Credit channel of monetary policy and housing finance in South Africa

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Abstract We study the transmission of monetary policy to credit conditions and aggregate demand in South Africa by employing data on household mortgages issued by non-bank financial institutions. Our results show that monetary tightening in South Africa induces further increase of the share of bank-based credit as compared to market-based credit, what contrasts with the results obtained for advanced economies (Iacoviello and Minetti, 2008). This finding is explained by a strong degree of affiliation of non-banks with the banking sector. The change in composition of credit supply influences the demand for housing implying that bank lending channel is operative.

Keywords: monetary policy transmission, credit channel, non-bank financial institutions.

JEL Classification Numbers: C32, E52, G21, G23.

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1 Introduction

As argued by Bernanke and Blinder (1988, 1992) and Bernanke and Gertler (1995), changes in monetary policy could be consequential for real economy due to workings of the credit channel. In particular, the supply of loans does not merely follow changes in the demand for credit induced by variation in the user cost of capital and/or income, as suggested by the ‘money view’. Due to credit market imperfections monetary policy shocks have an impact on the external finance premium, the latter being a wedge between the cost of external funds and the opportunity cost of internal funds. As a result, demand for loans of credit-dependent firms and households might not be satisfied, what influences decisions of these agents to invest and spend.

The evidence on the credit channel of monetary policy in emerging economies is limited and at times controversial. In case of South Africa, given the history of stock issuance for raising funds by gold mining companies since late 1880’s and the high volume of the Johannesburg Stock Exchange equity market capitalisation nowadays, the country is regarded as a representing a typical market-based financial structure (Gambacorta et al., 2014). Hence, following the conventional predictions of monetary policy theory, one would expect low efficiency of the bank lending channel of monetary policy transmission in South Africa. However, banks are a predominant source of borrowed funds for firms in the country, whereas the share of debt securities in total borrowing of non-financial corporates is only around 15\% \footnote{The share of credit in total borrowing of non-financial corporates in 2019Q2 is 85.79\%, while the share of debt securities is 14.21\%. The ratio of credit to non-financial corporates is expressed as a percentage of the sum of total credit plus domestic debt securities. The share of bank credit in total borrowing of the private non-financial sector is 90.78\%. Source: BIS debt securities statistics and BIS credit statistics.}, what effectively makes a bank-based financial structure for borrowed funds in the country. As for housing finance, the role of the banking sector is even more pronounced, as it accounts for more than 90\% of credit issued to finance house purchases\footnote{Data sources: National Credit Regulator and Lightstone Properties Data.}. To shed light on the workings of the credit channel in South Africa, we aim to provide evidence on the impact of monetary policy shocks starting from the inflation targeting regime adoption in 2000 and to evaluate the importance
of the bank lending channel of monetary policy transmission.

The relevance of our study is underpinned by necessity to choose a particular structure of model economy for the monetary policy analysis. Variations of the conventional New Keynesian model have been developed for this purpose to account for financial frictions in different forms. Some of these models introduce macrofinancial linkages stemming from imperfections on the demand side of credit - they capture how the state of borrowers’ balance sheets affects their access to external financing thereby introducing the ‘balance sheet channel’ of monetary transmission\(^3\). Other contributions incorporate balance sheets variables of financial intermediaries as factors leading to amplification and propagation of shocks, thus accounting for the ‘bank lending channel’\(^4\). These two channels have contrasting implications for the ability and willingness of households to borrow and spend, hence it is important to differentiate between them empirically.

Different characteristics of the housing finance system in South Africa and its institutional background might underlie different degree of the bank lending channel effectiveness. Heavy dependence of households on bank housing loans with limited possibility to diversify away from banks and strong reliance of the latter on reservable retail deposits as a source of liabilities suggest that bank lending channel might play a substantial role. On the other hand, such features as high degree of standardisation of the mortgages’ issuance process and significant degree of the mortgages securitisation by banks could reduce potential importance of the bank lending channel\(^5\). Furthermore, one would expect borrowers’ balance sheet channel to be pronounced in the housing finance market due to the direct linkage of housing demand to households’ balance sheets\(^6\). In addition to this, the global financial crisis (GFC) has induced substantial changes in the financial sector regulation and potentially, in the banks’ business models. Hence, we

