Journal of Economics Library
www.kspjournals.org

Volume 3 June 2016 Issue 2

Disaggregated Credit Extension and Financial Distress in South Africa

By Leroi RAPUTSOANE [†]

Abstract. This study analyses the relationship between disaggregated credit extension and financial distress in South Africa. Of particular interest is to isolate the components of disaggregated credit extension that show a strong relationship with the measure of financial distress. The empirical results reveal that aggregate total domestic credit extension is robustly positively correlated with the composite indicator of financial distress, while there is a mixed relationship between the components of disaggregated credit extension and the composite indicator of financial distress. In particular, the study finds that total domestic credit extension, instalment sale credit, loans and advances to households, investments and total loans and advances are highly correlated with the composite indicator of financial distress. Therefore,the study conjures that these components could be aggregated into a single measure of credit extension that could be usedfor financial stability purposes in South Africa.

Keywords. Disaggregated credit extension, Financial distress.

JEL. C32, E44, E51, G21.

1. Introduction

Credit extension has been identified as one of the major causes of financial crises by the Basel Committee on Banking Supervision (2010a; 2011a). According to Davis (2009), although the episodes of financial instability are diverse in their details, the broad generic types can be distinguished as credit risk, market risk and liquidity risk where credit risk is associated with the failure of financial institutions due to trading losses as a result of default on debt by borrowers. Borgy et al. (2009) and Jeong (2009) suggest that the willingness of financial institutions to lend tends to rise during periods of booming economic conditions and to fall in periods of weakening economic conditions. This procyclical behaviour of credit extension by financial institutions can have adverse implications for economic activity by amplifying the fluctuations in the economic cycle, considerably prolonging and deepening the economic recessions. The booming economic conditions that are amplified by the procyclical behaviour of credit extensionare associated with the buildup of systemic financial vulnerability and distress, hence Schularick & Taylor (2012) and Taylor (2012), among others, argue that excessive credit extension is the foremost predictor of financial crises.

The recent global financial crisis has highlighted vulnerability of the financial system, its ability to generate economic instability through endogenous credit booms and has refocused attention on credit fluctuations as well as policy responses to avert future financial crises according to Schularick & Taylor (2012).

† Department of Economics, Tshwane University of Technology, Pretoria, South Africa.

. +27 12 3820869

. Raputsoanelj@tut.ac.za

In an effort to protect the financial system during periods of excessive credit growth, the Basel Committee on Banking Supervision (2010b) released a step by step guide on the use of credit extension as a common reference guide for implementing the countercyclical capital buffers for financial institutions. The recent proposals by the Basel Committee on Banking Supervision (2010a; 2011a) to use aggregate credit extension as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions necessitates understanding how credit extension behaves during the financially distressful times. Of particular importance is also to isolate the components of credit extension that fluctuate closely with financial distress to understand their potential importance as reference guides for implementing the countercyclical capital buffers for financial institutions in South Africa.

The recent global financial crisis has also demonstrated that financial instability can manifest in periods of low inflation and stable macroeconomic conditions as argues Gali (2014) and Gali & Gambetti (2015). This suggests that there is a possibility of disconnect between the economic cycle and the financial cycle hence a perfect comovement between these two phenomena may not exist in all instances. However, majority of existing literature examine the behaviour of aggregate sector credit extension over the economic cycle, including Borio et al. (2010; 2011) and Andersen et al. (2013). In order to fully understand the behaviour of credit extension, it is also desirable to examine its behaviour over the financial cycle. Although the Basel Committee on Banking Supervision (2010b; 2011a) proposes that aggregate credit extension be used as a reference guide for implementing the countercyclical capital buffers, credit extension can be disaggregated into a variety of components that can experience different and even diverging growth trends, affecting the aggregate sector credit extension measure, undermining its usefulness for financial stability purposes. As such, examining the behaviour of disaggregated sector credit extension over the financial cycle can isolate the components that show a strong positive relationship with the measure of financial distress. These components could be aggregated into a single measure of credit extension and used as a reference guide for implementing the countercyclical capital buffers for financial institutions instead of using the aggregate credit extension measure.

This study analyses the relationship between disaggregated credit extension and financial distress in South Africa. Financial distress is measured as the composite indicatorusing variables that cover the main segments of the South African financial market, including the bond and equity securities markets as well as the foreign exchange market. A similar index of financial stress has been used in Balakrishnan et al. (2009), Hakkio & Keeton (2009) and Lo Duca & Peltonen (2011), among others. Bayesian variable selection, which is detailed in Zeugner (2012) and was developed by Feldkircher & Zeugner (2009) is then used to uncover the comovements between the disaggregated credit extension and the composite measure of financial distress. Bayesian variable selection circumvents the high data dimensionality problem similar to dynamic factor models and large vector autoregressions.It also accounts for model uncertainty inherent in the variable selection providing an optimal way of capturing the linear relationships between the disaggregated credit extension and the constructed composite indicator of financial distress. Uncovering the comovements between the disaggregated credit extension and the composite indicator of financial distresscontributes to the growing literature that attempts to understand the behaviour of credit extension during periods of heightened financial distress and will help the financial sector regulators to improve the maintenance of a prudent and stable financial system.

