MACROECONOMIC VARIABLES UNDERLYING SYNCHRONISATION IN PROBABILITES OF DEFAULT OF SOUTH AFRICAN COMPANIES

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Abstract

This paper estimates the probability of default of South African companies and determines if the default probabilities are synchronized. It further investigates if a relationship exists between the macroeconomic variables and default probabilities. Eighty South African companies are analyzed for the period ranging from January 1997 to December 2010. The study uses the KMV (Kealhofer, Merton and Vasicek) model to estimate the probability of default while it uses the Dynamic Factor Model (DFM) to determine synchronization and to extract common factors that drive the probability of default. The results show that the estimated probability of default trend is able to depict events that impacted the South African economy, such as the Asian crisis, the dot com bubble and global financial crisis. The DFM reveals that South African companies' probabilities are synchronized and they are to a certain degree driven by the economic environment. The dependency of defaults on macroeconomic variables and the high synchronization of companies has policy implications.

Key Words: Probability of Default, KMV Model, Factor Analysis, Synchronization

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Chapter 1

Introduction

In the light of the 2008 financial turbulence the study of credit risk management is highly relevant. Credit risk assessment or the ability to predict business failures is an absolute necessity for stable financial and economic systems. The more accurate researchers can be in predicting the probability of default, the less likely it will be for economies to be taken by surprise by events such as the 2008 financial crisis. The accurate prediction of default is even more critical given that company defaults are destructive events, especially when a contagion or synchronisation effect is associated with them. The negative consequence of company failure is felt by many stakeholders, including: shareholders, creditors and employees; thus a broad spectrum of the economy is affected.

When a company defaults, the value of investors' and shareholders' investments decline as their expected returns become unrealisable. Consequently, due to poor company turnover, creditors are not paid which, in turn, poses challenges of servicing debt obligations. This makes employees of a company prone to losing their jobs, which also negatively impacts the government through contraction in tax revenue (Wu, 2010). In addition, consequences of bankruptcy are the numerous costs a company incurs when it defaults, for example, in lawyers' fees, accountants' fees and the opportunity cost of time used administering and managing bankruptcy (Warner, 1977).

The demise of companies like Enron in 2001 and Parmalat in 2003 had significant consequences for their shareholders. Shareholders of the American giant corporation Enron watched its share price drop from a high of $90 in December 2000 to almost zero in January 2001 (Bruno, 2001). Its investors experienced a huge loss of approximately $64.2 billion as the share price lost its intrinsic value, which led to the company being delisted on the stock exchange (Neuman, 2005). About 40 000 investors of the Italian based company Parmalat were also severely impacted when it became bankrupt. The equity value loss of Parmalat's shareholders was estimated to be roughly €2.495 billion. In addition, 160 000 bondholders were left stranded and 9 200 creditors filed claims when Parmalat became insolvent.

The consequences of the failure of those two companies not only impacted on the investors but also on their employees. As the Enron share plunged in value, a growing number of its employees became jobless; an estimated 4 000 where retrenched in December 2000 (Bruno, 2001). In addition to losing their jobs, those employees also lost nearly all their retirement savings. Some testified that they would have retired with $700 000 to $2 million due to returns from Enron's stock but were now left with virtually nothing except their social security payments (Caines *et al.*, 2002). The impact of the collapse of Enron spread further than its employees and investors, to its business partners. Enron's default was estimated to cost its main financial backer J.P. Morgan approximately $1 500 million and other banks also experienced huge losses; for instance, Barclays reportedly lost $100 million (International News, 3 December 2001). The spread of the one company's default to the other is due to synchronisation of defaults that exist between them; for example, Enron's default led to WorldCom's default a year later. The spread of defaults was also seen in the credit crunch; the default of Lehman Brothers was followed by events like AIG default, the Federal taking over Fannie Mae and Freddie Mac and acquiring of Bear Stearns by J.P. Morgan Chase to avoid bankruptcy (Johnson & McAfee, 2010).

In South Africa similar patterns of outcomes of company defaults were observed when Pamodzi Gold went into liquidation in April 2009 (Censorbugbear, 2009). Pamodzi had an estimated 15 000 employees who received their salaries late since October 2008, when it started experiencing financial problems and from February 2009 received only a portion of their salaries. Pamodzi's employees, mainly mineworkers, were often the bread winner of their family of about 8-to-11 individuals (Kleynhans, 2009). The large number of dependencies on the Pamodzi's employees broadens the spectrum of economic and social impact of its default. Pamodzi investors also lost significant amounts as the share price dropped from its listing price of R21.80 in December 2006 to R0.60 in February 2009 (Geena, 2009). The other parties that were severely impacted by Pamodzi's default were the creditors, who were estimated to be owed over R1 billion (Seccombe, 2009). The aftereffects of the collapse of Enron, Parmalat, Lehman Brothers and Pamodzi indicate that, regardless of the size of the company, the impact of its default has far reaching consequences and a major effect on their country's economy as a whole.

To mitigate the ensuing company default damages, which are further perpetuated by the synchronisation effect, it is crucial to understand the drivers and determinants of probability of default for accurate prediction of default. Various factors impact on a company's probability of default (Wu, 2010). The most intrinsic determinants of a company's probability of default are the idiosyncratic characteristics and management style. Over and above those factors, the state of the economy, such as, changes in interest rates, unemployment rate, gross domestic product (GDP) and inflation, play a significant role when predicting the probability of a company's default (Qu, 2008). The reasoning applied is that during economic expansion demand tends to be high and as a result companies yield high profits. The high profit improves a company's financial stability making it less likely to default. Whereas during a recession the contrary happens; there is less demand, a company yields less profit, which then increases their chance of defaulting. Applying this logic, it is reasonable to suspect that the economic conditions within which a company is operating play a significant role in its probability of default.

Other research studies indicate that to improve the accuracy of predicting a company's probability of default, macroeconomic factors should be taken into account (Harmele *et al.,* 2004; Harkbath *et al.*, 2006). Notably, the economic variables that are included in the models vary from country to country; and even where similar macroeconomic variables are considered across countries, their degree of influence still varies across the countries (Qu, 2008). Hence, research done in a different economy creates new knowledge on how macroeconomic factors in that specific economy affect a company's probability of default and also which economic variables have explanatory power.

To create similar crucial knowledge for stability of the financial and economic system this study is similarly conducted in South Africa, to better understand the dynamics of company defaults and the impact of the macroeconomic environment within the South African context. This study firstly estimates a company's probability of default, then investigates whether company defaults are synchronised, and finally establishes whether a relationship does exist between company defaults and macroeconomic variables within the South African economy. The probabilities of default of eighty South African companies are estimated using Merton's structural model, where a parameter called distance to default is calculated. The distance to default is estimated on a monthly basis for each company for the period January 1997 to December 2010. Then the distance to default is then analysed using a dynamic factor model, to establish whether the default rates of those eighty companies are synchronised. The dynamic model establishes synchronisation and identifies common factors that drive the company probabilities. The identified common factors are regressed against economic variables, to determine if a relationship exists between the factors and the macroeconomic variables.

Early studies analysing companies' probability of default or companies' faced with bankruptcy focused on using financial ratios (Beaver, 1966; Altman, 1968). By only considering internal financial data those models are overlooking the importance of the external economic environment when estimating company default rates. In acknowledging the significance of the external factors other than financial data, our model uses company trading market data to estimate probability of default. Merton's model, which is applied in this study, incorporates both financial and market data, for example, share price, to predict the company default rate. By expanding the spectrum of input variables into the default model the degree of accuracy of the model is improved.

Over and above market data, studies started including macroeconomic factors when estimating the likelihood of a company to default (Merton, 1974; Vasicek, 1987). The early studies that acknowledge the importance of macroeconomic factors when modelling companies' probability of default usually use one or more systematic risk factor(s) to include business cycle effects. Such models assume that processes affecting the probability of default are homogenous across all companies. This is a questionable assumption because macroeconomic conditions have different impacts on companies in different industries (Pesaran *et al.*, 2005). Structural models such as Merton's model, which focus on idiosyncratic company information, allow for company heterogeneity when modelling the probability of default. Hence, the estimation of probability of default in this paper relaxes the assumption of homogeneity and analyses the impact of each observed macroeconomic variable on each company's probability of default.

Most of the latest studies that estimate probability of default and understand its interplay with the macroeconomic variables are focused in developed countries (Qu, 2008). This research study creates knowledge within the African continent as well as in emerging markets by using South African companies as the basis for study. South Africa contributes more than 20% to Africa's GDP, thus a study that helps understand the prediction of default probabilities of companies better in South Africa creates knowledge in an African country that carries significant weight for the economy of the African continent. The knowledge from the results of the study shows that the estimated probabilities of default for companies often mimic events that impacted South African economy. The dynamic factor model reveals that the company defaults are synchronised and they are driven by five factors. When analysing the relationship between those five factors and macroeconomic variables it can be observed that to a significant degree the default rates are driven by the state of the economy.

The ability to accurately predict the probability of company defaults, assess the level of synchronisation of these defaults, and establish the impact of macroeconomic variables on the probabilities is crucial for the South African economy. It will assist owners and shareholders of companies to know how changes in the economy will affect their probability of defaulting and how one company's defaulting poses a threat on another company within the economy. In this way they can take advance action to either avoid the default or curb the costs of defaulting. It will assist investors to make more educated decisions when choosing their portfolio because they will not only look at the financials of the companies when choosing to invest; as already explained, idiosyncratic information doesn't tell the whole story. By applying the model, they will assess how economic conditions will affect the probability of the company they consider investing in to default, hence affecting their investment returns. The model will assist in corporate evaluation, in mergers and acquisitions the management of companies being merged need to have a thorough understanding of the risk they taking by being part of the other company; hence the usual corporate evaluation. While the financials of the other company are good indicators of their profitability, the managers need to have an understanding of how macroeconomic factors changes may impact the probability of defaulting; and this model will assist in evaluating that probability.

The rest of this paper is divided into five sections: A literature review is presented in Chapter 2, which discusses empirical studies for estimating probability of default, synchronisation of default as well the relationship between macroeconomic variables and company defaults. In Chapter 3 the methodology is outlined, firstly, of Merton's model, and then the dynamic factor model. In Chapter 4 a description of the data, data sources and the estimation process are provided. A report on the results of this study is presented in Chapter 5. Finally, Chapter 6 concludes the study and also presents recommendations and suggestions for further investigation.

Chapter 2

Literature Review

Credit risk assessment or the ability to predict business failures is an absolute necessity for a stable financial or economic system. The more accurate research studies can be in predicting this behaviour, the less likely economies will be taken by surprise by events such as the 2008 financial crisis. In an attempt to meet this need for more accurate credit risk models, researchers have done a considerable amount of work and development in this field. Study in credit risk modelling or specifically the modelling of probability of default is split into two main categories: The first set of models is reduced models, which rely mainly on accounting or company financials to estimate the default; the second set is structural models, which depend on market data to predict probability of default.

2.1 Reduced Models

The literature depending on company accounts data to predict business failure goes as far back as Altman's work in 1968. Altman uses financial ratios based on company's accounts data to predict corporate bankruptcy. In order to predict corporate bankruptcy he uses five financial variables, which have different weights in a discriminant analysis. The five predicator ratios used in the model are: working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total debt, and sales/total assets. The five ratios are applied in a discriminant analysis to estimate Z-scores that predict bankruptcy within a two year period.

The approach is further extended to use both linear and non-linear discriminant models. Altman *et al.* (1977) modified their work from a Z-core model to a Zeta approach, which can predict default of corporations five years prior to the default. The Zeta is a combination of linear and non-linear discriminant models. The non-linear model results indicate that it is more accurate for in-sample forecasts of bankruptcy but less reliable for out-of-sample forecasts. In 1995, Altman *et al.* modified their model to accommodate emerging markets as well as adapt it to be suitable not only for public companies but also private companies. In the modification they revised the fifth variable, sales/total asset to book value of equity. Numerous studies follow this work pioneered by Altman by further exploring ways to develop a more reliable and accurate bankruptcy prediction model.

Later developments of the approach moved to probit and logit models creating the ability to explicitly link the accounting variables to the Z-score and then directly compute the probability of default. These studies include work by Geroski and Gregg (1997), and Lennox (1999); as well as Bernahardsen (2001), Bunn and Redwood (2003), and Benito *et al.* (2004), Eklund *et al.* (2001).

Bunn (2003) uses a Company-Accounts-Based probit model to estimate the probability of a company failing. The model estimates probability of default for UK non-financial companies, both private and public. In this model both financial and non-financial variables are used to explain company failure. The model categorises company data into four groups: profitability, financial ratios, company characteristics, and one macroeconomic variable. The non-financial information is added to the model to enhance the explanatory power of accounting data. The accounting ratios included in the model are debt to assets ratio, current ratio and interest cover.

In 2006, Bandyopadhyay also added to the field of predicting corporate default using company data. He develops a model for emerging market, such as India, that can accurately predict bond default one year in advance and also predict corporate bankruptcy two years before the financial distress. In this study, as is also indicated in Bunn's (2003) study, the model reveals that inclusion of both financial and non-financial variables is useful for more accurate estimation of default risk. The logit model results indicate that probability of default is a function of the following company financial variables: overall total assets, working capital to assets, total sales relative total assets, solidity, solvency ratio as well as other company characteristics such as company age. The model has very high predictive power for both in-sample and out-of-sample forecasts, hence outperforming both works developed by Altman (1968 & 1995).

The main benefit of reduced-form models is that they develop a precision over time in estimating the probability of default. The drawback of these models is, however, the lack of clarity on which accounting or financial ratios are to be used as inputs for predicting default. Different researchers focus on certain variables, which makes the models subjective to researchers' choice. The models are also inflexible, given that financial variables are not published frequently, which restricts the ability to continually update the models. Another criticism is the fact that financial variables are reflective of the past state of a company, in a sense limiting the power of pre-empting the company's future. Financials portray the past leaving not much said about the future (Dionne *et al.,* 2006). High frequency data is deemed more relevant for forecasting probability of default.

2.2 Structural Methods

Unlike reduced-form models, structural models predominately rely on high frequency market information to predict probability of default. The use of market data in the structural approach make the models more flexible and easier to update, as company financials need not first be published to gather the information needed to estimate the probability of default. The structural approach has its origin in the work done by Merton (1974). Merton's technique is based on the on the Black-Scholes (1973) model for pricing European Options.

The Black-Scholes theory states that when stockholders have a call option on the company's assets the strike price is the company's debt level. On maturity date the stockholder will only benefit from exercising the option if the value of the strike price is greater than the value of the debt; hence, making a surplus after settling the debt. When the scenario is different and the debt level exceeds the strike price the option is not exercised, and the company defaults. Thus, the probability that the option is not exercised corresponds with the probability of the company defaulting. To estimate the probability of default the input variables that are factored into the evaluation process are the company's debt level, asset value, and equity price. Merton directly applies the Black-Scholes framework and calculates a parameter called distance to default, which is the interval or distance between the mean of the asset value and debt value. The greater is the distance to default, i.e. the distance between the asset value and the debt value, the lower the probability of the company to default.

