Did Basel III reduce bank spillovers in South Africa?*
*****Preliminary and Incomplete*****

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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 9 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 on bank performance.

Keywords: Systemic Risk, Financial Stability, Interconnectedness, South African banking sector, Basel III regulation
JEL Codes: G01, G18, G21, E50

1. Introduction

The recent turmoil in US regional banks has brought violently to the forefront the policy mixture, regulation effectiveness and toolkit of central banks. Despite the view that the global financial system is better monitored and more resilient after the 2008 financial crisis, the relaxation during Covid and the surprising speed of the recent bank runs set new questions on whether current central bank practices are able to deal with rapidly spreading

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contagion and spillover effects. The post-Covid landscape of economic slowdown, higher inflation and higher interest rates is radically different compared to the 15 years of quantitative easing and zero rates. South Africa is the largest economy in the continent and its banking sector, largely unaffected by the 2008 financial crisis, is characterised by a large degree of concentration. South African Reserve Bank (SARB) began the implementation of Basel III regulations in January 2013 with a transition period for banks until 2019. It is, therefore, timely to assess whether the new regulatory framework had an impact on bank stability and economic performance.

We contribute to the literature in S. Africa by specifically focusing on the interconnectedness aspect of bank systemic risk, and find that certain aspects of Basel III regulation managed to reduce bank connectedness. Relevant market-based measures and studies at a country level are largely absent from the literature and research on S. Africa uses different metrics to assess systemic risk. The topic is often discussed in conjunction with different concepts (e.g. shadow banking in Kemp (2017)), interconnectedness between African countries (Ogbuabor et al. (2016), Saidane et al. (2021)) or different data and metrics, such as balance sheet information. The importance of interconnectedness is emphasised by the 40% weight applied in that feature by SARB in its classification of systemically important financial institutions (SARB (2019)). In one of the scant 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 first goal is to examine interconnectedness and risk spillover effects between South Africa banks and identify the potential transmission channels of institutional failure (bank run, distress). We use a sample of 9 South African listed banks in 2008-2023 and use three different methods to construct indices. The first method is the Granger causality network approach of Billio et al. (2012), which yields the Dynamic Connectedness Index (DCI) The index measures the number of Granger causality connections between banks over time, indicating which banks affect/ are affected by the stock 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 LASSO regressions and CoVaR-based tail dependencies (system distress given firm distress) which result to a systemic risk index. The FRM index intends to capture the tail connectedness of bank returns in the network. The third approach is the Spillover Index (SI) of Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014), which captures variance decompositions between pairs of firms in the network. This index intends to capture the overall riskiness of banks. All methods can provide aggregate and firm specific results, making them suitable for both aggregate 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 regulation had an impact on standard economic and bank performance metrics, 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 the liquidity coverage ratio (LC) available at monthly frequency from the South African Reserve Bank (SARB) BA700 Monthly Reports[1]. We conduct a set of OLS regressions, VAR and 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. By contrast, there is no relationship during the 2008-2012 period prior to implementations. Liquid coverage, on the other hand, has no relationship. 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 connectendess 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 changes is, again, strong, but the effect on bank performance is weaker. Thus, Basel III implementation has

[1]SARB data for the Net Stable Funding Ratio are only available from 2019

been successful in mitigating the interconnectedness aspect of systemic risk in the S. 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 regulation does not have an impact on tail connectedness (FRM), and therefore is unable to reduce the probability of a systemic event; it can only mitigate its effect. In addition, the effect on bank performance, most notably return on equity, is limited. Our results are relevant both for SARB policymakers and banks, as they highlight avenues for further action as well as the achievements and shortcomings of recent regulation.

2. Literature review

In the aftermath of the financial crisis, Esterhuysen et al. (2011) detected an increase in South African systemic risk, although less severe than other international banks. This agrees with the experience 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 SADC framework. With the recent introduction of new regulation (Hollander et al. (2019) for an overview and critique), and the movement to a Twin Peaks regulatory regime with clearer and enshrined responsibilities and mandate (Van Heerden et al. (2020)), 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 negative in the short-run (Zhou and Tewari (2018)). Van Heerden and Van Niekerk (2021) provide a useful overview of the South Africa regulatory model. Batsirai et al. (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 need for macro-prudential banking regulation. Any toolkit of macro-prudential banking regulation should take into account the effects of a lax monetary policy framework. It is evident that the actions of regulators and policymakers can have great implications for the financial system, including potential contagion (Havemann (2019)).

Systemic risk literature 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) is 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 is also used by Manguzvane and Muteba Mwamba (2019), to show very similar findings on individual bank contribution and a rapid increase in systemic risk, and Leukes and Mensah (2019) to report an increase in spillovers during distressed periods and that banks and insurance firms are 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 MES 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)).

The general consensus is that systemic risk at the S. African banking sector has remained consistently high during the last decade when examining an individual institution vis-a-vis the benchmark, or looking at pairs of interactions. However, there is no discussion on how distress in one institution can be transmitted to others, how extensive and strong those channels of interaction can be, and what banks are the most or least connected. Interconnectedness measures, such as the ones we use, are notably absent from the literature. With the exception of Kemp (2017) and Saidane et al. (2021) (in a different context) we are not aware of a recent paper explicitly discussing bank interconnectedness in South Africa apart from Koziol (2022).

However, such approaches 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 et al. (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, there could be contagion effects that could weaken the union (Saidane et al. (2021)). Although large S. African banks are analysed in these studies, the policy context and implications differ greatly from ours, which serves as further motivation.

3. Data and methodology

3.1. Data description

A comprehensive description of the dataset and summary statistics can be found in Table A.17 in Appendix A. The sample consists of 9 South African (S.A.) banks listed in the Johannesburg Stock Exchange . 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 S.A. banks have been selected according to the SARB database, where they are listed as quoted and having a bank licence. This excludes conglomerates that also include a bank, e.g. Discovery, which is not listed as an entity separate from the conglomerate.

The means and standard deviations are reported on the raw levels of each variable, before applying log scale or taking first differences. The "Scale/ Difference" column denotes the transormations applied prior to estimation. The longest period is January 2008 – March 2023 as it covers the regulatory changes implemented in the aftermath of the global financial crisis, the stimulus-fuelled bull market, the Covid turmoil and the recent increase in inflation, energy prices and supply chain disruption. Regulatory and bank performance data are collected are collected as sector aggregates from the SARB B700 Monthly Reports. Stock prices in South African rand are collected daily from Refivitiv Eikon to calculate the log returns used in the estimation of DCI, SI and FRM. The indices are produced in daily frequency but the last observation of each month is used in model estimation, so their statistics are reported as monthly. Macroeconomic variables are available from SARB and Federal Reserve Economic Data (FRED) in monthly frequency, apart from the real retail property price index which (FRED) which is available in quarterly frequency and interpolated to monthly. Liquid Coverage is only available for 2015-2023. Bank performance variables are collected as sector aggregates from the SARB B700 Monthly Reports from 2009 onwards. The three indices are first-differenced when necessary. All other variables are in log scale and first differencing, where necessary due to non-stationarity, is denoted by (%).

3.2. Interconnectedness measures

3.2.1. Granger causality networks

Granger causality networks (Billio et al. (2012)) are a popular method to examine 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. The basic idea behind Granger causality is that 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 which 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 also can 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 modelled using a GARCH(1,1) process. Finally, we condense the network of interactions into the Dynamic Causality 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. The network illustrations and adjacency matrix can help locate the institutions that exert the highest influence to their competitors and can cause, act as conduits or receive systemic distress in the case of a negative shock.

3.2.2. Financial Risk Meter

The foundation of the second approach, Financial Risk Meter (FRM) by Mihoci et al. (2020) is CoVaR. It considers the tail event probability of bank j conditional on the distress of bank i, representing a bivariate tail dependence system. While the CoVaR approach yields a systemic risk measure associated with one particular financial institution relative to the financial system (or a bank), thus the VaR of the financial sector conditional on this financial institution being in distress, the FRM aims to simultaneously capture all interdependencies in one single number. This is achieved by conducting 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% VaR of an institution). The method condenses the high-dimensional tail stress into a single, straightforward real value index-type indicator, the FRM. Thus, the FRM is the average over the selected LASSO penalization terms and is calculated at each time step and for each node, and its size contains essential information on the active set of influential neighbouring nodes and on the contributors to systemic risk. For regulating authorities such as the Basel Committee on Banking Supervision, this simple but augmented indicator is of great benefit. The authors possess FRM codes in both Matlab and R and Granger causality codes on Matlab, so coding is not an issue. The reason for using both approaches is that Granger causality intends to capture the size of the network, while FRM the potential effect of distress within the network.

3.2.3. Spillover Index

The third approach, the Spillover Index (SI) relies on Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014). It includes constructing a total index of directional spillovers of stock returns volatility. The directional spillovers are based on generalised Forecast Error Variance Decompositions (FEVD) on the corresponding generalised VAR. 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 sum of the normalised FEVDs of 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) is divided by the number of series yields the total spillover index $S^g(H)$. For N assets including i, j and normalised generalised FEVDs $\theta_{i,j}$ the total Spillover index and directional Spillover Index $S^g_{i.}(H)$, which measures the spillovers received by asset i from all other assets j, are ,

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

$$S^g_{i.}(H) = \frac{\sum\limits_{i,j=1, i \neq j}^{N} \tilde{\theta}^g_{ij}(H)}{N} 100 \quad (3)$$

The difference $S^g_{i.}(H) - S^g_{.i}(H)$ 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).