Empirical evidence supporting the view that excessive credit extension is followed by financial crisesduring periods of booming economic conditions can be found in Taylor (2012) and Goodhart & Hofmann (2008) in industrialised countries as well asSchularick and Taylor (2012) and Jorda et al. (2011) in advanced countries. In particular, Taylor (2012) takes an historical perspective on macroeconomic and financial history to provide answers to the causes of financial crises and concludes that credit booms stand out as the most plausible predictors of financial crises since the beginning of modern finance capitalism in the late nineteenth century. Other empirical studies that link credit extension with financial crises include Goodhart & Hofmann (2008) who assess the linkages between money, credit, house prices and economic activity in industrialised countries and find that the effect of the shocks to money and credit are stronger when house prices are booming. Schularick & Taylor (2009) study the behaviour of money, credit, and macroeconomic indicators in 14 advanced countries and provide evidence that credit growth is an important predictor of financial crises. Jorda et al. (2011) study the macroeconomic dynamics before financial crises and find that credit growth tended to be elevated and the natural rate of interest low in the build up to recent global financial crises.

There also exists a rich, extensive and inexhaustible literature on banking sector vulnerability during financial crises episodes. The discussion that follows concentrates on the literature that identifies the periods of systemic financial distress using a composite indicator of financial vulnerability. This indicator is constructed from a variety of macroeconomic and financial sector specific variables and includes Illing & Liu (2006), Balakrishnan et al. (2009), Cardarelli et al. (2009), Hakkio & Keeton (2009) and Lo Duca & Peltonen (2011). Other studies go beyond the construction of the a composite indicator of financial vulnerability to analyse the effects of financial distress on selected macroeconomic and financial variables such as economic activity, interest rates, capital adequacy and liquidity following Demirguc-Kunt & Detragiache (1998; 1999). Studies in this area include Balakrishnan et al. (2009), Cardarelli et al. (2009) and Lo Duca & Peltonen (2011). This study takes a related but unique approach by constructing a composite indicator of financial distress and analysing its the relationship with disaggregated credit extension in South Africa.

The study is organised as follows. The next two sections discuss the composite indicator of financial distress and disaggregated credit extension, respectively. This is followed by the methodology and empirical results sections. The last section is the conclusion.

2. Financial distress indicator

Financial system distress is not directly observable but is presumably reflected in many financial market variables. The study will therefore attempt to identify the episodes of financial distress using an indicator constructed as a composite index of the variables that cover the main segments of the South African financial market, including bond and equity securities markets as well as the exchange rate market. The variables that are used to construct the indicator of financial distress were sourced from the South African Reserve Bank database. They span the period 2000 to 2012 and are denominated in monthly frequency. These variables were selected such that they capture the significant shifts in asset prices and liquidity shortages, abrupt upsurge in risk and uncertainty, as well as the vulnerability of financial institutions. They comprise the interbank bank spread, the sovereign bond spread, the A rated bond spread, the corporate bond spread, the stock market return, the financial sector return, the banking sector return and the nominal effective exchange rate return. The interbank bank spread is the spread between the 3 month Johannesburg Interbank Agreed Rate (JIBAR) rates and the 3 month Treasury bill rate. The sovereign bond spread is the spread between the 3 month treasury bill rate and the 10 year treasury bill rate. The A rated bond spread is the spread between the A rated Eskom bond and the 10 year treasury bill rate. The corporate bond spread is the spread between the FTSE/JSE All Bond yield and the 10 year treasury bill rate. The stock market return is the annualised change in the FTSE/JSE All Share stock market index. The financial sector return is the annualised change in the FTSE/JSE Financials stock market index. The banking sector return is the annualised change in the FTSE/JSE Banks stock market index. The nominal effective exchange rate return is the annualised change in nominal effective exchange rate.

The variables used to construct indicator of financial distress are also used by Balakrishnan et al. (2009), Cardarelli et al. (2009), Hakkio & Keeton (2009) and Lo Duca & Peltonen (2011). The bond spreads, sometimes referred to as credit spreads, measure the counter party or default risk premium over the treasury bill rate requested by investors, reflecting the difference in credit quality or risk between different bond measures. The stock market return measures were inverted so that the decline in these variables reflects the periods of benign financial distress. Other variables not included in the study include the stock market volatility and exchange market pressure index. In particular, the stock market volatility measures were not included because volatility only fluctuates above zero, which is at odds with the financial distress index constructed here that is allowed to fluctuate between positive and negative values.The financial distress indicator variables were standardised by subtracting their means and dividing them by their standard deviations. A value of 1 in the financial distress indicatorrepresents a 1 standard deviation difference from the mean value over the sample period. The financial distress variables were aggregated using the principal components analysis weighting scheme thatis normalised to 1. Principal components analysis reduces the dimensionality of a data set to decrease redundancy in the data and identify how different variables work together to create the dynamics of a system. The first principal component was used in weighting given that it maximizes the variance and spreads out the scores as much as possible.

The results for the principal components analysis weighting scheme used in the construction of the financial distress indicatorare reported in Table 1. The results show that the proportion of variance accounted for by the first principal component is 37.98 percent of the variance in the selected variables.The stock market return,the financial sector return and the banking sector return have the biggest weights or loadings of 15.65, 20.38 and 19.89 percent, respectively. These are followed by the sovereign bond spread and the nominal effective exchange rate return withloadings of 12.23 and 10.26 percent, respectively. The interbank bank spread, the A rated bond spread and the corporate bond spread have the smallest weights or loadings of 8.24, 9.23 and 3.71 percent, respectively. This means that the financial distress indicator is mainly explained by the movements in the stock market return, the financial sector return, the banking sector return, which are stock market measures. All these variables form part of the FTSE/JSE All Share stock market index, which is the is a market capitalisation weighted index of all the companies listed on the Johannesburg stock exchange.

