Credit Procyclicality and Financial Regulation in South Africa

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Abstract

This study assesses the behaviour of credit extension over the economic cycle to determine its usefulness as a reference guide for implementing the countercyclical capital buffers for financial institutions in South Africa. The study finds that the common reference guide for implementing the countercyclical capital buffers, which is based on the gap between the ratio of aggregate private sector credit to gross domestic product and its long term trend, increases during the economic cycle busts, while such a relationship is broken during the economic cycle booms. The study also finds that this common reference guide decreases during the upturns in the economic cycle, while it increases during the periods of downturns in the economic cycle. Thus credit extension should be used with caution as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions in South Africa.

JEL Classification: C32, E32, E61, G21

Key Words: Credit procyclicality, Financial regulation

1 Introduction

The recent financial crisis, experienced in 2008 and 2009, resulted in the worst economic recession the world has experienced since the great depression of the 1930s. The European Central Bank (2012) points out that the widespread distress in ?nancial markets following the recent financial crisis resulted in financial system dif?culties with some large financial institutions in advanced countries collapsing, and eventually, ceasing to exist. In the years leading up to the recent financial crisis, large financial institutions, such as Lehman Brothers,

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accumulated significant subprime mortgage related assets making them vulnerable to a downturn in that market. Lehman Brothers filed for bankruptcy in September 2008, causing ripple effects across global financial markets. Notable financial institutions that experienced problems due to the subprime mortgage crisis include Northern Rock, Bear Sterns, Fannie Mae and Freddie Mac, as well as American International Group. Shortly thereafter, three of the largest UK banks, Royal Bank of Scotland, HBOS and Lloyds Bank were put under administration. According to Brei et al. (2011), bank recapitalisations, primarily within G10 economies, totalled $1,380 billion by the end of 2010.

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 and considerably prolonging and deepening the recessions as suggested by Borgy et al. (2009) and Jeong (2009). Schularick and Taylor (2009) and Taylor (2012), among others, argue that excessive credit extension is the foremost predictor of financial crises. According to Guo and Stepanyan (2011), as a consequence of uncontrolled and rapid liberalisation and deregulation of the financial sector leading up to the financial crisis, imprudent and relaxed lending standards by financial institutions arose, necessitating a range of initiatives on regulatory, macroprudential and accounting principles to mitigate systemic risk in the financial system. Thus Schularick and Taylor (2009) argue that the recent financial crisis highlighted vulnerability of the financial system, its ability to generate economic instability through endogenous credit booms and has refocused attention on money and credit fluctuations, as well as policy responses to avert future financial crises.

In an effort to further strengthen the financial system following the recent financial crisis, the Basel III policy framework was introduced. This framework is sought to improve the quality and quantity of capital, enhance liquidity and leverage ratios, widen risk coverage, and supplement financial systems' stress testing approaches. The countercyclical capital buffers are among the key macroprudential policy proposals of Basel III and are detailed in the guide by Basel Committee on Banking Supervision (2010b). The countercyclical capital buffers aim is to protect the financial system from procyclicality of credit extension and hence protect financial institutions during periods of excessive credit growth. According to the Basel Committee on Banking Supervision (2010a, 2011a), countercyclical capital buffers will ensure that financial institutions have adequate capital to maintain the flow of credit in the economy in periods of broader financial system distress. Consequently, the Basel Committee on Banking Supervision has identified the gap between the ratio of aggregate private sector credit to GDP from its long term trend as a common reference guide for the implementation of the countercyclical capital buffers for financial institutions.

This study assesses the behaviour of credit extension over the economic cycle to determine its usefulness as a reference guide for implementing the countercyclical capital buffers for financial institutions in South Africa. Identifying and

appreciating the behaviour of credit extension over the economic cycle, whilst paying special attention to the proposals of the Basel Committee on Banking Supervision (2010b, 2011a), is a high priority for researchers and policymakers and will provide important policy implications for the implementation of countercyclical capital buffers for financial institutions in South Africa. Tan (2012) contends that one of the important gaps in a prudential approach to financial regulation policy analysis is in understanding the nature and the behaviour of credit extension over the economic cycle, while Hollo et al. (2012) argue that the recent financial crises have uncovered substantial gaps in theoretical and empirical frameworks for analysing, monitoring and regulating systemic risk in the financial system. Consequently, the study provides evidence of whether or not this common reference guide for setting countercyclical capital buffers that is based on the deviation of the ratio of private sector credit to GDP from its long term trend should be an important theme in the rapidly growing literature on prudential regulation of the financial system in South Africa.

According to the Basel Committee on Banking Supervision (2010b), the countercyclical capital buffers are to be fully implemented by 2015. These capital buffers are expressed as a ratio of financial institutions' risk weighted assets, where different classes of financial institution's assets have different risk weights associated with them. For instance, Basel III standardised risk weights for credit risk assigns a risk weight of 0 percent to cash and guaranteed deposits, 100 percent for unsecured residential mortgage exposures, while high volatility commercial real estate loans are assigned a risk weight of 150 percent of financial institution' assets. Basel III standardised risk weights for credit risk are detailed in the Basel Committee on Banking Supervision (2011a). The Basel Committee on Banking Supervision (2010b) has outlined the general guidelines on the use of the countercyclical capital buffers. The countercyclical capital buffers are to be set within the range of 0 and 2.5 percent in addition to the mandatory capital conservation buffers of 2.5 percent. The proposal is to use the deviation of private sector credit as a percentage of GDP from its long term trend as a guide for setting the counter cyclical buffers. The long term trend of private sector credit as a percentage of GDP is to be extracted using the Hodrick Prescott (1997) filter with the recommended smoothing parameter of 400 000.

