Determinants of corporate default: The case of South Africa

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by

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Abstract

There has been a heightened interest from different stakeholders to understand the main drivers of corporate default and the influence of business cycles on corporate default. There has also been a vast amount of research in trying to understand these drivers of corporate default at the micro and macro levels for both developed and emerging economies. This paper studies and quantifies the contribution of both firm specific and macroeconomic factors to corporate default rates for South African firms, both listed and delisted. The corporate default rate is estimated using Moody's KMV model and then the estimated corporate default rates are used in the Pooled OLS (POLS), Random Effect (RE) and Fixed Effect (FE) models to assess the effect of both firm specific and macroeconomic factors on corporate defaults. This exercise is done first for all the firms and then for subsamples of listed and delisted firms separately using data for the period 1997 to 2018. The list of explanatory variables investigated included micro factors for size, profitability, leverage, tangibility, growth and liquidity. I also included 3months T-bill rate and inflation for the macro variables. The finding was that the main drivers of corporate default in the South African economy are not too different from those seen in other countries, especially for listed firms. All the explanatory variables were at least significant according to one of the three panel models for listed firms and displayed the expected coefficient signs. On whether corporate defaults are cyclical or anti-cyclical? The results of this study suggest that corporate defaults are cyclical for all the firms (listed and delisted) even though the effect on delisted firms is lagged.

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1. Brief Outline of the Topic

Since the 2008 global financial crisis, there has been heightened interest from different regulatory bodies like the International Accounting Standards Board (IASB) and Bank for International Settlement (BIS), to understand the main drivers of corporate default, particularly quantifying the influence of business cycles. Researchers have also expended a lot of research effort trying to better understand these drivers of corporate default, both at the micro and macro levels for both developed and emerging economies. See for example studies by Antunes et al. (2016), Mirzaei et.al (2016), Zsigraiova (2014), Guo et al. (2014) and Giesecke, et al. (2014).

Probability of default is defined as the likelihood that the obligor will not be able to honour their payment obligation within a specified period, which is often one year. I understand from theory that a corporate probability of default is some function of company specific factors, industrial factors, and macroeconomic factors. An understanding of the relationship between these factors and corporate defaults can assist policy makers when devising policy to counter corporate defaults. Corporate defaults may result in firm liquidation, unemployment, lower taxes for government, among other things. Vlieghe (2001) in his study of liquidation within the UK companies highlight that high corporate defaults may cause fundamental damages to the banking system especially if the realised losses on the defaulted loans are unanticipated as this might lead to bank capital being eroded. High corporate defaults are also bad from a resource allocation perspective because when firms liquidate resources have to be reallocated to pay for the administrative cost of liquidation. Vlieghe (2001) further added that if default is due to illiquidity rather than insolvency, there is an additional welfare loss if the assets have a certain degree of speciality; that is, they are more profitable within the firm than if transferred to another owner.

One other reason of the interest in studying determinants of corporate defaults as mentioned above is the strong positive link with unemployment. There is a vast amount of research such as Bai (2016), Zsigraiova (2014) and Virolainen (2004) that shows that periods of high corporate defaults are associated with high unemployment. Another reason for the interest in firm default is that as firm defaults, government corporate tax base is reduced and this has an extended effect into the economy as government spending has to either decrease, impacting other firms which rely on government spending for income or government could increase the tax rate to compensate for the reduction, which also have a negative effect on other firms.

Not all corporate defaults are bad though, as (Vlieghe, 2001) puts it, it is good for less efficiently run firms to default as this might lead to a transfer of resources from inefficient to more efficient firms. In this way, default can be wealth enhancing(Vlieghe, 2001) .This is in line with Schumpeter (1942) idea on creative destruction. This refers to the restructuring process of capitalism were outdated, and inefficient production units and processes are replaced with new and innovative production units.

South Africa is no exception from any of the above issues. Data from the South African Reserve Bank (SARB) (2019) report shows that more a third (36%) of our banking sector credit exposure is to non-financial corporate firms. This combined with the fact that 24% of the credit exposure of banks is to household whom the majority are employed by non-financial corporate firms means that South Africa should be interested in understanding more about why firms default and in particular what are the determinants of defaults.

As an indication of their increased interest in corporate defaults, the IASB even introduced International Financial Reporting Standards (IFRS) 9 in 2014 as their new reporting standard for financial instrument. One of the pertinent features of IFRS9 is the requirement of impairment of the loan book to be calculated as lifetime expected loss instead of one-year loss. This requirement gives rise to the need to have a lifetime view of corporate default rate. So, an understanding of the relationship between corporate defaults and both the firm specific and macroeconomic factors is useful in forming corporate defaults outlook.

Probability of default is also an important component in the determination of credit risk. Virolainen (2004) defines credit risk as the risk of change in the portfolio value caused by an unexpected change in portfolio credit quality (“mark-to-market” approach) or as the risk of unexpected losses caused by defaults in the portfolio (“default mode” approach).Hence Probability of default (PD) is a key parameter in determining credit risk. Probability of default has become even more prominent with the introduction of Advanced-Internal Rating Based (AIRB) approach to credit risk modelling by banking regulators. This is because it features extensively in determining the capital requirement for banks. AIRB has also led to discussions

of not only how banks capital requirements should change with time but also with economic cycles.
One of the challenges that financial institutions face is to measure how the risk levels of their assets, changes overtime and with macroeconomic factors. Lowe (2002) mentions the lack of consensus on the relationship between the macroeconomy and credit risk, as a contributing factor to this challenge. He then presents two theories to illustrate these differing views(Lowe, 2002).

The first theory is that the economic cycle is roughly described by a sine wave. For such an economy, an upswing is always followed by a downswing. A forward-looking view of default risk will therefore show an increase in credit risk around the peak of an upswing in anticipation of the forthcoming downward swing. A reduction in credit risk can also be expected around the trough of a downswing in anticipation of an economic recovery (Lowe, 2002).

The second theory is based on the view that economic cycles are non-uniform and unpredictable. Thus, an upswing in the economy does not necessarily mean that there is a forthcoming downswing. This will mean that the current economic performance is the best indicator of the future. In this economy a forward-looking view of default risk will likely show a decrease in credit risk during the peak of the economic cycle and an increase in credit risk will be expected in an economic downturn (Lowe, 2002).

According to Lowe (2002), given the poor record of economic forecasters; most banks and regulators take the current performance of an economy as the best estimate of future economic performance. Assuming the current economic performance as the best estimate of future performance is in line with the second theory. If these banks and regulators happens to be incorrect in their assumptions and the economy is described by a sine wave as in the first economic cycle theory, this can then lead to an underestimation of credit risk in a boom and overestimation in a downturn, which could further lead to economic booms and busts. This view of banks and regulators taking the current economy as the best estimate of future economic performance is also supported by Allen and Saunders (2003). Allen and Saunders (2003) are of the view that banks reduce their lending activities in a downturn economy due to fear of a reduction in loan quality and increase in probability of default. The reduction in credit by banks further exacerbates the economic downturn. The opposite is the case when we are in an economic boom, where banks will increase their credit offering, thereby fuelling the boom even further which may lead to the economy overheating and possibly an inflationary spiral. These also further heighten the business cycles and increase financial instability. This create the need for further research to be done in incorporating both micro and macroeconomic factors into credit risk measurement and to economic upswing that are characterised by increase in credit and asset prices(Lowe, 2002).

An understanding of the relationship between both micro and macroeconomic factors and corporate defaults can assist to ascertain how much of an impact each of these factors have on credit risk. Both micro and macroeconomic variables probably play an important role in determining the future direction of credit risk(Shahnazarian & Åsberg- Sommar, 2008).

Statement of the problem and motivation

In light of the above, the study will give an understanding of the contribution of both firm specific and macroeconomic factors to corporate default rates for South African firms, both listed and delisted. This is important because most studies on corporate defaults have either focused on firm specific factors or macroeconomic factors, but not many studies focused on the impact of both firm specific and macroeconomic factors on corporate defaults. This study includes both listed and delisted firms in order to determine whether listing and being active in the stock market can be used as an explanatory factor in determining corporate default in the South Africa case and also enable researchers to understand whether default determinants are different for listed versus delisted firms. Including both listed and delisted firms also avoids the issue of survivorship bias seen in many studies that only use listed firms in their analysis. The issue of survivorship bias may lead to regression results with explanatory power of variables coefficient estimates which are significantly overstated(Davis, 1996). Furthermore, this study will enable researchers to understand if business cycles play a role in determining default rates. Hence the inclusion of a business cycle variable will aid in ascertaining whether corporate defaults are cyclical or anti-cyclical.

2 Objectives of the study

The main objectives of the study are:

i. To investigate the main drivers of corporate default rates in South Africa, using both listed and delisted firms.
ii. To investigate the impact of business cycles on corporate default rates in South Africa.
iii. To investigate whether corporate defaults are cyclical or anti-cyclical in South Africa.

Research Questions

The objectives above will be achieved by answering the following research questions:

i. What are the main corporate defaults rate drivers in South Africa?
ii. What is the impact of business cycles on corporate default rates?
iii. Are corporate defaults rates cyclical or anti-cyclical?

