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THE TRANSMISSION OF MONETARY POLICY IN SOUTH AFRICA BEFORE AND AFTER THE GLOBAL FINANCIAL CRISIS

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Abstract
This paper examines whether the transmission mechanism of monetary policy in South Africa has changed after the global financial crisis (GFC). We use a Bayesian vector autoregressive (BVAR) model with Minnesota priors and 15 monthly variables, extending the system of Christiano, Eichenbaum, with Evans (1999). The benefit of the BVAR approach is that it can accommodate a large cross section of variables without running out of degrees of freedom. To identify the change in the transmission process, we divide the sample size into two subsamples, namely the pre-GFC period (March 2001 to August 2008) and the post-GFC period (September 2008 to February 2016). The results indicate that a change in the transmission of monetary policy occurred after the GFC. The magnitude of the effect of a monetary policy shock on output is considerably greater in the pre-GFC period compared to the post-GFC period. Moreover, the impact of a policy shock on inflation is not statistically significant in the post-GFC period. The variance decomposition shows that the interest-rate channel has possibly weakened in the post-GFC period.
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1. INTRODUCTION

In the aftermath of the most recent global financial crisis (GFC), real short-term interest rates were very low compared to historical levels. However, at the same time, the credit extended to the private sector was declining gradually. The real ex ante repurchase rate (repo rate) measured –0.2% on average over the period 2009 to 2016[1] while growth in the credit extension to the private sector remained below 10% since 2010. This is in contrast with the period 2001 to 2008, when the low interest-rate environment saw credit growth rise by 17% on average. Furthermore, private-sector investment and consumption expenditure are still weak. The question then arises: has the transmission mechanism of monetary policy changed since the GFC?

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[1] The ex ante real interest rate is estimated as the difference between the policy rate, *i.e*. the repurchase rate, and the two-year-ahead inflation expectations obtained from the Bureau for Economic Research.

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There are many plausible explanations as to why the low interest-rate environment has not translated into higher credit growth, including structural bottlenecks to growth, weak economic conditions and deleveraging by both households and firms. Another plausible explanation is the effect of the legislative and regulatory frameworks adopted before and after the GFC, specifically the National Credit Act 34 of 2005 (NCA), which was implemented in June 2007, and the Basel II regulations, announced worldwide in July 2006 and implemented in South Africa in January 2008. The NCA was introduced to promote a fairer and more transparent credit market, protect consumers and their rights in the credit market, and limit the cost of credit. Basel II was intended to amend the international standards that controlled how much capital banks needed to hold in order to guard against the financial and operational risks they faced. These rules sought to ensure that banks with a large risk exposure held a greater amount of capital to ensure their solvency and overall stability. The Basel III regulations were implemented in January 2013 to address excessive risk taking by banks and thus impose more restrictions on credit lending. Finally, in March 2015, the Affordability Assessment Regulations (AARs) of the National Credit Regulator (NCR) became effective. The purpose of these regulations was to prevent reckless and indiscriminate lending by financial intermediaries.

Against this backdrop, this paper empirically investigates the validity of the hypothesis that a change occurred in the transmission of monetary policy after the GFC. To identify the change in the transmission, we divide the sample into two subsamples, namely the pre-GFC period (March 2001 and August 2008) and the post-GFC period (September 2008 and February 2016). We focus soley on the interest rate channel of transmission and only consider the period under the inflation-targeting regime. The monetary policy shock is identified using the Bayesian vector autoregressive (BVAR) approach with Minnesota priors and 15 monthly variables, expanding the system of Christiano *et al.* (1999). We prefer the BVAR approach because of its ability to deal with a large panel of time series without the risk of running out of degrees of freedom. When using a traditional vector autoregressive (VAR) approach with 15 monthly variables, we need to estimate at least 225 parameters. This is commonly known as "the curse of dimensionality". Without imposing prior information, it would be hard to obtain precise estimates of these 225 parameters from a traditional VAR and thus features such as impulse response functions (IRFs) and forecasts tend to be imprecisely estimated. It is therefore desirable to "shrink" the parameters and Minnesota priors offer a way of doing so. The priors incorporate the belief that more recent lag variables should provide more reliable information than distant ones and that own lag variables should explain more of the variation of a given variable than other lag variables in each equation. This ensures shrinkage of the parameters and decreases the risk of overfitting. Specifically, the BVAR approach via the imposition of Minnesota priors turns "the curse of dimensionality" into a blessing and solves the puzzling results which are common in traditional VAR approaches.

The monthly proxy of real economic activity is obtained from the nowcast of real gross domestic product (GDP) growth proposed by Kabundi *et al.* (2016). The monetary policy shock is approximated by a 100 basis points rise in the nominal repo rate. We then assess the reaction of the real GDP growth rate and the headline inflation rate from the entire sample, *i.e*. March 2001 to February 2016, and from each subsample. We use the forecast error variance (FEV) to evaluate the effectiveness of the monetary policy shock for different periods. Finally, we attempt to assess the impact of regulations on credit extended to the private sector using dummy variables and an event study.

The results reveal that GDP growth and inflation have a strong reaction to a monetary policy shock in the full sample period. GDP growth declines gradually and reaches the maximum impact 8 months after the shock. Similarly, inflation decreases gradually and attains its minimum level about 24 months after the shock. When we compare the transmission of monetary policy in the pre-GFC and post-GFC periods, we find that the size of the effect of the policy shock on output is significantly greater in the pre-GFC period, while the effect on inflation is statistically insignificant in the post-GFC period. Furthermore, the variance decomposition shows that the interest-rate channel may be weak in the post-GFC period. Possible factors underlying the weaker transmission include; the slow pace of deleveraging given the intensity of the GFC, the low business and consumer confidence, and the new regulations introduced since 2007. The results from the dummy variable analysis support the claim that regulations had somewhat of a negative effect on the supply of credit to the private sector since the GFC. For inflation, Kabundi and Mlachila (2019) and Kabundi *et al.* (2019) find evidence of a change in monetary policy since the GFC reflecting improved monetary policy credibility, better anchoring of inflation expectations, and flattening of the Phillips curve. This paper particularly focuses on the effects of regulations and business confidence as factors explaining the weak response of output to monetary shock after the GFC.

The rest of the paper is organised as follows. Section 2 discusses the literature review. Section 3 outlays the methodology used to test the change in the transmission of monetary policy, the BVAR model. In Section 4, we discuss the data, their transformation, and the transmission mechanism of monetary policy in the South African economy before and after the GFC. In addition, we investigate the impact of the introduction of different regulations on credit extended to the private sector. Section 5 concludes the paper with some policy recommendations.

2. LITERATURE REVIEW

Boivin *et al.* (2011) identify two types of monetary transmission mechanism, namely neoclassical channels and non-neoclassical channels. The neoclassical channels, which are also known as the traditional channels of monetary policy, are based on monetarist characterizations of the transmission mechanism by Friedman (1957), the life-cycle hypothesis by Ando and Modigliani (1963), as well as the neoclassical models of investment by Jorgenson (1963) and Tobin (1969). These channels focus on how interest-rate changes operating through investment, consumption, and trade impact on output and inflation. Therefore, the main channel of transmission is the interest-rate channel.

The non-neoclassical channels, also referred to as the credit channels, are based on frictions in the credit market due to asymmetric information between lenders and borrowers. Before the GFC, empirical evidence on the importance of these channels was mixed; see, for instance, Ramey (1993), Bean *et al.* (2002), and Iacoviello and Minetti (2008). However, after the GFC, more evidence showed that financial frictions affect the process of monetary policy transmission and generate distortions in the real economy; see, for example, Cecchetti *et al.* (2009) and Mishkin (2011). Empirical evidence after the GFC also showed that the interest-rate channel weakened during the GFC – see

Gambacorta *et al.* (2015) – suggesting that the traditional channel of monetary policy may have changed.

In the wake of the GFC, the monetary policy transmission mechanism gained much attention among policymakers and researchers, especially after aggressive policy easing proved to be less effective in stimulating output and inflation; see, for instance, Mishkin (2009). This led to empirical investigations on changes in the monetary policy transmission mechanism after a severe crisis. The findings, however, remain an unresolved issue. Schularick and Taylor (2012) study the behaviour of money, credit, and macroeconomic indicators on a historical dataset for 12 developed countries for the period 1870–2008. They document that despite the more aggressive monetary policy easing in response to financial crises after 1945, the impact on output remained minimal. Using ordinary least squares (OLS), Bech *et al.* (2014) examine the effect of monetary policy during economic downturns from a sample of 24 developed countries and data going back to the 1960s. They find that monetary policy easing during a non-crisis downturn leads to a stronger economic recovery compared to downturns associated with a financial crisis. Jannsen *et al.* (2015) use a panel VAR model for 20 advanced economies to investigate whether monetary policy has different effects on the economy during financial crises compared with non-crisis periods. However, unlike other investigations, they allow for heterogeneity in monetary policy transmission during the financial crisis period by differentiating between crisis periods accompanied by a recession and those accompanied by an expansion. These authors find that, when comparing crisis and non-crisis periods (without differentiating between recessionary and expansionary phases), the effects of a monetary policy shock on output and inflation are significantly greater and occur faster during a financial crisis. However, when they take heterogeneity into account, monetary policy loses its effectiveness on output and inflation during a financial crisis accompanied by an expansion compared to a financial crisis accompanied by a recession.

