2014	0
1151	South Africa	Gauteng	2013	0
1152	South Africa	Gauteng	2012	0
1153	South Africa	Gauteng	2009	0
1154	South Africa	Gauteng	2010	0
1155	South Africa	Western Cape	2008	0
1156	South Africa	Western Cape	2009	0
1157	South Africa	Western Cape	2010	0
1158	South Africa	Gauteng	2009	0
1159	South Africa	Gauteng	2010	0
1160	South Africa	Gauteng	2012	0

Firm Identifier	Country	Province	Year	default status
1161	South Africa	Gauteng	2013	0
1162	South Africa	Gauteng	2014	0
1163	South Africa	Gauteng	2011	0
1164	South Africa	Gauteng	2010	0
1165	South Africa	Gauteng	2009	0
1166	South Africa	Gauteng	2011	1
1167	South Africa	Gauteng	2009	0
1168	South Africa	Gauteng	2008	0
1169	South Africa	Gauteng	2010	1
1170	South Africa	Western Cape	2008	0
1171	South Africa	Gauteng	2010	1
1172	South Africa	Gauteng	2009	0
1173	South Africa	Mpumalanga	2009	0
1174	South Africa	Mpumalanga	2011	0
1175	South Africa	Mpumalanga	2010	0
1176	South Africa	Mpumalanga	2008	0
1177	South Africa	Mpumalanga	2012	0
1178	South Africa	Mpumalanga	2013	0
1179	South Africa	North West	2009	0
1180	South Africa	KwaZulu Natal	2009	0
1181	South Africa	KwaZulu Natal	2010	0
1182	South Africa	KwaZulu Natal	2011	1
1183	South Africa	Eastern Cape	2008	0
1184	South Africa	Eastern Cape	2010	0
1185	South Africa	Eastern Cape	2009	0
1186	South Africa	KwaZulu Natal	2011	1
1187	South Africa	Limpopo	2009	1
1188	South Africa	KwaZulu Natal	2009	0
1189	South Africa	Eastern Cape	2010	1
1190	South Africa	Eastern Cape	2008	0
1191	South Africa	Eastern Cape	2009	0
1192	South Africa	Gauteng	2014	0
1193	South Africa	Gauteng	2013	0
1194	South Africa	Gauteng	2010	0
1195	South Africa	Gauteng	2012	0
1196	South Africa	Gauteng	2009	0
1197	South Africa	Gauteng	2008	0
1198	South Africa	Gauteng	2011	0
1199	South Africa	Gauteng	2008	0
1200	South Africa	Gauteng	2008	1

Firm Identifier	Country	Province	Year	default status
1201	South Africa	Gauteng	2009	0
1202	South Africa	KwaZulu Natal	2009	0
1203	South Africa	Gauteng	2008	0
1204	South Africa	Gauteng	2009	0
1205	South Africa	Gauteng	2010	0
1206	South Africa	KwaZulu Natal	2009	0
1207	South Africa	Western Cape	2011	1
1208	South Africa	Western Cape	2009	0
1209	South Africa	Western Cape	2010	0
1210	South Africa	KwaZulu Natal	2009	1
1211	South Africa	Western Cape	2009	0
1212	South Africa	Western Cape	2011	1
1213	South Africa	Western Cape	2010	0
1214	South Africa	Gauteng	2008	0
1215	South Africa	Gauteng	2009	0
1216	South Africa	Limpopo	2009	0
1217	South Africa	Limpopo	2010	0
1218	South Africa	Eastern Cape	2011	0
1219	South Africa	Eastern Cape	2010	0
1220	South Africa	Gauteng	2009	0
1221	South Africa	Gauteng	2009	0
1222	South Africa	KwaZulu Natal	2014	0
1223	South Africa	KwaZulu Natal	2011	0
1224	South Africa	KwaZulu Natal	2012	0
1225	South Africa	KwaZulu Natal	2013	0
1226	South Africa	KwaZulu Natal	2010	0
1227	South Africa	KwaZulu Natal	2009	0
1228	South Africa	Gauteng	2009	0
1229	South Africa	Gauteng	2010	0
1230	South Africa	Gauteng	2011	0
1231	South Africa	Eastern Cape	2009	0
1232	South Africa	Gauteng	2011	0
1233	South Africa	Gauteng	2009	0
1234	South Africa	Gauteng	2012	0
1235	South Africa	Gauteng	2014	0
1236	South Africa	Gauteng	2013	0
1237	South Africa	Gauteng	2010	0
1238	South Africa	Gauteng	2009	0
1239	South Africa	Gauteng	2010	0
1240	South Africa	KwaZulu Natal	2008	0

Firm Identifier	Country	Province	Year	default status
1241	South Africa	Eastern Cape	2008	0
1242	South Africa	KwaZulu Natal	2009	1
1243	South Africa	Northern Cape	2010	0
1244	South Africa	Northern Cape	2011	0
1245	South Africa	Northern Cape	2012	0
1246	South Africa	Northern Cape	2013	0
1247	South Africa	Northern Cape	2014	0
1248	South Africa	Northern Cape	2009	0
1249	South Africa	Gauteng	2012	0
1250	South Africa	Gauteng	2014	0
1251	South Africa	Gauteng	2013	0
1252	South Africa	Gauteng	2011	0
1253	South Africa	Gauteng	2010	0
1254	South Africa	Gauteng	2009	1
1255	South Africa	Gauteng	2009	0
1256	South Africa	Gauteng	2010	0
1257	South Africa	Western Cape	2008	0
1258	South Africa	Western Cape	2008	0
1259	South Africa	Western Cape	2009	0
1260	South Africa	Western Cape	2010	1
1261	South Africa	Gauteng	2009	1
1262	South Africa	Eastern Cape	2012	0
1263	South Africa	Eastern Cape	2013	0
1264	South Africa	Eastern Cape	2008	0
1265	South Africa	Eastern Cape	2010	0
1266	South Africa	Eastern Cape	2011	0
1267	South Africa	Eastern Cape	2009	0
1268	South Africa	Gauteng	2009	0
1269	South Africa	Western Cape	2011	0
1270	South Africa	Western Cape	2012	0
1271	South Africa	Western Cape	2013	0
1272	South Africa	Western Cape	2014	0
1273	South Africa	Gauteng	2010	0
1274	South Africa	Gauteng	2009	0
1275	South Africa	Gauteng	2010	0
1276	South Africa	KwaZulu Natal	2011	0
1277	South Africa	KwaZulu Natal	2010	0
1278	South Africa	KwaZulu Natal	2009	0
1279	South Africa	Western Cape	2009	0
1280	South Africa	Gauteng	2009	0
1281	South Africa	KwaZulu Natal	2010	0
1282	South Africa	Free State	2009	0
1283	South Africa	Free State	2010	0
1284	South Africa	Free State	2014	0
1285	South Africa	Free State	2013	0

Firm Identifier	Country	Province	Year	default status
1286	South Africa	Free State	2012	0
1287	South Africa	Free State	2011	0
1288	South Africa	Mpumalanga	2010	0
1289	South Africa	Mpumalanga	2009	0
1290	South Africa	Western Cape	2009	0
1291	South Africa	Gauteng	2009	0
1292	South Africa	Gauteng	2010	0
1293	South Africa	Gauteng	2009	1
1294	South Africa	Eastern Cape	2011	1
1295	South Africa	Eastern Cape	2011	1
1296	South Africa	Limpopo	2012	1
1297	South Africa	Limpopo	2011	0
1298	South Africa	Limpopo	2010	0
1299	South Africa	Limpopo	2009	0
1300	South Africa	Gauteng	2010	0
1301	South Africa	Eastern Cape	2011	0
1302	South Africa	Eastern Cape	2013	0
1303	South Africa	Eastern Cape	2012	0
1304	South Africa	Eastern Cape	2014	1
1305	South Africa	Western Cape	2010	1
1306	South Africa	Western Cape	2009	0
1307	South Africa	KwaZulu Natal	2011	0
1308	South Africa	Gauteng	2010	0
1309	South Africa	Gauteng	2011	0
1310	South Africa	Gauteng	2009	0
1311	South Africa	Gauteng	2013	0
1312	South Africa	Gauteng	2014	0
1313	South Africa	Eastern Cape	2012	0
1314	South Africa	Eastern Cape	2013	0
1315	South Africa	Eastern Cape	2011	0
1316	South Africa	Eastern Cape	2014	1
1317	South Africa	Eastern Cape	2012	0
1318	South Africa	Eastern Cape	2013	0
1319	South Africa	Eastern Cape	2014	1
1320	South Africa	Eastern Cape	2010	0
1321	South Africa	Eastern Cape	2011	0
1322	South Africa	Eastern Cape	2011	0
1323	South Africa	Eastern Cape	2012	1
1324	South Africa	Eastern Cape	2010	0
1325	South Africa	Eastern Cape	2014	1
1326	South Africa	Eastern Cape	2012	0
1327	South Africa	Eastern Cape	2013	0
1328	South Africa	Eastern Cape	2011	0
1329	South Africa	Eastern Cape	2010	0
1330	South Africa	Eastern Cape	2012	1

Firm Identifier	Country	Province	Year	default status
1331	South Africa	Eastern Cape	2011	0
1332	South Africa	Eastern Cape	2010	0
1333	South Africa	Eastern Cape	2013	0
1334	South Africa	Eastern Cape	2014	1
1335	South Africa	Eastern Cape	2011	0
1336	South Africa	Eastern Cape	2010	0
1337	South Africa	Eastern Cape	2012	0
1338	South Africa	Eastern Cape	2011	1
1339	South Africa	Eastern Cape	2014	1
1340	South Africa	Eastern Cape	2013	0
1341	South Africa	Eastern Cape	2011	0
1342	South Africa	Eastern Cape	2010	0
1343	South Africa	Eastern Cape	2012	0
1344	South Africa	Gauteng	2010	0
1345	South Africa	Gauteng	2012	0
1346	South Africa	Gauteng	2013	0
1347	South Africa	Gauteng	2011	0
1348	South Africa	Gauteng	2009	1
1349	South Africa	Gauteng	2008	0
1350	South Africa	Western Cape	2009	0
1351	South Africa	KwaZulu Natal	2009	0
1352	South Africa	KwaZulu Natal	2014	0
1353	South Africa	Gauteng	2009	0
1354	South Africa	Gauteng	2010	0
1355	South Africa	Gauteng	2011	0
1356	South Africa	Gauteng	2012	0
1357	South Africa	KwaZulu Natal	2010	0
1358	South Africa	KwaZulu Natal	2011	1
1359	South Africa	Gauteng	2009	0
1360	South Africa	Gauteng	2011	0
1361	South Africa	Gauteng	2012	0
1362	South Africa	Gauteng	2013	0
1363	South Africa	Gauteng	2009	0
1364	South Africa	Gauteng	2010	0
1365	South Africa	Eastern Cape	2010	0
1366	South Africa	Gauteng	2009	0
1367	South Africa	Gauteng	2011	1
1368	South Africa	Gauteng	2010	0
1369	South Africa	Western Cape	2009	1
1370	South Africa	Gauteng	2011	0
1371	South Africa	Gauteng	2012	0
1372	South Africa	Gauteng	2013	0
1373	South Africa	Gauteng	2014	0
1374	South Africa	Gauteng	2010	0
1375	South Africa	Gauteng	2013	0

Firm Identifier	Country	Province	Year	default status
1376	South Africa	Gauteng	2014	0
1377	South Africa	Gauteng	2011	0
1378	South Africa	Gauteng	2012	0
1379	South Africa	Gauteng	2009	1
1380	South Africa	KwaZulu Natal	2008	0
1381	South Africa	KwaZulu Natal	2009	1
1382	South Africa	KwaZulu Natal	2011	1
1383	South Africa	Western Cape	2009	0
1384	South Africa	Western Cape	2010	0
1385	South Africa	North West	2010	1
1386	South Africa	Gauteng	2010	0
1387	South Africa	Gauteng	2011	0
1388	South Africa	Gauteng	2013	0
1389	South Africa	Gauteng	2012	0
1390	South Africa	Gauteng	2014	0
1391	South Africa	Free State	2008	0
1392	South Africa	Free State	2009	1
1393	South Africa	Eastern Cape	2011	1
1394	South Africa	Gauteng	2011	0
1395	South Africa	Gauteng	2012	0
1396	South Africa	Gauteng	2010	0
1397	South Africa	KwaZulu Natal	2010	0
1398	South Africa	KwaZulu Natal	2011	0
1399	South Africa	Gauteng	2010	0
1400	South Africa	Gauteng	2008	0
1401	South Africa	Gauteng	2009	0
1402	South Africa	Gauteng	2012	1
1403	South Africa	Gauteng	2011	0
1404	South Africa	Gauteng	2010	0
1405	South Africa	Limpopo	2008	1
1406	South Africa	Gauteng	2008	0
1407	South Africa	Gauteng	2009	0
1408	South Africa	Gauteng	2011	0
1409	South Africa	Gauteng	2011	0
1410	South Africa	Free State	2010	0
1411	South Africa	Free State	2011	0
1412	South Africa	Free State	2012	0
1413	South Africa	Gauteng	2011	0
1414	South Africa	Gauteng	2012	0
1415	South Africa	Western Cape	2010	0
1416	South Africa	Western Cape	2011	0
1417	South Africa	Western Cape	2012	0
1418	South Africa	Gauteng	2011	0
1419	South Africa	Gauteng	2012	0
1420	South Africa	Gauteng	2013	0

Firm Identifier	Country	Province	Year	default status
1421	South Africa	Gauteng	2010	0
1422	South Africa	Western Cape	2010	0
1423	South Africa	Western Cape	2011	0
1424	South Africa	Western Cape	2012	0
1425	South Africa	Western Cape	2010	0
1426	South Africa	Eastern Cape	2011	1
1427	South Africa	Eastern Cape	2010	0
1428	South Africa	KwaZulu Natal	2010	1
1429	South Africa	Gauteng	2010	1
1430	South Africa	Gauteng	2008	0
1431	South Africa	Gauteng	2009	1
1432	South Africa	Gauteng	2011	0
1433	South Africa	Gauteng	2012	0
1434	South Africa	Gauteng	2013	0
1435	South Africa	Gauteng	2014	0
1436	South Africa	Gauteng	2010	0
1437	South Africa	Gauteng	2010	0
1438	South Africa	Gauteng	2008	0
1439	South Africa	Gauteng	2011	1
1440	South Africa	Gauteng	2012	1
1441	South Africa	Gauteng	2009	0
1442	South Africa	Gauteng	2010	0
1443	South Africa	Gauteng	2011	0
1444	South Africa	Free State	2011	0
1445	South Africa	Western Cape	2011	0
1446	South Africa	Western Cape	2012	1
1447	South Africa	Gauteng	2012	0
1448	South Africa	Gauteng	2011	0
1449	South Africa	Gauteng	2013	0
1450	South Africa	Gauteng	2013	0
1451	South Africa	Eastern Cape	2011	0
1452	South Africa	Eastern Cape	2013	1
1453	South Africa	Eastern Cape	2012	0
1454	South Africa	Eastern Cape	2013	1
1455	South Africa	Eastern Cape	2012	0
1456	South Africa	Gauteng	2011	0
1457	South Africa	Gauteng	2012	0
1458	South Africa	Eastern Cape	2012	1
1459	South Africa	Western Cape	2013	1
1460	South Africa	Western Cape	2012	0
1461	South Africa	Gauteng	2011	0
1462	South Africa	Gauteng	2012	0
1463	South Africa	Gauteng	2010	0
1464	South Africa	Gauteng	2011	0
1465	South Africa	KwaZulu Natal	2013	0