The literature indicates a number of studies have been conducted to improve Merton's basic model. In 1984 the Merton's framework to forecast probability of default was further improved by Vasicek and Kealhofer, to produce the successfully commercialised model KMV (Kealhofer, Merton, & Vasicek, 1984) model. That model has an assumption of viewing a company's equity as a continual barrier option on the underlying value of the company's assets in a given time period (Lu, 2008). If a company's value falls below the threshold level (which is the default point) on or before the time period then the company defaults. The model has proven to outperform its peer models in predicting default and as result has been adopted by Moody's rating agency. The commercialised

Moody's KMV applies empirical distributions to convert distance to default to default probabilities known as Expected Default Frequency (EDF), which are specific for each individual company.

In 1979 Geske extended the Black-Scholes principle and applied Merton's framework by introducing the compound option. Merton states that, the stock is an option on the asset's value and allows one option to default on a pure discount bond. Geske takes this a step further when he states that if the stock is an option on the company assets, then an option on the stock is an option on an option or compound option, hence adding an alternative of multiple options defaulting in the model. So, unlike the simple Merton's balance sheet with a pure discount bond, Geske's balance sheet has a complicated capital structure, including, short term debt, subordinated debt, coupon payment and more, which makes the Geske model more reflective of a company's balance sheet.

In 1999 Deliandedis *et al.* assessed both the ability of Merton's and Geske's models for computing risk neutral probabilities. Given the importance of the dynamics underlying default probabilities in the credit market, their study investigates whether changes in risk neutral probabilities have the ability to forecast credit rating migrations to other levels or to default. Their model uses the Standard and Poors quarterly Compustat data as the basis for credit migration. The results show that both models do equally well, by producing default probabilities that are able to anticipate the impending changes in default months before the actual migration or default event. Both models are able to pre-empt both downgrades and upgrades by rating agency with equal precision. Both models also reflect that larger rating agencies changes and do not have earlier significance than smaller changes, so each alteration is signalled well in advance in spite of its magnitude. The only benefit the Geske's model has, given its complicated balance sheet structure, is the ability to incorporate multiple default opportunities. Hence, the Geske's model is able to reflect a company's tendency to default on short or current liabilities individually, but in most cases the default of the overall company is more important than its default on a specific liability. So, in spite of Merton's simple balance sheet structure, its default prediction performance is on par with Geske's model.

The accuracy and outperformance of Merton's model of other models is well represented in literature (Dionne *et al.*, 2006; Leland 2002). Kealhofer and Kurbat (2002) assess the prediction power of Merton's approach relative to debt ratings and accounting variables. The study is a response to researches conducted by rating agency Moody, which indicates that Merton's approach is not a sufficient measure of credit risk. The researchers found that Merton's model outperforms the ratings agency's model, which includes accounting ratios in predicting default. The study also proves that Merton's model contains any predictive information that is reflected by the debt ratings and accounting ratios. Thus adding debt ratings and accounting variables with the output of Merton's model as suggested by studies of Moody's rating agency doesn't improve the Merton's approach, but the researchers conclude that doing so actually degrades the performance of Merton's model.

Leland (2002) investigated the difference in probabilities of default generated by two alternative structural models. As Merton's approach is one of those structural models, it is important for credit risk management to understand how it differs and compares with its peers within the same pool of models. The first set of models is called exogenous default boundary, they apply the same frame work as Black-Scholes and Merton. The exogenous default models are restricted to one zero bond, where the default barrier is zero until maturity and the company will only default at maturity if the company's asset value is less than the bond's principal value. The second set of models is endogenous default boundary which takes a different approach in determining the boundary. The models assume the decision to default is an optimal choice made by managers who act to maximise the value of equity. The equity holders timeously assess whether it is worth meeting the promised debt service payments, if the answer is yes then the company does not default and they continue to service its debt. On the other hand, should the shareholders decide that it is not worth meeting the debt repayments, the company then defaults. Hence, the default boundary is based on the fundamentals of asset price movements, the amount and maturity of debt issued, the default cost, and corporate tax rates.

Comparing the probabilities of the two, the results show that the models produce similar default probabilities when their default boundaries are aligned. However, the endogenous default probabilities perform well for longer term maturities than the short term maturities. The other difference is the endogenous models' probabilities vary with the cost of default, whereas the exogenous models are invariant to cost. The ability of exogenous (Merton's approach) models to be invariant is beneficial when viewed from a sense that the magnitude of the probability of default should not be influenced by how much the default will cost. In a sense, this introduces biasness of probabilities to the size of company or cost of its default. The exogenous probabilities are more sensitive to volatility of assets value than endogenous probabilities. The high sensitivity characteristic is valuable to credit risk assessment as high volatility of assets could possibly reveal the instability of a company and, hence, its likelihood to default.

Cram *et al.* (2004) used a comprehensive bankruptcy database to compare information content of two accounting based models; Z-score Altman and O-score Ohlson models versus Black-Scholes Merton's model. That study, which spanned a wide period of time, from 1980 to 2000, and had a sample size of 14 303 individual companies, enabled a highly comprehensive comparison to be made. The results from their comparative study indicate that Merton's model incorporates significantly more information about the probability of default than any of the two reduced accounting based models. The results of the study are robust, even with modifications of the accounting models where updated coefficients based on the sample, as well as adjusting for industry effects and separating of parameters into lagged level and change components are incorporated to enhance the models. Still the results in Merton's model remain superior. The study also outlines additional advantages of Merton's model over and above its superior performance. The Merton's model can be modified to predict probability of default for any time horizon, whereas the other models would be inflexible to adopt this possibility. The study goes further to indicate that even adding industry and company specific data does little to improve the performance of Merton's model, implying that in its basic form the model is superior enough above the reduced accounting models.

Tudela and Young (2003) use the Merton approach to assess the default risk of UK non-financial public companies. Their research assesses the reliability of the predictions by examining their success in forecasting the failure or survival of companies. The study relaxes Merton's assumption that default occurs at maturity of debt. The model allows default to occur anytime on or before maturity whenever the company's value drops below the default point, therefore making the model more flexible in identifying the point of default. The efficiency of the default estimates are tested by examining the extent their predictive power improves by including other publically available information on company accounts. This development gave rise to a new kind of model, referred to as hybrid models. Hybrid models combine Merton's model with other company financial information. Their results indicate that the derived probabilities from the hybrid model provide strong signals of failure one year in advance before the default occurs and also outperforms the reduced model approach. However, it shows that the estimates from the hybrid model combined with additional company data only marginally outperform the Merton's model estimates.

Dionne *et al.* (2006) developed a hybrid model that combines the structural model probability of default with the company's financial variables. The hybrid model attempts to address the shortcoming of the structural model of over- or underestimating probabilities as well as the inflexibility of reduced models. The goal for that study was to assess how combining a continuous market valuation structural model with financial statements improves the prediction of company defaults. The exercise fits estimated probabilities from the structural model as explanatory variables in the reduced model for publically traded Canadian companies. The results indicated that the structural probabilities contribute significantly to explaining default probabilities when combined with accounting variables. The study also indicated that the ability of structural model's continuous update assist in making the combined hybrid model more dynamic. This enhances the model's explanatory power during the course of the year when financial variables are static. That study went a step further to analyse the correlation of structural probabilities of default of companies represented in the Canadian Bank database. The results show that there are significant correlations between the probabilities of default among companies. This insight gained from the study reveals that debt holders, such as banks, need to account for these correlations in their capital requirements in order to manage their credit exposure.

Given the good performance and high explanatory power of Merton's model portrayed in the literature previously inspected, much work is done using the model to answer credit and economic risk questions. Huang and Huang (2002) use structural Merton's model to answer the question of how much of the historically observed corporate-treasury yield spread is due to credit risk. The literature in this field has failed to reach consensus in solving the question. Solving the question is important for researchers as well as for practitioners in credit risk management because it will engender understanding of the link between corporate bonds and equity markets, which will have implication on the capital structure theory. The results indicate that applying structural models provides a consistent answer to the question. The solution is arrived at by calibrating structural models to be consistent with historical default loss experience. The benefit of the method is that the estimated credit spreads do actually realistically describe the real severity of expected default loss. The study concludes that for investment grade bonds of all maturities credit risk accounts for a smaller fraction of spread, whereas for junk bonds credit risk accounts for a larger fraction of the spread.

Vassalou and Xing (2004) apply Merton's approach to compute default measures for companies in order to assess the effect of default risk on equity returns. The researches use Merton's framework to estimate default likelihood indicators (DLI) instead of the usual probability of default. DLI are nonlinear functions of probability of default of each company, and differ from the usual KMV probabilities because they are not estimated using empirical distribution of defaults. That study indicates that both the size and book to market of the company are intimately related to default risk. The model concludes that high default risk companies earn higher returns only to the extent that they are small in size and great in book to market. This implies even if the company's risk is high but the above characteristics are not met, it will not earn higher returns than low risk companies. In this study the Merton's approach aided in providing further insight into the Fama and French study that indicates that SML (Size, Small Minus Large) and HML (Value, High Minus Low) are proxy for default risk. The model developed here indicates that although SML and HML contain default information they also contain pricing information, hence should be applied according when viewed as proxy for a company's default.

Bandyoypadhyay (2006) uses the Merton approach to quantify the default risk of publicly listed Indian companies, hence extending the application of Merton to emerging economies. In his study he finds that the Merton's model is able to predict default status of the company much earlier than its publically available default status from external rating agency. The model is also able to provide ordinal ranking of companies by their default risk, over and above its good early signals of default. The ability of the model to ordinal rank companies and its early warning of predictability are crucial to emerging market investors and banks for measurement of credit exposure, so as to allocate capital appropriately. Bandyoypadhyay conducts a second part of his study using similar Indian company data, where he uses the inputs of Merton's model in his earlier study to develop a hybrid credit scoring model. He enhances the Merton's model he built with additional financial and nonfinancial factors such as profitability and liquidity risk. He concludes that in a volatile equity market such as India addition of other factors to Merton's model improves its prediction ability and the model continues to outplay reduced form models.

2.3 Synchronisation

One of the major concerns in measuring and managing credit risk is the correlation or interdependence of probabilities of default. It is important for stability within a financial system to be able to accurately estimate cooperates' probability of default as outlined by the above literature but also of equal importance is measuring the level of correlation of cooperate default within an economy. The reason being synchronisation of company defaults results in default spreading across most companies. This contagion of defaults negatively impacts the broader economy, so synchronised company defaults poses systematic risk to the country. Synchronisation of company defaults is due to companies being exposed to common or correlated risk factors (Das *et al.,* 2007). The links between the companies is being in the same industry, exposed to the same legal system, a supplier-buyer relationship and one prominent reason resounding in most default correlation studies are being exposed to the same economic conditions (Egloff *et al.*, 2007; Lucas, 1995). Gieseke (2004) mentions default rates are strongly correlated to general macroeconomic factors, for example, interest rate. He also found that the synchronised effect is large especially when macroeconomic fundamentals are low. The study also shows that in a large portfolio of financial positions, macroeconomic fluctuations are the main source of risk when defaults are correlated.

Understanding the degree of synchronisation within a financial system assists in rating of companies, structuring of credit products, such as loans, and also pricing of derivatives. All of these parameters are important for managing risk within a country. Accurately capturing of correlation of company probability of default is imperative, given the number of credit risk tools depending on the correct assessment of correlation default. Scholars have over time developed and improved ways to assess synchronisation and a few studies within this field are considered below.

Zhou (2001) evaluates default correlation or the probability of default of more than one company, using the first-passage-time model of correlation. In this model a company defaults when its values first hit a default boundary. Therefore, estimating the default boundary between two companies amounts to calculating the probability of a two-dimensional stochastic process passing a boundary. Zhou shows that the first-passage-time model is easy to implement therefore it provides a tool for credit evaluation, risk management and capital allocation requirement. That study compares the model to Merton's type approach of default correlation and concludes that first-passage-time model outperforms Merton's approach in joint default probabilities and also concludes it's computationally more efficient. Valuzis (2008) estimates joint probabilities using the first-passage-time model. The model is a generalised version of Zhou's enriched by assuming stochastic behaviour of default risk, i.e., it can consider other exogenous type of financial risk like liquidity risk and market changes. Valuzis outlines the short fall of the model as being unable to define implied correlation due to limited data as result there is a needs for aggregation of data. Also the formula of joint probability of correlated default is not symmetric with respect to different companies' defaults. The approach only accommodates two companies at a time.

Das *et al.* (2007) investigate the determinants of correlated default probability for non-public US companies. They applied a comprehensive dataset of company level default probabilities estimated by applying the Merton's approach to examine the co-variation between the probabilities of defaults. The results indicate that systematic time-variation default probabilities are driven by economic wide volatility factors than by changing debt level. This leads to default being closely linked to a business cycle. That study also reveals that both default probabilities and default correlations vary over time due to economic conditions, which results in substantial variation in joint default risk. The analysis shows that when economic wide default probabilities double, joint correlation increases by more than that. The study also documents that the highest rated companies have high volatility over economic distress and also present the most highly correlated default probabilities. The insights of the study are deemed useful by the researchers for portfolio management and appropriate pricing of securities. The structural approach of measuring correlation is limited in calculation of joint probabilities and is outperformed by first passage models (Valuzis, 2008).

Fong *et al.* (2009) measure systemic linkage across Hong Kong banks applying the risk measure named CoVar. CoVar is a value-at-risk (Var) measure of a bank conditional on another bank being under stress on its equity. The CoVar measure is able to assess the co-movements of the default of a bank using quantile regression, by taking into account their nonlinear relationship. The CoVar has the ability to accurately estimate co-movements of a banks' risk measure during high volatility of equity prices and rising risk of financial institutions during a distressed period. The results of the study show that the default risks of Hong Kong banks were interdependent during the 2008 financial crisis. Both local and international banks operating in Hong Kong exhibit similar systematic interdependence, even though the international ones' should have a higher degree of commonality. They conclude that CoVar is a useful measure of interdependence among banks and can be used to develop macro prudential tools. The limitation observed with this model, however, is the need to run multiple regressions; as each regression can only assess the interdependence relationship of two banks at a time.

In order to address the limitation of estimation of joint probabilities for only two entities at a time, as seen in CoVar model, first passage model, structural models, dynamic factor analysis models are developed. Dynamic factor models are able to analyse a large dimension of data and hence can capture synchronisation of more than two entities at a time. The literature considered below shows the success of these models in modelling default probabilities.

Brasili and Vulpes (2006) analyse the co-movements in the fragility of banks in the European Union to determine to what degree the co-movement has increased since the establishment of the monetary union and Euro. They use a dynamic factor model to measure co-movement of the 15 Euro banks. The dynamic factor model allows the fragility measure of the banks, which is the distance to default, to be decomposed into three main components, which are: EU-wide, a country-specific and a bank level idiosyncratic component. The result shows that the EU wide component accounts for about 42% of the variance in the banking risk. The impact of the component increases over time showing that integration is strengthening among EU-banks, more so among larger banks. The analysis further reveals that the co-movements in the EU's banking fragility are to a certain extent due to macro shocks but, in addition to that, the banking system's specific factors also play a significant role. The study highlights that understanding co-movements in banks assists in terms of systemic stability, since the more correlated their risk is the higher the probability of widespread banking crises. Insights from such a study hold policy implications when it comes to structuring the European banking supervision.