Literature also shows empirical evidence that monetary policy is more effective after a crisis. Dahlhaus (2017) empirically investigates the effects of monetary policy conditional on financial stress using a smooth transition factor model which is based on the dynamic factor model. She finds that a monetary policy shock has stronger and more persistent effects on output, consumption, and investment during periods of a financial crisis than during "normal" times. She also finds that the balance-sheet channel is stronger during a financial crisis and that an expansionary monetary policy shock increases loans during a financial crisis while it has no significant effect on loans during times of low financial distress.

The view that monetary policy is less effective during a financial crisis is based on the notion that the transmission mechanism channels may be impaired (Jannsen *et al.*, 2015). More precisely, the interest-rate channel may be impaired. Mohanty (2012) argues that the GFC showed that the monetary policy transmission mechanism through the interest-rate channel may not be as effective as once perceived. Financial crises are often associated with a significantly large spread between policy rates and money markets rates, as financial institutions require a higher risk premium due to crisis-induced credit (Illes and Lombardi, 2013). This large spread consequently weakens the interest-rate pass-through. The cost of credit to households and firms may therefore increase during a financial crisis despite monetary policy easing (Karagiannis *et al.*, 2010). Gambacorta *et al.* (2015) find similar results.

Bouis *et al.* (2013) find that in times of financial market distress, financial institutions reduce their willingness and capacity to extend credit as they are faced with limited availability of funding and increased uncertainty about the future availability of funding. The authors also note that the ensuing deleveraging by banks in the aftermath of a crisis may also decrease the credit supply. Moreover, financial institutions may also find it difficult to extend credit supply and/or to meet minimum capital requirements due to poor balance sheets following financial crisis-induced credit losses (Foglia *et al.*, 2010). Against this backdrop, changes in monetary policy are likely to become less important for determining credit supply and demand in a financial crisis period compared to a non-crisis period (Jannsen *et al.*, 2015).

Mishkin (2009) argues that the transmission mechanism is not impaired. He contends that, had monetary policy not been aggressively eased, consumer spending and business investment would have been further restrained and would consequently have led to a more severe economic downturn. He also argues that a severe crisis, like the GFC, should be accompanied by even more aggressive easing. However, Bech *et al.* (2014) argue that substantial stimulus had already been provided and that the benefit of additional support would therefore be small. They also point out that very low interest rates may disguise underlying credit weakness and encourage banks to extend loans to low-quality borrowers.

Much of the research focuses on the developed countries. However, in Thailand, Waiquamdee and Boonyatotin (2008) use a VAR model to empirically investigate changes in Thailand's transmission mechanism after the financial crisis of 1997. These authors find that while the interest-rate channel is generally the most important transmission channel, its relative importance declined significantly after the 1997 financial crisis due to excess liquidity in the banking sector and a heightened degree of risk aversion in both the corporate and the banking sectors. Disyatat and Vongsinsirikul (2003) also use a VAR approach for the period 1993 to 2001. They find that the pass-through via the credit channel in Thailand declined after the 1997 crisis due to a weakened banking sector. However, the interest-rate pass-through remained strong. The literature on monetary policy transmission mechanisms is vast in South Africa; see, for instance, Kabundi and Ngwenya (2011) as well as Gumata *et al.* (2013). However, to the best of our knowledge, no study has yet been conducted that focuses on the change in the transmission mechanism after a severe financial crisis like the GFC with the main emphasis on the reaction of output. Hence, this study bridges the existing gap in the literature.

3. MODELS

3.1 Bayesian Vector Autoregressive

This paper follows closely the BVAR approach proposed by Banbura *et al.* (2010). Consider the following VAR(p) model:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + v_t \tag{1}$$

where Y_t is an $n \times 1$ vector of endogenous variables, $B_1, B_2, \ldots, B_p$ are $n \times n$ autoregressive matrices, c is an $n \times 1$ vector of constants, and $v_t \sim N(0, \Sigma)$ is an $n \times 1$ vector of independent and identically distributed (*iid*) error terms.

Equation (1) can also be written as:

$$Y_t = X_t B + v_t \tag{2}$$

where $X_t = \left\{ c_i, Y_{i,t-1}, Y_{i,t-2} \dots, Y_{i,t-p} \right\}$.

Equation (2) yields the following representation:

$$y = \left(I_n \otimes X\right) b + V \tag{3}$$

where $y = vec(Y_t)$, $b = vec(B)$, and $V = vec(v_t)$.

The BVAR model entails estimating equation 2 by imposing prior beliefs on the parameters of the endogenous variables, based on Litterman (1986), to overcome "the curse of dimensionality" which prevails in VAR models. Like Banbura *et al.* (2010), we use Minnesota priors which assume that the endogenous variables, Y_t, follow a random walk process or an autoregressive of order 1 (AR(1)) process. This is equivalent to shrinking the diagonal elements of B_1 in equation 2 towards one and the remaining elements in B_1, B_2, … B_p towards zero. The mean of the Minnesota prior distribution for the VAR coefficients can be written as:

$$p(b) \sim N(\tilde{b}_0, H) \tag{4}$$

where $\tilde{b}_0 = \begin{cases} \chi_i & \text{for } j = i,\ k = 1 \\ 0 & \text{otherwise} \end{cases}$

Litterman (1986) sets $\chi_i = 1$ for all i, which accounts for the high persistence in variables, and $\chi_i = 0$ for the prior belief of mean reversion in variables. The variance of the prior b, H is given by:

$$H = \begin{cases} \left(\frac{\tau}{l}\right)^2 & \text{for } j = i \\ \left(\frac{\sigma_i \tau}{\sigma_j l}\right) \epsilon & \text{for } j \neq i \end{cases}$$

where τ is the hyperparameter which controls for the tightness of the prior distribution around the random walk. If $\tau = 0$, then the posterior mean equals the prior, which means that the data do not influence the estimate. But when $\tau = \infty$, the posterior is the same as the OLS estimates, which entails that the prior belief is not informative. Generally, the choice of τ depends on the size of the model. We have $\tau \to 0$ when $n \to \infty$. l is lag length, which governs the rate at which the prior variance decreases. Hence, H is inversely related to l. σ_i and σ_j are obtained from the OLS estimation of autoregressive (AR) regressions of the variables included in the VAR model. The ratio of σ_i and σ_j therefore accounts for the scale difference between variable i and variable j. Finally, ε controls the variance of the prior on lags of variables other than the dependent variables.

It is worth mentioning that $\tilde{b}_0$ is an $n \times (n \times p + 1) \times 1$ vector of prior and H is a $[n \times (n \times p + 1) \times 1] \times [n \times (n \times p + 1) \times 1]$ matrix of a variance of priors with diagonal elements. Kadiyala and Karlsson (1997) show that the posterior distribution of the VAR coefficients conditional on Σ follow a normal distribution. We have:

$$p(b|\Sigma, Y_t) \sim N(M^*, V^*) \tag{5}$$

where $M^* = \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1} \left(H^{-1}\tilde{b}_0 + \Sigma^{-1} \otimes X_t' X_t \hat{b}\right)$ and $V^* = \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1}$ while $\hat{b}$ is the OLS estimates of the VAR coefficients, such as $\hat{b} = vec\left(\left(X_t' X_t\right)^{-1}\left(X_t' Y_t\right)\right)$.

It requires the inversion of the large matrix $[n \times (n \times p + 1) \times 1] \times [n \times (n \times p + 1) \times 1]$ to compute the mean conditional posterior distribution, which in turn slows down considerably the Gibbs sampling algorithm. Banbura *et al.* (2010) provide a remedial measure to this issue; they propose the inclusion of artificial data in the form of dummy variables in addition to the actual data. The weights placed on the artificial data represent the tightness of the prior.

Assume that we add T_D dummy observations Y_D and X_D in equation 2, such that:

$$b_0 = \left(\left(X_D' X_D\right)^{-1}\left(X_D' Y_D\right)\right) \text{ and } S = \left(Y_D - X_D b_0\right)' \left(Y_D - X_D b_0\right) \tag{6}$$

where $\tilde{b}_0 = vec(b_0)$.

The prior is of the normal inverted Wishart prior, represented as:

$$p(b|\Sigma) \sim N\left(\tilde{b}_0, \Sigma^{-1} \otimes \left(X_t' X_t\right)^{-1}\right) \text{ and } p(\Sigma) \sim iW\left(S, T_D - k\right) \tag{7}$$

where k is the number of regressors in each equation.

Hence, the conditional posterior distributions for the VAR coefficients are as follows:

$$p(b|\Sigma, Y_t) \sim N\left(vec\left(B^*\right), \Sigma \otimes \left(X^{*\prime} X^*\right)^{-1}\right) \text{ and } p(\Sigma|b, Y_t) \sim iW(S^*, T^*) \tag{8}$$

where $Y^* = [Y; Y_D]$, $X^* = [X; X_D]$, $T^* = T + T_D$, $B^* = \left(X^{*\prime} X^*\right)^{-1}\left(X^{*\prime} Y^*\right)$, and $S^* = (Y^* - X^* b)' (Y^* - X^* b)$.