The countercyclical capital buffers are to be implemented incrementally when the gap between private sector credit as a percentage of GDP and its long term trend is between 2.5 percent and 10 percent. This implies that the countercyclical buffer of 0 percent will apply when the gap between private sector credit as a percentage of GDP from its long term trend is less than 2.5 percent, whereas the countercyclical buffer of more than 0 to 2.5 percent applies when the gap between private sector credit as a percentage of GDP from its long term trend is between 2.5 and 10.0 percent. The operation of the countercyclical capital buffers is to be left to the judgement and discretion of relevant national authorities depending on whether they see systemic financial risks increasing or decreasing because of the differences in institutional arrangements across the world. More details on the implementation of countercyclical capital buffers can

be found in the Basel Committee on Banking Supervision (2010b, 2011a).

Empirical evidence on credit procyclicality is mixed, with the majority of studies finding evidence of credit procyclicality across a number of developed and emerging economies and across different financial crises. Bouvatiery et al. (2011) investigate credit procyclicality using a nonlinear framework for a sample of 17 OECD countries and find that credit extension is more procyclical in extreme booms and busts in the economic cycle in Canada, the United Kingdom and the United States, while it is less pronounced in one or both extreme regimes in Australia, Belgium, France, Finland, the Netherlands, Norway, and Spain. The other studies that find evidence of credit procyclicality, albeit without distinguishing between the different phases of the economic cycle, include Jeong (2009) for Korea, Angelini and Penetta (2009) for the 6 major developed economies, Jorda et al (2010) for 14 advanced countries. In a similar manner, Huidrom et al. (2010) find evidence of credit procyclicality for G7 countries, Xu (2012) for 33 advanced and emerging market economies, Guo and Stepanyan (2011) for emerging market economies, while Repullo and Saurina (2011) find evidence of credit procyclicality for developed economies. On the contrary, Bebczuk et al (2011) fail to find evidence of credit procyclicality in 144 developing and advanced countries, while Bertay et al. (2012) fail to do so in high income countries.

Akinboade and Makina (2009, 2010) and Fourie et al. (2011) have provided evidence of procyclicality of credit extension in South Africa. However, these studies analyse the behaviour of credit extension over the economic cycle, whereas the gap between the ratio of credit as a percentage of GDP and its long term trend is a more appropriate variable proposed by the Basel Committee on Banking Supervision (2010b, 2011a). Furthermore, these studies do not analyse the behaviour of credit extension during the different phases of the economic cycle. Van Vuuren (2012) uses the deviation of the gap between the ratio of credit as a percentage of gross national product as proposed by the Basel Committee on Banking Supervision (2010b). However, this study is concerned with the weaknesses of the prescribed method to construct the gap between credit as a percentage of GDP and its long term trend and hence it does not seek to uncover the behaviour of credit extension over the economic cycle. Moreover, the ratio of credit to GDP used in this study is different from official data such that its signals for the implementation of countercyclical capital buffers are inconsistent with those in the South African Reserve Bank's (2011) Financial Stability Report.

Empirical evidence supporting the view that credit extension increases during the booming economic periods, followed by financial crises can be found in Taylor (2012) as well as Goodhart and Hofmann (2008) in industrialised countries, Schularick and Taylor (2009) and Jorda et al. (2011) in 14 advanced countries. There are studies that also conclude that the use of the proposed gap between the ratio of aggregate private sector credit to GDP and its long term trend as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions may not be appropriate. These include Gersl and Jakubik (2010) as well as Giannone et al. (2012) for developed coun-

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tries, Repello and Saurina (2011) for developed countries, Edge and Meisenzahl (2011) for the United States, Gersl and Seidler (2012) for Czech Republic and Nigam (2013) in Uganda. However, these findings contrast with Borio et al. (2010, 2011) and Andersen et al. (2013) who conclude that this reference guide performs best in capturing the systemic vulnerabilities that consequently lead to financial crises in 36 countries and the United Kingdom, respectively. The use of the Hodrick Prescott filter proposed by the Basel Committee on Banking Supervision is also questioned by some studies given the end point problem and its sensitivity to ex post revisions of many macroeconomic variables. These include Gersl and Seidler (2012) for selected Central and Eastern European countries, Edge and Meisenzahl (2011) for the United States, Kelly et al. (2013) for Ireland as well as Van Vuuren (2012) in South Africa.

The next section outlines the methodology. Section 3 discusses the data. Section 4 discusses the empirical results, while section 5 concludes.