3.3. Regressions, VAR and VEC models

We specify two general regressions to examine the effect of regulation (Reg) on connectedness (CN) variable, given a vector of macroeconomic controls M or bank performance controls BP.

$$CN_t = \alpha + \beta_1 Reg_t + \beta_j M_t + \epsilon_t \quad (4)$$

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

Both are standard contemporaneous regressions. *Reg* refers to T1CA, TCA and Liquid

Coverage. Control includes a set of macroeconomic variables (GDP (%), 3-month interbank rate (%) CPI (%), Exports/ Imports ratio (%), M3 and Real Residential Property Price Index (%)) or a set of bank performance variables (Return on Equity (%), 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 Ten largest depositors to total funding (%)) depending on the case. All variables are in log scale and (%) denotes first log differences for stationarity. We use 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.

We assess Granger causality between interconnectedness indices and policy variables and the impact of policy shocks on systemic risk via Granger causality tests and the generalised Impulse Response Functions (IRF) of a list of VAR models over the 2008-2023, 2008-2012 and 2012-2023 periods. This captures the impact, significance and duration of policy shocks before and after Basel III regulation is introduced on a pairwise basis. To capture cointegration at the levels, rather than the percentage changes, of the variables, we expand to 3-dimensional VEC models with either GDP or RoE added. We report the generalised IRFs to examine the impact of policy shocks when all three factors are jointly considered.

4. Empirical results

4.1. Estimation of interconnectedness indices

Figure 1 reports the Dynamic Connectedness Index (DCI) for S.A. 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 throughout the period than a network. 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 implies a causal relationship from X to Y. If the square of row Y with column X is shaded, this implies bi-directional causality and if not, it is uni-directional.

For S.A. banks, there is a pronounced increase in the number of connections during the 2008-2010 financial crisis, rapidly collapsing after 2010. After 2013, DCI (Figure 1), Panel (a) remains stable at low levels apart from a surge in late 2015 that lasted for a year and reached the 2010 levels. Connectedness during Covid seems to be stable on average but more volatile. When US banks are added, the number of connections is persistently much higher. This is due to both the connections between US institutions but also because virtually all of them affect all other South African banks. The index remains consistently high until 2018, where it declines substantially but rises rapidly to its peak in 2020 during Covid. With the relaxation of Covid restrictions the index drops and returns to its long-run value. This creates distinct periods of high connectedness rather than a uniform behaviour, and the 2016 period, halfway during the Basel III implementation, is so pronounced. On the other hand, the relatively small sample leads to a small number of connections, which is also related to the high degree of concentration of the S.A. banking system.

The Financial Risk Meter graph in Panel (b) shows that tail connectedness has remained constantly low and stable apart from a notable sudden increase in mid-2014 and some lower, very brief, high points. Finally, the Spillover Index (SI) graph in Panel (b) shows a more nuanced image. Risk is reduced or stable at a low level between 2008 and 2015 but rapidly increasing after that, during the 2015-2017 period with a very high peak in 2016. This period coincides with global growth concerns and increased worry of systemic risk and is observed, to a lesser degree, in the DCI plot. The 2017 steep decline and subsequent increase during Covid also agree with international experience. Notably, after Covid, the contribution of Nedbank and Investec have grown considerably (Figure 2, Panel (b)). ABSA Bank has consistently low spillovers and Standard Bank consistently high, with the rest remaining at low levels.

The Granger causality network and the average adjacency matrix allow a closer look into the flow of causality. The largest institutions (FirstRand, Standard Bank) appear to be the most influential, although with notable contributions from smaller banks. Notably, ABSA Bank, the third largest in the country affects only Nedbank and RMB but is affected by six, highlighting potential exposure to spillover effects. The number of connections between smaller banks is moderate, showing the large clout of larger banks in the South African banking sector. Nedbank and RMB are the exceptions, with a high number of connections. This shows a rather more complex system that what is suggested by the expected vast influence of the three largest banks (FirstRand, ABSA and Standard Bank). FRND and STND affect all other banks apart from Finbond but are affected only by two institutions each. Smaller banks, on the other hand, affect each other to a moderate degree but not their larger counterparts.

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

$$Stab_t = \mu_{st} + \epsilon_t, \epsilon \sim N(0, \sigma^2) \tag{6}$$

where standard deviation is constant but there are two states $s = [1, 2]$ with low (μ_1) and high (μ_2) means respectively[2]. 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 quite clear. Both DCI and SI exhibit similar patterns, up until 2016, with State 1 dominating the plot. DCI is in the high mean State 2 until mid-2010, while during the same period SI has only two brief changes. After 2016, the behaviour becomes markedly different. While both measures are in State 2 in 2017, SI remains in it until the end of 2022, which is roughly the end of the Covid 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. 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 or interconnectedness,

[2]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

since they appear to be governed by different dynamics. Low causality is not seemingly accompanied by low overall risk spillovers.

4.2. Regression results with macroeconomic controls

We first estimate model (1) via OLS and robust regressions over the pre-Basel III implementation period (2008-2012), during and after its implementation (2013-2023) and for the whole period (2008-2023) for the sample of S.A.-listed banks when we control for macroeconomic variables. For DCI as dependent variable, the independent variables used are Tier 1 Capital Adequacy (Table 2), Total Capital Adequacy (Table 3) and Liquid Coverage (Table 4). The standard errors for simple OLS are in parentheses while with heteroskedasticity and autocorrelation robust standard errors are in brackets. We then repeat estimation with FRM and SI as dependent variables respectively.

There is a strong negative relationship between T1CA and DCI for both the 2013-2023 and 2008-2023 samples, which becomes insignificant in the Basel II period (2008-2012). The value of the coefficient is -0.53 after 2013, statistically significant at 1% and 5% confidence levels, but becomes insignificant at -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 with even stronger effects. The parameter values are -0.72 for OLS and -0.61 for robust OLS, 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 1-5%. The regression R^2 and F values show that all models are statistically significant. Thus, our findings suggest that the implementation of Tier 1 capital adequacy and total capital adequacy ratios managed to reduce the interconnectedness, and potential spillover effects, of the South African bank system.

We now focus on LC and its impact on connectedness. All control variables are statistically insignificant. For the 2015-2023 period, the Liquidity Coverage coefficient is positive with a value of 0.32 but statistically insignificant under OLS and robust errors. The F values are all statistically insignificant, which means that the model has very low explanatory power overall. Hence, we cannot draw any meaningful conclusions by using LC. 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 were homogeneous across regulatory variables and periods, we only report the case of FRM as dependent and T1CA as independent variable for brevity. The explanatory power and statistical significance of the model under OLS estimation are non-existent but F-values are significant at 1% level for 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 regulation did not manage to reduce, or have any impact, on tail connectedness across the network of banks in the sample.

We finally turn our attention to the Spillover Index (SI) under macroeconomic variables and TCA (Table 6), T1CA (Table 7) and LC (Table 8) as independent variable respectively. The results are similar but weaker to those under DCI. All three regulatory variables are insignificant for 2008-2023 and 2008-2012 but T1CA (TCA) are significant at 1% (5%) for the 2013-2023 period under OLS. The coefficients are negative, showing that the implemented regulation managed to reduce spillovers. The coefficients of the robust regressions are generally insignificant, as well as the parameters of the control variables. When LC is the independent variable (Table 8), its coefficient is insignificant.

4.2.1. Regression results with bank performance controls

We repeat the same estimations as earlier but substitute the macroeconomic variables with bank performance measures. After excluding possible candidates due to large correlations, we select 7 variables 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) and use the same independent variables. The most striking result is that none of the regressions has a statistically significant F-value, which casts doubt on the validity of the results (Tables 9, 10), 11 and 12). Both T1CA and TCA are, nevertheless, negative and significant in the 2013-20-23 period but insignificant in 2008-2012 for both DCI and SI. This finding is reversed, however, for the robust OLS regressions when SI is used. LC is also found to have a negative impact on SI (Table 8) but no impact on DCI (Table 4). The statistical significance of control variables is scarce for LC when SI is the dependent variable and most of them do not appear to play a role, but more frequent for DCI. There is no discernible pattern or consistency, and overall the regression results are non-informative when bank performance controls are used. As above, the FRM results are ommitted since they are statistically insignificant and uninformative.

4.3. Granger causality and policy shocks

Our regression results for the banking sector show a clear effect of regulatory policy on bank connectedness. It is important to assess the causality between DCI and TCA, T1CA and Liquidity Coverage and examine the effect of a policy change on connectedness.

We specify a VAR(2,1) model with one interconnectedness index (DCI, SI) and one policy variable (TCA, T1CA, LC) and one lag, according to the Akaike and Bayesian information criteria. We then estimate Granger causality and present the generalised Impulse Response Functions(IRF) to identify if 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 6 pairs of variables over the 2008-2012, 2013-2023 and 2008-2023 periods. There is bi-directional causality between Tier 1 Capital Adequacy and DCI as well as uni-directional causality from Total Capital Adequacy and DCI in 2013-2023. There is also uni-directional causality from T1CA and TCA to DCI in 2008-2023 and 2008-2012. There is no causality between Liquidity Coverage and DCI. 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 connectedness. On the other hand, requirements on highly liquid assets are not found to have an impact. A possible explanation may be the chronic liquidity issues of the S.African banking system, which cause frequent SARB interventions like in 2020. It must be noted, however, that capital ratios have consistently been above regulatory requirements for the periods in question. Our findings, thus, suggest that 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 roughly 11%. When we focus on causality between the Spillover Index and the three regulatory measures, however, we notice a strong causal relationship from LC to SI. We also find bi-directional 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.