By adding the artificial data, the computation of the mean of the posterior distribution requires the inversion of a $(n \times p+1) \times (n \times p + 1)$ matrix instead of a $[n \times (n \times p + 1) \times 1] \times [n \times (n \times p + 1) \times 1]$.

The dummy observations for general n variables VAR with p lags are of the following form:

$$Y_D = \begin{pmatrix} \frac{diag(\chi_1\sigma_1, \ldots, \chi_n\sigma_n)}{\tau} \\ 0_{n \times (p-1) \times n} \\ \ldots\ldots\ldots\ldots\ldots \\ diag(\sigma_1, \ldots, \sigma_n) \\ \ldots\ldots\ldots\ldots\ldots \\ 0_{1 \times n} \end{pmatrix}, \quad X_D = \begin{pmatrix} \frac{J_p \otimes diag(\sigma_1, \ldots, \sigma_n)}{\tau} & 0_{np \times 1} \\ \ldots\ldots\ldots\ldots\ldots & \ldots \\ 0_{n \times np} & 0_{n \times 1} \\ \ldots\ldots\ldots\ldots\ldots & \ldots \\ 0_{1 \times n} & c \end{pmatrix} \tag{9}$$

where χ_i are prior means for the coefficients on the first lags of the dependent variables, and $j_p = diag(1, \ldots, p)$.

4. EMPIRICAL RESULTS

4.1 Change in the Transmission Mechanism

We extend the seven variable VAR considered by Christiano *et al.* (1999) and use a dataset containing 15 monthly time series obtained from the South African Reserve Bank (SARB). The dataset consists of:

1. real variables, such as GDP growth;
2. nominal variables, including headline inflation and the commodities price index;
3. financial variables, such as the rand/dollar exchange rate, the repo rate, and the effective lending rate.

The identification strategy involves dividing the variables into two categories, namely slow-moving and fast-moving variables. Slow-moving variables, such as real and nominal series, react slowly to a monetary policy shock while fast-moving variables, mainly financial series, react instantly to a monetary policy shock. We also include the US Federal Reserve funds rate as an exogenous variable to account for global factors, and include business confidence, household and corporate sector credit as well as a measure for banking sector leverage.[2] All of the series are logged, except for those in percentages.

Fig. 1 depicts the change in the transmission mechanism of monetary policy in the pre-GFC period compared to the post-GFC period. Monetary policy appears to be more effective in stimulating output and inflation in the pre-GFC period. More specifically, the real interest rate was relatively low between 2004 and 2007, with the real ex ante repo rate measuring 3.1% on average. This low interest-rate environment boosted growth in the residential property market, which subsequently saw a rise in both output and inflation.[3] However, after the GFC, the real ex ante repo rate turned negative and was much lower than the 2004–2007 level, nevertheless economic growth remained lacklustre. This paper attempts to explain this conundrum with the main focus on the effects of regulations and confidence.

Fig. 2 depicts the IRFs derived from the BVAR using the entire sample (*i.e.* March 2001 to February 2016). GDP growth immediately declines after a 100 basis points increase in the repo rate and reaches the minimum level of −0.18% eight months after the shock. The effect fades away gradually over time, suggesting that monetary policy has short-term effects on real variables, consistent with theory. Inflation reacts slowly and reaches the minimum level approximately two years after the policy shock, and like GDP growth, the effect dissipates gradually.

Household loans decrease following a policy shock and gradually attains a minimum of −0.65% 28 months after the shock. We find evidence of a puzzle. That is, we observe a positive response of corporate loans to a policy shock that lasts for about a year. Loans, however, subsequently decline and reach a maximum impact of −1.12% at about 36 months. The impact of a policy shock on mortgage loans is not statistically significant. As

[2] See Appendix A for a full description of the dataset.

[3] The residential property boom caused a rapid increase in mortgage loans. This subsequently translated into a sharp rise in total credit extension since mortgage advances form the largest component of household credit.

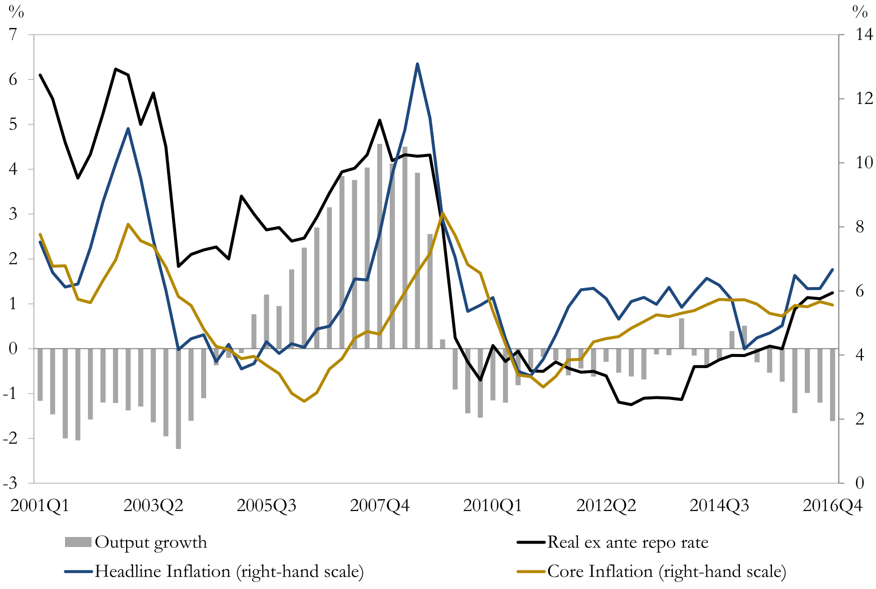

Figure 1. Output growth, inflation, and real interest rates [Colour figure can be viewed at wileyonlinelibrary.com]

a robustness check for the behaviour of credit to changes in the policy rate we evaluate the pass through of the repo rate to interest rates banks charge on household loans, corporate loans and mortgage advances (see Table D1 in Appendix D). The results show evidence of a transmission mechanism of monetary policy to the various lending rates. This is in contrast with Fig. 2 where mortgage loans do not react to monetary policy shock, which can be attributed to lack of response in the post-GFC period. The BCI decreases after the shock and reaches a minimum level of −0.55 in less than a year. However, the impact is short-lived.

Fig. 3 depicts the IRFs from the pre-GFC subsample, which covers the period from March 2001 to August 2008. The response of GDP growth to a monetary policy shock in the pre-GFC period is similar to that in the full-sample period. GDP growth decreases and reaches the minimum level at about a year. Inflation, on the other hand, responds quite differently to a policy shock in the pre-GFC period compared to the full-sample period. Inflation increases after the shock and remains positive for about 20 months, indicative of a price puzzle. The price puzzle can be interpreted as policymakers' reaction to higher inflation. This is particularly true in South Africa, where inflation rose substantially in the wake of the GFC. Monetary policy authority was compelled to react aggressively with a 500 basis point hike in the policy rate from June 2006 to June 2008. Inflation then decreases and reaches the minimum level after 36 months, with the magnitude of the response being relatively larger than that of the full-sample period. We also find a puzzling result for corporate loans. Corporate loans react positively to a policy shock and the impact lasts for about 12 months before turning negative and reaching a minimum of −1.02%. Household loans and mortgage advances, on the other hand, respond negatively. The response of mortgage loans to the shock is slightly larger than

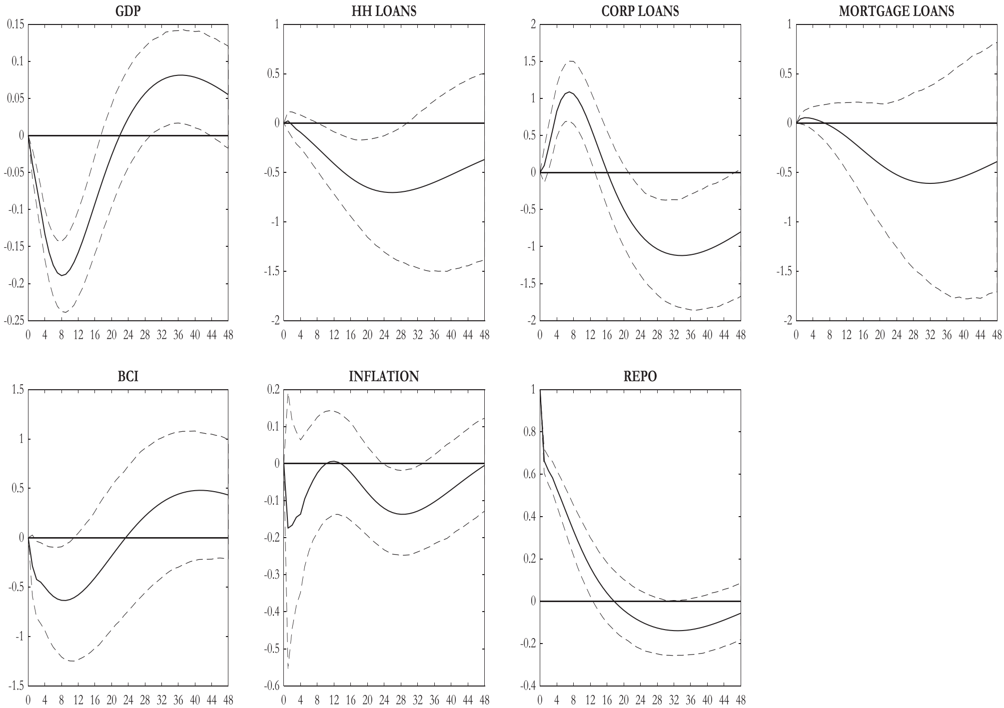

Figure 2. Impulse response functions: full sample

that of household loans, but the effects on both loans lasts for more than three years. Interestingly, mortgage loans reacts significantly to a monetary policy shock in the pre-GFC period which is in contrast with Fig. 2. The BCI responds negatively and reaches a maximum of −0.98 eight months after the shock. The effect declines gradually and becomes statistically insignificant after 20 months.

