South African Reserve Bank Working Paper Series WP/24/07

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Authorised for publication by Konstantin Makrelov

15 April 2024

SOUTH AFRICAN RESERVE BANK

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Did Basel III reduce bank spillovers in South Africa? *

Ilias Chondrogiannis† and Serena Merrino‡

Abstract

We examine the effect of post-2010 banking regulation in South Africa on financial stability, macroeconomic variables and bank performance. We focus on risk spillovers and increased network and tail connectedness between banks, using a sample of nine listed South African banks in 2008–2023. The implementation of Basel III regulation, particularly capital adequacy ratios, has reduced connectedness-related risks but there is weak evidence of an effect of regulation on bank performance.

JEL classification

G01, G18, G21, E50

Key words

Systemic risk, financial stability, interconnectedness, South Africa, banks, Basel III

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* We gratefully acknowledge the financial support of the South African Reserve Bank (SARB) in the form of the 2023 Call for Papers Research Honorarium. We would like to thank Laurence Harris, Chris Loewald, Konstantin Makrelov, Janet Terblanche, SARB staff and the participants of the SARB Policy Dialogue for useful comments.

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1. Introduction

The 2023 bankruptcy of United States regional banks has revived the regulatory discussion around the policy mixture, effectiveness and toolkit of bank supervisors. Despite the view that the global financial system is better monitored and more resilient after the 2008 financial crisis, the post-COVID-19 landscape of economic slowdown, increased inflation and interest rates and the surprising speed of recent bank runs raise important questions about the ability of regulators to deal with rapidly spreading contagion and spillover effects. This issue is vitally important for South Africa, which in the last 15 years has endured recessions, the taper tantrum incident, the implementation of Basel III regulations and, presently, significant energy infrastructure and governance issues. Nevertheless, South Africa is the largest economy on the continent and is a prominent emerging market. Although its banking sector showed resilience during the global financial crisis, it is characterised by a very high degree of concentration. According to the World Bank database, the assets of the five largest banks amounted to 99.3% of total commercial banking assets in 2021. A systemic event and potential spillover effects in such a tightly connected banking sector operating in an unstable environment may be quite harmful. The 40% weight on bank interconnectedness assigned by SARB in its classification of systemically important financial institutions (SARB 2019) further emphasises the feature's importance. It is thus both vital and timely to assess whether the recently implemented Basel III framework had an impact on bank stability and economic performance, and whether it managed to increase the resilience of the South African banking sector.

Our first goal is to examine interconnectedness and risk-spillover effects in a representative sample of nine listed South African banks and identify the potential transmission channels of institutional failure, such as a bank run or distress, in the 2008−2023 period. We construct three different interconnectedness indices. The first method is the Granger causality network approach of Billio et al. (2012), which produces the dynamic connectedness index (DCI). The index measures the number of Granger causality connections between banks over time, indicating which banks affect or are affected by the stock price movements of a given institution. The connections can also be interpreted as a network of systemic risk diffusion (Nivorozhkin and Chondrogiannis

2022). The second method is the financial risk meter (FRM) of Mihoci et al. (2020), an aggregate tail risk indicator that relies on least absolute shrinkage and selection operator (LASSO) regressions and co-value at risk (CoVaR) tail dependencies (system distress given firm distress), which are combined into a systemic risk index. The FRM index captures the tail connectedness of bank returns in the network. The third approach is the spillover index (SI) of Diebold and Yilmaz (2012, 2014), which captures variance decompositions between pairs of firms in the network. This index captures the overall riskiness of banks. All three methods can provide aggregate and firm-specific results, making them suitable for both aggregated and disaggregated estimation.

Our second goal is to examine the relationship between systemic risk interconnectedness, regulatory changes and bank and economic performance. Specifically, we want to assess whether the implementation of Basel III regulations had an impact on standard economic and bank performance proxies, connectedness between banks and the exact nature of those relationships. The regulatory variables we use are Tier 1 capital adequacy (T1CA), total capital adequacy (TCA) and liquidity coverage (LC) ratios, available at monthly frequency from the SARB BA700 monthly reports.[1] We conduct a set of OLS and robust regressions as well as vector autoregressive (VAR) and vector error correction (VEC) estimations for the entire 2008−2023 period, the 2008−2012 sub-sample prior to regulatory adoption and the 2013−2023 subsample during and after Basel III adoption.

We find that capital adequacy ratios have a clear negative impact on bank connectedness and risk spillovers but no effect on tail risk dependency for the 2013−2023 period. However, there is no relationship during the 2008−2012 period prior to implementations. Liquidity coverage, on the other hand, is not related to bank connectedness. The result holds when controlling for both economic and bank performance proxies. In addition, there is causality between both capital adequacy ratios and both DCI and SI, but no causality with FRM. A regulatory policy shock has a lasting but not permanent effect on connectedness in 2013−2023 but no effect in 2008−2012. When connectedness, economic performance and regulatory metrics are considered jointly, the findings are persistent. The impact of a regulatory policy change is again strong, but the effect on bank

[1] SARB data for the net stable funding ratio (NSFR) are only available from 2019 onwards.

performance is weaker. Thus, Basel III implementation has been successful in mitigating the interconnectedness aspect of systemic risk in the South African banking sector, but only partially. Although capital adequacy ratios seem to have created buffers and a relative degree of autonomy for each bank, liquidity coverage plays a smaller role. Crucially, Basel III regulations do not have an impact on tail connectedness (FRM), and therefore are unable to reduce the probability of a systemic event; they can only mitigate its effect. In addition, the effect on bank performance, most notably return on equity, is limited.

We thus contribute to the literature in two ways. Firstly, we fill the gap in interconnectedness research and its relationship with regulation at a country level for South Africa. Market-based studies on interconnectedness for South Africa are largely absent from the literature, despite the importance of the topic for the South African banking sector and the potential consequences of distress in a systemically important institution. Earlier research focuses on measures of systemic risk that do not account for interconnectedness, or discusses interconnectedness in a significantly different framework and with varying aims (e.g. shadow banking in Kemp 2017), interconnectedness between African countries (Ogbuabor et al. 2016; Saidane, Sène and Kanga 2021) and non-market-based data such as balance sheet information. In one of the few papers that focuses on spillovers due to adverse stock market shocks, Koziol (2022) finds that the concentrated structure of the South African banking system has a positive effect on shock absorption, but the gradual shift towards more similar asset portfolios has increased exposure to price-mediated contagion. Our second contribution is to show the successes and limitations of recent regulatory policy and identify areas for improvement in a manner that is relevant, applicable and useful for SARB policymakers and commercial banks. Basel III has increased capital buffers without affecting profitability, but liquidity shortages have not improved.

2. Literature review

In the aftermath of the financial crisis, Esterhuysen, van Vuuren and Styger (2011) detected an increase in South African bank systemic risk, although they find that it is less severe than that faced by other international banks. This finding aligns with the experiences of Brazil, China and India, which were much less affected by the crisis (the Chinese stimulus package notwithstanding). Regulatory interest is summarised in

Zongwe (2011), who is pre-emptively concerned about the lack of liquidity and capital standards in the Southern African Development Community framework. With the recent introduction of new regulation (see Hollander and van Lill (2019) for an overview and critique) and the movement to a Twin Peaks regulatory regime with clearer, enshrined responsibilities and mandates (see van Heerden, van Niekerk and Huls (2020) and van Heerden and van Niekerk (2021) for an overview), we are motivated to examine its success. Rapid credit growth, a main source of financial instability, comes at a huge cost to economic growth due to the financing of risky and unsustainable investments (Ibrahim and Alagidede 2018). Political institutions have a positive impact on credit risk in the long run but a negative impact in the short run (Zhou and Tewari 2018). Batsirai, Tsegaye and Khamfula (2018) argue that monetary policy alone proved to be less efficient in mitigating the effects of systemic risk, particularly during the 2007 financial crisis, necessitating the implementation of macroprudential banking regulation. It is evident that the actions of regulators and policymakers can have great implications for the financial system, including preventing potential contagion (Havemann 2019).

The literature on systemic risk in South Africa is characterised by the popularity of "bank versus market" metrics and the consensus that systemic risk during the last decade has increased. For example, Chatterjee and Sing (2021) are typical in using ΔCoVaR (Tobias and Brunnermeier 2016), marginal expected shortfall (Acharya et al. 2017) and SRISK (Brownlees and Engle 2017) to find increased systemic risk and probabilities of an economic downside. CoVaR yields similar findings on individual bank contributions as well as a rapid increase in systemic risk (Manguzvane and Muteba Mwamba 2019). Leukes and Mensah (2019) report an increase in spillovers during distressed periods and find banks and insurance firms to be the highest contributors to systemic risk. However, CoVaR is not designed to measure spillover effects but rather tail co-dependency between pairs of institutions. External macroeconomic factors significantly affect spikes in systemic risk, measured by SRISK (Foggitt et al. 2017). Credit derivatives increase marginal expected shortfall in the long run but equity derivatives and increased liquidity decrease it, while liquidity has a positive relationship with systemic risk in the short run (Zhou 2021).

When examining an individual institution against the benchmark or looking at pairs of interactions, the general consensus is that systemic risk in the South African banking sector has remained consistently high during the last decade. However, there is scant discussion of how distress in one institution can be transmitted to others, how extensive and strong those channels of interaction can be, and which banks are the most or least connected. Interconnectedness measures, such as the ones we use, are notably absent from the literature. According to our knowledge, Koziol (2022) and Kemp (2017) are the only papers that explicitly discuss bank interconnectedness in the South African banking system, with Kemp (2017) connecting the issue with shadow banking.

However, interconnectedness measures are used to assess influence from abroad at a country level for groups of African economies. The methodologies include networks of variance decompositions (Ogbuabor et al. 2016), a variant of which we also employ, and default probabilities and distance to default (Saidane, Sène and Kanga 2021). There is significant transfer of risk from other countries to South Africa’s banking sector, while the amount of foreign capital invested in a bank is found to be a strong predictor of a bank’s international exposure (Manguzvane and Muteba Mwamba 2022). Most banks in the West African Economic and Monetary Union have a very low probability of default but there is a high joint probability of default for most pairs of banks. If the financial strength of large banking groups deteriorates, contagion effects could weaken the union (Saidane, Sène and Kanga 2021). Although large South African banks are analysed in these studies, the policy context and implications differ greatly from ours, which serves as further motivation for this study.

3. Data and methodology

3.1 Sample description

A comprehensive description of the dataset and summary statistics can be found in Table 17 in the annexure. The sample consists of nine South African banks listed on the Johannesburg Stock Exchange that have a bank licence, according to the SARB database.[2] This excludes conglomerates that also include a bank, for example Discovery, which is not listed as a banking entity separate from the conglomerate.

[2] Transaction Capital is excluded due to limited data and Absa Group is represented by Absa Bank. Finbond, a mutual bank, is included due to its size, after having verified that its presence does not distort the results.

The means and standard deviations are reported on the raw levels of each variable before taking logs or first differences. The “Scale/Difference” column denotes the transformations applied prior to estimation. The longest period is January 2008−March 2023 and covers the regulatory changes implemented in the aftermath of the global financial crisis, the stimulus-fuelled bull market, the COVID-19 turmoil, supply chain disruptions and the recent increase in inflation and energy prices. Regulatory and bank performance data are collected as monthly sector aggregates from the SARB BA700 Reports from 2008 and 2009 onwards respectively. Daily stock prices in South African rand are from Refinitiv Eikon and are used for log returns in the estimation of DCI, SI and FRM. The indices are produced daily, but the value at the end of each month is used in model estimation, so their statistics are reported as monthly. The three indices are first-differenced when necessary. Macroeconomic variables are available from SARB and Federal Reserve Economic Data (FRED) in monthly frequency, apart from the real retail property price index (RRPPI), which is available in quarterly frequency and interpolated to monthly. All variables are in log scale; first differences, if necessary due to non-stationarity, are denoted by the percentage symbol.

We separate estimation for all methods into three periods. These are 2008−2023 (whole sample period), 2008−2012 (pre-Basel III implementation) and 2013−2023 (during/after Basel III implementation), with the following exceptions. Bank performance metrics are only available from 2009 onwards, which reduces the whole and pre-Basel III periods by one year, or twelve monthly observations. In addition, liquidity coverage is available from 2015 onwards. The time frames are clearly denoted in all cases as a reminder to the reader.

3.2 Interconnectedness measures

3.2.1 Granger causality networks

Granger causality networks (Billio et al. 2012) are a popular method for examining potential spillovers and transfers of risk between institutions. The framework allows us to identify the direction of spillovers in stock returns in a sample of banks. Time series *j* Granger-causes another time series *i* if the information contained in the past values of both *i* and *j* is more useful in predicting the value of *i* than the information based only on the past values of *i*. Formally,

$$(j \to i) = \begin{cases} 1, & \text{if } j \text{ Granger-causes } i \\ 0, & \text{otherwise} \end{cases}$$

and $(j \to j) \equiv 0$. This leads to a set of causal relationships between pairs of firms that can be visualised as connections between N nodes, scaled by bank market capitalisation, where each node represents a bank. This is the Granger causality network. The network can also be represented as an N_t-dimensional adjacency matrix A_t, with its elements $\alpha_{ijt} = \{0,1\}$. A value of 1 means that node *j* Granger-causes node *i*, while a value of 0 means there is no Granger causality. Returns are assumed to follow a generalised autoregressive conditional heteroskedasticity GARCH(1,1) model. This helps us identify the institutions with the greatest influence over their competitors, which can cause, transfer or receive systemic distress if a negative shock occurs. Finally, we condense the network of interactions into the dynamic connectedness index (DCI), defined as

$$\binom{N_t}{2}^{-1} \sum_{i=1}^{N_t} \sum_{j=1}^{N_t} \alpha_{ijt} \tag{1}$$

where α_{ij} denotes a causal connection between banks *i* and *j*. DCI thus captures the number of statistically significant Granger causality relationships among all pairs of financial institutions over time.

3.2.2 Financial risk meter

The second approach, FRM by Mihoci et al. (2020), is based on CoVaR. It considers the tail event probability of bank *j* conditional on the distress of bank *i*, representing a bivariate tail dependence system. While CoVaR associates a particular financial institution with the financial system or another firm, and thus measures the value-at-risk of the financial sector conditional on the financial institution being in distress, FRM aims to simultaneously capture all interdependencies in one number. This is achieved via LASSO quantile regressions using stock returns and macroeconomic variables as risk factors (system nodes) at a 5% level, thus creating a network of CoVaR dependencies (since the bottom quantile corresponds to the 5% value-at-risk of an institution). The method condenses the high-dimensional tail stress into a single, straightforward real value index-type indicator: the FRM. Thus, FRM is the average over the selected LASSO penalisation terms and is calculated at each time step and for each node. Its size contains essential information on the active set of influential neighbouring nodes and on the contributors to systemic risk. The reason for using both approaches is that Granger causality aims to capture the size of the network, while FRM aims to capture the potential effect of distress within the network.