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3Among these models are, for example, Greenwald and Stiglitz (1993), Kiyotaki and Moore (1997), Suarez and Sussman (1997), Bernanke et al. (1999), Iacoviello (2005), Khan and Thomas (2013), Moll (2014).
4See, for example, Diamond and Rajan (2005, 2011), Bruche and Suarez (2010), Iacoviello (2015), Ferrante (2018), etc.
5Due to high mortgage standardisation and securitisation in South Africa the relative illiquidity of mortgages matters less for the banks - they have less incentive to keep a buffer against liquidity shocks and shift their assets to more liquid loans and securities (Iacoviello and Minetti, 2008).
6Bernanke et al. (1995) argue that characteristics such as down-payment requirements, upfront transaction costs, etc. underpin the importance of balance sheet channel for the mortgage loans’ issuance.
also investigate whether the workings of the monetary transmission mechanism in South Africa have changed over the GFC.

The identification challenge of the current research question is to disentangle the bank lending and the balance sheet subchannels\textsuperscript{7}. If changes in policy induce weakening of banks’ and households’ balance sheets, then reduction of loans availability could be a result of either of these two channels being operative. The use of bank-loan level data and/or loans application data allows to deal with this challenge, as it enables to control for credit demand by making use of multiple lending relationships of borrowers\textsuperscript{8,9}. This type of data is not available in South Africa at the moment, hence, an alternative approach should be taken.

To isolate the effect of the bank lending channel we employ disaggregated data on mortgage loans issued by banks and non-bank credit institutions. These two types of financial intermediaries fund their lending activity differently - banks rely on reservable retail deposits that constitute 70% of their liabilities, while non-bank credit providers are not allowed to issue deposits and use market funding - debt securities and loans. This difference allows to identify the bank lending channel, because banks’ reserves and retail deposits go down following monetary policy tightening, what is not the case for the wholesale funding instruments used by non-banks. Significant change in the share of housing loans provided by non-banks in the total volume of mortgages following monetary contraction implies that the source of funding of lending activity matters, and that the bank lending channel is operative. Following Ludvigson (1998) and Iacoviello and Minetti (2008), we assume that changes in household demand for mortgages from different lenders induced by tight money conditions are the same\textsuperscript{10}.

\textsuperscript{7}The terms ‘channel’ and ‘subchannel’ are used interchangeably here, as the bank lending and the borrowers’ balance sheet channels are regarded as independent channels in the literature, and also considered as components of credit channel.

\textsuperscript{8}Bank-loan loan data and/or loans application microdata is employed, for example, in Khwaja and Mian (2008), Jimenez et al. (2012), Abuka et al. (2019).

\textsuperscript{9}Another approach used in the literature employs bank-level data; it assumes that bank-specific characteristics influence the supply of loans, while loan demand is largely independent from them and is affected mostly by macro factors. This type of identification strategy and bank-level data is used, for instance, in Kashyap and Stein (2000), Altunbas et al. (2009, 2010). A simple theoretical microfoundation is provided Ehrmann et al. (2003) and Gambacorta and Mistrulli (2004).

\textsuperscript{10}We have reviewed the terms of lending of the major South African banks and non-bank credit issuers and found that for personal housing loans these terms are broadly the same. So, bank and non-bank mortgages can be considered by potential borrowers as perfect substitutes.
Large Bayesian vector autoregression (LBVAR) approach of Banbura et al. (2010) is employed to enable us to deal with the large size of our system and to control for the risk of overfitting. Responses of a range of macroeconomic, financial and bank balance sheet variables to monetary policy tightening are analysed. Chow tests are used to confirm the presence of the structural break in the LBVAR model parameters over the GFC period. Therefore, the two subsamples are analysed - from the beginning of the inflation targeting regime by the South African Reserve Bank until the beginning of the downturn in South Africa induced by the GFC (2000M1-2008M8), and the period after the GFC until the latest data point available (2010M1-2019M3).