Cipollini and Missaglia (2007) use a dynamic factor model to investigate industry specific default rate proxies in Italy, taking into account their relation with business cycle credit factors. The estimation of portfolio loss density is obtained through an estimation of few principal components driving the dynamics of a large data set, including both default and macroeconomic variables. The density forecasts are estimated by engaging both a direct and indirect method of prediction. The direct method produces density forecast by employing shock to principal components which are proxy for static factors. The indirect method generates density predictions by applying shock to the dynamic factors. In stage one of the analysis the direct method outperforms the indirect, when it comes to out of sample prediction of financial distress. Secondly, the direct method forecasting of principal components has the least sensitive measures of portfolio credit risk to multifactor model specifications. The study concludes by indicating that the benefits of credit risk diversification are inclined to decrease as the number of factors increase, especially when applying the indirect method.

Dynamic factor models do not only measure synchronisation for company probabilities but their dynamic feature assists in assessing co-movement within any spectrum. Eickmeirer (2006) assesses the co-movements and heterogeneity in the Euro area by fitting a dynamic factor model to quarterly macroeconomic variables. That study investigates the number of common factors driving the Euro economy, to discover whether the Euro countries share common trends and whether the common shocks have a macroeconomic interpretation. The results show that there are five factors driving the Euro economy, four of which are domestic. The study indicates that the five factors are non-stationary, which implies that the Euro countries share five common trends, where the source of non-stationarities for individual countries is driven by both common and idiosyncratic factors. Investigation of heterogeneity of countries according to the unweighted dispersion measurement shows that inflation and output are heterogeneous, due to idiosyncratic characteristics of individual countries. However, when using the weighted dispersion measurement the asymmetric common shocks drive inflation and output of the Euro area at certain time periods. The results also reveal that output and inflation impulse response are similar across most countries. The insights of the study hold implications for national policy making designed to carry out structural reforms, given that some of the countries' heterogeneity is idiosyncratic.

Ludvingson and Ng (2009) apply the dynamic factor model to investigate the possible linkage between the predictability of excess returns of bonds and macroeconomic variables. The authors highlight that the benefit they gain from applying the dynamic model is that they are able to summarize a large sample of macroeconomic variables into just a few drivers. As a result this approach eradicates dependence on imperfect proxy of macroeconomic drivers and also makes it possible to see the impact of unobservable information of the participants of financial markets. They observe that there is a strong link between the predictability of excess bond returns and macroeconomic activity. They find that inflationary and real factors which are highly correlated with employment and output have higher predictability power of excess returns than forward returns and yield spreads. This implies misspecification in literature, which focuses only on pure financial factors, eliminates important information for future bond returns. The insight from the dynamic factor model suggest that bond investors should be compensated for risk associated with recession, this insight was overlooked by previous literature which focused mainly on few financial variables.

2.4 Macroeconomics and Probability of default

The literature considered above shows that many studies have been done to accurately predict probabilities of default as well as correctly capture synchronisation of those probabilities. This ensures that models are continually being modified and improved, to be able to increase their accuracy and hence dampen the element of surprise for credit risk crisis. The ability to accurately predict default of companies is a sufficient element in risk management but what is even greater importance is to understand the underlying drivers of probability of default. Understanding factors influencing company defaults is a useful risk tool, as it will help investors and company owners to mitigate their risk as they observe certain dynamics of the default drivers. The studies considered below investigate the importance of macroeconomic environment on probabilities of default.

Vlieghe (2001) investigated the determinants of corporate failure in the United Kingdom using aggregate time series data. That study supports of the Bank of England's research on the cause and consequences of financial health or distress within the UK. He found such a study important as it has an effect on the bank's capital. Since, if the realised losses are due to corporate defaults and are unanticipated, this leads to a weakening of the banking system, among other reasons. The results show that the debt to GDP ratio, real interest rates, and real wages have a long-term relationship with corporate failures and also have a better explanatory power on liquidations than accounting data such as capital gearing ratios or aggregate profits. The change in the level of defaulting is driven by different economic factors. A rise in default within the UK in the early 1990s within the sample period is due to an increasing level of indebtedness, whereas the decline in 1992 is due to declining real wages, recovery of the domestic growth, and decreasing real interest rates. Short run effects on default are driven by property prices and nominal interest rates. In this study of UK corporates the spread of corporate bonds over government bonds has no explanatory power on the liquidation rate.

Virolainen (2004) estimates a macroeconomic credit risk model for the Finnish corporate sector for 1986 to 2003. The advantages of the time span of the study are that it includes a severe recession period, with higher than average probability of defaults and very large loan losses for the Finnish banks in the early 1990s. This helps to curb the shortcomings of stress testing with a model that has benign historical data. Another advantageous feature of the study is that it estimates industry specific default rates, which provide more accurate results than models based on aggregate corporate sector defaults. The findings of the study indicate a robust relationship between industry specific default rates and macroeconomic variables. The factors found to be significant are GDP, interest rates, and corporate indebtedness. The strength of interest rates varies prominently across industry and the agricultural sector default rates are less sensitive to macroeconomic factors. The established link between the economy and corporate default rates formed the basis for a stress testing exercise. The stress testing exercise indicated that the current favourable macroeconomic environment, strong financial position of the Finnish corporate and low interest rates lead to very low credit risk within the Finnish corporate sector.

Hamerle *et al.* (2004) forecast credit default risk within the loan portfolio by estimating default probabilities and default correlations. They use Merton's type approach to estimate default probability and model asset correlation by a measure of comovement of asset values of two obligors. The goal of the study is to accurately forecast credit portfolio risk within the German banking industry by applying information available till the point of prediction. The results show that the inclusion of macroeconomic risk drivers significantly improves the forecasts of default probabilities. The macroeconomic variables that enhance the probabilities were business climate index, the unemployment rate and systematic growth in new order of the construction industry. The model also indicated that most of co-movements were due to lagged risk drivers, implying the default rate or loss distribution can be forecasted based on the lagged risk drivers which will reduce default uncertainty. An additional development of the model is its ability to forecast individual borrowers default probabilities and to estimate correlation between those borrowers simultaneously. They conclude that the simultaneous estimation of the two parameters makes it easy to validate the default probabilities, hence probabilities of and correlation shouldn't ever be estimated individually.

Couderc and Renault (2005) studied times-to-default using the rating agency Standard and Poor's rated data. They decompose explanatory errors of probabilities of default over time and investigate what influences the behaviour of default probabilities. That study analysed default behaviour with respect to stock and bond market indicators, and also business cycle indicators which they state are usually overlooked in credit literature. They further explored the sensitivity of default probabilities to past economic conditions. The results show that financial variables have weak explanatory power and the overall changes in default probabilities should not only be attributed to financial variables, such as equities and their volatility, but also to business cycle indictors and the behaviour of credit markets. Economic components are shown to contribute to probabilities over a three-to-five-year period. The study also shows that models that depend solely on financial variables to predict default either under evaluate default peaks or overstate defaults during benign default periods. Economic trends and large past shocks are critical in default behaviour, since they provide the ability to account for lower speed and higher persistence of the default cycle.

Hackbarth (2006) formulated an approach for analysing the impact of macroeconomic conditions on credit risk and dynamics of capital choice. Applying the reduced type model, the contingent claims model illustrates that operating cash flow depends on current economic conditions. This implies that it is beneficial for companies to adapt their probabilities of default and financing policies to the position of the economy. The study then further demonstrates that the linkage of credit risk, capital structure and macroeconomic conditions hold a range of implications for the company. The company's optimal default policy is represented by a different defaulting threshold for each state of the economy; also the defaulting thresholds are countercyclical, which results in higher default rates during recessions. The model is also applied to predict the observed leverage ratios and also shows that the leverage ratio should be countercyclical, which has an impact on the capital structure of the company. The study concludes that a company can adjust its capital structure dynamically both in size and in pace to depend on economic conditions.

Carling *et al.* (2007) construct a duration model to explain the survival time of default for borrowers in the business loan portfolio of a bank. The purpose of the study was to investigate the quantitative importance of macroeconomic variables on company default risk over and above the idiosyncratic risk factors. A reduced-form model using financial statements is used to quantify to what extent factors drive default behaviour in a corporate sector. The financial based model is used instead of stock price based structural model in this case because most of the companies in the study are not publically traded and the researchers had an advantage of access to large company specific data of over 50 000 companies. The findings indicated that the economic factors have a significant explanatory power on company default in addition to financial ratios. The output gap, yield curve and household expectations are instrumental for evolution of company default risk over time. The comparison of a company specific default risk model and the one that includes both company specific and macroeconomic factors shows that the latter model outperforms the former. The study also reveals that idiosyncratic risk factors increase monotonically over the survival period of loan of company, implying that these factors need to be complemented in order to obtain consistent default risk estimates.

Nguyen (2007) analysed the relationship between Japan's industry risk and macroeconomic factors. The study proposed a simple risk measure based on cash flow distribution of all companies in a given industry. Similarly to a cash flow risk model, the measure evaluates the likelihood of a shortfall of cash flow for a hypothetical company which is a representative of the industry. Companies are in financial distress when their cash flow drops below zero. By applying a similar thought process as Merton's model, the distance to default is defined as the ratio of the representative company's average cash flows to their standard deviation. That study shows that the dynamics of the time series of industry risk are significantly related to changes in macroeconomic environment. In particular the risk in the export oriented industry increases when the Japanese currency strengthens, as seen in equity based studies. On the other hand, the risk of domestic industries is more sensitive to domestic demand. The research also reveals that interest rate spreads impact both industries but influence capital intensive industries more; as could be expected, given the negative correlation between interest rate spreads and fixed capital formation.

Shahnazarian and Sommar (2008) apply the vector error correction model to study the relationship between average expected default frequency and macroeconomic variables. Their study is constructed as an exercise to support the stability analysis of Riskbank in order to assess credit risk in the Swedish banking system. Given that the operations of banks are dominated by granting of credit, credit risk is significant risk facing the banking system. The expected default frequency (EDF), which measures the likelihood of default, is estimated by the structural Moody's KMV model. The economic variables the model considers are: inflation, manufacturing output and short term interest rates. The model estimates the relationship between the EDF and macroeconomic variables and uses the estimates coefficients and the forecasted macroeconomic variables to predict future credit quality. The results indicate that an increase in manufacturing output results in lower EDF, rising inflation increases EDF, and short term interest rate has the strongest impact on EDF leading to an increase in EDF and hence poorer credit quality. Developing the model that links the quality of credit with the dynamics of macroeconomic variables makes it possible to undertake scenario analyses where credit risk of banks can be appraised on the basis of different economic factor development.

Qu (2008) analysed the relationship between macroeconomic variables and probability of default, to determine how the macroeconomic factors contribute to explaining the probability of default on an industry level. The proxy for probability of default is monthly EDF from the Swedish Central Bank, estimated using the Merton's KMV model. The exogenous macroeconomic variables considered are: industrial output, consumer inflation, unemployment, interest rate spread, exchange rates, and share prices. The multifactor fixed effect model analyses the relationship and indicates that all macro factors have a different effect on probability of default and the impact varies across countries. In Sweden, which is that study's main focus country, the result shows that changes in exchange rate, industrial output, interest rates, and spread influence the probability of default. Seen from a quantitative view point, the exchange rate has the highest influence on probability of default, whereas the spread has the least impact. The results also reveal that the quality of company impacts its sensitivity to economy; the more stable the company the less sensitive it will be to changes of macro factors. The different Swedish industries react similarly to macroeconomic changes but with different magnitudes.

Rolwes and Simons (2008) explore the relationship between the probabilities of default of Dutch companies and macroeconomic factors using the logit model. The researchers highlighted that the use of the simple logit model is advantageous since it is straightforward and easy to understand, yet gives robust results and also takes the correlation of defaults within sectors into account. The model also addresses the disadvantage of macroeconomic risk model of short time span, where the data is shorter than the business cycle as a result compromising the impact of the business cycle on probability of default. This issue was handled by enlarging the time span of the study from 1983 to 2006, allowing ample time to capture the effects of different business cycles on company defaults. The results show that a superior relationship exists between GDP growth and oil prices with probability of default but a less intense relation with interest and exchange rates. The first lag of the logit default rate has a highly significant coefficient, indicating that the impact of the persistent macroeconomic shocks increase over time.

Jacobson *et al.* (2008) studied the interaction between macroeconomic fluctuations and default risk when applying a reduced model at a company level. They used a large data set of macroeconomic variables from the Swedish economy and they split the sample period into two parts. The first part is used to estimate the model and latter to provide an assessment of the impact of economic aggregate fluctuation on the default risk over and above the company idiosyncratic variables. Firstly, the model indicates that aggregate fluctuations are significant for default rates of both publically and privately owned companies. The results of a logit model based on company variables and macroeconomic variables are able to explain the peaking of default frequencies during the Swedish banking crisis of the early 1990s and the period of lower default frequencies in the late 1990s. The model portrays very robust and successful out of sample forecast, which indicates that the economy is a very prominent factor in estimating default probabilities. They argue that according to their results the state of the economy shifts the distribution of default risk over time, hence the most important source of information over and above the idiosyncratic company variables.

Bottazzi (2009) assessed whether the inclusion of macroeconomic variables in addition to the company's financial variables leads to a better understanding of the causes of company default, and also assist in improving the probability of accurately distinguishing healthy companies from the ones that are in distress. That study also aimed to investigate the notion by credit rating agents that companies' distress – especially in the short-term – is primarily due to poor financial conditions. The study includes both public and non-public companies in Italy broadening the spectrum of usually (public companies) covered credit risk modelling exercise. The results show that directly adding macroeconomic factors improves understanding the process leading to company defaults. The model also reveals that healthy and distressed companies have different characteristics that are based on both their financial position as well as the impact of economic variables. The exercise also indicates that economic variables have a strong statistical significance both further away from the default occurrence and also in the short run to the default event. Therefore, contrary to the rating agency perception, the explanatory and predictive power of economic variables does not weaken closer to the default event.

Souto (2009) constructed credit risk indicators for banks in Brazil banks using Merton's approach, to assess the extent of vulnerabilities with the banking sector. The credit risk indicators are used to compare the banks' risk profile and to examine the impact of potential shocks to the different risk indicators. That study simplified the Merton's model to accommodate the lack of market data within the Brazilian banking system; instead of equity data, it used the balance sheet data. In spite of its simplicity the variant Merton's model is able to capture volatility using balance sheet data; this preserves the functionality of the model, given that volatility is a key feature in estimating credit risk indicators; especially during a time of distress. The estimated default parameters prove to be sound measures of credit risk; they are able to portray the deterioration of risk in the Brazilian banking sector following the Brazilian 2000 crisis. When the indictors are regressed against the macro financial variables they show that the banks are impacted distinctively by the parameter. But of all parameters real rates, inflation and system's default rate have a prominent impact across all banks.