Figure 10 reports the generalised IRFs of a policy shock of one standard deviation on DCI. The results are similar to 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, similarly to 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 2-3 onwards. This is a striking finding that shows a highly persistent impact of Basel III regulation as well as further policy changes. The IRFs between the Spillover Index 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. Therefore, the intuition is the same that a regulatory shock had a negative impact after Basel III was introduced but no effect beforehand. The IRFs for SI (Figure 5) show a similar yet more pronounced behavior. The IRFs of SI when both T1CA and TCA are shocked (Panel c) are significant and for longer duration over 2013-2023 compared to 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 Liquity Coverage is used (Figure 6), there is no impact of a shock on DCI but there is impact on SI, albeit brief. This is an important result as LC often appears to be insignificant, and agrees 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 but extends to the pro-Basel III period. Liquidity Coverage plays a role on overall risk spillovers but not on causality. The impact of policy shocks on the systemic risk measures supports the effectiveness of regulation, although its impact varies.

4.4. Vector Error Correction impulse response functions

The VAR models in the previous section are unable to describe contemporaneous relations, do not include macroeconomic or performance variables and, due to differencing, cannot take into account cointegration at the levels of the variables. The common approaches to address these issues is estimating either a 3-dimensional SVAR or VEC model between a connectedness measure, a performance measure and a macro or bank performance measure. We opt for VEC since there is little a priori ground to impose restrictions on the variables via ordering or using Cholesky decomposition. 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 macro proxy and RoE as bank performance proxy due to their wide use and focus on 4 models. This allows us to focus on the effect of a policy shock on interconnectedness, economic growth and bank performance as well as long- and short-run causality in a more comprehensive manner. The models are estimated 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.

We specify a series of VEC(3) models with one cointegration relationship based on the results of the Johansen test and the BIC and AIC information criteria for the optimal number of lags. The first VEC(3) model includes DCI, T1CA and GDP (VEC 1), the second includes SI, T1CA and GDP (VEC 2), the third includes DCI, LC and GDP (VEC 5) and the fourth includes SI, LC and GDP (VEC 6). A final combination is FRM, LC and GDP (VEC 7), the only combination for FRM that produces statistically significant results. We also specify a series of VEC(0) models with 1 cointegration relationship, based on the same test and information criteria, that include DCI, T1CA and RoE (VEC 3) and SI, LC and RoE (VEC 4). The VECMs with SI, T1CA and RoE and DCI, LC and RoE are omitted due to the absence of cointegration and the insignificant results of the corresponding SVAR. We report the estimation results and generalised impulse response functions for all three cases with our prime focus being on interconnectedness and GDP or RoE being affected by the other two variables. The parameter estimates for VEC 1 and VEC 2 are reported in Table 14, for VEC 3 and 4 in Table 15 and for VEC 5 and 6 in Table 16 .

When DCI is the dependent variable in VEC 1, the error correction term is negative and significant at 1% level for the 2008-2023 and 2013-2023 periods but 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 even more telling. The error correction term in the 2008-2012 period is positive, practically zero yet statistically significant at 1% but negative and insignificant for the whole sample and post-Basel III adoption period. The lagged terms of DCI are all insignificant in 2008-2012 but DCI_1 and DCI_3 negative and significant in 2012-2023 and 2008-2023. A similar pattern is observed for $T1CA_1$. This implies that the adoption of Basel III regulation dampened the weak long-run relationship between systemic risk interconnectedness and economic output, which used to cause economic instability, yet did not manage to have to a long-run positive impact on growth. The findings are largely similar when SI is used instead of DCI in VEC 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 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 spillover risk stopped having an impact on economic output in the long-run due to regulation.

The results when bank performance (RoE) is introduced in VEC 3 are, again, similar in nature (Table 15 Panel a). The error correction term for DCI as 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 regulation had a causal effect on bank interconnectedness. However, when RoE is the dependent variable, the error correction term goes from positive and significant at 1% level in the 2009-2012 period to insignificant for the whole sample and the 2013-2023 period. This implies that regulation had no effect, either positive or negative, on bank performance but did have an impact in stability. When SI, LC and RoE are introduced in VEC 4 (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 5 and 6 (Table 16), which are the variants under LC as regulatory measure, are quite mixed. Liquidity Coverage has no impact on DCI but when GDP becomes the independent variable there are very strong positive long- and short-sun 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 variables, the results and intuition are largely similar to VEC 5. 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 VEC 7 are surprisingly strong, with a negative and statistically significant error correction term but also interesting lagged effects: LC_{-1} has a positive but LC_{-3} a negative parameter, which denotes an initial increase in systemic risk followed by a reduction later. This is the only time when the FRM results matter.

The generalised IRFs show whether there is a positive or negative impact of a shock on one variable on another variable.They allow us to compare between 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 being the impulse variable and DCI the response variable (VEC 1), i.e. 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 shows 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 quite stronger in the 2013-2023 period compared to 2008-2012. This demonstrates a stronger positive effect of regulatory changes on economic output compared to the pre-Basel III period. We now move to the IRFs of VEC 2 (Figure 8), where DCI is replaced by SI. With the exception of figures (a) and (e), all IRFs are statistically insignificant. A regulatory policy shock would have a brief positive shock around 5 periods after implementation in 2013-2023 but no further consequences. All IRFs for VEC 3 (Figure 9), where DCI, RoE and T1CA are included, are insignificant. When LC is used instead of T1CA (Figure 16), a policy shock has no statistically significant impact on Roe although the IRFs are negative (Panel a), a there is a positive shock on GDP in accordance with the VEC 5 results above (Panel b) but a negative, statistically significant, impact on SI for up to 5 periods and a longer-lasting positive impact on GDP (Panel c). Contrary to earlier results, LC does appear to positively affect GDP. Finally, the IRF of FRM when LC is shocked is statistically significant at period 3 and settles at a negative level.

Overall, the results suggest that regulatory capital ratios managed to reduce overal riskiness spillovers and causality in the network of banks. The impact of regulation on GDP output is present but less pronounced and mostly absent on bank performance, but high liquidity coverage is associated with an increase in GDP.

4.4.1. Conclusion

We estimate three interconnectedness indices that capture different aspects of risk spillover effects and assess the impact of Basel III implementation in the South African banking system on financial stability, bank performance and the macroeconomy. The Dynamic Connectedness Index captures the crisis transition mechanism based on the aggregate Granger causality relationships in stock returns. The Spillover Index captures overall riskiness spillovers based on forecast error variance decompositions of bank stock returns. The Financial Risk Meter is an index of CoVaR-type tail dependence between the banks in the sample. We then use three regulatory measures (Tier 1 Capital Adequacy, Total Capital Adequacy and Liquidity Coverage) and examine 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. T1CA and TCA have a negative relationship with DCI and SI, which implies that regulation managed to increase bank autonomy to some extent by reducing both spillovers of overall riskiness and the impact of potential domino effects, despite the large concentration of the South African banking sector. The impact of Liquidity Coverage is more complex. It appears to have a limited impact on interconnectedness, which is mostly related to reductions of overall risk spillovers. However, it has a strong positive effect on economic output. However, the success is only partial. The contemporaneous effects when controlling for bank performance are non-existent, while Return on Equity is often not associated with any kind of impact. On the other hand, macroeconomic measures, particularly GDP, are found to be affected positively more often - but not always. The complete failure to reduce tail risk spillovers, as shown by the absence of any meaningful results on the Financial Risk Meter, is a stark reminder that capital ratios may act as buffers and may help mitigate the impact of a systemic event, but can do very little to reduce its probability of occurence (Jordà et al. (2021)).

Therefore, regulatory success is only partial. To some extent, bank interconnectedness has been successfully mitigated by the implementation of Basel III, and, in that sense, regulation has had a positive effect on financial stability. However, that effect relates to how much capital would be available, according to the regulator, if a systemic event occurs. In other words, regulation acts as a mitigation rather than prevention mechanism. This is related to the contemporary discussion on whether higher capital buffers are used as alternative monetary policy tools, e.g. as means to reduce credit creation instead of increasing interest rates (Davies (2023)). Although our findings cannot provide an argument to that discussion, they provide evidence that gradually increasing capital ratios led to a reduction of a particular aspect of systemic risk. Basel III regulation neither increased nor reduced bank performance and the limited impact of Liquidity Coverage is a symptom of the chronic liquidity problems of the South African banking system. Our reports are useful to both policymakers and banks, since they highlight the successes and limitations of the implemented measures by emphasising the need to reduce tail risk and improve liquidity.