Table 1. *Principal components and normalised weights for the financial distress indicator variables*

Variable	Principal Components	Normalised
Interbank Bank Spread	0.213682	0.082362
Sovereign Bond Spread	0.317411	0.122344
A Rated Bond Spread	0.249826	0.096294
Corporate Bond Spread	0.096137	0.037055
Stock Market Return	0.406071	0.156517
Financial Sector Return	0.528941	0.203876
Banking Sector Return	0.516124	0.198936
Real Exchange Rate Return	0.26623	0.102616
Total	2.594422	1.000000
Proportion of Variance	0.379800	0.379800

Notes: Own calculations with data from the South African Reserve Bank database

As depicted in Figure 1, the turning points of the financial distress indicator, particularly the peaks, are consistent with the milestones in global as well as the South African episodes of financial distress. These turning points of the financial distress indicator indicate 2 distinct instances of heightened financial distress between 2000 and 2012. The first instance of heightened financial distress began towards the end of 2001 and lasted till the middle of 2003. The second instance of heightened financial distress began towards the end of 2007 and lasted till the middle of 2009. This composite indicator of financial distress is also comparable to those constructed by Cardarelli et al. (2009), Hakkio & Keeton (2009) and Lo Duca & Peltonen (2011) for developed countries, among others. The only exception is that the financial distress indicators for developed countries show heightened financial distress starting from the middle of 2010, which coincides with the onset of the sovereign debt crisis. The plots of the rest of the financial distress indicator variables are available from the author on request.

3. Disaggregated credit extension

As discussed above, the Basel Committee on Banking Supervision (2010a; 2011a) has proposed the use of aggregate credit extension as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions. This necessitates understanding how credit extension behaves during the financially distressful times. Of particular importance is also to understand how the components of credit extension fluctuate relative to the indicator of financial distress. As with the indicator of financial distress variables, disaggregated credit extension variables were sourced from the South African Reserve Bank database. They span the period 2000 to 2012 and are denominated in monthly frequency. The disaggregated credit extension comprise total domestic credit extension, net credit to government sector, total credit to private sector, loans and advances to households, total loans and advances, other loans and advances, mortgage advances, leasing finance, instalment sale credit, bills discounted and investments. According to the South African Reserve Bank (2013) Quarterly Bulletin, total domestic credit extension comprises total of credit extended to the private sector and net credit extended to the government sector.Total loans and advances constitutes total of instalment sale credit, leasing finance, mortgage advances and other loans and advances, while total credit extended to the private sector is made up of total of investments, bills discounted instalment sale credit, leasing finance, mortgage advances, and other loans and advances.

Financial distress indicator

Total domestic credit extention

Figure 1. *Evolution of the financial distress indicator and total domestic credit extension*

The disaggregated credit extension variables are expressed in annual growth rates. These variables were also expressed as a ratio of gross domestic product with no discernible difference in the results as will be discussed below. In order to understand the composition of total domestic credit extension, first, thecontributions of disaggregated credit extension variables to total domestic credit extension were computed and they are shown in Table 2.Total domestic credit extension is mainly made up of total credit to private sector and total loans and advances with contributions of 96.87 percent and 90.36 percent, respectively. The contributions of loans and advances to households, mortgage advances, other loans and advances and instalment sale credit then follow at 48.93 percent, 43.56 percent, 33.50 percent and 10.23 percent, respectively. Investments, net credit to government sector, leasing finance and bills discounted contribute least to total domestic credit extension at 5.97 percent, 3.13 percent, 3.08 percent and 0.54 percent, respectively.

Table 2. *Contributions of disaggregated credit extension variables to total domestic credit extension and their correlations with the financial distress indicator*

Variable	Contributions	Correlations
Total Dom Credit Extension	1.000000	0.637247
Net Credit to Government Sector	0.031303	-0.056506
Total Credit to Private Sector	0.968697	0.470431
Loans and Advances To households	0.489369	0.221355
Total Loans and Advances	0.903584	0.387411
Other Loans and Advances	0.334952	0.490629
Mortgage Advances	0.435616	0.222716
Leasing Finance	0.030765	0.036235
Instalment Sale Credit	0.102251	0.444062
Bills Discounted	0.005421	0.121878
Investments	0.059693	0.262659

Notes: Own calculations with data from the South African Reserve Bank database

The correlations of the annual growth rates of the disaggregated credit extension variables with the financial distress indicator are also shown in Table 2. Total domestic credit extension is highly correlated with the indicator of financial distress with the correlation coefficient of 0.63 followed by total credit to the private sector, other loans and advances, instalment sale credit and total loans and advances around 0.40.The rest of the other disaggregated credit extension variables have relatively low correlations with financial distress indicator, while the correlation of net credit to government sector is negative.The evolution of annual growth rate in total domestic credit extension is depicted in Figure 1. Total domestic credit extension stayed relatively flat from 2000 to 2002. It then increased sharply and remained high to late 2003, where it subsequently fell until early 2004. There is a sustained increase in total domestic credit extension from early 2004 till 2008and a subsequent decrease to 2010 followed by an increase to the end of 2012. According to the South African Reserve Bank (2013) Quarterly Bulletin, the sharp rise in credit extension in January 2003 does not indicate an increase in underlying credit demand but is a result the increase in investments category due to regulatory and accounting changes. The plots of the rest of the disaggregated credit extension variables are available from the author on request.