Overall increases in these factors lead to an increase of the individual bank's probability of default. The VAR analysis also indicated similar results with default rate being most responsive to interest rate shocks.

Bonfim (2009) investigated the determinants of credit risk by evaluating idiosyncratic company characteristics and macroeconomic dynamics. The researcher assessed how systematic factors which simultaneously affect companies condition the evolution of aggregate default rates. When exploring the links between credit risk on aggregate level and macroeconomic variables, they observed that there is a significant connection between credit risk and macroeconomic development. The results indicate that periods of economic growth which are accompanied by credit growth introduce tendencies of excessive risk taking. The imbalance is created because of the deterioration of credit risk during economic slowdown. An investigation of over 30 000 companies in Portugal revealed that default probabilities are impacted by idiosyncratic factors, such as: profitability, liquidity and investment policy. However, after controlling for most important company specific credit risk drivers, the characteristics are not able to explain the difference in the default probabilities. When macroeconomic variables and company specific data are included in the model, the performance of the model improves significantly. The researcher concludes that from a financial stability perspective banks and financial intermediaries should include both macroeconomic dynamics and company characteristics when evaluating credit risk.

Gaffeo and Santoro (2009) use panel data for Italian regions to study the relationship between business failures and macroeconomic dynamics. That study indicates there is a long-term relationship between business failure, trend output, interest rate spread and inflation. The long-term relationship informs the determinants of credit risk. The study also reveals that there is a long-term impact running form macroeconomic variables to business failures but not the other way round. Furthermore, the insights from the study hold policy implications, they suggest that fiscal and monetary policy arrangements could impact business failures and hence probability of defaulting differently over the short- and long-term. For example, business failure or defaulting of a company will not be impacted by short-term standard countercyclical polices aimed at targeting of fluctuation of GDP but policies that impact companies' real wages rates and interest rate payments. Daud *et al.* (2008) also investigate the macroeconomic determinants of corporate failures in Malaysia. In the study an autoregressive distributed lag bound test is employed to determine the linkage between corporate failures and macroeconomic variables. Similarly to that of Santoro and Gaffeo's study, the results indicate there is a long run relationship between the lending rate and inflation with corporate failure. Their study also stressed that there are significant policy implications for execution of monetary policy with regard to defaulting of companies a within a specific business cycle.

The studies considered above indicate in ways more than one that macroeconomic variables play a crucial role in accurately predicting probability of default. The prominence of macroeconomic variables in predicting default is seen in both structural and reduced models. So, regardless of the base model, researchers use macroeconomic variables to enhance the predictability of the base model. The research in this paper focuses on structural models because they are validated in literature (as reviewed above) to outperform reduced models and hence will form a more reliable base model for studying the relationship of probabilities of default and macroeconomic variables within the South African context.

Chapter 3

Methodology

3.1 The KMV (Kealhofer, Merton, & Vasicek) probability of default model

The Merton (1974) KMV model calculates a company's probability of default for a given period. The model is based on the option pricing theory of Black and Scholes (1973); which states, the company's equity is viewed as an option on the underlying value of the company's assets because equity holders are residual claimants on the company's assets after all other obligations have been met. The strike price of the call option is the book value of the company's liabilities. When the company's value falls below the strike price then the equity value equals zero and the equity holders transfer the company's ownership to the debt holders.

The probability of default of a company increases as the value of the assets approaches the book value of the liabilities, the company will eventually default when the market value of the assets is insufficient to repay the liabilities. Thus, the company's probability of default is dependent on the company's capital structure, the volatility of the assets returns, and the current assets value.

The three main elements for calculating a company's probability of default are:

Asset Value: the market value of the company's assets. This is a measure of the prospect of the company and the industry of which it is a part. It is calculated from the present value of the future free cash flows produced by the company's assets discounted back at the proper discount rate (Crosbie & Bohn, 2003).

Asset Risk: the uncertainty or risk of the assets value. The value of the company's assets is an estimate; therefore, uncertainty is inherent in the estimation process. Asset Risk is measured by asset volatility, which is the standard deviation of the annual percentage change in the asset value. Asset volatility relates to both the size and nature of the company's business, hence it measures both company and industry risk (Crosbie & Bohn, 2003).

Leverage: the company's contractual liabilities; which includes short term, long-term liabilities, convertible debt, preferred equity, and common equity. The relevant measure of the company's assets is always their market value. The book value of the liabilities relative to the market value of assets is the pertinent measure of the company's leverage; given that it is the amount the company must repay to its debtors (Crosbie & Bohn, 2003).

The distance to default is a function of the above factors; it combines the three into a single measure of default, which then compares the market net worth of the company to the size of one standard deviation move in the asset value.

The formula for Distance to Default is as follows:

$$[\text{Distance to Default}] = \frac{[\text{Asset value}] - [Default\ Point]}{[Asset\ Value][Asset\ volatility]}$$

The probability of default is derived from the above formula once the distribution of assets is determined. Hence the information required for computing the company's probability of default is attained from company's traded financial statement and market price of the company's debt and equity.

The study computes the probability of default in the following 3 steps:

- Estimating the market value and volatility of the company's assets from the market value and volatility of equity and book value of debt

- Computing of distance to default using the asset value and asset volatility derived in the previous step

- Finally, the calculation of probability of default which is derived from distance to default

3.1.1 Estimation of Asset Value and Volatility of Asset Returns

The KMV-Merton model incorporates two particular assumptions:

The first assumption states that the total value of a company is assumed to follow a geometric Brownian motion and is represented as follows:

$$V = \mu V \partial t + \sigma_v V \partial W \qquad (1.1)$$

where

V is the total value of a company

μ is the expected continuously compounded return on V,

σ_v is the volatility of company value,

dW is a standard Weiner process.

The second assumption of the model is that the company has just a single homogenous class of bond maturing in T periods. The company promises to pay the bond to the bondholder at maturity T.

Under the two assumptions the value of the equity is described as a function of the total value of the company by the Black Scholes-Merton's formula. The put-call parity equates the value of the company's debt to the value of the risk free discount bond minus the value of the put option written on the company, where the strike price equals the face value of debt and a time to maturity of T.

According to Merton's model the company's equity value satisfies the following:

$$E = VN(d_1) - e^{-rT} FN(d_2), \qquad (1.2)$$

where

E is the market value of the company's equity

F is the face value of the company's debt

r it the instantaneous risk free rate

N(•) is the cumulative standard normal distribution function,

d_1 is given by

$$d_1 = \frac{\ln\left(\frac{V}{F}\right) + \left(r + 0.5\sigma_v^2\right)T}{\sigma_v \sqrt{T}} \tag{1.3}$$

then $d_2 = d_1 - \sigma_V \sqrt{T}$.

The model makes use of the two equations: equation (1.1) expresses the value of a company's equity as a function of the company's value and equation (1.2) relates the volatility of the company's value to the volatility. Applying Merton's assumptions, the value of equity is a function of the value of the company and time, so it follows directly from Ito's lemma that

$$\sigma_V = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_v \tag{1.4}$$

Using Black-Scholes Merton model, it can be shown that $\frac{\partial E}{\partial V} = N(d_1)$ so that under Merton's model's assumptions the volatilities of the company and its equity are related by

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V \tag{1.5}$$

where d_1 is defined by equation (1.3).

The market value of the company's equity E is observed in the markets by multiplying the company's outstanding share by its current stock price, whereas V is inferred. Following from this, then the volatility of equity σ_E is estimated while the underlying company volatility σ_v must also be inferred.

In order to estimate V and σ_v the study follows the process presented below:

- First step σ_E is estimated from historical stock returns data

- Second step is selecting the forecast window T, which is assumed to be one year hence T=1
- Third step calculates the face value by equating it to the book value of the company's total debt
- Fourth step collects the risk free rate and the market equity of the company

Once the above process is carried out, there are only two unknowns (V and σ_v) in equation (1.2) and equation (1.5). By simultaneously solving equation (1.2) and (1.5), the values of V and σ_v are estimated. In practice Crosbie and Bohn (2001) observe that market leverage doesn't easily converge to give sound results for equation (1.5). To address this problem an iterative procedure is used. An initial value of $\sigma_v = \sigma_E[\frac{E}{E(E+F)}]$ is used in equation (1.2) to estimate the market value of each company's assets on a daily basis. Then the implied return is calculated every day and the return series is used to estimate new σ_v and μ. The iterative process of σ_v is carried out until it converges where absolute difference between consecutive σ_v's is less than 10^{-3}. In this paper a SAS program is applied to carry out the iterative process in order to solve the two equations simultaneously.

3.1.2 Calculation of Distance to Default

Once the values of V and σ_v are estimated can easily be calculated by computing the following function:

$$DD = \frac{\ln\left(\frac{V}{F}\right) + \left(\mu + 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \qquad (1.6)$$

Calculation of default probability

The matching implied probability of default which is also referred to as expected default frequency (EDF) is:

$$KMV = N\left(-\left(\frac{Ln\left(\frac{V}{F}\right) + \left(\mu + 0.5\sigma_V^2\right)T}{\sigma_v\sqrt{T}}\right)\right) = N(-DD) \qquad (1.7)$$

3.2 The Dynamic Factor Model

Once probability of default for each company is calculated on a monthly basis, the outcome is a large panel of data which is further analysed. To determine whether macroeconomic variables play a role in company probability of default and to establish if company defaults are synchronised, the dynamic factor model (DFM) is applied. The DFM presents the ability to analyse large dimensional data as presented by the panel of company defaults estimated every month for each company. The process extracts a few common factors that drive the panel of data, hence dealing with misinterpretation of data due to information overload.

The DFM expresses individual time series as the sum of two unobserved components: a common component driven by a small number of common factors, and an idiosyncratic component which is specific to each variable which, in this case, will be specific to each company. This approach is similar to the traditional factor models by Sargent and Sims (1977) and Geweke (1977). Further development from the traditional factor model to DFM models accommodates the possibility of serial correlation and weak cross-sectional correlation of idiosyncratic components, as in Charmberlain (1983) and Chamberlain and Rothschild (1983). Models of this kind have also been applied by Eickmeier (2006), Forni *et al.* (2000), and Kabundi and Nadal De Simone (2011).

In order to decouple the idiosyncratic component and the common component the following DFM process is conducted:

Consider a vector of time series variable[1] $Y_t = (y_{1t}, y_{2t}, \dots, y_{Nt})'$ that can be expressed as the sum of two latent components, a common component $X_t = (x_{1t}, x_{2t}, \dots, x_{Nt})'$ which is driven by a few factors that are common to the whole panel of probability of defaults and an idiosyncratic component $E_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{Nt})'$ which is specific to each company. The two components are orthogonal to each other; hence they can be represented as follows:

$$Y_t = X_t + E_t$$
$$Y_t = CF_t + E_t \qquad (2.1)$$

where

[1] The time series variables including a vector of probability of defaults.

$F_t = (f_{1t}, f_{2t}, \dots, f_{rt})'$ is a vector or r common factor and

$C = (c_1', c_2', \dots, c_N')'$ is a N x r matrix of factor loadings, with r <<N.

The common component X_t is a linear combination of common factors that is driven by a limited number of common shocks that are similar for all probability of defaults. But the impact of the common shocks differs from one company to the other, due to different factor loadings. In this model, contrary to the standard common component analysis, the idiosyncratic component is driven by idiosyncratic shocks that are specific to each company. The dynamic factor model used in this framework differs from the static factor model in that it treats lagged or dynamic factors F_t as additional static factors. As a result both lagged and contemporaneous factors are included in the common factors.

To identify the number of common factors extracted both the number of time series and observations must be large. When this applies Stock and Waston (1998) show that the idiosyncratic component, which is weakly correlated by construction, vanishes through application of the law of large numbers as $T, N \to \infty$, therefore the common component can easily be estimated in a consistent manner by using standard principal component analysis. The first r eigenvalues and eigenvectors are calculated from the variance-covariance matrix, $cov(Y_t)$:

$$X_t = VV'Y_t \tag{2.2}$$

And since the factor loadings C=V, Equation (1) becomes

$$F_t = V'Y_t \tag{2.3}$$

From (1), the idiosyncratic component is

$$E_t = Y_t - X_t \tag{2.4}$$

There are a number of ways to determine the number of factors in the DFM. Bai and Ng (2002) developed criteria guiding the selection of the number of factor in a large dimensional panel. The principal component analysis (PCA) is used to establish the number of factors in DFM. The PCA suggests that the selection of a number of factors be based on the first eigenvalues and the principal components are added until the increase in the explained variance is less than a specific $\alpha = 0.05$. Similar to Forni *et al.* (2009), F_t is approximated by an autoregressive representation of order 1.

$$F_t = BF_{t-1} + \mu_t \qquad (2.5)$$

where B is an r x r matrix and μ_t an r x t vector of residuals. Equation (2.5) is the reduced form model of the common component of Equation (2.1).

Chapter 4

Data and Estimation

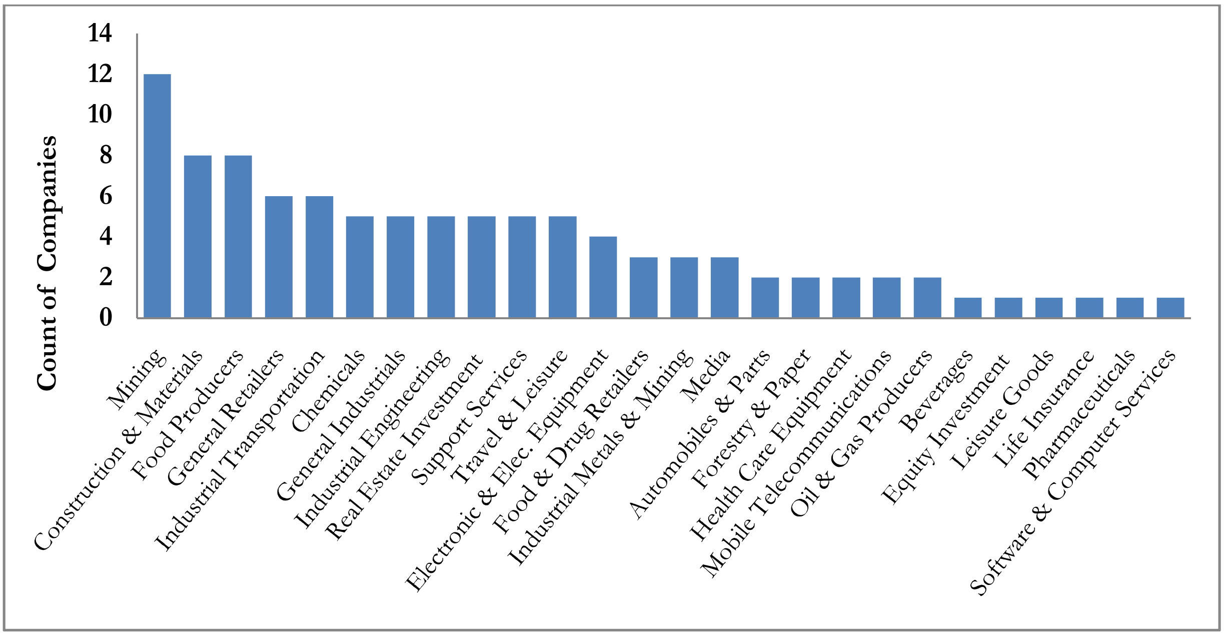
4.1 Data

The research population sample was initially made up of 100 companies within South Africa. All 100 companies are listed on the Johannesburg Stock Exchange (JSE) and are non-financial companies; modelling probability of defaults for financial institution is more intricate, given the structure of the business. The full list of company names and their respective industries is presented in the Appendix. The sample size is in line with that of studies done previously for the estimation of probability of default; Bandyopadhyay (2006) randomly selected 104 companies to determine probability of default for companies within India in different industries. Nguyen (2007) and Gaffeo (2009) used a similar sample size of less than 100 companies per industry to determine the same estimation.