3.2.3 Spillover index

The third approach, the spillover index (SI) is the total index of directional spillovers of stock returns volatility (Diebold and Yilmaz (2012, 2014). The directional spillovers are based on generalised forecast error variance decompositions (FEVD) on the corresponding generalised VAR model. The limitations of Cholesky decomposition and ordering in orthogonalised VAR models are, therefore, absent. The variances are divided into own variance shares (H-step ahead error variances in forecasting series x_i that are due to shocks in x_i) and spillover variances (H-step ahead error variances in forecasting series x_i that are due to shocks in x_j) and then the generalised FEVDs are calculated and normalised to sum to 1. The total spillover index $S^g(H)$ is the sum of the normalised FEVDs due to shocks in other series (i.e. the sum of all FEVDs of *i* due to shocks in all other series across all *i*) divided by the number of series. For *N* assets including *i, j* and normalised generalised FEVDs $\theta_{i,j}$, the total SI and directional SI $S_{i.}{}^{g}(H)$, which measures the spillovers received by asset *i* from all other assets *j*, are

$$S^g(H) = \frac{\sum\limits_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} 100 \tag{2}$$

$$S_{i.}^g(H) = \frac{\sum\limits_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} 100 \tag{3}$$

The difference $S_{i.}^{g}(H) - S_{.i}^{g}(H)$ yields the net spillovers for a particular firm. We select a parametrisation of two lags and H=4. A complete description can be found in Diebold and Yilmaz (2012).

In order to detect the presence of different regimes in the connectedness indices, we estimate a two-state dynamic regression Markov switching model of the form

$$Stab_t = \mu_{st} + \epsilon_t, \epsilon \sim N(0, \sigma^2) \quad (4)$$

where the standard deviation is constant but there are two states s = [1,2] with low (μ_1) and high (μ_2) means respectively. Estimations with different standard deviations across states led to markedly similar standard deviation parameters and marginally lower information criteria, so we opted for the simple model.

3.3 Models and methodology

To assess the relationship between bank regulation and interconnectedness while controlling for macroeconomic and bank performance indicators, we specify the following generic ordinary least squares (OLS) regressions estimated over the three sample periods 2008/9−2012, 2008/9−2023, 2013−2023. For regulatory variable indicator *Reg*, connectedness measure *CN* and vectors *M,BP* of macroeconomic or bank performance controls respectively, the models are

$$CN_t = \alpha + \beta_1 Reg_t + \beta_j M_t + \epsilon_t \quad (5)$$

$$CN_t = \alpha + \beta_1 Reg_t + \beta_j BP_t + \epsilon_t \quad (6)$$

Both are standard contemporaneous regressions. *Reg* represents Tier 1 capital adequacy, total capital adequacy or liquidity coverage, depending on the case. *M*, the vector of macroeconomic variables, includes gross domestic product (GDP, %), the three-month interbank rate (%), consumer price index (CPI, %), the Exports/Imports ratio (%), M3 and the Real Residential Property Price Index (%). *BP*, a vector of bank performance variables, includes return on equity (RoE, %), the cost-to-income ratio (%), net interest income to interest-earning assets, operating expenses to total assets (%), liquid assets held to liquid asset requirements (%), short-term liabilities to total liabilities (%) and 10 largest depositors to total funding (%). All variables are in log scale and % denotes first log differences for stationarity. We estimate the models using OLS regressions with and without heteroskedasticity robust errors as well as robust regressions to take into account the possible impact of outliers in the sample. Each of the equations (1) and (2) denotes the six combinations of *CN* (*DCI, SI, FRM*) and *Reg* (*T*1*CA, TCA, LC*) under the set of controls *M* or *BP*.

Our next aim is to detect whether a change in regulatory policy has an impact on interconnectedness. We thus estimate a series of two-dimensional VAR models in first differences and examine their generalised impulse response functions (IRFs) in order to assess whether a shock in regulation has a statistically significant effect on systemic risk before Basel III is implemented, after and during its implementation and over the whole sample period. This is, again, a pairwise estimation between pairs of regulatory variables (T1CA, TCA, LC) and interconnectedness indices (DCI, FRM, SI).

Our final aim is to examine causal relationships between interconnectedness, bank regulation and economic or bank performance measures for each of the three sample periods. We first conduct Granger causality tests between the same pairs of regulatory and connectedness measures as those used in the VAR models. Then we estimate sets of three-dimensional vector error correction models (VECMs) at the levels of the variables and examine the coefficients as well as their generalised IRFs. Each VECM contains a regulatory variable, an inderconnectedness index and either GDP or RoE as economic and bank performance proxies respectively. This expands on the regressions and VAR models, since cointegration at the levels of the variables, long- and short-run effects and persistence in policy changes can also be taken into account.

4. Empirical results

4.1 Estimation of interconnectedness indices

Figure 1 shows the DCI for South African banks of Granger causality relationships identified daily between January 2008 and March 2023. The index captures the number of pairwise causality connections of an institution to others (IO), conditional on its type (IOO). Figure 2, Panel a, illustrates the network and average adjacency matrix for the whole period, and Panel b illustrates variance spillovers from and to each bank, as well as net spillovers. The adjacency matrix is a more comprehensive way to depict average Granger connections. The rows determine whether the row institution affects the column institution. If the square in the row of bank X and the column of bank Y is shaded, this denotes a causal relationship from X to Y. If the square of row Y with column X is shaded, bi-directional causality is denoted; if not, it is unidirectional.

DCI records a pronounced increase in the number of connections during the 2008−2010 financial crisis and a large, rapid decrease afterwards. After 2013, DCI (Figure 1, Panel a) remains stable at low levels, apart from a surge in late 2015 that lasts for a year and reaches 2010 levels. Connectedness during COVID-19 is moderately higher and more volatile than pre-COVID-19 levels but still well below the 2010 and 2015 peaks. The relatively small sample leads to a small number of connections, which is also related to the high degree of concentration of the banking system. The FRM graph in Panel b shows that tail connectedness has remained low and stable apart from a notable sudden increase in mid-2014 and some lower, very brief, high points. Finally, the SI graph in Panel b shows a more nuanced image. Risk is reduced or stable at a low level between 2008 and 2015 but increases rapidly during the 2015−2017 period, with a very high peak in 2016. This period coincides with global growth and systemic risk concerns and is observed, to a lesser degree, in the DCI plot. The steep decline in 2017 and subsequent increase during COVID-19 also reflect international experience. Notably, after COVID-19, the contribution of Nedbank and Investec have grown considerably (Figure 2, Panel b). Absa Bank has consistently low spillovers and Standard Bank consistently high spillovers, with the rest remaining at low levels.

The adjacency matrix shows that the largest institutions (FirstRand, Standard Bank, Absa) the most influential, although contributions from smaller banks are present. FirstRand and Standard Bank affect all other banks apart from Finbond but are affected by only two institutions each. Notably, Absa Bank, the third-largest in the country, affects only Nedbank and RMB but is affected by six banks, highlighting potential exposure to spillover effects. The number of connections between smaller banks is moderate, showing the clout of larger banks in the South African banking sector. Nedbank and RMB, with five connections each, are the exceptions. This shows a rather more complex system than is suggested by the perceived vast influence of the three largest banks. Smaller banks, on the other hand, moderately affect each other but do not affect their larger counterparts.

We complete the analysis of the indices with the Markov switching results and assess whether there are different regimes in each index. The joint plots of the indices and the transition probabilities can be found in Figure 3, while Table 1 reports the parameter estimates. In all cases the transition probabilities are remarkably persistent, which implies that the changes between the high and low regimes are clear. Both DCI and SI exhibit similar patterns up until 2016, with the low mean State 1 (low connectedness) dominating the plot. DCI is in the high mean State 2 until mid-2010, while SI has only two brief changes during the same period. After 2016, the behaviour is markedly different. While both measures are in State 2 in 2017, SI remains in it until the end of 2022 (roughly the end of the COVID-19 period), with a brief break, and then switches to State 1. On the other hand, DCI remains in State 1 throughout 2017−2023, with one very brief change. Overall, DCI exhibits more and very short changes from State 1 to State 2 but spends much more time in the low mean state. On the other hand, overall spillover riskiness appears to have remained consistently high until the end of COVID-19. FRM remains almost entirely in State 1, apart from two blips when the massive peaks are realised. This supports our initial intuition to examine three different aspects of interconnectedness, since they appear to be governed by different dynamics. Low causality does not seem to be accompanied by low overall risk spillovers.

4.2 Relationships between regulatory measures and connectedness

4.2.1 Regression results with macroeconomic controls

The regression results show that an increase in capital adequacy ratios leads to a reduction in both interconnectedness and total risk spillovers between banks after the introduction of Basel III. On the other hand, liquidity does not have an impact and tail risk is not affected by regulation. We estimate models (1) and (2) via OLS and robust regressions over the pre-Basel III period (2008−2012), during and after its implementation (2013−2023) and for the whole period (2008−2023), rotating the pairs of connectedness indices and regulatory variables while keeping the control variables in each model the same. We first present the results under macroeconomic controls, with DCI as the dependent variable over the three periods, and Tier 1 capital adequacy (Table 2), total capital adequacy (Table 3) and liquidity coverage (Table 4) as independent variables. The standard errors for simple OLS are in parentheses while heteroskedasticity and autocorrelation robust standard errors are in brackets. We then repeat the estimation with FRM and SI as dependent variables.

There is a strong negative relationship between T1CA and DCI in both the 2013−2023 and 2008−2023 samples, which becomes insignificant in the 2008−2012 period. The value of the coefficient is -0.53 after 2013 and is statistically significant at 1% and 5% but becomes insignificant with a value of -0.10 prior to 2012. The result for the robust regression is similar, where the parameter value of -0.46 is statistically significant at 1%. The same finding holds for TCA but with even stronger effects. The parameter values are -0.72 for OLS and -0.61 for robust OLS, which are statistically significant at 1% and 5% for the 2013−2023 period and insignificant for 2008−2012. For the whole sample, the regulatory variable is, again, negative and significant at 1% and 5%. The regression R^2 and F statistics show that all models are statistically significant. Finally, with LC as the independent variable, all controls are statistically insignificant. For the 2015−2023 period, the liquidity coverage coefficient is positive, with a value of 0.32, but is statistically insignificant under OLS and robust errors. The F-statistic is statistically insignificant, which means that the model has very low explanatory power. Hence, we cannot draw any meaningful conclusions from LC. Thus, our findings suggest that the implementation of Tier 1 capital adequacy and total capital adequacy ratios reduced interconnectedness and causality network effects among South African banks, but liquidity provisions did not have any impact.

When we examine tail connectedness using the FRM index (Table 5), we also find that the coefficients of T1CA, TCA and LC, as well as most controls, are statistically insignificant. Since the results are homogeneous across regulatory variables and periods, we only report the case of FRM as the dependent and T1CA as the independent variable. The explanatory power and statistical significance of the model under OLS estimation are non-existent, but F-values are significant at 1% level for the robust regression. This is sensible, given the tremendous peak in FRM. Also, most of the macroeconomic variables are statistically significant for the robust OLS in 2013−2023 and exhibit a reasonable negative relationship with FRM. To some extent, we can conclude that the implementation of Basel III regulations did not manage to reduce or otherwise impact on tail connectedness across the network of banks in the sample.

We finally turn our attention to SI under macroeconomic variables and with TCA (Table 6), T1CA (Table 7) and LC (Table 8) as independent variables. The results are similar but slightly weaker than those under DCI. All three regulatory variables are insignificant for 2008−2023 and 2008−2012 but T1CA and TCA are significant at 1% and 5% respectively for the 2013−2023 period under OLS. The coefficients are negative, showing that the implemented regulation reduced spillovers. The coefficients of the robust regressions are generally insignificant, as are the parameters of the control variables. When LC is the independent variable (Table 8), its coefficient is insignificant. We conclude that spillovers of overall riskiness have been reduced due to an increase in capital adequacy after Basel III.

4.2.2 Regression results with bank performance controls

We then estimate model (2), which includes the same combinations of indices and regulatory measures as model (1) but with bank performance variables as controls. After excluding possible candidates due to large correlations, we select seven controls that range from commonly used metrics (return on equity) to measures that reflect the high concentration of the South African banking sector (10 largest depositors). Table 9 and Table 10 report the results for Tier 1 capital adequacy and total capital adequacy when DCI is the dependent variable. Both ratios have a statistically significant (1%) negative effect on connectedness after 2013 and in the 2008−2023 period but no effect in 2008−2012. This is robust to the findings of the previous section. However, when SI becomes the dependent variable, the F-statistics are all insignificant (Table 11 and Table 12). Nevertheless, both regulatory variables have an unreliable negative effect on the SI after 2013 but not prior to Basel III.

LC is also found to have a negative impact on SI, but the F-statistic is insignificant (Table 8). LC does not have an effect on DCI under bank performance controls (Table 4). Few control variables are statistically significant when LC and SI are used. When DCI and LC are combined, more controls are significant. There is no discernible pattern or consistency, and overall the regression results are not informative when bank performance controls are used. As above, the FRM results are omitted as they are statistically insignificant and uninformative.

Overall, after controlling for bank performance, Basel III regulations have an impact on causal networks among banks but do not affect total risk spillovers. This provides more nuance, although the results for capital adequacy ratios are still robust.

4.3 Granger causality and policy shocks

Our results thus far show a clear effect of regulatory policy on bank connectedness, but they are based on correlation coefficients and do not consider lags. It is important to assess the causal relationships between DCI and TCA, T1CA and LC and examine whether a change in capital adequacy and liquidity ratios can lead to a change in connectedness. The findings support our earlier conclusions and show mostly unidirectional causality, with some bidirectional cases, from regulatory ratios to the connectedness indices after 2013 but not before.

We specify a VAR(2,1) model with one interconnectedness index (DCI, SI), one policy variable (TCA, T1CA, LC) and one lag, according to the Akaike and Bayesian information criteria. We then test for Granger causality and present the generalised IRFs to identify whether a one-standard-deviation shock of the policy variable has an impact on bank connectedness (for completeness, we also report the opposite). Table 13 reports Granger causality for the six pairs of variables over the 2008−2012, 2013−2023 and 2008−2023 periods. There is bidirectional causality between Tier 1 capital adequacy and DCI as well as unidirectional causality from total capital adequacy and DCI in 2013−2023. There is also unidirectional causality from T1CA and TCA to DCI in 2008−2023 and 2008−2012. No causal relationships are found between liquidity coverage and DCI but, in contrast, there is a strong causal relationship from LC to SI. There is also bidirectional causality between TCA and SI and causality from T1CA to SI in 2013−2023. This is similar to our findings for DCI. However, for the 2008−2023 period, causality flows from SI to both TCA and T1CA.

Our results show that regulatory variables Granger-cause bank connectedness in a persistent, robust manner, since most of the p-values are below 5%. There is, therefore, an impact of capital ratios and, to an extent, regulatory policy on both interconnectedness (DCI) and total risk spillovers (SI). On the other hand, requirements for highly liquid assets do not impact causal relationships between banks but do affect overall riskiness (SI). A possible explanation for the lack of a relationship between LC and SI may be the chronic liquidity issues of the South African banking system. Although capital ratios often exceed regulatory requirements for the periods we consider, they increase steadily after 2013. Our findings thus suggest that the capital buffer policy can have an impact even for well-capitalised banks, instead of focusing only on those close to the prudential capital ratio of about 11%.