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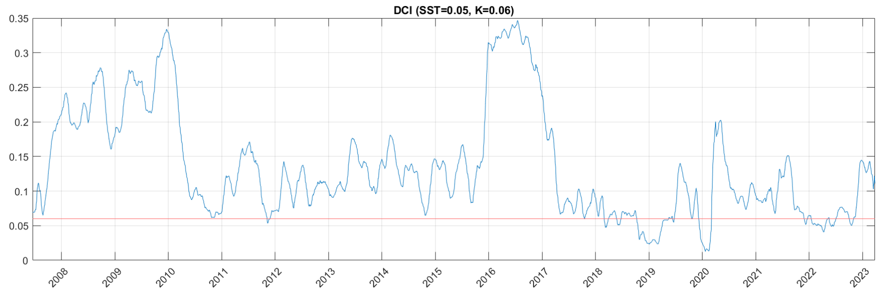
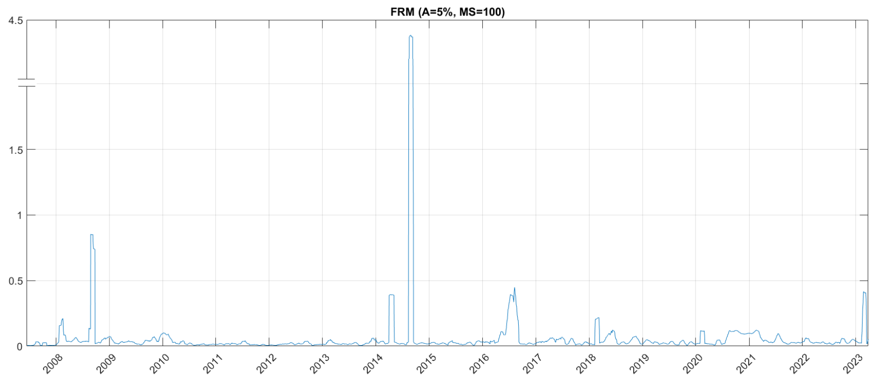
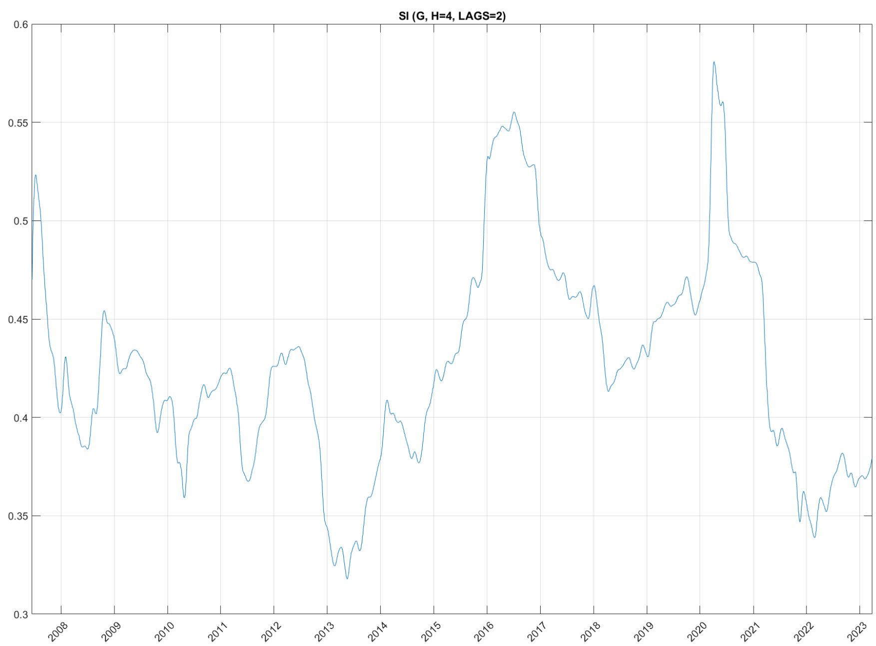


(a) Dynamic Connectedness Index

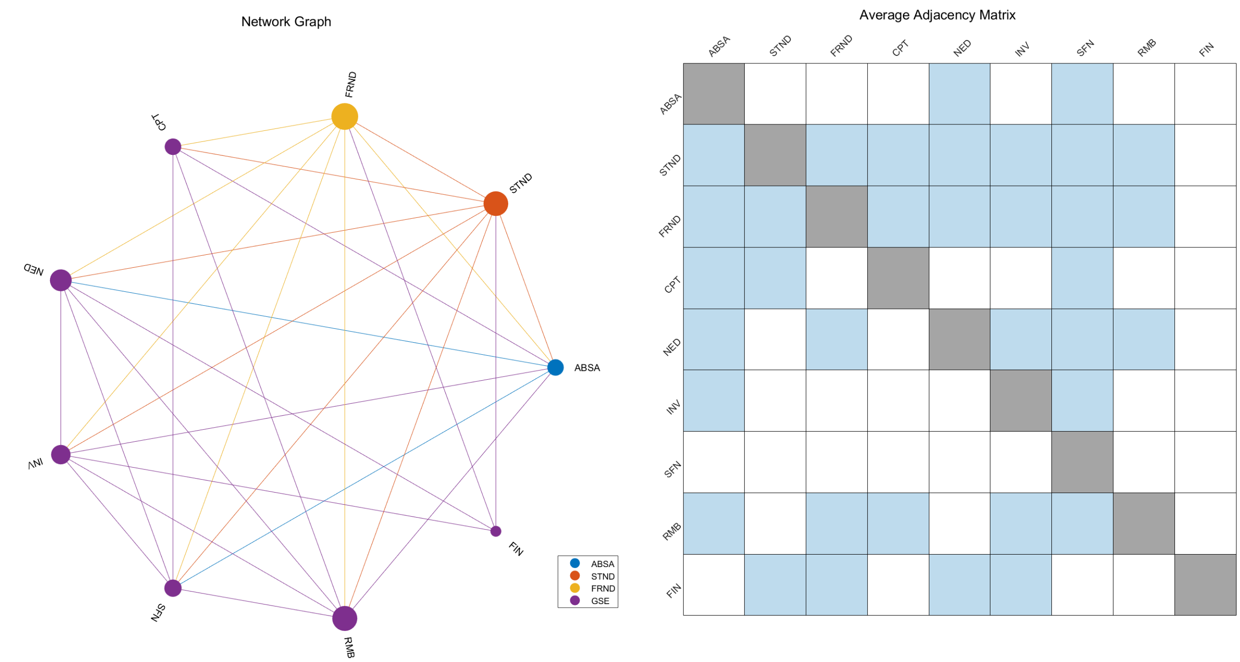


(b) Financial Risk Meter

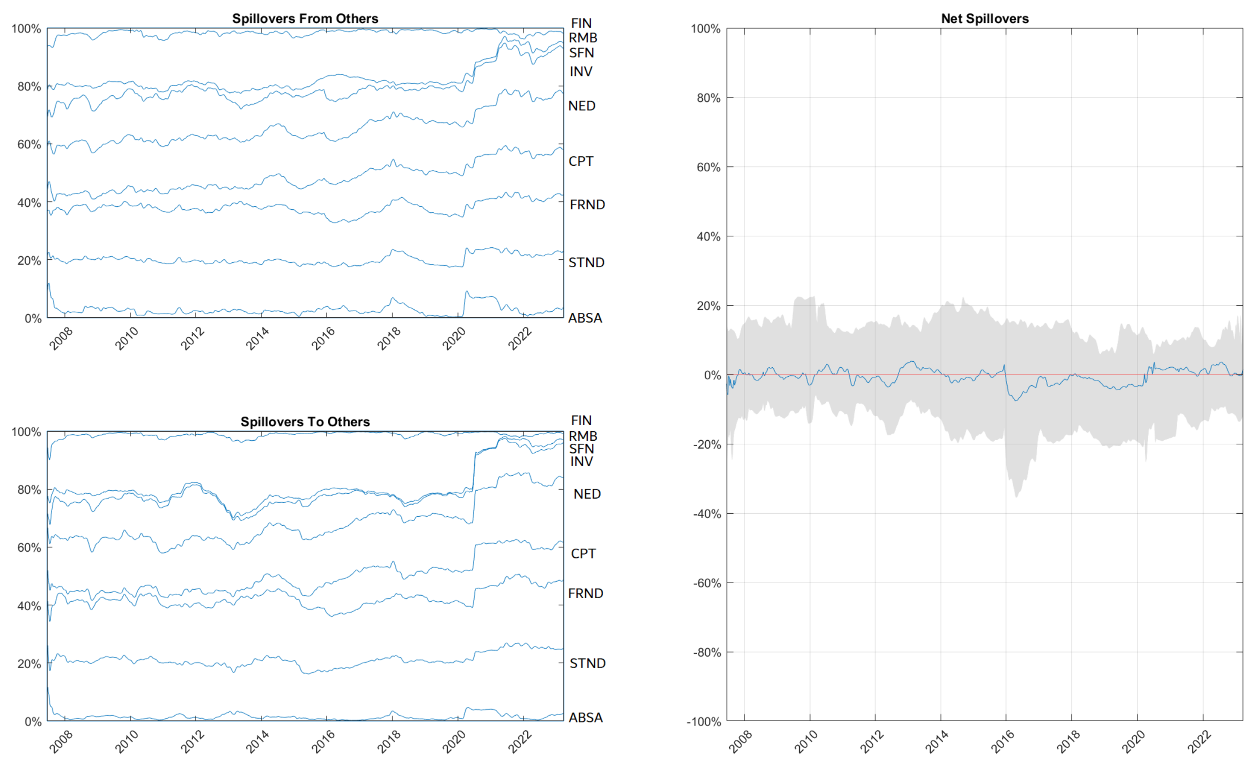


(c) Spillover Index (SI)

FIGURE 1
Interconnectedness indices, 2008-2023

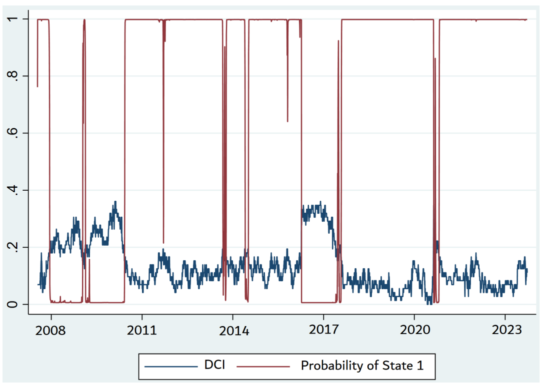


(a) Interconnectedness network of Granger-caused connections and average adjacency matrix, 2008 - 2023. Blue cells denote causality from bank X to other banks (rows) and from other banks to bank X (columns).