4. Empirical methodology

To identify thecomovements between disaggregated credit extension and the financial distress indicator, Bayesian Variable Selection, also known as Bayesian model averaging or Bayesian model selection, is used. In reduced form models, a typical data analysis approach is to select a set of explanatory variables and make inferences using the preselected set of explanatory variables. However, O'Hara & Sillanpaa (2009) argue that this approach has a serious disadvantage that the dependence of the inferences is limited to the set of explanatory variables selected for inclusion in the model resulting in omitted variable bias. Thus when there are many potential explanatory variables, a challenge arises as to which variables are to be included in the model and how important they are. Bayesian variable selection circumvents the high dimensionality problem in explanatory variables given the relatively large data set that is used in the analysis. There is a growing trend in the literature of using high dimensional data where information usually scatters through a large number of interrelated time series given thathigh dimensional data reveals patterns in the data that are not accounted for by the mainstream economic theory.

Dynamic factor models and large Vector Autoregressions have been used to circumvent the high data dimensionality problem. However, the problem of selection of relevant variables remains. According to Amini & Parmeter (2011; 2012), Bayesian Variable Selection circumvents this challenge by estimating models for all possible combinations of all explanatory variables and constructing a weighted average over all the possible models. It accounts for the model uncertainty inherent in the variable selection by averaging over the best models based on posterior model probability. It provides an optimal way of capturing the linear relationships in the data and efficiently minimises the estimated parameters towards the stylised representation of the data leading to sound inference. The advantage of analysing high dimensional data using Bayesian Variable Selection is the revelation of interdependence and connections among the economic variables, leading to a new way of understanding their economic relationships.

The Bayesian Variable Selection approach adopted in this study is detailed in Zeugner (2012) and was developed by Feldkircher & Zeugner (2009). The empirical model is specified as follows

$$y_\gamma = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon \quad , \quad \varepsilon_\gamma \sim N\left(0, \sigma_\gamma^2 I\right) \tag{1}$$

where y_γ is the dependent variable, α_γ is a constant, X_γ is a vector of explanatory variables, β_γ are coefficients and ε_γ is the error term with mean 0 and variance σ_γ^2. Given the high dimensional data in X_γ, the challenge is to identify the variables to include in the model. To circumvent this problem, Bayesian Variable Selection estimates all possible combinations of X_γ and constructs a weighted average over them such that if X_γ contains K variables where 2^K variable combinations are estimated and hence 2^K models.

The model weights for averaging are derived from posterior model probabilities from Bayes theorem as follows

$$p\left(M_\gamma \middle| y, X\right) = \frac{p\left(y \middle| M_\gamma, X\right) p\left(M_\gamma\right)}{p\left(y \middle| X\right)} = \frac{p\left(y \middle| M_\gamma, X\right) p\left(M_\gamma\right)}{\sum_{s=1}^{2^K} p\left(y \middle| M_s, X\right) p\left(M_s\right)} \tag{2}$$

where $p\left(M_\gamma \middle| y, X\right)$ is the posterior model probability. Posterior model probability is proportional to the product of the probability of the data given the model $p\left(y \middle| M_\gamma, X\right)$ and the prior model probability $p\left(M_\gamma\right)$ and is inversely proportional to the constant integrated likelihood over all models $p\left(y \middle| X\right)$. $p\left(\beta_\gamma \middle| y, X\right) = \sum_{\gamma=1}^{2^K} p\left(\beta_\gamma \middle| M_\gamma, y, X\right) p\left(M_\gamma \middle| X, y\right)$ is the posterior distribution assuming that M_γ is the true model, β_γ are the parameters, while the unconditional coefficients are defined as $E\left(\beta_\gamma \middle| y, X\right) = \sum_{\gamma=1}^{2^k} p\left(\beta_\gamma \middle| y, X, M_\gamma\right) p\left(M_\gamma \middle| y, X\right)$. The prior model probability has to be proposed based on prior knowledge or believe.

The reviews of the Bayesian Variable Selection approach by Amini & Parmeter (2011; 2012) argue that this method has not received extensive use in empirical economics research and that its use has been limited to studying the determinants of economic growth until recently. However, this approach is quickly gaining popularity in other fields of empirical economics research and has recently been used to study the determinants of currency crises and asset price bubbles by Crespo-Cuaresma & Slacik (2009) and Crespo-Cuaresma (2010), to forecast inflation by Korabillis & Koop (2012) and to predict real time economic activity by Faust et al. (2013). In an almost similar study to the current study, Feldkircher (2012) used Bayesian Variable Selection study the determinants of vulnerability to the recent global financial Crisis using a data set comprising 97 variables measuring macroeconomic, financial, fiscal risks, among others.

5. Empirical Results

The Bayesian Variable Selectionapproach developed by Feldkircher & Zeugner (2009) was used to uncover the potential variables that display comovements with the indicator of financial distress. As detailed in Zeugner (2012), Bayesian Variable Selection requires the specification of the prior distributions on the model parameters and the model space, the Markov chain Monte Carlo sampler, the number of draws that the sampler runs to be retained and the number of the first iterations (burn-ins) to be omitted from the estimation results.The information about the sampling procedure is reported in Table 3,the number of burn-in draws for the Markov chain Monte Carlo sampler was set to 100 000 draws, while the number of iteration draws for the Markov chain Monte Carlo (MCMC) sampler to be retained was set to 1 000 000 draws. The number of best models for which information was stored was set to 5 000 where the best models are used for convergence analysis concerning the likelihoods and the Markov chain Monte Carlo frequencies, together with the likelihood based inference.