It is evident from Fig. 4 that the transmission of monetary policy changed after the GFC. The response of GDP growth to a percentage increase in the repo rate is smaller in the post-GFC period compared to pre-GFC. GDP growth decreases immediately after the policy shock and attains a maximum impact of −0.08% in the post-GFC period compared to −0.18% in the pre-GFC period. The reaction of inflation to a monetary policy shock is statistically insignificant, suggesting that inflation may not be as sensitive to changes in the policy rate in the post-GFC period. These results are in line with Kabundi and Mlachila (2019) and Kabundi *et al.* (2019) who attribute the absence of reaction of inflation to monetary policy shock to an improvement in monetary policy credibility, which is reflected by the anchoring of inflation expectations, the anchoring of inflation expectations, the flattening of the Phillips curve, and a muted exchange rate pass-through. Figs A1 and A2 in Appendix A provide a clearer picture of the difference in the responses of GDP growth and the inflation rate. We also run the IRFs using manufacturing production instead of GDP growth, as a robustness check, and find similar results (see Figs A3–A5 in Appendix A).

The monetary policy shock has a relatively small impact on credit demand in the post-GFC period compared to pre-GFC. Corporate loans and mortgage advances slightly

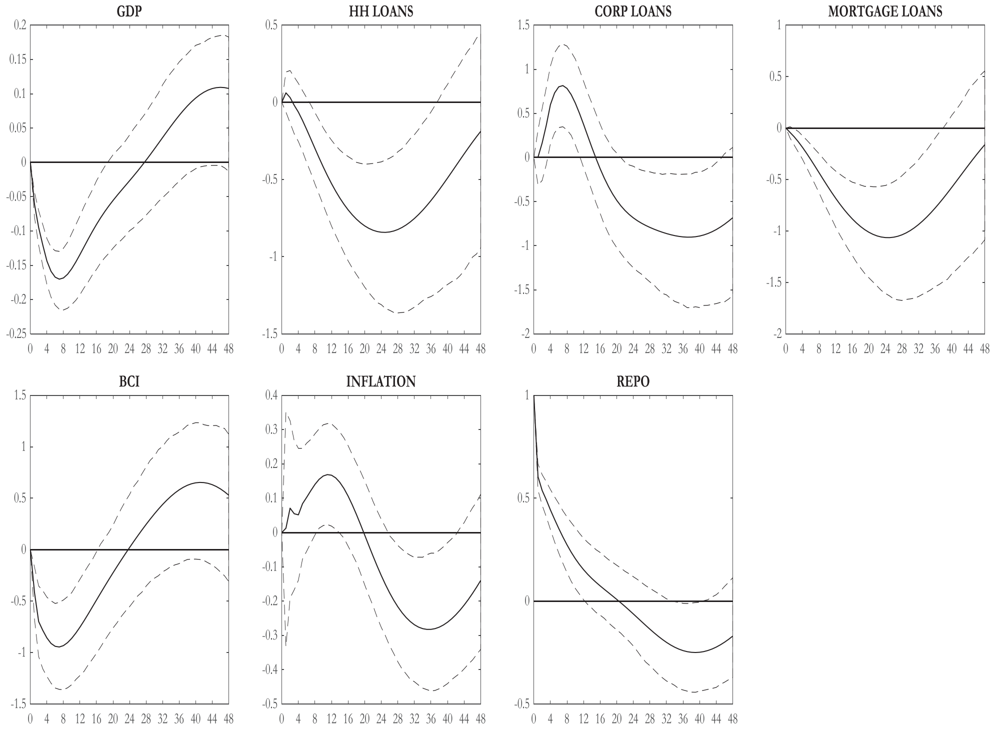

Figure 3. Impulse response functions: before the global financial crisis

increase after the policy shock, however, this is short-lived and the effect soon becomes statistically insignificant. The responses of household loans and the BCI are statistically insignificant.

Table 1 reports the FEVs, which quantify how important the monetary policy shock is in explaining the variation in each of the variables. The results support the findings depicted in Figs 3 and 4, namely that the effect of a monetary policy shock on GDP growth, inflation, and the BCI tend to be higher in the pre-GFC period than post-GFC. We also find that over longer time horizons a larger portion of the variation in inflation is explained by the monetary policy shock in the pre-GFC period compared to the full sample period. This suggests that the pre-GFC effects are bigger for longer time horizons, in this instance 24 months. This finding corroborates the observations in Fig. 3, where the reaction of inflation becomes statistically significant only after 20 months. The repo rate reports larger FEVs in the post-GFC period. These values echo the aggressive reaction of the SARB to the crisis with a 550 basis points cut in the repo rate from December 2008 to September 2010. This suggests that although the shock is large in the second period, its transmission to GDP growth and inflation turns out to be weak. The weak response of real GDP and inflation can be due to several factors, as suggested in the next section.

4.2 Factors Explaining the Weak Transmission Mechanism

A key factor contributing to the lack of response of the real economy to changes in the policy rate is that confidence has been too low. Fig. 5 shows the movement in growth in

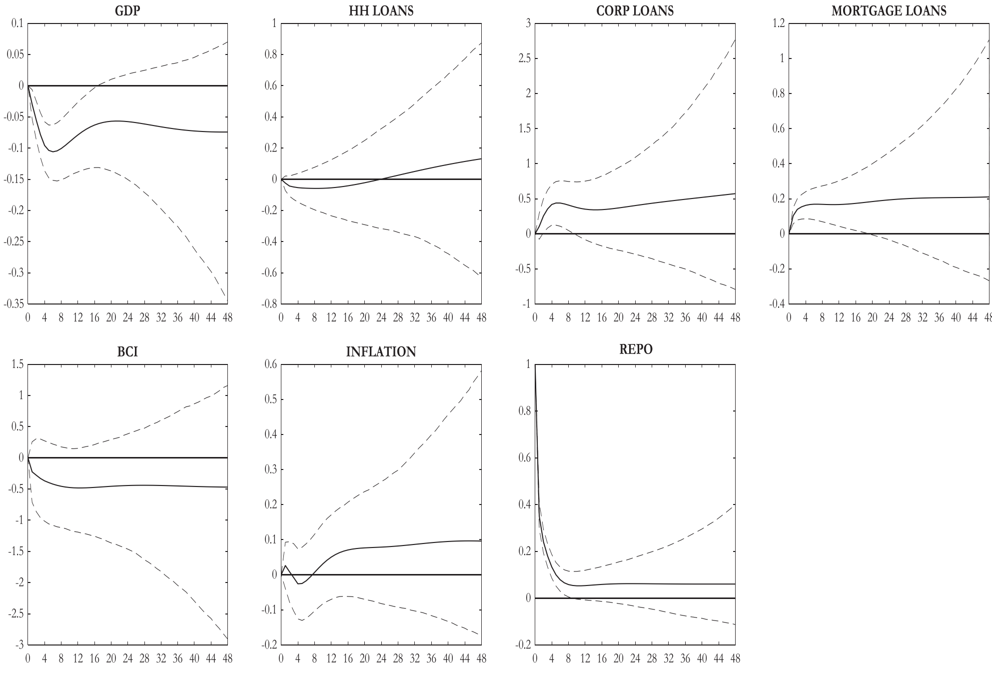

Figure 4. Impulse response functions: after the global financial crisis

Table 1. Forecast error variance

	Horizon	Full sample	Pre-crisis	Post-crisis
GDP	6	7.44	14.23	3.30
	12	14.98	21.19	5.16
	24	10.69	17.45	4.36
BCI	6	0.79	4.48	0.21
	12	1.47	8.51	0.57
	24	1.22	9.31	1.20
Inflation	6	0.10	0.03	0.03
	12	0.11	0.21	0.05
	24	0.15	0.39	0.44
Repo	6	55.30	48.52	58.00
	12	31.20	30.32	42.50
	24	21.63	24.97	29.37
Money Supply (M3)	6	0.62	1.29	0.32
	12	0.52	1.23	0.57
	24	1.60	4.78	0.72

private-sector investment, business confidence, and consumer confidence. It is evident from the figure that firms and consumers have been unwilling to increase their investment and consumption expenditure in the post-GFC period, putting further strain on economic activity. Business confidence has measured below the neutral 50 mark for most of the post-GFC period,[4] while consumer confidence has consistently been below the long-term average reading of +4 since the second half of 2014. And while business confidence has been relatively constant since 2009, with only a downward trend towards the

[4] This observation is consistent with the finding in Fig. 4.