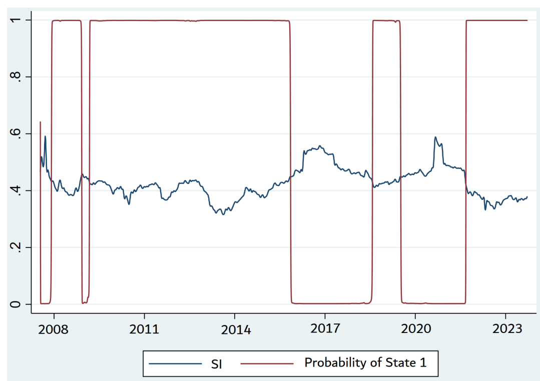


(b) Spillovers from and to each bank (left) and net spillovers.

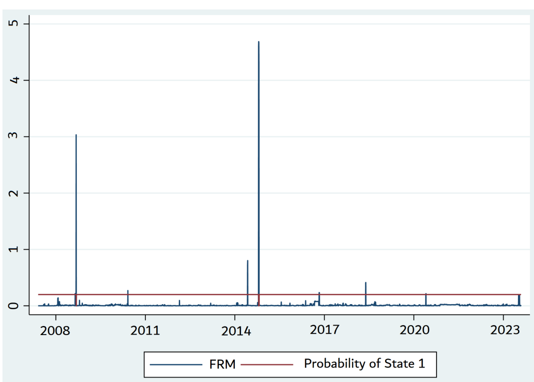
FIGURE 2
Granger causality and Spillover graphs



(a) DCI



(b) SI



(c) FRM

FIGURE 3
Interconnectedness indices (blue) and transition probabilities (red), 2008-2023

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

TABLE 1
Dynamic regression Markov switching results

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.

	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
Squared 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***

TABLE 2
Regressions for DCI, T1CA and Macroeconomic controls

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.

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
Squared 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***

TABLE 3
Regressions for DCI, TCA and Macroeconomic controls

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.

	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
Squared Error	0.0891	0.0789		0.0747	0.0755
Observations	98	98		98	98
F	0.5481	0.1300		5.5500***	5.0700***

TABLE 4
Regressions for DCI, LC, and Macroeconomic (Panel a) or Bank Performance (Panel b) controls

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.

	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
Squared Error	0.0637	0.0386	0.0513	0.0396	0.0669	0.0464
Observations	183	183	60	60	123	123
F	0.897986543	5.84***	1.1143	1.29	1.965*	4.05***

TABLE 5
Regressions - FRM Macro

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.

	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
Squared 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***

TABLE 6
Regressions for SI, TCA and Macroeconomic controls

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.

	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
Squared 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***

TABLE 7
Regressions for SI, T1CA and Macroeconomic controls

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.

	OLS	**Robust OLS**		OLS	**Robust OLS**
IV: SI	Panel (a), 2015-2023		SI: DCI	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
Squared 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

TABLE 8
Regressions for SI, LC and Macroeconomic (Panel a) and Bank Performance controls (Panel b)

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.

	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
Squared 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***

TABLE 9
Regressions for DCI, T1CA and Bank Performance

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.

	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
Squared 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***

TABLE 10
Regressions for DCI, TCA and Bank Performance

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.

	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
SE	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

TABLE 11
Regressions for SI, T1CA and Bank performance controls

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.

	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 Square	0.0480	0.0602	0.1750	0.1710	0.0707	0.0520
Adjusted R Square	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

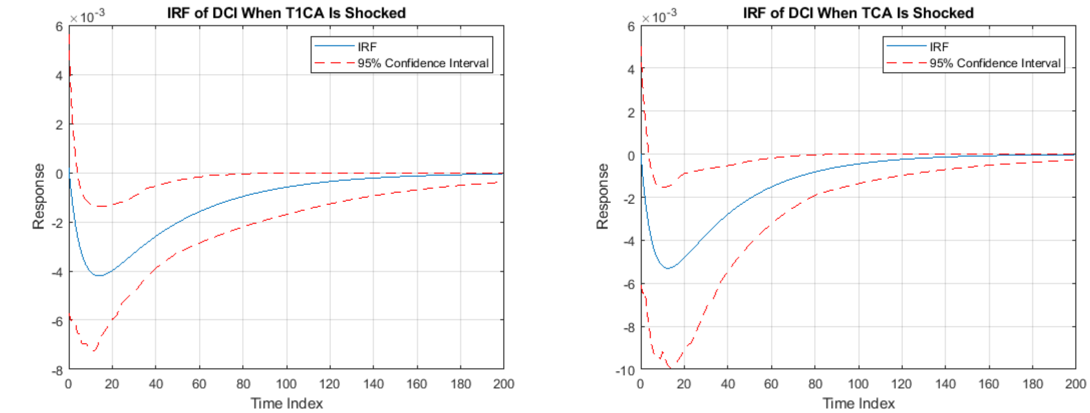
TABLE 12
Regressions for SI, TCA and Bank performance controls

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.

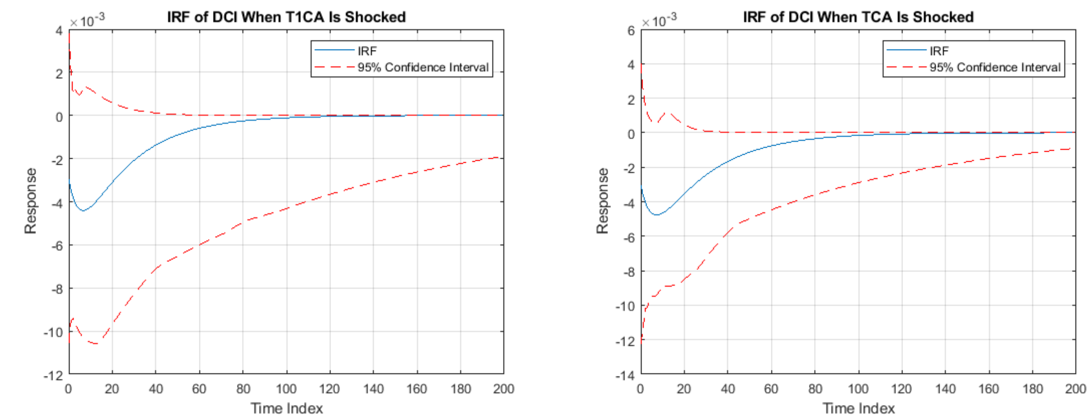
Granger causality flow	Statistic	p-value	Statistic	p-value	Statistic	p-value
	2008-2012		2013-2023		2008-2023	
T1CA → DCI	3.1577	0.0756	4.3949	0.0361	6.0295	0.0141
DCI → T1CA	2.654	0.1033	3.1510	0.0759	1.4312	0.2316
	2008-2012		2013-2023		2008-2023	
TCA → DCI	2.9644	0.0851	5.2981	0.0214	7.0507	0.0079
DCI → TCA	1.7181	0.1899	2.4598	0.1168	1.2020	0.2729
			2015-2012			
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
			2015-2012			
LC → SI			14.0160	0.0073		
SI → LC			7.6216	0.1065		

TABLE 13
Granger Causality relationships

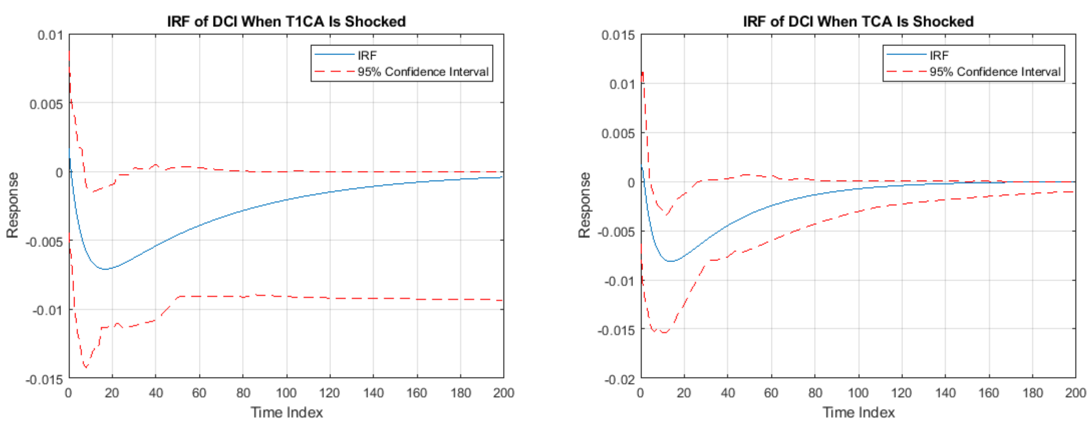
Note: Granger causality between the Basel III regulatory variables TCA, T1CA and LC and interconnectedness indices DCI, SI for the respective period. The arrow denotes the flow of causality. The null hypothesis is that no causality exists and therefore p-values below 0.1 (in bold) imply rejection of 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.