Firm Identifier	Country	Province	Year	default status
1466	South Africa	KwaZulu Natal	2014	0
1467	South Africa	KwaZulu Natal	2012	0
1468	South Africa	Mpumalanga	2009	1
1469	South Africa	Gauteng	2012	0
1470	South Africa	Gauteng	2011	0
1471	South Africa	Gauteng	2013	0
1472	South Africa	Gauteng	2010	0
1473	South Africa	Gauteng	2010	0
1474	South Africa	Gauteng	2011	0
1475	South Africa	Gauteng	2012	0
1476	South Africa	Gauteng	2013	0
1477	South Africa	Gauteng	2011	0
1478	South Africa	Gauteng	2012	0
1479	South Africa	Gauteng	2013	1
1480	South Africa	Gauteng	2010	1
1481	South Africa	Gauteng	2012	1
1482	South Africa	Gauteng	2011	0
1483	South Africa	Gauteng	2010	0
1484	South Africa	North West	2010	1
1485	South Africa	North West	2009	0
1486	South Africa	Gauteng	2010	1
1487	South Africa	Mpumalanga	2012	1
1488	South Africa	Mpumalanga	2011	0
1489	South Africa	Gauteng	2012	0
1490	South Africa	Gauteng	2014	0
1491	South Africa	Gauteng	2013	0
1492	South Africa	Western Cape	2012	0
1493	South Africa	Western Cape	2014	0
1494	South Africa	Western Cape	2013	0
1495	South Africa	Gauteng	2011	1
1496	South Africa	North West	2012	1
1497	South Africa	Gauteng	2013	1
1498	South Africa	Gauteng	2012	0
1499	South Africa	Gauteng	2011	0
1500	South Africa	Western Cape	2011	0
1501	South Africa	Western Cape	2012	0
1502	South Africa	Western Cape	2010	0
1503	South Africa	Western Cape	2014	0
1504	South Africa	Western Cape	2013	0
1505	South Africa	Northern Cape	2012	0
1506	South Africa	Northern Cape	2013	0
1507	South Africa	Northern Cape	2014	0
1508	South Africa	Northern Cape	2011	0
1509	South Africa	Gauteng	2014	0
1510	South Africa	Gauteng	2013	0
1511	South Africa	Gauteng	2012	0
1512	South Africa	Gauteng	2011	0
1513	South Africa	Gauteng	2012	0
1514	South Africa	Gauteng	2013	0
1515	South Africa	Gauteng	2011	0
1516	South Africa	Gauteng	2011	0
1517	South Africa	Gauteng	2012	0
1518	South Africa	Gauteng	2013	0
1519	South Africa	Western Cape	2012	0
1520	South Africa	Western Cape	2013	0

Firm Identifier	Country	Province	Year	default status
1521	South Africa	Western Cape	2014	0
1522	South Africa	Eastern Cape	2011	0
1523	South Africa	Eastern Cape	2010	0
1524	South Africa	Eastern Cape	2012	1
1525	South Africa	Western Cape	2012	0
1526	South Africa	Western Cape	2014	0
1527	South Africa	Western Cape	2013	0
1528	South Africa	Western Cape	2011	0
1529	South Africa	KwaZulu Natal	2013	0
1530	South Africa	KwaZulu Natal	2014	0
1531	South Africa	Gauteng	2012	0
1532	South Africa	Gauteng	2011	0
1533	South Africa	Western Cape	2011	1
1534	South Africa	KwaZulu Natal	2012	0
1535	South Africa	KwaZulu Natal	2013	0
1536	South Africa	KwaZulu Natal	2011	0
1537	South Africa	KwaZulu Natal	2014	0
1538	South Africa	Western Cape	2011	1
1539	South Africa	Western Cape	2011	0
1540	South Africa	Western Cape	2014	0
1541	South Africa	Western Cape	2012	0
1542	South Africa	Western Cape	2013	0
1543	South Africa	KwaZulu Natal	2014	0
1544	South Africa	Gauteng	2012	1
1545	South Africa	Gauteng	2012	1
1546	South Africa	North West	2012	1
1547	South Africa	KwaZulu Natal	2014	0
1548	South Africa	KwaZulu Natal	2013	0
1549	South Africa	KwaZulu Natal	2012	0
1550	South Africa	Gauteng	2012	1
1551	South Africa	Western Cape	2012	1
1552	South Africa	KwaZulu Natal	2012	0
1553	South Africa	Mpumalanga	2012	1
1554	South Africa	Mpumalanga	2012	0
1555	South Africa	Mpumalanga	2013	1
1556	South Africa	KwaZulu Natal	2014	0
1557	South Africa	KwaZulu Natal	2013	0
1558	South Africa	Mpumalanga	2012	0
1559	South Africa	Mpumalanga	2014	1
1560	South Africa	Mpumalanga	2013	0
1561	South Africa	Mpumalanga	2012	0
1562	South Africa	Mpumalanga	2013	0
1563	South Africa	Mpumalanga	2014	0
1564	South Africa	Gauteng	2012	0
1565	South Africa	Gauteng	2013	1

Table 21: Raw Data - Assets and Liabilities

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1000	R 17 817 901	R 29 453 955	R 12 579 073	R 17 103 008	R 5 238 828
1001	R 3 943 867	R 11 800 524	R 3 943 867	R 5 449 986	R 0
1002	R 8 358 631	R 13 976 886	R 4 765 992	R 7 213 146	R 3 592 639
1003	R 9 679 971	R 17 647 358	R 6 297 852	R 10 660 941	R 3 382 119
1004	R 14 635 370	R 26 058 880	R 7 029 464	R 13 808 142	R 7 605 906
1005	R 13 880 296	R 23 329 965	R 6 002 815	R 12 104 498	R 7 877 481
1006	R 72 726 000	R 175 930 000	R 65 817 000	R 123 639 000	R 6 909 000
1007	R 62 383 000	R 167 501 000	R 56 363 000	R 125 251 000	R 6 020 000
1008	R 22 033 629	R 60 503 838	R 22 033 629	R 42 197 313	R 0
1009	R 19 998 782	R 63 680 337	R 19 998 782	R 47 837 552	R 0
1010	R 17 712 040	R 65 680 036	R 17 712 040	R 45 554 447	R 0
1011	R 6 091 690	R 13 151 758	R 3 565 925	R 1 076 677	R 2 525 765
1012	R 5 719 873	R 12 937 852	R 3 885 005	R 1 542 508	R 1 834 868
1013	R 2 985 189	R 4 640 165	R 1 002 244	R 135 140	R 1 982 945
1014	R 181 268 454	R 374 911 030	R 155 224 347	R 253 066 286	R 26 044 107
1015	R 181 268 454	R 374 911 030	R 155 224 347	R 253 066 286	R 26 044 107
1016	R 1 582 530	R 5 263 235	R 1 582 530	R 5 174 774	R 0
1017	R 25 676	R 6 929 243	R 25 676	R 5 854 104	R 0
1018	R 25 676	R 6 929 243	R 25 676	R 5 854 104	R 0
1019	R 4 825 401	R 21 736 320	R 4 825 401	R 762 335	R 0
1020	R 11 246 601	R 21 172 095	R 4 291 150	R 900 424	R 6 955 451
1021	R 8 742 865	R 20 971 743	R 2 013 042	R 883 733	R 6 729 823
1022	R 5 305 621	R 15 399 915	R 3 518 121	R 13 557 536	R 1 787 500
1023	R 5 305 621	R 15 399 915	R 3 518 121	R 13 557 536	R 1 787 500
1024	R 6 432 171	R 16 429 662	R 3 457 171	R 14 300 398	R 2 975 000
1025	R 10 471 252	R 12 379 818	R 2 285 310	R 11 135 066	R 8 185 942
1026	R 1 847 659	R 11 878 568	R 1 847 659	R 10 733 542	R 0
1027	R 2 266 349	R 12 737 358	R 1 563 164	R 1 808 875	R 703 185
1028	R 53 315 858	R 115 109 741	R 19 717 172	R 8 039 021	R 33 598 686
1029	R 43 394 956	R 94 552 990	R 13 851 064	R 12 818 493	R 29 543 892
1030	R 1 970 940	R 5 176 000	R 0	R 0	R 1 970 940
1031	R 1 970 940	R 5 176 000	R 0	R 0	R 1 970 940
1032	R 453 607	R 2 143 195	R 433 989	R 273 298	R 19 618
1033	R 453 607	R 2 143 195	R 433 989	R 273 298	R 19 618
1034	R 451 069	R 2 108 235	R 425 920	R 323 097	R 25 149
1035	R 446 754	R 1 848 307	R 419 863	R 325 391	R 26 891
1036	R 668 589	R 1 974 699	R 658 629	R 636 575	R 9 960
1037	R 3 298 042	R 4 628 873	R 2 647 601	R 223 457	R 650 441
1038	R 56 014 451	R 330 716 404	R 52 310 731	R 107 656 435	R 3 703 720
1039	R 330 397 766	R 202 601 767	R 330 397 766	R 144 527 406	R 0
1040	R 11 127 335	R 13 107 268	R 9 898 454	R 7 528 851	R 1 228 881

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1041	R 1 419 601	R 14 027 973	R 1 419 601	R 1 047 074	R 0
1042	R 1 117 367	R 32 282 233	R 1 117 367	R 2 881 115	R 0
1043	R 7 700 012	R 22 696 481	R 7 700 012	R 12 698 292	R 0
1044	R 4 910 510	R 22 116 467	R 2 535 510	R 11 845 692	R 2 375 000
1045	R 8 931 021	R 19 050 377	R 2 383 370	R 14 740 251	R 6 547 651
1046	R 2 615 574	R 19 321 231	R 1 740 574	R 14 684 868	R 875 000
1047	R 6 903 314	R 17 781 373	R 1 355 663	R 13 325 108	R 5 547 651
1048	R 3 696 657	R 18 245 221	R 571 657	R 14 006 546	R 3 125 000
1049	R 17 886 058	R 19 989 961	R 2 480 543	R 3 743 400	R 15 405 515
1050	R 2 006 979	R 19 047 011	R 727 951	R 1 741 693	R 1 279 028
1051	R 19 780 130	R 25 579 529	R 19 780 130	R 5 345 244	R 0
1052	R 14 933 691	R 21 764 706	R 14 933 691	R 4 172 371	R 0
1053	R 11 378 387	R 28 796 892	R 5 971 175	R 6 059 608	R 5 407 212
1054	R 11 378 387	R 28 796 892	R 5 971 175	R 6 059 608	R 5 407 212
1055	R 5 567 261	R 32 334 034	R 4 433 561	R 7 933 076	R 1 133 700
1056	R 24 706 061	R 26 638 697	R 24 706 061	R 7 419 501	R 0
1057	R 11 799 805	R 79 188 441	R 7 990 096	R 7 606 671	R 3 809 709
1058	R 11 799 805	R 79 188 441	R 7 990 096	R 7 606 671	R 3 809 709
1059	R 11 799 805	R 79 188 441	R 7 990 096	R 7 606 671	R 3 809 709
1060	R 16 111 137	R 78 096 559	R 13 266 357	R 14 919 381	R 2 844 780
1061	R 20 015 494	R 91 375 764	R 15 573 148	R 19 172 287	R 4 442 346
1062	R 3 979 458	R 52 353 485	R 3 979 458	R 6 607 648	R 0
1063	R 5 736 616	R 8 142 536	R 5 536 662	R 1 828 359	R 199 954
1064	R 5 251 433	R 4 640 999	R 3 785 298	R 2 655 198	R 1 466 135
1065	R 364 905 982	R 672 432 831	R 108 702 341	R 47 870 768	R 256 203 641
1066	R 2 715 580	R 8 057 335	R 1 588 814	R 1 549 252	R 1 126 766
1067	R 1 826 280	R 14 743 000	R 804 563	R 1 433 029	R 1 021 717
1068	R 14 408 168	R 14 281 555	R 12 155 422	R 10 925 666	R 2 252 746
1069	R 17 171 340	R 17 162 576	R 9 899 292	R 13 574 222	R 7 272 048
1070	R 10 638 335	R 40 394 382	R 10 638 335	R 18 634 502	R 0
1071	R 9 191 757	R 36 547 672	R 8 750 962	R 18 167 054	R 440 795
1072	R 9 975 516	R 43 662 384	R 9 187 213	R 20 536 572	R 788 303
1073	R 15 715 073	R 15 550 624	R 5 909 067	R 3 156 674	R 9 806 006
1074	R 13 868 421	R 14 970 925	R 5 698 447	R 3 981 234	R 8 169 974
1075	R 31 262 000	R 57 105 000	R 26 119 000	R 43 296 000	R 5 143 000
1076	R 32 280 000	R 62 867 000	R 26 351 000	R 44 030 000	R 5 929 000
1077	R 27 126 627	R 61 484 770	R 23 513 182	R 39 678 261	R 3 613 445
1078	R 24 427 383	R 58 110 362	R 22 613 656	R 43 866 818	R 1 813 727
1079	R 19 008 220	R 53 860 550	R 17 325 261	R 36 821 065	R 1 682 959
1080	R 18 377 596	R 51 072 502	R 14 486 995	R 36 932 474	R 3 890 601

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1081	R 1 070 911	R 14 347 516	R 817 651	R 165 017	R 253 260
1082	R 26 114 439	R 294 672 559	R 17 949 576	R 14 643 617	R 8 164 863
1083	R 26 114 439	R 294 672 559	R 17 949 576	R 14 643 617	R 8 164 863
1084	R 26 114 439	R 294 672 559	R 17 949 576	R 14 643 617	R 8 164 863
1085	R 26 114 439	R 294 672 559	R 17 949 576	R 14 643 617	R 8 164 863
1086	R 25 677 186	R 268 386 825	R 16 910 320	R 34 613 854	R 8 766 866
1087	R 11 533 050	R 18 487 264	R 10 590 022	R 13 277 552	R 943 028
1088	R 20 229 730	R 43 983 940	R 17 556 080	R 39 731 772	R 2 673 650
1089	R 15 207 049	R 40 688 917	R 13 959 406	R 37 335 261	R 1 247 643
1090	R 918 964	R 20 270 090	R 918 964	R 215 574	R 0
1091	R 74 073 296	R 114 644 813	R 12 503 320	R 8 409 972	R 61 569 976
1092	R 69 538 950	R 107 519 408	R 11 779 161	R 8 518 090	R 57 759 789
1093	R 110 160 755	R 356 458 766	R 82 611 132	R 97 317 304	R 27 549 623
1094	R 132 439 860	R 430 223 327	R 97 498 134	R 121 414 967	R 34 941 726
1095	R 3 709 125	R 8 079 431	R 3 589 182	R 994 564	R 119 943
1096	R 3 685 794	R 9 212 388	R 3 146 288	R 1 640 465	R 539 506
1097	R 3 685 794	R 9 212 388	R 3 146 288	R 1 640 465	R 539 506
1098	R 1 944 406	R 8 635 181	R 1 603 920	R 1 483 881	R 340 486
1099	R 22 181 272	R 28 499 290	R 1 360 872	R 2 377 526	R 20 820 400
1100	R 7 773 490	R 16 250 656	R 7 773 490	R 7 199 160	R 0
1101	R 7 773 490	R 16 250 656	R 7 773 490	R 7 199 160	R 0
1102	R 2 829 587	R 6 230 883	R 45 439	R 289 686	R 2 784 148
1103	R 2 145 639	R 6 276 388	R 48 827	R 335 191	R 2 096 812
1104	R 4 510 299	R 8 645 641	R 4 510 299	R 6 767 959	R 0
1105	R 4 286 133	R 8 988 779	R 4 286 133	R 7 101 365	R 0
1106	R 4 187 989	R 9 293 184	R 4 184 969	R 8 026 631	R 3 020
1107	R 1 687 151	R 3 730 272	R 1 687 151	R 1 880 930	R 0
1108	R 2 792 936	R 5 235 548	R 2 790 614	R 3 591 412	R 2 322
1109	R 1 559 261	R 3 068 407	R 1 273 930	R 1 691 903	R 285 331
1110	R 1 576 617	R 3 917 456	R 1 576 400	R 2 149 503	R 217
1111	R 94 968	R 2 265 551	R 94 968	R 64 971	R 0
1112	R 111 847	R 2 290 884	R 111 847	R 147 640	R 0
1113	R 48 583	R 178 561	R 42 647	R 83 925	R 5 936
1114	R 8 699 654	R 29 030 628	R 5 732 524	R 31 298	R 2 967 130
1115	R 10 282 894	R 29 257 660	R 5 991 898	R 164 370	R 4 290 996
1116	R 21 811 156	R 43 301 828	R 14 507 335	R 11 485 388	R 7 303 821
1117	R 15 043 830	R 38 055 257	R 9 917 895	R 9 200 024	R 5 125 935
1118	R 29 279 653	R 58 870 905	R 19 270 470	R 22 432 344	R 10 009 183
1119	R 18 082 255	R 42 725 330	R 15 964 357	R 21 620 970	R 2 117 898
1120	R 25 804 980	R 53 931 818	R 19 134 686	R 25 981 814	R 6 670 294