Table 3. *Bayesian variable selection sampling procedure*

Sampling procedure	Statistic	Sampling procedure	Statistic
Mean no. of repressors	5.7369	Model prior	Random
Draws	1 000 000	g-Prior	BRIC
Burn ins	100 000	MCMC	Birth death
Model space	2048		

Notes: Draws are the MCMCsampling routines from posterior distributions, Burn ins are the number of initial MCMC draws that are discarded, g-Prior is the Zellner's (1986) prior for the regression coefficients of a multiple regression, MCMC is the Markov chain Monte Carlo sampler and BRIC is the hyperparameter on Zellner's (1986) g-prior for the regression coefficients. More details can be found in Zeugner (2012).

The birth/death sampler was used for the model Markov chain Monte Carlosampler. The hyperparameter on Zellner's (1986) g-prior for the regression coefficients, BRIC, which is similar to the benchmark prior recommended by Fernandez, Ley & Steel (2001) was used. The chosen model prior is the beta binomial model prior with random theta suggested by Ley & Steel (2009). Given that there are 11 disaggregated credit extension variables, the model space is 2028.

The Bayesian variable selection results are reported in Table 4. The PIP is the posterior inclusion probability and represents the sum of posterior model probabilities for models where covariates where included. The results show that total domestic credit extension was included in all the estimated models with the posterior inclusion probability of 100 percent such that all the posterior model mass rests on models that include this variable. This is followed by Instalment Sale Credit, Loans and Advances to households, Investments and Total Loans and

Table 4 . *Bayesian variable selection results for disaggregated credit extension variables*

Variable	PIP	Post Mean	Post SD	Cond.Pos.Sign
Total Dom credit Ext	1.000000	0.655393	0.049828	1.000000
Instalment Sale Credit	0.999771	0.115116	0.027775	1.000000
Loans & Advances to HH	0.998427	-0.203102	0.039927	0.000000
Investments	0.967394	-0.022296	0.007716	0.000000
Total Loans & Advances	0.951601	-0.373515	0.257911	0.002871
Total Credit to Pvt Sect	0.216525	0.019704	0.120172	0.783503
Mortgage Advances	0.145275	0.020416	0.098333	0.950632
Other Loans & Advances	0.137137	0.014775	0.079409	0.461400
Leasing Finance	0.125091	0.001201	0.006831	0.890983
Bills Discounted	0.098072	-0.000005	0.001077	0.678318
Net Credit to Govt Sect	0.097629	-0.000002	0.000034	0.002131

Notes: *PIP* is Posterior Inclusion Probability and represents the sum of posterior model probabilities for models where covariates where included. *Post mean* are the size of coefficients averaged over all models. *Post SD* is posterior standard deviation for the coefficients. *Cond. Pos. Sign* is Conditional Position Sign and represents posterior probability of a positive coefficient expected value conditional on inclusion. More details can be found in Zeugner (2012).

Advances with the posterior inclusion probabilities of more than 95.00 percent. The posterior inclusion probabilities of total credit to private sector, mortgage advances, other loans and advances as well as leasing finance range between 21.65 percent and 12.51 percent, while the posterior inclusion probabilities of bills discounted and net credit to government sector are the lowest at 9.81 percent and 9.76 percent, respectively. Based on the posterior inclusion probabilities, total domestic credit extension, instalment sale credit, loans and advances to households, investments and total loans and advances have important comovements with the financial distress indicator, while the opposite is true for the rest of the other variables.

Post mean is the posterior mean. It represents the size of coefficients averaged over all models. Total domestic credit extension, instalment sale credit, total credit to private sector, mortgage advances, other loans and advances and leasing finance have positive coefficients meaning that they increase during periods of heightened financial distress and fall during periods of benign financial distress. The opposite is true for loans and advances to households, investments and total loans and advances, which decrease during periods of heightened financial distress and increase during periods of low financial distress given their negative posterior means. Cond. Pos. Sign is the conditional position sign. It represents the posterior probability of a positive coefficient expected value conditional on inclusion. The results show absolute certainty of a positive sign for total domestic credit extension and instalment sale credit and absolute certainty of a negative sign for loans and advances to households and investments, while the certainty of a positive sign for other loans and advances is almost borderline.

Figure 2 is the pictorial depiction of the results reported in Table 4. It shows the cumulative model inclusion probabilities of the variables based on the best 235 models as well as the posterior coefficient densities.The blue colour in Figure 2 corresponds to positive coefficients, a red colour to negative coefficients and the white colour to noninclusion. Considering the posterior means, the estimated results reveal that a unit increase in total domestic credit extension and instalment sale credit is associated with a 65.54 percent and 11.5 percent increase in the financial distress indictor, while a unit increase in loans and advances to households, investments and total loans and advances results in a 20.31 percent, 2.23 percent and 37.35 percent decrease in the financial distress indictor, respectively. The posterior means for total credit to private sector, mortgage advances, other loans and advances, leasing finance, bills discounted and net credit to government sector show relatively negligible comovements between these variables and the financial distress indicator.There is almost zero comovement between leasing finance, bills discounted and net credit to government sector.