Figure 4 reports the generalised IRFs of a policy shock of one standard deviation on DCI. The results are similar to our earlier findings on Granger causality and regressions. The IRF of DCI when T1CA or TCA is shocked is statistically significant in 2013−2023 and 2008−2023 but not in 2008−2012. The function takes negative values, implying a negative reaction to an increase in regulatory requirements, similar to the regressions. However, the observed convergence back to the steady state is very slow and is finalised after 120 periods. The IRF peaks at around period 10 and becomes statistically significant from periods 2 and 3 onwards. This is a striking finding that shows a highly persistent impact of Basel III regulations as well as the impact of further policy changes. The IRFs between the SI and the two regulatory ratios are also statistically significant in 2008−2023 and 2013−2023, although for shorter periods, and converge back to equilibrium faster. The intuition is again that a regulatory shock had a negative impact after Basel III was introduced but no effect beforehand. The IRFs for SI (Figure 5) show similar yet more pronounced behaviour. The IRFs of SI when both T1CA and TCA are shocked (Panel c) are significant and have a longer duration over 2013−2023 than the IRFs of DCI, yet are insignificant over 2008−2012 (Panel b). Over the entire sample (Panel a) they are statistically significant for a brief period and slowly converge to the long-run equilibrium. The conclusion is that policy shocks have a more lasting impact on overall risk spillover. Notably, when liquidity coverage is used (Figure 6), there is no impact of a shock on DCI but there is an impact on SI, albeit brief. This is an important result as LC often appears to be insignificant, and aligns with the earlier findings on Granger causality. The FRM results are not reported as no Granger causality is detected for all three regulatory variables, either from or to FRM.

We conclude that regulatory policy appears to have a clear impact on overall riskiness, proxied by SI. Its impact on the causality network in the banking system is present and extends to the pre-Basel III period. Liquidity coverage plays a role in overall risk spillovers but not in causality. The impact of policy shocks on the systemic risk measures confirms the effectiveness of regulation, although its impact varies.

4.4 The impact of regulatory shocks on connectedness

The VAR models above provide some evidence of the impact of changes in regulatory ratios on the connectedness aspect of systemic risk. However, they do not take into account the influence of macroeconomic factors or bank performance. Also, cointegration is ignored almost a priori in a VAR, since the inputs are first-differenced and in most cases stationary. We expand our analysis by including regulatory shocks, which also serves as a robustness check on causality. We estimate a series of three-dimensional VECMs that include a connectedness measure, a regulatory measure and either a macro or bank performance measure. This mirrors our earlier approach. We opt for VECMs over structural VAR models since there are few a priori grounds to impose restrictions on the variables via ordering or a Cholesky decomposition, including cointegration restrictions (which a VECM does not require). Based on earlier results, we drop FRM due to poor performance and TCA as it is largely similar to the more conservative T1CA. We select GDP as a macro proxy and RoE as a bank performance proxy due to their wide use and focus on four models. This allows us to focus on the effect of a policy shock on interconnectedness, economic growth and bank returns, as well as long- and short-run causality, in a more comprehensive manner. As earlier, estimation is over the 2008/2009−2012 pre-Basel III period, the 2013−2023 post-adoption period and the 2008/2009−2023 whole sample period, which contains the actual policy shift by default.

Each VECM is calibrated according to the Johansen test for cointegration and the Bayesian and Akaike information criteria for the optimal number of lags. Most of the models are VEC(3) with one cointegration relationship and three lags, apart from two which are VEC(0) with one cointegrating relationship. The VEC(3) models are VECM 1

(DCI, T1CA and GDP), VECM 2 (SI, T1CA and GDP), VECM 3 (DCI, LC and GDP), VECM 4 (SI, LC and GDP) and VECM 5 (FRM, LC and GDP). VECM 5 is the only model containing FRM that produces statistically significant results. The VEC(0) models are VECM 6 (DCI, T1CA and RoE) and VECM 7 (SI, LC and RoE). The models with SI, T1CA and RoE and DCI, LC and RoE are omitted due to the absence of cointegration and the insignificant results of the alternative corresponding structural VAR model. We report the estimation results and generalised IRFs for all three cases, with our primary focus on interconnectedness and on GDP or RoE being affected by the other two variables. The parameter estimates for VECMs 1 and 2 are reported in Table 14, for VECMs 3, 4 and 5 in Table 15 and for VECMs 6 and 7 in Table 16.

When DCI is the dependent variable in VECM 1, the error correction term is negative and significant at 1% level for the 2008−2023 and 2013−2023 periods but is insignificant for the pre-Basel III period. This agrees with our earlier results that capital adequacy ratios had a clear impact on bank interconnectedness. When GDP is the dependent variable, the results are telling. The error correction term in the 2008−2012 period is practically zero and significant at 1% but negative and insignificant for the whole sample and post-Basel III adoption periods. The lagged terms of DCI are all insignificant in 2008−2012 but DCI_1 and DCI_3 become negative and significant in 2012−2023 and 2008−2023. T1CA_1 exhibits a similar pattern. This implies that the adoption of Basel III regulations after 2013 dampened the weak long-run relationship between systemic risk interconnectedness and economic output, which had previously caused economic instability. However, it did not have a long-run positive impact on growth. The findings are largely similar when SI is used instead of DCI in VECM 2. The error correction term is negative and statistically significant in the 2013−2023 period but insignificant in the 2008−2012 and 2008−2023 periods when SI is the dependent variable. This, again, demonstrates the impact of regulation. When GDP is the dependent variable, the error correction term is, again, significant but essentially zero in 2008−2012, becomes negative and significant for the 2008−2023 sample but is insignificant in the post−2013 period. SI_1 and SI_2 are negative but SI_3 positive and all are statistically significant. This again implies that regulation caused spillover risk to stop having an impact on economic output in the long run.

The results when bank performance (RoE) is introduced in VECM 6 are, again, robust (Table 16, Panel a). The error correction term for DCI as the dependent variable is insignificant for the 2009−2012 period but negative and significant at 1% level for the 2009−2023 and 2013−2023 periods, which shows that Basel III regulations had a causal effect on bank interconnectedness. However, when RoE is the dependent variable, the error correction term goes from positive and significant at the 1% level in the 2009−2012 period to insignificant for the whole sample as well as the 2013−2023 period. This implies that regulation had no effect, either positive or negative, on bank performance but did have an impact on stability. When SI, LC and RoE are introduced in VECM 7 (Panel b), there is no long-run causality from the independent variables to SI, but there is causality when RoE is the dependent variable. This is one of the few occasions where a regulatory variable is found to have an effect on a bank performance measure.

The parameters of VECMs 3, 4 and 5 (Table 15), which are the variants with LC as the regulatory measure, are mixed. Liquidity coverage has no impact on DCI, but when GDP becomes the independent variable there are very strong positive long- and short-run effects. All LC lags are positive and statistically significant at 5% and 1%, along with the negative error correction term, which denotes a positive impact on GDP. At the same time, the signs of the spillover lags are mixed: DCI_1 is negative but DCI_3 is positive. When DCI is replaced by SI, the error correction term becomes statistically significant and positive, which denotes an unstable relationship. On the other hand, when GDP is the dependent variable, the results and intuition are largely similar to VECM 6. Thus, an increased liquidity coverage ratio is expected to lead to increased economic output. In addition, LC is the only measure that has an impact on FRM. The results of VECM 5 are surprisingly strong, with a negative and statistically significant error correction term but also interesting lagged effects: LC_{-1} has a positive and LC_{-3} a negative parameter, which denotes an initial increase in systemic risk followed by a reduction later. This is one of the rare occasions where estimation with FRM included produces statistically significant results.

The generalised IRFs show whether a shock on one variable has a positive or negative impact on another variable. They allow us to compare the pre-2012 and post-2013 periods and determine whether regulatory policy shocks have a different effect on bank risk, performance and economic output. We first focus on T1CA as the impulse variable and

DCI as the response variable (VECM 1) − that is, the effect on DCI if T1CA is shocked by one standard deviation. The respective IRFs (Figure 7) change from positive (2008−2012) to negative (2013−2023) long-term values. However, the 2013−2023 IRF contains a positive jump for the first periods before it settles to negative values. This may demonstrate an initial increase in connectedness as the entire sector tries to adapt to the policy change simultaneously, until the negative long-term effect is realised. For the same periods, the impact of a one-standard-deviation shock of T1CA on GDP is positive, albeit stronger in the 2013−2023 period than the 2008−2012 period. This demonstrates a stronger positive effect of regulatory changes on economic output relative to the pre-Basel III period.

We now move to the IRFs of VECM 2 (Figure 8), where DCI is replaced by SI. With the exception of subfigures (a) and (e), all the IRFs are statistically insignificant. A regulatory policy shock would have a brief positive shock around five periods after implementation in 2013−2023 but no further consequences. All the IRFs in Figure 9, where DCI, RoE and T1CA are included (VECM 6), are insignificant. When liquidity coverage is the regulatory variable (Figure 10), LC has a positive, statistically significant impact on GDP when both DCI (Panel a, VECM 3) and SI (Panel b, VECM 4) are included. Notably, the impact on GDP under SI lasts longer, for about five periods. Panel b also illustrates a negative impact on SI, while there is no such effect on DCI (Panel a). Finally, Panel c (VECM 7) shows that a policy shock has no statistically significant impact on RoE or SI, although the IRFs are negative.

To conclude, the results suggest that regulatory capital ratios reduced overall risk spillovers and causality in the network of banks. The impact of regulation on GDP output is present but less pronounced and is negligible on bank performance, although high liquidity coverage is associated with an increase in GDP.

5. Conclusion

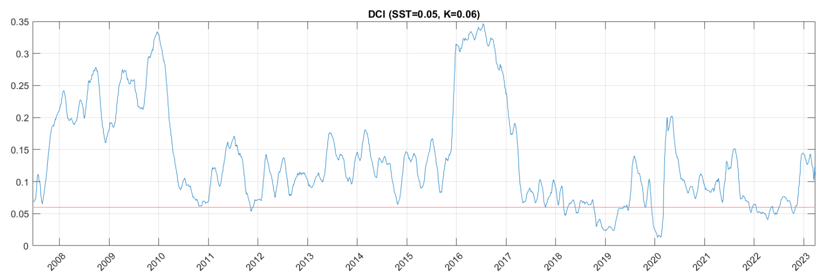
In this paper, we examined whether the adoption and implementation of the Basel III regulatory framework in the South African banking sector reduced connectedness risks in the country’s banking system and whether it had an impact on bank performance and stability. We estimated three interconnectedness indices that capture different aspects of risk spillover effects and assessed the impact of Basel III implementation in the South African banking system on financial stability, bank performance and the macroeconomy. The DCI captures the crisis transition mechanism based on aggregate Granger causality relationships in stock returns. The SI captures overall riskiness spillovers based on forecast error variance decompositions of bank stock returns. The FRM is an index of CoVaR-type tail dependence between the banks in the sample. We used three regulatory measures (Tier 1 capital adequacy, total capital adequacy and liquidity coverage) and examined whether their implementation after 2012 reduced spillover risks and whether there was an impact on bank performance and the real economy.

We find that the adoption of capital buffer ratios had a clear and robust impact on reducing Granger causality relationships and overall risk spillovers. The regulatory capital ratios T1CA and TCA are negatively related to DCI and SI, despite the concentration of the South African banking sector. The increase in bank resilience via increased capital buffers also increased autonomy to some extent, reducing both risk spillovers and the impact of potential domino effects. The impact of liquidity coverage is mixed. It is negatively related to overall risk spillovers when controlling for bank performance but does not affect tail risk or causality connections. Nevertheless, liquidity coverage has a strong positive effect on economic output. The lack of meaningful results when FRM is included illustrates the failure of Basel III to reduce tail risk spillovers. This is a stark reminder that capital ratios may act as buffers and help mitigate the impact of a systemic event, but they can do little to reduce the likelihood of its occurrence (Jordà et al. 2021).

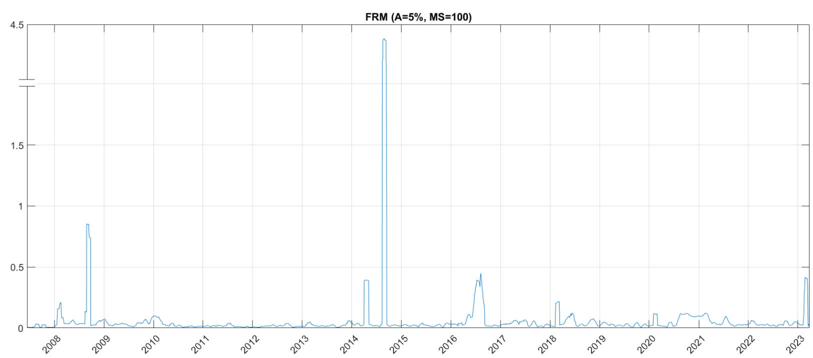
Regulatory success is thus only partial. Bank interconnectedness has to some extent been mitigated by Basel III regulations, and in that sense regulation improved financial stability. In that framework, regulatory policy acts as a mitigation rather than prevention mechanism, and its final outcome depends on how much capital would be available in the case of a systemic event. This result relates to the contemporary discussion on what role bank regulation plays in practice and, specifically, whether higher capital buffers are used as alternative monetary policy tools — for example as a means to reduce credit creation instead of increasing interest rates (Davies 2023). As a tangent to that discussion, we provide evidence that gradually increasing capital ratios can lead to a reduction in a particular aspect of systemic risk without affecting bank profitability. Basel III regulations neither improved nor worsened bank performance, and the limited impact of liquidity coverage is a symptom of the chronic liquidity problems of the South African banking system. These findings are useful to both policymakers and banks, as they highlight the successes and limitations of the implemented measures by emphasising the need to reduce tail risk and improve liquidity.

Figure 1: Interconnectedness indices, 2008−2023

(a) Dynamic connectedness index



(b) Financial risk meter



(c) Spillover index (SI)

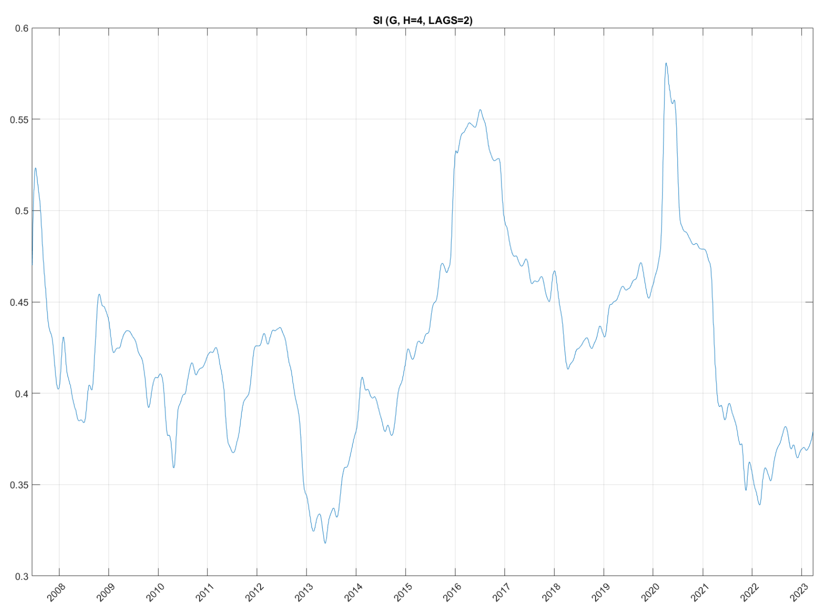
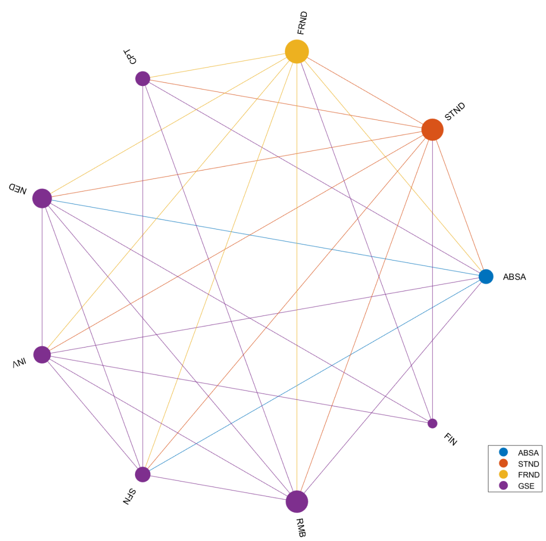
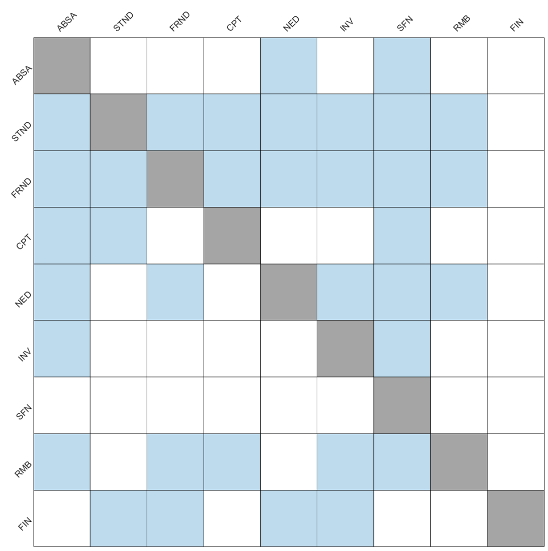


Figure 2: Granger causality and spillover graphs, 2008−2023

(a) Interconnectedness network of Granger-caused connections



(b) **Average adjacency matrix.** Blue cells denote causality from bank X to other banks (rows) and from other banks to bank X (columns).