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1121	R 42 755 534	R 73 478 403	R 23 279 844	R 37 089 950	R 19 475 690
1122	R 1 020 913	R 33 100 606	R 1 020 913	R 395 980	R 0
1123	R 3 699 645	R 32 192 972	R 1 062 489	R 648 583	R 2 637 156
1124	R 10 889 774	R 34 673 063	R 1 261 052	R 1 012 614	R 9 628 722
1125	R 826 423	R 8 647 841	R 826 423	R 224 400	R 0
1126	R 3 983 104	R 13 682 986	R 3 983 104	R 7 740 607	R 0
1127	R 3 031 839	R 13 585 323	R 3 031 839	R 2 399 408	R 0
1128	R 3 272 115	R 18 467 106	R 3 272 115	R 2 780 710	R 0
1129	R 2 069 558	R 20 220 560	R 2 069 558	R 2 118 396	R 0
1130	R 391 598	R 13 282 572	R 391 598	R 2 713 622	R 0
1131	R 302 535	R 13 133 250	R 302 535	R 3 225 572	R 0
1132	R 235 089	R 13 726 249	R 235 089	R 4 149 461	R 0
1133	R 109 014	R 5 443 798	R 109 014	R 2 293 942	R 0
1134	R 15 741 823	R 42 799 002	R 6 364 363	R 693 009	R 9 377 460
1135	R 7 441 124	R 13 643 458	R 5 987 628	R 4 693 767	R 1 453 496
1136	R 8 929 311	R 21 499 799	R 8 105 311	R 10 760 424	R 824 000
1137	R 6 260 950	R 23 228 727	R 2 944 950	R 8 265 015	R 3 316 000
1138	R 5 575 603	R 20 004 248	R 3 282 034	R 629 833	R 2 293 569
1139	R 8 630 664	R 23 104 731	R 4 659 033	R 2 970 772	R 3 971 631
1140	R 63 697	R 12 480 143	R 63 697	R 213 006	R 0
1141	R 89 251	R 375 092	R 63 660	R 95 683	R 25 591
1142	R 35 653 001	R 99 623 712	R 35 653 001	R 42 992 002	R 0
1143	R 60 626 779	R 103 243 654	R 50 120 591	R 62 226 854	R 10 506 188
1144	R 45 721 403	R 79 861 685	R 32 049 790	R 46 530 727	R 13 671 613
1145	R 40 383 079	R 82 885 418	R 30 320 363	R 45 536 863	R 10 062 716
1146	R 13 785 073	R 15 170 608	R 8 418 091	R 8 618 911	R 5 366 982
1147	R 134 267 726	R 229 530 352	R 78 156 995	R 50 559 498	R 56 110 731
1148	R 957 907	R 841 538	R 579 428	R 549 297	R 378 479
1149	R 1 568 443	R 1 347 820	R 670 883	R 877 910	R 897 560
1150	R 4 609 724	R 34 194 065	R 4 609 724	R 9 641 507	R 0
1151	R 4 828 757	R 28 550 047	R 4 828 757	R 11 088 997	R 0
1152	R 5 456 297	R 31 501 134	R 5 456 297	R 13 811 306	R 0
1153	R 3 505 977	R 13 519 753	R 3 505 977	R 12 012 119	R 0
1154	R 1 723 434	R 29 859 376	R 1 723 434	R 11 526 444	R 0
1155	R 2 869 113	R 1 001 130	R 851 960	R 11 280	R 2 017 153
1156	R 2 126 706	R 2 010 997	R 786 521	R 1 072 612	R 1 340 185
1157	R 1 688 473	R 7 132 130	R 958 284	R 5 751 547	R 730 189
1158	R 122 333	R 165 572	R 34 501	R 43 414	R 87 832
1159	R 62 046 770	R 95 740 592	R 14 104 714	R 22 941 404	R 47 942 056
1160	R 50 608 164	R 86 856 974	R 12 224 699	R 20 082 662	R 38 383 465

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1161	R 50 608 164	R 86 856 974	R 12 224 699	R 20 082 662	R 38 383 465
1162	R 50 608 164	R 86 856 974	R 12 224 699	R 20 082 662	R 38 383 465
1163	R 60 425 115	R 93 009 974	R 8 152 822	R 19 598 793	R 52 272 293
1164	R 4 093 127	R 7 199 066	R 2 571 970	R 2 489 878	R 1 521 157
1165	R 4 518 410	R 6 018 045	R 3 101 116	R 3 044 221	R 1 417 294
1166	R 5 544 221	R 8 871 854	R 1 910 167	R 4 679 354	R 3 634 054
1167	R 1 702 299	R 4 762 140	R 627 066	R 520 056	R 1 075 233
1168	R 2 025 638	R 5 179 304	R 521 290	R 715 372	R 1 504 348
1169	R 1 725 009	R 4 150 601	R 1 370 443	R 2 261 347	R 354 566
1170	R 3 633 563	R 12 169 382	R 3 633 563	R 9 129 516	R 0
1171	R 100 253	R 363 965	R 48 206	R 13 426	R 52 047
1172	R 61 967	R 255 967	R 17 933	R 11 495	R 44 034
1173	R 38 731 791	R 72 172 937	R 34 459 474	R 35 845 744	R 4 272 317
1174	R 51 209 423	R 188 975 547	R 47 363 449	R 101 701 061	R 3 845 974
1175	R 33 907 512	R 133 416 513	R 33 907 512	R 76 193 778	R 0
1176	R 15 370 434	R 49 236 315	R 9 622 060	R 22 519 523	R 5 748 374
1177	R 55 248 000	R 224 156 000	R 55 248 000	R 129 552 000	R 0
1178	R 44 072	R 232 936	R 44 072	R 133 526	R 0
1179	R 11 721 291	R 17 201 818	R 8 334 454	R 11 745 330	R 3 386 837
1180	R 3 158 367	R 19 654 395	R 3 158 367	R 1 031 569	R 0
1181	R 5 624 840	R 19 422 553	R 3 055 245	R 1 376 445	R 2 569 595
1182	R 12 762 464	R 28 846 566	R 3 696 374	R 1 872 372	R 9 066 090
1183	R 2 630 176	R 5 618 500	R 1 255 226	R 2 292 405	R 1 374 950
1184	R 1 674 041	R 4 276 553	R 831 445	R 1 721 485	R 842 596
1185	R 1 734 739	R 5 072 557	R 859 829	R 2 113 749	R 874 910
1186	R 896 328	R 2 169 422	R 791 604	R 960 973	R 104 724
1187	R 1 572 110	R 13 536 387	R 1 572 110	R 1 086 957	R 0
1188	R 16 296 822	R 18 882 191	R 11 871 033	R 349 283	R 4 425 789
1189	R 6 477 397	R 20 843 015	R 1 088 704	R 231 257	R 5 388 693
1190	R 6 477 397	R 20 843 015	R 1 088 704	R 231 257	R 5 388 693
1191	R 6 477 397	R 20 843 015	R 1 088 704	R 231 257	R 5 388 693
1192	R 19 876 572	R 36 192 595	R 13 792 560	R 8 738 460	R 6 084 012
1193	R 11 208 689	R 26 613 279	R 10 196 538	R 8 101 403	R 1 012 151
1194	R 17 455 825	R 27 589 891	R 9 462 309	R 8 308 632	R 7 993 516
1195	R 11 018 361	R 23 789 747	R 7 776 447	R 7 183 358	R 3 241 914
1196	R 10 870 627	R 20 173 768	R 6 345 772	R 7 873 981	R 4 524 855
1197	R 6 052 000	R 12 694 000	R 4 581 000	R 5 770 000	R 1 471 000
1198	R 13 678 493	R 24 903 889	R 7 923 292	R 11 467 572	R 5 755 201
1199	R 8 641 475	R 12 418 939	R 8 195 353	R 9 428 082	R 446 122
1200	R 1 030 613	R 3 047 640	R 1 030 613	R 1 123 246	R 0

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1201	R 2 135 835	R 5 579 225	R 1 426 885	R 2 563 213	R 708 950
1202	R 1 156 224	R 3 819 559	R 473 724	R 552	R 682 500
1203	R 9 152 972	R 17 355 547	R 6 545 512	R 8 526 534	R 2 607 460
1204	R 963 589	R 790 705	R 179 828	R 329 580	R 783 761
1205	R 963 589	R 790 705	R 179 828	R 329 580	R 783 761
1206	R 453 404	R 555 959	R 81 916	R 503 257	R 371 488
1207	R 2 865 216	R 5 352 979	R 99 276	R 178 536	R 2 765 940
1208	R 2 865 216	R 5 352 979	R 99 276	R 178 536	R 2 765 940
1209	R 2 865 216	R 5 352 979	R 99 276	R 178 536	R 2 765 940
1210	R 821 980	R 925 554	R 215 995	R 515 552	R 605 985
1211	R 1 090 105	R 1 259 808	R 250 105	R 28 641	R 840 000
1212	R 3 419 902	R 3 885 092	R 436 508	R 63 673	R 2 983 394
1213	R 2 711 785	R 3 190 858	R 761 891	R 172 974	R 1 949 894
1214	R 20 995 318	R 45 057 275	R 5 343 787	R 6 949 630	R 15 651 531
1215	R 25 524 630	R 130 817 382	R 4 915 112	R 7 119 942	R 20 609 518
1216	R 1 852 765	R 3 343 040	R 817 750	R 738 948	R 1 035 015
1217	R 1 852 765	R 3 343 040	R 817 750	R 738 948	R 1 035 015
1218	R 1 212 869	R 8 585 705	R 296 895	R 183 512	R 915 974
1219	R 1 541 223	R 8 302 504	R 302 210	R 475 714	R 1 239 013
1220	R 3 276 098	R 3 002 595	R 1 286 560	R 2 284 907	R 1 989 538
1221	R 8 740 582	R 27 573 969	R 7 942 775	R 9 431 209	R 797 807
1222	R 31 196 140	R 39 016 355	R 23 218 352	R 28 257 254	R 7 977 788
1223	R 10 580 866	R 14 727 608	R 8 965 461	R 11 547 359	R 1 615 405
1224	R 17 442 364	R 22 380 958	R 13 901 354	R 18 743 860	R 3 541 010
1225	R 31 262 340	R 38 215 340	R 20 208 581	R 27 623 343	R 11 053 759
1226	R 8 448 787	R 12 782 542	R 6 688 348	R 9 167 886	R 1 760 439
1227	R 7 960 636	R 14 728 575	R 6 013 160	R 10 429 391	R 1 947 476
1228	R 452 308	R 1 357 778	R 179 097	R 614 856	R 273 211
1229	R 452 308	R 1 357 778	R 179 097	R 614 856	R 273 211
1230	R 452 308	R 1 357 778	R 179 097	R 614 856	R 273 211
1231	R 402 791	R 595 865	R 142 291	R 253 743	R 260 500
1232	R 3 952 509	R 6 880 972	R 3 952 509	R 1 328 972	R 0
1233	R 2 573 084	R 4 586 748	R 2 573 084	R 1 035 876	R 0
1234	R 4 051 810	R 7 804 371	R 4 051 810	R 1 892 737	R 0
1235	R 5 626 058	R 13 231 017	R 5 626 058	R 2 755 023	R 0
1236	R 3 955 096	R 9 708 982	R 3 955 096	R 2 808 469	R 0
1237	R 2 970 526	R 5 504 385	R 2 970 526	R 2 143 831	R 0
1238	R 1 554 388	R 2 911 793	R 1 306 492	R 2 644 725	R 247 896
1239	R 1 736 178	R 3 607 936	R 1 528 355	R 3 340 533	R 207 823
1240	R 369 216	R 569 103	R 236 616	R 162 358	R 132 600

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1241	R 60 104 138	R 93 259 315	R 11 687 478	R 12 588 846	R 48 416 660
1242	R 884 664	R 1 063 399	R 496 964	R 537 319	R 387 700
1243	R 18 289 880	R 57 991 504	R 6 020 789	R 597 655	R 12 269 091
1244	R 39 561 743	R 76 687 754	R 8 323 489	R 1 124 294	R 31 238 254
1245	R 39 561 743	R 76 687 754	R 8 323 489	R 1 124 294	R 31 238 254
1246	R 39 561 743	R 76 687 754	R 8 323 489	R 1 124 294	R 31 238 254
1247	R 63 976 475	R 145 665 777	R 14 578 288	R 7 631 170	R 49 398 187
1248	R 8 981 129	R 12 848 154	R 4 235 901	R 2 494 219	R 4 745 228
1249	R 63 813 127	R 85 214 613	R 46 730 027	R 59 038 504	R 17 083 100
1250	R 89 867 044	R 136 690 290	R 82 352 702	R 119 945 092	R 7 514 342
1251	R 68 062 959	R 104 299 982	R 55 879 909	R 86 138 807	R 12 183 050
1252	R 38 509 864	R 85 425 810	R 37 990 692	R 64 164 510	R 519 172
1253	R 35 131 055	R 86 059 957	R 34 883 513	R 66 731 485	R 247 542
1254	R 635 145	R 824 383	R 223 215	R 624 868	R 411 930
1255	R 19 285 000	R 27 778 000	R 16 441 000	R 21 123 000	R 2 844 000
1256	R 20 299 000	R 31 187 000	R 15 103 000	R 24 556 000	R 5 196 000
1257	R 764 808	R 1 101 838	R 453 608	R 330 878	R 311 200
1258	R 3 360 034	R 3 550 703	R 2 136 030	R 1 656 073	R 1 224 004
1259	R 4 124 835	R 3 411 074	R 1 906 002	R 1 924 509	R 2 218 833
1260	R 7 045 445	R 5 962 730	R 5 106 754	R 5 200 106	R 1 938 691
1261	R 770 573	R 1 367 320	R 227 476	R 1 206 356	R 543 097
1262	R 127 797 804	R 174 572 438	R 113 735 685	R 105 568 824	R 14 062 119
1263	R 133 051 551	R 182 413 948	R 121 684 309	R 125 679 784	R 11 367 242
1264	R 42 790 000	R 69 033 000	R 36 285 000	R 44 029 000	R 6 505 000
1265	R 86 781 328	R 133 014 182	R 56 480 738	R 69 492 476	R 30 300 590
1266	R 110 973 678	R 170 275 270	R 89 489 058	R 114 231 981	R 21 484 620
1267	R 85 305 000	R 120 430 000	R 49 304 000	R 75 113 000	R 36 001 000
1268	R 439 151	R 1 065 414	R 167 912	R 678 414	R 271 239
1269	R 83 652 399	R 114 470 544	R 52 191 876	R 42 228 280	R 31 460 523
1270	R 36 402 164	R 152 030 534	R 9 540 554	R 57 087 384	R 26 861 610
1271	R 36 402 164	R 152 030 534	R 9 540 554	R 57 087 384	R 26 861 610
1272	R 36 402 164	R 152 030 534	R 9 540 554	R 57 087 384	R 26 861 610
1273	R 436 811	R 4 157 602	R 436 811	R 1 312 581	R 0
1274	R 3 301 258	R 1 858 483	R 3 301 258	R 1 393 031	R 0
1275	R 2 528 402	R 1 630 325	R 2 528 402	R 1 384 768	R 0
1276	R 995 536	R 727 627	R 345 536	R 313 331	R 650 000
1277	R 1 277 818	R 1 044 573	R 327 818	R 336 414	R 950 000
1278	R 1 529 246	R 1 758 137	R 279 246	R 713 416	R 1 250 000
1279	R 916 191	R 1 148 997	R 505 591	R 287 079	R 410 600
1280	R 543 350	R 592 184	R 328 204	R 168 209	R 215 146
1281	R 3 625 140	R 6 098 845	R 2 728 284	R 4 302 335	R 896 856
1282	R 1 814 006	R 3 222 391	R 371 759	R 1 378 247	R 1 442 247
1283	R 1 347 100	R 3 097 853	R 185 857	R 1 386 147	R 1 161 243
1284	R 357 139	R 3 250 005	R 155 939	R 2 180 768	R 201 200
1285	R 424 185	R 3 080 199	R 105 954	R 2 037 711	R 318 231