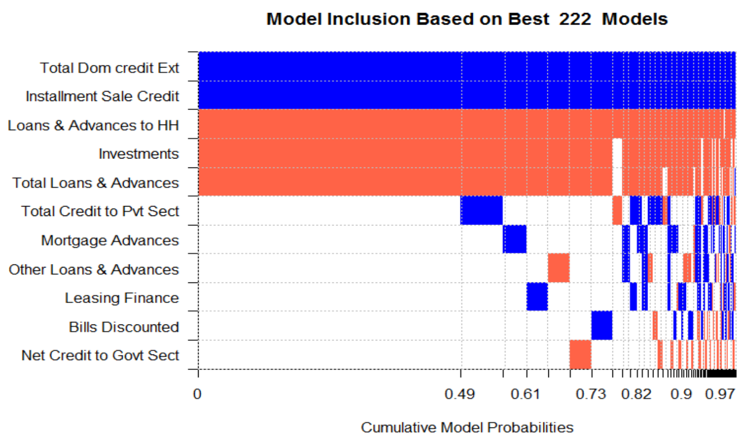


Figure 2. *Model inclusion probabilities for disaggregated credit extension variables*

On the rest of the results, Figure 3 shows that the posterior model size peaks at 5 meaning that only 5 disaggregated credit extension variables are important for the indicator of financial distress as witnessed in Table 3. Figure 4 depicts the correlation of 1.00 between the Markov chain Monte Carlo iteration counts and the posterior model probabilities for the best 50 models which indicates a good degree of convergence.

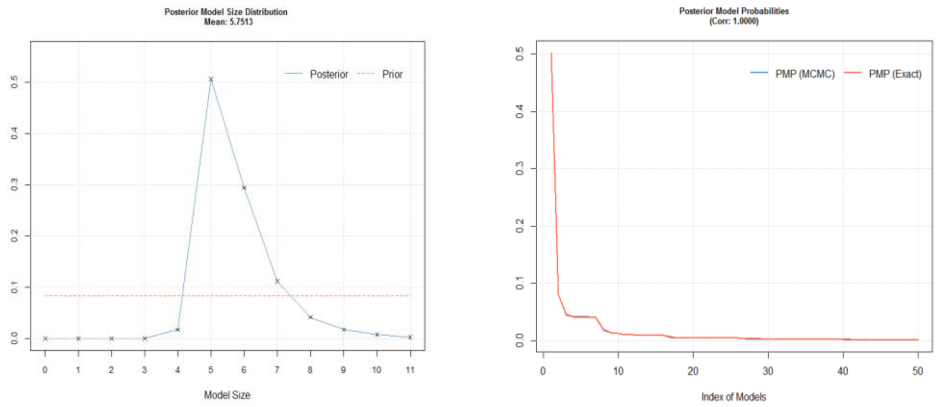
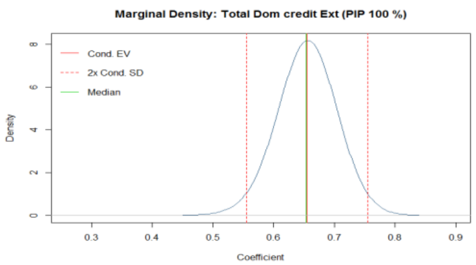
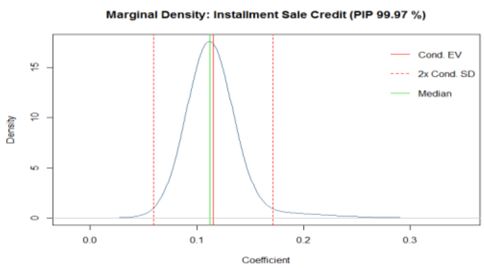


Figure 3. *Posterior model size and probabilities for disaggregated credit extension variables*

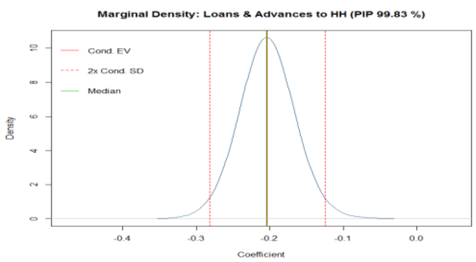
The Basel Committee on Banking Supervision (2010b) at the Bank of International Settlements has identified credit extension as being procyclical and one of the major causes of the financial crises. To this end, it released a step by step guide on the use of credit extension as a common reference guide for implementing the countercyclical capital buffers for financial institutions. One of the steps in this guide involves calculating the aggregate private sector credit as a percentage of gross domestic product. To account for this proposal, the ratio of disaggregated credit extension variables to gross domestic product was used. However, there was no discernible difference in the results.



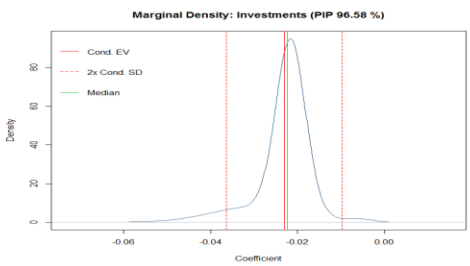
Total domestic credit extension



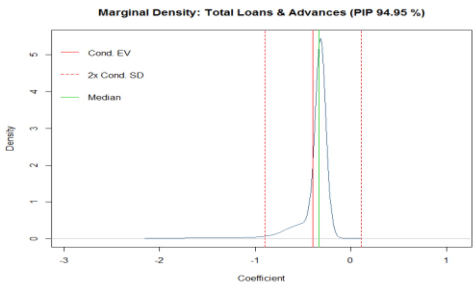
Instalment sale credit



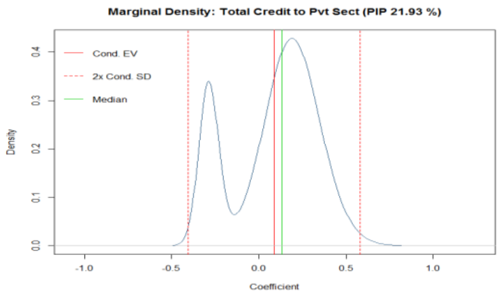
Loans and advances to households



Investments



Total loans and advances



Total credit to private sector

Figure 4. *Posterior coefficient densities for disaggregated credit extension variables*

The European Banking Federation (2011) argues that the analysis of credit extension that is focused on short term disturbances do not account for medium term trends related to business cycle fluctuations. To account for this argument, smooth splines with the smoothing parameter set at different values, from 0.10 to 0.60 were applied to all the variables to smooth out the month to month fluctuations in the variables. In a similar manner, there was no discernible difference in results.

