Alternative measures of credit extension for countercyclical buffer decisions in South Africa

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27 October 2015

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October 2015

Abstract

This paper analyses the behaviour of alternative measures of credit extension for countercyclical buffer decisions in South Africa. The cyclical properties of three alternative measures of credit extension are examined over the economic and the financial cycles. The results show that the deviation of the ratio of private sector credit extension to gross domestic product from its long term trend is countercyclical with the economic cycle. The results also show that the deviation of the logarithm of private sector credit extension from its long term trend is procyclical with both the economic and the financial cycle. The annual percent change in private sector credit extension generally performs poorly in cyclical terms with both the economic and the financial cycle. Consequently, of the three alternative measures of private sector credit extension considered, the deviation of the logarithm of private sector credit extension from its long term trend could be used as a common reference guide for implementing the countercyclical capital buffers for financial institutions in South Africa.

JEL Classification: C32, E44, E51, G21
Keywords: Credit extension, Countercyclical capital buffers

1. Introduction

The procyclicality of credit extension is identified as one of the major causes of financial crises. Taylor (2012) and Goodhart and Hofmann (2008) provide evidence that excessive credit extension during the booming economic conditions is followed by financial crises in industrialised countries while Schularick and Taylor (2012) and Jorda et al. (2013) provide similar evidence in advanced economies. Borgy et al. (2009) argue that the procyclical behaviour of credit extension can have adverse implications for economic activity by amplifying the fluctuations in the economic cycle, considerably prolonging and deepening the economic recessions. Consequently the Basel Committee on Banking Supervision (BCBS) has proposed that credit extension be monitored and used as a common reference guide for implementing the countercyclical capital buffers for financial institutions. According to the BCBS (2010a, 2011), the aim of the countercyclical capital buffers is to strengthen financial institutions against the build up of systemic finanicial risks due to the procyclical nature of credit extension and to ensure that financial institutions have adequate capital to maintain the flow of credit during periods of broader financial system distress.

The BCBS (2010a) released a step by step guide to calculate and to use the gap between the ratio of aggregate private sector credit to GDP from its long term trend as a common reference guide for implementing the countercyclical capital buffers. The first two steps to calculate this common reference guide for implementing the countercyclical capital buffers involve calculating aggregate private sector credit as a percentage of GDP and then to calculating the deviation of credit as a percentage of GDP from its Hodrick Prescott (1997) trend. Although the literature provide evidence supporting the view that credit extension is procyclical, several studies conclude that the use of the BCBS (2010b) proposed gap between the ratio of aggregate private sector credit to GDP and its long term trend as a common reference guide for countercyclical capital buffers for financial institutions may not be appropriate. These include Gersl and Jakubik (2011), Repello and Saurina (2011) as well as Giannone et al. (2012) in developed countries, Edge and Meisenzahl (2011) for the United States, Gersl and Seidler (2012) for the Czech Republic and Nigam (2013) in Uganda. However, these

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findings contrast with Borio et al. (2010, 2011), Andersen et al. (2014) and Drehmann and Juselius (2014) who conclude that the proposed reference guide performs best in capturing the systemic vulnerabilities that consequently lead to financial crises in a number of countries.

In South Africa, Bernstein et al (2014) assess the behaviour of the BCBS (2010b) proposed gap between the ratio of private sector credit to GDP and its long term trend over the economic cycle and find that it is not procyclical. In particular, the study finds that credit extension decreases during the expansion phase of the business cycle, while it increases during the contraction phase of the business cycle. Thus they conclude that credit extension should be used with caution as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions. A similar conclusion is reached in other countries where evidence fails to establish the procyclicality of the of BCBS (2010b) proposed guide to implememting the countercyclical capital buffers. The reason for this conclusion is that the countercyclical nature of the proposed measure of credit extension would suggest implementation of capital buffers during contractionary economic conditions and their withdrawal during expansionary economic conditions which could have adverse consequences for macroeconomic stability. Drehmann and Tsatsaronis (2014) acknowledge the countercyclical shortcoming of the proposed reference guide across a panel of 53 countries over the period 1980-2013. However, they reason that the negative correlation coincides with periods when the credit extension gap is low such that it is of no consequence for the countercyclical capital buffers.