(a) 2008-2023

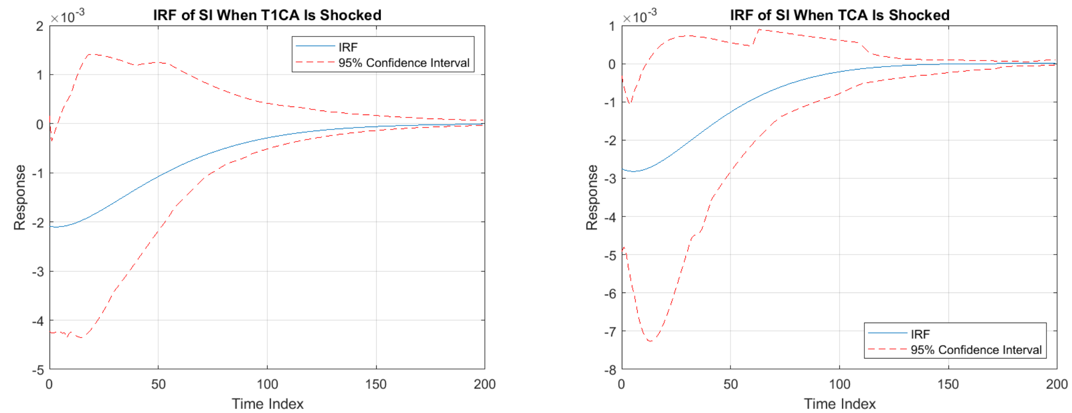


(b) 2008-2012

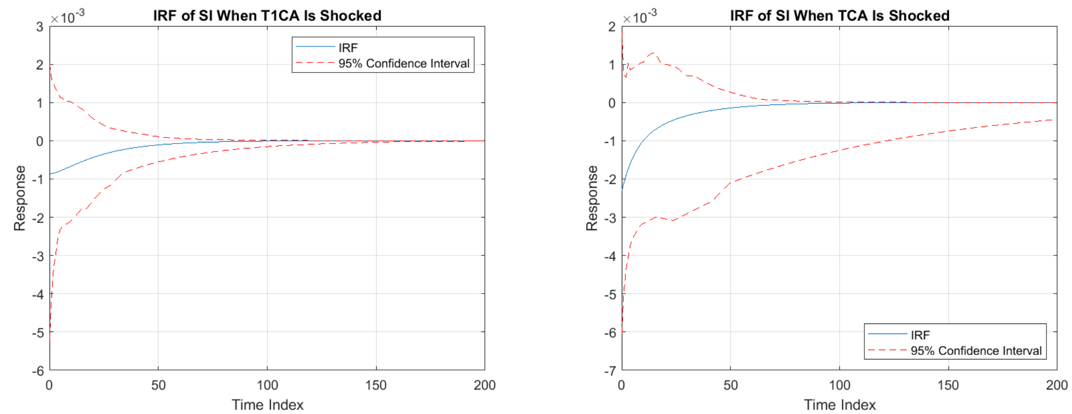


(c) 2013-2023

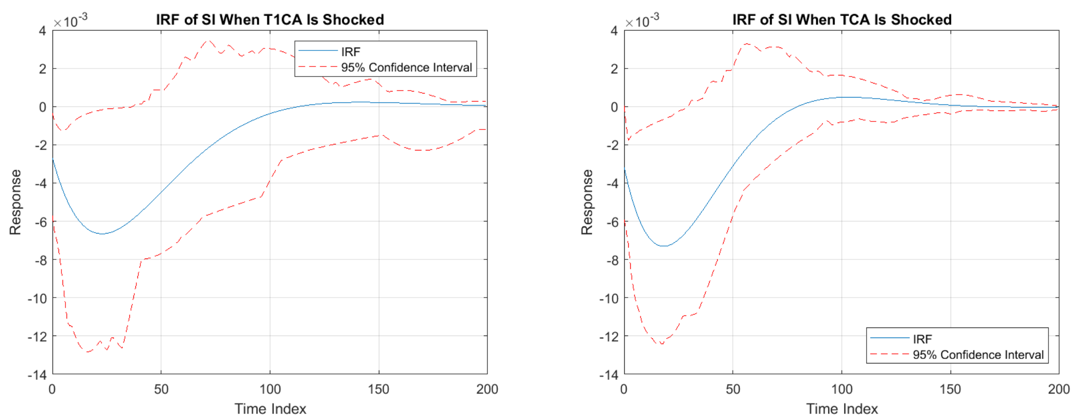
FIGURE 4
VAR IRFs for DCI



(a) 2008-2023

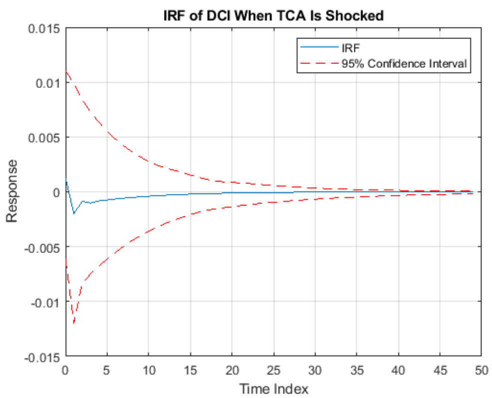


(b) 2008-2012

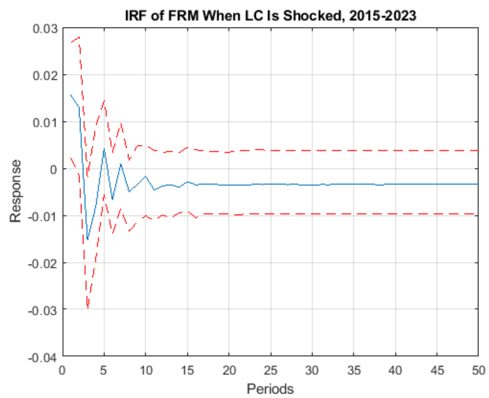


(c) 2013-2023

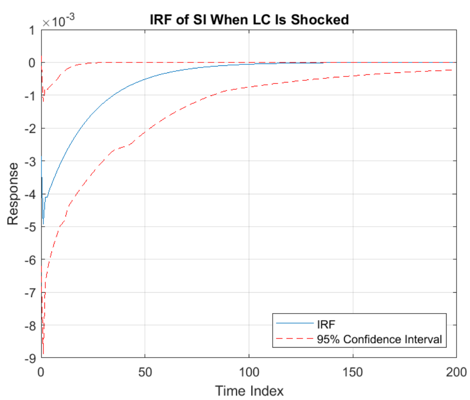
FIGURE 5
VAR IRFs for SI



(a) VAR IRF, 2015-2023, DCI



(b) VAR IRF, 2015-2023, SI



(c) VEC IRF, 2015-2023, FRM LC GDP

FIGURE 6
IRFs for LC

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)**

TABLE 14
VEC 1 and VEC 2 estimates

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

	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)

(a) VEC 3 (DCI, T1CA, RoE)

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

(b) VEC 4 (SI, LC, RoE)

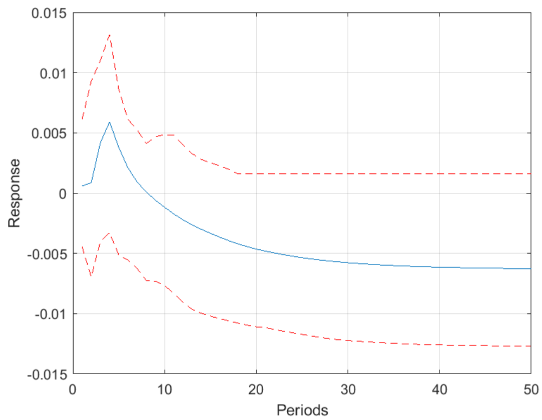
TABLE 15
Vec 3 and VEC 4 estimates

Note: VEC 3 is a 3-dimensional VEC(0) model with one cointegrating relationship and DCI, T1CA and RoE as variables. VEC 4 is a 3-dimensional VEC(0) model with one cointegrating relationship and SI, LC and RoE as variables. Lags are determined by the AIC, BIC and Schwarz criteria. Standard errors in parentheses. Statistical significance at 1%, 5% and 10% denoted by (*), (**) and (***) respectively.

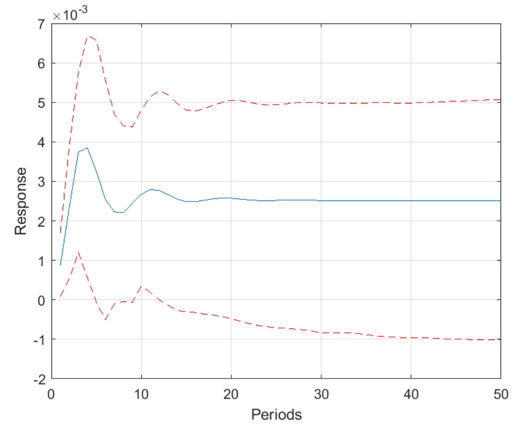
VEC 5	Dependent Variable	ECT	LC_{-1}	LC_{-2}	LC_{-3}	GDP_{-1}	GDP_{-2}	GDP_{-3}	DCI_{-1}	DCI_{-2}	DCI_{-3}
2015-2023	DCI	-0.0704	-0.1022	-0.0495	-0.1809	0.1140	0.4185	0.2915	0.0004	-0.1828	0.0067
		(0.0525)	(0.0945)	(0.1017)	(0.0963)	(0.5262)	(0.5742)	(0.5060)	(0.1125)	(0.1119)	(0.1140)
	GDP	-0.0235	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 6	**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 7	**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)

TABLE 16
VEC 5, VEC 6 and VEC 7 estimates

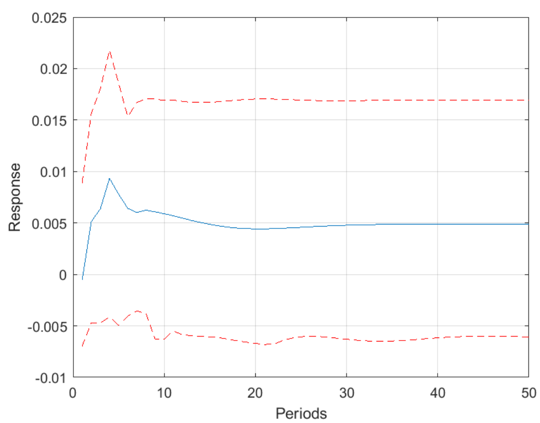
Note: VEC 5 is a 3-dimensional VEC(3) model with one cointegrating relationship and DCI, LC and GDP as variables. VEC 6 is a 3-dimensional VEC(0) model with one cointegrating relationship and SI, LC and GDP as variables. VEC 7 is a 3-dimensional VEC(3) model with one cointegrating relationship and FRM, LC and GDP as variables. Lags are determined by the AIC, BIC and Schwarz criteria. Standard errors in parentheses. Statistical significance at 1%, 5% and 10% denoted by (*), (**) and (***) respectively.