(c) Spillovers from and to each bank (left) and net spillovers.

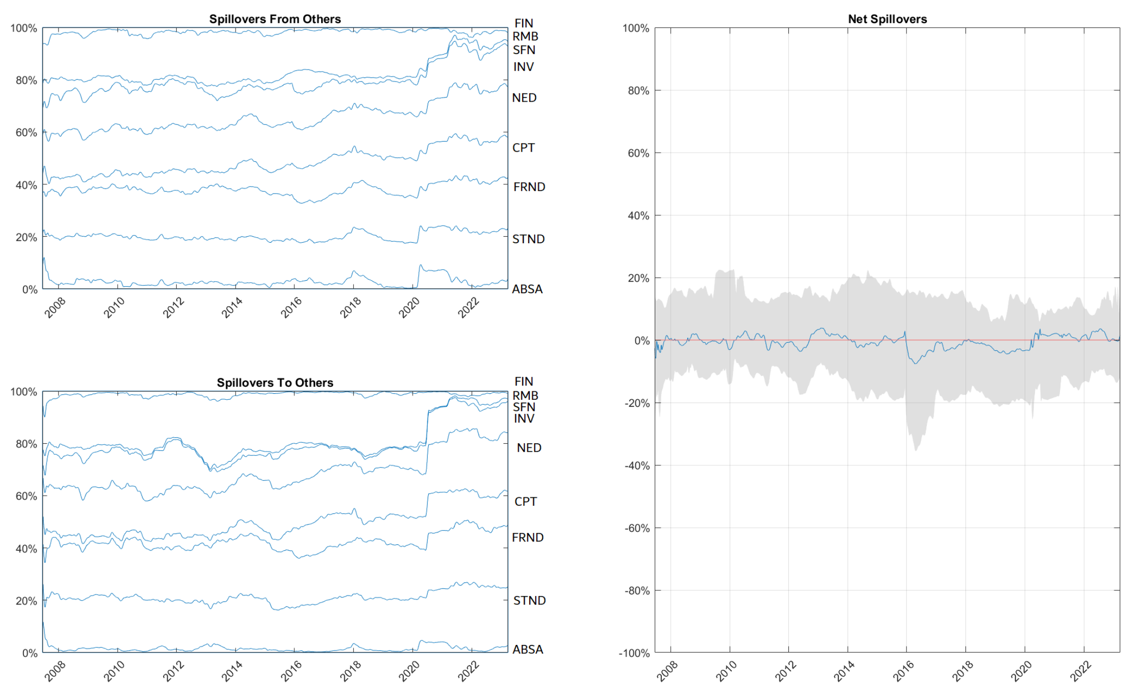
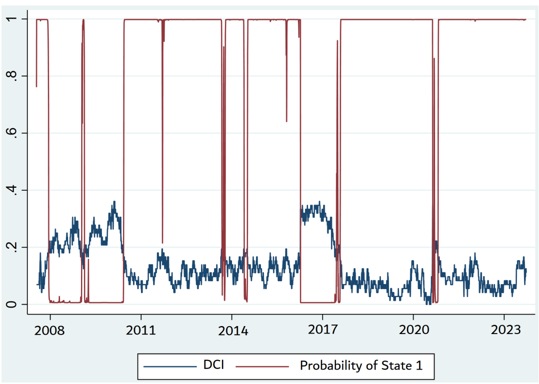
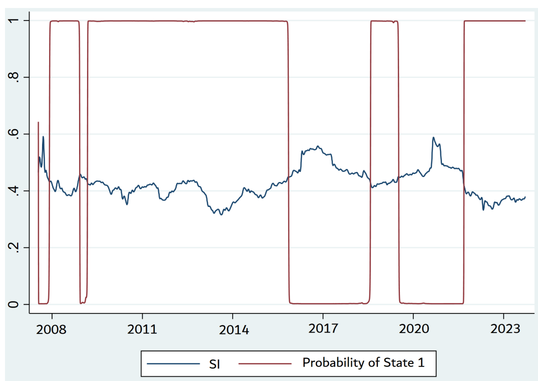


Figure 3: Interconnectedness indices (blue) and transition probabilities (red), 2008−2023

(a) DCI



(b) SI



(c) FRM

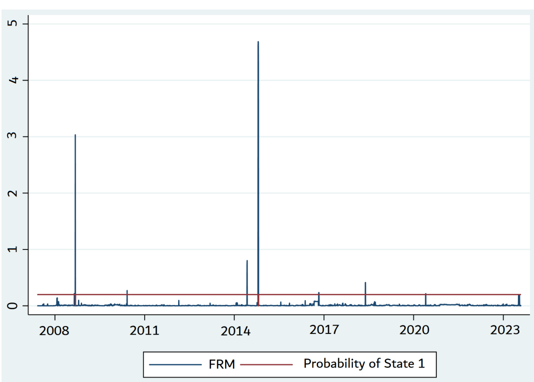


Table 1: Dynamic regression Markov switching results

Panel A: Parameter estimates								
SI			DCI			FRM		
μ_1	0.3958	(0.0007)***	μ_1	0.0954	(0.0009)***	μ_1	0.0433	(0.0027)***
μ_2	0.4871	(0.0010)***	μ_2	0.2510	(0.0018)***	μ_2	21.2665	(0.0760)***
σ	0.0330	(0.0004)	σ	0.0433	(0.0005)	σ	0.1698	(0.0019)***

Panel B: Transition probabilities from (row)/to (column)								
SI			DCI			FRM		
	1	2		1	2			
1	0.9986	0.0014	1	0.9980	0.0020	1	1	0.0000
2	0.0025	0.9975	2	0.0063	0.9937	2	0.0000	1

Note: Statistical significance at 1% (***), 5% (**) and 10% (*). Parameter standard errors in parentheses. Each transition probability row denotes the probability to move from the respective state to each other, e.g. $p_{12} = 0.064$ is the probability to move from State 1 to State 2.

Table 2: Regressions for DCI, T1CA and macroeconomic controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: DCI	2008−2023		2008−2012		2013−2023	
Intercept	-1.0106	-1.3893	0.89687	0.90556	-1.5196	-1.4215
	(0.3005)***	(0.2859)***	(1.1262)	(1.2110)	(0.4200)***	(0.37339)***
	[0.4770]**		[1.8223]		[0.7208]**	
T1CA	-0.3876	-0.4213	-0.1001	-0.1064	-0.5323	-0.3970
	(0.0564)***	(0.0537)***	(0.3204)	(0.3445)	(0.1024)***	(0.0910)***
	[0.1154]***		[0.4537]		[0.2394]**	
GDP (%)	-0.5217	-0.0837	-0.2417	0.1587	-0.6467	-0.1887
	(0.5107)	0.4859	(5.1322)	(5.5188)	(0.5557)	(0.4941)
	[0.2435]**		[8.0910]		[0.2517]**	
3m IB rate (%)	0.0506	0.0500	0.2569	0.2601	0.0140	-0.0129
	(0.0265)*	(0.0252)**	(0.1164)**	(0.1252)**	(0.0322)	(0.028674)
	[0.0725]		[0.1774]		[0.0852]	
CPI (%)	1.0440	1.7459	2.3148	2.4521	0.0022	1.2500
	(1.3864)	(1.3191)	(1.8015)	(1.9372)	(1.7758)	(1.5789)
	[1.5288]		[1.4536]		[1.2654]	
Exp/Imp	0.1101	0.1732	-0.0433	-0.0463	0.1324	0.1447
	(0.0509)**	(0.0484)***	(0.0823)	(0.0885)	(0.0650)**	(0.0578)**
	[0.0649]*		[0.1159]		[0.1042]	
M3	-0.0192	-0.0172	-0.0318	-0.0329	-0.0119	0.0012
	(0.0100)**	(0.0095)*	(0.0110)***	(0.0118)***	(0.0199)	(0.0177)
	[0.0102]*		[0.0146]**		[0.0278]	
RRPPI (%)	0.6325	0.7117	4.8735	5.0312	-4.8404	-1.136
	(1.6197)	(1.5412)	(2.0488)**	(2.2032)**	(3.2130)	(2.8567)
	[1.4928]		[3.1778]		[5.7816]	
R^2	0.3442	0.3970	0.6745	0.6480	0.2420	0.2660
Adjusted R^2	0.3179	0.3730	0.6307	0.6010	0.1958	0.2210
Standard error	0.0676	0.0640	0.0471	0.0506	0.0712	0.0637
Observations	183	183	60	60	123	123
F	13.1194***	16.5***	15.3941***	13.7***	5.2438***	5.95***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences. More detail about the variables can be found in the Annexure.

Table 3: Regressions for DCI, TCA and macroeconomic controls

IV: DCI	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
	2008−2023		2008−2012		2013−2023	
Intercept	-1.2401	-1.6230	1.1066	1.1097	-1.7402	-1.7090
	(0.3114)***	(0.2981)***	(1.1417)	(1.2270)	(0.4250)***	(0.3845)***
	[0.4884]**		[1.7320]		[0.7693]**	
TCA	-0.5137	-0.5508	-0.04213	-0.0528	-0.6721	-0.5415
	(0.0700)***	(0.0670)***	(0.3712)	(0.3990)	(0.1180)***	(0.1068)***
	[0.1347]***		[0.4757]		[0.2877]**	
GDP (%)	-0.5062	-0.0133	0.4971	0.9311	-0.6045	-0.1169
	(0.5022)	(0.4807)	(4.6454)	(4.9927)	(0.5436)**	(0.4919)
	[0.2326]**		[7.0167]		[0.2376]	
3m IB rate (%)	0.0481	0.0513	0.2802	0.2830	0.0133	-0.0060
	(0.0267)*	(0.0250)**	(0.1052)**	(0.1131)**	(0.0317)	(0.0287)
	[0.0678]		[0.1500]**		[0.0808]	
CPI (%)	0.0481	1.6807	2.2799	2.4076	-0.3184	1.1697
	(1.3668)	(1.3085)	(1.8042)	(1.9390)	(1.7495)	(1.5831)
	[1.5133]		[1.4477]		[1.2252]	
Exp/Imp	0.1261	0.1926	-0.0457	-0.0493	0.1491	0.1727
	(0.0506)**	(0.0485)***	(0.0836)	(0.0899)	(0.0643)	(0.0582)***
	[0.0673]*		[0.1210]		[0.1048]	
M3	-0.0214	-0.0196	-0.0313	-0.0323	-0.0153	-0.0022
	(0.0098)**	(0.0094)**	(0.0112)***	(0.0120)***	(0.0196)	(0.0177)
	[0.0108]**		[0.0150]**		[0.0284]	
RRPPI (%)	0.5822	0.73471	4.9663	5.1441	-4.4204	-1.4514
	(1.5951)	(1.527)	(2.0344)**	(2.1865)**	(3.0831)	(2.7899)
	[1.5229]		[3.0568]		[5.3916]	
R^2	0.3243	0.3800	0.6750	0.6490	0.2139	0.2380
Adjusted R^2	0.29720	0.3550	0.6313	0.6010	0.1661	0.1920
Standard error	0.0686	0.0646	0.0470	0.0506	0.0726	0.0639
Observations	183	183	60	60	123	123
F	11.9962***	15.3000***	15.4312***	13.7000***	4.4704***	5.1400***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 4: Regressions for DCI, LC, and macroeconomic (Panel a) or bank performance (Panel b) controls