The countercyclical nature of the BCBS (2010b) proposed gap between the ratio of private sector credit to GDP and its long term trend implies that it should be used with caution and not as a mechanical rule. It also suggests that alternative indicators could be used in conjunction with the credit extension gap given that no indicator is flawless and that a combination of indicators is better. Behn et al (2013) and Drehmann and Juselius (2014) find more precise early warning signals of financial crises in the asset price gap measure that is calculated following the BCBS (2010b) suggested steps and also in the debt service ratio. Nevertheless, Drehmann and Tsatsaronis (2014) argue that adopting a single, simpler and easy to calculate reference guide for implementing the countercyclical capital buffers is more desirable to facilitate communication between policy makers, financial institutions and the public. This paper analyses the behaviour of alternative measures of credit extension for countercyclical buffer decisions in South Africa. In particular, the cyclical properties of three alternative measures of credit extension are examined over the economic and the financial cycles. Consequently, the study will uncover a single measure that has the ability of capture the cyclical evolution of the economic and the financial cycles for countercyclical buffer decisions in South Africa ensuring that the countercyclical capital buffers are accumulated in good times and dispensed during the buildup phase of financial vulnerability.

The paper is organised as follows. The next section discusses the data, section 3 outlines the econometric methodology, section 4 discusses the empirical results and section 6 concludes.

2. Data Description

Monthly data spanning the period 2000-2014 is used in the estimation. The data is sourced from the South African Reserve Bank database. Three measures of credit extension were considered. These are credit ratio, credit growth and credit logs. Credit ratio is the BCBS (2010b) proposed gap between the ratio of private sector credit extension to GDP and its long term trend. This variable is constructed based on the detailed step by step guidelines proposed by the BCBS (2010b). Step 1 involves calculating aggregate private sector credit as a percentage of GDP and step 2 involves calculating the deviation of credit as a percentage of GDP from its Hodrick Prescott (1997) trend. The BCBS (2010b) suggests using a smoothing parameter of 400 000 for quarterly data. However, the normal smoothing parameter of 14 400 for monthly data was used. 12 additional data points were forecasted at the end of the data series to circumvent the end point problem following the proposition by Mise et al. (2005). Credit growth is the annual percentage change in private sector credit extension. Credit logs is the deviation of private sector credit extension, in logarithms, from its Hodrick Prescott (1997) trend. As with credit ratio, the normal smoothing parameter of 14 400 for monthly data was used and 12 additional data points were forecasted at the end of the data series to circumvent the end point problem.

In addition to the three measures of credit extension, the economic cycle and the financial cycle were also considered. The economic cycle is the difference between the coincident business cycle indicator and its Hodrick Prescott (1997) trend. The coincident business cycle indicator is constructed at monthly frequency by combining various equally weighted indicators of economic activity such as production, sales, income and employment. The difference between gross domestic product (GDP) and its Hodrick Prescott (1997) trend is often used to measure the business cycle. However, GDP is not available at a monthly frequency in South Africa. As with the other variables, the normal smoothing parameter for monthly data was used and 12 additional data points were forecasted at the end of the data series to circumvent the end point problem. The financial cycle is the composite indicator comprising the variables that cover the main segments of the South African financial market including the bond and equity securities markets, foreign exchange market as well as money and commodity markets. The choice of this variable follows Drehmann and Tsatsaronis (2014) who argue that the relevant cycle for evaluating the procyclicality of credit extension is the financial cycle whose boom and bust characterise the financial system. The financial cycle is similar to the index of financial stress proposed by Illing and Liu (2006), Balakrishnan et al. (2009), Hakkio and Keeton (2009) and Lo Duca and Peltonen (2011), Borio (2012) and Raputsoane (2014), among others, while Kliesen et al. (2012) provide a comprehensive survey of such indexes.

The financial cycle is constructed using 15 variables. These variables and their descriptions are presented in Table 1. They comprise the interbank spread, future spread, sovereign bond spread, A rated bond spread, corporate bond spread, stock market return, financial sector return, banking sector return, financial sector beta, banking sector beta, nominal effective exchange rate return, property market return, commodity market return, oil market return and VIX S&P500. These variables were standardised by subtracting their means and dividing them by their standard deviations. The financial cycle variables were aggregated using the principal components analysis weighting scheme that is normalised to 1. Principal components analysis is a method that reduces the dimensionality of the data to decrease redundancy in the variables and to identify how the different variables work together to create the dynamics of the 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 show that the proportion of variance in the selected variables accounted for by the first principal component is 29.57 percent. The stock market return, financial sector return, banking sector return and VIX S&P500 accounted for most of the variance in the finanical cycle, while the future and corporate bond spreads as well as the financial and banking sector betas contributed the least. The results of principal components analysis are not reported and are available from the author.