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1286	R 749 661	R 2 979 098	R 86 586	R 1 665 817	R 663 075
1287	R 937 221	R 3 004 002	R 56 982	R 1 528 401	R 880 239
1288	R 13 238 822	R 14 871 683	R 11 242 982	R 10 657 224	R 1 995 840
1289	R 13 159 500	R 14 315 578	R 9 620 667	R 9 206 220	R 3 538 833
1290	R 4 709 232	R 6 933 465	R 4 709 232	R 875 470	R 0
1291	R 54 453	R 1 071 839	R 54 453	R 496 139	R 0
1292	R 54 453	R 1 071 839	R 54 453	R 496 139	R 0
1293	R 3 870 869	R 3 336 661	R 1 014 086	R 952 755	R 2 856 783
1294	R 16 086 105	R 11 848 507	R 12 305 651	R 3 125 549	R 3 780 454
1295	R 15 458 404	R 11 682 762	R 10 237 904	R 3 125 549	R 5 220 500
1296	R 4 226 348	R 5 066 750	R 4 226 348	R 2 227 105	R 0
1297	R 4 510 927	R 6 652 533	R 4 510 927	R 2 931 758	R 0
1298	R 3 552 746	R 7 304 139	R 3 552 746	R 3 164 666	R 0
1299	R 3 109 565	R 6 545 941	R 3 109 565	R 2 935 421	R 0
1300	R 5 218 334	R 6 623 346	R 4 617 738	R 3 726 651	R 600 596
1301	R 101 910 682	R 766 897 988	R 101 910 682	R 16 143 146	R 0
1302	R 63 726 650	R 788 643 435	R 63 726 650	R 16 500 276	R 0
1303	R 82 327 511	R 765 757 710	R 82 327 511	R 33 532 305	R 0
1304	R 78 620 518	R 815 073 442	R 78 620 518	R 88 393 767	R 0
1305	R 2 833 986	R 3 587 724	R 2 833 986	R 1 341 290	R 0
1306	R 2 833 986	R 3 587 724	R 2 833 986	R 1 341 290	R 0
1307	R 259 181	R 2 076 623	R 259 181	R 1 079 643	R 0
1308	R 2 951 799	R 3 214 504	R 1 485 135	R 1 156 299	R 1 466 664
1309	R 2 433 210	R 4 335 626	R 1 769 509	R 1 674 968	R 663 701
1310	R 12 816 284	R 27 109 440	R 12 816 284	R 21 562 940	R 0
1311	R 839 884	R 1 023 536	R 389 884	R 823 671	R 450 000
1312	R 842 061	R 1 446 452	R 542 061	R 1 297 386	R 300 000
1313	R 2 189 532	R 2 126 239	R 998 750	R 300	R 1 190 782
1314	R 3 570 301	R 1 728 119	R 967 988	R 338	R 2 602 313
1315	R 1 939 561	R 2 258 720	R 27 547	R 10	R 1 912 014
1316	R 4 212 968	R 1 789 470	R 1 052 375	R 3 535	R 3 160 593
1317	R 2 065 709	R 2 498 529	R 1 020 475	R 300	R 1 045 234
1318	R 3 177 376	R 2 175 361	R 1 086 306	R 671	R 2 091 070
1319	R 4 225 851	R 2 366 521	R 204 128	R 17 162	R 4 021 723
1320	R 1 212 250	R 2 578 439	R 5 600	R 30 427	R 1 206 650
1321	R 1 546 416	R 2 504 192	R 1 447	R 12 755	R 1 544 969
1322	R 717 462	R 1 868 008	R 37 645	R 0	R 679 817
1323	R 1 215 514	R 2 152 118	R 521 863	R 290	R 693 651
1324	R 616 008	R 1 831 565	R 17 793	R 93 507	R 598 215
1325	R 3 361 127	R 1 080 128	R 1 143 937	R 26 954	R 2 217 190
1326	R 1 850 506	R 1 080 803	R 992 679	R 34 467	R 857 827
1327	R 2 576 634	R 1 110 339	R 767 230	R 27 910	R 1 809 404
1328	R 743 698	R 765 827	R 9 100	R 70 806	R 734 598
1329	R 287 112	R 1 010 653	R 9 100	R 75 432	R 278 012
1330	R 1 679 904	R 2 417 731	R 764 557	R 100	R 915 347

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1331	R 1 067 326	R 1 987 754	R 43 895	R 100	R 1 023 431
1332	R 836 739	R 1 340 443	R 16 855	R 100	R 819 884
1333	R 4 081 479	R 3 198 130	R 996 754	R 71 657	R 3 084 725
1334	R 5 156 673	R 3 101 070	R 1 078 565	R 102 978	R 4 078 108
1335	R 1 574 320	R 1 790 005	R 5 601	R 36 018	R 1 568 719
1336	R 1 449 980	R 1 886 098	R 8 829	R 61 477	R 1 441 151
1337	R 2 156 110	R 2 169 507	R 0	R 300	R 2 156 110
1338	R 1 597 811	R 1 630 009	R 0	R 3 410	R 1 597 811
1339	R 2 347 508	R 2 314 635	R 528 673	R 7 082	R 1 818 835
1340	R 1 858 206	R 2 061 945	R 484 075	R 21 164	R 1 374 131
1341	R 1 207 223	R 1 525 941	R 24 562	R 10 700	R 1 182 661
1342	R 988 326	R 1 533 643	R 5 600	R 40 463	R 982 726
1343	R 1 200 666	R 1 635 040	R 0	R 16 685	R 1 200 666
1344	R 11 206 508	R 8 080 804	R 4 308 843	R 2 370 090	R 6 897 665
1345	R 40 709 686	R 59 590 074	R 35 971 411	R 53 637 733	R 4 738 275
1346	R 56 778 219	R 106 045 750	R 15 734 359	R 29 944 875	R 41 043 860
1347	R 9 111 251	R 14 577 429	R 3 253 682	R 8 125 015	R 5 857 569
1348	R 29 027 000	R 86 663 000	R 5 818 000	R 2 216 000	R 23 209 000
1349	R 29 027 000	R 86 663 000	R 5 818 000	R 2 216 000	R 23 209 000
1350	R 2 076 082	R 1 497 334	R 490 282	R 213 286	R 1 585 800
1351	R 29 955	R 7 566 256	R 29 955	R 548 170	R 0
1352	R 29 955	R 7 566 256	R 29 955	R 548 170	R 0
1353	R 3 560 381	R 5 292 825	R 560 382	R 1 087 188	R 2 999 999
1354	R 3 560 381	R 5 292 825	R 560 382	R 1 087 188	R 2 999 999
1355	R 3 560 381	R 5 292 825	R 560 382	R 1 087 188	R 2 999 999
1356	R 3 560 381	R 5 292 825	R 560 382	R 1 087 188	R 2 999 999
1357	R 38 404 543	R 24 935 090	R 425 604	R 1 473 449	R 37 978 939
1358	R 12 373 902	R 31 550 690	R 464 814	R 4 274 415	R 11 909 088
1359	R 3 237 200	R 12 608 108	R 637 376	R 496 118	R 2 599 824
1360	R 2 617 567	R 3 883 570	R 1 537 708	R 2 422 218	R 1 079 859
1361	R 4 643 992	R 7 111 771	R 1 305 435	R 2 604 573	R 3 338 557
1362	R 3 387 832	R 6 601 724	R 1 050 551	R 4 370 458	R 2 337 281
1363	R 2 401 396	R 4 142 830	R 641 396	R 3 076 629	R 1 760 000
1364	R 2 401 396	R 4 142 830	R 641 396	R 3 076 629	R 1 760 000
1365	R 2 082 360	R 1 919 854	R 665 698	R 416 666	R 1 416 662
1366	R 1 361 401	R 1 588 981	R 1 361 401	R 316 148	R 0
1367	R 4 546 194	R 4 902 991	R 1 382 185	R 1 039 661	R 3 164 009
1368	R 3 013 907	R 3 571 536	R 949 042	R 1 001 170	R 2 064 865
1369	R 13 437 029	R 16 525 729	R 11 269 229	R 11 598 498	R 2 167 800
1370	R 9 527 026	R 5 727 565	R 8 361 985	R 3 234 212	R 1 165 041
1371	R 9 527 026	R 5 727 565	R 8 361 985	R 3 234 212	R 1 165 041
1372	R 9 527 026	R 5 727 565	R 8 361 985	R 3 234 212	R 1 165 041
1373	R 9 527 026	R 5 727 565	R 8 361 985	R 3 234 212	R 1 165 041
1374	R 10 218 494	R 6 519 071	R 7 972 301	R 3 394 252	R 2 246 193
1375	R 3 967 536	R 8 051 416	R 3 670 254	R 5 187 323	R 297 282

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1376	R 6 306 741	R 12 474 213	R 5 748 093	R 8 382 761	R 558 648
1377	R 3 699 385	R 10 818 682	R 3 052 174	R 5 610 209	R 647 211
1378	R 3 699 385	R 10 818 682	R 3 052 174	R 5 610 209	R 647 211
1379	R 5 377 455	R 5 581 584	R 316 343	R 1 994 285	R 5 061 112
1380	R 5 061 705	R 8 300 330	R 5 061 705	R 2 783 683	R 0
1381	R 7 842 361	R 13 168 755	R 7 842 361	R 5 283 521	R 0
1382	R 459 970 585	R 735 281 024	R 105 471 844	R 9 882 469	R 354 498 741
1383	R 1 583 522	R 1 904 753	R 511 744	R 810 885	R 1 071 778
1384	R 1 289 998	R 2 236 184	R 456 987	R 980 799	R 833 011
1385	R 65 573 252	R 82 518 215	R 37 481 018	R 53 234 364	R 28 092 234
1386	R 4 243 068	R 7 415 736	R 2 243 068	R 240 926	R 2 000 000
1387	R 6 231 028	R 19 996 147	R 6 841	R 412 297	R 6 224 187
1388	R 9 310 439	R 23 993 493	R 39 891	R 2 579 011	R 9 270 548
1389	R 9 273 969	R 24 053 176	R 3 421	R 2 411 322	R 9 270 548
1390	R 8 251 867	R 23 301 345	R 0	R 2 761 198	R 8 251 867
1391	R 57 998	R 1 152 236	R 57 998	R 31 359	R 0
1392	R 6 502 317	R 8 247 975	R 0	R 1 259 500	R 6 502 317
1393	R 33 222 000	R 89 945 000	R 19 664 000	R 45 876 000	R 13 558 000
1394	R 1 759 112	R 1 244 741	R 1 416 590	R 111 157	R 342 522
1395	R 1 759 112	R 1 244 741	R 1 416 590	R 111 157	R 342 522
1396	R 1 653 564	R 1 321 482	R 1 124 314	R 100 873	R 529 250
1397	R 1 078 192	R 964 840	R 629 192	R 86 546	R 449 000
1398	R 769 895	R 968 530	R 158 316	R 54 049	R 611 579
1399	R 703 890	R 976 727	R 257 394	R 218 817	R 446 496
1400	R 1 940 715	R 2 532 130	R 825 648	R 1 388 466	R 1 115 067
1401	R 1 682 773	R 2 543 127	R 827 882	R 1 509 309	R 854 891
1402	R 16 192 123	R 43 514 367	R 12 516 441	R 6 418 364	R 3 675 682
1403	R 15 033 712	R 33 857 454	R 9 702 951	R 5 318 880	R 5 330 761
1404	R 22 580 209	R 41 673 502	R 17 178 169	R 11 985 977	R 5 402 040
1405	R 3 725 164	R 4 383 368	R 2 725 619	R 2 050 238	R 999 545
1406	R 13 282 144	R 17 864 865	R 13 161 564	R 10 987 201	R 120 580
1407	R 10 814 496	R 15 758 338	R 10 766 264	R 9 895 336	R 48 232
1408	R 760 775	R 1 015 524	R 149 245	R 83 395	R 611 530
1409	R 3 069 568	R 2 556 160	R 108 980	R 674 844	R 2 960 588
1410	R 1 547 711	R 1 270 778	R 767 916	R 57 942	R 779 795
1411	R 1 547 711	R 1 270 778	R 767 916	R 57 942	R 779 795
1412	R 1 547 711	R 1 270 778	R 767 916	R 57 942	R 779 795
1413	R 1 090 990	R 1 113 286	R 485 030	R 96 687	R 605 960
1414	R 1 090 990	R 1 113 286	R 485 030	R 96 687	R 605 960
1415	R 1 381 460	R 1 205 298	R 647 792	R 87 803	R 733 668
1416	R 1 738 869	R 951 284	R 1 004 869	R 148 373	R 734 000
1417	R 1 738 869	R 951 284	R 1 004 869	R 148 373	R 734 000
1418	R 1 679 619	R 849 386	R 1 085 789	R 101 295	R 593 830
1419	R 1 679 619	R 849 386	R 1 085 789	R 101 295	R 593 830
1420	R 1 679 619	R 849 386	R 1 085 789	R 101 295	R 593 830