We detect significant changes in the workings of the credit channel before and after the GFC. While the broad credit channel is found to be operative in both subsamples, housing loans availability following monetary contraction is reduced to a greater extent, i.e. banks charge higher spreads on mortgages after the GFC. The bank lending channel is found to be operative after the GFC, as monetary tightening increases the share of bank supply of housing loans. The direction of impact of tight money on changes in the housing finance market structure observed in South Africa is opposite to the one found for European economies as documented in Iacoviello and Minetti (2008). We interpret this result by affiliation of non-banks in South Africa with the banking sector, whereby responses of banks’ balance sheet variables following monetary policy shocks induce changes in lending activity of non-banks. Banks serving as underwriters for housing loans issued by non-banks, do not only reduce credit risk of the latter by redistributing it, but also contribute to imposing greater interconnectedness between the banking sector and non-banks, what reinforces the effect of the bank lending channel.

We demonstrate that the type of mortgage provider and her terms of loans availability have real effects - households reduce their demand for houses, when the share of funding for house purchases they receive from banks goes down. This evidence is in line with theoretical predictions of effect of the bank lending channel, which says that availability of bank credit supply has a significant positive impact on borrowers’ spending. In terms of relevant theoretical structure, our results imply that it is essential to incorporate the bank lending channel of
monetary transmission in theoretical model used for monetary policy analysis. We suggest
that recent theoretical contributions incorporating features of financial intermediaries’ balance
sheets should be employed in the case of South African economy, what would also allow to
analyse the role of macroprudential regulation explicitly\textsuperscript{11}.

We focus our analysis on the housing finance market for several reasons. First, mortgage
loans take the biggest share in the asset portfolio of the South African banking sector (see figure
1). Hence, it is essential to establish the presence and the nature of the credit channel transmis-
sion for this type of credit for understanding the macrofinancial linkages in the South African
economy. Second, housing market is particularly exposed to the credit channel, and therefore it
represents a better environment to capture its presence than the broader economy. Specifically,
due to relative illiquidity of housing loans, banks might find it optimal to reallocate their asset
portfolios and reduce the share of housing loans on their balance sheets, when they anticipate
negative liquidity shocks (Iacoviello and Minetti, 2008). Third, banking sector dominates as
a housing loans provider in South Africa. Limited availability of credit supply in this market
could have significant impact on household spending on house purchases. Lastly, housing has
a significant bearing on the business cycle due to the fact that housing investment is a volatile
component of aggregate demand, and because changes in house prices have implications on
investment and consumption via wealth effects.

The workings of the credit channel in South Africa has already been analysed in Ludi and
Ground (2006), Gumata et al. (2013) and Loate and Viegi (2015). However, none of these works
accounts for structural breaks and investigates how the credit channel transmission has changed
over the GFC. Furthermore, only Loate and Viegi (2015) aim to disentangle the effects of the
bank lending and the balance sheet channels. They use an alternative approach to identify
the bank lending channel by controlling for differences in small and big banks’ structure of
liabilities. Our work can be seen as complementary to these studies.

This paper is organised as follows. Section 2 presents the empirical methodology used for

\textsuperscript{11} The examples of these DSGE-type model contributions incorporating bank lending channel of monetary
policy transmission include Gertler and Karadi (2010), Iacoviello (2015) and Ferrante (2018), among others
analysis of the credit channel. Section 3 describes the data, while section 4 discusses the results obtained.

2 Empirical methodology

To analyse the credit channel and to disentangle the bank lending channel from the balance sheet channel we follow the approach of Iacoviello and Minetti (2008) by using data on the relative share of non-bank credit providers on the market of housing loans. In doing that, we employ the large Bayesian VAR methodology as suggested by Banbura et al. (2010) to estimate impulse response functions.

To assess the presence of the credit channel, we run two vector autoregression models at monthly and quarterly data frequencies. First, we estimate a large VAR on monthly frequency data to analyse the effect of monetary contraction on a large set of macroeconomic and bank balance sheet variables. The prime goal of this step is to demonstrate the potential quantitative importance of the credit channel, if it is present in the data. Still, the outcome of reduction of bank loans outstanding and/or issued following a monetary tightening shock does not necessarily reflect the credit channel being operating, as reduction of the loan volumes is also consistent with the decrease in demand for housing loans. On the other hand, credit channel could be operative in the case of increase in loan volumes; this is a possible outcome, because the households’ demand for loans could be strong enough, such that households compensate reduction in their wealth from external sources, what outweighs the decreasing supply of loans.