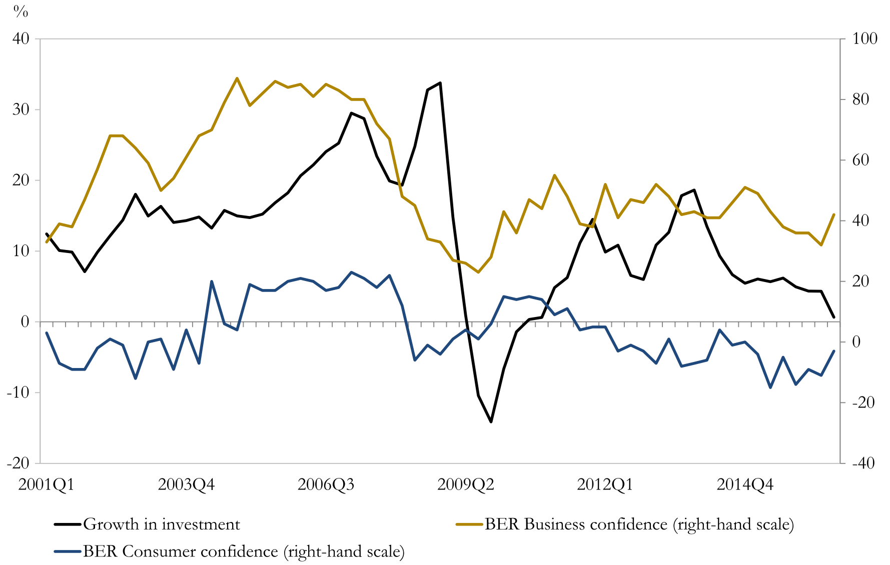

Figure 5. Investment and confidence [Colour figure can be viewed at wileyonlinelibrary.com]

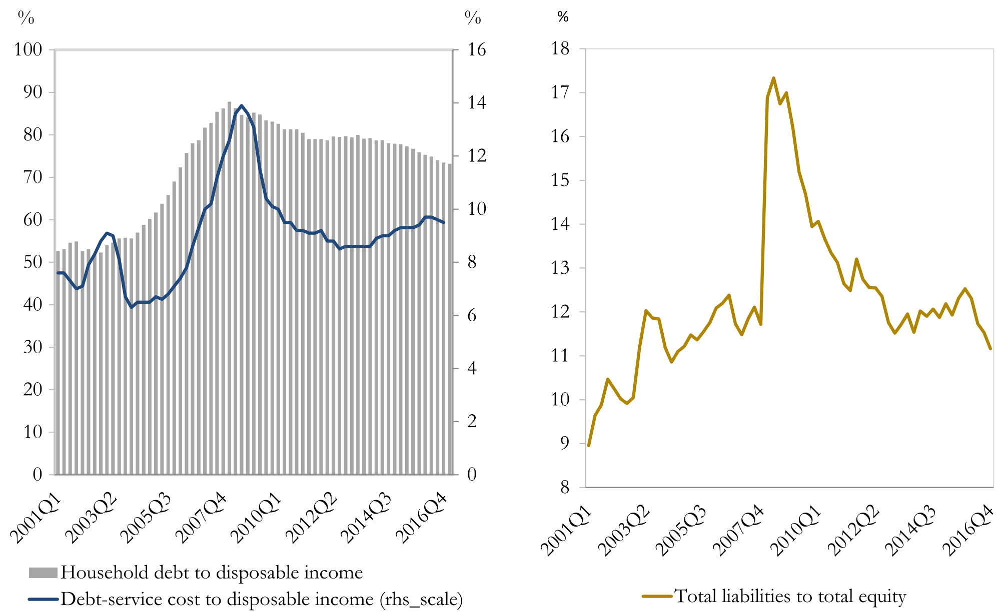

Figure 6. Deleveraging of households and financial intermediaries [Colour figure can be viewed at wileyonlinelibrary.com]

end of the sample, consumer confidence has exhibited a downward trend since 2009. This has translated into subdued investment growth, measuring 5.8% on average in the post-GFC period compared to 18.2% on average in the pre-GFC period.

In addition to their low confidence, consumers are still deleveraging as their balance sheets were severely impaired by the GFC. Fig. 6 shows the leverage ratios of the household and banking sector. It is evident that both sectors experienced deleveraging in the post-GFC period. This is expected, as severe financial crises often mark the end of periods of credit and consumption booms and are thus characterised by strong balance-sheet adjustments and deleveraging.[5] In this environment, changes in monetary policy are likely to become weak in determining credit supply and demand. The household debt-to-disposable-income ratio peaked at 87.8% in 2008Q1 after growth in household sector credit extension outpaced disposable income growth from 2003 to 2008. This was on the back of a residential property market boom which resulted in a rapid increase in mortgage loans. In the post-GFC period, however, the ratio trended downwards and reached a 10-year low of 74% in 2016Q3. Moreover, the debt-service costs of households have trended upwards since 2014, reflecting the consolidation of debt as well as the impact of the SARB's interest-rate hiking cycle.

The debt-to-equity ratio of the banking sector increased rapidly over 2007 to 2008 and reached an all-time high of 17% in 2008Q4 as equity prices declined following the GFC. However, the ratio declined considerably after the GFC, registering 11.2% in 2016Q4. The downward trend may be explained by the amended capital requirements under the Basel II regulations, which likely enabled a rise in equity relative to liabilities.

Besides the low confidence and the slow deleveraging process of households since the GFC, the credit supplied could also be affected by the numerous regulations introduced since 2007. Fig. 7 depicts the relationship between growth in credit extension to the private sector and regulatory changes. Growth in credit extension to the private sector decreased after the NCA came into effect in June 2007 and declined even further during the GFC. Credit growth also decreased after the implementation of the Basel II regulations. However, this was likely driven by the effects of the NCA and the GFC as these regulations were more concerned with matching capital accumulation with the level of risk exposure. Credit extension remained relatively constant following the implementation of the Basel III regulations in July 2013, with only a slight decline in November 2012 prior to the date on which Basel III became effective. This is surprising, since these regulations were aimed at regulating the excessive uptake of high-risk weighted assets by banks and consequently imposed more restrictions on credit lending. Credit growth also decreased after the AARs came into effect in September 2015.

In order to obtain a clearer picture of the regulatory impact, we empirically investigate the effect of each regulatory framework on private sector credit extension using an OLS dummy regression. The dummy variables are assigned a value of one from the date of implementation of each respective regulation and zero elsewhere. We also include the real US Federal Reserve funds rate and real repo rate to account for possible global and domestic factors that could have an impact on credit extension.[6] Table 2 reports the average credit growth observed after the regulations came into effect. The results show that average credit growth decreased significantly after the NCA and Basel II regulations came into effect compared to the period before their implementation. The date of implementation of the NCA and Basel II regulations are very close to one another such that the

[5] See Reinhart and Rogoff (2008) for more details on the impact of a severe financial crisis on the balance sheets of households, firms, and banks.

[6] The real US Fed funds rate and real repo rate are estimated using CPI inflation and headline CPI inflation for the US and South Africa, respectively.

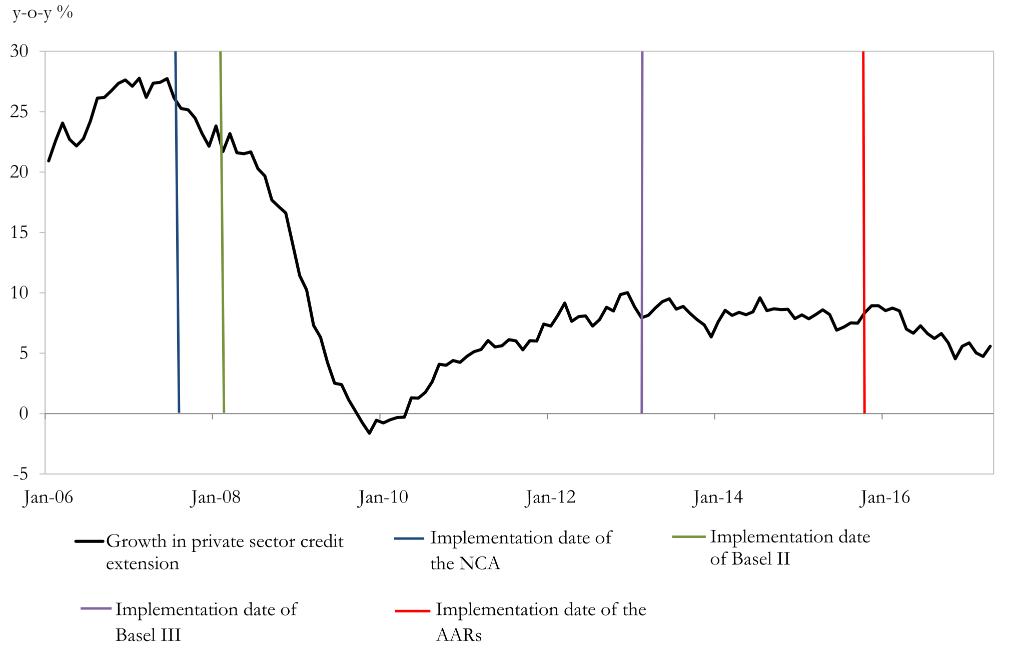

Figure 7. Regulations and credit growth [Colour figure can be viewed at wileyonlinelibrary.com]