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1421	R 1 470 268	R 1 273 899	R 703 668	R 93 184	R 766 600
1422	R 1 300 680	R 1 322 016	R 801 280	R 203 245	R 499 400
1423	R 804 927	R 1 301 539	R 136 778	R 54 079	R 668 149
1424	R 804 927	R 1 301 539	R 136 778	R 54 079	R 668 149
1425	R 1 127 366	R 1 238 964	R 572 166	R 148 843	R 555 200
1426	R 7 156 878	R 1 405 735	R 1 744 541	R 12 490	R 5 412 337
1427	R 6 333 192	R 2 824 327	R 441 534	R 6 083	R 5 891 658
1428	R 2 052 715	R 15 383 228	R 2 052 715	R 6 686 635	R 0
1429	R 2 332 148	R 8 388 957	R 2 332 148	R 2 729 664	R 0
1430	R 82 375	R 341 507	R 82 375	R 215 871	R 0
1431	R 369 371	R 439 508	R 3 225	R 133 001	R 366 146
1432	R 5 063 579	R 8 495 703	R 3 321 921	R 1 408 700	R 1 741 658
1433	R 6 972 959	R 12 681 894	R 4 045 896	R 2 906 141	R 2 927 063
1434	R 6 972 959	R 12 681 894	R 4 045 896	R 2 906 141	R 2 927 063
1435	R 6 972 959	R 12 681 894	R 4 045 896	R 2 906 141	R 2 927 063
1436	R 4 825 931	R 6 730 361	R 1 184 265	R 3 752 207	R 3 641 666
1437	R 8 916 800	R 9 561 483	R 8 561 478	R 7 433 796	R 355 322
1438	R 2 350 481	R 3 330 194	R 1 969 671	R 2 876 235	R 380 810
1439	R 2 000 572	R 1 725 570	R 2 000 572	R 1 705 579	R 0
1440	R 19 004 172	R 28 408 775	R 1 296 300	R 2 364 444	R 17 707 872
1441	R 19 004 172	R 28 408 775	R 1 296 300	R 2 364 444	R 17 707 872
1442	R 19 004 172	R 28 408 775	R 1 296 300	R 2 364 444	R 17 707 872
1443	R 19 004 172	R 28 408 775	R 1 296 300	R 2 364 444	R 17 707 872
1444	R 35 208	R 824 965	R 35 208	R 499 270	R 0
1445	R 104 697 301	R 142 291 598	R 23 028 304	R 14 903 253	R 81 668 997
1446	R 214 883	R 349 198	R 77 528	R 75 741	R 137 355
1447	R 2 471 218	R 8 077 547	R 2 471 218	R 3 018 532	R 0
1448	R 1 660 152	R 7 801 225	R 1 660 152	R 2 439 215	R 0
1449	R 4 396 623	R 14 735 168	R 4 396 623	R 8 273 206	R 0
1450	R 4 396 623	R 14 735 168	R 4 396 623	R 12 889 932	R 0
1451	R 1 216 177	R 1 127 636	R 1 332	R 54 374	R 1 214 845
1452	R 3 651 769	R 1 939 551	R 710	R 263 216	R 3 651 059
1453	R 2 627 434	R 1 687 888	R 0	R 63 306	R 2 627 434
1454	R 1 756 993	R 1 549 185	R 0	R 8 725	R 1 756 993
1455	R 1 649 707	R 1 538 747	R 0	R 41 887	R 1 649 707
1456	R 15 615 714	R 10 304 817	R 12 511 704	R 5 210 270	R 3 104 010
1457	R 15 615 714	R 10 304 817	R 12 511 704	R 5 210 270	R 3 104 010
1458	R 2 426 251	R 57 629 162	R 2 316 894	R 2 495 201	R 109 357
1459	R 1 261 520	R 1 451 695	R 1 261 520	R 1 312 773	R 0
1460	R 1 070 895	R 1 997 064	R 1 043 406	R 1 950 972	R 27 489
1461	R 1 755 057	R 2 255 211	R 81 057	R 112 824	R 1 674 000
1462	R 1 181 315	R 2 076 099	R 53 915	R 362 189	R 1 127 400
1463	R 16 064 098	R 23 227 260	R 6 953 892	R 7 258 934	R 9 110 206
1464	R 16 152 496	R 26 046 466	R 8 398 690	R 9 517 530	R 7 753 806
1465	R 34 860 985	R 62 534 686	R 13 126 135	R 46 712 461	R 21 734 850

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1466	R 39 519 633	R 62 691 095	R 12 167 351	R 48 142 360	R 27 352 282
1467	R 39 384 207	R 64 120 802	R 7 244 592	R 46 565 447	R 32 139 615
1468	R 424 233	R 706 123	R 59 985	R 186 895	R 364 248
1469	R 12 037 971	R 7 793 071	R 9 569 000	R 3 111 000	R 2 468 971
1470	R 13 577 887	R 9 673 599	R 9 360 651	R 3 749 353	R 4 217 236
1471	R 11 941 521	R 8 912 220	R 11 210 066	R 5 507 453	R 731 455
1472	R 13 777 133	R 11 193 951	R 8 253 176	R 4 643 186	R 5 523 957
1473	R 958 933	R 1 030 956	R 78 933	R 70 120	R 880 000
1474	R 958 933	R 1 030 956	R 78 933	R 70 120	R 880 000
1475	R 958 933	R 1 030 956	R 78 933	R 70 120	R 880 000
1476	R 958 933	R 1 030 956	R 78 933	R 70 120	R 880 000
1477	R 10 928 312	R 9 902 460	R 5 838 308	R 427 397	R 5 090 004
1478	R 9 095 413	R 8 163 914	R 4 851 068	R 706 691	R 4 244 345
1479	R 10 663 730	R 9 995 129	R 6 268 505	R 930 213	R 4 395 225
1480	R 74 148 390	R 105 053 625	R 62 713 350	R 52 274 308	R 11 435 040
1481	R 16 988 656	R 10 057 911	R 14 440 600	R 5 948 398	R 2 548 056
1482	R 15 692 766	R 10 326 948	R 11 474 392	R 5 657 812	R 4 218 374
1483	R 12 748 030	R 10 083 609	R 7 234 569	R 4 907 200	R 5 513 461
1484	R 135 453	R 395 688	R 135 453	R 257 688	R 0
1485	R 135 453	R 395 688	R 135 453	R 257 688	R 0
1486	R 3 401 261	R 13 732 328	R 2 885 829	R 6 987 015	R 515 432
1487	R 25 609 071	R 30 386 899	R 7 188 937	R 12 883 561	R 18 420 134
1488	R 26 532 906	R 36 358 462	R 5 555 828	R 16 301 875	R 20 977 078
1489	R 22 855 713	R 61 652 046	R 18 380 492	R 3 027 238	R 4 475 221
1490	R 17 484 240	R 48 289 878	R 8 957 275	R 3 832 646	R 8 526 965
1491	R 13 440 217	R 48 953 768	R 7 009 505	R 7 382 872	R 6 430 712
1492	R 199 091 920	R 130 908 426	R 165 047 132	R 6 962 586	R 34 044 788
1493	R 107 913 768	R 120 296 961	R 84 553 359	R 3 618 948	R 23 360 409
1494	R 96 152 772	R 123 189 701	R 66 478 206	R 3 017 749	R 29 674 566
1495	R 2 410 207	R 2 650 789	R 306 138	R 597 562	R 2 104 069
1496	R 92 148	R 4 451 588	R 92 148	R 1 187 584	R 0
1497	R 15 089 892	R 45 407 191	R 8 884 188	R 6 246 465	R 6 205 704
1498	R 10 700 457	R 43 644 194	R 2 871 405	R 4 560 312	R 7 829 052
1499	R 233 818	R 23 036 153	R 233 818	R 1 901 782	R 0
1500	R 16 638 777	R 49 366 410	R 14 114 035	R 38 244 789	R 2 524 742
1501	R 14 836 520	R 50 545 041	R 13 964 221	R 40 314 702	R 872 299
1502	R 11 294 574	R 44 271 298	R 10 973 895	R 33 204 979	R 320 679
1503	R 13 638 147	R 53 538 620	R 12 303 159	R 39 579 090	R 1 334 988
1504	R 7 001 385	R 45 067 980	R 6 582 257	R 34 587 916	R 419 128
1505	R 33 555 365	R 45 892 880	R 18 464 229	R 7 846 781	R 15 091 136
1506	R 9 956 823	R 47 684 554	R 9 956 823	R 8 860 066	R 0
1507	R 28 699 486	R 69 346 296	R 28 699 486	R 27 571 045	R 0
1508	R 26 830 044	R 44 078 865	R 7 041 787	R 10 059 735	R 19 788 257
1509	R 19 509 179	R 16 923 218	R 18 670 582	R 7 560 062	R 838 597
1510	R 18 497 009	R 17 799 148	R 16 428 459	R 8 633 970	R 2 068 550
1511	R 15 001 358	R 17 569 123	R 11 160 108	R 9 360 600	R 3 841 250
1512	R 16 996 218	R 18 734 315	R 11 370 708	R 11 335 551	R 5 625 510
1513	R 12 109 184	R 7 409 266	R 7 377 498	R 1 937 537	R 4 731 686
1514	R 12 250 051	R 7 947 284	R 9 320 715	R 2 751 373	R 2 929 336
1515	R 13 970 976	R 11 157 893	R 6 723 608	R 4 961 036	R 7 247 368
1516	R 14 116 164	R 10 127 735	R 8 490 183	R 4 871 037	R 5 625 981
1517	R 14 116 164	R 10 127 735	R 8 490 183	R 4 871 037	R 5 625 981
1518	R 14 116 164	R 10 127 735	R 8 490 183	R 4 871 037	R 5 625 981
1519	R 13 905 150	R 41 286 560	R 13 905 150	R 32 778 475	R 0
1520	R 13 905 150	R 41 286 560	R 13 905 150	R 32 778 475	R 0

Firm Identifier	Total Liabilities	TotalAssets	Current Liabilities	current assets	Long Term Debt
1521	R 13 905 150	R 41 286 560	R 13 905 150	R 32 778 475	R 0
1522	R 92 100 403	R 105 490 206	R 79 714 896	R 78 727 525	R 12 385 507
1523	R 57 389 551	R 91 205 474	R 56 822 301	R 68 041 749	R 567 250
1524	R 52 481 285	R 80 703 080	R 43 009 574	R 54 209 766	R 9 471 711
1525	R 35 036 618	R 69 455 696	R 29 658 811	R 34 590 451	R 5 377 807
1526	R 44 587 607	R 91 986 321	R 37 770 053	R 47 915 740	R 6 817 554
1527	R 35 739 935	R 73 953 078	R 30 069 663	R 38 150 641	R 5 670 272
1528	R 34 210 753	R 64 649 610	R 25 524 908	R 33 840 524	R 8 685 845
1529	R 14 840 198	R 11 325 295	R 10 390 116	R 5 315 233	R 4 450 082
1530	R 14 965 126	R 10 818 893	R 12 447 314	R 6 709 576	R 2 517 812
1531	R 15 332 505	R 7 997 510	R 10 711 890	R 3 038 144	R 4 620 615
1532	R 14 266 432	R 9 770 671	R 8 055 092	R 4 243 618	R 6 211 340
1533	R 9 349 691	R 10 666 907	R 3 265 269	R 347 910	R 6 084 422
1534	R 235 302 080	R 444 173 462	R 217 689 595	R 428 799 757	R 17 612 485
1535	R 235 302 080	R 444 173 462	R 217 689 595	R 428 799 757	R 17 612 485
1536	R 159 897 092	R 364 662 757	R 159 622 307	R 352 148 630	R 274 785
1537	R 172 385 565	R 393 333 321	R 169 648 414	R 378 995 365	R 2 737 151
1538	R 27 233 082	R 54 082 590	R 2 233 082	R 13 408 039	R 25 000 000
1539	R 17 155 652	R 27 490 014	R 16 552 231	R 26 725 600	R 603 421
1540	R 22 628 365	R 52 244 928	R 22 628 365	R 45 403 736	R 0
1541	R 14 740 728	R 33 215 597	R 14 740 728	R 30 338 958	R 0
1542	R 12 715 457	R 37 253 356	R 12 473 574	R 28 538 285	R 241 883
1543	R 15 216 499	R 16 375 476	R 9 948 655	R 5 681 879	R 5 267 844
1544	R 1 290 495	R 1 336 794	R 89 936	R 65 890	R 1 200 559
1545	R 26 143 161	R 119 867 607	R 25 295 185	R 45 416 339	R 847 976
1546	R 26 687 004	R 39 997 237	R 22 341 749	R 32 271 860	R 4 345 255
1547	R 2 546 682	R 9 090 143	R 2 546 682	R 5 231 628	R 0
1548	R 1 646 650	R 8 970 531	R 1 646 650	R 4 341 795	R 0
1549	R 1 045 448	R 5 383 462	R 1 045 448	R 2 957 316	R 0
1550	R 433 436	R 4 038 052	R 433 436	R 2 298 115	R 0
1551	R 22 168 762	R 52 399 811	R 22 168 762	R 29 312 192	R 0
1552	R 51 861 150	R 169 737 969	R 51 861 150	R 26 537 321	R 0
1553	R 380 114	R 522 976	R 220 194	R 146 230	R 159 920
1554	R 86 481 604	R 183 434 369	R 79 717 326	R 81 283 860	R 6 764 278
1555	R 212 550 251	R 315 991 013	R 160 443 534	R 166 447 379	R 52 106 717
1556	R 89 861	R 184 803	R 78 705	R 149 524	R 11 156
1557	R 97 150	R 188 901	R 79 256	R 150 660	R 17 894
1558	R 352 207	R 605 302	R 276 640	R 163 513	R 75 567
1559	R 487 404	R 866 402	R 340 343	R 230 147	R 147 061
1560	R 487 404	R 866 402	R 340 343	R 230 147	R 147 061
1561	R 10 708 517	R 10 634 940	R 8 588 060	R 3 053 029	R 2 120 457
1562	R 5 167 087	R 17 447 582	R 3 197 843	R 9 349 411	R 1 969 244
1563	R 4 461 282	R 24 785 593	R 2 492 038	R 12 431 641	R 1 969 244
1564	R 10 574 379	R 29 070 731	R 8 355 626	R 7 466 102	R 2 218 753
1565	R 10 374 111	R 32 721 933	R 8 840 373	R 9 588 972	R 1 533 738

Table 22: Raw data - Income and profits

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1000	R 81 107 781	R 3 350 370	R 1 147 289	R 545 026	R 1 913 298
1001	R 26 177 503	R 2 035 264	R 589 587	R 706 249	R 1 602 149
1002	R 35 554 762	R 3 004 588	R 718 175	R 1 158 797	R 2 488 567
1003	R 50 117 177	R 4 210 044	R 826 686	R 2 033 713	R 3 627 453
1004	R 66 193 885	R 4 610 832	R 1 087 656	R 1 808 420	R 3 455 145
1005	R 59 650 491	R 3 818 729	R 722 714	R 1 651 588	R 3 024 035
1006	R 342 031 000	R 27 927 000	R 4 001 000	R 18 428 000	R 27 927 000
1007	R 342 765 000	R 6 577 000	R 3 527 000	R 1 914 000	R 6 577 000
1008	R 105 409 862	R 24 347 675	R 1 411 791	R 14 310 157	R 21 000 372
1009	R 126 729 901	R 27 700 495	R 1 464 383	R 15 744 313	R 24 282 574
1010	R 100 242 082	R 16 211 386	R 809 139	R 10 005 398	R 12 610 573
1011	R 15 161 114	R 369 577	R 0	R 310 013	R 369 577
1012	R 15 545 786	-R 235 778	R 0	-R 235 778	-R 235 778
1013	R 3 297 842	R 834 437	R 143 378	R 474 795	R 618 173
1014	R 621 919 177	R 26 798 698	R 7 784 815	R 10 306 906	R 26 798 698
1015	R 621 919 177	R 26 798 698	R 7 784 815	R 10 306 906	R 26 798 698
1016	R 5 149 091	R 112 291	R 6 869	R 70 644	R 104 986
1017	R 4 169 250	-R 86 729	R 13 643	-R 130 470	-R 116 827
1018	R 4 169 250	-R 86 729	R 13 643	-R 130 470	-R 116 827
1019	R 9 703 679	R 1 370 181	R 1 090 740	-R 28 978	R 1 215 770
1020	R 9 523 065	R 2 140 607	R 1 087 669	R 1 052 938	R 2 140 607
1021	R 7 501 064	R 2 108 779	R 961 907	R 857 738	R 1 819 645
1022	R 9 368 352	R 693 677	R 394 108	R 280 320	R 693 677
1023	R 9 368 352	R 693 677	R 394 108	R 280 320	R 693 677
1024	R 8 355 411	R 473 790	R 148 761	R 81 139	R 263 042
1025	R 10 003 496	R 598 933	R 218 784	R 169 300	R 453 965
1026	R 7 182 495	R 548 870	R 139 081	R 181 396	R 391 596
1027	R 12 736 657	R 1 995 810	R 229 581	R 1 296 004	R 1 995 810
1028	R 131 597 706	R 29 550 925	R 4 513 978	R 5 660 410	R 12 969 700
1029	R 99 195 762	R 25 071 945	R 5 080 450	R 4 637 326	R 10 929 578
1030	R 756 000	R 381 876	R 201 877	R 179 999	R 381 876
1031	R 756 000	R 381 876	R 201 877	R 179 999	R 381 876
1032	R 1 386 075	R 60 921	R 8 300	R 52 621	R 60 921
1033	R 1 386 075	R 60 921	R 8 300	R 52 621	R 60 921
1034	R 1 174 248	R 78 749	R 11 140	R 67 609	R 78 749
1035	R 783 578	R 68 108	R 14 514	R 53 594	R 68 108
1036	R 2 353 779	R 2 089 065	R 1 358 971	R 525 668	R 2 089 065
1037	R 649 880	R 280 651	R 188 305	R 554	R 188 859
1038	R 297 021 300	R 41 475 670	R 4 551 250	R 17 804 865	R 28 932 631
1039	R 234 463 718	R 21 902 823	R 7 979 258	-R 21 929 760	R 21 902 823
1040	R 48 374 158	R 2 410 969	R 223 239	R 867 504	R 1 690 790