Another goal for estimating this BVAR model is to evaluate the impact of monetary contraction on the spread between a mortgage interest rate and a benchmark safe interest rate of comparable maturity. Given that in South Africa lending rates on housing loans are predominantly flexible, such that banks could adjust them in the changing macroeconomic and/or financial environment, we use the 3 months interbank interest rate as a benchmark rate. A rise in the spread is an indication of an increasing external finance premium following monetary tightening, what is consistent with the credit channel predictions.
After that we estimate a large BVAR model to analyse the effect of monetary tightening on the ratio of housing loans issued by non-bank credit providers to all housing loans, which we refer to as a MIX variable following Kashyap et al. (1993) and Ludvigson (1998). If wholesale sources of funding are not a perfect substitute for retail deposits for banks, then the reduction in deposits after monetary contraction entails the decrease of mortgages issued by banks to a greater extent than reduction of housing loans from non-banks. As a necessary condition, the MIX variable features a significant change, if the bank lending channel is operative. If the market of funding for house purchases is such that households can compensate the reduction of bank loans issuance with increase of mortgages issued by non-banks, then the demand for housing would be fully satisfied. If shocks to the MIX variable explain dynamics of housing market, then bank lending channel is regarded as operative.

Following the argument of Iacoviello and Minetti (2008), index of house prices is used as a measure of the housing market cyclicality. In contrast to utilizing housing investment, employing house prices has advantages. First, it is the ability to capture demand changes more promptly and also to fit into explanation of the monetary policy transmission in a more meaningful way. Specifically, house prices influence credit supply shifts through their impact on the wealth of borrowers and also on the net worth of financial intermediaries, which is not the case for housing market quantities.

With the objective of better understanding the workings of the credit channel, we benefit from using a large size of model that allows to take into account disaggregated data series. In particular, employing various components of banks’ and households’ balance sheets would reduce the risk of omitted variable bias thus helping to form a more detailed picture of monetary policy shocks affecting the credit and macro variables. To address the issue of over-parameterization that VAR models are prone to, unless a small number of variables is used, we resort to the large Bayesian VAR methodology suggested in Banbura et al. (2010). In line with their approach, we apply Bayesian shrinkage that is shown to produce accurate forecasts and credible impulse responses, when data on as much as twenty macroeconomic variables is utilized. Shrinkage filters out the unsystematic component and extracts the relevant signal, as
various macro data series deliver similar information characterized by their strong collinearity. The degree of shrinkage is set relative to the size of the model, such that over-fitting is controlled for. Following the original methodology of Banbura et al. (2010), the variables are modelled in levels, what allows to keep information contained in the trends.

For the large vector of random variables $Y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})'$, the VAR(p) model considered is:

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + u_t,$$

where $u_t$ is an $n-$dimensional Gaussian white noise with covariance matrix $E u_t u'_t = \Psi$, $c = (c_1, ..., c_n)'$ is an n-dimensional vector of constants and $A_1, ..., A_p$ are an $n \times n$ autoregressive matrices. The Minnesota prior belief on the parameters as suggested by Litterman (1986) are imposed by setting the first and second moments of the prior distribution of the coefficients to control for overfitting:

$$E[(A_k)_{ij}] = \begin{cases} 
\delta_i, & \text{if } i = j, k = 1, \\
0, & \text{otherwise}
\end{cases}$$

(2)

$$V[(A_k)_{ij}] = \begin{cases} 
\frac{\lambda^2}{\pi^2}, & \text{if } i = j, \\
\nu \frac{\lambda^2}{\pi^2} \frac{\sigma_i^2}{\sigma_j}, & \text{otherwise}
\end{cases}$$

(3)

Hence, the diagonal elements of $A_1$ are shrunk toward one and the remaining coefficients in $A_1, \ldots, A_p$ are shrunk to zero, implying that all the equations are centered around the random walk with drift. The coefficients $A_1, \ldots, A_p$ are assumed to be a priori independent and normally distributed, the covariance matrix of the residuals is assumed to be diagonal, fixed and known: $\Psi = \Sigma$, where $\Sigma = diag(\sigma_1^2, \ldots, \sigma_n^2)$, while the prior on the intercept is diffuse.