	OLS	Robust OLS		OLS	Robust OLS
IV: DCI	Panel a, 2015−2023		IV: DCI	Panel b, 2015−2023	
Intercept	0.2020	0.0057	Intercept	-0.8697	-0.8163
	(0.4013)	(0.3584)		(0.1708)***	(0.1726)***
	[0.2992]			[0.4253]**	
LC ratio (%)	0.3202	0.1378	LC ratio (%)	0.1360	0.0833
	(0.2488)	(0.2222)		(0.2389)	(0.2415)
	[0.1840]			[0.1493]	
GDP (%)	-0.3427	-0.3655	RoE (%)	-0.3341	0.28227
	(0.7159)	(0.6395)		(2.0751)	(2.0976)
	[0.2761]			[2.9958]	
3m IB rate (%)	0.0114	-0.0420	CtoI (%)	-1.7580	-1.6542
	(0.0456)	(0.0407)		(0.3057)***	(0.3090)***
	[0.0992]			[0.7593]**	
CPI (%)	1.9676	0.9208	NII	4.6898	3.9249
	(2.4154)	(2.1574)		(1.7484)***	(1.7674)**
	[2.1585]			[3.1015]	
Exp/Imp ratio	-0.0135	-0.0100	OpExp (%)	-4.6982	-4.3939
	(0.0962)	(0.0859)		(1.6544)***	(1.6723)**
	[0.0643]			[2.2474]**	
M3	0.0043	0.0122	LA/LAreq (%)	0.4871	0.55458
	(0.0248)	(0.0222)		(0.3795)	(0.38365)
	[0.0241]			[0.2060]**	
RRPPI (%)	4.6547	6.4002	SL/TL(%)	0.3427	0.8192
	(4.1328)	(3.6524)		(0.6556)	(0.6627)
	[4.5022]			[0.5484]	
			10LD/TF (%)	-0.0519	-0.1142
				(0.0699)	(0.0706)
				[0.0581]	
R^2	0.0409	0.1140		0.3330	0.3130
Adjusted R^2	-0.0337	0.0452		0.2730	0.2520
Standard error	0.0891	0.0789		0.0747	0.0755
Observations	98	98		98	98
F	0.5481	0.1300		5.5500***	5.0700***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 5: Regressions for FRM, T1CA and macroeconomic controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: FRM	2008−2023		2008−2012		2013−2023	
Intercept	-0.3651	0.0177	0.6228	-0.0209	-0.6032	-0.4437
	(0.2711)	(0.1641)	(1.2271)	(0.9474)	(0.3784)	(0.2625)*
	[2.7196]		[1.1797]		[0.2955]**	
T1CA	-0.0112	0.0116	0.0481	-0.0822	-0.0045	0.0005
	(0.0532)	(0.0322)	(0.3491)	(0.2695)	(0.0989)	(0.0687)
	[0.0532]		[0.3258]		[0.0884]	
GDP (%)	-0.0037	-0.0029	-1.9567	-1.6593	-0.0069	-0.0048
	(0.0103)	(0.0062)	(5.5918)	(4.3174)	(0.0114)	(0.0079)
	[0.5609]		[5.9578]		[0.0029]**	
3m IB rate (%)	-0.0114	-0.0027	0.0499	-0.0229	-0.0273	-0.0392
	(0.0248)	(0.0150)	(0.1269)	(0.0979)	(0.0297)	(0.0206)*
	[0.0227]		[0.1290]		[0.0118]**	
CPI (%)	-1.2234	0.7266	-0.8304	0.4482	-1.4666	0.3316
	(1.3031)	(0.7889)	(1.9629)	(1.5155)	(1.6743)	(1.1616)
	[1.0137]		[2.0744]		[1.0993]	
Exp/Imp ratio	0.0761	0.0033	-0.064	-0.0423	0.1031	0.0645
	(0.0461)	(0.0279)	(0.0897)	(0.0693)	(0.0577)*	(0.0400)
	[0.0505]		[0.0577]		[0.0251]***	
M3	0.0025	0.0029	-0.0232	-0.0013	0.0456	0.0332
	(0.0093)	(0.0056)	(0.0119)*	(0.0092)	(0.0185)**	(0.0128)**
	[0.0110]		[0.0151]		[0.0066]***	
RRPPI (%)	-0.4002	-0.156	0.3257	0.4012	-2.5345	-1.7571
	(1.5145)	(0.9169)	(2.2323)	(1.7235)	(3.0141)	(2.0912)
	[1.1285]		[2.2204]		[1.1122]**	
R^2	0.0347	0.189	0.1304	0.148	0.1068	0.198
Adjusted R^2	-0.0039	0.157	0.0134	0.0338	0.0525	0.149
Standard error	0.0637	0.0386	0.0513	0.0396	0.0669	0.0464
Observations	183	183	60	60	123	123
F	0.90	5.84***	1.1143	1.29	1.965*	4.05***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 6: Regressions for SI, TCA and macroeconomic controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: SI	2008−2023		2008−2012		2013−2023	
Intercept	-0.2601	-0.0161	0.1119	0.3451	-0.3876	0.1568
	(0.1494)*	-0.1270	(0.96864)	(0.9124)	(0.1876)**	(0.1564)
	[0.1810]		[0.8901]		[0.2641]	
TCA	-0.0617	-0.0178	0.1226	0.2752	-0.1215	-0.0093
	(0.0343)*	-0.0291	(0.3085)	(0.2906)	(0.0507)**	(0.0423)
	[0.0348]*		[0.3118]		[0.0602]	
GDP (%)	-1.3037	-0.8332	2.1387	-0.6082	-1.3285	-0.7845
	(0.2447)***	(0.2079)***	(3.0472)	(2.8702)	(0.2291)***	(0.1911)***
	[0.3935]***		[2.5796]		[0.4176]***	
3m IB rate	0.0240	0.0100	0.1027	0.0930	0.0181	-0.0021
	(0.0127)*	-0.0108	(0.0843)	(0.0794)	(0.0136)	(0.0113)
	[0.0129]*		[0.0785]		[0.0157]	
CPI (%)	0.58311	0.2378	0.0511	0.4272	0.5469	0.1922
	(0.6665)	(0.5664)	(1.4392)	(1.3556)	(0.7480)	(0.6237)
	[0.6267]		[1.2600]		[0.7204]	
Exp/Imp ratio	0.0458	0.0022	0.0877	0.0956	0.0463	-0.038477
	(0.0243)*	-0.0206	(0.0698)	(0.0657)	(0.0282)	(0.0235)
	[0.0331]		[0.0541]		[0.0440]	
M3	0.0217	0.0133	0.0092	0.0094	0.0440	-0.0185
	(0.0127)*	-0.0108	(0.0187)	(0.0177)	(0.0213)**	(0.0178)
	[0.0178]		[0.0253]		[0.0267]*	
RRPPI (%)	1.9468	1.2164	2.0379	0.6494	0.6411	0.8795
	(0.7421)***	(0.6307)*	(1.3577)	(1.2790)	(1.3169)	(1.0980)
	[0.6991]***		[1.3380]		[1.4724]	
R^2	0.2050	0.1290	0.1450	0.1130	0.2990	0.2150
Adjusted R^2	0.1740	0.0940	0.0297	-0.0062	0.2560	0.1670
Standard error	0.0330	0.0280	0.0376	0.0354	0.0306	0.0255
Observations	183	183	60	60	123	123
F	6.46	3.7***	1.26	0.948	7***	4.5***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 7: Regressions for SI, T1CA and macroeconomic controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: SI	2008−2023		2008−2012		2013−2023	
Intercept	-0.2126	0.0097	0.8297	1.2242	-0.3397	0.1739
	(0.1413)	(0.1200)	(0.9715)	(0.9120)	(0.1822)*	(0.1516)
	[0.1743]		[0.9738]		[0.2587]	
T1CA	-0.0420	-0.0090	0.3245	0.5113	-0.0951	-0.0038
	(0.0274)	(0.0232)	(0.2771)	(0.2602)*	(0.0435)**	(0.0362)
	[0.0283]		[0.2985]		[0.0517]*	
GDP (%)	-1.2976	-0.8174	4.3821	2.123	-1.3323	-0.7798
	(0.2457)***	(0.2087)***	(3.5284)	(3.3121)	(0.2309)***	(0.1921)***
	[0.3957]***		[3.0312]		[0.4230]***	
3m IB rate	0.0251	0.0104	0.1791	0.1898	0.0182	-0.0022
	(0.0128)*	(0.0109)	(0.0961)*	(0.0902)**	(0.0136)	(0.0113)
	[0.0131]*		[0.0938]*		[0.0159]	
CPI (%)	0.6091	0.2615	-0.0412	0.3838	0.6101	0.2047
	(0.6677)	(0.5672)	(1.4212)	(1.3341)	(0.7480)	(0.6222)
	[0.6264]		[1.2004]		[0.7261]	
Ex/Imp (%)	0.0422	0.0002	0.0786	0.0875	0.0423	-0.0402
	(0.0240)*	(0.0204)	(0.0670)	(0.0629)	(0.0280)	(0.0233)*
	[0.0330]		[0.0569]		[0.0440]	
M3	0.0216	0.0129	0.0090	0.0057	0.0432	-0.0194
	(0.0127)*	(0.0108)	(0.0183)	(0.0172)	(0.0214)**	(0.0178)
	[0.0178]		[0.0250]		[0.0267]	
RRPPI (%)	1.9298	1.1985	2.0953	0.6832	0.5852	0.9206
	(0.7439)**	(0.6319)*	(1.3425)	(1.2602)	(1.3533)	(1.1257)
	[0.6998]***		[1.3467]		[1.5056]	
R^2	0.2010	0.1250	0.1640	0.1560	0.2930	0.2140
Adjusted R^2	0.1690	0.0901	0.0518	0.0423	0.2500	0.1670
Standard error	0.0331	0.0281	0.0372	0.0349	0.0307	0.0255
Observations	183	183	60	60	123	123
F	6.3000***	3.5700***	1.4600	1.3700	6.8100***	4.4900***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 8: Regressions for SI, LC and macroeconomic (Panel a) and bank performance controls (Panel b)

	OLS	Robust OLS		OLS	Robust OLS
IV: SI	Panel a, 2015−2023		IV:SI	Panel b, 2015−2023	
Intercept	-0.1837	0.1548	Intercept	-0.1131	-0.0399
	(0.1294)	(0.1047)		(0.0831)	(0.0690)
	[0.1776]			[0.0883]	
LC ratio (%)	-0.0049	0.0088	LC ratio (%)	-0.2633	-0.0548
	(0.0869)	(0.0704)		(0.1162)**	(0.0965)
	[0.1084]			[0.1873]	
GDP (%)	-1.3509	-0.7285	RoE (%)	-0.0121	0.1873
	(0.2446)***	(0.1980)***		(1.0092)	(0.8377)
	[0.4338]***			[1.5941]	
3m IB rate (%)	0.0390	0.0031	CtoI (%)	-0.2014	-0.0690
	(0.0162)**	(0.0131)		(0.1487)	(0.1234)
	[0.0194]**			[0.1575]	
CPI (%)	0.7034	0.2347	NII (%)	0.9847	-0.3272
	(0.8471)	(0.6857)		(0.8503)	(0.7058)
	[0.7134]			[0.9516]	
Exp/Imp ratio	0.0619	-0.0317	OpExp (%)	-1.0555	0.3237
	(0.0332)*	(0.0269)		(0.8046)	(0.6678)
	[0.0462]			[1.05578]	
M3	0.0531	-0.0106	LA/LAreq (%)	0.2921	-0.1331
	(0.0225)	(0.0182)		(0.1846)	(0.1532)
	[0.0275]*			[0.34617]	
RRPPI (%)	-0.4511	-0.5551	SL/TL (%)	-0.5993	-0.2025
	(1.4405)	(1.166)		(0.3188)*	(0.2647)
	[1.3783]			[0.3273]	
			10LD/TF (%)	-0.0127	-0.0022
	0.3360	0.2080		-0.0340	0.0282
	0.2840	0.1460		[0.0189]	
R^2	0.3360	0.2080	R^2	0.1120	0.0282
Adjusted R^2	0.2840	0.1460	Adjusted R^2	0.0320	-0.0592
Standard error	0.0313	0.0253	Standard error	0.0363	0.0302
Observations	98	98	Observations	98	98
F	6.5***	3.37***	F	1.4000	0.3220

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 9: Regressions for DCI, T1CA and bank performance

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: DCI	2008−2023		2008−2012		2013−2023	
Intercept	-0.5626	-0.4790	-0.8615	-0.8434	-0.5932	-0.4033
	(0.1233)***	(0.1090)***	(0.6548)	(0.7018)	(0.1605)***	(0.1426)***
	[0.1619]***		[0.8093]		[0.2754]**	
T1CA	-0.1989	-0.1163	-0.2752	-0.2779	-0.3466	-0.2328
	(0.0959)**	-0.0848	(0.3804)	(0.4077)	(0.1164)***	(0.10344)**
	0.1233		[0.4917]		[0.1361]**	
RoE (%)	0.6915	-1.1326	-2.7546	-2.7293	1.0876	0.0552
	(1.347)	-1.1906	(2.3049)	(2.4702)	(1.742)	(1.5486)
	1.5453		[2.2528]		[2.0203]	
CtoI (%)	-0.4801	-0.6078	-0.6760	-0.6356	-0.0124	-0.0578
	(0.2058)**	(0.1819)***	(0.3807)*	(0.4080)	(0.3018)	(0.26831)
	0.3495		[0.5568]		[0.4361]	
NII (%)	0.0011	-0.6059	-0.6079	-0.6872	1.8263	1.3498
	(0.8915)	(0.7880)	(1.4405)	(1.5438)	(1.4720)	(1.3085)
	1.4106		[1.0461]		[1.6823]	
OpExp (%)	-0.9362	-0.7877	-1.2874	-1.3378	-2.3781	-1.7047
	(0.8424)	-0.7446	(1.1314)	(1.2126)	(1.3575)*	(1.2067)
	1.1046		[0.8520]		[1.4712]	
LA/LAreq (%)	0.4606	0.5980	0.6626	0.6778	0.2657	0.3759
	(0.2349)*	(0.2076)***	(0.3168)**	(0.3395)*	(0.3044)	(0.27058)
	[0.1450]***		[0.3156]		[0.1825]	
SL/TL (%)	0.1673	0.8265	-0.4168	-0.3504	0.2845	1.1936
	(0.3626)	(0.3205)**	(0.5915)	-0.6339	(0.4661)	(0.4143)***
	0.2770		[0.3552]		[0.3195]	
10LD/TF (%)	0.0061	-0.0756	0.1056	0.0999	-0.0095	-0.1018
	(0.0495)	(0.0437)*	(0.0985)	-0.1055	(0.0580)	(0.0515)**
	0.0454		[0.0773]		[0.0500]	
R^2	0.2660	0.3870	0.6410	0.6010	0.1770	0.2220
Adjusted R^2	0.2300	0.3570	0.5670	0.5190	0.1190	0.1670
Standard error	0.0709	0.0627	0.0524	0.0562	0.0746	0.0663
Observations	171	171	48	48	123	123
F	7.3300***	12.8000***	8.7***	7.3400***	3.06***	4.07***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 10: Regressions for DCI, TCA and bank performance

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: DCI	2008−2023		2008−2012		2013−2023	
Intercept	-0.6583	-0.5357	-0.6446	-0.6801	-0.6930	-0.5013
	(0.1369)***	(0.1211)***	(0.6724)***	(0.7190)	(0.1686)***	(0.1517)***
	[0.2101]***		[0.8970]		[0.3171]**	
TCA	-0.2942	-0.1736	-0.1564	-0.1948	-0.4666	-0.3400
	(0.0102)**	(0.1002)*	(0.4198)	(2.5422)	(0.1343)***	(0.1208)***
	[0.1756]*		[0.6020]		[0.1793]***	
RoE (%)	0.7078	-1.1837	-3.0220	-2.9352	0.9349	0.0054
	(1.3357)	(1.1822)	(2.3774)	(2.5422)	(1.7189)	(1.5459)
	[1.5683]		[2.4109]		[2.0486]	
CtoI (%)	-0.4131	-0.5644	-0.8005	-0.7362	0.0753	0.0296
	(0.199)**	(0.1761)***	(0.3443)**	(0.3681)*	(0.2955)	(0.2658)
	[0.3565]		[0.5627]		[0.3955]	
NII (%)	-0.0704	-0.5998	-0.8682	-0.8980	1.8606	1.4988
	(0.8831)	(0.7817)	(1.3961)	(1.4928)	(1.4514)	(1.3053)
	[1.3892]		[1.1358]		[1.7004]	
OpExp (%)	-0.9158	-0.8238	-1.2354	-1.2868	-2.3913	-1.8420
	(0.8331)	(0.7374)	(1.1562)	(1.2364)	(1.3387)*	(1.2039)
	[1.0860]		[0.9254]		[1.4264]*	
LA/LA req (%)	0.4713	0.6080	0.6793	0.6917	0.2753	0.3745
	(0.2331)**	(0.2063)***	(0.3172)**	(0.3392)**	(0.3003)	(0.2701)
	[0.1463]***		[0.3179]**		[0.1837]	
SL/TL (%)	0.1834	0.8445	-0.4277	-0.3655	0.2997	1.1519
	(0.36006)	(0.3187)***	(0.5941)	(0.6353)	(0.4601)	(0.4138)***
	[0.2774]		[0.3441]		[0.3219]	
10LD/TF	0.0058	-0.0773	0.1036	0.0986	-0.0108	-0.1007
	(0.0491)	(0.0435)*	(0.0992)	(0.1061)	-0.0573	(0.0515)*
	[0.0461]		[0.0790]		[0.0504]	
R^2	0.2760	0.3930	0.6370	0.5980	0.1970	0.2310
Adjusted R^2	0.2410	0.3630	0.5630	0.5150	0.1410	0.1770
Standard error	0.0704	0.0623	0.0527	0.0563	0.0736	0.0662
Observations	171	171	48	48	123	123
F	7.7400***	13.1000***	8.5600***	7.2400***	3.500***	4.2800***