3. Literature Review

The few empirical studies that have been done on the impact of macroeconomic factors on corporate defaults have been conducted within the developed economy framework. Empirical studies done by (Vlieghe (2001), Virolainen (2004), Shahnazarian and Åsberg- Sommar, (2008), Simons and Rolwes (2008), Guo and Bruneau (2014)) are among a few empirical studies that were completed on the impact of macroeconomic factors on defaults and focused on the United States and European economies. There is also not a whole lot of notable empirical studies done within the African context or economy which looks at the impact of both firm specific and macroeconomic factors on corporate defaults. Studies by Mirzaei, Ramakrishnan and Bekri (2016), Figlewski, Frydman and Liang (2012), Carling, Jacobson and Linde´, et al. (2007) and Clive (1999) are some of the studies which looked at both firm specific and macroeconomic determinants of corporate defaults but were not based on African economies.

The objective of this paper is to fill this gap in literature by assessing the determinants of corporate defaults for the South African economy. In order to do so, I first needed to find a way of estimating corporate defaults. According to Carling, Jacobson and Linde´, et al. (2007), broadly speaking there are three approaches to modelling defaults for an entire portfolio. The first approach uses an empirical derived relationship between default rate and normally distributed "index" of macroeconomic factors (Koyluoglu & Hickman, 1998).This is what Carling, Jacobson and Linde´, et al. (2007) terms econometric models, and they went further to give an example of the McKinsey's CreditPortfolioView. The McKinsey's *CreditPortfolioView* is a simple logistic model where default risk is a function of "index" of macroeconomic factors and a number of firm specific factors. The *CreditPortfolioView* model was used by Virolainen (2004) to model probability of default based on the macroeconomic variables for Finland. He models the average default rate for sector j by the following logistic function.

$$P_{j,t}=\frac{1}{1+exp\ (y_{j,t})}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where $P_{j,t}$ and $y_{j,t}$ is the default rate and the macroeconomic index for sector j at time t, respectively. The expectation from equation 1 is that of a negative relationship between the macroeconomic index ($y_{j,t}$) and the default rate ($p_{j,t}$), so a higher value for $y_{j,t}$ implies lower default rate. Equation 1 above can be transformed to make the macroeconomic index ($y_{j,t}$) the subject of the formula.

$$L(p_{j,t}) = \ln\left(\frac{1-p_{j,t}}{p_{j,t}}\right) = y_{j,t} \quad \text{...(2)}$$

The macroeconomic index for sector j is determined from the following regression:

$$y_{j,t} = \beta_{j,0} + \beta_{j,1}x_{1,t} + \beta_{j,2}x_{2,t} + \ldots + \beta_{j,n}x_{n,t} + \upsilon_{j,t} \quad \text{..(3)}$$

Where β_j is a set of regression coefficients to be estimated for the j^{th} sector, $x_{i,t}$($i = 1, 2,\ldots, n$) is the set of explanatory macroeconomic factors and $\upsilon_{j,\ t}$ is a random error assumed to be independent and identically normally distributed.

Virolainen (2004), in her study to develop a macroeconomic level framework for stress testing credit risk; models the relationship between macroeconomic factors and corporate defaults by sector for the Finish economy over the period 1986 to 2003. She looked at the following three key macroeconomic factors: GDP, interest rate and corporate indebtedness. The macroeconomic index in equation 3 above is modelled for six sectors in the Finnish economy using the static seemingly unrelated regression (SUR) method. The sectors considered were agriculture, manufacturing, construction, trade, transport and Others. The expectation on the relationship of the macroeconomic variables based on equation 3 is that GDP and macroeconomic index are positively related, while corporate indebtedness and interest rate are negatively related with macroeconomic index. These expectation stems from the expectation in equation 1 of a negative relation between default rate and the macroeconomic index. Given that I expect the default rate to be negatively related to GDP and macroeconomic index has a negative relationship with the default rate then it means that GDP and macroeconomic index are positively related. The same logic can be used to deduce the expected relationship between macroeconomic index and both corporate indebtedness and interest rates.

Virolainen (2004) found significant and expected results for both GDP and corporate indebtedness with the macroeconomic indices across all sectors; Interest rate showed a significant and expected relationship for all sectors but trade and transport. The unexpected relationship within the transport sector changed to an expected relationship when a dummy variable was included for the period 1993 to 2004.

Virolainen (2004) findings were that GDP is negatively related with default rate, while corporate indebtedness displayed a positive relationship with default rate. Interest rate also showed a positive relationship with defaults since higher interest rate led to an increase in corporate defaults. She also checked if there are any additional regressors that can be added to increase the explanatory power of the regression. The following macroeconomic variables were all considered; inflation, real wage rate growth, oil price, property price, long-run interest rate and unemployment. Only unemployment was found to be of significance, as it possessed the best additional explanatory power. It was however left out of the regression because of its strong collinearity with GDP (Virolainen, 2004).

The second approach in the estimation of corporate defaults is the structural Merton model based on the firm capital structure; where default is recorded when the firm asset value falls below the total liabilities (Carling, Jacobson, Linde´, & Roszbach, 2007). The probability of default depends on the amount by which the asset value exceeds the liabilities and also on the volatility of the assets (Koyluoglu & Hickman, 1998). Carling, Jacobson and Linde´, et al. (2007) went on further to mention the two Merton structural models namely; Credit Metrics method by JP Morgan and the Kealhofer, McQuown and Vasicek (KMV) Portfolio Manager model(Carling et al., 2007).One study that used the structural Merton model is by Shahnazarian and Åsberg- Som (2008).They used a structural Merton model to estimate the Expected Default Frequency(EDF) in their study of the relationship between EDF and macroeconomic factors using Vector Error Correction Model (VECM) for Sweden (Shahnazarian & Åsberg- Sommar, 2008).

The econometric model and structural Merton model approaches discussed thus far have some similarity in that they both use Monte Carlo simulations to calculate portfolio risk, and are also bottom up model in that default rates are calculated at individual firm level and then aggregated(Carling et al., 2007).

The third approach is rather a top-down actuarial model. A well-known and public available example of this model is the Credit Suisse's CreditRisk+ (Carling, Jacobson, Lindé, & Roszbach, 2002). CreditRisk+ only concerns itself with whether an obligor has defaulted or not and no assumption is made about the cause of default (Gordy, 2000). The defaults of different obligors are correlated, and their correlation depends on how much default is driven by the system factor 'x'. Conditional on 'x' the default of each obligor can be modelled by independently distributed Bernoulli distribution with outcomes default and no-default (Gordy, 2000).

Given the easiness, accessibility and abundance of research on the approaches, the study follows in the direction of Shahnazarian and Åsberg- Sommar (2008) and use the structural Merton model. Shahnazarian and Åsberg- Sommar(2008) use Industrial production index (IDY), domestic consumer price index (CPI) and nominal domestic three-month Treasury bill rate (R3M) to measure macroeconomic impact on EDF(Shahnazarian & Åsberg- Sommar, 2008).They studied the long-term relationship between probability of default and three macroeconomic factors namely GDP, CPI and three-months treasury bill rate. Like Shahnazarian and Åsberg- Sommar (2008), I also measure probability of default using expected default frequency (Carling et al., 2002).The study however goes a bit further than Shahnazarian and Åsberg- Sommar (2008) in that I also assess the impact of firm specific factors together with the macroeconomic factors on probability of default.

Shahnazarian and Åsberg- Sommar (2008) also found a significant relationship between EDF and their three macroeconomic factors of interest. Industrial production index (IDY) had negative effect on EDF, while both domestic consumer price index (CPI) and nominal domestic three-month interest rate for treasury bills (R3M) had a positive effect on EDF for the Swedish economy. GDP and interest rate are the most considered macroeconomic factors (Jakubik, 2006).This is because GDP is seen as a good proxy for business cycles as during economic downturn periods, the expectation is that GDP would be low and vice versa. Jakubik (2006) points out that, a decline in GDP growth will possibly lead to a decrease in corporate earnings, wage growth, price of assets and employment, which will in turn lead to deterioration in loan portfolio quality. The same can be said for interest rate, since an increase in interest rate increases the cost of corporate and household financing and decrease the market value of assets(Jakubik, 2006). Vlieghe (2001) also finds that the decrease in liquidation rate for UK firms after 1992 was due to the increase in GDP, and lower real wage and real interest(Vlieghe, 2001).

In their investigation of corporate default prediction for the Iranian economy; Mirzaei, Ramakrishnan and Bekri (2016) also included GDP, interest rate and inflation as their macroeconomic explanatory variables on top of the firm specific factors they had selected. Mirzaei, Ramakrishnan and Bekri (2016) found interest rate to be the macroeconomic factor with the most influence on default for the Iranian economy. They found a positive and significant relationship between interest rate and default. Their finding was that higher interest rate leads to higher defaults. They went on to further add that the reason interest rate has such a significant influence on the Iranian firms default rate was that for emerging economies interest rate are generally high and volatile (Mirzaei, Ramakrishnan, & Bekri, 2016). Mirzaei, Ramakrishnan and Bekri (2016) also found a negative significant relationship between GDP per capita and default rate. Their finding was that an increase in GDP per capita lead to a decrease in defaults. The effect of inflation on default for Iranian firms was found to be insignificant.

The selection of macroeconomic variables is also supported by the empirical findings of few other studies done in different countries on the impact of macroeconomic variables on defaults. Simon and Rolwes (2008) assessed the relationship between GDP growth, interest rate, exchange rate, stock market return and volatility and oil prices on defaults of Dutch firms using a logit model. They found a strong and convincing negative relationship between GDP growth and defaults for the Dutch economy. This is in line with the expectation that lower GDP growth will mean less sales and hence less income and reduced ability to meet the financial obligations. The following sectors showed the strongest of relationship; Industry and mining; financial and corporate service; transport, storage and communication. Demand for construction work was found to be negatively related to the level of short-term interest rate within the Dutch economy (Simons & Rolwes, 2008).