2   Methodology

The stylised observed behaviour of many macroeconomic variables is that they exhibit asymmetric features over time. Hamilton (2005) provides evidence of dramatic breaks in the behaviour of macroeconomic indicators during ?nancial crises. Sims and Zha (2004) and Davig (2004) provide evidence of abrupt changes in the behavior of macroeconomic indicators due to shifts in government policy. According to van Dijk et al. (2002), Hamilton (2008) and Borio et al. (2011), the fluctuations in macroeconomic variables tend be different during the periods of booms and busts, where expansions and upturns in these variables are gradual and protracted, while the contractions and downturns are abrupt and dramatic. To capture these stylised observed behaviour of macroeconomic variables, the models with regime switching features, where a regime switch happens when the transition variable is at a certain threshold, were proposed by Terasvirta (1994) by outlining the steps involved in specifying and estimating these type of models. Terasvirta (1998) and van Dijk et al. (2002, 2003) also provide a survey of the recent developments related to these models.

The variants of the Logistic Smooth Transition Autoregressive model are specified to study the behaviour of credit as a percentage of GDP over the economic cycle. Assuming two regimes, the Logistic Smooth Transition Autoregressive model is specified as follows

$$Y_t = \begin{cases} \beta_L + \beta_{L1}Y_{t-d} + ... + \beta_{Lm}Y_{t-(m-1)d}\left(1 - G\left(Z_t, \gamma, \theta\right)\right) + \varepsilon_t, Z_t \leq \theta \\ \beta_H + \beta_{H1}Y_{t-d} + ... + \beta_{Hm}Y_{t-(m-1)d}\left(G\left(Z_t, \gamma, \theta\right)\right) + \varepsilon_t, \theta < Z_t \end{cases} \quad (1)$$

where

$$G = P(Z_t, \gamma, \theta) = \left(1 + \exp - \gamma\left(Z_t - \theta\right)\right)^{-1} \quad (2)$$

and

$$Z_t = \varphi_1 X_t + \varphi_2 X_{t-1} + ... + \varphi_m X_{t-(m-1)d} \quad (3)$$

Y_t is the regime switching variable, X_t is a transition variable, while G is the monotonic transition function that is bounded between 0 and 1, specified as a logistic function with a threshold variable. Z_t is the smoothing parameter, γ, determines the speed and smoothness of transition between regimes, and θ measures the threshold location. The model parameters are β, while the threshold parameters are φ. m is the embedding dimension, d is the time delay, while L and H are the 'low' and 'high' regimes, respectively.

The Logistic Smooth Transition Autoregressive model can take different forms, depending on how the logistic function $G(Z_t, \gamma, \theta)$ is specified, resulting in different types of regime switching behaviours. In the event that the transition variable is in levels $Z_t = X_{t-d}$, the model distinguishes between periods of positive and negative values of the transition variable hence the model behaves differently during expansions and contractions in the transition variable. Enders and Granger (1998) also suggest that the model can distinguish between periods of upturns and downturns in the transition variable when the transition variable is first differences $Z_t = \Delta X_{t-d}$ hence the model behaves differently when the transition variable is increasing and when it is decreasing. For a more detailed discussion on specification and the various forms of Threshold Autoregressive models, see Terasvirta (1994,1998), van Dijk et al. (2002, 2003) and Aznarte et al. (2013).

Following the preceding discussion, the following Logistic Smooth Transition Autoregressive models with various forms of nonlinearity will be estimated. The Logistic Smooth Transition Autoregressive model is specified as follows

$$
\begin{aligned}
CRT\_Gap_t = & \left(\beta_L + \beta_{L1} CRT\_Gap_{t-d} + ... + \beta_{Lm} CRT\_Gap_{t-(m-1)d}\right) \\
& (1 - G(Z_t, \gamma, \theta)) + (\beta_H + \beta_{H0} CRT\_Gap_{t-d} + ... + \beta_{Hm} \\
& CRT\_Gap_{t-(m-1)d}) (G(Z_t, \gamma, \theta)) + \varepsilon_{t+s}
\end{aligned}
$$

$$(4)$$

where

CRT_Gap_t is the deviation of the ratio of credit to GDP from its long term trend. The following transition functions are specified. The first transition function is specified as $G = (1 + \exp{-\gamma(ECN\_CY_t - \theta)})^{-1}$ where the transition variable is the economic cycle or the gap between the coincident business cycle indicator and its long term trend, ECN_CY_t. The second transition function is specified as $G = (1 + \exp{-\gamma(\Delta ECN\_CY_t - \theta)})^{-1}$ where the transition variable is the change in the economic cycle or the gap between coincident business cycle indicator and its long term trend, ΔECN_CY_t. As discussed above, the first transition function distinguishes between periods of booms and busts in the transition variable or when the transition variable is positive and negative. The transition variable in this instance is the levels of the gap between the coincident business cycle indicator and its long term trend or the change in economic cycle. The second transition function distinguishes between periods of upturns and downturns in the transition variable or when the transition variable is increasing and decreasing. The transition variable in this instance is the first difference of the gap between the coincident business cycle indicator and its long term trend or the change in economic cycle. Thus, the study will establish

how the gap between the ratio of aggregate private sector credit to GDP and its long term trend behaves during periods of expansions and contractions in the economic cycle or, in other words, when the economic cycle is positive and when it is negative. The study will further establish how the gap between the ratio of aggregate private sector credit to GDP and its long term trend behaves during periods of upturns and downturns in the economic cycle or, in other words, when the economic cycle is increasing and when it is decreasing.