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 11: Regressions for SI, T1CA and bank performance controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: SI	2008−2023		2008−2012		2013−2023	
Intercept	-0.0839	-0.0552	-0.5416	-0.6905	-0.1372	-0.0837
	(0.0618)	-0.0503	(0.4409)	(0.4013)*	(0.0764)	(0.0637)
	[0.1619]***		[0.3900]		[0.2754]**	
T1CA	-0.0776	-0.0500	-0.3713	-0.4406	-0.0882	-0.0280
	(0.0481)	-0.0392	(0.2561)	(0.2331)*	(0.0554)	-0.0462
	0.1233		[0.2280]		[0.1361]**	
RoE (%)	-0.8836	-0.5470	-1.1039	0.1848	-0.4561	-0.1400
	(0.6750)	-0.5498	(1.5519)	(1.4124)	(0.8290)	(0.6913)
	1.5453		[1.2242]		[2.0203]	
CtoI (%)	0.1394	0.0884	0.4373	0.4361	0.0783	-0.0446
	(0.1031)	-0.0840	(0.2563)*	(0.2333)*	(0.1436)	(0.1198)
	0.3495		[0.2248]*		[0.4361]	
NII (%)	0.8294	0.4548	0.5259	1.1582	1.0012	-0.1789
	(0.4468)*	(0.3639)	(0.9699)	(0.8827)	(0.7004)	(0.5841)
	1.4106		[0.6369]		[1.6823]	
OpExp (%)	-0.2309	0.0713	0.3385	0.0813	-0.6483	0.4348
	(0.4222)	-0.3439	(0.7618)	(0.6933)	(0.6460)	(0.5387)
	1.1046		[0.4856]		[1.4712]	
LA/LAreq (%)	0.0035	-0.2137	-0.1010	-0.1039	0.0602	-0.1889
	(0.1177)	(0.0959)**	(0.2133)	(0.1941)	(0.1448)	(0.1208)
	[0.1450]***		[0.2485]		[0.1825]	
SL/TL (%)	-0.0314	-0.1507	0.7128	0.1123	-0.1648	-0.1199
	(0.1817)	-0.1480	(0.3983)*	(0.3625)	(0.2218)	-0.1850
	0.2770		[0.5116]		[0.3195]	
10LD/TF (%)	0.0112	0.0019	-0.0690	-0.0194	0.0128	0.0052
	(0.0248)	-0.0202	(0.0663)	(0.0603)	(0.0276)	-0.0230
	0.0454		[0.0572]		[0.0500]	
R^2	0.0388	0.0574	0.1710	0.1410	0.0619	0.0505
Adjusted R^2	-0.0087	0.0109	0.0011	-0.0355	-0.0039	-0.0161
Standard error	0.0355	0.0289	0.0353	0.0321	0.0355	0.0296
Observations	171	171	48	48	123	123
F	0.817	1.23	1.01	0.799	0.94	0.758

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

Table 12: Regressions for SI, TCA and bank performance controls

	OLS	Robust OLS	OLS	Robust OLS	OLS	Robust OLS
IV: SI	2008−2023		2008−2012		2013−2023	
Intercept	-0.1231	-0.078218	-0.58149	-0.85104	-0.16644	-0.096851
	(0.0688)*	-0.0560	(0.4495)	(0.4090)**	(0.0809)**	(0.0675)
	[0.0615]**		[0.4584]		[0.0716]**	
TCA	-0.1167	-0.0737	-0.4242	-0.5822	-0.12286	-0.044105
	(0.0569)**	(0.0463)	(0.2806)	(0.2554)**	(0.0644)*	(0.0538)
	[0.0554]**		[0.2890]		[0.0684]*	
RoE (%)	-0.8755	-0.5319	-0.9222	0.4521	-0.4948	-0.1463
	(0.6710)	(0.5463)	(1.5894)	(1.4462)	(0.8246)	(0.6884)
	[0.9575]		[1.3310]		[1.3411]	
CtoI (%)	0.1682	0.1060	0.3991	0.4551	0.1072	-0.0257
	(0.1000)*	-0.0814	(0.2302)*	(0.2094)**	(0.1418)	(0.1183)
	[0.1088]		[0.2212]*		[0.1793]	
NII(%)	0.8019	0.4394	0.4109	1.0182	1.0152	-0.1638
	(0.4437)*	(0.3612)	(0.9333)	(0.8493)	(0.6963)	(0.5813)
	[0.5311]		[0.6327]		[1.0017]	
OpExp (%)	-0.2242	0.0597	0.5172	0.3090	-0.6556	0.4172
	(0.4186)	(0.3408)	(0.7730)	(0.7034)	(0.6422)	(0.5361)
	[0.4792]		[0.4752]		[0.9004]	
LA/LAreq (%)	0.0077	-0.2028	-0.0891	-0.0822	0.0623	-0.1865
	-0.1171	(0.0953)**	(0.2121)	(0.1930)	(0.1441)	(0.1203)
	[0.1992]		[0.2508]		[0.2490]	
SL/TL (%)	-0.0249	-0.1446	0.7057	0.2259	-0.1611	-0.1198
	(0.1809)	(0.1473)	(0.3972)*	(0.3614)	(0.2207)	(0.1842)
	[0.1927]		[0.4964]		[0.2080]	
10LD/TF (%)	0.0111	0.0019	-0.0657	-0.0171	0.0124	0.0052
	(0.02467)	(0.0201)	(0.0663)	(0.0604)	(0.0275)	-0.0229
	[0.0142]		[0.0557]		[0.0190]	
R^2	0.0480	0.0602	0.1750	0.1710	0.0707	0.0520
Adjusted R^2	0.0010	0.0138	0.0056	0.000971	0.0055	-0.0145
Standard error	0.0354	0.0288	0.0352	0.0320	0.0353	0.0295
Observations	171	171	48	48	123	123
F	1.02	1.3	1.03	1.01	1.08	0.782

Note: Standard errors in parentheses, heteroskedasticity robust standard errors in brackets. Statistical significance denoted at 1% (***), 5% (**) and 10% (*) levels. (%) denotes variables in first differences.

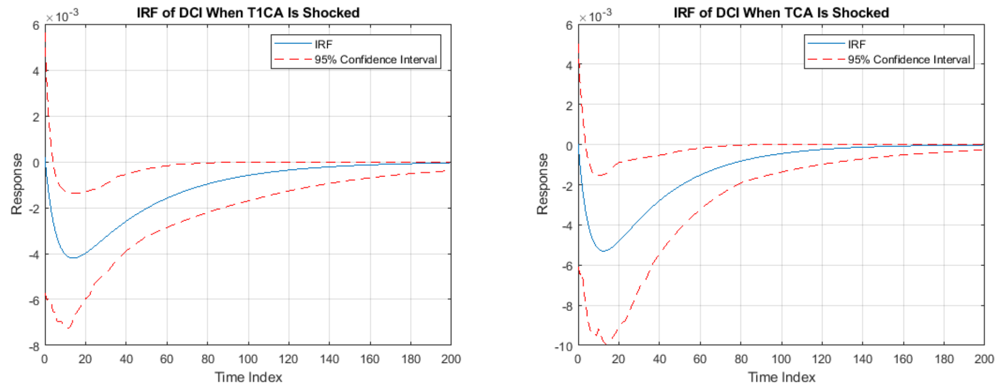
Table 13: Granger causality relationships

Granger causality flow	Statistic	p-value	Statistic	p-value	Statistic	p-value
	2008−2012		2013−2023		2008−2023	
T1CA → DCI	3.1577	0.0756	4.3949	0.0361	6.0295	0.0141
DCI → T1CA	2.654	0.1033	3.1510	0.0759	1.4312	0.2316
	2008−2012		2013−2023		2008−2023	
TCA → DCI	2.9644	0.0851	5.2981	0.0214	7.0507	0.0079
DCI → TCA	1.7181	0.1899	2.4598	0.1168	1.2020	0.2729
			2015−2023			
LC → DCI			0.6073	0.4358		
DCI → LC			2.4758	0.1156		
	2008−2012		2013−2023		2008−2023	
T1CA → SI	2.0419	0.5638	4.965	0.0259	3.3775	0.1848
SI → T1CA	0.0758	0.4721	2.1054	0.1468	6.2161	0.0445
	2008−2012		2013−2023		2008−2023	
TCA → SI	2.0054	0.1567	5.8191	0.0159	3.1611	0.2059
SI → TCA	0.8101	0.3681	3.0099	0.0828	7.5741	0.0227
			2015−2023			
LC → SI			14.0160	0.0073		
SI → LC			7.6216	0.1065		

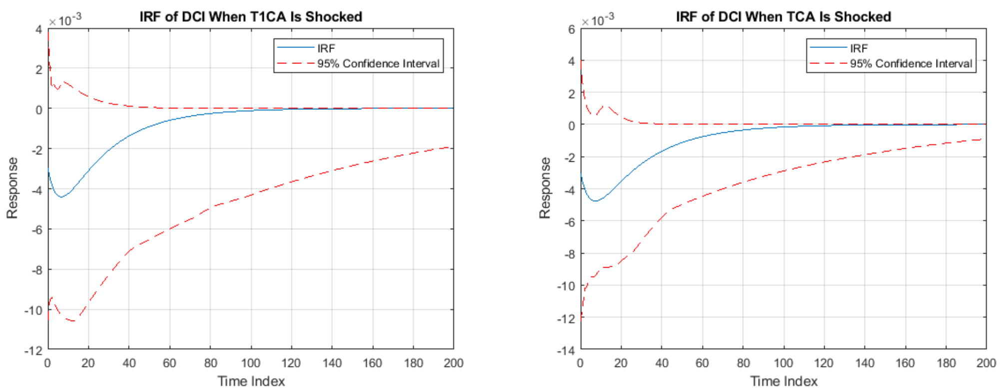
Note: Granger causality between the Basel III regulatory variables TCA, T1CA and LC and interconnectedness indices DCI, SI for the respective period. The arrow denotes the flow of causality. The null hypothesis is that no causality exists and therefore p-values below 0.1 imply rejection of the null in favour of the alternative hypothesis that causality of the specified direction exists. VAR lags are automatically selected according to the Akaike, Bayesian and Schwarz information criteria for each test.

Figure 4: VAR impulse responses for dynamic connectedness index

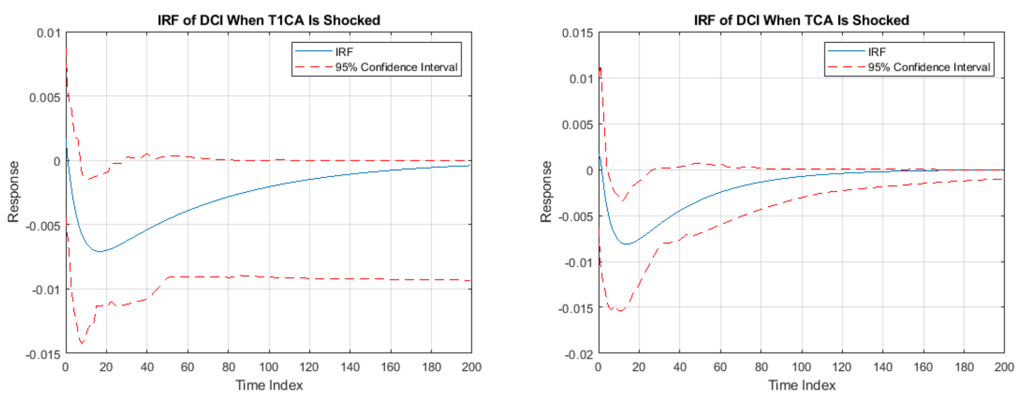
(a) 2008–2023



(b) 2008–2012



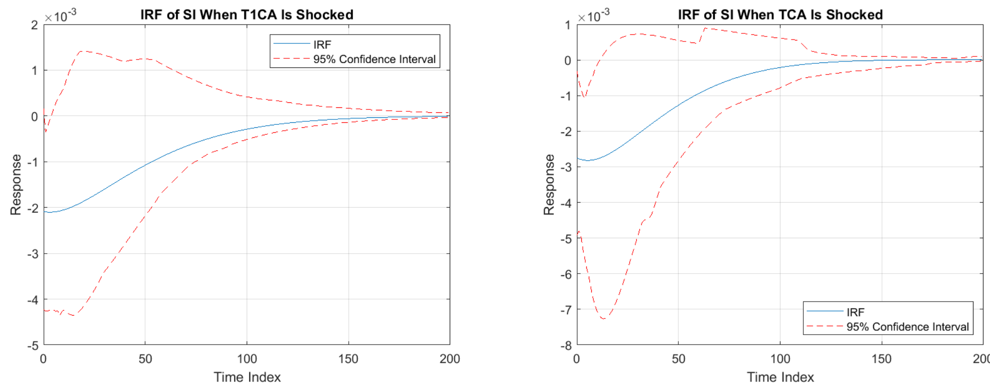
(c) 2013–2023



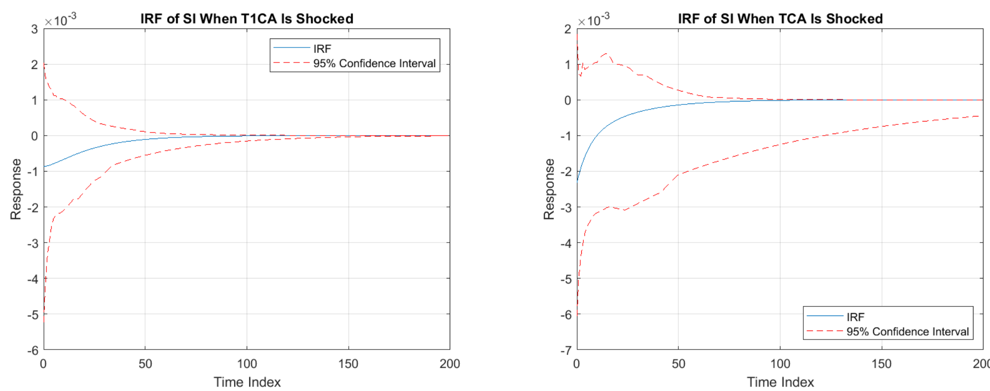
Note: Impulse response functions of two-dimensional VAR models with DCI as connectedness measure and T1CA (left) or TCA (right) as regulatory measures over 2008–2023 (Panel a), 2008–2012 (Panel b) and 2013–2023 (Panel c).