They also found the level of exchange rate and oil price to be a significant driver of defaults within the Dutch economy. Exchange rate is calculated as the amount of foreign currency required to purchase a unit of domestic currency. This means that an increase in the exchange rate is seen as an appreciation of the local currency. The sign of the relationship between exchange rate and default rate was positive and significant for the following sectors: transport, communication, storage, trade, catering and financials. This means that a higher level of the currency exchange rate will lead to an increase in default rate, so a lower level of an exchange rate is favoured since it leads to lower defaults. The relationship between oil price and default rate was also positive. This means that an increase in the price of oil is associated with an increase in default for the Dutch economy (Simons & Rolwes, 2008).

Koopman and Lucas (2005) found a strong significant robust negative relationship between GDP and business defaults over long frequency cycles of 11 years using United States data over the period 1933 to 1997 (Koopman & Lucas, 2005). Zsigraiova (2014) examined the relationship of corporate defaults with inflation, unemployment and GDP growth within the Czech Republic economy. Three month lagged GDP growth and unemployment showed a strong negative and positive relationship with defaults respectively at a 1% significance level. Only inflation was insignificant even at a 10% significance level (Zsigraiova, 2014). Herrmann, Liebig and Tödter (2004) modelled German firms default for the period 1991 to 2000 using a model that include only firm specific data and another model that also incorporate growth within the construction industry and unemployment rate and business climate index. They found that adding these macroeconomic variables in the model improve the accuracy of the PD's forecasts for German firms by reducing the variance of the forecasts (ForecastingCreditPortfolioRisk, 2004).

Shahnazarian and Åsberg- Sommar (2008) selection of macroeconomic variables was based on research done by Carling, Jacobson and Lindé, et al. (2002) for the Swedish economy. Carling, Jacobson and Lindé, et al. (2002) used a reduced form duration model based on observations of 50 000 firms from 1994 to 2000. They then answered amongst other questions, if the corporate rating class transition from high risk to low risk is in line with the development within the Swedish economy. Their duration model included both firm specific and macroeconomic variables. Using the loan data they had, they were able to segment their data and showed significant difference in default rate by loan term, loan type and sector(Carling et al., 2002). Important to note that such segmentation by loan characteristics was not possible with the dataset since I did not have access to loan details. I do however also show expected default frequency by sector in the study.

Carling, Jacobson, Linde and Roszbach (2007) investigated a number of economic variables in order to determine if there is macroeconomic impact on corporate default rates over and above the firm specific factors. They graphed Swedish macroeconomic variables against corporate default rate to try and identify potential strong relationships. Based on the exercise and economic theory they identified three macroeconomic variables that should have significant impact on default rates. The three macroeconomic variables were household expectations, output gap as a measure of aggregate demand and the yield curve. On the basis of economic theory worsening household expectations is associated with higher defaults, while a higher aggregate demand in comparison to production capacity will create a negative output gap and a reduction in defaults(Carling et al., 2007). Yield curve is seen as an indicator of future economic activity in that an increasing yield curve indicates expected improvement in economic activity and hence lowers defaults(Carling et al., 2007). Interpreting an upward sloping yield curve as an increase in the difference between long and short term rate, an upward slopping yield curve will encourage banks to renegotiate and extend terms of loan that would have otherwise been allowed to default and this will reduce the default rates(Carling et al., 2007).

Carling, Jacobson, Linde and Roszbach(2007) findings were that macroeconomic variables have an effect on default rates over and above that of accounting ratios(Carling et al., 2007).They found a significant negative relationship between expected default and output gap, as increase in economic demand lead to a reduction in default risk. The spread between long term and short-term rate also showed a significant negative relationship with default risk. This meant that an increase in the spread will lead to a decrease in default risk, as banks will have an incentive to renegotiate loan terms on the brink of bankruptcy(Carling et al., 2007).They also found improvement in the regression fit when they incorporated household expectations of the Swedish economy. There was a strong negative relationship between household expectations and default risk(Carling et al., 2007).

Carling, Jacobson, Linde and Roszbach (2007) as already mentioned incorporated both firm specific and macroeconomic factors in one of their models. They included total sales as a measure of firm size, EBITDA over total assets as a measure of profitability, total liabilities over total assets was their leverage ratio and their also included inventory over total sales as the inverse of inventory turnover. All the above firm specific variables had expected coefficient signs. Firm size had a negative coefficient, which means that as total sales or firm size increases, default risk is expected to decrease. Profitability had a negative coefficient as well, meaning an increase in EBITDA relative to total assets lead to a decrease in default risk. Both the leverage ratio and the inverse inventory turnover had a positive coefficient, meaning an increase in the leverage ratio or a decrease in inventory turnover lead to an increase in default risk.

The search for firm specific factors that play a role in the determination of firm default was extended to a number of studies. One of the studies is Mirzaei, Ramakrishnan and Bekri

(2016), who in their investigation of the probability of default across the different industries for Iranian listed firms, selected specific factors that they believe allows for a very comprehensive company analysis. They included in their analysis financial ratios that measure firm profitability, liquidity, leverage and activity. Using a logistic regression model, they found significant relationship between liquidity, profitability and activity with probability of default. Mirzaei, Ramakrishnan and Bekri (2016) used net profit as percentage of total assets to measure profitability. The found a negative significant relationship between profitability and default. Their interpretation was that Iranian firms with more profits are more able to pay their debt obligations and hence less likely to default, so a higher level of profitability is associated with a lower level of default(Mirzaei et al., 2016). Liquidity was measured as current assets as a percentage of current liabilities. Mirzaei, Ramakrishnan and Bekri (2016) findings was that there is a negative relationship between liquidity and default. This is because firms with higher liquidity have a higher ability to repay their debt without incurring too much cost or requiring external finance, so a higher liquidity is associated with lower level of default. Mirzaei, Ramakrishnan and Bekri (2016) measured activity as sales overcurrent assets. They found firm activity to have a significant negative relationship with default; meaning a higher level of sales relative to current assets was associated with low defaults. Mirzaei, Ramakrishnan and Bekri (2016) measured leverage as long-term loan over equity and did not find any overall significant relationship between leverage and defaults.

Clive (1999) investigated failing listed companies in the United Kingdom (UK). He identified profitability, leverage, cashflow, company size, sector and the economic cycle to be important determinant of company failure. Clive (1999) deemed his data to be quite sufficient as he had an unbalanced panel data with a maximum of 949 UK listed firms over a period of 8 years. Clive (1999) expectation from empirical research on profitability was that given the higher going concern value of more profitable firm, more profitable firm are less likely to go bankrupt and firm with higher leverage are more likely to be bankrupt. The expectation on cashflow is that the higher the firm cashflow the less likely the firm is to default as the firm can just use some of the cash for debt servicing. Large company are usually well known and can use their reputation to easily access external finance and are thus less likely to be bankrupt(Clive, 1999).

Clive (1999) findings using a linear probit model were in line with his expectations. The size factor which was measured by the number of employees had a significant negative coefficient, which means that as the number of employees or firm size increases there is a small chance of firm failure. The cash ratio factor which he measured as the level of cash over current liabilities had a significant negative coefficient indicating that a firm with low cash has a high chance of failure. Clive (1999) also found a significant positive relationship between leverage and firm failure and this indicated that a firm with high leverage has a higher chance of failure. Profitability was measured using return on capital which was found to be insignificant in the linear probit model. Only when non-linear relationships were considered did profitability show a negative significant relationship with firm failure.

Gwatidzo, Ntuli and Mlilo (2016) in their study of capital structure determinants in South Africa mention that firms with more tangible assets can negotiate for more loans and even at a lower cost than other firms as their can pledge their tangible assets as collateral. This may lead to firms with more tangible assets having more debt and more likely to default. So, the expectation is that of a positive relationship between asset tangibility and firms' default. Gwatidzo, Ntuli, and Mlilo (2016) also assessed the level of growth opportunities a firm has, as a possible explanatory variable in the determination of the firm debt level. Their use market to book asset value ratio as a measure of growth opportunities and their expectation was that firms with more growth opportunities tend to borrow less and are thus less likely to default all else equal. I therefore expect a negative relationship between firm default and growth opportunities.

All the empirical research discussed above, found a significant negative relationship between GDP and defaults. Studies by Vlieghe (2001), Virolainen (2004), Jakubik (2006), Shahnazarian & Åsberg- Sommar (2008) and Mirzaei, Ramakrishnan, and Bekri (2016) discussed above lead us to expects a positive relationship between interest rate and expected default. On the basis of the above studies, I include interest rate and inflation as possible determinants of corporate defaults in my study. I include business cycles in the assessment of corporate defaults by including the following research question as already mentioned: What is the impact of business cycles on corporate default rates? I later show in the study that GDP and business cycles are highly correlated and this makes the business cycle indicator to be a good proxy for assessing the impact of GDP on corporate defaults. As already mention, the study however goes a bit further than only looking at macroeconomic factors. I also assess the impact of firm specific factors on expected default frequency. I include in the list of firm specific factors, a measure of size, profitability, tangibility, leverage, growth and liquidity as possible determinants of corporate defaults.