No study in existing literature seeks to uncover the comovements between the disaggregated credit extension and the composite indicator of financial distress using the approach that is adopted in this study hence there is a challenge for comparing the results this study.However, the results have important implications for the proposal by the Basel Committee on Banking Supervision (2010a; 2011) to use credit extension as a common reference guide for implementing the countercyclical capital buffers after identifying that it isprocyclical and one of the major causes of the financial crises.The results provide evidence that the aggregate measure of credit extension has a robust and positive relationship with the composite measure of financial distress. However, the relationship between the disaggregated components of credit extension the composite measure of financial distress is mixed with some components showing positive and negative relationships with the indicator of financial distress while such a relationship between the other components of credit extension and financial distress is relatively weak. Thus aggregate credit extension could be used as a common reference guide for implementing countercyclical capital buffers. Alternatively, the components of disaggregated credit extension that show a strong positive relationship with the measure of financial distress could be aggregated into a single measure and used as a reference guide for implementing the countercyclical capital buffers for financial institutions.

6. Conclusion

This study analysed the relationship between disaggregated credit extension and financial distress in South Africa. Financial distress was measured as the composite indicator comprising the variables that cover the main segments of the South African financial market, including bond and equity securities markets as well as the exchange rate market. Principal components analysis weighting scheme was used in the construction of the composite indicator financial distress. Bayesian Variable Selection was then used to uncover the comovements between disaggregated credit extension and the financial distress indicator. The empirical results generally provide evidence that the aggregate measure of credit extension has a robust and positive relationship with the composite measure of financial distress, while such a relationship is mixed for the disaggregated components of credit extension. In particular, the results provide evidence that total domestic credit extension, instalment sale credit, loans and advances to households, investments and total loans and advances are highly correlated to the composite indicator of financial distress, while the opposite is true for total credit to private sector, mortgage advances, other loans and advances, leasing finance, bills discounted and net credit to government sector.

The recent global financial crisis has demonstrated that financial instability can manifest in periods of low inflation and stable macroeconomic conditions. This suggests a possibility of a possible disconnect between the economic cycle and the financial cycle. Thus fully understanding the behaviour of credit extension over the financial cycle is of equal importance to understanding its behaviour over the economic cycle. Moreover, credit extension can be disaggregated into a variety of categories that can experience different and perhaps diverging growth trends, affecting the aggregate credit extension variable. As such, examining the behaviour of disaggregated credit extension over the financial cycle can isolate those components that show a strong positive relationship with the measure of financial distress. Given its strong relationship with measure of financial distress, aggregate credit extension could be used as a common reference guide for implementing the countercyclical capital buffers. However, a more desirable measure of credit extension that can be used for financial stability purposescould be constructed by aggregating the components of disaggregated credit extension that show a strong relationship with the measure of financial distress such as instalment sale credit, loans and advances to households, investments and total loans and advances. Aggregating such components into a single measure of credit extension would provide a better reference guide for implementing the countercyclical capital buffers for financial institutions.

Future research could study the how disaggregated credit extension behaves during the different periods of financial distress by isolating the different phases of the composite indicator of financial distress such as upturns and downturns as well as booms and busts.

References

Amini, S.M. & Parmeter, C.F. (2011). Bayesian model averaging in R, *Journal of Economic and Social Measurement*, 36(4), 253-287. doi. 10.3233/JEM-2011-0350

Amini, S.M. & Parmeter, C.F. (2012). A Review of the BMS Package for R. *Journal of Applied Econometrics*, 27(5), 870-876. doi. 10.1002/jae.2288

Andersen, H., Giese, J., Bush, O., Castro, C., Farag, M. & Kapadia, S. (2013). Conference on Financial Stability Analysis, Cleveland: Federal Reserve Bank of Cleveland, May 31.

Balakrishnan, R., Danninger, S., Elekdag, S. & Tytell, I. (2009). The Transmission of Financial Stress from Advanced to Emerging Economies. IMF *Working Paper*, No. 09/133. doi. 10.5089/9781451872804.001

Basel Committee on Banking Supervision. (2010a). Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems. Bank of International Settlements, December

Basel Committee on Banking Supervision. (2010b). Guidance for National Authorities Operating the Countercyclical Capital Buffer. Bank of International Settlements, December

Basel Committee on Banking Supervision. (2011). Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems. Bank of International Settlements, Revised Version, June

Borgy, V., Laurent, C., & Jean-Paul, R. (2009). Asset price boom bust cycles and credit: What is the scope of macro prudential regulation?. *Working Paper*, Basel: Bank of International Settlements, doi. 10.2139/ssrn.1630093

Borio, C., Drehmann, M., Gambacorta, L., Jiminez, G. & Trucharte, C. (2010). Countercyclical capital buffers: Exploring options. Bank of International Settlements, *Working Paper*, No. 317. doi. 10.2139/ssrn.1648946

Borio, C., Drehmann, M. & Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: The role of credit aggregates. Bank of International Settlements, *Working Paper*, No. 355. [Retrieved from].