Figure 5: VAR impulse responses for spillover index

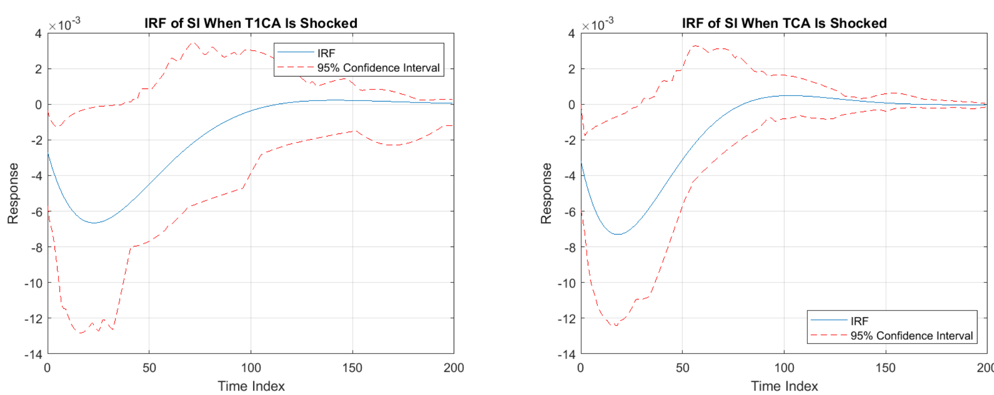
(a) 2008–2023



(b) 2008–2012



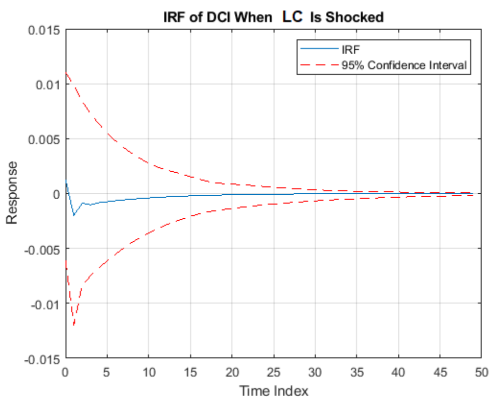
(c) 2013–2023



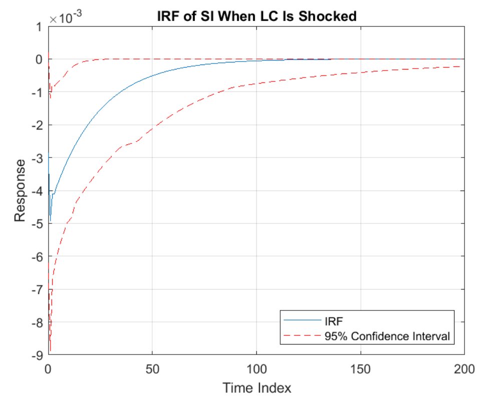
Note: Impulse response functions of two-dimensional VAR models with SI as connectedness measure and T1CA (left) or TCA (right) as regulatory measures over 2008–2023 (Panel a), 2008–2012 (Panel b) and 2013–2023 (Panel c).

Figure 6: VAR and VECM 5 impulse responses for liquidity coverage

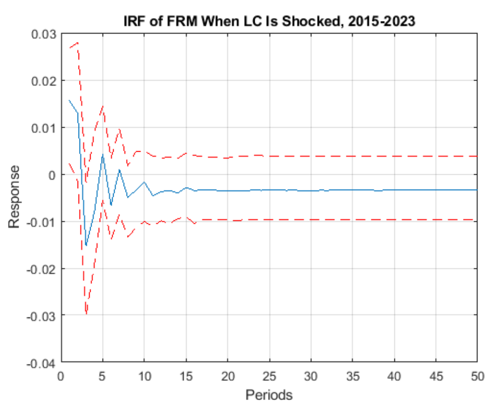
(a) VAR (DCI), 2015–2023



(b) VAR (SI), 2015–2023



(c) VECM 5 (FRM, LC, GDP), 2015–2023



Note: Panel a illustrates the IRF of a two-dimensional VAR model with DCI as connectedness measure and LC as regulatory measure. Panel b illustrates the IRF of a two-dimensional VAR model with SI as connectedness measure and LC as regulatory measure. Panel c illustrates the IRF of a three-dimensional VECM model (VECM 5) with FRM, LC and GDP. In all cases, the response is to a shock on liquidity coverage.

Table 14: VEC 1 and VEC 2 estimates

VEC 1	Dependent variable	ECT	$T1CA_{-1}$	$T1CA_{-2}$	$T1CA_{-3}$	GDP_{-1}	GDP_{-2}	GDP_{-3}	DCI_{-1}	DCI_{-2}	DCI_{-3}
2008–2023	DCI	-0.1760	0.0910	0.3265	0.2574	-0.2018	0.1426	.1115	0.0497	-0.0573	-0.0182
		(0.0474)***	(0.2015)	(0.1936)*	(0.1944)	(0.4347)	(0.4937)	(0.4104)	(0.0798)	(0.0805)	(0.0812)
	GDP	-0.0073	0.0766	0.0485	-0.0117	0.5115	0.0857	-0.4150	-0.0345	-0.0023	0.0457
		(0.0076)	(0.0321)**	(0.0308)	(0.0310)	(0.0692)***	(0.0786)	(0.0653)***	(.0127)***	(0.0128)	(0.0129)***
2008–2012	DCI	-0.0058	0.4855	0.1669	0.4018	24.9293	-36.2478	12.1331	-0.0552	-0.0079	-0.1030
		(0.0092)	(0.4321)	(0.3862)	(0.3981)	(82.4571)	(146.4302)	(69.7938)	(0.1447)	(0.1457)	(0.1497)
	GDP	0.0001	-0.0004	0.0003	-0.0001	2.4049	-2.0439	0.6088	-0.0001	-0.0002	-0.0002
		(0.0000)***	(0.0004)	(0.0004)	(0.0004)	(0.0791)***	(0.1405)***	(0.0670)***	(0.0001)	(0.0001)	(0.0001)
2013–2023	DCI	-0.2129	0.0990	0.4028	0.2576	-0.2284	0.1181	0.1719	0.0582	-0.0968	-0.0096
		(0.0626)***	(0.2671)	(0.2608)	(0.2614)	(0.4774)	(0.5328)	(0.4410)	(0.0992)	(0.0997)	(0.1019)
	GDP	-0.0046	0.1220	0.0638	-0.0345	0.4808	0.1170	-0.4294	-0.0446	-0.0065	0.0594
		(.0111)	(0.0474)***	(0.0463)	(0.0464)	(0.0847)***	(0.0945)	(0.0783)***	(0.0176)**	(0.0177)	(0.0181)***
VEC 2	**Dependent variable**	**ECT**	$T1CA_{-1}$	$T1CA_{-2}$	$T1CA_{-3}$	GDP_{-1}	GDP_{-2}	GDP_{-3}	SI_{-1}	SI_{-2}	SI_{-3}
2008–2023	SI	-0.0218	-0.2660	0.0746	0.2261	0.4452	0.3385	0.1582	0.1344	0.1930	0.0405
		(0.0214)	(0.1842)	(0.1816)	(0.1809)	(0.4219)	(0.4719)	(0.4007)	(0.0812)*	(0.0828)**	(0.0830)
	GDP	-0.0065	0.0465	0.0397	-0.0227	0.5309	-0.0174	-0.3293	0.002	-0.0399	0.0428
		(0.0036)*	(0.0313)	(0.0308)	(0.0307)	(0.0716)***	(0.0801)	(0.0681)***	(0.0138)	(0.0141)***	(0.0141)***
2008–2012	SI	-0.0055	-0.1404	-0.1721	-0.1836	24.7152	-41.9556	19.1272	0.1115	0.1978	-0.1409
		(0.0075)	(0.4635)	(0.4193)	(0.4348)	(93.3371)	(163.4103)	(76.5878)	(0.1558)	(0.1567)	(0.1635)
	GDP	0.0000	-0.0003	0.0003	-0.0003	2.3946	-2.0375	0.6137	-0.0002	-0.0003	-0.0000
		(0.0000)***	(0.0004)	(0.0004)	(0.0004)	(0.0791)***	(0.1384)***	(0.0649)***	(0.0001)	(0.0001)**	(0.0001)
2013–2023	SI	-0.0638	-0.2407	0.2556	0.4414	0.2841	0.2963	0.1950	0.0803	0.1554	0.0947
		(0.0228)***	(0.2212)	(0.2193)	(0.2208)**	(0.4473)	(0.4668)	(0.3989)	(0.0984)	(0.0994)	(0.1025)
	GDP	-0.0053	0.0801	0.0508	-0.0264	0.4824	-0.0330	-0.3073	-0.0384	-0.0693	0.0529
		(0.0047)	(0.0460)*	(0.0455)	(0.0458)	(0.0929)***	(0.0969)	(0.0828)***	(0.0204)*	(0.0206)***	(0.0213)**

Note: VEC 1 is a three-dimensional VEC(3) model with one cointegrating relationship and DCI, T1CA and GDP as variables. VEC 2 is a three-dimensional VEC(0) model with one cointegrating relationship and SI, T1CA and GDP as variables. Lags are determined by the Akaike, Bayesian and Schwarz information criteria. ECM denotes the error correction term. Standard errors in parentheses. Statistical significance at 1%, 5% and 10%, denoted by (*), (**) and (***) respectively.

Table 15: VECM 3, 4 and 5 estimates

VEC 3	Dependent variable	ECT	LC_{-1}	LC_{-2}	LC_{-3}	GDP_{-1}	GDP_{-2}	GDP_{-3}	DCI_{-1}	DCI_{-2}	DCI_{-3}
2015–2023	DCI	-0.0704	-0.1022	-0.0495	-0.1809	0.1140	0.4185	0.2915	0.0004	-0.1828	0.0067
		(0.0525)	(0.0945)	(0.1017)	(0.0963)	(0.5262)	(0.5742)	(0.5060)	(0.1125)	(0.1119)	(0.1140)
	GDP	-0.0235	0.0393	0.0508	0.0518	0.4325	0.1175	-0.2972	-0.0468	-0.0032	0.0534
		(0.0092)**	(0.0166)**	(0.0179)***	(0.0169)***	(0.0923)***	(0.1008)	(0.0888)***	(0.0198)**	(0.0196)	(0.0200)***
VEC 4	**Dependent variable**	**ECT**	LC_{-1}	LC_{-2}	LC_{-3}	GDP_{-1}	GDP_{-2}	GDP_{-3}	SI_{-1}	SI_{-2}	SI_{-3}
2015–2023	SI	0.0472	-0.0663	-0.0652	-0.1700	0.4326	0.1216	-0.0937	0.0693	0.0849	0.0947
		(0.0171)***	(0.0357)*	(0.0385)*	(0.0364)***	(0.2341)*	(0.2276)	(0.2039)	(0.1089)	(0.1089)	(0.1161)
	GDP	-0.0240	0.0435	0.0414	0.0537	0.4515	-0.0186	-0.1177	-0.0786	-0.1623	0.1509
		(0.0073)***	(0.0153)***	(.0165)**	(0.0156)***	(0.1003)***	(0.0975)	(0.0873)	(0.0466)*	(0.0467)***	(0.0497)***
VEC 5	**Dependent variable**	**ECT**	LC_{-1}	LC_{-2}	LC_{-3}	GDP_{-1}	GDP_{-2}	GDP_{-3}	FRM_{-1}	FRM_{-2}	FRM_{-3}
2015–2023	FRM	-0.7603	0.2979	-0.2804	-0.3373	0.7648	-0.8275	1.8603	-0.3183	-0.3442	-0.1302
		(0.0000)***	(0.1692)*	(0.1724)	(0.1647)**	(0.8790)	(1.0252)	(0.8703)**	(0.1787)*	(0.1489)**	(0.1116)
	GDP	-0.0100	0.0264	0.0382	0.0624	0.5560	-0.0476	-0.3305	0.0483	0.0342	0.0172
		(0.0220)	(0.0189)	(0.0192)**	(0.0184)***	(0.0980)***	(0.1143)	(0.0970)***	(0.0199)**	(0.0166)**	(0.0124)

Note: VECM 3 is a three-dimensional VEC(3) model with one cointegrating relationship and DCI, LC and GDP as variables. VECM 4 is a three-dimensional VEC(3) model with one cointegrating relationship and SI, LC and GDP as variables. VECM 5 is a three-dimensional VEC(3) model with one cointegrating relationship and FRM, LC and GDP as variables. Lags are determined by the Akaike, Bayesian and Schwarz information criteria. ECM denotes the error correction term. Standard errors in parentheses. Statistical significance at 1%, 5% and 10%, denoted by (*), (**) and (***) respectively.

Table 16: VECM 6 and 7 estimates

(a) VECM 6 (DCI, T1CA, RoE)

	Dependent variable	ECT
2009–2023	DCI	-0.1526 (0.0396)***
	RoE	0.0003 (0.0072)
2009–2012	DCI	-0.0218 (0.0223)
	RoE	0.0124 (0.0026)***
2013–2023	DCI	-0.1661 (0.0466)***
	RoE	0.0062 (0.0088)

(b) VECM 7 (SI, LC, RoE)

	Dependent variable	ECT
2015–2023	SI	-0.0486 (0.0301)
	RoE	-0.0370 (0.0128)***

Note: VECM 6 is a three-dimensional VEC(0) model with one cointegrating relationship and DCI, T1CA and RoE as variables. VECM 7 is a three-dimensional VEC(0) model with one cointegrating relationship and SI, LC and RoE as variables. Lags are determined by the Akaike, Bayesian and Schwarz information criteria. ECM denotes the error correction term. Standard errors in parentheses. Statistical significance at 1%, 5% and 10%, denoted by (*), (**) and (***) respectively.

Figure 7: Impulse responses (blue) and 5% confidence intervals (red) of VECM 1 (DCI, T1CA, GDP)

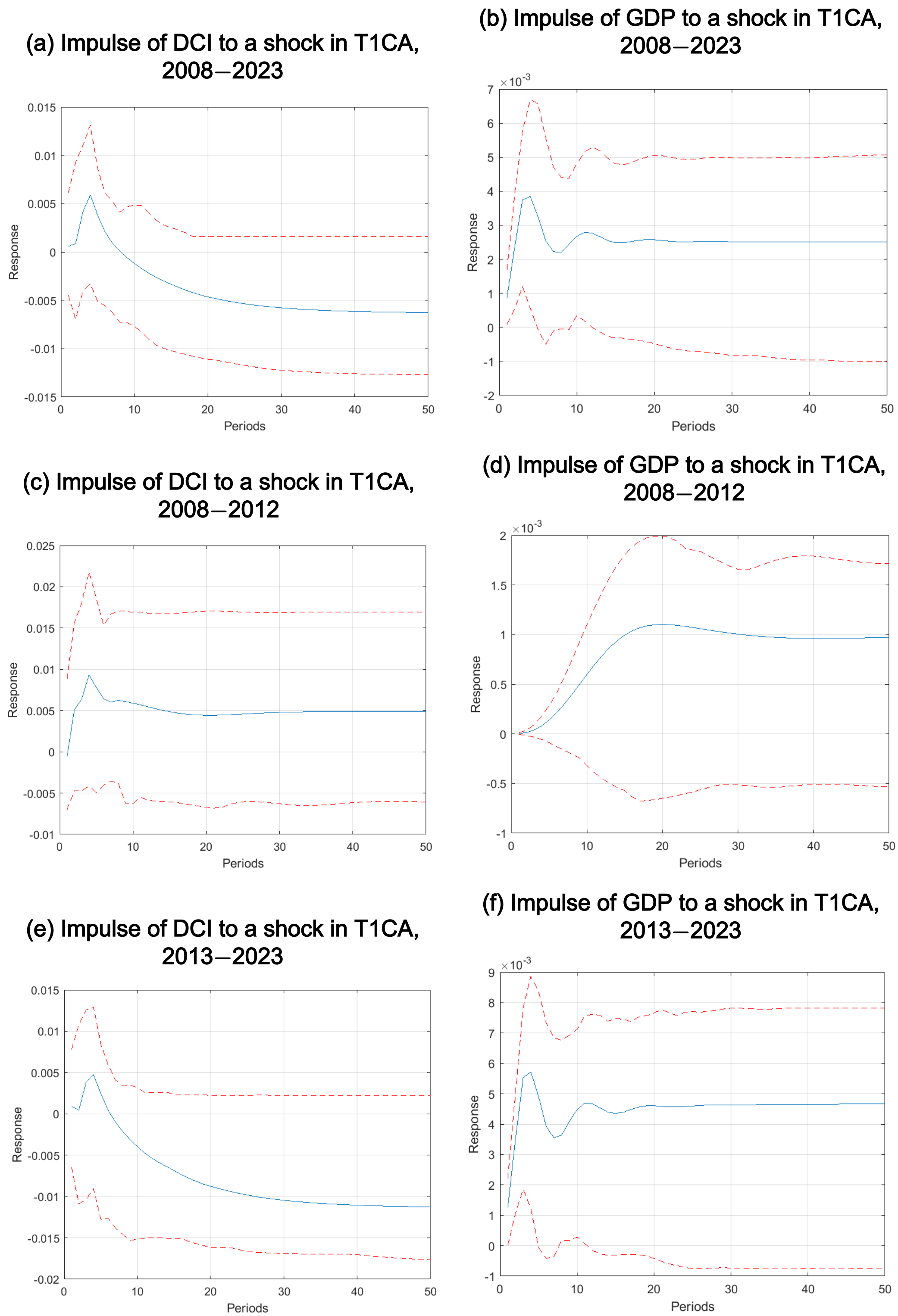


Figure 8: Impulse responses (blue) and 5% confidence intervals (red) of VECM 2 (SI, T1CA, GDP)