4. Data

I based my analysis on non-financial firms. The belief is that the risk drivers of financial firms are different from that of non-financial firms. I also need a business cycle dummy variable given that I also investigate the impact of business cycles on corporate default rates. This business cycle dummy variable will take the value of one for a downturn phase in the economy and zero for an upturn. This then also means that my sample data need to cover at least one downturn and one upturn phase of an economic cycle (Simons & Rolwes, 2008). Assuming a full economic cycle to be a period of at least 7 years and after trimming for outliers, my sample period was taken to be the period 1997 to 2018.The sample data consists of 412 Johannesburg Stock Exchange (JSE) firms over the period 1997 to 2018.My firm level data is composed of 190 firms that are currently listed on the JSE and 222 JSE firms that are now delisted. The split between delisted and listed is based on the fact that, we expect the level of risk between listed and delisted firms to be different, with the later expected to have a higher probability of default. My sample include all non-financial firms that had at least one full year of listing on the JSE between the period 1997 to 2018. My sample covers all JSE industries or sectors with the exception of financial firms. Given the difference in the number of firms' representation across the different sectors within the JSE, certain sectors are more represented than others.

I sourced the firm level data for calculating the Expected Default Frequency from the IRESS BFA database. Macroeconomic variables data is sourced from the Federal Reserve Economic Data (FRED) website and data on the accounting ratios used to calculate the firm specific factors was sourced from the IRESS BFA database.

5. Methodology

The Methodology section is divided into two parts based on the objectives as stated in the literature review section. The first objective is to investigate the main drivers of corporate default rates in South Africa. Given that I use a quantitative research method in this study, South Africa corporate firms' defaults data was needed. Given the difficulty in ascertaining such data reliably for all listed and delisted firms in South Africa, an estimation technique for the firm probability of default was used.

Similar to Shahnazarian and Åsberg- Sommar (2008), I estimate probability of default using the Expected Default Frequency (EDF). EDF is a function of distance to default. EDF is based on a structural Merton model which looks at a firm capital structure, where default is recorded when the firm asset value falls below the total liabilities (Carling et al., 2007). EDF depends on the amount by which the asset value exceeds the liabilities and also on the volatility of the assets (Koyluoglu & Hickman, 1998).The amount by which the asset value exceeds the liabilities is known as the distance to default. The distance to default (DD) is measured in number of standard deviations (volatility); this makes it possible to compare default frequencies between companies, irrespective of their size (Shahnazarian & Åsberg- Sommar, 2008).

After estimating the default probability[1], I investigate the impact of macro and micro economic factors on defaults rates of South African firms. The model to be estimated is as follows:

EDF = f (firm characteristics, macroeconomics factors, other)

The more specific model to be estimated is given as follows:

$$EDF_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_{1j} X_{jit} + \sum_{j=1}^{v} \beta_{2j} Z_{jt} + u_i + \varepsilon_{it} \text{ ....}(4)$$

X stands for all firm characteristics defined in Table 1 below and Z stands for all macroeconomic factors defined in Table 1. So X_{jit} stands for firm characteristic ***j*** for firm ***i*** at time *t*. Z_{jt} stands for macroeconomic factor j at time *t*. The macroeconomic factors are not

[1]The reader is referred to Annexure for a detailed description of the method used.

firm specific. β_{1j} describes the relationships between the firm characteristic j and the EDF, while β_{2j} shows the relationship between the macroeconomic factor j and the EDF. The last components (u_i and e_{it}) stand for the well-behaved composite. u_i is the unobserved firm specific effect as it captures heterogeneous features of the individual firm that we cannot directly observe and e_{it} is the error term. I will run the model for the listed, delisted and all the JSE firms. The above equation gives estimates of two important parameters in the study (β_1 and β_2). The β_1 vector describes the relationships between the firm specific explanatory variables and the EDF, while β_2 vector shows the relationship between the macroeconomic variables and the EDF, u_i is the unobserved firm specific effect as described above. The coefficient estimates to the above equation would enable us to answer the research question; What are the main corporate defaults rate drivers in South Africa?

Before I estimate the regressions, using equation 4 above, I further analyse the factors by looking at their descriptive statistics and their correlation matrices below. I start by showing the definitions of the firm and macro-economic factors together with the expected signs of their relationship with EDF from the literature review. This is done in Table1 below. I then follow by showing the factors descriptive statistics in Table 2 and the correlation matrices in Table 3.

Table 1: Variables used in the study and their definitions

Variable	**Definition**	**Expected Coefficient Sign**
3 months T-bill rate	Interest Rates, Government Securities, Treasury Bills for South Africa	Positive
CPI	Consumer Price Index: All Items for South Africa, Index 2010=100, Not Seasonally Adjusted	Positive
Size	Natural log of total assets	Negative
Asset Tangibility	Fixed assets to total asset ratio	Positive
Growth	Market to book value of total assets	Negative
Profitability	EBIT to total asset ratio	Negative

Liquidity	Current Assets to Current liabilities ratio	Negative
Leverage	Total Liabilities to Shareholder Equity ratio	Positive

The above expected coefficient signs indicate the expected relationship between the factors and corporate default rates from the studies reviewed in the literature review section.

Table 2: Descriptive statistics for the All Firms (Listed and Delisted)

All firms	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Inflation
Mean	19%	0%	20.9	1.6	2.4	2.3	0.3	8.5%	5.4%
Median	2%	9%	20.8	0.9	1.5	1.2	0.2	7.3%	5.5%
Std. Dev.	28%	279%	2.0	14.4	13.7	48.8	0.2	2.9%	2.2%
Skewness	1.4	-60.3	0.0	42.4	41.9	62.5	0.9	1.1	-0.5

Listed	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Inflation
Mean	15%	7%	21.6	1.8	2.5	1.52	0.3	8.5%	5.4%
Median	0.5%	10%	21.7	0.9	1.4	1.2	0.2	7.3%	5.5%
Std. Dev.	0.3	0.3	2.2	16.7	15.8	3.14	0.2	2.9%	2.2%
Skewness	1.7	-13.9	-0.1	43.4	40.0	37.8	0.8	1.1	-0.5

Delisted	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Inflation
Mean	25%	-13%	19.7	1.2	2.3	3.5	0.2	8.5%	5.4%
Median	8%	7%	19.7	0.9	1.5	1.08	0.2	7.3%	5.5%
Std. Dev.	0.3	4.6	1.9	8.8	9.0	80.42	0.2	2.9%	2.2%
Skewness	1.0	-37.1	-0.1	-14.7	30.7	38.01	1.1	1.1	-0.5

Notes: EDF stands for Expected Default Frequency and R3M stands for 3 Months Treasury Bill Rate

Listed firms are on average less likely to default as shown by the lower EDF of 15% in comparison to that of delisted, which has an average EDF of 25%. This is further supported by the fact that listed firms are on average larger in size and more profitable relative to delisted. Another important observation from Table 2 above is that listed company are slightly more leveraged, liquid and their assets base contain more fixed assets relative to delisted. I also assessed the correlation between EDF and macroeconomic variables of interest (CPI and 3 months T-bill rate) and the firm specific factors (Size, Profitability, Tangibility, Leverage, Liquidity and Growth).Below is the correlation matrices of the factors, first for all the JSE firms and then for listed and delisted firms.

Table 3: Correlation Matrix for All Firms (Listed and Delisted)

All firms	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Infla tion
EDF	1.00								
Profitability	-0.07	1.00							
Size	-0.34	0.13	1.00						
Leverage	0.05	0.00	-0.02	1.00					
Liquidity	-0.02	0.00	-0.07	-0.01	1.00				
Growth	0.03	-0.99	-0.10	0.00	0.00	1.00			
Tangibility	0.00	0.03	0.12	0.01	-0.06	-0.02	1.00		
R3M	0.09	0.01	-0.23	0.00	-0.03	-0.01	-0.01	1.00	
Inflation	0.07	0.03	0.00	0.00	0.00	-0.03	0.00	0.43	1.00

Listed	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Infla tion
EDF	1.00								
Profitability	-0.19	1.00							
Size	-0.27	0.20	1.00						
Leverage	0.08	-0.03	-0.04	1.00					
Liquidity	-0.03	0.00	-0.07	-0.01	1.00				
Growth	-0.09	-0.41	-0.07	0.01	-0.01	1.00			
Tangibility	-0.02	0.06	0.13	0.02	-0.06	0.02	1.00		
R3M	0.11	0.03	-0.18	-0.02	-0.04	0.01	0.06	1.00	
Inflation	0.12	0.01	-0.01	0.00	0.00	0.00	0.00	0.42	1.00

Delisted	EDF	Profit ability	Size	Leverage	Liquidity	Growth	Tangibility	R3M	Infla tion
EDF	1.00								
Profitability	-0.07	1.00							
Size	-0.36	0.19	1.00						
Leverage	0.00	0.00	-0.03	1.00					
Liquidity	-0.02	0.01	-0.11	0.02	1.00				
Growth	0.05	-0.99	-0.17	0.00	-0.01	1.00			
Tangibility	0.06	0.03	0.05	-0.02	-0.08	-0.03	1.00		
R3M	0.02	0.02	-0.21	0.05	0.01	-0.02	-0.08	1.00	
Inflation	0.00	0.04	0.04	0.01	0.02	-0.04	-0.01	0.45	1.00

Source: Own calculations using data from the IRESS BFA database and FRED

Looking at Table 3 above all the factors have expected correlation coefficient signs with EDF for both listed and delisted firms except growth. Growth is positively correlated with EDF for all the firms and delisted firm’s correlation matrices. This is against the expectations as stipulated in table 1. Growth is again highly correlated with profitability with a correlation of negative 99% for all firms and delisted. On the basis of the strong correlation between growth and profitability, which poses serious multicollinearity concerns, I decided to omit growth from the delisted and all firm's regression variable list.