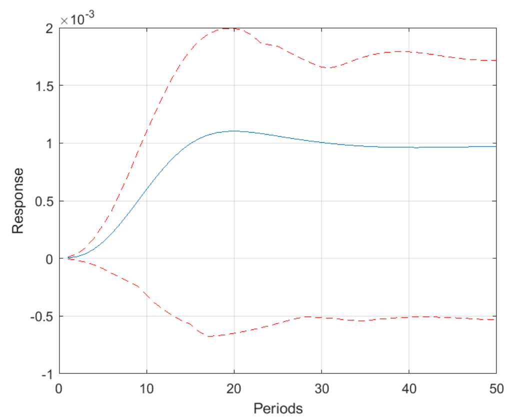
(a) IRF of DCI when T1CA is shocked, 2008-2023



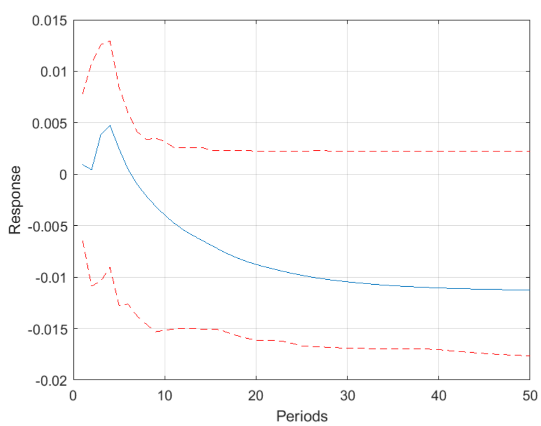
(b) IRF of GDP when T1CA is shocked, 2008-2023



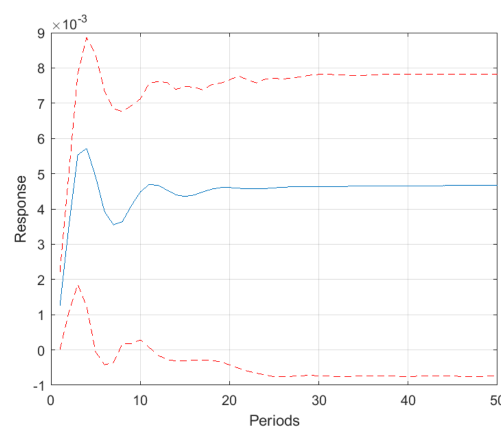
(c) IRF of DCI when T1CA is shocked, 2008-2012



(d) IRF of GDP when T1CA is shocked, 2008-2012

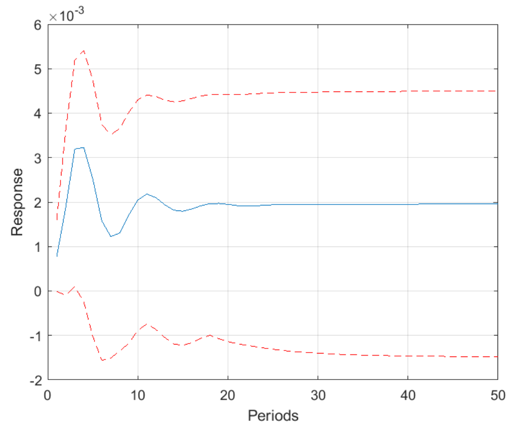


(e) IRF of DCI when T1CA is shocked, 2013-2023

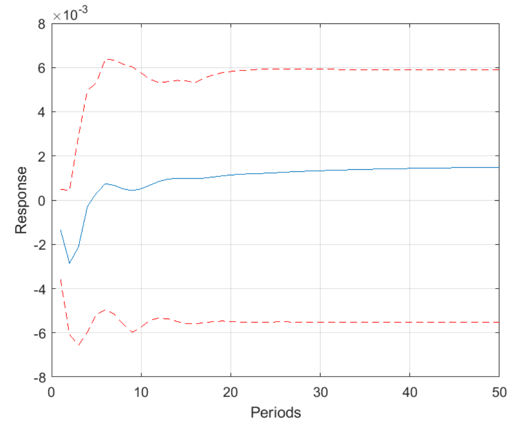


(f) IRF of GDP when T1CA is shocked, 2013-2023

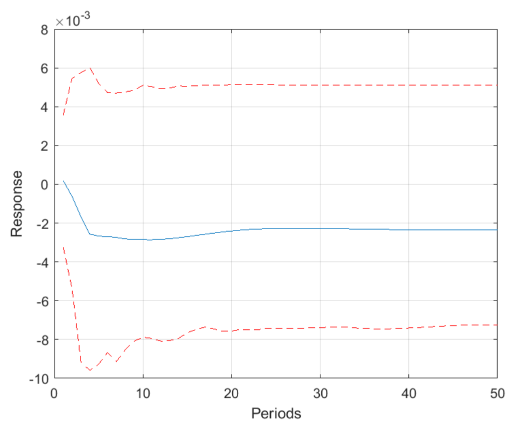
FIGURE 7
Impulse Response Functions (IRF) and 5% confidence intervals of VEC 1



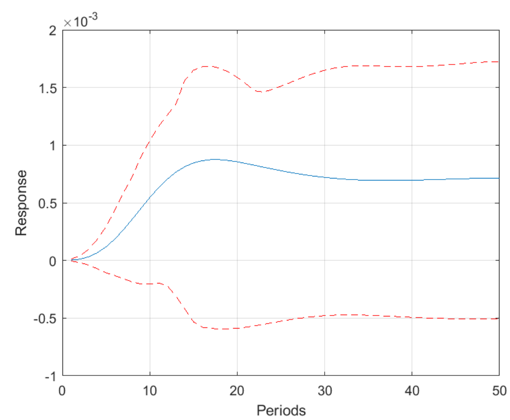
(a) IRF of SI when T1CA is shocked, 2008-2023



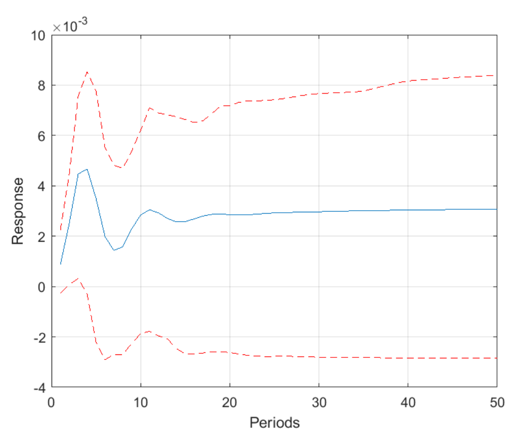
(b) IRF of GDP when T1CA is shocked, 2008-2023



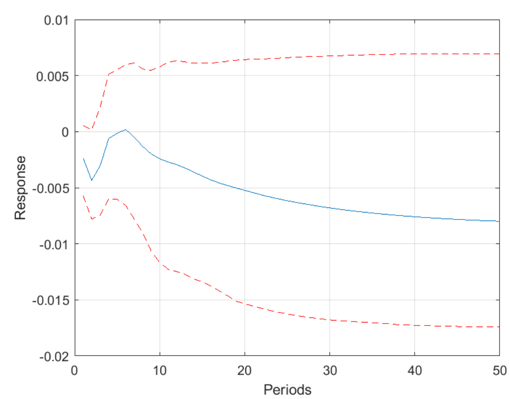
(c) IRF of SI when T1CA is shocked, 2008-2012