3   Data description

Monthly data spanning the period January 2000 to December 2012 is used. This data is sourced from the South African Reserve Bank database. The gap between the ratio of private sector credit to GDP and its long term trend is constructed based on the detailed step by step guidelines proposed by the Basel Committee on Banking Supervision (2010b). Step 1 involves calculating the aggregate private sector credit as a percentage of GDP, while step 2 involves calculating the deviation of credit as a percentage of GDP from its one sided Hodrick Prescott trend. The Basel Committee on Banking Supervision (2010b) suggests using a smoothing parameter of 400 000 for quarterly data which is equivalent to a smoothing parameter of 3 600 000 for monthly data. The choice of the gap between credit as a percentage of GDP and its long term trend as a common reference guide for setting the countercyclical capital buffers is motivated by the proposals of the Basel Committee on Banking Supervision (2010b, 2011a). This common reference guide for countercyclical capital buffers attempts to ensure that financial institutions have adequate capital to maintain a steady flow of credit in the economy in periods of financial distress and to prevent future financial crises given that excessive credit extension has been identified as one of the main causes of the financial distress.

In a similar manner, the economic cycle is measured as the difference between the coincident business cycle indicator and its Hodrick and Prescott trend using the normal smoothing parameter of 14 400 for monthly data. The business cycle indicators are economic measures that track economic activity such that they rise during the expansionary phase of the economic cycle and fall during the contractionary phase of the economic cycle in the manner that they coincide with the peaks and troughs in the economic cycle. The South African Reserve Bank constructs the coincident business cycle indicator at monthly frequency by combining various indicators of economic activity, including the aggregate indicators of production, sales, income and employment, into a single indicator of the turning points in the economic cycle in South Africa. The choice of this variable is motivated by the observation of the Basel Committee on Banking supervision (2010a, b, 2011a) that the upturns in the economic cycle are characterised by strong credit extension whereas the downturns in the economic cycle are characterised by restrained credit extension.

The use of the Hodrick Prescott filter (1997) is problematic given that it suffers from the so called end point problem such that the trend of the time series

tends to approach the mean of the data towards the end of the sample. The Hodrick Prescott filter calculation proposed by the Basel Committee on Banking Supervision is also questioned by some studies, such as Gersl and Seidler (2012) and Edge and Meisenzahl (2011), on the grounds that it is not necessarily a suitable indicator of excessive credit growth and that it is sensitive to the ex post revisions of many macroeconomic time series and the availability of new data points. However, among the filters that are commonly used to decompose most economic time series into their trend and cyclical components, the Hodrick Prescott filter is the most popularly used filter in empirical economic literature. To substantiate its popularity, the Basel Committee on Banking Supervision (2011b) has proposed its use despite its well known weaknesses. Ravn and Uhlig (2002) also argue that the Hodrick Prescott filter will remain one of the standard methods for detrending economic time series, despite the availability of sophisticated band pass filters such as the Baxter King filter. It is also possible to circumvent the end point problem when using the Hodrick Prescott filter. For instance, this study follows the proposition by Mise et al. (2005) by forecasting additional data points at the end of the data series to correct the end point problem.

The descriptive statistics of the main variables are presented in Table 1, while the evolutions of the main variables are depicted in Figure 1. The gap between credit as a percentage of GDP and its long term trend decreased from 2000 reaching an all-time low in early 2002. It then increased sharply and remained high to late 2003, where it subsequently fell until the middle of 2004. There is a sustained increase in gap between credit as a percentage of GDP and its long term trend from mid 2004 till early 2009, where it fell abruptly until 2012. The economic cycle declined from 2000 to late 2003. It then increased steadily, reaching a peak in early 2008 where it subsequently fell abruptly to mid 2009 following the recent financial crisis only to increase again to 2012.

4 Empirical results

The estimated results and the measures of model adequacy are presented in Table 2. The Logistic Smooth Transition Autoregressive model is specified in an autoregressive manner necessitating the determination of the number of lags. The lags selection involved using the Akaike Information Criterion, the Bayesian Information Criterion and the Hannan Quin Information Criterion. They all pointed to the lag order of 2 in the autoregressive model. However, the lag order of 1 was used in the estimation of the specified variants of the Logistic Smooth Transition Autoregressive model because the coefficients for the lag order of 2 were consistently statistically insignificant in estimation across all the models.

The following tests for model adequacy were implemented to assess the robustness of the estimated Logistic Smooth Transition Autoregressive models. These included the test for non-linearity test of full order Logistic Smooth Transition Autoregressive model against full order Autoregressive model, the residual

variance, the Akaike Information Criterion and the Mean Absolute Percentage Error, which is the forecasting accuracy measure. The Akaike Information Criterion and the residual variance choose the Logistic Smooth Transition Autoregressive model with the second transition function, which distinguishes between periods of upturns and downturns or when the economic cycle is increasing and decreasing, as the best model amongst the specified alternatives. The Mean Absolute Percentage Error points to the Logistic Smooth Transition Autoregressive model with the first transition function, which distinguishes between periods of positive and negative growth in the economic cycle or when the economic cycle is positive and negative, as the model with the best forecasting performance.