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1041	R 8 616 072	-R 19 139 967	R 0	-R 13 883 540	-R 19 262 253
1042	R 9 495 760	R 2 040 882	R 1	R 1 369 733	R 1 920 439
1043	R 29 628 698	R 2 616 319	R 0	R 1 857 829	R 2 616 319
1044	R 28 429 309	R 4 216 766	R 279 204	R 2 432 293	R 3 540 195
1045	R 27 111 052	R 2 906 345	R 374 255	R 352 280	R 870 424
1046	R 32 827 610	R 5 013 644	R 73 828	R 1 799 268	R 2 572 811
1047	R 21 706 491	R 3 324 025	R 218 165	R 758 703	R 1 283 297
1048	R 18 967 327	R 1 334 196	R 248 111	R 354 701	R 740 712
1049	R 2 957 031	R 2 630 248	R 1 673 103	R 538 730	R 2 630 248
1050	R 4 865 813	R 898 850	R 154 487	R 506 755	R 740 749
1051	R 12 156 348	R 1 352 308	R 895 697	R 315 383	R 1 352 308
1052	R 14 425 952	R 1 733 026	R 657 322	R 170 508	R 1 733 026
1053	R 27 497 500	R 6 107 870	R 1 014 024	R 1 464 848	R 3 079 233
1054	R 27 497 500	R 6 107 870	R 1 014 024	R 1 464 848	R 3 079 233
1055	R 38 454 867	R 6 839 469	R 2 014 195	R 785 725	R 5 519 780
1056	R 46 768 008	-R 91 715	R 3 317 112	-R 1 060 729	-R 91 715
1057	R 74 261 326	R 4 219 104	R 929 657	R 982 269	R 1 938 102
1058	R 74 261 326	R 4 219 104	R 929 657	R 982 269	R 1 938 102
1059	R 74 261 326	R 4 219 104	R 929 657	R 982 269	R 1 938 102
1060	R 78 344 168	R 16 296 705	R 1 767 805	R 12 554 134	R 14 287 437
1061	R 86 907 674	R 10 774 561	R 2 415 245	R 3 121 319	R 8 550 161
1062	R 40 797 038	R 7 498 692	R 214 878	R 6 568 115	R 6 782 993
1063	R 11 091 194	-R 169 550	R 171 394	-R 340 944	-R 169 550
1064	R 6 945 868	-R 1 419 737	R 325 532	-R 2 841 356	-R 2 296 533
1065	R 263 869 666	R 46 977 235	R 33 378 056	-R 14 197 846	R 19 180 210
1066	R 5 361 315	R 671 582	R 448 766	R 26 955	R 475 721
1067	R 5 782 046	R 487 021	R 453 479	-R 184 036	R 269 443
1068	R 20 578 190	R 1 570 948	R 941 062	R 266 678	R 1 207 740
1069	R 28 742 159	R 2 751 777	R 2 318 352	R 117 849	R 2 436 201
1070	R 48 340 854	R 3 177 884	R 852 622	R 2 376 326	R 3 177 884
1071	R 50 968 845	R 669 057	R 1 150 262	-R 109 896	R 669 057
1072	R 51 447 960	R 1 777 030	R 796 912	R 277 765	R 1 777 030
1073	R 20 406 960	R 45 588	R 1 638 885	-R 2 347 310	-R 708 425
1074	R 17 959 700	R 294 238	R 810 033	-R 1 123 442	-R 313 409
1075	R 102 957 000	R 11 698 000	R 1 823 000	R 3 507 000	R 6 828 000
1076	R 115 894 000	R 9 401 000	R 2 853 000	R 1 613 000	R 5 205 000
1077	R 109 983 729	R 7 072 465	R 3 814 194	R 2 662 523	R 6 723 998
1078	R 97 756 453	R 3 850 983	R 2 391 382	R 1 456 342	R 3 850 983
1079	R 96 512 850	R 5 941 114	R 2 245 304	R 2 036 309	R 5 457 321
1080	R 93 387 942	R 2 854 344	R 2 113 064	R 246 831	R 2 359 895

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1081	R 14 573 734	R 2 572 171	R 227 150	R 494 250	R 1 367 610
1082	R 220 510 865	R 60 519 404	R 4 117 002	R 41 000 470	R 57 978 153
1083	R 220 510 865	R 60 519 404	R 4 117 002	R 41 000 470	R 57 978 153
1084	R 220 510 865	R 60 519 404	R 4 117 002	R 41 000 470	R 57 978 153
1085	R 220 510 865	R 60 519 404	R 4 117 002	R 41 000 470	R 57 978 153
1086	R 141 145 686	R 16 279 284	R 2 912 377	R 6 785 707	R 14 021 303
1087	R 53 664 583	R 8 495 172	R 380 912	R 4 875 161	R 7 408 173
1088	R 94 870 081	R 3 616 153	R 0	R 2 160 821	R 3 592 527
1089	R 118 866 128	R 7 371 108	R 0	R 4 801 597	R 7 341 211
1090	R 2 353 779	R 2 089 065	R 1 358 971	R 525 668	R 2 089 065
1091	R 44 896 502	R 8 507 425	R 9 981 696	-R 2 634 728	R 6 751 010
1092	R 45 840 055	R 1 382 830	R 5 649 060	-R 4 209 597	-R 130 421
1093	R 393 180 801	R 42 828 922	R 8 622 364	R 24 087 173	R 42 828 922
1094	R 531 363 782	R 102 214 961	R 8 207 491	R 53 629 560	R 80 736 395
1095	R 11 796 443	R 1 961 761	R 271 629	R 1 690 132	R 1 961 761
1096	R 9 290 487	R 341 265	R 379 779	-R 331 458	R 341 265
1097	R 9 290 487	R 341 265	R 379 779	-R 331 458	R 341 265
1098	R 10 394 369	R 13 293	R 562 563	-R 549 270	R 13 293
1099	R 6 415 473	R 3 012 669	R 1 997 339	R 404 095	R 2 241 656
1100	R 24 048 347	R 1 467 267	R 74 578	R 1 049 597	R 1 335 672
1101	R 24 048 347	R 1 467 267	R 74 578	R 1 049 597	R 1 335 672
1102	R 2 487 130	R 1 430 279	R 381 694	R 1 048 585	R 1 430 279
1103	R 1 800 843	R 857 009	R 342 925	R 514 084	R 857 009
1104	R 24 541 534	R 1 672 485	R 225 256	R 739 695	R 1 279 514
1105	R 26 683 730	R 925 777	R 322 516	R 142 975	R 542 647
1106	R 23 477 401	R 868 894	R 198 295	R 553 237	R 868 894
1107	R 2 693 348	-R 568 321	R 0	-R 422 631	-R 568 321
1108	R 3 008 061	R 1 198 597	R 148 677	R 684 788	R 1 098 173
1109	R 3 074 363	R 1 093 812	R 263 828	R 583 404	R 1 008 445
1110	R 2 852 162	R 235 976	R 0	R 100 938	R 133 144
1111	R 2 171 976	R 274 617	R 110 737	R 88 643	R 199 380
1112	R 2 198 977	R 59 167	R 95 712	-R 112 553	-R 16 841
1113	R 150 955	R 5 345	R 1 667	-R 5 823	-R 4 156
1114	R 3 102 000	R 2 693 497	R 891 131	R 1 297 704	R 2 693 497
1115	R 3 188 236	R 2 816 151	R 1 108 233	R 1 229 701	R 2 816 151
1116	R 33 525 896	R 3 478 484	R 1 010 882	R 2 047 657	R 3 478 484
1117	R 38 481 802	R 3 273 397	R 1 344 451	R 1 371 280	R 2 865 205
1118	R 65 661 479	R 8 938 086	R 1 579 205	R 4 929 486	R 6 508 691
1119	R 61 969 143	R 2 880 348	R 984 663	R 875 567	R 2 381 425
1120	R 73 510 254	R 16 395 958	R 0	R 13 671 503	R 13 671 503

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1121	R 74 936 322	R 7 414 720	R 2 162 528	R 5 252 192	R 7 414 720
1122	R 11 259 621	R 1 502 183	R 364 474	R 913 304	R 1 502 183
1123	R 9 429 435	R 3 540 385	R 238 137	R 425 861	R 2 732 338
1124	R 12 519 168	R 657 539	R 140 915	R 366 945	R 657 539
1125	R 547 795	R 132 842	R 0	R 89 981	R 132 842
1126	R 18 617 373	R 1 838 827	R 0	R 1 673 906	R 1 838 827
1127	R 12 580 764	-R 1 102 804	R 436 287	-R 1 278 143	-R 1 102 804
1128	R 13 750 529	R 3 514 088	R 672 068	-R 337 915	-R 70 752
1129	R 8 718 596	-R 3 461 355	R 512 400	-R 3 121 938	-R 3 461 355
1130	R 9 730 534	R 2 583 107	R 515 916	R 1 168 622	R 2 031 700
1131	R 6 351 134	R 731 653	R 622 165	R 62 269	R 731 653
1132	R 8 881 396	R 2 836 488	R 375 557	R 1 770 668	R 2 836 488
1133	R 1 867 727	-R 1 350 111	R 0	-R 1 432 236	-R 2 247 840
1134	R 29 720 072	R 13 436 203	R 3 682 360	R 5 774 637	R 11 844 566
1135	R 30 763 250	R 2 959 287	R 148 400	R 1 902 004	R 2 906 058
1136	R 46 066 426	R 6 893 678	R 79 196	R 4 715 743	R 6 854 488
1137	R 57 005 812	R 7 139 250	R 82 378	R 4 397 289	R 7 111 057
1138	R 12 719 026	R 1 536 095	R 519 368	R 167 562	-R 475 292
1139	R 12 054 452	R 1 658 405	R 607 768	R 562 094	R 369 427
1140	R 1 304 212	-R 2 480 786	R 352 060	-R 2 099 474	-R 2 480 786
1141	R 460 958	R 128 204	R 2 910	R 85 195	R 118 745
1142	R 258 628 890	R 17 120 165	R 3 174 203	R 8 128 234	R 15 510 711
1143	R 231 032 520	R 9 591 427	R 5 366 425	R 1 406 713	R 7 297 574
1144	R 159 924 924	R 9 823 771	R 2 330 847	R 5 443 451	R 9 823 771
1145	R 187 735 463	R 10 862 493	R 5 363 642	R 3 304 646	R 8 953 011
1146	R 27 526 927	-R 183 739	R 893 345	-R 2 183 555	-R 1 290 210
1147	R 259 002 298	R 27 159 828	R 8 486 488	R 13 201 879	R 27 070 010
1148	R 6 869 196	R 243 215	R 138 959	R 104 256	R 243 215
1149	R 5 415 292	-R 149 338	R 75 478	-R 220 995	-R 149 338
1150	R 37 316 193	R 2 546 699	R 91 369	R 1 498 664	R 2 366 522
1151	R 41 280 800	R 2 072 330	R 116 991	R 457 383	R 1 702 346
1152	R 46 764 115	R 4 753 452	R 191 136	R 2 465 497	R 4 309 445
1153	R 41 531 161	R 5 355 399	R 61 304	R 3 734 815	R 5 355 399
1154	R 45 754 364	R 4 705 360	R 317 962	R 2 198 142	R 4 177 640
1155	R 5 807 983	-R 540 704	R 334 331	-R 1 241 296	-R 906 965
1156	R 6 562 493	R 48 430	R 295 884	-R 627 625	-R 331 741
1157	R 16 762 402	R 5 399 317	R 239 069	R 4 810 598	R 5 049 667
1158	R 129 917	R 11 841	R 7 290	-R 9 359	-R 2 069
1159	R 106 196 613	R 20 390 131	R 9 956 319	R 1 257 835	R 10 363 080
1160	R 94 772 075	R 16 969 156	R 6 120 588	R 2 879 921	R 9 000 509

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1161	R 94 772 075	R 16 969 156	R 6 120 588	R 2 879 921	R 9 000 509
1162	R 94 772 075	R 16 969 156	R 6 120 588	R 2 879 921	R 9 000 509
1163	R 102 786 598	R 19 298 268	R 7 799 312	R 1 570 904	R 10 018 711
1164	R 10 158 915	-R 751 920	R 226 119	-R 978 039	-R 751 920
1165	R 9 208 178	R 623 435	R 608 033	R 15 402	R 623 435
1166	R 12 043 540	R 3 224 080	R 473 142	R 2 750 938	R 3 224 080
1167	R 4 698 534	R 1 171 921	R 177 124	R 490 124	R 867 448
1168	R 5 021 680	R 1 629 120	R 149 038	R 847 202	R 1 414 732
1169	R 14 375 295	R 1 269 256	R 42 474	R 590 120	R 862 085
1170	R 20 277 998	R 1 699 360	R 528 582	R 654 151	R 1 699 360
1171	R 65 386	R 1 872	R 7 183	-R 9 724	-R 4 129
1172	R 70 074	R 15 618	R 6 570	R 6 972	R 11 895
1173	R 75 744 097	-R 2 555 034	R 992 617	-R 3 795 546	-R 4 285 029
1174	R 337 600 035	R 73 836 382	R 3 659 631	R 47 994 299	R 73 836 382
1175	R 404 402 644	R 177 547 412	R 225 015	R 130 394 808	R 177 547 412
1176	R 125 229 335	R 20 017 193	R 604 328	R 12 871 951	R 18 749 466
1177	R 271 452 000	R 26 576 000	R 844 000	R 23 068 000	R 26 576 000
1178	R 387 075	R 83 324	R 372	R 48 669	R 83 324
1179	R 39 053 911	R 4 209 476	R 983 136	R 1 389 058	R 2 967 136
1180	R 10 394 272	R 1 600 654	R 0	R 1 435 332	R 1 600 654
1181	R 12 591 088	R 2 764 916	R 635 719	R 1 110 860	R 2 137 066
1182	R 11 137 676	R 3 441 715	R 622 730	R 2 053 759	R 2 748 270
1183	R 2 282 158	R 594 466	R 73 628	R 324 193	R 447 363
1184	R 1 200 445	-R 452 993	R 218 295	-R 575 497	-R 494 718
1185	R 2 729 987	R 1 103 638	R 247 153	R 536 005	R 783 069
1186	R 1 629 844	-R 150 448	R 83 100	-R 185 846	-R 195 014
1187	R 6 604 233	R 2 524 909	R 1 268 989	R 891 703	R 2 524 909
1188	R 0	R 770 940	R 165 658	R 31 127	R 242 123
1189	R 3 522 695	-R 980 898	R 759 161	-R 1 510 107	-R 1 206 683
1190	R 3 522 695	-R 980 898	R 759 161	-R 1 510 107	-R 1 206 683
1191	R 3 522 695	-R 980 898	R 759 161	-R 1 510 107	-R 1 206 683
1192	R 53 807 098	R 3 663 773	R 655 584	R 934 062	R 1 952 892
1193	R 61 125 762	R 3 750 809	R 614 543	R 929 904	R 1 939 606
1194	R 41 446 708	R 2 784 434	R 671 064	R 830 924	R 1 841 379
1195	R 65 149 445	R 4 157 254	R 870 116	R 1 010 363	R 2 274 398
1196	R 39 976 205	R 3 642 066	R 498 742	R 1 839 536	R 2 727 590
1197	R 32 497 000	R 1 584 000	R 285 000	R 433 000	R 974 000
1198	R 59 268 381	R 4 431 394	R 1 199 050	R 1 065 496	R 2 678 904
1199	R 25 252 320	R 1 713 834	R 359 988	R 754 878	R 1 360 356
1200	R 2 734 347	-R 329 297	R 214 903	-R 685 302	-R 470 399