To allow for correlation between the residuals of different variables it is necessary to abandon the assumption of the covariance matrix of the residuals being fixed and diagonal and adopt the modification proposed by Kadiyala and Karlsson (1997). Specifically, for the VAR re-written
in the form:

$$Y = XB + U,$$  \hspace{1cm} (4)

where $Y = (Y_1, ..., Y_T)'$, $X = (X_1, ..., X_T)'$, $X = (Y'_{t-1}, ..., Y'_{t-p}, 1)'$, $U = (u_1, ..., u_T)'$ and $B = (A_1, ..., A_p, c)'$ is the $k \times n$ matrix containing all coefficients and $k = np + 1$, the Normal inverted Wishart prior takes the form:

$$\text{vec}(B)|\Psi \sim N(\text{vec}(B_0), \Psi \otimes \Omega_0) \text{ and } \Psi \sim iW(S_0, \alpha_0)$$  \hspace{1cm} (5)

The prior hyperparameters $B_0$, $\Omega_0$, $S_0$ and $\alpha_0$ are chosen such that prior expectations and variances of $B$ coincide with the traditional Minnesota prior. The expectation of $\Psi$ is equal to the fixed residual covariance matrix $\Sigma$ of the Minnesota prior. Following Banbura et al. (2010), the dummy observations approach is used to implement the Normal inverted Wishart prior (5). To specify, the dummy observations added are:

$$Y_d = \begin{pmatrix} \text{diag}(\delta_1 \sigma_1, ..., \delta_n \sigma_n)/\lambda \\ 0_{n(p-1) \times n} \\ \vdots \\ \text{diag}(\sigma_1, ..., \sigma_n) \\ \vdots \\ 0_{1 \times n} \end{pmatrix},$$  \hspace{1cm} (6)

$$X_d = \begin{pmatrix} J_p \otimes \text{diag}(\sigma_1, ..., \sigma_n)/\lambda & 0_{np \times 1} \\ \vdots & \vdots \\ 0_{n \times np} & 0_{n \times 1} \\ \vdots & \vdots \\ 0_{1 \times np} & \epsilon \end{pmatrix},$$  \hspace{1cm} (7)

where $J_p = \text{diag}(1, 2, ..., p)$. The first block of dummies sets prior beliefs on the autoregressive
coefficients, the second block imposes the prior on the covariance matrix, while the third block of dummies implements the uninformative prior for the intercept with $\epsilon$ being a very small number.

Thus, the dummies (6) and (7) are introduced into the original regression model (4):

$$ Y_* = X_* B + U_*, $$  

where $T_* = T + T_d$, $Y_* = (Y', Y_d')$, $X_* = (X', X_d')$ and $U_* = (U', U_d')'$. Banbura et al. (2010) demonstrate that dummy observations (6) and (7) introduced to the original regression in this way help to address the problem of matrix inversion.

The value of hyperparameter $\lambda$ that sets the overall tightness of the prior distribution around the random walk or white noise and controls the relative importance of the prior beliefs with respect to the information contained in the data, is chosen relative to the size of the model. Setting the value of $\lambda$ higher for large systems allows to control for overfitting (De Mol et al., 2008). We set tightness to the value that ensures in-sample fit of our large model to be the same as a small monetary policy VAR estimated by OLS (Banbura et al., 2010), which is conventionally used in the literature and consists of the aggregate demand, inflation and nominal interest rate variables.

Following Bernanke et al. (2005), Christiano et al. (1999) and Stock and Watson (2005), the monetary policy shock is identified by recursive identification scheme. All the variables are divided into two classes: slow-moving and fast-moving. The identification assumption employed is that slow-moving variables do not respond contemporaneously to a monetary policy shock, with the information set of the monetary authority containing the current values of the slow-moving variables and values of the fast-moving variables with the lag. The variables are ordered as $Y_t = (X_t, r_t, Z_t)'$, where $X_t$ contains the slowly moving variables, $r_t$ is the monetary policy instrument, being the repurchase rate of the SARB, while $Z_t$ contains the fast-moving variables. It is assumed that monetary policy shock is orthogonal to all the other shocks in the economy.