For the purpose of this study, the estimation of probability of default for each company is covered for the period January 1997 to December 2010. That period is broad enough to cover different cycles of economy, i.e., both periods of expansion and contraction of economic growth. This will ensure that the dynamics of the relationship of defaults and macroeconomic variables are observed and understood for different cycles of the economy. The assigning of the 14-year period restricted the sample to 80 companies within South Africa, as it meant for the company to be included in the study it should have been listed on the JSE for at least those 14 years. Despite the reduction of the population sample size, it was still possible that companies from different industries could be included in the research population. Figure 1 illustrates the broad spectra of the industries that are represented in the sample, which well represents the industries listed on the JSE. The companies are skewed toward mining companies, given they had been listed longer on the JSE. The skewness of the industries is inherent to the JSE, given that second to ALTX[2] (companies which were excluded in the study because the index only started in 2003) mining companies are dominant on JSE

[2] ALTX is the alternative exchange which is a division on JSE. It is a market focused on good quality, small and medium sized high growth companies

Figure 4.1: Companies per Industry



The financial variables, current liabilities, and long-term liabilities needed for the model are extracted from the companies' financial statements, which are sourced from the ShareMagic database owned by Profile Data. The trading data for each company is sourced from McGregor BFA. The market data that is sourced is the daily closing share prices and the number of outstanding shares per company so as to calculate market capitalisation of each company on a daily basis. The daily average yield of government bond is then used as a risk free rate is extracted from IHS-Global Insights South Africa. All the three data bases, ShareMagic, McGregor BFA and Global Insights are reliable sources of data because they are external data publishing companies that supply data to investors and financial institutions.

4.2 Estimation

The statistical (SAS) program used to estimate each company's probability of default requires data to be organised into two data sets. The one data set contains monthly observations. The monthly file comprises JSE company identifier, date (combination of month and year) and risk free rate. The daily file comprises JSE company identifier, date in daily SAS format, share price and current outstanding number of shares. The program then uses the two raw data files to estimate the intermediary input variables needed by the KMV model to compute each company's probability of default. The other input variables are σ_E (which is the volatility of stock return), F (Face value of debt), T (time period where T=1 year). E is the market value of each company denoted in millions of rand and is product of share price and outstanding shares. Similar to Vasslou and Xing (2003), face value of debt F is equal to current liabilities plus half of the long-term debt.

Extreme values for each variable are observed from the data collected. To deal with these outliers to ensure that the statistical results are not corrupted the following winsorizing process is carried out (Bharath & Shumway, 2008). For all observations higher than the 99th percentile of each variable are set to that value. In a similar way for any values lower than the first percentile of each variable they are set to that value.

The output of the KMV model is a large panel of data, where all 80 South African companies have a probability estimated for each month spanning from January 1997 to 2010 December. The large dimension data set is further analyzed by factor analysis to extract common factors that drive company default in South Africa. The next step after the factors are identified is to determine which macroeconomic variables underlie the factors. A panel of South African macroeconomic variables that are available on a monthly basis is collected from IHS-Global Insights South Africa for the period January 1997 to December 2010. The economic variables considered are nominal variable, real variables as well as financial variables to ensure a comprehensive representation of South Africa's economic dynamics. All the non-negative variables are logged (except interest rates) and adjusted for seasonality where seasonality was observed. The nonstationary variables that had trends are de-trended using Hodrick Prescott filter, de-trending is preferred rather than differencing because it preserves the history of the variable. These variables that are not trend stationary are differenced and DF-GLS test of Elliot, Rothenberg, and Stock instead of the commonly used ADF is used to assess the degree of integration. To ensure that no serial correlation is present the Schwarz information criterion is used to select the appropriate lag length. In cases where a robust cross-check is needed to be made about the presence of unit root, the KPSS test by Kwaitowski, Phillips, Schmidt, and Shin with the null hypothesis of stationarity is used.

Once the variables are all in their stationary form they are each correlated with each factor to determine which of the economic variables have a strong relationship with the factors. This process then guides the choice of the independent variables that are regressed against each of the factors if the common factors of the company default can be predicted by economic variables. The regression analysis is conducted using the OLS method. Finally, each factor is expressed as a function of independent macroeconomic variables that play a significant role in the factors predictability.

Chapter 5

Empirical Results

This section outlines the results of the models applied during this study. Firstly, the results of the KMV probability of default model which is used to estimate probability of default for domestic companies are presented in Section 5.1. Then the results of the factors analysis, where the DFM model is used to determine if the probabilities of the South African companies are synchronised, are discussed in Section 5.2. Finally, the relationship between the common factors of the probabilities of default and macroeconomic variables are assessed, to determine if there is a link between the probabilities and the economy. The result of which is presented in Section 5.3.

5.1 KMV Model

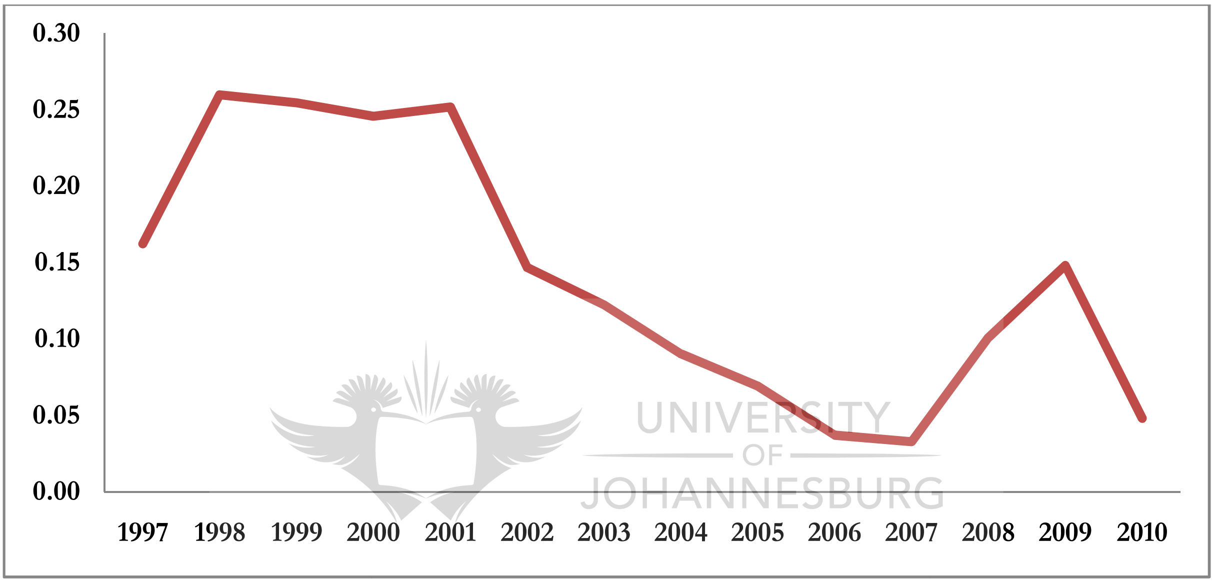
The descriptive statistics of the average annual probability of default (PD) for all 80 companies included in the research population as well as segmented by industry are indicated in Table 5.1. The industries presented in the table represent at least six of the broad South African economic sectors, portraying diverse the representation of South African (SA) companies used in the study. The financial sector is specifically excluded from this study, given the particularity of modelling probability of default in that sector and the other sectors not included don't have a sizeable company representation for the study period.

Table 5.1: Descriptive Statistics of Annual Average Probability of Default

Descriptive Statistics	All Companies	Construction	Agriculture	Trade	Manufacturing	Mining	Services
		Construction & Materials	Food Producers	General Retailers	Industrial Transportation	Mining	Support Services
Mean	0.11	0.18	0.06	0.18	0.19	0.12	0.10
Median	0.09	0.14	0.02	0.19	0.13	0.10	0.10
Standard Deviation	0.08	0.15	0.07	0.09	0.20	0.09	0.09
Variance	0.01	0.02	0.01	0.01	0.04	0.01	0.01
Range	0.22	0.42	0.22	0.27	0.57	0.28	0.25
Minimum	0.01	0.00	0.00	0.04	0.00	0.01	0.00
Maximum	0.23	0.42	0.22	0.32	0.57	0.29	0.25
Sum	1.53	2.54	0.78	2.51	2.69	1.67	1.34
Count of year	14	14	14	14	14	14	14

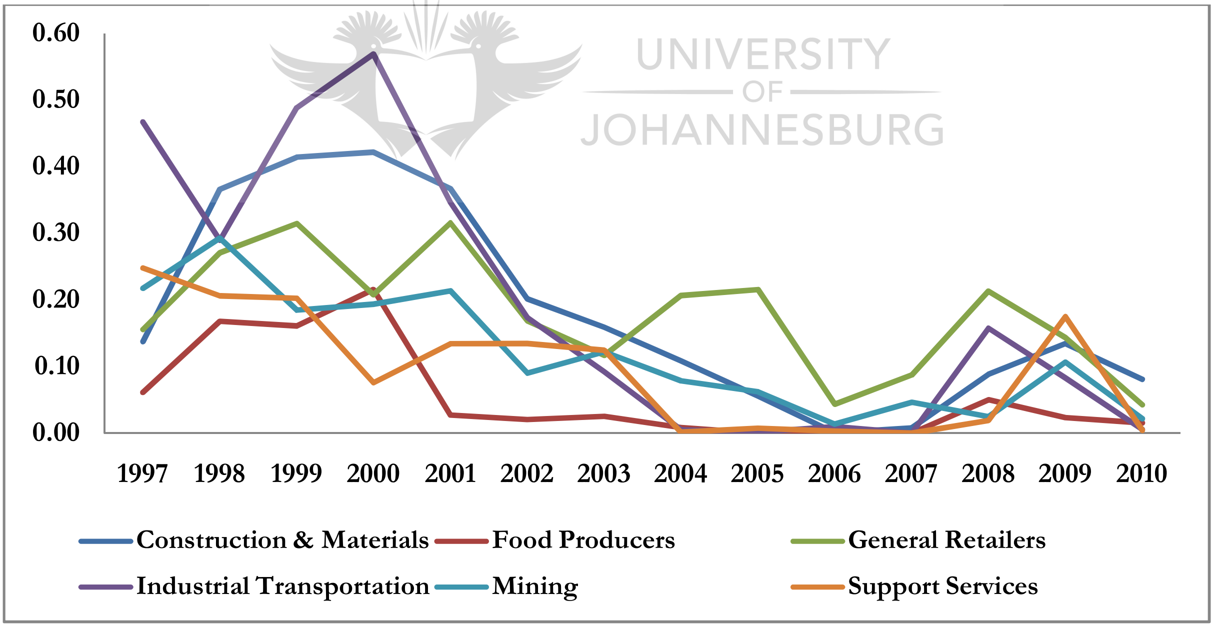
Figure 5.1 maps the overall average of probability of default for all companies over time. The probability of default in 1997 to 1998 is high; this is explained by the impact of the Asian crisis on emerging markets, such as South Africa. During that period the rand depreciated drastically and asset prices plummeted, as international investors became risk averse about emerging markets. The risk averseness of investors put pressure on the economy, which exerted negative business conditions on domestic companies; hence the increase in probability of default.

Figure 5.1: Overall Probability of Default



The PD trends upwards also in 2000; this upward movement characterises the burst of the dot com bubble. During that period the SA economy faced the decrease in the value of the Rand as well as huge downward adjustments of internet and information technology shares, which lead to the liquidation of some companies. This period of distress in the economy influenced the PD to trend upward to a peak point during the 2000. The PD also exhibits a trajectory in 2001; in that year between September and December 2001, the Rand depreciated by 26% (Knedlik, 2006). The possible factors that impacted the Rand during that period, as identified by the Myburgh Commision of Inquiry in 2002, were the shortfall in the trade balance, the net open forward position of the Reserve Bank, the reduced appetite for emerging markets in internal capital markets, the September 11 bombing of the twin towers in the US, the delay of privatisation of Telekom service provider, and the contagion effect from the political and social troubles of Zimbabwe (Myburgh ,2002). All these reasons contributed to the depreciation of the rand hence, the eroding the domestic companies trading advantage; which then influenced the PD into an upward trend. Then from 2002 to 2007 the PD followed a downtrend; this was underpinned by the favourable economic conditions during that period, economic growth reached peaks of 5.6% real GDP growth during periods of less volatility. Then the 2008-2009 global financial crisis hit and lead to a rising of the PD as the domestic economy went into a temporary recession during that period. The muted economic growth posed dire economic conditions for conducting business, hence the rise in companies' PD. It is interesting to note that the emerging market crisis had a larger impact on probability of default than did the financial crisis. The dot com crisis and 2001 depreciation of Rand portray higher PD compared to the recent crisis. From the figure it is clear that the trend pattern that the PD followed depicts the dynamics of the South African economic environment, illustrating that the state of the economy is embedded in the companies' probability of default. This outcome set a good premise for the last section of the results where the relationship between companies' PD and macro economic variables is assessed.

Figure 5.2: Probability of Default by Industry



The PDs of each of the industry are plotted over time in Figure 5.2. The figure illustrates that the PD trends of the different sectors have developed a similar trending pattern over time. The similarity in the trends signals a common impact or reaction to common factors across sectors, where these factors could possibly be macroeconomic factors, given that Figure 5.1 shows that the average PD mimics economic dynamics. The sectors' PD, like the average PD, peaks during the 1997 – 1998 Asian crisis, the 2000 dot com bubble crisis, and the 2008 – 2009 financial crisis. The graph also shows that some industries are more sensitive to certain crisis periods. Constructions and materials seem to be more sensitive during the Rand depreciation crisis, since some of the production materials are imported; therefore increasing the production costs. On the other hand, general retailers have the highest PD peak during the global financial crisis, as people's incomes were constrained; hence eroding their purchasing power. The less people buy the retailers goods the less the profit the general retailers' would have made, hence increasing their PD relative to the other industries.