Table 2. The effect of regulations

	Dependent variable: credit growth			
	NCA	**Basel II**	**Basel III**	**AARs**
Constant	2.36***	3.45***	0.34	0.27
	(0.68)	(0.81)	(0.39)	(0.35)
Credit growth(−1)	0.94***	0.90***	0.97***	0.97***
	(0.02)	(0.03)	(0.02)	(0.02)
Real repo rate	−0.27***	−0.39***	−0.03	0.00
	(0.10)	(0.11)	(0.07)	(0.06)
Real US Fed funds rate	−0.04	−0.02	0.03	0.03
	(0.10)	(0.11)	(0.10)	(0.10)
NCA	−1.77***			
	(0.50)			
Basel II		−2.66***		
		(0.61)		
Basel III			−0.20	
			(0.31)	
AARs				−0.20
				(0.37)
Adj R^2	0.96	0.96	0.96	0.96

Note: The real US Fed funds rate and the real repo rate are estimated using CPI inflation and headline inflation, respectively. Standard errors are reported in parentheses. ***,**,* denotes "statistically significant" at 1%, 5% and 10%, respectively.

NCA dummy variable also includes Basel II regulations. To empirically separate the effect of the two regulations we use the event study with a six-month window in Appendix B. Basel III regulations and the AARs are not statistically significant. Nevertheless, this still suggests that regulations played some role in curbing credit growth, as suggested by the event study (see Table B2 in the Appendix B). The results remain unchanged when we use the prime lending rate, the real prime rate, and the effective lending rate.[7] We also conduct an event study as a robustness check for the OLS dummy regression and the results also point to the regulations having a negative effect on credit growth.[8]

5. CONCLUSIONS

This paper investigates the change in the transmission of monetary policy since the GFC using monthly data covering the real, nominal, and financial sectors of the South African economy from March 2001 to February 2016. The results, based on a BVAR approach with 15 variables, suggest that a change in the response of GDP growth and inflation may have occurred. The two variables react more forcefully before the GFC than after the GFC. The FEVs also support these findings.

It therefore seems that besides factors such as structural bottlenecks to growth, lack of business and consumer confidence, the slow pace of the deleveraging process by households and financial intermediaries, and the implementation of new regulations may have hindered the economy from taking advantage of historically low interest rates. The analysis based on dummy variables provides evidence that the implementation of various regulations since the GFC have had significant effects on credit extended to the private sector. It would seem that these regulations affected the balance sheets of financial intermediaries, thus curbing the supply of credit.

To be effective, monetary policy should be combined with other policies like macroprudential policy and fiscal policy after a severe financial crisis. However, this is only possible if the country has substantial fiscal space before the crisis. It is therefore recommended for the country to ensure a sound fiscal position in good times. In addition, policymakers should reduce uncertainty during and after the crisis as it affects negative the transmission of monetary policy. Finally, the right time to implement of regulations which affect balance sheets of households and corporates is when these agents have completed the deleveraging process.

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[7] See Table C1 in Appendix C.
[8] See Table B2 in Appendix B.

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APPENDIX A. THE BVAR MODEL

A1. List of Variables

Table A1. List of variables and treatments for the BVAR model

Variables	Treatment
GDP (nowcasting model)[1]	2
Industrial production[1]	2
Headline CPI[1]	5
Total commodity price index[1]	5
Total loans to the household sector[1]	5
Mortgage advances[1]	5
SACCI Business confidence index (BCI)[1]	1
Headline inflation, nominal[1]	2
Repo rate, nominal	1
Weighted average lending rates	1
Rand/dollar exchange rate	5
US Federal Reserve funds rate	1
Banking sector leverage ratio	1
M3	5
Total reserves (gold and other foreign reserves)	5

[1]= slow-moving variables, 1 = not logged and $\chi_i = 0$,
2 = not logged and $\chi_i = 1$, 5 = natural log and $\chi_i = 1$.

A2. Impulse Response Functions

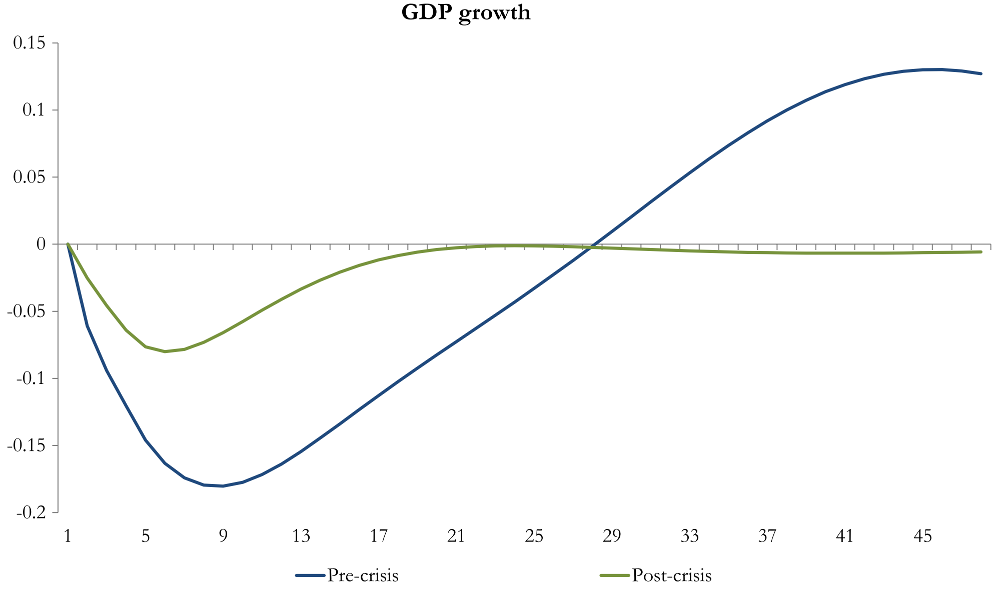

Figure A1. IRFs of GDP growth before and after the GFC [Colour figure can be viewed at wileyonlinelibrary.com]

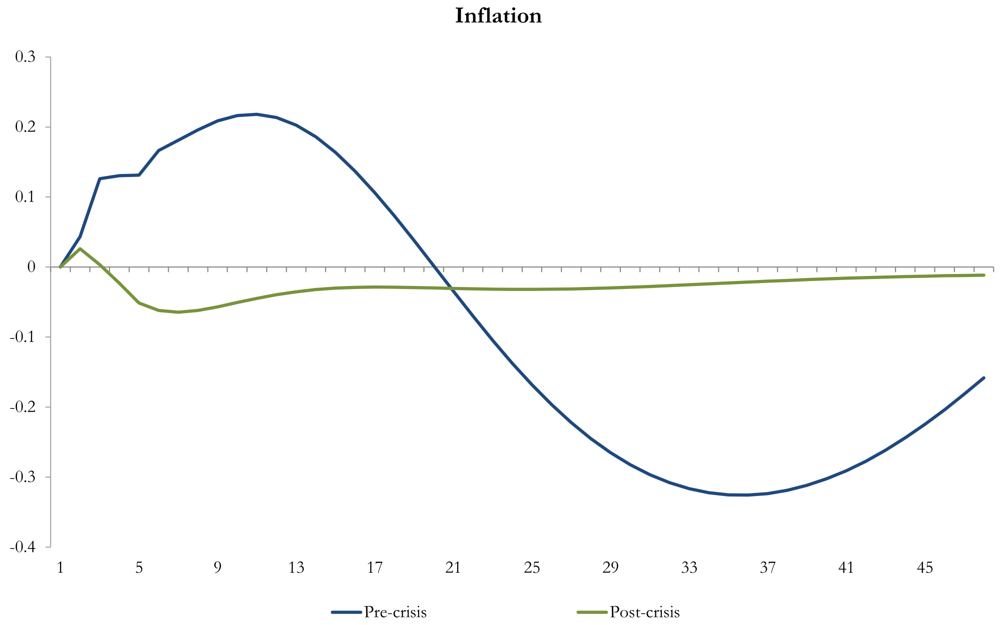

Figure A2. IRFs of inflation before and after the GFC [Colour figure can be viewed at wileyonlinelibrary.com]