We set $B = CD^{1/2}$ as an $n \times n$ lower diagonal Cholesky matrix of the covariance of the
residuals of the reduced form VAR, such that $CDC' = E[u_t u'_t] = \Psi$ and $D = diag(\Psi)$. Using $C$ to perform linear transformation of the VAR residuals, such that $C(-1)u_t = e_t = (e_{1t}, \ldots, e_{nt})'$, the monetary policy shock is defined as the row of $e_t$ that corresponds to the position of $r_t$ in $Y_t$. The structural VAR is formulated as:

$$F_0Y_t = \nu + F_1Y_{t-1} + \ldots + F_pY_{t-p} + e_t, e \sim WN(0, D), \quad (9)$$

where $\nu = C(-1)c, F_0 = C(-1)$ and $F_j = C(-1)A_j, j = 1, \ldots, p$. Thus impulse responses are computed following Canova (1991) and Gordon and Leeper (1994) to generate draws for the posterior of $(A_1, \ldots, A_p, \Psi)$, where for each draw $\Psi$, $B$ and $C$ are computed and $F_j$ are calculated.

3 Data

Our first dataset contains thirty one macroeconomic, financial and banks balance sheet variables at monthly frequency and covers the period from 2000M1 until 2019M3. We choose 2000M1 as a beginning of the sample, as this is the date of the beginning of the inflation targeting regime implemented by the Reserve Bank of South Africa. The last available observation at the time of writing is 2019M3, thus this date is taken as the end of the sample. There are 232 observations for each series in the first dataset.

Data on a number of important indicators – for instance, the MIX variable showing the share of non-banks in mortgages’ issuance, the ratio of households’ debt to their disposable income, the level of households’ net wealth, etc, - is available on quarterly frequency. Thus, additionally we use another dataset with quarterly frequency data containing twenty one variable. We include less variables in the second dataset, because the number of observations at quarterly frequency is smaller – seventy seven observations.

Using a set of Chow tests - the sample-split test, break-point test and Chow forecast test, - we find a significant change in models’ parameter values during the period of the global financial
crisis. The period 2008M9 – 2009M12 is excluded from the sample due to extreme variables’ volatility at the times of the GFC. Hence, the periods analysed are 2000M1-2008M8 – from the beginning of inflation targeting and before the GFC, and 2010M1 – 2019M3 – from after the end of the GFC until the period of the latest data point available.

Logarithm is applied to all of the series in our dataset, that are not expressed in rates. The random walk prior, i.e. $\delta_i = 1$, is used for non-stationary variables, whereas for stationary variables the white noise prior is utilized: $\delta_i = 0$. The dataset specification is provided in table 1 in the Appendix.

4 Results

Figure 4 shows the responses of a number of macro, financial and bank balance sheet variables to a monetary contraction, when monthly data from 2000M1 until 2008M8 is used for the LBVAR model estimation, while figure 5 shows responses estimated over the sample from 2010M1 until 2019M3. The posterior coverage intervals are at 0.68 and 0.9 levels.

The evidence for the period before the GFC supports the presence of the broad credit channel. The spread charged by banks on mortgage loans increases by 0.2 pp following 1 pp exogenous increase of the policy rate, while the volume of household mortgages outstanding on banks balance sheets goes down by 2.5%. The reduction of bank deposits is observed - total deposits go down by 1.6%, while demand deposits fall by 4%. At the same time there is no significant change in the volume of debt securities issued by banks. Thus, banks appear not to substitute the reduction of reservable deposits by the wholesale market funding on the liabilities side of their balances. The balance sheets shrinkage could induce reduction of loan supply by banks, reflected in lower volumes and higher spreads. This suggests that propagation of monetary policy tightening could occur via the bank lending channel. However, the evidence obtained so far is not conclusive about whether the bank lending channel is operative, as reduction of mortgages availability could also occur due to households’ balance sheet deterioration and the resulting increase in the cost of external finance. We are unable to disentangle the effects of
two subchannels at this stage, as no data on non-bank housing loans issuance is available for the period before the GFC.