Listed firms EDF display a correlation with both profitability and leverage that is significant relative to that of delisted with a correlation of negative 19% and positive 8% for profitability and leverage respectively versus that of negative 7% and 0% for delisted firms. Size is the firm specific factor that shows the highest level of correlation with firm EDF for both listed and delisted firms.

6. Expected Default Frequency Estimation

In this paper, probability of default is estimated using Expected Default Frequency (EDF) as mention before. The Moody's KMV iterative process is used to solve for the company total market asset value and then compare the estimated value to the company total debts to get a measure of the distance to default. I then assume normality of asset price to convert distance to default into EDF. An important point to keep in mind is how I interpret probability of default as the as the likelihood that the obligor will not be able to honour their payment obligation within a specified period, which is often one year. This then means that an EDF calculated based on 31 December 2008 data, is the probability that the firm will fail to honour their debt obligation in the year 2009 (1 January 2009 to 31 December 2009).

I show the analysis of Expected Default Frequency (EDF) in the graphs that follows based on the year of the financial data used. Figure 1 below shows the EDF of both listed and delisted firms together with a South African business cycle dummy. I sourced South Africa Reserve Bank (SARB) business cycle indicator information from South African Reserve Bank (2019) report. The business cycle indicator shows in which periods did the economy experience an upturn or downward phase. Figure 1 below then shows periods that South African economy experienced a downward phase as a dummy variable of 1 and the upturn as a dummy variable of zero.

Figure 1: Expected Default Frequency for all JSE non-financial corporates (1997-2018)

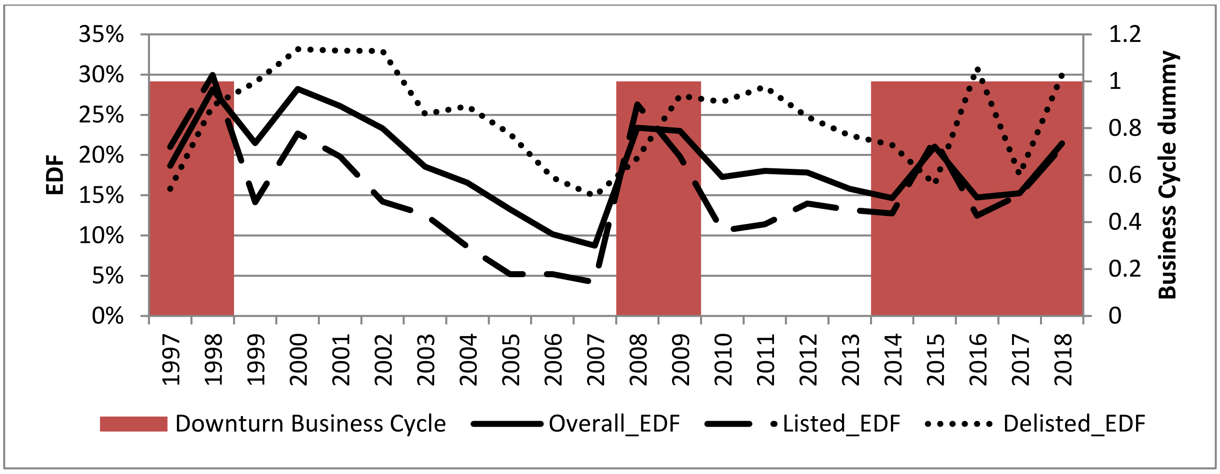


Figure 1 shows that on average, and in majority of the case, the default rates for delisted firms were higher than those for listed firms. The listed firms average EDF was 15% relative to the delisted entities average of 25% which makes JSE delisted firm 1.65 times more likely to default on average over the period 1997 to 2018.This may because listed firms are on average larger in size and more profitable relative to delisted as shown in Table 2 in the Methodology section. Listed and/or large firms are more visible in the market and as such they are associated with lower degrees of information asymmetry and more likely to use equity finance than debt finance and hence less likely to default since they do not have as much debt (Gwatidzo, Ntuli, & Mlilo, 2016).

Overall, the EDF fluctuates overtime and is largely driven by the business cycle as can be seen in the upward spikes in the EDF for periods of downturn business cycle. The South Africa Rand experienced a currency crisis in 1998 and 2001, which could be a possible explanation for the significant increase in EDF in 1998 and the downturn in the business cycle. The 2001 Rand crisis had less severe macroeconomic consequences as supported by Figure 1 above. Bhundia and Ricci(2006) states that a 28% depreciation of the Rand against the US dollar in the third quarter of 1998 was accompanied by a 7% increase in the prime lending rate, a 40% drop in share prices and a contraction of quarter on quarter GDP. The effect of this can be seen in huge upward spike in both the listed and delisted Expected Default Frequency (EDF) in 1998. The general trend in the EDF for all firms during the period 2001 to 2007 was actually downwards since South Africa and the world at large were in an economic upturn which saw a rise in the market asset of firms. The upward spike between 2008 and 2009 is due to the global financial crisis and this is also seen as a downturn phase in the South African business cycle. The EDF for listed firms increased by 22% from 4% in 2007 to 26% in 2008.The effect of the global financial crisis on the delisted firms was more measured, with an increase of 5% in EDF from 2007 to 2008 and then another increase of 7% in 2008 to 2009. The gradual or lagged filtering of the effect of the global financial crisis on delisted firms led to the peak of the EDF only being reached in 2009 unlike listed firms were the peak was in 2008. 2010 to 2014 was largely stable for both listed and delisted firms. An upward spike was also witnessed post 2014. This maybe because there has been huge increase in the level of credit extended to non-financial corporates since late 2010(*Financial Stability Review*, 2019) and this has led to the level of debt, especially USD denominated debt increasing significantly during the period 2010 to 2013 at a faster rate than supported by the growth in the economy. There was another EDF upward spike from 2017 onwards during a downturn period in our economy. The spike is probably due to the increased credit that has been extended to the firms since late 2010 as already mentioned, coupled with the downturn phase in our business cycle. Looking at the post 2014 spikes, again the delisted firms seem to experience the peak of the upward spike a year later after the listed.

The above indicates that if I analyse default rates for South African corporate companies between 1997 and 2018 and only look at the listed firms I will bias the EDF measure downward; that is the probability of default would measure lower that it is supposed to be. So, my analysis should look at both listed and delisted firms.

Chow Structural Break test

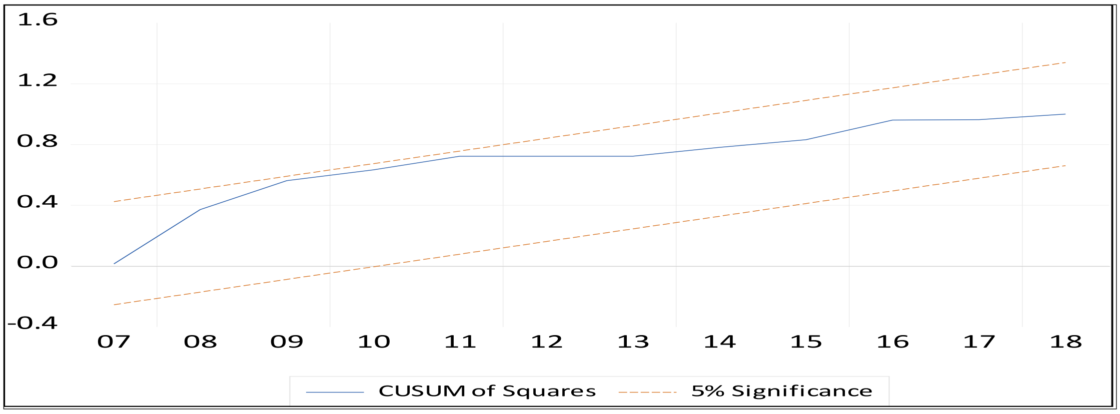
Looking at the EDF graph in figure 1, I assess the possibility of a structural break in the year 2008. Using a Chow structural break test I fail to reject the null hypothesis of no structural break in the data at that point. I show the results from the Chow structural break test below:

Table 4: Chow structural break test

Chow Breakpoint Test: 2008			
Null Hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation Sample: 1997 2018			
F-statistic	4.631292	Prob. F(10,2)	0.1905
Log likelihood ratio	70.06014	Prob. Chi-Square (10)	0
Wald Statistic	46.31292	Prob. Chi-Square (10)	0

The F-statistic has a p-value of 19% which means the F statistic is significant at a 5% significance level, so I fail to reject the null as already mentioned. I conclude that the data has no structural break. In order to supplement the above results, I also show the results of the CUSUMSQ Plot in figure 2 below which further support the fact that the data does not have a structural break. The CUSUMSQ stays within the 5% significance level even though it comes close to the upper bound from the year 2009 till 2011.