Cardarelli, R., Elekdag, S. & Lall, S. (2011). Financial stress and economic contractions. *Journal of Financial Stability*, 7(2), 78-97. doi. 10.1016/j.jfs.2010.01.005

Crespo Cuaresma, J. & Slacik, T. (2009). On the determinants of currency crises: The role of model uncertainty. *Journal of Macroeconomics*, 31(4), 621-632. doi. 10.1016/j.jmacro.2009.01.004

Crespo Cuaresma, J. (2010). Can emerging asset price bubbles be detected?. Paris: Organisation for Economic Co-operation and Development, *Working Paper*, No. 772. doi. 10.1787/5kmdfmztmqtj-en

Davis, E.P. (2009). Theories of financial instability and their practical relevance. Course on Financial Instability, Tallinn: Estonian Central Bank, December 9-11. [Retrieved from).

Demirguc-Kunt, A., & Detragiache, E. (1998). The determinants of banking crises in developing and developed Countries. IMF *Staff Papers*, No. 45(1), 81-109. doi. 10.2307/3867330

Demirguc-Kunt, A. & Detragiache, E. (1999). Monitoring banking sector fragility: A multinomial logit approach. IMF *Working Paper*, No. 99-147, doi. 10.5089/9781451856712.001

European Banking Federation. (2011). Credit Cycles and Their Role in Macroprudential Policy. Report to Economic and Monetary Affairs Committee, European Banking Federation, November. [Retrieved from].

Faust, J., Gilchrist, S., Wright, J.H., & Zakrajssek, E. (2013). Credit Spreads as Predictors of Real-Time Economic Activity: A Bayesian Model-Averaging Approach. *Review of Economics and Statistics*, 95(5), 1501–1519. doi. 10.1162/rest_a_00376

Feldkircher, M. (2014). The determinants of vulnerability to the global financial crisis 2008 to 2009: Credit growth and other sources of risk. *Journal of International Money and Finance*, 43, 19-49. doi. 10.1016/j.jimonfin.2013.12.003

Feldkircher, M., & Zeugner, S. (2009). Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in Bayesian model averaging. IMF *Working Paper*, No. 09/202, doi. 10.5089/9781451873498.001

Fernandez, C., Ley, E., & Steel, M. (2001). Benchmark priors for Bayesian model averaging. *Journal of Econometrics*, 100(2), 381-427. doi. 10.1016/s0304-4076(00)00076-2

Gali, J., (2014). Monetary policy and rational asset price bubbles. *American Economic Review*, 104(3), 721-752. doi. 10.1257/aer.104.3.721

Gali, J., & Gambetti, L. (2015). The effects of monetary policy on stock market bubbles: Some evidence. *American Economic Journal*, 7(1), 233–257. doi. 10.1257/mac.20140003

Giese, J., Andersen, H., Bush, O., Castro, C., Farag, M., & Kapadia, S. (2014). The credit-to-GDP gap and complementary indicators for macroprudential policy: Evidence from the UK. *International Journal of Finance & Economics*, 19(1), 25-47, doi. 10.1002/ijfe.1489

Goodhart, C., & Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1), 180-205. doi. 10.1093/oxrep/grn009

Hakkio, G., & Keeton, W. (2009). Financial stress: What is it, how can it be measured, and why does it matter?. *Economic Review*, 94(2), Federal Reserve Bank of Kansas City. [Retrieved from].

Illing, M., & Liu, Y. (2006). Measuring financial stress in a developed country: An application to Canada. *Journal of Financial Stability*, 2(3), 243-265. doi. 10.1016/j.jfs.2006.06.002

Jeong, H. (2009). The procyclicality of bank lending and its funding structure: The case of Korea. *Conference Paper*, Bank of Korea. doi. 10.2139/ssrn.1663501

Jorda, O., Schularick, M., & Taylor, A. (2011). When credit bites back: Leverage, business cycles, and crises. NBER *Working Paper*, No. 17621, doi. 10.3386/w17621

Koop, G., & Korobilis, D. (2012). Forecasting inflation using dynamic model averaging. *International Economic Review*, 53(3), 867-886. doi. 10.1111/j.1468-2354.2012.00704.x

Ley, E., & Steel, M.F.J. (2009). On the effect of prior assumptions in Bayesian model averaging with applications to growth regression. *Journal of Applied Econometrics*, 24(4), 651-674. doi. 10.1002/jae.1057

Lo Duca, M., & Peltonen, T. (2011). Macro-financial vulnerabilities and future financial stress - assessing systemic risks and predicting systemic events. European Central Bank *Working Paper*, No. 1311. doi. 10.2139/ssrn.1803075

O'Hara, R.B., & Sillanpaa M.J. (2009). A review of Bayesian variable selection methods: What, how and which. *Bayesian Analysis*, 4(1), 85-117. doi. 10.1214/09-ba403

Schularick, M., & Taylor, A.M., (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review*, 102(2), 1029-1061. doi. 10.1257/aer.102.2.1029

South African Reserve Bank. (2013). *Quarterly Bulletin*. Pretoria: South African Reserve Bank, September

Taylor, A. (2012). External imbalances and financial crises. NBER *Working Paper*, No. 18606, doi. 10.5089/9781484322260.001

Zellner, A. (1986). On assessing prior distributions and Bayesian regression analysis with g-prior distributions. in, *Bayesian Inference and Decision Techniques: Essays in Honour of Bruno de Finetti*, (Eds)Goel, P.K. &Zellner, A., Amsterdam: North Holland

Zeugner, S. (2012). Bayesian model averaging with BMS. *R-package, Vs. 0.3.1*, The R Project for Statistical Computing, [Retrieved from].

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal. This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by-nc/4.0).