The evolutions of the variables are depicted in Figure 1. The economic cycle decreased from 2000 and reached a low in late 2003. It then increased steadily reaching an all time high in late 2008. It subsequently fell abruptly to reach a low in 2009 following which it increased steadily until 2012 from where it remained rangeboud to the end of the sample. The evolution of the financial cycle closely mimics that of the economic cycle. It shows three distinct instances of heightened financial stress, the first instance of which began towards the end of 2001 and lasted till the middle of 2003. Heightened financial stress in this period coincides with the bursting of the tech bubble in early 2000, the U.S. 9/11 terror attacks which contributed to the rapid depreciation of the South African rand in late 2001, later to be followed by the Iraq war in early 2003. The second instance began towards the end of 2007 and lasted until the middle of 2009. This period coincided with the 2007 US subprime crisis and 2008 global financial crisis. The third instance occurred between 2010 and 2012, which coincides with the sovereign debt crisis which affected mostly the European countries with limited impact on South Africa.

Three measures of credit extension are plotted against the economic and the financial cycles. The credit growth and credit logs measures tend to mirror the evolution of the economic and the financial cycles relatively better than credit ratio. This is particularly the case with the credit logs measure whose turning points almost perfectly coincide with those of the economic and the financial cycles. On the contrary, the evolution of credit ratio is opposite to that of the economic and the financial cycles. In particluar, this measure decreased steadily to the middle of 2007. It then increased significantly and reached a peak at the beginning of 2010. It subsequently fell dramatically until 2012 where it increased gradually to the beginning of 2014 before tappring off to the end of the sample. Thus the peak phases of the BCBS (2010b) proposed credit ratio measure coincide with the trough phases of both the economic and the financial cycles. The correlations of the variables are presented in Table 2. The economic and the financial cycles show a weak positive correlation with each other. The credit growth and credit logs measures show a positive correlation with the economic and the financial cycles measures. The correlation between the credit logs and the financial cycles measures is relatively high at about 0.6591. On the contrary, the credit ratio measure is negatively correlated with the economic and the financial cycles measures, even though its correlation is almost nonexistent with the financial cycle measure. The results of the correlations largely confirm the evolutions of the variables that are depicted in Figure 1.

3. Empirical methodology

The empirical methodology is the variable selection appproach introduced by Bartels (1997). This method was first proposed by Leamer (1978) and its detailed description can be found in Hoeting et al (1999). The method emphasises variable importance when selecting relevant variables in high dimensional data where information may usually be scatters through a large number of potential explanatory variables hence the method overcomes the omitted variable bias. More specifically, the method estimates models for all possible combinations of all explanatory variables and constructs a weighted average over all the possible models. This accounts for the model uncertainty inherent in variable selection by averaging over the best models which provides an optimal way of capturing the relationships in the data and hence it efficiently minimises the estimated parameters towards the stylised representation of the data leading to sound inference. According to Varian (2014), this variable selection method is able to analyse high dimensional data, revealing interdependence among the variables, leading to a new way of understanding their relationships.

Following Zeugner (2012), 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 the mean of 0 and variance of σ_γ^2. In the event of high dimensional data in X_γ, the challenge is to identify the variables to include in the model. To circumvent this problem, the variable selection appproach 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

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

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

$$p\left(y \middle| X\right). \quad p\left(\beta_\gamma \middle| y, X\right) = \sum_{\gamma=1}^{2^K} p\left(\beta_\gamma \middle| M_\gamma, y, X\right) p\left(M_\gamma \middle| X, y\right) \tag{3}$$

which is the posterior distribution assuming that M_γ is the true model. β_γ are the parameters, while the unconditional coefficients are defined as

$$E\left(\beta_\gamma \middle| y, X\right) = \sum_{\gamma=1}^{2^k} p\left(\beta_\gamma \middle| y, X, M_\gamma\right) p\left(M_\gamma \middle| y, X\right) \tag{4}$$

The prior model probability has to be proposed based on prior knowledge or believe. The variable selection method is implemented using the algorithm developed by Feldkircher and Zeugner (2009), with detailed description and reviews in Zeugner (2012) and Amini and Parmeter (2011, 2012) respectively.