Non-linearity in the full order Logistic Smooth Transition Autoregressive model is accepted for both models where models with the first and the second transition functions are compared to their respective full order Autoregressive counterpart models. Although not reported here, the Terasvirta's neural network test for non-linearity in Granger et al (1993) pointed to non linearity in both the gap between credit to GDP ratio and its long term trend and the economic cycle measure. As discussed above, the specified Logistic Smooth Transition Autoregressive model determines the location of the thresholds in transition variables endogenously such that the locations of the thresholds are not user defined. To determine the threshold location of the Logistic Smooth Transition Autoregressive model, a grid search is implemented. According to Aznarte (2008), the grid search involves estimating the model for a grid of di?erent values of the threshold variable and taking the best ?t as the threshold estimate.

As discussed above, the first transition function is specified as $G = (1 + \exp -G = \gamma(ECN\_CY_t - \theta))^{-1}$ where the transition variable is the economic cycle or the gap between the coincident business cycle indicator and its long term trend, ECN_CY_t. This first transition function distinguishes between periods of booms and busts in the transition variable or when the economic cycle is positive and when it is negative. The transition variable in this instance is the levels of the gap between the coincident business cycle indicator and its long term trend or the change in economic cycle. The second transition function is specified as $G = (1 + \exp -\gamma(\Delta ECN\_CY_t - \theta))^{-1}$ where the transition variable is the change in the gap between coincident business cycle indicator and its long term trend or the change in the economic cycle. The second transition function distinguishes between periods of upturns and downturns in the transition variable or when the transition variable is increasing and when it is decreasing. Similarly, the transition variable in this instance is the first difference of the gap between the coincident business cycle indicator and its long term trend or the change in economic cycle.

The results pertaining to the first transition function are reported in Table 2. The grid search finds a statistically significant threshold at 2.9 percent in the economic cycle. Thus the deviation of credit to GDP ratio from its long term trend behaves differently when the economic cycle is greater than the threshold level of 2.9 percent compared to when it is below or equal to this threshold

level. The deviation of the ratio of credit to GDP from its long term trend increases by a statistically significant 74.4 percent relative to its recent past in the low regime, or when the economic cycle is below 2.9 percent. In the high regime, or when the economic cycle is above 2.9 percent, the deviation of credit to GDP ratio from its long term trend decreases by 2.6 percent relative to its recent past. However, this is statistically insignificant. The parameter that measures the speed and smoothness of transition between regimes in the threshold variable is 0.56 and is statistically significant. This implies a relatively smooth and slow speed of adjustment between the high and the low regimes. However, it is important to note that the statistical significance of this variable is often not a concern and is seldom reported. Thus, the parameter measuring the speed and smoothness of transition is often allowed to be dimension free as suggested by Terasvirta (1994), given that its size points to the various forms of the transition function.

Given that credit extension is procyclical as identified by the Basel Committee on Banking Supervision (2010a, 2010b, 2011a), the gap between the ratio of aggregate private sector credit to GDP and its long term trend was expected to increase during periods of expansions in the economic cycle, while the opposite is true during periods of contractions in the economic cycle. However, the empirical results reveal a statistically significant positive relationship of the gap between the ratio of aggregate private sector credit to GDP and its long term trend relative to its recent past during the economic cycle busts or when the economic cycle is below or equal to 2.9 percent. However, such a relationship cannot be ascertained during the economic cycle booms or when the economic cycle is above 2.9 percent. This implies that the relationship of gap between the ratio of aggregate private sector credit to GDP and its long term trend is countercyclical during the economic cycle busts, while such a relationship is broken during the booming periods in the economic cycle. Thus the hypothesis that the gap between the ratio of aggregate private sector credit to GDP and its long term trend increases during periods of expansions in the economic cycle, while the opposite is true during periods of contractions in the economic cycle is not satisfied during both the economic cycle booms and busts.

According to the results pertaining to the second transition function, also reported in Table 2, the grid search finds a statistically significant threshold at 0.09 percent in the change in the economic cycle. Thus the deviation of credit to GDP ratio from its long term trend behaves differently when the change in the economic cycle measure is greater than the threshold level of 0.09 percent compared to when it is below or equal to this threshold level. The deviation of credit to GDP ratio from its long term trend increases by a statistically significant 99.3 percent relative to its recent past in the low regime, or when the change in economic cycle is below or equal to 0.09 percent. In the high regime, or when the change in economic cycle is above 0.09 percent, the deviation of credit to GDP ratio from its long term trend decreases by a statistically significant 13.7 percent relative to its recent past. The parameter that measures the speed and smoothness of transition between regimes in the threshold variable is 102.2 but is statistically insignificant. This implies a possible relatively high and

abrupt speed of adjustment between the high and the low regimes. However, as discussed above, the statistical significance of this parameter is often not a concern and is seldom reported and hence it is often allowed to be dimension free, given that its size points to the various forms of the transition function.