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1201	R 12 363 945	R 2 011 088	R 124 853	R 816 525	R 1 282 444
1202	R 675 600	R 535 399	R 366 623	R 162 874	R 529 497
1203	R 29 385 431	R 4 738 152	R 1 263 584	R 2 722 725	R 4 709 615
1204	R 3 196 316	R 113 780	R 90 796	-R 117 889	-R 27 093
1205	R 3 196 316	R 113 780	R 90 796	-R 117 889	-R 27 093
1206	R 3 006 703	R 154 287	R 70 487	R 18 120	R 95 654
1207	R 924 128	R 1 277 639	R 323 076	R 56 808	R 1 154 491
1208	R 924 128	R 1 277 639	R 323 076	R 56 808	R 1 154 491
1209	R 924 128	R 1 277 639	R 323 076	R 56 808	R 1 154 491
1210	R 1 362 378	R 206 184	R 68 533	R 37 382	R 121 184
1211	R 1 761 078	R 364 406	R 140 248	R 53 544	R 209 631
1212	R 2 917 167	R 941 396	R 347 686	R 130 117	R 525 545
1213	R 2 685 457	R 612 285	R 230 702	R 243 767	R 417 773
1214	R 43 914 331	R 9 952 992	R 1 798 869	R 2 720 080	R 4 917 109
1215	R 55 346 299	R 12 480 118	R 2 403 993	R 3 242 116	R 6 366 818
1216	R 64 232 743	R 1 039 022	R 74 212	R 630 783	R 962 639
1217	R 64 232 743	R 1 039 022	R 74 212	R 630 783	R 962 639
1218	R 2 021 831	R 434 616	R 117 089	R 222 310	R 237 678
1219	R 3 338 772	R 1 213 658	R 209 768	R 620 277	R 1 004 367
1220	R 6 200 628	-R 141 752	R 145 644	-R 351 349	-R 231 944
1221	R 38 266 783	R 12 500 928	R 345 736	R 8 098 471	R 11 849 224
1222	R 41 723 680	R 3 822 554	R 2 700 996	R 1 022 215	R 3 822 554
1223	R 19 992 271	R 784 885	R 951 689	-R 166 804	R 784 885
1224	R 23 886 055	R 1 491 088	R 819 416	R 671 672	R 1 491 088
1225	R 41 015 823	R 2 105 828	R 513 957	R 1 591 565	R 2 105 828
1226	R 16 860 061	R 1 066 565	R 657 717	-R 77 944	R 382 038
1227	R 12 882 886	R 211 152	R 1 194 916	-R 1 668 996	-R 474 080
1228	R 2 743 396	R 616 225	R 373 311	R 217 072	R 609 205
1229	R 2 743 396	R 616 225	R 373 311	R 217 072	R 609 205
1230	R 2 743 396	R 616 225	R 373 311	R 217 072	R 609 205
1231	R 1 618 870	R 163 212	R 49 476	R 50 626	R 100 102
1232	R 17 893 135	R 697 158	R 138 065	R 324 687	R 589 019
1233	R 13 370 274	R 308 507	R 188 028	R 85 540	R 308 507
1234	R 17 887 773	R 779 301	R 122 623	R 372 959	R 640 622
1235	R 20 878 479	R 1 184 969	R 317 891	R 856 498	R 1 033 470
1236	R 17 220 497	R 2 732 508	R 254 723	R 524 690	R 923 343
1237	R 17 490 438	R 610 303	R 185 483	R 305 870	R 610 303
1238	R 35 227 073	R 721 195	R 69 294	R 356 875	R 571 935
1239	R 45 374 901	R 932 513	R 60 274	R 514 353	R 774 653
1240	R 1 080 213	R 112 155	R 28 886	R 13 823	R 48 918

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1241	R 7 500 204	-R 8 467 836	R 2 075 894	-R 9 946 779	-R 11 933 653
1242	R 2 722 459	R 85 207	R 59 656	R 15 651	R 83 688
1243	R 5 753 055	-R 2 356 490	R 4 022	-R 1 701 969	-R 2 356 490
1244	R 4 277 465	-R 2 105 707	R 469 908	-R 1 854 444	-R 2 105 707
1245	R 4 277 465	-R 2 105 707	R 469 908	-R 1 854 444	-R 2 105 707
1246	R 4 277 465	-R 2 105 707	R 469 908	-R 1 854 444	-R 2 105 707
1247	R 10 938 940	-R 4 863 660	R 3 496 813	-R 6 019 549	-R 4 863 660
1248	R 0	-R 318 885	R 0	-R 1 534 596	-R 1 450 792
1249	R 155 276 040	-R 23 604 259	R 3 579 221	-R 23 250 149	-R 23 604 261
1250	R 259 188 059	R 21 407 876	R 4 107 842	R 10 435 604	R 18 582 463
1251	R 235 990 855	R 25 717 035	R 4 322 412	R 15 329 292	R 23 645 013
1252	R 158 377 940	R 1 540 642	R 3 374 724	-R 589 684	R 1 540 640
1253	R 171 076 186	R 36 390 664	R 3 558 534	R 30 408 065	R 36 390 662
1254	R 2 440 228	R 50 571	R 66 167	-R 19 488	R 42 003
1255	R 102 016 000	R 6 283 000	R 525 000	R 3 502 000	R 5 495 000
1256	R 116 262 000	R 6 673 000	R 1 205 000	R 3 290 000	R 5 923 000
1257	R 2 263 632	R 155 847	R 58 544	-R 21 574	R 28 903
1258	R 15 522 034	R 1 865 217	R 146 788	R 840 571	R 987 520
1259	R 9 737 422	R 277 404	R 293 257	-R 886 413	-R 593 156
1260	R 12 495 884	-R 196 907	R 0	-R 934 352	-R 934 352
1261	R 27 694 097	R 19 363	R 71 822	-R 86 921	-R 15 099
1262	R 520 900 383	R 25 980 817	R 3 620 809	R 6 481 755	R 15 668 188
1263	R 605 703 360	R 37 867 628	R 3 102 560	R 16 352 421	R 26 131 838
1264	R 178 184 000	R 17 897 496	R 601 585	R 10 917 089	R 16 117 982
1265	R 296 105 580	R 30 555 353	R 7 163 095	R 13 705 913	R 26 498 725
1266	R 381 712 349	R 31 176 473	R 3 626 889	R 14 394 087	R 23 848 410
1267	R 238 317 000	R 21 553 000	R 3 073 000	R 6 820 000	R 12 679 000
1268	R 3 425 525	R 158 134	R 39 781	R 63 441	R 129 134
1269	R 58 328 994	R 5 137 462	R 3 222 184	-R 1 312 499	R 2 199 983
1270	R 49 007 764	R 1 610 668	R 2 218 543	-R 2 513 750	-R 1 239 026
1271	R 49 007 764	R 1 610 668	R 2 218 543	-R 2 513 750	-R 1 239 026
1272	R 49 007 764	R 1 610 668	R 2 218 543	-R 2 513 750	-R 1 239 026
1273	R 6 440 491	R 870 190	R 359 376	R 118 215	R 477 591
1274	R 0	R 1 512 278	R 356 352	R 880 391	R 1 236 743
1275	R 2 493 489	R 1 218 400	R 383 799	R 544 698	R 928 497
1276	R 4 920 074	R 338 057	R 84 764	-R 42 797	R 41 967
1277	R 4 491 502	R 339 434	R 152 924	-R 150 053	R 2 871
1278	R 4 276 498	R 303 515	R 164 783	-R 197 828	-R 33 045
1279	R 1 793 181	R 37 810	R 37 717	-R 107 194	-R 71 231
1280	R 559 072	-R 10 092	R 20 862	-R 89 625	-R 61 681
1281	R 13 433 187	R 2 299 101	R 140 494	R 1 465 585	R 2 166 506
1282	R 3 808 729	R 1 233 416	R 184 220	R 599 271	R 1 025 943
1283	R 3 518 336	R 836 402	R 226 868	R 296 360	R 593 701
1284	R 5 270 588	R 779 884	R 92 537	R 523 195	R 714 765
1285	R 4 685 441	R 814 161	R 57 024	R 478 685	R 640 258

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1286	R 3 636 767	R 600 420	R 78 281	R 246 901	R 341 210
1287	R 2 830 011	R 746 914	R 113 719	R 362 483	R 489 289
1288	R 89 673 152	R 2 442 432	R 577 074	R 302 515	R 1 604 985
1289	R 72 113 748	R 3 062 678	R 594 670	R 1 028 003	R 2 120 222
1290	R 10 678 945	R 1 924 388	R 77 451	R 1 289 013	R 1 764 880
1291	R 2 073 504	R 265 309	R 11 239	R 133 317	R 199 009
1292	R 2 073 504	R 265 309	R 11 239	R 133 317	R 199 009
1293	R 25 837 844	R 513 004	R 63 684	R 224 035	R 287 719
1294	R 77 675 217	R 1 465 881	R 799 447	R 15 380	R 875 984
1295	R 17 490 438	R 610 303	R 185 483	R 305 870	R 610 303
1296	R 18 296 772	-R 271 634	R 323 316	-R 594 950	-R 271 634
1297	R 13 755 731	-R 459 117	R 381 847	-R 684 479	-R 459 117
1298	R 18 181 718	R 1 585 450	R 315 755	R 1 113 210	R 1 585 450
1299	R 4 341 536	-R 414 387	R 272 736	-R 687 123	-R 414 387
1300	R 47 164 103	R 1 855 894	R 233 681	R 437 378	R 1 241 510
1301	R 34 968 159	R 33 442 720	R 35 738 894	-R 23 676 965	R 32 946 051
1302	R 71 694 216	R 90 178 685	R 33 100 392	R 36 561 414	R 89 304 592
1303	R 55 271 748	R 51 261 097	R 39 508 293	R 28 652 893	R 49 581 825
1304	R 74 461 154	R 92 684 515	R 32 629 809	R 30 502 848	R 91 483 442
1305	R 7 340 696	R 673 878	R 259 453	R 144 844	R 404 297
1306	R 7 340 696	R 673 878	R 259 453	R 144 844	R 404 297
1307	R 6 346 364	R 767 938	R 129 484	R 402 961	R 596 262
1308	R 10 134 232	R 786 106	R 136 031	R 266 667	R 426 772
1309	R 12 638 433	R 1 496 321	R 63 793	R 723 657	R 1 068 872
1310	R 71 681 319	R 4 587 429	R 882 269	R 2 508 430	R 4 325 088
1311	R 9 655 769	R 293 861	R 66 474	R 126 589	R 200 490
1312	R 9 717 271	R 627 270	R 61 582	R 432 849	R 551 033
1313	R 1 698 920	-R 183 992	R 186 750	-R 370 742	-R 183 992
1314	R 1 264 017	-R 715 868	R 314 551	-R 1 833 167	-R 1 518 616
1315	R 1 146 231	-R 68 182	R 243 901	-R 312 083	-R 68 182
1316	R 2 181 784	-R 46 293	R 351 985	-R 448 149	-R 96 164
1317	R 376 643	-R 444 307	R 74 289	-R 520 246	-R 445 957
1318	R 324 299	-R 660 398	R 433 689	-R 1 434 835	-R 1 001 146
1319	R 528 048	-R 636 709	R 166 970	-R 838 240	-R 671 270
1320	R 379 613	-R 395 568	R 119 470	-R 515 038	-R 395 568
1321	R 191 621	-R 241 515	R 156 999	-R 398 514	-R 241 515
1322	R 908 967	-R 48 520	R 59 077	-R 107 597	-R 48 520
1323	R 1 009 538	-R 164 185	R 28 754	-R 192 939	-R 164 185
1324	R 1 214 924	R 219 131	R 57 744	R 149 848	R 219 131
1325	R 40 688	-R 518 846	R 266 602	-R 814 703	-R 548 101
1326	R 110 384	-R 711 361	R 80 761	-R 792 122	-R 711 361
1327	R 2 000	-R 499 600	R 151 110	-R 694 592	-R 543 482
1328	R 90 166	-R 604 997	R 96 415	-R 701 412	-R 604 997
1329	R 394 123	-R 464 107	R 28 344	-R 492 451	-R 464 107
1330	R 1 833 973	-R 138 423	R 44 178	-R 182 601	-R 138 423

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1376	R 22 666 773	R 2 078 681	R 435 963	R 735 966	R 993 616
1377	R 18 787 200	R 2 538 578	R 498 494	R 218 172	R 676 140
1378	R 18 787 200	R 2 538 578	R 498 494	R 218 172	R 676 140
1379	R 11 855 896	R 517 282	R 234 355	R 204 029	R 438 384
1380	R 9 565 000	R 911 303	R 366 000	R 328 303	R 730 303
1381	R 11 687 737	R 590 954	R 237 699	R 98 211	R 376 026
1382	R 54 677 884	R 1 145 715	R 162 042	R 741 434	R 903 476
1383	R 4 035 145	-R 293 046	R 125 146	-R 571 433	-R 446 287
1384	R 6 259 479	R 269 198	R 128 832	-R 75 313	R 53 519
1385	R 198 632 621	R 3 736 705	R 3 242 140	-R 799 738	R 2 145 089
1386	R 103 939	R 48 557	R 137 748	-R 213 653	-R 75 905
1387	R 195 626	-R 142 083	R 455 359	R 126 679	-R 579 354
1388	R 3 556 333	R 1 129 077	R 541 277	-R 134 965	R 332 968
1389	R 2 034 020	R 1 169 329	R 487 642	R 914 158	R 600 343
1390	R 4 589 912	R 2 594 863	R 544 552	R 924 091	R 1 828 012
1391	R 96 624	R 24 238	R 0	R 24 238	R 24 238
1392	R 571 597	-R 294 410	R 60 662	-R 355 072	-R 294 410
1393	R 240 501 000	R 50 789 000	R 3 756 000	R 29 442 000	R 45 224 000
1394	R 1 321 167	-R 11 818	R 46 374	-R 182 288	-R 206 803
1395	R 1 321 167	-R 11 818	R 46 374	-R 182 288	-R 206 803
1396	R 808 323	-R 538 127	R 75 853	-R 689 341	-R 684 405
1397	R 1 388 367	R 56 918	R 75 311	-R 136 988	-R 99 172
1398	R 1 321 343	-R 48 757	R 43 044	-R 240 726	-R 197 682
1399	R 1 736 149	-R 579 829	R 81 247	-R 934 454	-R 853 207
1400	R 1 608 301	R 158 795	R 43 646	R 81 756	R 158 795
1401	R 2 284 375	R 51 222	R 48 709	R 2 513	R 51 222
1402	R 49 559 308	R 6 208 969	R 1 931 330	R 1 379 701	R 3 964 153
1403	R 63 213 316	R 9 615 879	R 2 576 708	R 3 493 900	R 7 459 170
1404	R 48 376 173	R 10 791 998	R 4 072 145	R 2 835 361	R 8 178 232
1405	R 5 096 148	R 740 110	R 225 606	R 192 374	R 498 139
1406	R 29 490 550	R 1 476 634	R 356 540	R 105 457	R 461 997
1407	R 25 172 115	R 1 796 864	R 421 083	R 361 121	R 782 204
1408	R 2 026 271	-R 43 068	R 51 451	-R 344 117	-R 292 666
1409	R 7 844 294	R 1 078 142	R 118 717	R 538 859	R 657 576
1410	R 1 099 142	-R 173 657	R 87 074	-R 312 786	-R 348 018
1411	R 1 099 142	-R 173 657	R 87 074	-R 312 786	-R 348 018
1412	R 1 099 142	-R 173 657	R 87 074	-R 312 786	-R 348 018
1413	R 1 875 693	R 213 537	R 45 402	-R 12 639	R 27 848
1414	R 1 875 693	R 213 537	R 45 402	-R 12 639	R 27 848
1415	R 1 149 023	-R 92 426	R 96 838	-R 259 421	-R 263 810
1416	R 1 196 026	-R 199 763	R 55 095	-R 611 421	-R 794 101
1417	R 1 196 026	-R 199 763	R 55 095	-R 611 421	-R 794 101
1418	R 1 029 857	-R 144 209	R 49 762	-R 633 865	-R 819 108
1419	R 1 029 857	-R 144 209	R 49 762	-R 633 865	-R 819 108
1420	R 1 029 857	-R 144 209	R 49 762	-R 633 865	-R 819 108