(d) IRF of GDP when T1CA is shocked, 2008-2012

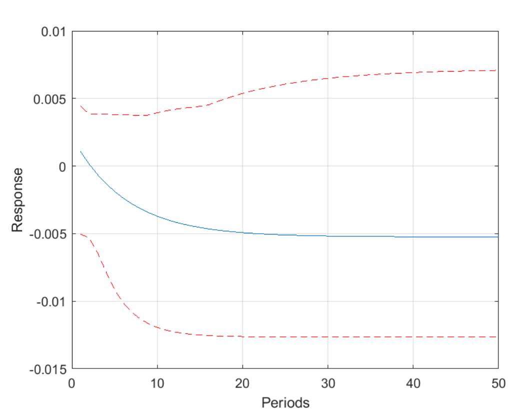


(e) IRF of SI when T1CA is shocked, 2013-2023

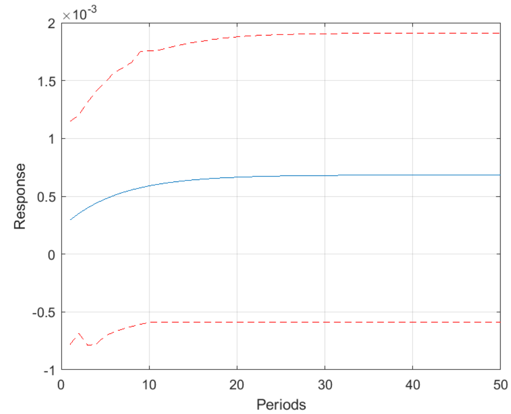


(f) IRF of GDP when T1CA is shocked, 2013-2023

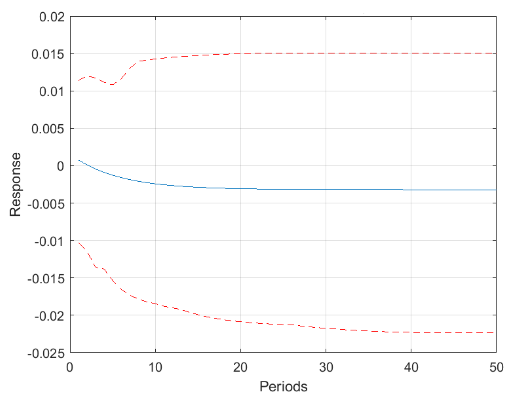
FIGURE 8
Impulse Response Functions (IRF) and 5% confidence intervals of VEC 2



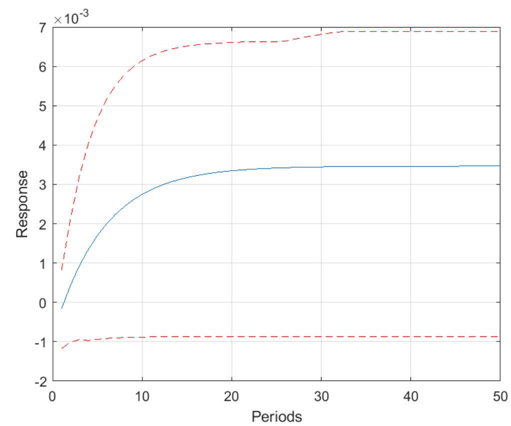
(a) IRF of DCI when T1CA is shocked, 2008-2023



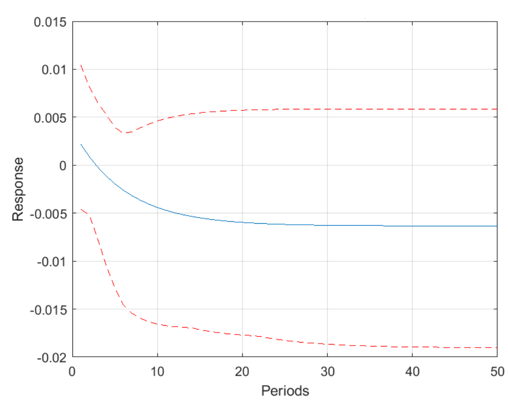
(b) IRF of RoE when T1CA is shocked, 2008-2023



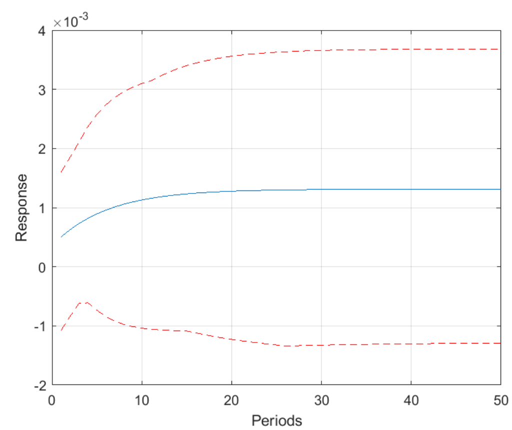
(c) IRF of DCI when T1CA is shocked, 2008-2012



(d) IRF of RoE when T1CA is shocked, 2008-2012

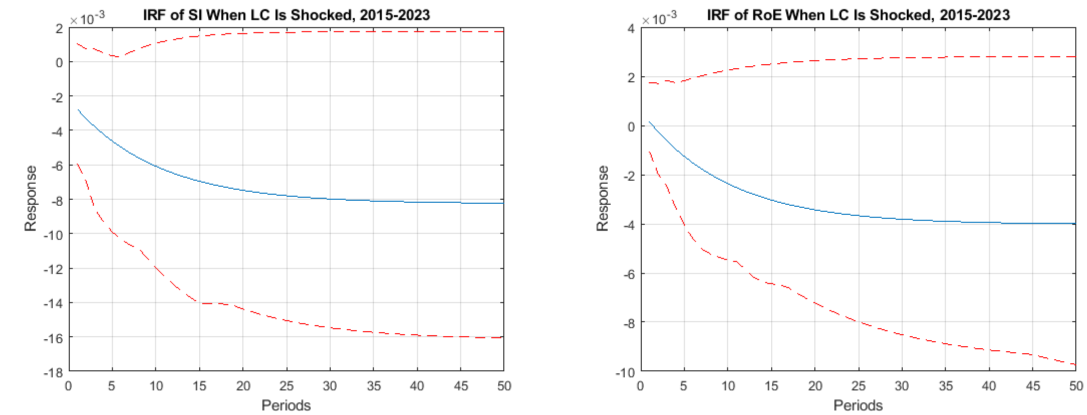


(e) IRF of DCI when T1CA is shocked, 2013-2023

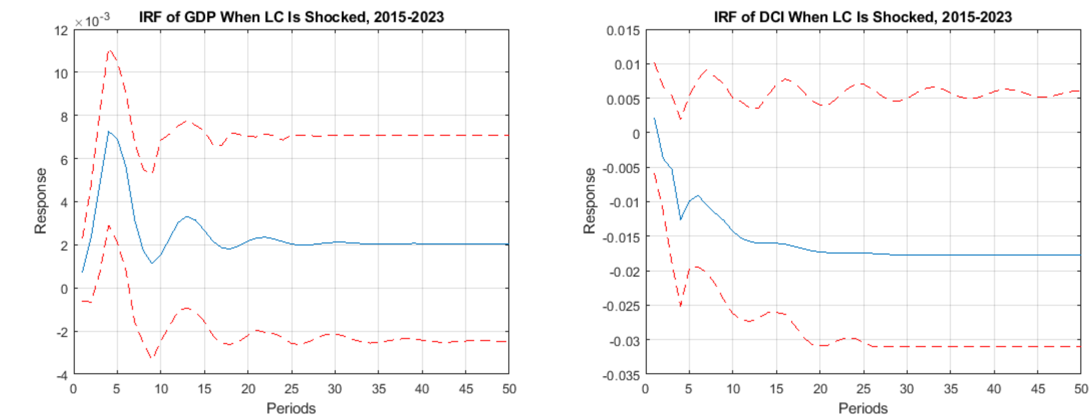


(f) IRF of RoE when T1CA is shocked, 2013-2023

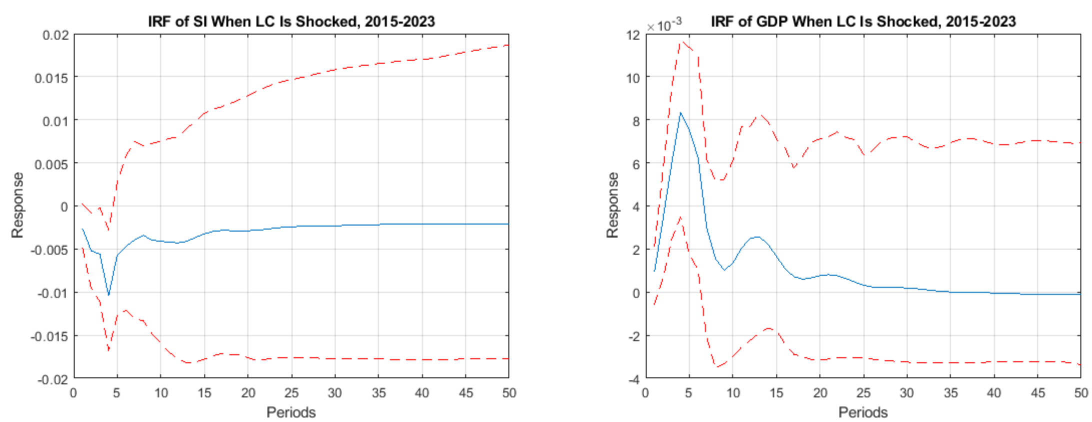
FIGURE 9
Impulse Response Functions (IRF) and 5% confidence intervals of VEC 3



(a) VEC 4 (SI, LC, RoE)



(b) VEC 5 (DCI, LC, GDP)



(c) VEC 6, SI, LC, GDP

FIGURE 10
Impulse Response Functions (IRF) and 5% confidence intervals of VECMs 4, 5 and 6

Appendix A.

Variable	Source	Period/ Frequency	Scale/ difference	Abbreviation	Obs	Mean	SD
			Market variables				
Stock price ('000 Rand) Dynamic	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
Ten largest depositors to total funding	SARB	09-23, M	Log %	10LD/TF	171	0.1288	0.0505
			Macroeconomic variables				
Gross Domestic Product 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
Consumer Price Index	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)							

TABLE A.17
Sample summary statistics, before logs or differencing