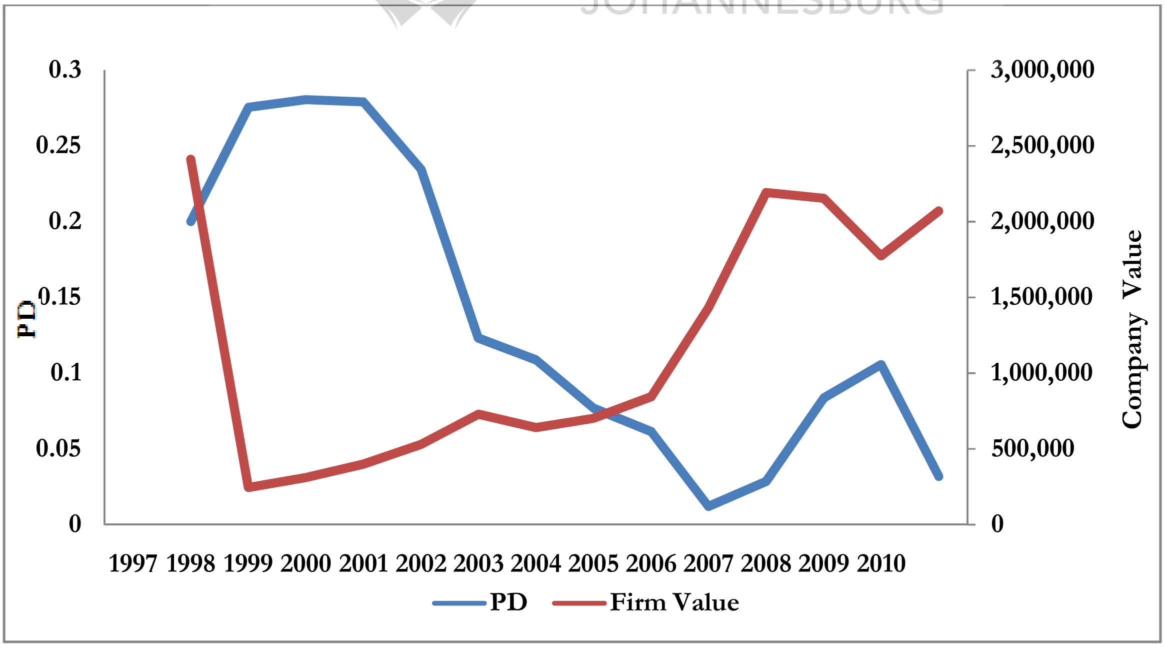
Table 5.2: Default Correlations of Industries Probability of Default

Industries	Construction & Materials	Food Producers	General Retailers	Industrial Transportation	Mining	Support Services
Construction & Materials	1					
Food Producers	0.81	1				
General Retailers	0.76	0.44	1			
Industrial Transportation	0.81	0.78	0.55	1		
Mining	0.9	0.72	0.74	0.71	1	
Support Services	0.76	0.43	0.75	0.52	0.82	1
Overall Average	**0.84**	**0.69**	**0.71**	**0.73**	**0.82**	**0.72**

Correlation coefficients in Table 5.2 indicate that the PDs of the industries are synchronised, where five of the six sectors have an average correlation coefficient of above 70%, the lowest of the six being 68%. The highest correlation among the industries is between mining and construction, implying that default in the mining sector will most likely have a spill over effect to the construction industry or vice versa. This can be explained among other factors by the fact that those two industries trade within an export and import business model, which makes them highly susceptible to the state of the global economy. Both industries are heavily dependent on labour, and are greatly affected by worker strikes which, in South Africa, occur with regularity within these industries. The least correlated sectors are agriculture, as in food producers, and support services; which shows that those sectors face less common factors that drive their PDs. An example of such a factor is climate, which plays a significant role in the agricultural sector but plays a minimal role on a support service such as a hospital.

Figure 5.3 maps company value against PD. The graph shows that PD and company value have an inverse relationship. This relationship indicates that the larger the company the less the likelihood of it failing. This is expected, given that large corporates reveal a sound financial position, as they have been in business for some time relative to most small companies. They draw on their experience to conduct business efficiently and profitability. In addition, big corporates can raise funding – which is crucial to the operation of the company – much more easily than small companies because investors find them more favourable as they have been in the market for long period of time. Among other reasons, these reasons most likely explain why the bigger the company the less likely for it to default. The KMV model has the ability to embed this inverse relationship and Lu (2008) obtains similar results in his default forecasting exercises using the KMV model, which portrays the robustness of the model.

Figure 5.3: Probability of Default versus Company Value



5.2 Factor Analysis

The large matrix [80×168] of companies' probability of default is further analysed by running the factor model through a panel of eighty companies' monthly PD for a period of 14 years; the results of the model are as follows:

Table 5.3: Eigenvalues and Variance Share

Count	Eigenvalues	Cumulative Variance Share
1	0.25	0.25
2	0.13	0.38
3	0.08	0.46
4	0.07	0.52
5	0.06	0.58
6	0.04	0.63
7	0.04	0.66
8	0.03	0.70
9	0.03	0.73
10	0.03	0.75

Table 5.3 lists the eigenvalues and the cumulative variance share common component; where the variance share indicates how much each successive eigenvalue or factors explains the variance of the PD. The variance share is used as a measure of degree of synchronisation within SA companies' PDs. The principal component criterion is used to choose the number of factors underlying the synchronisation; where the factors are added until the explained variance is less than the specific $\alpha = 0.05$. From Table 5.3 we observe that there are five factors where $\alpha > 0.05$. The five factors explain 58% of the variance of South African companies' probability of default. This implies that 58% of the variance observed in the PD of a company is not due to idiosyncratic company factors but to common factors that impact the broader scale of domestic companies, indicating that the companies' PDs are synchronised. So if a company defaults and 58% of the variance in its PD is common to other companies, then the spread of such a default is high to other companies which could possibly create a contagion defaulting effect to the broader economy. Seen positively, such a

default of a company can be used as a signal to other SA companies to take impeding measures against defaulting, given that there is synchronisation of companies' PD in SA.

Table 5.4 presents variance share by industry that indicate a variance share of above 80%. This implies that these companies have PDs that are very sensitive to the overall SA PD. The first sector is the Industrial Transportation Sector indicating a variance share of 94%; this implies it is highly synchronised with the state of PD in South African economy. If the overall PD in SA rises, the company in this sector will be strongly impacted by the rise, hence its PD will also rise and, in the same manner, if the overall PD in SA should decline so will this company's PD. Looking at the industry representation of companies with above 80% variance, we see that the high level of synchronisation is spread across a broad spectrum of industry; which indicates that synchronisation is not skewed to a specific industry. Looking at market capitalisation of the company it also shows that synchronisation with the overall PD is not skewed to large or small companies; it is spread across companies of all size. From this we can conclude that the level of synchronisation is not size or industry specific.

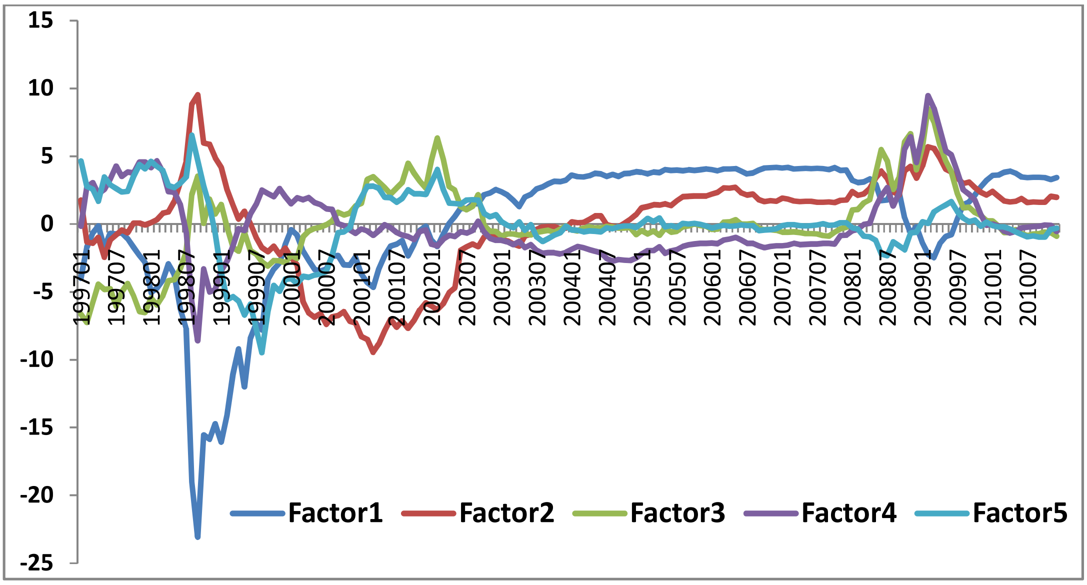
Table 5.4: Variance Share by Industry and Market Capitalisation

Variance Share	Industry	Market Capitalisation
0.94	Industrial Transportation	R 437,048,195
0.87	Support Services	R 16,500,000
0.87	Mining	R 3,259,184
0.85	Construction & Materials	R 722,703,144
0.85	Construction & Materials	R 553,092,441
0.84	General Industrials	R 148,381,064
0.83	Industrial Engineering	R 2,654,151,084

Note: Market Capitalisation is quoted as at 23 August 2011

The next step after establishing the synchronisation of South African company default is to understand the characteristics of the factors. The five factors are plotted over time, as presented in Figure 5.4. The graph shows that each factor presents a unique trend. This portrays the orthogonal characteristic of the factors to one another, indicating that each extracted factor represents a distinct characteristic driving the sample companies' PDs. The robustness of the model is seen here, where five factors have the ability to capture the driving force of the PD of 80 companies from various industries.

Figure 5.4: Factors



The five factors were then tested for stationarity before they were regressed against the economic variables, to determine the predictability of economic variables on the factors. From Table 5.5 it can be seen that the first three factors have a unit root using DF-GLS and become stationary at the first level of differencing. On the other hand, Factor 4 and 5 are stationary at level when using the KPSS test.

Table 5.5: Stationary Tests

Variable	DF-GLS	KPSS
Factor 1	-1.386 [0]	0.043*** [1]
Factor 2	-1.705 [0]	0.106*** [1]
Factor 3	-0.962 [0]	0.139*** [1]
Factor 4		0.183*** [0]
Factor 5		0.080*** [0]

Note: **** indicates significance at 1% level and the figure in the brackets indicate the level of differencing

To this stage it is understand that the characteristics of the factors and their significant ability to explain 58% of the variance in SA companies' PD but the five factors, due to their latent nature, can still not be observed. Hence the factors are a black box, where one needs to dig deeper to identify the observable factors that underpin them. Once identified, they can be used as risk measures that can be tracked to assess the overall level of probability of default within SA, although tracking of the underlying driver is not part of this study but more their identification. In an attempt to identify their nature, each factor is regressed against economic variables to see if they are underpinned by the economic environment.

5.3 Identification of Factors

Before investigating the economic dynamics underlying each factor the combined explanatory power that the factors have on the average PD must be established as well as the direction of the relationship of each factor to PD.

Table 5.6: Regression of Factors on Probability of Default

	PD
Intercept	0.1290
	(0.0000)
Factor 1	-0.0153
	(0.0000)
Factor 2	-0.0088
	(0.0000)
Factor 3	0.0034
	(0.0000)
Factor 4	0.0054
	(0.0000)
Factor 5	0.0009
	(0.0447)
R-Squared	**0.9731**
Adj R-Squared	**0.9723**

Note: Estimated T-statistics are in the brackets

From Table 5.6 it be seen that all the factors are significant at the 5%; this is as expected, given the criterion that was used to choose the factors. The overall explanatory power of the factors is 97%, given by the adjusted R-squared. The sign of the coefficients of each of the factors gives the direction of the relationship of each factor to the PD. Factors 1 and 2 have negative coefficients, which indicate an inverse relationship; so an increase in those factors results in a decrease in companies' PD. On the other hand, Factors 3, 4 and 5 have positive coefficients, which indicate that an increase in those factors results in an increase in companies' PD. This relationship between factors and PD is important, as it will assist in relating the economic environment to PD once each factor has been identified.

Table 5. 7: Regression of Economic Variables on Factors

	Factor1	Factor 2	Factor 3	Factor 4	Factor 5
Intercept	167.6975	-175.4845	44.2951	74.9505	-3.0417
	(0.0023)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Lead_Ind_L	75.5922				
	(0.0000)				
Yield_10	-1.0288				
	(0.0000)				
Eledis_L	-78.6328				
	(0.0000)				
BCI	12.3190				
	(0.0892)				
Mine_ind_L		42.9300			
		(0.0000)			
Gld_prc		19.3980			
		(0.0000)			
BuildpV_L		9.3087			
		(0.0000)			
Lag_Ind_L		71.4458			
		(0.0000)			
Coin_Ind_L		-80.1938			
		(0.0000)			
Eff_exav_L			-30.4850		
			(0.0000)		
Parfn_L			8.5091		
			(0.0000)		
ALSI_L			-5.0039		
			(0.0017)		
Liq_Vol_L			2.4991		
			(0.0137)		
Buildpl_ch			-0.0191		
			(0.0246)		
Min_gld_L				-37.8410	
				(0.0001)	
Tot_veh_pch				-0.0314	
				(0.0051)	
M3				0.07823	
				(0.0014)	
T_91					0.1907
					(0.0173)
Absa_hprc_L					95.506
					(0.0000)
R_dollar_L					21.7382
					(0.0000)
Whsales_ind_L					-40.0083
					(0.0002)
R-Squared	**0.7919**	**0.7775**	**0.6933**	**0.3234**	**0.3110**
Adj R-Squared	**0.7868**	**0.7706**	**0.6857**	**0.3111**	**0.2897**

Note: Estimated T-statistics are in the brackets

Table 5.8: Full Detail of Economic Variables

Dependent Variable	Abbreviation of Independent Variables	Full Detail of Independent Variables
Factor 1	Lead_Ind_L	Leading indicator (Composite business cycle indicators)
	Yield_10	Daily average bond yields for 10yrs and longer
	Eledis_L	Electricity available for distribution in SA
	BCI	Business Confidence Index
Factor 2	Mine_ind_L	Mining production Index (Indicators of real economic activity)
	Gld_prc	Gold spot price
	BuildpV_L	Building plans passed
	Lag_Ind_L	Lagging indicator (Composite business cycle indicators)
	Coin_Ind_L	Coincident indicator (Composite business cycle indicators)
Factor 3	Eff_exav_L	Effective exchange rate of the rand
	Parfn_L	Wholesale prices of Paraffin: Gauteng
	ALSI_L	All shares Index
	Liq_Vol_L	Total number of liquidations – Voluntary
Factor 4	Buildpl_ch	Building plans passed (% change)
	Min_gld_L	Mining production including gold
	Tot_veh_pch	Total number of vehicles sold
Factor 5	M3	Money Supply:M3
	T_91	91 days Treasury bills rates
	R_dollar_L	Rand Dollar Exchange Rate: SA cents per USD
	Absa_hprc_L	Absa house price index
	Whsales_ind_L	Wholesale Trade Index(Indicators of real economic activity)

5.3.1 Identification of Factor 1

Table 5.7 shows that Factor 1 has four underlying economic variables impacting its variance. All four of the variables have significant explanatory power at 10%. The Adjusted R-squared is 79%, which is high and implies that the independent variables together explain 79% of the variance of Factor 1. Hence, Factor 1 is a combination of all the four variables. Each variable has a specific relationship with Factor 1 and the direction of the relation is assessed using the signs of the coefficients.