Figure 2: CUSUMSQ Plot



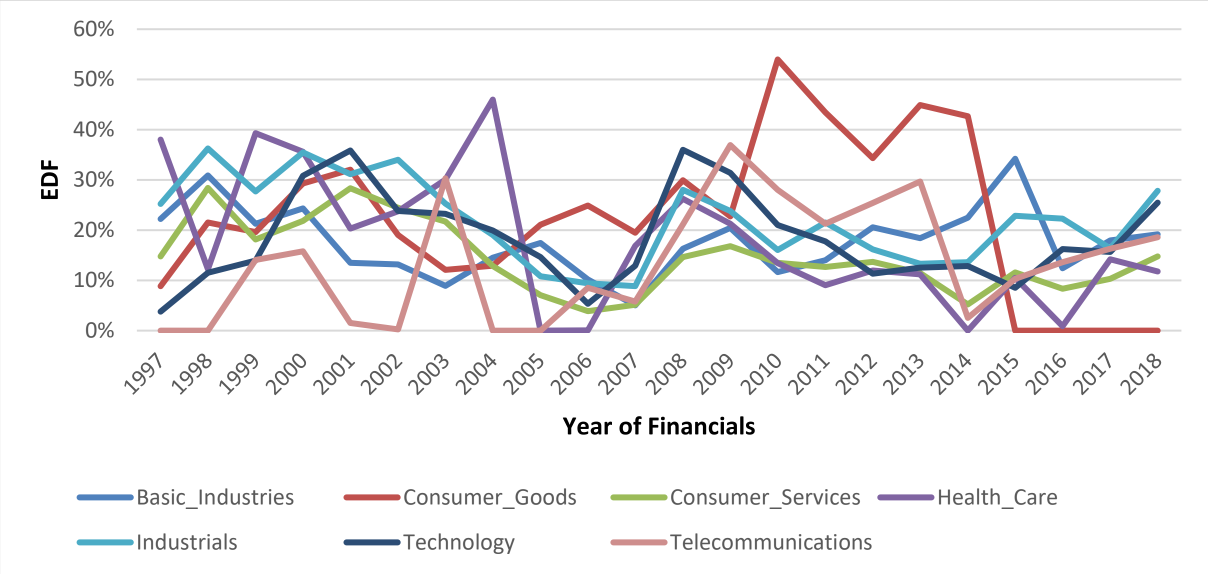
I also extended the graphical analysis of the EDF to include segmentation by sector. I divided the 412 non-financial JSE listed and delisted firms into the different JSE sectors. The number of firms per sector are shown in the table below.

Table 5: Number of firms per JSE Sector

Sector	Number of Firms
Basic Industries	109
Consumer Goods	41
Consumer Services	80
Health Care	15
Industrials	111
Oil and Gas	1
Technology	44
Telecommunications	11

The EDF for Oil and Gas sector was too volatile due to having only one entity in the sample and hence removed from figure 3 below.

Figure 3: Expected Default Frequency by Sector



Consumer goods experienced a steep jump in EDF in the period 2010 to 2014, which led to most of the firms delisting in that period. There has been a steep increase in household debt from 2010 till 2013 (*SARB*, 2019). The debt pressure on household and the fact that the South African economy has not been doing well ever since the global financial crisis, seem to have negatively affected the consumer goods sector the worst. The average GDP for South Africa was 1.5% for the period 2011 to 2018, way below the average for the study period of 2.6%. The consumer goods sector is cyclical, that is probably why it was more affected by all these issues. The Technology sector was mainly negatively affected by the Dot.com bubble burst of early 2000, with it having the steepest rise in EDF during that period. I also see all the sectors were severely affected by the 2008-2009 financial crisis as depicted in their high EDF for the year 2008 in figure 3 above. In general, the movement in EDF is aligned for most of the sectors and the same trend is displayed across the period, with the impact of business cycles shared across all the sectors. I therefore conclude to run the panel data regression models for the listed, delisted and all JSE firms.

7. Results on the determinants of EDF

Now that I have estimated the Expected Default Frequency (EDF),I move on to the next part of the research question, which is to investigate what the main corporate defaults rate drivers in South Africa are. As I have mention before, to test for the existence of a strong and significant relationship between the EDF and macroeconomic variables, I also assess the impact of firm specific factors on EDF. This is so that I can correctly quantify how much of the variation in probability of default is due to macroeconomic factors.

Panel Data Unit root test

I first run the panel data unit root test on the dependent (EDF) and all the explanatory variables (Size, Profitability, Tangibility, Leverage, Growth, Liquidity, R3M and Inflation).I reject the null hypothesis of a unit root in favour of the alternative and conclude that the variables are all stationarity .The summary of Panel unit root tests performed and their null hypothesis is shown in the table below.

Table 6: Panel unit root test Methods

	Statistic									Prob.**
Panel unit root test Methods	EDF	Size	Profitability	Tangibility	Leverage	Growth	Liquidity	R3M	Inflation	All variables
Null:										
Levin, Lin & Chu t	-267	-17	-114	-123	-52	-989	-48	-91	-35	0
Null:										
Im, Pesaran and Shin W-stat	-2927	-4	-28	-17	-17	-92	-18	-28	-26	0
ADF - Fisher Chi-square	1690	836	1646	1058	1261	1705	1461	1230	1311	0
PP - Fisher Chi-square	1748	1152	1607	1021	1381	1819	1786	1616	1245	0

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

All the variables had p-values of zero for all the test methods. So, I reject the null hypothesis of a unit root for all the variables (dependent and explanatory) in favour of the alternative as already mentioned above.

Panel Data Regression Analysis

The data is a short unbalance panel, where N=412 and a maximum T of 21 observation periods. The choice to use panel data is based on the fact that this is expected to increase the precision of the estimation by pooling of firm data over several time periods (1997-2018), since the pooling of firm data increases the observations. This also enable us to learn more about evolution of the different firms' behaviour across different times (economic cycles). I am able to assess how the different firms EDF evolved during boom periods and recessionary periods. I can control for individual-specific effect, time-invariant effect and any unobserved heterogeneity whose presence could lead to bias if not taken account of. I show again the equation of interest below, now with a business cycle dummy. This is so that I can answer the research question; What is the impact of business cycles on corporate default rates? I showed in figure 1 in the Expected Default Frequency estimation section that the spikes in the EDF were generally around downturn phase periods in our business cycle. Everything else stay the same as explained in equation 4 of the Methodology section.

$$EDF_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_{1_j} X_{jit} + \sum_{j=1}^{v} \beta_{2_j} Z_{jt} + u_i + \beta_3 D_t + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where:

D_t=1 if in a downturn business cycle phase,0 if in an upturn phase.

I estimate three versions of panel regression models. I show the panel regression results from the above equation for Pooled OLS regression (POLS), Fixed Effect (FE) and Random Effect (RE) in the next section.

8. Results and Interpretation

As mentioned in the previous section, I run three versions of panel regressions as stipulated in equation 5 in the previous section. I also run three panel data regression models for the listed, delisted and all JSE firms. I first run the three versions of panel regressions for all the firms with a listed dummy. The listed dummy variable takes the value of 1 if the firm is listed and zero if the firm is delisted. The results below showed the listed dummy to be significant under the POLS and RE, but insignificant under the FE. The results are shown in table 7 below.

Table 7: Estimated Regressions Coefficients for all JSE firms with listed dummy

Sample: 1997 2018			
Periods included: 22			
Cross-sections included: 407			
Total panel (unbalanced) observations: 3961			
Explanatory Variables	POLS	RE	FE
C	1.06	0.92	0.22
	(22.83)***	(12.8)***	(1.17)
Profitability	0.00	0.00	0.00
	(-1.66)*	(-1.09)	(-1.47)
Size	-0.04	-0.04	-0.01
	(-20.35)***	(-10.67)***	(-1.35)
Leverage	0.001	0.001	0.00
	(3.07)***	(2.09)**	(1.3)
Liquidity	-0.001	-0.001	-0.001
	(-3.02)***	(-3.57)***	(-3.19)***
Tangibility	0.06	0.08	0.10
	(2.88)***	(3.01)***	(2.75)***
R3M	-0.28	-0.14	0.48
	(-1.67)*	(-0.8)	(2.34)**
Inflation	0.57	0.39	0.14
	(2.45)**	(1.9)*	(0.67)
Listed dummy	-0.03	-0.05	0.06
	(-2.94)***	(-2.98)***	(0.23)
Business cycle dummy	0.05	0.05	0.04
	(5.45)***	(6.05)***	(3.87)***
R-squared	0.13	0.05	0.43
Adjusted R-squared	0.13	0.05	0.37
F-statistic	61.60	22.95	6.55
Prob(F-statistic)	0.00	0.00	0.00
Durbin-Watson stat	0.96	1.28	1.45

t-statistics are in parenthesis and *, **, *** show the level of significance at 10%,5% and 1% respectively

Given the insignificance of the listed dummy under the FE model, I also run the regressions with all the firms but without the listed dummy. As can be seen in the results below, removing the listed dummy lead to the unobserved firm specific effect becoming significant at a 5% significance level for the FE model and no reduction in the r-squared of all the regressions.