4. Empirical results

The variable selection method used to analyse the behaviour of alternative measures of credit extension for countercyclical buffer decisions in South Africa is Bayesian. Therefore, it 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 or burnins to be omitted from the estimation results. These are presented in presented in Table 3. The number of iterations and burnins for the Markov chain Monte Carlo sampler were set to 110 000 and 10 000, respectively. The birth death sampler was used for the model Markov chain Monte Carlo sampler while the model prior for intermediate model size is beta binomial with random theta. The hyper parameter on Zellner's (1986) g prior is BRIC and it behaves like the combination of the Bayesian information criterion and the risk inflation criterion. Similar model statistics were chosen in all the estimated models for the financial stress index and the economic cycle.

The post estimation model statistics of the financial cycle and the economic cycle models are presented in Table 4. They show that the model space is 8.00 given that there are 3 alternative measures of credit extension. The mean number of regressors, which shows the average number of regressors with relatively high probability of inclusion in the estimated models, is 1.92 for the financial stress index model and 2.27 for the economic cycle model. Thus both the financial cycle and the economic cycle models predict 2 variables on average with relatively high probability of inclusion in the estimated models. PMP Correlation shows that the degree of convergence between the prior and the posterior model probabilities is reasonably high for all the estimated models at 0.99 for the financial cycle model and 1.00 for the economic cycle model. The Shrinkage factor, which is a goodness of fit indicator, is 0.99 for the financial cycle and the economic cycle models. These show an almost perfect goodness of fit for both models.

The variable selection results of the financial cycle and the economic cycle models are presented in Table 5. As explained in the data description section, credit growth is the annual percent change in total credit extended to the domestic private sector, credit ratio is the the deviation of the ratio of private sector credit extension to GDP from its long term trend and credit logs is deviation of the logarithm of private sector credit extension from its long term trend. The PIP is the posterior inclusion probability and represents the sum of posterior model probabilities for all the models where covariates were included. Post Mean is the posterior mean and measures the size of the coefficients averaged over all the models where covariates were included. Post SD is the posterior standard deviation and measures the standard deviations of the coefficients averaged over all the models where covariates were included. Pos Sign is the conditional position sign and measures the posterior probability of a positive coefficient averaged over all the models where covariates were included.

For the economic cycle model, the posterior standard deviations show that credit ratio and credit logs were included in all the estimated models with posterior standard deviation of 1.00. These were followed by the credit growth with posterior inclusion probability of 0.27. Thus the posterior inclusion probability mass rests on models that include the credit ratio and credit logs which are the measure of the ratio of credit extension to GDP and the measure credit extension that is based on logarithms, respectively. The posterior means show that, when credit ratio increases by 1 percent, the economic cycle decreases by 0.45 percent, while, when the credit growth and credit logs increase by 1 percent, the economic cycle increases by 0.01 percent and by 0.30 percent, respectively. The posterior standard deviations show that the credit ratio and the credit log are the statistically significant covariates at 5 percent level of significance, while the credit growth is not. The conditional position signs show that credit ratio had a negative coefficient, while credit growth and credit logs had positive coefficients in all the models where these covariates were included.

For the financial cycle model, the posterior standard deviations show that credit logs was included in all the estimated models with posterior inclusion probability of 1.00. This was followed by the credit growth with posterior inclusion probability of 0.58 and then credit ratio with posterior inclusion probability of 0.34. Thus the posterior inclusion probability mass rests on models that include credit logs, which is the measure of credit extension that is based on logarithms. The posterior means show that, when credit growth increases by 1 percent, the financial cycle decreases by 0.06 percent, while when the credit ratio and credit logs increase by 1 percent, the financial cycle increases by 0.03 percent and by 0.66 percent, respectively. The posterior standard deviations show that the credit log is the only statistically significant covariate at 5 percent level of significance, while the credit growth and the credit ratio are not. The conditional position signs show that credit growth had a negative coefficient, while credit ratio and credit logs had positive coefficients in all the models where these covariates were included.

In general, the economic cycle model shows that the deviation of the ratio of private sector credit to GDP from its long term trend and the deviation of the logarithm of private sector credit extension from its long term trend are the statistically significant covariates at 5 percent level of significance. The economic cycle model further shows that the ratio of private sector credit to GDP from its long term trend is countercyclical with the economic cycle while the deviation of the logarithm of private sector credit extension from its long term trend is procyclical. The financial cycle model shows that the deviation of the logarithm of private sector credit extension from its long term trend is the only statistically significant covariate at 5 percent level of significance. The financial cycle model further shows that the deviation of the logarithm of private sector credit extension from its long term trend is procyclical with the financial cycle. Credit growth, which is the annual percent change in private sector credit extension, has generally performed poorly in both the economic and the financial cycle model.