The leading indicator and Business Confidence Index (BCI) both have a positive relationship with Factor 1, hence a negative relationship with PD, given the direction of the relationship observed between Factor 1 and PD in Table 5.7. This is expected, given that a positive outlook on the South African economy which is observed when the leading indicator increases will dampen the domestic companies' PD as their business environment becomes favourable. This is because a growing economy enables companies to be profitable, consequently lessening their likelihood of defaulting. Similarly the inverse relationship between PD and BCI is expected, since an uptick in BCI implies that current and futuristic state of the economy is satisfactory for doing business in SA; hence causing a decline in PD.

On the other hand, bond yield and electricity distribution have a negative relationship with Factor 1, hence a positive relationship with PD. The positive relationship between bond yield and PD is expected, given that bond prices and yields have an inverse relationship; thus a low demand of bonds causes bond prices to decrease and bond yields to increase. A decrease in the demand of government bonds could possibly be due to risky or uncertain economic conditions in a country. Consequently, the unsettling economic condition will increase bond yields; which then increases the PD of companies in that specific country. The positive relationship between electricity available for distribution in SA and PD is different from expectation. The counter behaviour is explained by the cost that is borne by SA companies in order to increase the electricity available for distribution. This cost gets passed to companies in terms of tariff hikes, as observed recently in SA, when new plants are built; this in return increases the cost of doing business in SA, which leads to an increase in PD.

5.3.2 Identification of Factor 2

Factor 2 is dependent on five economic variables, as seen in Table 5.7. The five economic variables are significant at 5% and they collectively explain 77% of the variance of Factor 2; which implies that the variance of Factor 2 is heavily influenced by the dynamics of the five economic variables together.

All the variables, except the coincidence indicator, have a positive relationship with Factor 2; which leads to a negative relationship with PD as per the relationship between Factor 2 and PD. The reasons for the direction of the relationship between the variables and the PD are as follows: An upward trending lagging indicator is reflective of a prior healthy state of the economy. Companies that experience a preceding booming economy would currently be harvesting profits which were made during the economic boom, making them less likely to default. On the other hand, an increase in coincident indicator leads to an increase of the PD, given the inverse relation of Factor 2 and PD. This unexpected behaviour suggests that the economy is emerging from recession; that is even though the economy is currently growing as indicated by increasing coincident indicator, the profits of companies are still benign, given the past period of dampened growth. An upward trending mining indicator insinuates an expected increment in mining production. Increasing mining production positively impacts GDP, which leads to favourable economic conditions for doing business in SA; hence a decrease in PD. A gold price increase causes an increment of Factor 2, where an increment in Factor 2 decreases PD. An increase in gold price in a mining country like SA leads to economic growth and a growing economy is conducive for business; hence a decrease in PD. The higher the number of building plans passed, the higher Factor 2; hence the lower the PD. An augmentation in the building plans is indicative of an expanding economy; expansion in the economy creates favourable business conditions, thus decreasing PD.

5.3.3 Identification of Factor 3

Table 5.7 outlines that Factor 3 has four underlying economic drivers. The four variables which are predominately financial variables are significant at 5%. They cooperatively account for 69% of the variance of Factor 3, as indicated by the Adjusted R-squared; revealing that the state of economy is still the main driver of variance at this stage.

An effective exchange rate of the Rand and the All Shares Index have a negative relation with Factor 3 and hence a negative relationship with PD, given the direction of the relationship between PD and Factor 3 as shown in Table 5.7. An increase in the effective exchange rate results in a decline in PD, given that a rise in the effective exchange rate implies the Rand is depreciating against all its trading partner currencies. The depreciating Rand makes goods produced by SA companies to be more competitive internationally, as they are cheaper. The affordability of the goods in the market increases their demand and hence lifts revenue, which strengthens the financial position of domestic companies; therefore dampening their likelihood of defaulting. The All Share Index increases when high volumes of shares are being bought due to high demand. The increased sales of shares leads to an increase in company market capitalisations, as more investors inject funds into the companies, therefore diminishing their likelihood to default.

On the other hand, fuel prices – represented by paraffin prices – and liquidations have a positive relationship with Factor 3 and hence a positive relationship with PD. Rising fuel prices increases the cost of production as well as transportation. This increase in the cost of doing business dampens company profits, therefore increasing company PDs. Increments in liquidation means companies are defaulting, which implies SA's business environment is unfavourable; these unfavourable conditions deplete company profits, therefore leading to an increase in PD.

5.3.4 Identification of Factor 4

Factor 4 has three underlying independent economic variables. The three variables are significant at 5% and they jointly explain 54% of the variance of Factor 4. It can be noted that as more factors are added, the economic variables become less impactful; which implies that they are not the only drivers underlying the variance of the factors. This reveals that in conjunction with economic variables there are other dynamics that are common to a company's PD. These other factors could include: company laws and regulations that govern SA companies, e.g., labour laws, the company taxes to be paid, and the political stability of the country. All of those factors have an impact on the business environment and therefore have a potential to influence a company's PD.

Factor 4 has a positive relation with PD, which implies that an increase in Factor 4 leads to an increase in PD. From Table 5.7 it can be observed that all the independent variables have negative coefficients, which implies that in their individual capacities lead to a decrease in Factor 4; when a decrease in Factor 4 would lead to an increase in PD. Growth in building plans is indicative of a growing property market, where growth in the property market is supportive of economic growth; which enhances the business conditions, hence the decrease in PD.

Both a rise in total number of vehicles sold and an increase in mining production results in a decline in Factor 4, where a decline in the latter lowers PD. A country where there is an increase in mining production and vehicles sold illustrates an increase in economic activity. Increasing economic activity propels economic growth, which makes a country more attractive for business, which leads to companies harvesting more profits, and hence a decrease in PD.

5.3.5 Identification of Factor 5

Factor 5 has five economic drivers and together they explain only 29% of the variance of Factor 5. Although the five factors are significant at 5%, this factor has most of its variance rooted in other drivers than macroeconomic variables. These drivers could possibly be in addition to those mentioned in the regression analysis for Factor 4 and include: international economic pressures such as a decrease demand of SA exports due to suppressed global economic growth and risk averseness of investors in relation to emerging markets like South Africa.

An increase in money supply leads to an increase in Factor 5, and an increase Factor 5 results in an increase of PD. Increasing money supply is a harbinger of inflation; increase in inflation erodes return on investments, which decreases the appetite for investors to invest in the country, hence increasing PD as companies struggle for funding. Increase in short term rates, as represented by 91 days treasury bills rates, cause Factor 5 to increase; which leads to an increase in PD. A rise in rates makes it difficult for companies to acquire credit, which they need for expansion of their business. Constrained supply of funds for businesses as well as an increase in their debt servicing cost is likely to increase PD. A rise in house prices leads to an increase in Factor 5, which results in an increase in PD. Increasing house prices lead to high rentals; which implies that business costs have increased, therefore eroding profits and increasing PD. An increase in the Rand Dollar exchange rate also causes an increase PD. A depreciating Rand increases import costs; this erodes company profits as their input costs for doing business increases, hence the increase of PD. Growth in wholesale trade results in a decline in PD. An increasing wholesale indicator implies that the retail sector will be increasing its production, which means increased economic activity, which will lead to economic growth; hence a decrease in PD.

Chapter 6

Conclusion

This paper estimates the probability of default of South African companies and determines if default probabilities are synchronized. The study goes a step further and investigates if a relationship exists between the macroeconomic variables and default probabilities. It analyses 80 South African companies for the period ranging from January 1997 to December 2010. The KMV model is used to estimate the probability of default while the DFM is used to determine synchronization and to extract common factors that drive the probability of default. The extracted common factors are then regressed against macroeconomic variables to establish if there is a relationship between the factors and the economy.

The results of the study show that the estimated probability of default trend is able to depict events that have impacted the South African economy, such as the Asian crisis, the dot com bubble, global financial crisis and other country specific events like September 11 booming of twin towers in the US that impacted SA market. During these events the probability of default increases given the distress in the economy which impacts negatively on domestic companies leading to the upward trend in the probability of default. The analysis of the estimated probability of default indicates that the PD trends of different sectors have similar patterns over the period of the study. The correlation of analysis of different sector PDs show that they are highly correlated, which possibly signals a common impact or reaction to common factors.

Applying the DFM we find that there are five common factors that are underlying the companies' probability of default. The five factors explain 58% of the variance of South African companies' probability of default. This implies that 58% of the variance observed in the PD of a specific company is not due to idiosyncratic company factors but due to common factors that impact the broader scale of domestic companies, indicating that companies' PDs are synchronized. So if 58% of the variance in the company's PD is common to other companies then the spread of such a default is high to other companies which could possibly create a contagion defaulting effect to the broader economy. On a positive side such a default of a company can be used as a signal to other companies to take impeding measures against defaulting, given the synchronization of companies' PD in SA.

The five factors are then regressed against economic variables, and each is found to have a significant relationship with certain economic variables. Factor 1 is dependent on composite business cycle leading indicator, electricity available for distribution in South Africa, bond yields and business confidence index. Factor 2 is dependent on mining production index, gold price, building plans, and coincident and lagging composite business cycle indicators. Factor 3 has a significant relationship with effective exchange rate of the rand, fuel price, ALSI and number of liquidations. Factor 4 is dependent on minding production, number of vehicles sold and growth in building plans. Factor 5 has a significant relationship with money supply, interest rates, rand dollar exchange rate and wholesale trade index. The regressions reveal that the common factors underlying the South African companies' PD have a relationship with macroeconomic variables.

The dependency of PD on macroeconomic variables and the high synchronization of companies has policy implications. Interest rate which is lever used by monetary policy to keep inflation within the 3-6% target band has a positive relationship with companies' PDs therefore an increase in interest rate will lead to an increase in PDs. In times of high inflation the monetary policy would increase interest rate to curb inflation, but given the positive relationship between rates and PD, the MPC would also need to consider the impact the increase would have on domestic companies' PD. The synchronization of the PDs creates an environment where an increase in rates will have a broader defaulting contagion across the economy. In exercising its mandate of curbing inflation by increasing rates, the MPC would then need to ensure that other macroeconomic variables that have a negative relationship with companies' PDs, such as business confidence index, leading and lagging business cycle indicators and wholesale trade index which are indicative of a favourable economy are on the increase. The favourable economic environment will then mitigate the negative impact of increasing rates on the domestic companies' PD.

The relationship of PD and macroeconomic variables also highlights the importance of the world's economy on SA companies. Macroeconomic variables such as fuel prices, exchange rates and bond yield which are influenced by factors outside of SA are shown to have a significant relationship with PD. This implies that owners of SA companies need to consider both local and international economic factors for the success of their companies, since both factors impact the survival of their businesses.

The study in this paper can further be extended in the following way. Examine the forecasting performance of macroeconomic variables on PD; by caring out both in and out sample forecasting exercise. Once the forecasting exercise is done, one will be able to track the propensity of companies defaulting in the SA by observing the dynamics of the economy. Secondly it would be of interest to do an industry classified study, where instead of finding the drivers of all SA companies, one can take a step further and investigate the PD drivers by sector and see how they differ across sectors. This would aid companies in different sector to understand what dynamics in the economy mean specifically for them. Finally one could also study the growing companies such as ALTX within the SA environment and see how their PD's macroeconomic exposure differs from mature companies which formed the sample population in this study.

Appendix:
List of companies and their industries

JSE Sticker	Full Name	Industry
ADR	Adcorp Holdings Ltd.	Support Services
AFE	AECI Ltd.	Chemicals
AFR	AFGRI Ltd.	Food Producers
AFX	African Oxygen Ltd.	Chemicals
ALT	Allied Technologies Ltd.	Mobile Telecommunications
AMS	Anglo American Platinum Ltd.	Mining
AOO	African and Overseas Enterprises Ltd.	General Retailers
APN	Aspen Pharmacare Holdings Ltd.	Pharmaceuticals & Biotechnology
ARI	African Rainbow Minerals Ltd.	Mining
ART	Argent Industrial Ltd.	Industrial Metals & Mining
ASR	Assore Ltd.	Mining
ATN	Allied Electronics Corporation Ltd.	Electronic & Electrical Equipment
BAW	Barloworld Ltd.	General Industrials
BCF	Bowler Metcalf Ltd.	General Industrials
BDM	Buildmax Ltd.	Construction & Materials
BEL	Bell Equipment Ltd.	Industrial Engineering
BSR	Basil Read Holdings Ltd.	Construction & Materials
BVT	The Bidvest Group Ltd.	Support Services
CAT	Caxton and CTP Publishers and Printers Ltd.	Media
CKS	Crookes Brothers Ltd.	Food Producers
CLH	City Lodge Hotels Ltd.	Travel & Leisure
CLS	Clicks Group Ltd.	Food & Drug Retailers
CNL	Control Instruments Group Ltd.	Electronic & Electrical Equipment
CRG	Cargo Carriers Ltd.	Industrial Transportation
CRM	Ceramic Industries Ltd.	Construction & Materials
CSB	Cashbuild Ltd.	General Retailers
CUL	Cullinan Holdings Ltd.	Travel & Leisure
DAW	Distribution and Warehousing Network Ltd.	Construction & Materials
DLV	Dorbyl Ltd.	Automobiles & Parts
DON	The Don Group Ltd.	Travel & Leisure
DRD	DRDGOLD Ltd.	Mining
DST	Distell Group Ltd.	Beverages
DTA	Delta EMD Ltd.	Chemicals
DTC	Datatec Ltd.	Software & Computer Services
EHS	Evraz Highveld Steel and Vanadium Ltd.	Industrial Metals & Mining
ELR	ELB Group Ltd.	Support Services
FBR	Famous Brands Ltd.	Travel & Leisure
GND	Grindrod Ltd.	Industrial Transportation
GRF	Group Five Ltd.	Construction & Materials
GRT	Growthpoint Properties Ltd.	Real Estate Investment & Services
HAR	Harmony Gold Mining Company Ltd.	Mining
HCI	Hosken Consolidated Investments Ltd.	Equity Investment Instruments
HDC	Hudaco Industries Ltd.	Industrial Engineering
HWN	Howden Africa Holdings Ltd.	Industrial Engineering
ILV	Illovo Sugar Ltd.	Food Producers