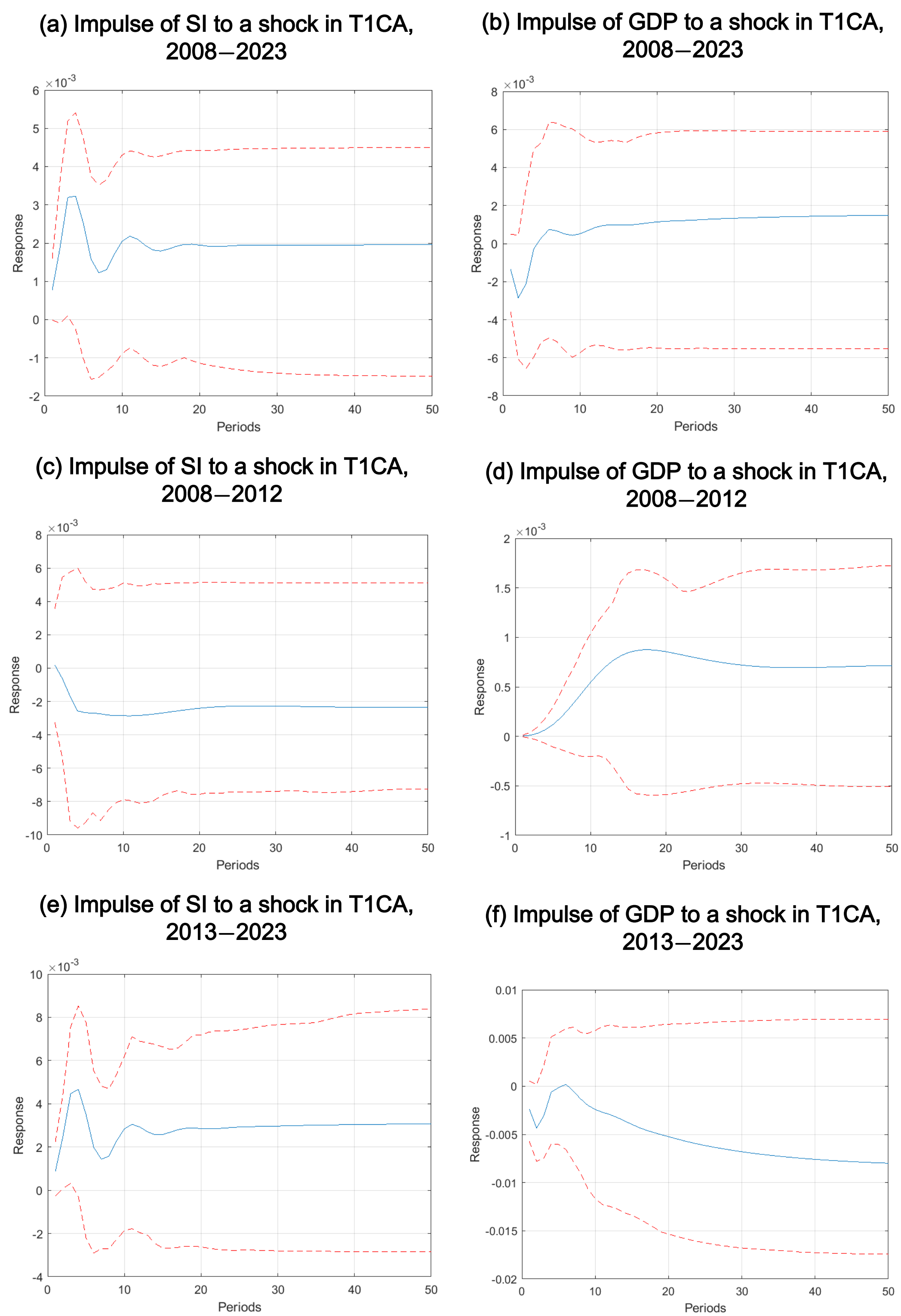


Figure 9: Impulse responses (blue) and 5% confidence intervals (red) of VECM 6 (DCI, T1CA, RoE)

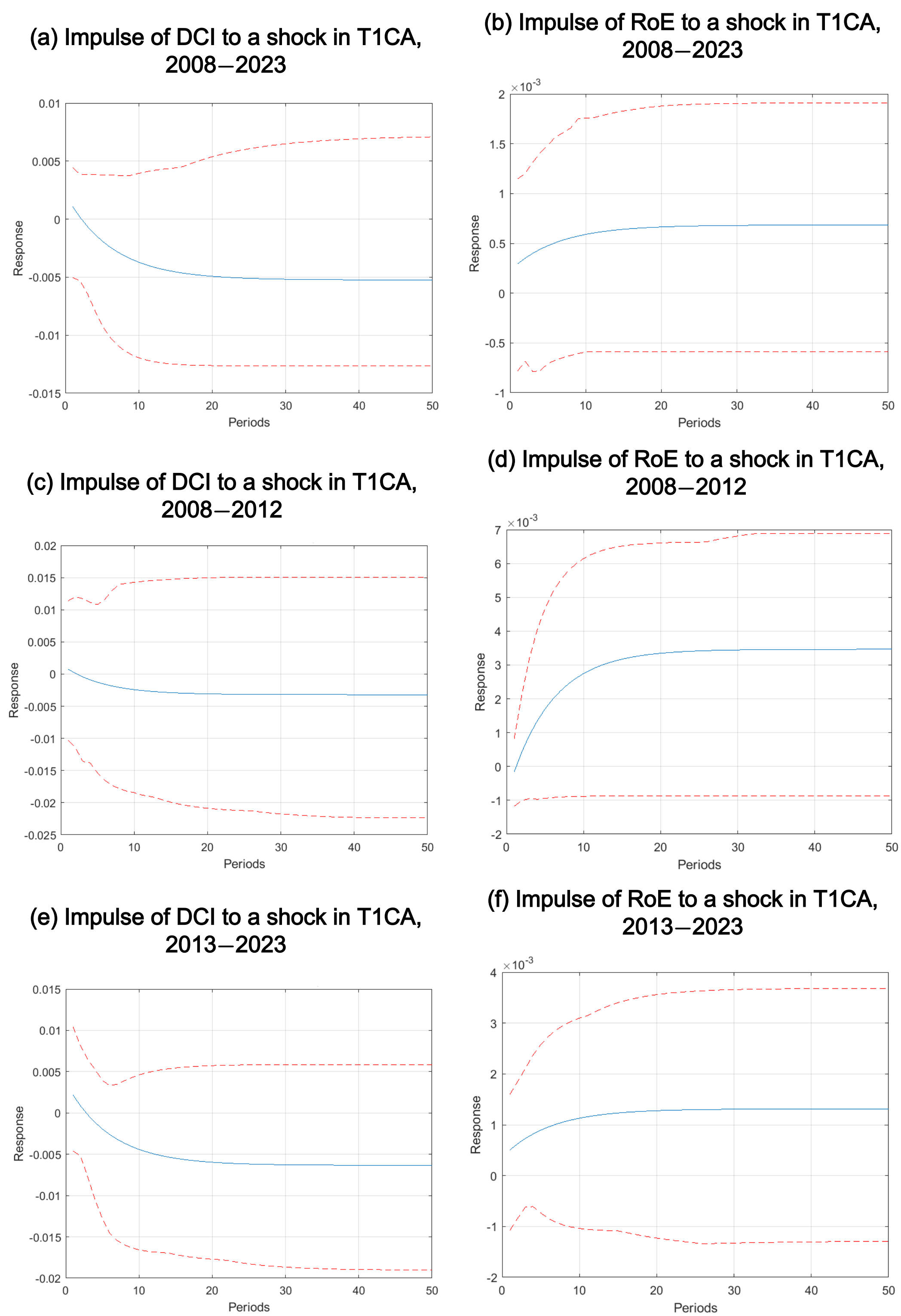
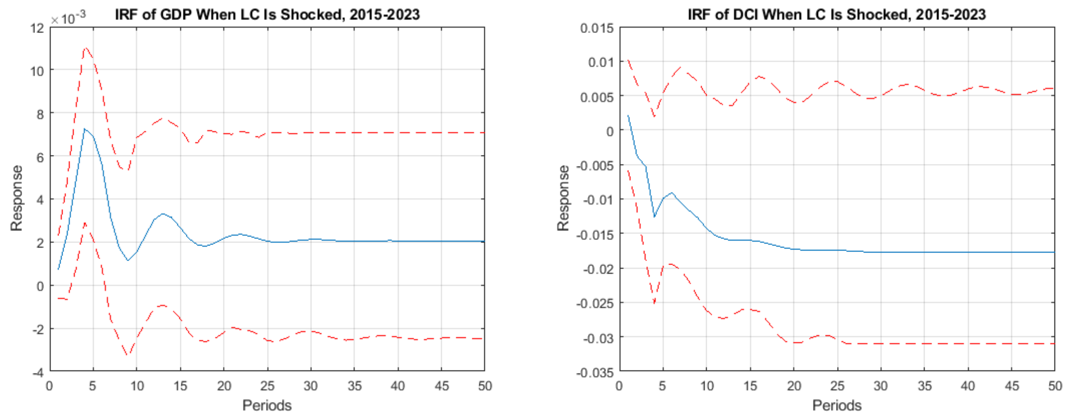
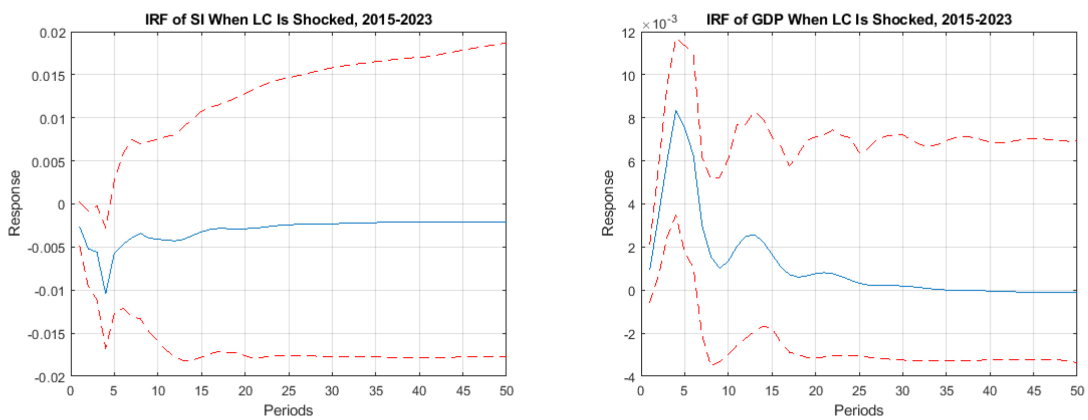


Figure 10: Impulse responses (blue) and 5% confidence intervals (red) of VECMs 3, 4 and 7

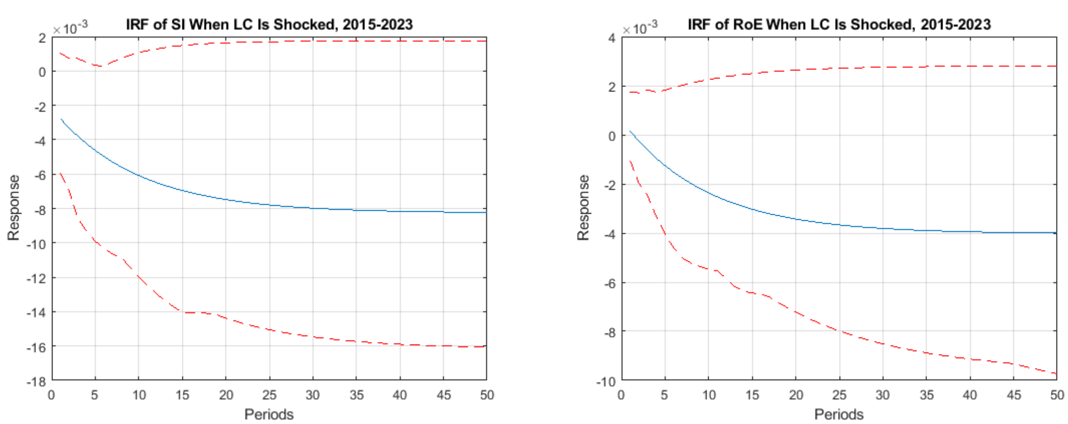
(a) VECM 3 (DCI, LC, GDP)



(b) VECM 4 (SI, LC, GDP)



(c) VECM 7 (SI, LC, RoE)



Annexure

Table 17: Sample summary statistics, before logs or differencing

Variable	Source	Period/ Frequency	Scale/ Difference	Abbreviation	Obs	Mean	SD
			Market variables				
Stock price ('000 rands)	Eikon	08-23, D			38060	23.7300	34.762
			Regulatory variables				
Tier 1 capital adequacy	SARB	08-23, M	Log	T1CA	183	0.1242	0.0145
Total capital adequacy	SARB	08-23, M	Log	TCA	183	0.1537	0.0144
Liquidity coverage ratio	SARB	15-23, M	Log	LC	99	1.2573	0.2373
			Bank performance variables				
Return on equity	SARB	09-23, M	Log %	RoE	171	0.1509	0.0239
Cost-to-income ratio	SARB	09-23, M	Log %	CtoI	171	0.5557	0.0249
Non-interest income	SARB	09-23, M	Log %	NII	171	1.0730	0.2011
Operating expenses to total assets	SARB	09-23, M	Log %	OpExp	171	0.0291	0.0019
Liquid assets held to liquid asset req's	SARB	09-23, M	Log %	LA/LAreq	171	2.2715	0.5472
Short-term liabilities to total liabilities	SARB	09-23, M	Log %	SL/TL	171	0.5527	0.0264
10 largest depositors to total funding	SARB	09-23, M	Log %	10LD/TF	171	0.1288	0.0505
			Macroeconomic variables				
GDP index	FRED	08-23, M	Log %	GDP	183	99.6744	1.8582
3-month interbank rate	FRED	08-23, M	Log %	3m IB rate	183	0.0474	0.0188
CPI	FRED	08-23, M	Log %	CPI	183	102.5451	22.5596
Exports/Imports ratio	FRED	08-23, M	Log	Exp/Imp	183	104.0333	14.1957
M3 growth	FRED	08-23, M	Log %	M3	183	7.6705	3.8843
Real residential property price index	FRED	08-23, Q	Log %	RRPPI	62	99.2529	3.5403

List of banks

Absa Bank Ltd (ABSA)	Nedbank Group Ltd (NED)
Finbond Group Ltd (FNB)	Capitec Bank Holdings Ltd (CPT)
RMB Holdings Ltd (RMB)	Standard Bank Group Ltd (STND)
Sasfin Holdings Ltd (SFN)	FirstRand Ltd (FRND)
Investec Ltd (INV)	

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