A3. Robustness check for the IRFs

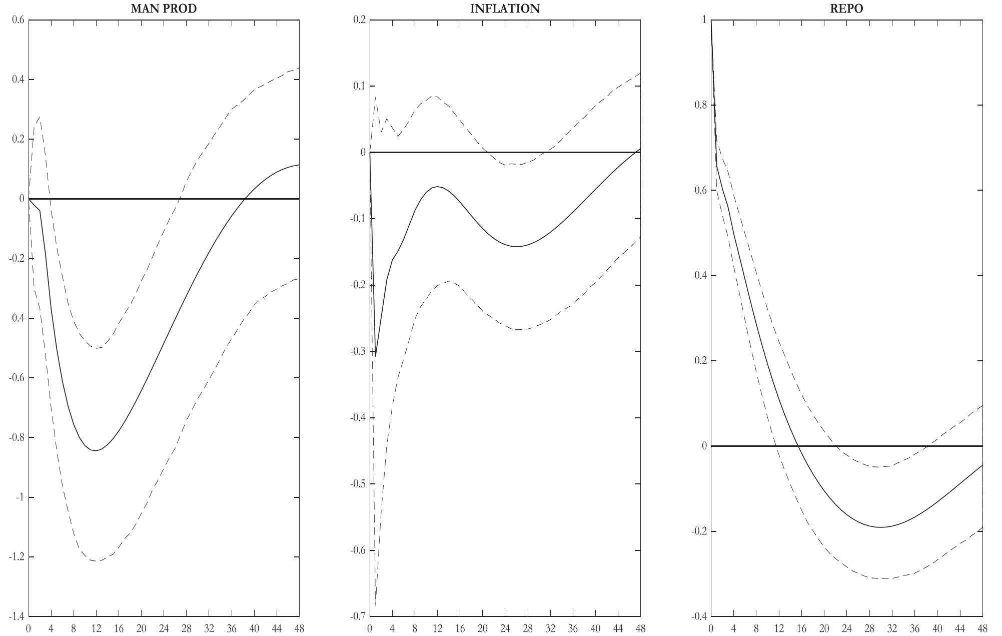

Figure A3. IRFs using manufacturing production: Full period sample

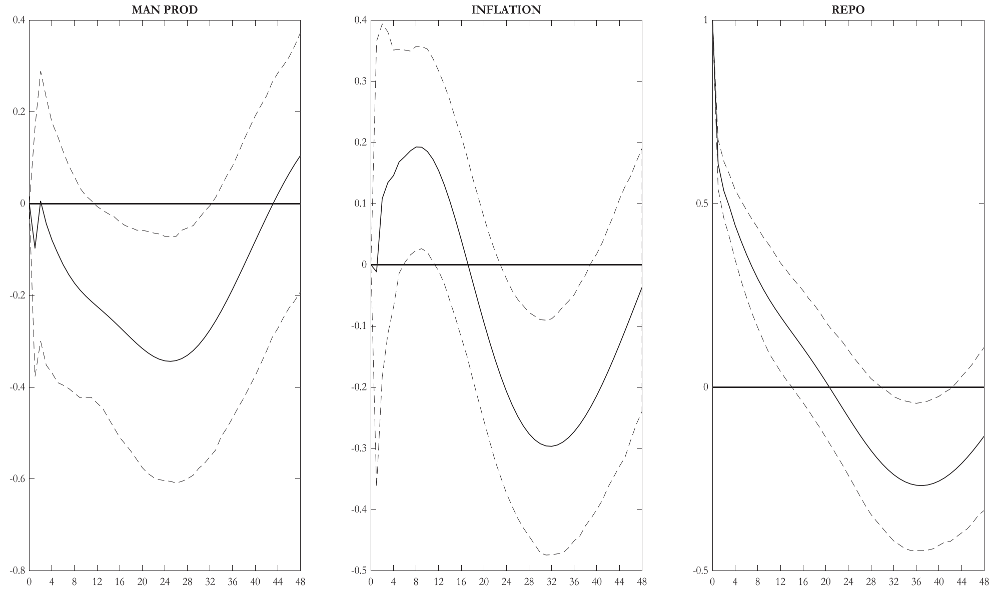

Figure A4. IRFs using manufacturing productions: Pre-GFC sample

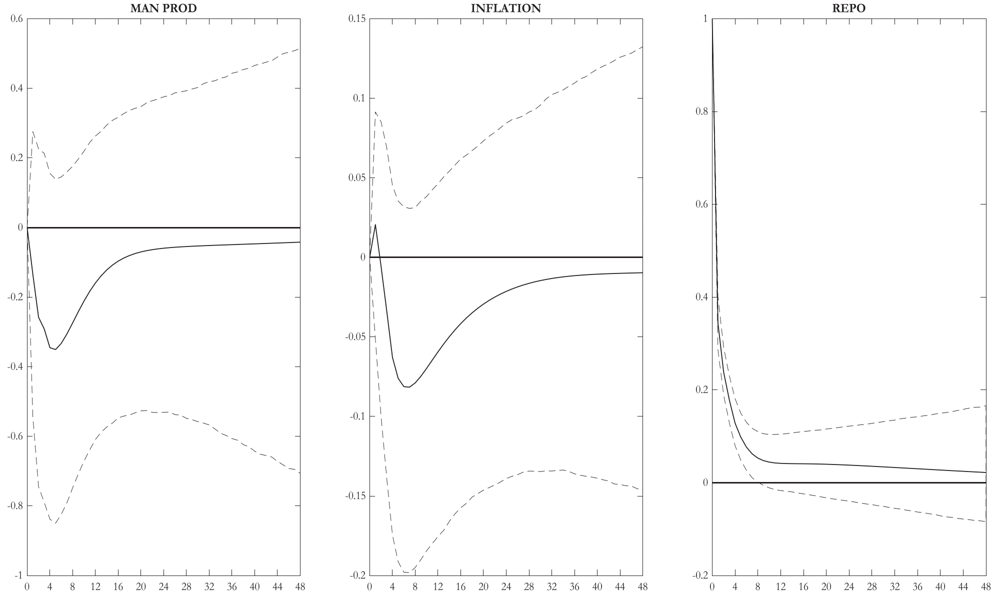

Figure A5. IRFs using manufacturing production: Post-GFC sample

APPENDIX B. NONPARAMETRIC EVENT STUDY

B1. The Model

In the paper, we present a number of plausible explanations as to why the low interest rate environment seen in the post GFC period did not translate into higher credit growth. One of these explanations is the possible effect of the legislative and regulatory frameworks – *i.e.* the NCA, Basel II, Basel III, and the AARs of the NCR – on credit growth. To empirically investigate this, we conduct an OLS dummy regression as well as a nonparametric event study, where the latter serves as a robustness check. The usefulness of event studies arises from the fact that the size of abnormal performance at the time of an event provides a measure of the impact of the event on the subject of interest. Moreover, nonparametric tests are ideal in the presence of non-normality and asymmetry due to small sample sizes. We use the generalised-rank test proposed by Kolari and Pynnonen (2011), as it has more empirical power relative to other nonparametric tests. The generalised-rank test also accounts for skewed abnormal returns, unlike the sign test and it overcomes the shortfall of the Corrado rank test of losing power as the length of the event window increases (Cowan, 1992). Moreover, the test is fairly robust to abnormal return serial correlation, event-induced volatility, and cross-sectional correlation of abnormal returns due to event day clustering (Kolari and Pynnonen, 2011). This is ideal for our analysis, as the data used is strongly correlated, and the event dates of the regulations are the same for each data series.

We estimate the growth in credit as follows:

$$C_{it} = \beta_{0i} + \beta_{1i} GDP_t + \beta_{2i} HPI_t + \beta_{3i} REPO_t + \beta_{4i} i_t + \varepsilon_{it} \tag{10}$$

where C_{it} is the growth in credit type i on month-t; GDP_t is the monthly GDP growth rate obtained from the nowcast proposed by Kabundi *et al.* (2016); HPI_t is the house price index; $REPO_t$ is the real repurchase rate[9]; i_t is the US Federal Reserve funds rate used to account for possible global factors that may have an impact on credit, and ε_{it} is the zero mean disturbance term.

The abnormal returns (ARs) are obtained from differencing the realised and predicted growth in the credit extended on month-t in the event window:

$$AR_{it} = C_{it} - \left(\hat{\beta}_{0i} + \hat{\beta}_{1i} GDP_t + \hat{\beta}_{2i} HPI_t + \hat{\beta}_{3i} REPO_t + \beta_{4i} i_t\right) \tag{11}$$

where $\hat{\beta}_{0i}$, $\hat{\beta}_{1i}$, $\hat{\beta}_{2i}$, $\hat{\beta}_{3i}$ and $\hat{\beta}_{4i}$ are estimated coefficients of the explanatory variables, obtained from the estimation window using OLS. Note that we use the same coefficients for the event window, L_1.

Let $t = 0$ indicate the month when the event occurred, $t = T_0 + 1, T_0 + 2, \ldots, T_1$, the estimation window period relative to the event, and $t = T_1 + 1, T_1 + 2, \ldots, T_2$, the event window period relative to the event. We define $L_1 = T_1 - T_0$ as the length of the estimation window and $L_2 = T_2 - T_1$ as the length of the event window. This gives

[9] This is the ex post real repurchase rate calculated using headline inflation.

the estimation period $L = L_1 + L_2$. Given the abnormal returns AR_{it}, the standardised abnormal returns (SARs) are defined as:

$$SAR_{it} = \frac{AR_{it}}{S_{AR_j}} \tag{12}$$

where S_{AR_j} is the standard deviation of the regression prediction errors in the AR. The SAR defined above is the standardised residual of the regression estimated in the estimation window.