The evidence from the VAR estimated over the sample after the GFC reveals the different influence of the broad credit channel. In particular, the credit channel is manifested in the higher costs of mortgages for households, as the spread of the mortgage rate over the benchmark riskless rate charged by banks goes up by 0.6 pp. At the same time, there is no significant change in the volume of housing loans following policy tightening after the GFC. No significant change in reservable deposits and debt securities issued by banks is observed, so the responses of these variables are not suggestive of the workings of the bank lending channel. As compared to the period before the GFC, the reduced availability of bank mortgages is reflected in the increase of spread of the greater size and persistency.

To disentangle the effects of bank lending and balance sheet channels, we proceed to analyse the households’ balance sheet data and data on mortgages issued by non-banks at quarterly frequency, which is available for the period after the GFC. Variables characterising households’ balance sheets and expenses - debt to net wealth ratio, real net wealth value and debt service cost as a share of disposable income - do not show a significant response to monetary policy tightening (see figure 6). This suggests that the space for workings of the balance sheet channel is limited after the GFC.

The MIX variable - the share of non-banks in the overall volume of housing loans issuance - features negative response to policy contraction (see figure 6). Equivalently, the share of housing loans provided by banks increases under tight money. Given our previous result based on analysis of the data of monthly frequency, that the volume of mortgages on banks’ balance sheets does not change significantly following monetary contraction, the negative change in MIX implies that the absolute volume of housing loans issued by non-bank credit providers goes down significantly. Interestingly, the direction of the impact we obtain is opposite to what has been shown for the European economies by Iacoviello and Minetti (2008)\textsuperscript{12}.

\textsuperscript{12}Iacoviello and Minetti (2008) demonstrate that in countries featuring the significant response of the share of non-banks to tight money - the UK, Germany and Finland - this response is positive.
The evidence of reduced absolute volume of housing loans issued by non-banks is not surprising, when the affiliation and/or the ownership structure of non-banks is considered. The biggest non-bank mortgage provider in South Africa - SA Homeloans\textsuperscript{13} - is partly owned by Standard Bank, one of the big four banks in the country. Standard Bank underwrites the majority of housing loans issued by SA Homeloans, thereby taking on credit risk of its subsidiary. Unwillingness of Standard Bank to extend loans following policy tightening manifests itself in reduced volumes of mortgages extended by SA Homeloans. Thus, non-bank credit sector in South Africa could be thought of as a ‘housing loans branch’ of a banking sector, such that changes in risk attitudes and liabilities of banks are transmitted to the asset side/loans portfolio of non-bank credit providers.

As figure 7 shows, the exogenous change in the structure of supply of the housing loans induces significant change in household demand for housing. Specifically, a positive innovation to the MIX variable - the increase of the share of mortgages provided by non-banks - entails lower/more sluggish demand. First, house prices fall significantly by 4% following the exogenous reduction of the share of bank mortgages issuance. Second, ‘time on market’ - the average number of weeks that properties stay at the market from the moment they are advertised until the buyer is found - increases significantly by 65%. This result implies that the type of mortgage provider and her terms of loans availability have real effects - households reduce their demand for houses, when the share of funding for houses purchases from banks goes down. This result is in line with the prediction of effect of the credit channel, which states that availability of bank credit has a positive impact on borrowers’ spending.

Finally, we show that the role of the credit channel has changed after the GFC. In particular, we employ the forecast error variance decomposition to demonstrate the contribution of the policy rate and the household balance sheet variables to explaining the variation in household mortgages outstanding, in household mortgages issued and in spread of the mortgage rate over the benchmark. As table 2 shows, repo rate explains 13.24% of variation of the household mortgages outstanding, 35.83% of variation of the household mortgages issued and 36.11% of