The Basel Committee on Banking Supervision (2010a, 2010b, 2011a) has identified that credit extension is procyclical, as discussed above, hence the gap between the ratio of aggregate private sector credit to GDP and its long term trend is expected to increase during the upturns in the economic cycle, while the opposite is true during the downturns in the economic cycle. The empirical results reveal a statistically significant positive relationship of the gap between the ratio of aggregate private sector credit to GDP and its long term trend relative to its recent past during the downturns in the economic cycle. The empirical results further reveal a statistically significant negative relationship of the gap between the ratio of aggregate private sector credit to GDP and its long term trend relative to its recent past during the upturns in the economic cycle. This implies that the gap between the ratio of aggregate private sector credit to GDP and its long term trend decreases during the periods when the economic cycle is increasing, while the opposite is true during the periods in which the economic cycle is decreasing.

Given these observed dynamics in the gap between the ratio of aggregate private sector credit to GDP and its long term trend, the conclusion is that its use as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions may not be appropriate in South Africa. This conclusion is supported by the findings in a number of studies in other countries, including Gersl and Jakubik (2010), Giannone et al. (2012), Repello and Saurina (2011), Edge and Meisenzahl (2011), Gersl and Seidler (2012) and Nigam (2013). However, this is in contrast to Borio et al. (2010, 2011) and Andersen et al. (2013) who conclude that the gap between the ratio of credit to GDP and its long term trend performs best given that it captures the build up of systemic vulnerabilities that consequently lead to financial crises. In particular, Repello and Saurina (2011) argue that the fact that credit usually lags the business cycle, especially in downturns, compounds the problem.

In summary, the empirical results in this study provide evidence that credit extension increases during the economic cycle busts, while that relationship is broken during the booming phase of the economic cycle. The results also reveal that credit extension increases during the periods of economic downturns and decreases during the periods of economic upturns. The implication for this observed behaviour in the gap between the ratio of aggregate private sector credit to GDP and its long term trend relative to the economic cycle is that mechanically applying the suggested reference guide for implementation of countercyclical buffers would tend to increase capital requirements during the economic downturns so that it may end up exacerbating rather than improving the procyclicality of credit extension with dire consequences for the South African economy, consistent with Repullo and Saurina (2011) as well as Giannone et al. (2012), among others, in other economies.

5   Conclusion

The purpose of this study was to examine the behaviour of credit extension over the economic cycle in South Africa to assess its usefulness as a reference guide for implementing the countercyclical capital buffers for financial institutions. The study was motivated by the suggestions by the Basel Committee on Banking Supervision (2010a, 2011a) at the Bank of International Settlements which has identified credit extension as one of major causes of financial crises. as a result, the Basel Committee on Banking Supervision (2010a, 2011a) has proposed the implementation of the countercyclical capital buffers for financial institutions using credit extension as a common reference guide to limit credit procyclicality and its associated systemic and economic risks. The study finds that the gap between the ratio of aggregate private sector credit to GDP and its long term trend increases during the economic cycle busts, while such a relationship is broken during the economic cycle booms. It also finds that the gap between the ratio of aggregate private sector credit to GDP and its long term trend decreases during the upturns in the economic cycle, while it increases during the periods of downturns in the economic cycle. Therefore the conclusion is that the gap between the ratio of aggregate private sector credit to GDP and its long term trend should be used with caution, and not mechanically or uniformly as a common reference guide to determine the level of the countercyclical capital buffers for financial institutions in South Africa. Future research could study behaviour of disaggregated credit extension over the economic cycle. Understanding the cyclical behaviour of other economic aggregates, over and above one proposed reference guide that is based on credit extension by the Basel Committee on Banking Supervision is another avenue for future research.

References

[1] Akinboade O. A. and Makina, D. (2010). "Econometric Analysis of Bank Lending and Business Cycles in South Africa," Applied Economics, 42(29), p. 3803-3811.

[2] Akinboade O. A. and Makina, D. (2009). "Bank Lending and Business Cycles: South African Evidence," African Development Review, 21(3), p. 476-498.

[3] Andersen, H., Giese, J., Bush, O., Castro, C., Farag, M. and Kapadia, S. (2013). "The Credit-to-GDP Gap and Complementary Indicators for Macroprudential Policy: Evidence from the UK," Conference on Financial Stability Analysis: Using the Tools, Finding the Data, Cleveland: Federal Reserve Bank of Cleveland.

[4] Angelini, P. and Panetta, F. (2009). "Financial Sector Pro-Cyclicality Lessons from the Crisis," Occasional Paper, 44, Rome: Bank of Italy.

[5] Aznarte, A. L., Di Narzo, A. F. and Stigler, M. (2013). "tsDyn: Nonlinear Time Series Models with Regime Switching," R package, Version 0.9-32.

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

[7] Basel Committee on Banking Supervision. (2010b). "Guidance for National Authorities Operating the Countercyclical Capital Buffer," Basel Committee on Banking supervision, Basel: Bank of International Settlements.