5. Conclusion

This paper analyses the behaviour of alternative measures of credit extension for countercyclical buffer decisions in South Africa. The cyclical properties of three alternative measures of credit extension are examined over the economic and the financial cycles. The results show that the deviation of the ratio of private sector credit extension to GDP from its long term trend is countercyclical with the economic cycle. The results also show that the deviation of the logarithm of private sector credit extension from its long term trend is procyclical with both the economic and the financial cycles. The annual percent change in private sector credit extension generally performs poorly in cyclical terms with both the economic and the financial cycles. Consequently, of the three alternative measures of private sector credit extension considered, the deviation of the logarithm of private sector credit extension from its long term trend could be used as a common reference guide for implementing the countercyclical capital buffers for financial institutions in South Africa.

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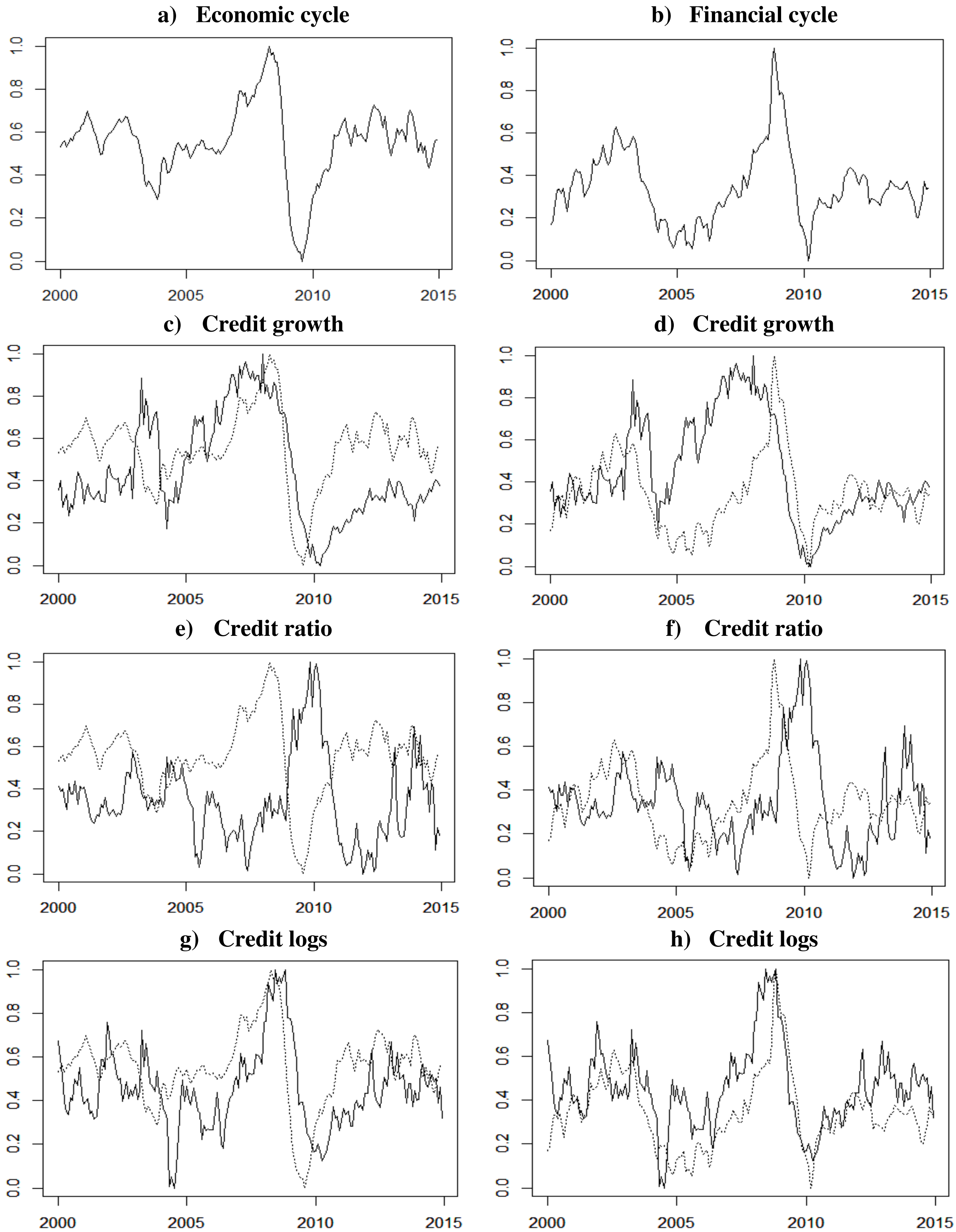
Appendix

Figure 1. Plots of the main variables



Notes: Own calculations with data from South African Reserve Bank. The dotted line replicates the financial cycle and the economic cycle in each panel, respectively. All variables were standardised between the scale of 0-1 by subtracting their minimum values and dividing them by the difference between the maximum and the minimum values.