\textsuperscript{13}The share of SA Homeloans in the issuance of non-bank housing loans is about 80%. 
variation of the spread of mortgage rate over JIBAR before the GFC. The respective numbers for the period after the GFC are 3.06%, 1.68% and 1.83%, what stands in a stark contrast with the contribution of the monetary policy shocks before the GFC. The importance of the household balance sheet variables in explaining the volumes of mortgages and the spread has also gone down. Real household net wealth explains 18.56% of the variance of household mortgages outstanding before the GFC and only 5.86% after the GFC. The role of macroeconomic factors has instead increased. Specifically, CPI explains 19.33% of household outstanding mortgages variation before the GFC and 32.84% after the GFC; aggregate demand conditions/GDP explain only 3.37% of the spread variability before the GFC and 10.92% after the GFC. The role of policy shock in explaining the balance sheet variables of households - real net wealth, and debt to real net wealth - has also gone down (see table 2). These results imply that importance of the broad credit channel - and of the balance sheet channel in particular, - has reduced after the GFC.

5 Conclusion

This paper provides evidence on the effectiveness of the credit channel of monetary transmission in South Africa. What is the impact of monetary policy shocks on homeloans availability? What is the role of bank supply in driving housing loan volumes? Does the bank loan supply affect the demand for housing? To answer these questions, we disentangle the effect of the bank lending subchannel by exploiting the data on mortgages issued by nonbank financial institutions relative to the total volume of homeloans granted. Identification of the bank lending channel relies on the fact that banks and nonbank credit providers fund their lending activity from different sources. Bank liabilities are dominated by reservable retail deposits, while nonbanks use market-based funding. Monetary tightening affects these funding sources differently: bank deposits are subject to shrinking, what is not the case for long-term debt securities issued by nonbanks. Changes in composition of homeloan supply following monetary policy shocks allow to identify the bank lending channel.
Our results support the presence of the bank lending channel in South Africa. We find the significant effect of monetary policy shocks on the composition of mortgage supply by banks and nonbanks. Importantly, the direction of this effect is the opposite to the one documented by Iacoviello and Minetti (2008) for Finland and the UK - two advanced economies, where the bank lending channel is found to be operative, while the same identification approach is used. In South Africa the share of banks in home loans supply following tight money increases further, while in two aforementioned economies it goes down. We argue that South Africa is a case of within-financial sector transmission of monetary policy shocks, as there is a strong affiliation of nonbanks to the banking sector. Not only banks provide unsecured loans to nonbanks, but also play a role in their decisions about lending issuance. As a result, shrinking of the bank sector funding and willingness to extend credit serves as a within-financial sector channel, which works to decrease loan volumes granted by nonbank financial institutions.

With regards to the broad credit channel, we demonstrate that the effect of monetary policy shocks on availability of bank mortgages has changed over the GFC. While before the GFC tight money reduce availability of mortgages, this is not the case after the GFC, when no significant change in availability is found. By analyzing the responses of bank income statement variables, we conclude that pressures on profitability due to weaker demand for loans and market competition play a key role in this change.
6 References


7 Appendix

Figure 1. Assets on banks’ balance sheets, % of total assets.

Figure 2. Liabilities on banks’ balance sheets, % of total liabilities.
Figure 3. Share of mortgages issued by nonbank credit providers, %.

Source: National Credit Regulator
<table>
<thead>
<tr>
<th>Series</th>
<th>Frequency</th>
<th>Data source</th>
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<td>CPI</td>
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Figure 4. Impulse response functions to a monetary policy shock, 2000M1-2008M8.

[Diagrams showing impulse response functions for various economic variables]

Note. Impulse response functions to a 1 pp monetary policy shock and the corresponding posterior coverage intervals at 0.68 and 0.9 levels. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. 

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Figure 5. Impulse response functions to a monetary policy shock, 2010M1-2019M3.

Note. Impulse response functions to a 1 pp monetary policy shock and the corresponding posterior coverage intervals at 0.68 and 0.9 levels. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. 
Figure 6. Impulse response functions to 1 pp contractionary monetary policy shock, 2010Q1-2019Q1.

Note. Impulse response functions to a 1 pp monetary policy shock and the corresponding posterior coverage intervals at 0.68 and 0.9 levels. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$.

Figure 7. Impulse response functions to 1 pp positive shock to MIX, 2010Q1-2019Q1.

Note. Impulse response functions to a 1 pp monetary policy shock and the corresponding posterior coverage intervals at 0.68 and 0.9 levels. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. 
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