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

[9] Basel Committee on Banking Supervision. (2011b). "The Transmission Channels Between the Financial and Real Sectors: A Critical Survey Of The Literature," Basel Committee on Banking supervision, Basel: Bank of International Settlements, Revised Version.

[10] Borio, C., Drehmann, M., Gambacorta, L., Jiminez, G. and Trucharte, C. (2010). "Countercyclical Capital Buffers: Exploring Options," Working Paper, 317, Basel: Bank of International Settlements.

[11] Borio, C., Drehmann, M. and Tsatsaronis, K. (2011). "Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates," Working Paper, 355, Basel: Bank of International Settlements.

[12] Bebczuk, R., Burdisso, T., Carrera, J. and Sangiacomo, M. (2011). "A New Look into Credit Procyclicality: International Panel Evidence," Working Paper, No. 201155, Buenos Aires: Central Bank of Argentina.

[13] Borgy, V., Laurent, C. and Jean-Paul, R. (2009). "Asset-Price Boom-Bust Cycles and Credit: What is the Scope of Macro-Prudential Regulation?" Working Paper, 263, Basel: Bank of International Settlements.

[14] Bouvatiery, V., Lopez-Villavicencioz, A. and Mignonx, V. (2011). "Short-Run Dynamics in Bank Credit: Assessing Nonlinearities in Procyclicality," Banking and Insurance e-Journal.

[15] Brei, M., Gambacorta, L. and Goetz, P. (2011). "Rescue Packages and Bank Lending," Working Paper, 357, Basel: Bank of International Settlements.

[16] Davig, T. (2004). "Regime-Switching Debt and Taxation, Journal of Monetary Economics," 51(4), p. 837-859.

[17] Edge, R. and Meisenzahl, R. (2011). "The Unreliability of Credit-to-GDP Ratio Gaps in Real-Time: Implications for Countercyclical Capital Buffers," Working Paper, 2011-37, Washington DC: Federal Reserve Board.

[18] European Central Bank. (2012). "Money and Credit Growth after Economic and Financial Crises: A Historical Global Perspective," Monthly Bulletin, Frankfurt: European Central Bank, p. 69-85.

[19] Fourie, L., Botha, I. and Mears, R. (2011). "Credit extension in South Africa: A business cycle perspective for the period 1985 to 2009," African Journal of Business Management, 5(34), p. 13074-13083.

[20] Gersl, A. and Jakubik, P. (2010). "Procyclicality of the Financial System and Simulation of the Feedback Effect," Financial Stability Report, Prague: Czech National Bank, p. 110-119.

[21] Gersl, A. and Seidler, J. (2012). "Excessive Credit Growth as an Indicator Of Financial (In)Stability and its Use in Macroprudential Policy," Working Paper, 42541, Munich: Munich Personal RePEc Archive.

[22] Giannone, D., M. Lenza, and L. Reichlin (2012). "Money, Credit, Monetary Policy and the Business Cycle in the Euro Area," Discussion Paper 8944, London: Centre for Economic Policy Research.

[23] Goodhart, C. and Hofmann, B. (2008). "House Prices, Money, Credit, and the Macroeconomy," Oxford Review of Economic Policy, 24(1), p. 180-205

[24] Granger, C. W. J., Lin, C. and Terasvirta, T. (1993). "Power of the Neural Network Linearity Test," Journal of Time Series Analysis, Vol. 14, No. 2, March

[25] Guo, K. and Stepanyan, V. (2011). "Determinants of Bank Credit in Emerging Market Economies," Working Paper, 11/51, Washington DC: International Monetary Fund.

[26] Hamilton, J. D. (2005). "What's Real About the Business Cycle?" Review, 87(4), St. Louis: Federal Reserve Bank of St. Louis, p. 435-452

[27] Hamilton, J. D. (2008). "Regime-Switching Models," in Durlauf, S. and Blume, L. (eds.), New Palgrave Dictionary of Economics, 2nd ed. London: Palgrave McMillan.

[28] Hodrick, R. and Prescott, E. C. (1997). "Postwar U.S. Business Cycles: An Empirical Investigation," Journal of Money, Credit, and Banking, 29(1), p 1-16

[29] Hollo, D., Kremer, M. and Lo Duca, M. (2012). "CISS: A Composite Indicator of Systemic Stress in the Financial System," Working Paper, 1426, Frankfurt: European Central Bank.

[30] Huidrom, R., Kose, A. and Otrok, C. (2010). "Do Credit Shocks Matter? A Global Perspective," Working Paper, 10/261, Washington DC: International Monetary Fund.

[31] Jeong, H. (2009). "The Procyclicality of Bank Lending and its Funding Structure: The Case of Korea," Bank of Korea International Conference on the Credit Crisis: Theoretical Perspectives and Policy Implications.

[32] Jorda, O., Schularick, M. and Taylor, A. (2011). "When Credit Bites Back: Leverage, Business Cycles, and Crises," Working Paper, 17621, Massachusetts: National Bureau of Economic Research.

[33] Kelly, R., McQuinn, K. and Stuart, R. (2013). "Exploring the Steady-State Relationship Between Credit and GDP for a Small Open Economy: The Case of Ireland," Working Paper, 1531, Frankfurt: European Central Bank.