The cumulative abnormal return (CAR) on credit type i over τ event period (CAR period) is defined as:

$$CAR_{i\tau} = \sum_{t=t_1+1}^{t_1+\tau} AR_{it} \tag{13}$$

with $T_1 \leq t_1 \leq T_2 - \tau$ and $1 \leq \tau \leq L_2$. The corresponding standardised cumulative abnormal return (SCAR) is defined as:

$$SCAR_{i\tau} = \frac{CAR_{i\tau}}{S_{CAR_i}} \tag{14}$$

where S_{CAR_i} is the standard deviation of the prediction errors in the CAR. Under the null hypothesis of no event, both S_{AR_j} and S_{CAR_i} are distributed with mean zero and unit variance.

In order to account for possible event-induced volatility, we follow closely Boehmer *et al.* (1991) and re-standardise the SCAR with the cross-sectional standard deviation to get the re-standardised SCAR:

$$SCAR_i^* = \frac{SCAR_{i\tau}}{S_{SCAR_{i\tau}}} \tag{15}$$

where $S_{SCAR_{i\tau}} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(SCAR_{i\tau} - \overline{SCAR}_\tau \right)^2}$ is the cross-sectional standard deviation of $SCAR_{i\tau}$, and $\overline{SCAR}_\tau = \frac{1}{n} \sum_{i=1}^{n} SCAR_{i\tau}$. If the event date is the same for all the credit types in the sample, then the cross-sectional independence breaks down due to cross-sectional correlation. Kolari and Pynnonen (2011) therefore suggest that the S_{CAR_i} in equation (B6) should be adjusted for cross-sectional correlation.

$SCAR_i^*$ is a zero mean and unit variance random variable. Therefore, we use $SCAR_i^*$ as the AR and define the generalised AR as follows:

$$GSAR_{it} = \begin{cases} SCAR_{it}^* & \text{for } t_1 + 1 \leq t \leq t_1 + \tau \\ SAR_{it} & \text{for } t = T_0 + 1, \ldots, t_1, t_1 + \tau + 1, \ldots, T_2 \end{cases}$$

The CAR period is considered to be the one time point in which the generalised standardised abnormal return (GSAR) is equal to the re-standardised SCAR. For the other time points, the GSAR is equal to the usual SAR. This ensures that any likely effect of the event that takes place within the periods $t_1 + 1$ and $t_1 + \tau$ is concentrated in the $SCAR^*_{it}$, which, under the null hypothesis, behaves like any other standardised return but starts to deviate from the returns under the alternative hypothesis due to the event effect (Kolari and Pynnonen, 2011).

In order to derive the rank test, we define the demeaned standard abnormal rank as follows:

$$U_{it} = \frac{Rank(GSAR_{it})}{(T+1) - \frac{1}{2}} \tag{16}$$

where, under the null hypothesis of no mean event, the effect is $E[U_{i0}] = 0$ for all $i = 1, \ldots, n$.

Kolari and Pynnonen (2011) propose two rank tests, namely the generalised rank t-statistic (GRANK-T) test and the generalised rank z-statistic (GRANK-Z) test. We use the GRANK-T test as it tends to be more robust to event day clustering, which causes cross-sectional correlation. Given the null hypothesis of no mean effect, the GRANK-T test statistic is defined as:

$$GRANK_t = Z\left(\frac{T-2}{T-1-Z^2}\right)^{\frac{1}{2}} \tag{17}$$

where $Z = \frac{\bar{U}_0}{S_{\bar{U}}}$, $S_{\bar{U}} = \sqrt{\frac{1}{T}\sum_{t \in T} \bar{U}_t^2}$ and $\bar{U}_t = \frac{1}{N}\sum_{i=1}^{N} U_{it}$. $\bar{U}_{i0}$ is the mean of the standardised rank in the event date, and N is the number of the different types of credit granted in the overall sample.

Kolari and Pynnonen (2011) demonstrate that:

$$t_{grank} = Z\sqrt{\frac{T-2}{T-1-Z^2}} \xrightarrow{d} t_{T-2} \tag{18}$$

As $N \to \infty$, the distribution converges to a t-distribution with the degree of freedom T–2.

list of variables

Table B1. List of variables and treatments for the event study

Variables	Treatment
Total credit extension to the private sector	5
Total credit extension to the household sector	5
Total credit extension to the corporate sector	5
Household instalment sales credit	5
Household leasing finance	5
Household mortgage advances	5
Household overdrafts	5
Household general loans and advances	5
Household credit cards	5
Corporate investment	5
Corporate bills	5
Corporate instalment sales credit	5
Corporate leasing finance	5
Corporate mortgage advances	5
Corporate overdrafts	5
Corporate general loans and advances	5
Corporate credit cards	5
Household disposable income	2
GDP (nowcasting model)	2
Absa house price index	5
Effective lending rate, nominal	1
US Federal Reserve funds rate	1

1 = no transformation, 2 = first difference, 5 = first difference of natural log.

B3. Empirical results

Table B2 presents the empirical results of the nonparametric event study. The GRANK-T test statistics are significant at the 1% level for all four regulations, meaning that the null hypothesis that the implementation of these regulations has had no impact on the behaviour of credit growth is rejected for all four regulations. Moreover, negative test statistics indicate that the sample mean credit growth is smaller than the hypothesised mean credit growth, which is consistent with the findings based on the dummy variable analysis. This suggests that regulations may have played a role in curbing the extend of credit growth.

Table B2. The effect of the regulations

Regulation	GRANK-T	*p*-value
NCR	−8.72	0.00
Basel II	−9.11	0.00
Basel III	−11.96	0.00
AARs	−13.23	0.00

APPENDIX C. ROBUSTNESS CHECK FOR THE DUMMY VARIABLE ANALYSIS

Table C1. Empirical results on the dummy variable analysis

Explanatory variables	Dependent variables			
	Prime interest rate	**Real prime interest rate**	**Effective lending rate**	**Real effective lending rate**
Constant	3.54***	3.55***	4.70***	2.85***
	(0.08)	(0.06)	(0.14)	(0.16)
Repo rate	0.98***	0.96***	0.76***	0.90***
	(0.01)	(0.01)	(0.01)	(0.03)
NCA	0.08***	−0.03	0.12*	0.35**
	(0.04)	(0.05)	(0.07)	(0.16)
Adj R^2	0.99	0.99	0.95	0.90
Constant	3.56***	3.57***	4.60***	2.60***
	(0.08)	(0.06)	(0.14)	(0.15)
Repo rate	0.98***	0.96***	0.77***	0.94***
	(0.01)	(0.01)	(0.01)	(0.03)
Basel II	−0.06	−0.05	0.19**	0.65***
	(0.04)	(0.05)	(0.07)	(0.15)
Adj R^2	0.99	0.99	0.95	0.90
Constant	3.65***	3.54***	4.40***	2.80***
	(0.07)	(0.03)	(0.11)	(0.07)
Repo rate	0.98***	0.96***	0.79***	0.92***
	(0.01)	(0.01)	(0.01)	(0.02)
Basel III	−0.01	−0.03	0.52***	0.89***
	(0.05)	(0.04)	(0.07)	(0.11)
Adj R^2	0.99	0.99	0.96	0.92
Constant	3.64***	3.52***	4.70***	3.07***
	(0.06)	(0.02)	(0.10)	(0.06)
Repo rate	0.98***	0.96***	0.76***	0.85***
	(0.01)	(0.01)	(0.01)	(0.02)
AARs	0.01	0.01	0.51***	0.71***
	(0.05)	(0.05)	(0.09)	(0.15)
Adj R^2	0.99	0.99	0.96	0.90

Note: Standard errors are reported in parentheses. ***, ** and * denote significant at 1%, 5%, and 10% respectively.

For the real prime interest rate and real effective lending rate we use the real repo rate as an explanatory variable.

APPENDIX D. ROBUSTNESS CHECK FOR THE PASS THROUGH OF MONETARY POLICY TO CREDIT EXTENSION

Table D1 shows that there is evidence of a pass through of monetary policy to interest rates on household loans, corporate loans and mortgage advances. This is statistically significant at the one percent significance level. Mortgage interest rates exhibit the largest impact to a change in the repo rate, followed by interest rates on corporates loans and household loan rates. While the supply of loans can be affected by different factors such as competition in the banking sector, funding market conditions and regulatory changes, the repo rate plays a significant role.

Table D1. Impact of a change in the repo rate on lending rates

Dependent variable	**Effective lending rates**	**Household loan rates**	**Corporate loan rates**	**Mortgage loan rates**
Constant	0.01	0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Repo rate	0.52***	0.42***	0.69***	0.79***
	(0.06)	(0.06)	(0.09)	(0.04)
Effective lending rate (−1)	0.01	–	–	–
	(0.07)	–	–	–
Household loan rates (−1)	–	0.25***	–	–
	–	(0.08)	–	–
Corporate loan rates (−1)	–	–	−0.15*	–
	–	–	(0.08)	–
Mortgage loan rates (−1)	-	-	-	−0.11**
	–	–	–	(0.05)
Adjusted R-squared	0.45	0.42	0.40	0.64

Note: The pass through of monetary policy is identified using the first difference method. Standard errors are reported in parentheses. ***,**,*denotes "statistically significant" at 1%, 5% and 10%, respectively.