Table 1. Financial distress indicator variables

Variable	Description
Interbank spread	Spread between the 3 month Johannesburg Interbank Agreed Rate (JIBAR) rates and the 3 month Treasury bill rate
Future spread	Spread between the 3 month Forward Rate Agreements (FRAs) and the 3 month treasury bill rate
Sovereign bond spread	Spread between the 3 month treasury bill rate and the 10 year treasury bill rate
A rated bond spread	Spread between the A rated Eskom bond and the 10 year treasury bill rate
Corporate bond spread	Spread between the FTSE/JSE All Bond yield and the 10 year treasury bill rate
Stock market return	Annual change in the FTSE/JSE All Share stock market index
Financial sector return	Annual change in the FTSE/JSE Financials stock market index
Banking sector return	Annual change in the FTSE/JSE Banks stock market index
Financial sector beta	CAPM beta of the one year rolling window of the annual FTSE/JSE Financials stock market index returns
Banking sector beta	CAPM beta of the one year rolling window of the annual FTSE/JSE Banks stock market index returns
Nominal eff. exchange rate return	Annual change in nominal effective exchange rate
Property market return	Annual change in the average price of all houses compiled by the ABSA bank
Commodity market return	Annual change in the Economist's commodity price index
Oil market return	Annual change in the Brent crude oil price
VIX S&P500	Chicago Board's implied volatility of the S&P 500 index

Notes: Own calculation with data from South African Reserve Bank.

Table 2. Correlations of the main variables

	Economic cycle	Financial cycle	Credit ratio	Credit growth	Credit logs
Economic cycle	1.000000	0.125044	-0.585577	0.430845	0.433451
Financial cycle	0.125044	1.000000	-0.026345	0.231285	0.659162
Credit ratio	-0.585577	-0.026345	1.000000	-0.413571	-0.208053
Credit growth	0.430845	0.231285	-0.413571	1.000000	0.527424
Credit logs	0.433451	0.659162	-0.208053	0.527424	1.000000

Notes: Own calculations with data from South African Reserve Bank.

Table 3. Pre estimation statistics

	(i) Economic cycle model	(ii) Financial cycle model
Draws	1100000	1100000
Burnins	100000	100000
MCMC	Birthdeath	Birthdeath
Model prior	Random	Random
g Prior	BRIC	BRIC

Notes: Own calculations with data from South African Reserve Bank. Draws is the number of iterations that that the MCMC sampler runs, Burn ins is the number of the iterations to be omitted, MCMC is Markov chain Monte Carlo sampler, Model prior is the mass on intermediate model size and g Prior is the hyper parameter.

Table 4. Post estimation statistics

	(i) Economic cycle model	(ii) Financial cycle model
Model space	8.0000	8.0000
PMP Correlation	1.0000	0.9999
Mean regressors	2.2737	1.9200
Shrinkage factor	0.9945	0.9945

Notes: Own calculations with data from South African Reserve Bank. Model space is the parameter size of the models, PMP Correlation is the correlation between the prior and the posterior model probabilities and the Shrinkage factor is a goodness of fit indicator.

Table 5. Variable selection results

	(i) Economic cycle model			(ii) Financial cycle model		
	Credit growth	**Credit ratio**	**Credit logs**	**Credit growth**	**Credit ratio**	**Credit logs**
PIP	0.273836	1.000000	0.999855	0.579827	0.340127	1.000000
Post Mean	0.014307	-0.450380	0.302973	-0.061820	0.027036	0.661816
Post SD	0.035689	0.052465	0.059257	0.064344	0.049020	0.067868
Pos Sign	1.000000	0.000000	1.000000	0.000000	1.000000	1.000000

Notes: Own calculations with data from South African Reserve Bank. PIP is the posterior inclusion probability, Post Mean is the posterior mean, Post SD is the posterior standard deviation and Pos Sign is the conditional position sign.