[34] Mise, E., Kimand, T. H. and Newbold, P. (2005). "On Suboptimality of the Hodrick-Prescott Filter At Time Series Endpoints," Journal of Macroeconomics, 27(1), p. 53-67.

[35] Nigam, K. (2013). "Credit to GDP as a Forward Looking Indicator of Systemic Credit Risk: A Critical Evaluation Using Data from Uganda," Working Paper, 11/2013, Kampala: Bank of Uganda.

[36] Ravn, M. O. and Uhlig, H. (2002). "On Adjusting the Hodrick-Prescott Filter for the Frequency Of Observations," Review of Economics and Statistics, 84(2), p. 371-375.

[37] Repullo, R. and Saurina, J. (2011). "The Countercyclical Capital Buffer of Basel III: A Critical Assessment," Discussion Paper DP8304, Madrid: Bank of Spain.

[38] Schularick, M. and Taylor, A. (2009). "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870–2008," Working Paper, 15512, Massachusetts: National Bureau of Economic Research.

[39] Sims, C. A. and Zha, T. (2004). "Were There Regime Switches in U.S. Monetary Policy?" American Economic Review, 96(1), p. 54-81.

[40] South African Reserve Bank. (2011). "Note on the Countercyclical Capital Buffer and its Possible Application in South Africa," Financial Stability Review, Pretoria: South African Reserve Bank, p. 43-50.

[41] Tan, T. (2012). "Determinants of Credit Growth and Interest Margins in the Philippines and Asia," Working Paper, 12/123, Washington, DC: International Monetary Fund.

[42] Taylor, A. (2012). "External Imbalances and Financial Crises," Working Paper, 18606, Massachusetts: National Bureau of Economic Research, December.

[43] Terasvirta, T. (1994). "Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models," Journal of the American Statistical Association, 89(425), p. 208-218.

[44] Terasvirta, T. (1998). "Modelling Economic Relationships with Smooth Transition Regressions," in A. Ullah and D.E.A. Giles (eds.), Handbook of Applied Economic Statistics. New York: Marcel Dekker, p. 507-52.

[45] Van Dijk, D., Terasvirta, T. and Franses, P. (2002) "Smooth Transition Autoregressive Models: A Survey of Recent Developments," Econometric Reviews, 21(1), p. 1-47.

[46] Van Dijk, D., Terasvirta, T., Stefan, L. and Lundbergh, S. (2003). "Time Varying Smooth Transition Autoregressive Models," Journal of Business and Economic Statistics, 21(1), p. 104-121.

[47] Van Vuuren, G. (2012). "Basel III Countercyclical Capital Rules: Implications for South Africa," South African Journal of Economic and Management Sciences, 15(3), p. 309-24.

[48] Xu, T. (2012). "The Role of Credit in International Business Cycles," Working Paper, 12-36, Ottawa: Bank of Canada.

Table 1: Descriptive Statistics

	Credit to GDP Ratio Gap	**Output Gap**
Mean	0.328942	-0.095886
Median	-0.863840	0.044168
Maximum	12.63187	8.370497
Minimum	-7.009280	-9.897661
Std. Dev.	4.844974	4.077444
Skewness	0.846577	-0.092239
Kurtosis	2.721114	2.755195
Jarque-Bera	19.13956	0.610752
Probability	0.000070	0.736846

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

Table 2: Logistic Smooth Transition Autoregressive models results

	Model with the first transition		**Model with the second transition**	
	Coefficient	Std error	Coefficient	Std error
β_L	-1.763553	0.436555***	-0.179506	0.151658
β_{L1}	0.743563	0.055579***	0.993083	0.029706***
β_H	6.268304	2.063481***	0.124137	0.255954
β_{H1}	-0.025840	0.174182	-0.137344	0.055903**
γ	0.559756	0.258273**	102.18010	135.26266
θ	2.944476	1.131184***	0.089820	0.020819***
AIC	179.0000		129.0000	
$MAPE$	200.1000		170.9000	
$\mathrm{Re}\,sid\_Var$	2.918000		2.115000	
$NonLin\_test$	38.47100	0. 178352	1.4794000	0.225770

Notes: The first transition function is specified as $G = \left(1 + \exp - \gamma \left(ECN\_CY_t - \theta\right)\right)^{-1}$ where the transition variable is the economic cycle or the gap between the coincident business cycle indicator and its long term trend, ECN_CY_t. The second transition function is specified as $G = \left(1 + \exp - \gamma \left(\Delta ECN\_CY_t - \theta\right)\right)^{-1}$ where the transition variable is the change in the gap between coincident business cycle indicator and its long term trend or the change in the economic cycle, ΔECN_CY_t. Statistical significance codes: *** = 1%, ** = 5%, * = 10%, AIC is the Akaike Information Criterion, $MAPE$ is the Mean Absolute Percentage Error, $\mathrm{Re}\,sid\_Var$ is the Variance of the Residuals, $NonLin\_test$ is the Non linearity test of full order Logistic Smooth Transition Autoregressive model against full order Autoregressive model, which is the F-test with associated p-values.

Figure 1: Evolution of the main Variables

Credit to GDP Ratio Gap

Output Gap