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1421	R 1 041 108	-R 114 979	R 90 003	-R 273 212	-R 288 292
1422	R 1 926 487	R 125 712	R 79 269	-R 84 277	-R 38 555
1423	R 1 536 462	-R 225 491	R 42 965	-R 458 115	-R 415 150
1424	R 1 536 462	-R 225 491	R 42 965	-R 458 115	-R 415 150
1425	R 2 591 678	R 193 469	R 80 129	-R 53 170	R 8 858
1426	R 1 382 907	-R 79 713	R 540 904	-R 2 242 278	-R 1 701 374
1427	R 22 305	-R 761 480	R 244 324	-R 3 508 965	-R 3 264 641
1428	R 105 838 788	-R 231 048	R 2 461 662	-R 2 692 710	-R 231 048
1429	R 12 999 677	R 997 682	R 465 561	-R 366 886	R 98 675
1430	R 960 476	-R 122 684	R 0	-R 146 243	-R 146 243
1431	R 1 080 140	R 52 701	R 0	R 27 742	R 27 742
1432	R 20 677 707	R 3 936 684	R 440 737	R 1 808 823	R 2 900 289
1433	R 35 903 307	R 5 787 823	R 575 340	R 2 229 911	R 3 673 411
1434	R 35 903 307	R 5 787 823	R 575 340	R 2 229 911	R 3 673 411
1435	R 35 903 307	R 5 787 823	R 575 340	R 2 229 911	R 3 673 411
1436	R 17 717 713	R 3 383 090	R 830 941	R 1 137 846	R 2 434 665
1437	R 40 241 156	R 1 524 924	R 518 320	R 307 026	R 825 346
1438	R 2 728 286	-R 4 722	R 52 909	-R 164 610	-R 122 291
1439	R 0	-R 270 899	R 0	-R 275 102	-R 275 102
1440	R 6 695 498	R 5 011 932	R 343 221	R 4 550 092	R 4 893 313
1441	R 6 695 498	R 5 011 932	R 343 221	R 4 550 092	R 4 893 313
1442	R 6 695 498	R 5 011 932	R 343 221	R 4 550 092	R 4 893 313
1443	R 6 695 498	R 5 011 932	R 343 221	R 4 550 092	R 4 893 313
1444	R 3 604 921	R 145 681	R 39 525	R 3 990	R 43 516
1445	R 57 846 524	R 1 873 802	R 1 535 444	R 131 671	R 1 873 802
1446	R 347 407	R 49 548	R 10 066	R 28 836	R 49 548
1447	R 12 844 088	R 219 483	R 0	R 219 483	R 219 483
1448	R 11 264 353	R 1 525 484	R 0	R 1 525 484	R 1 525 484
1449	R 33 621 694	R 4 782 918	R 0	R 4 782 918	R 4 782 918
1450	R 33 621 694	R 9 182 698	R 0	R 9 182 698	R 9 182 698
1451	R 136 213	R 12 358	R 100 909	-R 88 551	R 12 358
1452	R 420 238	-R 567 913	R 204 759	-R 772 672	-R 567 913
1453	R 292 395	-R 716 220	R 134 785	-R 851 005	-R 716 220
1454	R 0	R 54 659	R 107 287	-R 96 851	R 10 436
1455	R 0	R 55 295	R 92 650	-R 111 060	-R 18 410
1456	R 75 670 110	-R 1 508 532	R 653 306	-R 2 036 858	-R 1 508 532
1457	R 75 670 110	-R 1 508 532	R 653 306	-R 2 036 858	-R 1 508 532
1458	R 134 674	-R 4 239 413	R 2 009 340	-R 8 066 902	-R 6 057 562
1459	R 6 017 805	-R 648 832	R 131 750	-R 780 582	-R 648 832
1460	R 6 278 006	-R 231 971	R 109 725	-R 341 696	-R 231 971
1461	R 3 871 636	-R 76 001	R 62 270	-R 138 271	-R 76 001
1462	R 5 008 042	R 464 134	R 69 504	R 394 630	R 464 134
1463	R 27 262 645	R 3 972 811	R 1 637 495	R 646 158	R 2 288 953
1464	R 36 349 993	R 7 002 161	R 1 512 744	R 2 721 503	R 4 241 867
1465	R 93 001 293	R 8 582 975	R 0	R 6 591 394	R 6 591 394

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1466	R 92 800 940	R 14 329 092	R 2 490 260	R 6 497 661	R 11 851 701
1467	R 93 447 193	R 8 049 454	R 0	R 6 162 463	R 6 162 463
1468	R 3 488 595	R 236 594	R 39 669	R 68 728	R 120 525
1469	R 70 982 000	R 1 603 000	R 617 419	-R 316 419	R 301 000
1470	R 69 118 041	R 585 741	R 944 043	-R 1 592 660	-R 648 617
1471	R 79 730 205	R 4 085 500	R 654 959	R 2 153 238	R 2 808 197
1472	R 46 231 021	-R 1 748 841	R 773 656	-R 3 283 921	-R 2 510 265
1473	R 1 185 245	-R 61 164	R 83 652	-R 333 690	-R 250 038
1474	R 1 185 245	-R 61 164	R 83 652	-R 333 690	-R 250 038
1475	R 1 185 245	-R 61 164	R 83 652	-R 333 690	-R 250 038
1476	R 1 185 245	-R 61 164	R 83 652	-R 333 690	-R 250 038
1477	R 24 722 923	R 93 871	R 0	-R 754 284	R 93 871
1478	R 30 934 618	R 160 994	R 0	R 94 350	R 160 994
1479	R 27 628 502	R 330 597	R 0	R 262 901	R 330 597
1480	R 65 814 090	-R 29 817 988	R 6 268 069	-R 36 086 057	-R 29 817 988
1481	R 76 282 204	R 722 354	R 618 123	-R 1 573 849	-R 955 726
1482	R 63 511 969	-R 1 005 751	R 825 334	-R 2 761 271	-R 1 935 937
1483	R 29 933 250	-R 2 341 407	R 262 268	-R 3 172 885	-R 2 910 617
1484	R 1 776 867	R 293 254	R 0	R 204 411	R 238 397
1485	R 1 776 867	R 293 254	R 0	R 204 411	R 238 397
1486	R 10 133 561	R 1 998 065	R 0	R 878 617	R 1 145 302
1487	R 42 440 744	R 3 656 325	R 2 379 207	-R 3 609 000	-R 1 018 180
1488	R 37 906 080	R 9 590 982	R 2 351 808	R 2 651 742	R 5 003 550
1489	R 39 912 343	R 5 018 026	R 3 332 063	-R 2 044 990	R 66 188
1490	R 18 497 287	-R 3 791 806	R 20 551	-R 4 707 913	-R 6 424 278
1491	R 21 745 292	R 831 213	R 1 391 061	-R 3 282 782	-R 3 438 301
1492	R 22 571 016	-R 8 453 390	R 2 795 665	-R 16 662 613	-R 13 866 948
1493	R 24 770 147	-R 518 890	R 2 845 190	-R 8 456 152	-R 5 610 962
1494	R 22 412 678	-R 2 548 791	R 3 225 576	-R 10 977 162	-R 7 751 586
1495	R 2 547 728	-R 359 324	R 88 210	-R 672 299	-R 584 089
1496	R 4 038 318	-R 631 838	R 141 554	-R 1 124 238	-R 982 684
1497	R 14 848 503	-R 2 100 713	R 1 203 368	-R 3 304 081	-R 2 100 713
1498	R 11 216 304	-R 1 208 234	R 372 751	-R 1 580 985	-R 1 208 234
1499	R 1 474 346	-R 1 881 592	R 38 154	-R 1 919 746	-R 1 881 592
1500	R 56 527 596	R 7 679 967	R 121 832	R 4 909 150	R 7 679 967
1501	R 58 906 557	R 12 287 588	R 175 920	R 8 687 994	R 12 287 588
1502	R 64 044 718	R 10 090 155	R 120 492	R 6 787 939	R 10 090 155
1503	R 63 916 348	R 3 245 307	R 100 082	R 2 028 848	R 1 933 960
1504	R 47 657 746	R 3 012 479	R 57 871	R 2 347 855	R 3 012 479
1505	R 63 230 289	-R 599 194	R 5 082 088	-R 4 911 306	-R 1 671 155
1506	R 18 989 351	R 759 137	R 3 548 548	-R 903 172	R 759 137
1507	R 101 316 824	R 7 368 932	R 6 452 595	R 961 518	R 7 368 932
1508	R 39 502 177	-R 7 920 997	R 2 123 931	-R 7 751 179	-R 8 594 919
1509	R 147 829 948	R 6 351	R 451 568	-R 1 785 281	-R 1 333 713
1510	R 149 617 757	-R 1 210 253	R 445 871	-R 3 212 391	-R 2 766 520
1511	R 129 371 150	R 3 592 676	R 357 904	R 1 340 716	R 2 087 073
1512	R 81 565 081	R 1 548 596	R 406 856	R 945 971	R 1 548 596
1513	R 55 692 970	-R 1 169 808	R 647 607	-R 1 817 415	-R 1 169 808
1514	R 64 071 047	R 1 107 807	R 424 829	R 636 863	R 1 107 807
1515	R 53 952 161	-R 3 246 154	R 7 546	-R 3 253 700	-R 3 246 154
1516	R 53 146 721	-R 4 197 870	R 401 272	-R 4 599 142	-R 4 197 870
1517	R 53 146 721	-R 4 197 870	R 401 272	-R 4 599 142	-R 4 197 870
1518	R 53 146 721	-R 4 197 870	R 401 272	-R 4 599 142	-R 4 197 870
1519	R 90 179 545	R 7 378 349	R 1 507 118	R 137 697	R 2 592 203
1520	R 90 179 545	R 7 378 349	R 1 507 118	R 137 697	R 2 592 203

Firm Identifier	Revenue	EBITDA	Interest Exp	Net Income	EBIT
1521	R 90 179 545	R 7 378 349	R 1 507 118	R 137 697	R 2 592 203
1522	R 127 601 159	-R 19 042 481	R 4 556 708	-R 19 364 562	-R 22 015 243
1523	R 134 921 560	-R 4 876 263	R 2 161 222	-R 7 214 552	-R 7 836 059
1524	R 112 841 825	R 762 515	R 4 853 331	-R 5 338 425	-R 2 535 577
1525	R 81 073 545	R 5 706 253	R 1 444 147	R 3 067 507	R 5 706 253
1526	R 126 554 554	R 12 365 542	R 1 090 920	R 11 281 046	R 12 365 542
1527	R 95 381 034	R 7 026 771	R 1 161 017	R 4 127 401	R 7 026 771
1528	R 99 508 708	R 3 257 969	R 1 393 151	R 1 963 299	R 3 257 969
1529	R 76 894 648	-R 140 927	R 365 325	-R 1 620 541	-R 1 255 216
1530	R 78 855 357	R 4 470 741	R 3 532 780	-R 461 330	R 3 071 450
1531	R 58 735 532	-R 1 201 653	R 669 698	-R 2 839 231	-R 2 169 533
1532	R 54 224 462	-R 7 480 645	R 226 545	-R 7 707 190	-R 7 480 645
1533	R 4 913 841	R 1 133 598	R 733 978	-R 479 231	R 254 747
1534	R 395 426 072	R 22 623 771	R 16 579 481	R 4 105 717	R 21 262 797
1535	R 395 426 072	R 22 623 771	R 16 579 481	R 4 105 717	R 21 262 797
1536	R 407 522 234	R 23 326 000	R 14 316 174	R 5 588 890	R 21 926 910
1537	R 442 540 547	R 26 158 549	R 17 378 788	R 6 417 670	R 24 410 815
1538	R 0	R 17 174 077	R 827 005	R 9 835 143	R 17 174 077
1539	R 54 315 311	R 3 009 367	R 631 378	R 1 705 097	R 3 009 367
1540	R 76 219 055	R 4 948 529	R 627 876	R 4 067 893	R 4 948 529
1541	R 54 878 282	R 3 706 312	R 800 054	R 2 091 427	R 3 706 312
1542	R 58 071 124	R 4 317 826	R 683 864	R 3 004 245	R 4 317 826
1543	R 10 429 987	-R 37 698	R 942 488	-R 541 087	-R 40 609
1544	R 2 151 000	R 203 788	R 117 007	R 29 679	R 146 686
1545	R 41 372 548	R 4 043 317	R 3 222 716	R 820 601	R 4 043 317
1546	R 99 765 892	R 4 023 777	R 622 550	R 1 962 400	R 2 655 156
1547	R 16 343 659	R 906 254	R 152 236	R 476 246	R 906 254
1548	R 12 054 487	-R 198 455	R 165 456	-R 91 629	-R 198 455
1549	R 11 944 376	-R 557 052	R 30 221	-R 470 425	-R 557 052
1550	R 2 053 752	R 6 712	R 0	R 4 945	R 6 712
1551	R 64 971 204	-R 2 189 310	R 0	-R 2 189 310	-R 2 189 310
1552	R 622 100	-R 2 713 282	R 0	-R 2 713 283	-R 2 713 283
1553	R 831 490	R 81 693	R 10 925	R 15 605	R 33 997
1554	R 367 591 854	R 23 240 361	R 1 281 896	-R 617 475	R 1 944 267
1555	R 494 755 235	R 46 172 557	R 2 439 478	R 8 593 936	R 15 527 478
1556	R 228 066	R 14 089	R 3 480	R 3 191	R 6 671
1557	R 251 945	R 10 646	R 5 248	-R 1 257	R 3 991
1558	R 826 090	R 78 705	R 27 207	-R 72 064	-R 72 828
1559	R 960 238	R 262 214	R 26 614	R 58 355	R 107 827
1560	R 960 238	R 262 214	R 26 614	R 58 355	R 107 827
1561	R 17 548 864	R 1 278 852	R 846 114	-R 215 625	R 630 490
1562	R 28 534 816	R 6 465 530	R 1 025 832	R 4 595 702	R 5 843 220
1563	R 40 835 891	R 10 142 082	R 1 070 076	R 5 893 472	R 9 387 001
1564	R 40 729 993	-R 289 220	R 1 719 849	-R 5 717 608	-R 2 853 476
1565	R 31 727 707	-R 7 509 678	R 1 862 591	-R 14 888 507	-R 11 651 971

Appendix B: Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

07 August 2018

Kosana Tokelo

Dear Tokelo

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

Gordon Institute of Business Science
Reg. No. 99/19816/08
26 Melville Road, Illovo, Johannesburg
PO Box 787602, Sandton, 2146, South Africa
telephone (+27) 11 771 4000
fax (+27) 11 771 4177
website gibs.co.za
University of Pretoria