JSE Sticker	Full Name	Industry
IMP	Impala Platinum Holdings Ltd.	Mining
IPL	Imperial Holdings Ltd.	Industrial Transportation
IVT	Invicta Holdings Ltd.	Industrial Engineering
JDG	JD Group Ltd.	General Retailers
JSC	Jasco Electronics Holdings Ltd.	Electronic & Electrical Equipment
KAP	KAP International Holdings Ltd.	General Industrials
KGM	Kagiso Media Ltd.	Media
KIR	Kumba Iron Ore Ltd.	Industrial Engineering
LBH	Liberty Holdings Ltd.	Life Insurance
MAS	Masonite (Africa) Ltd.	Construction & Materials
MDC	Mediclinic International Ltd.	Health Care Equipment & Services
MFL	Metrofile Holdings Ltd.	Support Services
MOB	MoneyWeb Holdings Ltd.	Industrial Transportation
MPC	Mr Price Group Ltd.	General Retailers
MRF	Merafe Resources Ltd.	Mining
MTA	Metair Investments Ltd.	Automobiles & Parts
MTN	MTN Group Ltd.	Mobile Telecommunications
NCS	Nictus Ltd.	General Retailers
NHM	Northam Platinum Ltd.	Mining
NPK	Nampak Ltd.	General Industrials
NPN	Naspers Ltd.	Media
NTC	Netcare Ltd.	Health Care Equipment & Services
NWL	Nu-World Holdings Ltd.	Leisure Goods
OCE	Oceana Group Ltd.	Food Producers
OCT	Octodec Investments Ltd.	Real Estate Investment & Services
OMN	Omnia Holdings Ltd.	Chemicals
PAM	Palabora Mining Company Ltd.	Industrial Metals & Mining
PAP	Pan African Resources PLC	Real Estate Investment & Services
PET	Petmin Ltd.	Mining
PIK	Pick n Pay Stores Ltd.	Food & Drug Retailers
PMM	Premium Properties Ltd.	Real Estate Investment & Services
PPC	Pretoria Portland Cement Company Ltd.	Construction & Materials
RBW	Rainbow Chicken Ltd.	Food Producers
RLO	Reunert Ltd.	Electronic & Electrical Equipment
RTO	Rex Trueform Clothing Company Ltd.	General Retailers
SAP	Sappi Ltd.	Forestry & Paper
SBL	Sable Holdings Ltd.	Real Estate Investment & Services
SCL	SacOil Holdings Ltd.	Oil & Gas Producers
SHP	Shoprite Holdings Ltd.	Food & Drug Retailers
SIM	Simmer and Jack Mines Ltd.	Mining
SNU	Sentula Mining Ltd.	Mining
SOL	Sasol Ltd.	Oil & Gas Producers
SOV	Sovereign Food Investments Ltd.	Food Producers
SPA	Spanjaard Ltd.	Chemicals
SPG	Super Group Ltd.	Industrial Transportation
SUI	Sun International Ltd.	Travel & Leisure
TBS	Tiger Brands Ltd.	Food Producers
TFG	The Foschini Group Ltd.	General Retailers
TON	Tongaat Hulett Ltd.	Food Producers
TPC	Transpaco Ltd.	General Industrials
TRE	Trencor Ltd.	Industrial Transportation
TSX	Trans Hex Group Ltd.	Mining
WBO	Wilson Bayly Holmes - Ovcon Ltd.	Construction & Materials
WNH	Winhold Ltd.	Support Services
YRK	York Timber Holdings Ltd.	Forestry & Paper

Bibliography

Ahmad, A. H., Daud, S. N. M., & Marzuki, A. (2008). Macroeconomic determinants of corporate failures in Malaysia. *International Journal of Business and Management*, 3(3):3-10.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance,* 23:589-609.

Altman, E., Haldeman, R., & Narayanan, P. (1977). ZETA analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance,* 1(1):29-54.

Altman, E., Hartzell, J., & Peck, M. (1995). *Emerging markets corporate bonds: A scoring system.* Salomon Brothers Inc, New York.

Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds: Logistic and Z-score model approached. *The Journal of Risk Finance*, 7:255-272.

Basel Committee on Banking Supervision. (2004). International convergence of capital measurement and capital standards: A revised framework. *BIS report*, June 2004.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Empirical Research in Accounting, Selected Studies*, 77-111.

Benito, A., Delgado, F., & Pagés, J. (2004). A synthetic indicator of financial pressure for Spanish firms. *Banco de España* Working Paper No. 411.

Bernhardsen, E., Eklund, T., & Larsen, K. (2001). Model for analysing credit risk in the enterprise sector. *Norges Bank Economic Bulletin*, Q3 01.

Bharath, S. T. & Shumway, T. (2008). Forecasting default with Merton distance to default model. *Oxford Journal, Review of Financial Studies*, 21(3): 1339-1369.

Black, F. & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy,* 81(3): 637-654.

Bohn, J. & Crosbie, P. (2003). Modelling default risk: Modeling methodology. *Moody's KMV Report*: 18 December.

Bonfim, D. (2009). Credit risk driver: Evaluating the contribution of firm level information and the macroeconomic dynamics. *Journal of Banking and Finance*, 33:281-299.

Bottassi, G., Grazzi, M., Secchi, N., & Tamagni, F. (2009). Financial and economic determinants of firm default. University of PISA, Laboratory of Economics and Management, Working Paper 6/2009.

Brasili, A. & Vulpes, G. (2006) Banking integration and co-movements in EU banks' fragility. MPRA, UniCredit Group.

Bruno, C. (2005). Parmalat and other major financial frauds – Prevention , investigatio and control. ICC Commercial Crime Services 6th Annual Lecture.

Bunn, P. & Redwood, V. (2003, Dec.). Company-accounts-based modelling of business failures. *Bank of England Financial Stability Review.*

Caines, R, W., Dickes, L., & Sridharan, V. U. (2002). The social impact of business failure: Enron. *American Journall of Business*, 17.

Carling, K., Jacobson, T., Linde, J., & Roszbach, K. (2007). Corporate credit risk modelling and the macroeconomy. *Journal of Banking and Finance*, 31:845-868.

Censorbugbear (2009, April 17). Welkom, Orkney families pray for reliet from Pamodzi Gold Mine's bankruptcy. Accessed 22 March 2010 on http://censorbugbear-reports.blogspot.com/2009/03/welkom-goldminers-starve-but-bullion.html

Chamberlain, G., (1983). Funds, factors and diversification in arbitrage pricing model. *Econometrica*, 51:1281-1304.

Chamberlain, G., & Rothschild, M. (1983). Arbitrage, factor structure and mean-variance analysis in large markets. *Econometrica*, 52:1305-1324.

Cipollini, A. & Missaglia, G. (2007). Dynamic factora analysis of industry sector default rates and implication for portfolio credit risk modelling. MPRA, University of Essex.

Cram, D. P., Hillegeist, S. A., Keating, E. K., & Lundstedt, K. G. (2004). Assessing the probability of bankrupcy. *Review of Accounting Studies*, 9:5-34.

Couderc, F. & Renault, O. (2005). Times-to-default: Life cycle, global and industry cycle impacts. University of Geneva and FAME, Working Paper 142/2005.

Das, S. R., Duffie, D., & Kapadia, N. (2007). Common failings: How corporate defaults are correlated. *The Journal of Finance*, LXII(1): 93-117.

Delianedis, G. & Robert, G. (1999). Credit risk and risk neutral default probabilities: Information about migration and defaults. The Anderson School of UCLA.

De Wet, A. & Van Eyden, R. (2007). Linking global economic dynamics to a South African specific credit portfolio. Unversity of Pretorial Department of Economics, Working Paper 2007-19.

Dionne, G., Laajimi, S., Mejri, S., & Petrescu, M. (2006). Estimation of the default risk of publicly traded Canadian companies. Bank of England, Working Paper 2006-28.

Eickmeier, S. (2006). Comovements and heterogeneity in the Euro area analyzed in a non-stationary dynamic factor model. Discussion Paper, Series 1: Economic Studies 31.

Egloff, D., Leippold, M., & Vanini, P. (2007). A simple model: of credit contagion. *Journal of Banking & Finance* 31: 2475-2492.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33(1), 3-56.

Fong, T., Fung, L., Lam, L., & Yu, I. (2009). *Measuring* the interdedependence of banks in Hong Kong. Research Department, Hong Kong Monetary Authority, Working Paper 19/2009.

Forni, M., Giannone, D., Lippi, M., & Reichlin, L. (2000). The generalized dynamic factor model: Identification and estimation. *Review of Economics and Statistics*, 82(4):540-554.

Gaffeo, E. & Santoro, E. (2009). Business failures, macroeconomic risk and the effect of recession on long-run growth: A panel cointegration approach conditions. *Journal of Financial Economics,* 61:435-452.

Geena, P. (26 March 2009). Pamodzi Gold: What went wrong? *CommodityOnline*. Accessed 22 March 2010 on http://www.commodityonline.com/news/Pamodzi-Gold-What-went-wrong-16370-3-1.html

Geske, R. (1979). A note on an analytical valuation formula for unprotected American call options on stocks with known dividends. *Journal of Financial Economic*, 7(1):375-380.

Geweke, J. (1977). The dynamic factor analysis of economic time series. In: Aigner, D.J., & Golberger, A.S. (Eds.). Latent Variables in Socio-Economic Models. North-Holland, Amsterdam.

Giesecke, K. (2004). Correlated default with incomplete information. *Journal of Banking & Finance,* 28: 1521-1545.

Hackbarth, D., Miao, J., & Morellec, E. (2006). Capital structure, credit risk and macroeconomic conditions. *Journal of Financial Economics*, 82:519-550.

Hamerle, A., Liebig, T., & Scheule, H. (2004). Forecasting credit portfolio risk. Deutsche Bundesbank, ISBN: 3-935821-82-4.

Huang, J. & Huang, M (2002). How much of the corporate-treasury yield spread is due to credit risk?. *NYU* Working Paper no. S-CDM-02-05.

Igan, D., Kabundi, A., Nadal De Simone, F., Pinheiro, M., & Tamirisa, N. (2011). Housing, credit and real activity cycles: Characteristics and comovement. *Journal of Housing Economics,* 20:210-231.

Internation News. (2003, 3 Dec.). Enron bankruptcy has global consequences. *Insurance Journal.*

Jacobson, T., Kindell, R., Linde, J., & Roszbach, K. (2008). Firm default and aggregate fluctuations. Federal Bank of Philadelphia, Working Papers no. 18-21.

Jakubik, P. (2006). Does credit risk vary with economic cycles? The case of Finland. Institute of Economic Studies, Faculty of Social Sciencs, Charles University, Working Paper 11/2006.

Jimenez, G. & Mencia, J. (2009). Modelling the distribution of credit losses with observable and latent factors. *Journal of Empirical Finance*, 16: 235-253.

Johnson, N. & McAfee L. (2010). Major financial institutions in the crisis: What happened and governments' responses. Working Paper March 2010.

Kabundi, A. & Nadal De Simone, F. (2011). France in the global economy: A structural approximate dynamic factor model analysis. *Journal of Empirical Economics*, 14(2):311-342.

Kealhofer, S. & Kurbat, M. (2002). The default prediction power of Merton's approach, relative to debt ratings and accounting variables. KMV LLC.

Kleynhans, J. (2009, May). Pamodzi liquid requires baby steps to recovery. *Labour News.*

Knedlik, T. (2006). Signalling currency crises in South Africa. South Africa Reserve Bank conference.

Koopman, S. J., Kraussl, R., Lucas, A., & Monteiro, A. B. (2009). Credit cycles and macro fundamentals *Journal of Empirical Finance*, 16: 42-54.

Leland, H. E. (2002). Predictions of expected default frequencies in structural model of debt. Haas School of Business, University of California, Berkeley, *Journal of Investment Management*, 2(2): 2004Q2.

Lu, Y. S. (2008). Default Forecasting in KMV. Dissertation, University of Oxford.

Lucas, D. J. (1995). Default correlation and credit analysis. *The Journal of Fixed Income,* 4(4): 76-87.

Ludvigson, S. C. & Ng, S. (2009). Macro factors in bond risk premia. *Oxford Journal, Review of Finance Studies*, 22(12): 5027-5067.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2): 449-470.

Neuman, E. J. (2005). The Impact of the Enron accounting scandal on impressions of managerial control.

Nguyen, H. G. (2005). Using neutral network in predicting corporate failure. *Journal of Social Science,* 4: 199-202.

Nguyen, P. (2007). Macroeconomic factors and Japan's industry risk. *Journal of Multinational Financial Management*, 17:173-185.

Pesaran, M. H. & Schuermann, T. (2003). Credit risk and macroeconomic dynamics. *Federal Reserve Bank of New York*, Working Paper, 2006/33.

Pesaran, M. H., Schuermann, T., Treutler, B., & Weiner, S. C. (2005). Macroeconomic dynamics and credit risk: A global perspective. *Journal of Money, Credit and Banking,* 38:1211-1261.

Qu, Y. (2008). Macro economic factors and probability of default. *European Journal of econmetircs, Finance and Administrative Science*, 13:192-215.

Rowel, F. & Simons, D. (2008). Macroeconomic default modelling and stress testing. *International Journal of Central Banking*, 5(2): 177-203.

Sargent, T. J. & Sims, C. A. (1977). Business cycle modelling without pretending to have too much of a priori economic theory. In: Sims, C. A. (Ed.). New Methods in Business Research. Federal Reserve Bank of Minneapolis, Minneapolis.

Seccombe, A. (2009, 10 Sept.). IDC applies for Pamodzi Golf liquidation. *Miningmx*.

Shanazarian, H. & Sommer P. (2008). Macroeconomic impact on expected default frequency risks. Bank research paper 51/2008.

Souto, M., Tabak, B. M., & Vazquez, F. (2009). Linking financial and macroeconomic factors to stress-test credit risk indicators for Brazilian banks. IMF Monetary and Capital Markets Department, Working Paper 189/2009.

Tudela, M. & Young, G. (2003). A Merton-Model approach to assessing the default risk of UK public companies. *The Bank of England* Working Paper no. 194. ISSN:1368-5562.

Valuzis, M. (2008). On the probabilities of correlated defaults: A first passage time approach. Nonlinear Analysis: Modelling and Control, 13(1):117-133.

Vasicek, O. (1987). Probability of loss on loan portfolio, KMV Corporation:12 February 1987.

Vassalou, M. & Xing, Y. (2004). Default risk equity returns. *The Journal of Finance*, LIX(2): 831-868.

Virolainen, K. (2004). Macro stress testing with a macroeconomic credit risk model for Finland. Bank of Finland Discussion Papers, 18/2004

Vlieghe, G. W. (2001). Indicators of fragility in the UK corporate sector. The Bank of England Working Paper, ISSN: 1368-5562.

Warner, J. B., (1977). Bankruptcy costs: Some evidence. *Journal of Finance*, 17:337-347.

Wilson, T. (1998). Portfolio credit risk. *FRBNY Economic Policy Review*, 1998, Oct.

Wu, W. (2010). Beyond business failure prediction. *Experts Systems with Applications,* 37:2371-2376.

Zhou, C. (2001). An analysis of default correlations and multiple defaults. *Oxford Journal, The Review of Financial Studies*, 14(2): 555-576.