Table 8: Estimated Regressions Coefficients for all JSE Firms

Sample: 1997 2018			
Periods included: 22			
Cross-sections included: 407			
Total panel (unbalanced) observations: 3961			
Explanatory Variables	POLS	RE	FE
C	1.09	0.96	0.25
	(23.89)***	(13.48)***	(2.1)**
Profitability	0.00	0.00	0.00
	(-1.62)	(-1.02)	(-1.47)
Size	-0.04	-0.04	-0.01
	(-22.98)***	(-12.07)***	(-1.34)
Leverage	0.001	0.001	0.00
	(-2.97)***	(2.02)**	(1.3)
Liquidity	-0.001	-0.001	-0.001
	(-3.12)***	(-3.66)***	(-3.19)***
Tangibility	0.05	0.08	0.10
	(2.76)***	(2.84)***	(2.75)***
R3M	-0.25	-0.15	0.48
	(-1.51)	(-0.9)	(2.35)**
Inflation	0.60	0.42	0.14
	(2.57)***	(2.04)**	(0.66)
Business cycle dummy	0.05	0.05	0.04
	(5.12)***	(5.95)***	(3.87)***
R-squared	0.13	0.05	0.43
Adjusted R-squared	0.13	0.05	0.37
F-statistic	67.36	24.53	6.56
Prob(F-statistic)	0.00	0.00	0.00
Durbin-Watson stat	0.96	1.28	1.45

t-statistics are in parenthesis and *, **, *** show the level of significance at 10%,5% and 1% respectively

Looking at table 8 above, all the r-squared of the three models have remained unchanged after removing the listed dummy. Liquidity, tangibility and business cycle dummy are all significant at 1% level across all the three versions of panel regression models. The unobserved firm specific effect is significant at a 5% level across all the panel models. Size, leverage and inflation rate are only significant in the POLS and RE model, while 3 months T-bill rate was only significant for the FE model. All the explanatory variables that are significant at least at a 10% level displayed the expected coefficient signs as stipulated in table 1 in the Methodology section. I also show the regression results for listed firms in table 9 below.

Table 9: Estimated Regressions Coefficients for Listed JSE Firms

Sample: 1997 2018			
Periods included: 22			
Cross-sections included: 190			
Total panel (unbalanced) observations: 2496			
Explanatory Variables	POLS	RE	FE
C	0.73	0.51	-0.32
	(13.38)***	(5.83)***	(-2.07)**
Profitability	-0.15	-0.12	-0.11
	(-6.71)***	(-4.92)***	(-4.09)***
Size	-0.03	-0.02	0.01
	(-13.35)***	(-5.77)***	(2.09)**
Leverage	0.001	0.001	0.001
	(3.99)***	(3.18)***	(2.2)**
Liquidity	-0.001	-0.001	-0.001
	(-2.17)**	(-3.41)***	(-3.2)***
Tangibility	-0.03	0.07	0.13
	(1.2)	(1.68)*	(3.0)***
Growth	-0.02	-0.01	-0.01
	(-9.41)***	(-8.97)***	(-7.3)***
R3M	0.26	0.76	1.98
	(1.3)	(3.91)***	(8.15)***
Inflation	0.69	0.40	-0.03
	(2.61)***	(1.65)*	(-0.46)
Business cycle dummy	0.08	0.07	0.05
	(7.48)***	(7.76)***	(4.2)***
R-squared	0.16	0.08	0.42
Adjusted R-squared	0.16	0.08	0.37
F-statistic	54.55	25.55	8.54
Prob(F-statistic)	0	0.00	0
Durbin-Watson stat	1.06	1.26	1.48

t-statistics are in parenthesis and *, **, *** show the level of significance at 10%,5% and 1% respectively

Looking at table 9 above, it can be seen that profitability, growth and business cycle dummy are significant at 1% level across all the three versions of panel regression models. All the explanatory variables are at least significant according to one of the three panel models. All explanatory variables that are significant at least a 10% level displayed the expected coefficient signs as stipulated in table 1 in the Methodology section. As I have already mentioned in the analysis of figure 1 in the Expected Default Frequency Estimation section that the effect of the business cycle, especially the global financial crisis was gradual or lagged for delisted firms. The delisted firm's regression is run with the business cycle dummy lagged by a year. The regression results are shown in table 10 below.

Table 10: Estimated Regressions Coefficients for Delisted JSE Firms

Sample: 1997 2018			
Periods included: 22			
Cross-sections included: 218			
Total panel (unbalanced) observations: 1465			
Explanatory Variables	POLS	RE	FE
C	1.57	1.38	0.96
	(15.46)***	(9.98)***	(4.63)***
Profitability	0.00	0.00	0.00
	(0.18)	(0.58)	(0.41)
Size	-0.07	-0.06	-0.04
	(-14.5)***	(-8.45)***	(-3.51)***
Leverage	0.00	0.00	0.00
	(-0.51)	(-0.39)	(-0.29)
Liquidity	-0.002	-0.001	-0.001
	(-2.32)**	(-1.71)*	(-1.26)
Tangibility	-0.08	-0.13	-0.14
	(2.07)**	(2.38)**	(1.92)*
R3M	-0.54	-0.90	-0.97
	(-1.48)	(-2.43)**	(-2.25)**
Inflation	0.81	0.91	0.85
	(2.05)**	(2.6)***	(2.29)**
Lagged (Business cycle dummy)	0.05	0.04	0.04
	(2.4)**	(2.54)**	(2.19)**
R-squared	0.16	0.06	0.54
Adjusted R-squared	0.15	0.05	0.45
F-statistic	28.78	9.86	6.05
Prob(F-statistic)	0.00	0.00	0.00
Durbin-Watson stat	0.92	1.36	1.65

t-statistics are in parenthesis and *, **, *** show the level of significance at 10%,5% and 1% respectively

Table 10 above shows that the unobserved firm specific effect and size are significant at 1% level across all the three versions of panel regression models. Inflation and lagged business cycle dummy are significant at a 5% level across all the panel models. The coefficient sign on the 3 months T-bill rate is against expectation, even though 3 months T-bill rate was significant for the RE and FE model at a 5% significance level. Though the coefficients for liquidity and tangibility are comparable and have the same signs across the three models, the significance level of these coefficients is different. Liquidity was significant for both POLS and RE regressions at 5% and 10% significance level respectively, while tangibility was significant at 5% for POLS and RE models and at 10% significance level for the FE model. All explanatory variables that are significant at least at a 10% level displayed the expected coefficient signs as stipulated in table 1 in the Methodology section except for 3 months T-bill rate.

The regression results above reveal that the drivers of corporate defaults are not all the same across listed and delisted firms. The next research question was whether the EDF vary significantly based on whether we are in a recession or boom period. Looking at the business cycle dummy significance level across the different models gives the answer to the question. Business cycle seem to be quite significant at least for listed firms, as the business cycle dummy was significant at a 1% level across all the three panel data models. The same can be said about the regression for all firms in general, as the business cycle dummy remained significant for all the panel models at a 1% level. The delisted firms are only impacted by the business cycle gradually as indicated in the significant lagged business dummy variable at a 5% level across all the panel models. The coefficient of the business cycle dummy is also positive for both listed and delisted firms in all the regression results table above. Given that the business cycle dummy was assigned a value of one in an economic downturn and zero in an upturn, a positive coefficient means that probability of default is expected to significantly increase in an economic downturn relative to an upturn. This support the notion that corporate defaults are cyclical; hence corporate defaults will increase in a recession and reduce in an economic boom. Firm size also seems to be one of the main drivers of defaults for delisted firms.

The Hausman test was performed to assess whether the Fixed Effects or Random Effects regression results were more appropriate. Fixed effects allow arbitrary correlation between u_i and X_{jit}, while random effects does not. So, I run the Hausman (1978) test with the null hypothesis that u_i is uncorrelated with X_{jit}.Hausman test is used to evaluate whether there is a statistically significant difference between FE and RE estimators. We give an overview of how the results of the test are interpreted below.

<u>Hausman (1978) test</u>

- H_0: Random Effect(RE) is more appropriate; that is , α_i is uncorrelated with x_{it}
- H_1: Fixed Effect(FE) is more appropriate; that is, α_i is correlated with x_{it}

β refers to the vector of coefficients for time varying firm specific variables and below is the test statistic:

$$H = (\hat{\beta}_{\mathrm{FE}} - \hat{\beta}_{\mathrm{RE}})'[\mathrm{Var}(\hat{\beta}_{\mathrm{FE}}) - \mathrm{Var}(\hat{\beta}_{\mathrm{RE}})]^{-1}(\hat{\beta}_{\mathrm{FE}} - \hat{\beta}_{\mathrm{RE}})$$

A large value of the Hausman test statistic leads to the rejection of H_0 and to the conclusion that FE is present. When H_0 is rejected we use the FE and vice versa. I show the Hausman test results in the table below.

Table11: Hausman Test Results

Correlated Random Effects - Hausman Test			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	88.214799	6	0

The Hausman test statistic is large (88.2) and has a p-value of 0 which is less than the 5% significance level, so this means I reject H_0 in favour of H_1. The conclusion is that the Fixed Effects (FE) method is more appropriate as u_i is correlated with X_{jit}.

9. Conclusion

Understanding the cause and drivers of corporate defaults remain a very topical subject for bankers, regulators and researchers. In this study the idea was to add to this debate by answering the question about the main drivers of corporate defaults for both listed and delisted and assess whether the corporate default drivers are different for listed versus delisted firms. The study also investigated the significance of business cycles in determining corporate defaults and whether the level of significance is the same for listed versus delisted firms. In order to do so, this study estimated corporate defaults using Expected Default Frequency(EDF).Using EDF as the estimates of corporate defaults, the study then run 3 versions of panel data regressions(POLS,FE and RE) between EDF and the possible micro and macro explanatory variables which were selected based on previous research as shown in the literature review section. The list of explanatory variables investigated included micro factors for size, profitability, leverage, tangibility, growth and liquidity. I also included 3 months T-bill rate and inflation for the macro variables.

The finding was that the main drivers of corporate default in the South African economy are not too different from those seen in other countries, especially for listed firms. All the explanatory variables were at least significant according to one of the three panel models for listed firms and displayed the expected coefficient signs. Looking at the results under the fixed effect model, only inflation was found to be insignificant. This is in line with studies by Mirzaei, Ramakrishnan and Bekri (2016) and Zsigraiova(2014),both of which found inflation to be insignificant as well. On whether corporate defaults for listed firms Are corporate defaults rates cyclical or anti-cyclical? The findings was that corporate defaults is very cyclical for listed firms as supported by business cycle dummy being positive and significant at 1% level across all the panel data regressions. The expectation is that corporates defaults would increase in a downturn phase of the business cycle and versa vice.

The regression results for delisted and hence for all firms combined, were different from those of listed firms. Profitability and leverage were not significant at a 10% level for all the panel regression models for delisted firms. Profitability remained insignificant at a 10% level even when I included all the firms together (listed and delisted). The findings are in line with the survivorship bias displayed when only currently listed firms are included in a regression model. This effect of survivorship bias seen with using only listed firms in the regression is supported by Davis (1996) ,whose findings also showed that failure to account for survivorship bias may lead in regression results with explanatory power of variables coefficient estimates which are significantly overstated (Davis, 1996).This seem to be the case when I compare the significance of the explanatory variables between regression based only on the currently listed firms against the one based on all the firms(listed and delisted). On whether corporate defaults are cyclical or anti-cyclical? The finding is that corporate defaults remain cyclical and significant at 1% level across all the panel data regressions when I combine all the firms together (listed and delisted) even though the effect on delisted firms is lagged.

This paper add to the debate of the impact of business cycle on corporate defaults and credit risk and the implications of this on policy makers, banks and regulators. The finding of this paper is that corporate defaults are cyclical; an increase in corporate defaults is seen during an economic downturn and vice versa. The implication of this is that credit risk is expected to increase during an economic downturn. Hence banks and bank regulators need to assess the impact of the increase in credit risk in an economic downturn in determining the appropriate required level of bank's capital in an economic downturn versus an upturn, as the increase in credit risk is likely to lead to an increase in the bank's regulatory capital requirements in anticipation of the increase in defaults.

10. References

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11. Annexure

Distance to Default

As already mentioned, distance to default is the structural Merton based measure of default using the firm capital structure, where default is recorded when the firm asset value falls below some default point, where the default point is a function of the firm total liabilities.
I assume that the asset value of firm (V_A) follows a Geometric Brownian Motion (GBM):

$$dV_A = \mu_A V_A dt + \sigma_A V_A dW_t \quad \text{......(6)}$$

Where W_t is a Standard Brownian Motion (Wiener Process), V_A is value of the asset, σ_A its volatility and μ_A is the drift (mean of the asset value). I model the market asset value, assuming GBM around the actual mean asset value. Some of the arguments for using GBM to model asset price are that a GBM process only assumes positive values, just like asset value. Another argument in favour of the GBM is that, I only need to specify only the mean asset value and volatility is sufficient to be able to simulate the asset value

Given that the shareholders have limited liability, the equity value received by the shareholders at maturity (T) is capped at minimum of zero. If at maturity (T), the firm asset value (V_T) is less or equal to the value of its debt (D_T) then the equity value would be zero(Duan & Wang, 2012).
For convenience, I chose to denote D_T as F.The equity value to the shareholders at maturity if the firm asset value (V_T) is greater than the face value of its debt (F) at maturity would then be($V_T - F$).If I take S_t to be the equity value at time t, then the equity value at maturity S_T is equal to max($V_T - F, 0$).

Given that the asset value (V_t) is log-normally distributed and by applying the Ito's lemma to equation 6, I then have implied probability of default known as the Expected Default Frequency(EDF) (Bharath & Shumway, 2008):

$$EDF = P_t = \Pr\left[-\frac{lnV - ln\mathrm{F} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A \sqrt{t}} \geq W_t \right] \quad \text{......}(7)$$

Then I have the Moody KMV (Kealhofer, McQuown and Vasicek) estimation formula for Distance to Default (DTD) as shown below:

$$\frac{lnV - lnF + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} = Distance\ to\ Default(DTD) \quad \text{..}(8)$$

Hence:

$$P_t = N(-DTD)$$

Just to elaborate on how the probability of default is measured using equation 8 above. The default probability would be the likelihood that the firm market asset value falls in the area of asset return distribution that falls under the total debt or what is generally refer to as a default boundary point(DPt).The default event is thus modelled by assuming the log asset value, falling below a certain threshold or default boundary point(DPt).Depending also on the market volatility and asset price movements as a result, the market asset value would either fall below the default boundary(DPt) and default would be triggered or the market asset value remains above the default boundary(DPt) and no default would occur.

I use equation 8 above to calculate the Expected Default Frequency (EDF) which is the estimate of corporate defaults. In order to use equation 8, I need to define or estimate the variables that are used as inputs in the equation. I provide the input variables definitions and estimation approaches below:

Total Debt/Default Boundary Point (F): Goris (2015) defines default point as the minimum value of the company's assets at which point the company will not be able to make its debt repayment. There is a vast amount of literature that advocate that default point is somewhere between the short-term liabilities and the firm total liabilities as some firms do not necessarily default when the value of their total assets is below their total liabilities. They argue that the reason why some firm continue to trade and service their debt even at level of asset value below total liabilities is the breathing space offered by the long term nature of some of their

liabilities(Crosbie & Bohn, 2003).
To calculate the default point Moody's-KMV expresses the default point (DP) as follows:

$$DP_t = STL_t + 0.5 \cdot LTL_t \quad \text{...(9)}$$

Where DP_t is the default point, STL_t is the Short-term liabilities and LTL_t is the long-term liabilities, all at time t.

In this paper, I assume that the default point is somewhere between the firm short-term liabilities and total liabilities in line with the Moody's KMV as shown in equation 9 above. Default Point (DP_t) is represented by (F)in the Distance to Default (DTD) formula (equation 8) above. When DP_t or (F) increases, I expect the Distance to Default to reduce and consequently Expected Default Frequency to increase.

Asset Value (V_t): This is the market value of the firm assets. One way to get this asset market value is to use the discounted present value of the firm future expected cash flow to be generated from these assets. This means that I can view the market capitalisation (equity) value, as the value the investor place on the asset after considering its operational and debt obligation. Under the Moody's KMV method, I solve for the market asset value using an iterative procedure as described by (Duan & Wang, 2012). Under the naive assumption I solve for asset value using the equation below:

$$Market\ Asset\ Value = Market\ Capitalisation + Total\ Debt \quad \text{...........}(10)$$

In the paper, I solve for the market asset value using the Moody iterative process.

Asset value is represented by (V)in the Distance to Default (DTD) formula (Equation 8) above. When Asset value (V)increases, I expect the Distance to Default to increase and consequently Expected Default Frequency to decrease.

- **Asset Volatility(σ_A):** The preferred or common way to calculate volatility of the asset return is to take the volatility/standard deviation of the daily return in market asset value and then annualise it by multiplying the σ_{daily} by the square root of the number of days in a year that one can trade. The usual assumption is that there are 252 days in a year that the stock market is open for trading. So, the annualized volatility is then given by the formula:

- $\sigma_{A} = \sigma_{daily}\sqrt{252}$

Asset volatility is represented by (σA)in the Distance to Default (DTD) formula (equation 8) above. When Asset volatility (σA)increases, I expected the Distance to Default to decrease and consequently Expected Default Frequency to increase.

- **Mean Annual Asset return (μ):** One way to calculate the mean annual asset return is to calculate the daily return and sum them over the 252 days that one can trade in a year. Mean Annual Asset return is represented by (μ)in the Distance to Default (DTD) formula (Equation 8) above. When Mean Annual Asset returns(μ)increases, I expect the Distance to Default to increase and consequently Expected Default Frequency to decrease.

- **Time Period (T):** This is the time period over which we are measuring the Distance to Default. As I have already mentioned, probability of default is defined as the likelihood that the obligor will not be able to honour their payment obligation within a specified period, which is one year. So, our time period (T) is a year or 252 trading days. If I increase the time period (T), I expect the Distance to Default to decrease and consequently Expected Default Frequency to increase. I base this expectation on the fact that, as the time period (T) increases, the asset volatility (σA) will also increase over the new longer period. As I have already mentioned an increase asset volatility (σA) lead to a decrease in Distance to Default.

Duan and Wang (2012) mention the biggest challenge in implementing equation 8 above as the fact that the Asset value (V_t) is not directly observable and has to be estimated, as the main challenge in the implementation. If Asset value (V_t) has to be estimated, so has to be its mean (μ) and volatility (σA).Hence I run a couple of iterations in the estimation of the market asset value (V_t).

Crosbie and Bohn (2003) described the KMV method as an iterative procedure consisting of the following step:

Step 1: Apply an initial guess of σ_A to equation 8 to obtain a time series of implied asset values and hence continuously compounded asset returns.

- For the initial value of σ_A, I assume $\sigma_A = \sigma_E$

Step 2: Use the time series of continuously compounded asset returns to obtain updated estimates for μ and σ_A.

Step 3: Go back to Step 1 with the updated σ_A, unless convergence has been achieved.