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David M. Ndwiga

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74

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# Bank credit portfolio allocation in pre and post Covid times - The power of inherent risks

David M. Ndwiga

## Abstract

*The study seeks to determine how the bank credit allocation has evolved in pre – covid, covid and post covid era amid possible uncertainties. Study focused on credit risk, liquidity risk, industry competition and operating efficiency for 2010 – 2021 period. Panel Autoregressive Distributed Lag and panel Generalized Method of Moments were applied for bank level data while sectoral level Autoregressive Distributed Lag models were applied for sectoral analysis. The study found credit, liquidity, covid are all negatively related to bank credit allocation. In addition, interaction of covid with credit and liquidity risks reveal that the effect of liquidity risk is more pronounced. Recovery era simulation posits that personal household sector would register the highest allocation with real estate sector allocation being last. The study calls for more vigilance in the post pandemic times as credit risk is likely to reveal itself amid relaxation in loan reclassification. Further, a more proactive monetary policy is advocated for to address the liquidity distribution challenges.*

# 1.0 Introduction

## 1.1 Background of the study

**In the advent of Covid – 19 pandemic, the banking industry globally has witnessed unprecedented changes with credit portfolio reallocation being eminent in the bank's loan book.** To this effect, the quality of the banking industry assets has generally deteriorated owing to increased defaults thus limiting the bank capability and appetite towards advancing more loans. In addition, increase in the loan provision amid increase in non – performing loans has been evident during Covid times in attempt to cushion banks from possible credit losses. It's notable that all these developments are happening amid declining bank earning. Arising from these development is the inefficiency in credit allocation hence adverse effect on credit intermediation that is crucial in support post - Covid recovery process.

According to European Central Bank (2020) and the IMF (2020b), the banking industry stress testing, to assess the sensitivity of bank capital ratios under adverse conditions reveal that banks that are most at risk include those that entered the crisis with existing idiosyncratic problems or those heavily exposed to the sectors most affected by the COVID-19 crisis, and whose capital ratios might not withstand the upcoming challenges. The deterioration in asset quality and rising loan losses following the COVID-19 pandemic is therefore likely to further weaken banks' capabilities to absorb higher loan losses and possibly their lending supply. This analysis findings signifies the power of inherent risks in so far as determination of bank's portfolio allocation and appetite for loans advances is concerned.

The effect of the pandemic on the banking industry resilience and ability to absorb more loans and advances is underscored in this study. Deterioration of the bank assets quality during pandemic arising from high defaults risks posed a risk of potential capital erosion. Of concern here therefore is the assessment of the bank capital that would be needed to absorb higher loan losses and the subsequent capital erosion of banks' regulatory capital ratios in pandemic period. However, its notable that though deterioration in bank assets quality could be linked to Covid – 19 pandemic, the effects on the industry resilience is totally different where the industry was already suffering from low asset quality even prior to the pandemic (ECB, 2020g).

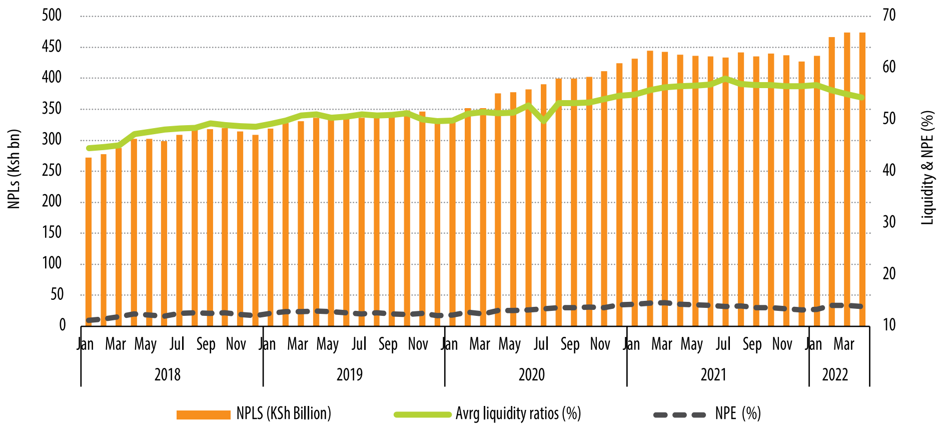
Therefore, a study on the inherent risks emanating from the pandemic and how these affects banks' credit supply crucial. Therefore, this study seeks to assess to what extent did the inherent market risks affect bank credit allocation during the COVID-19 pandemic era and secondly is to examine how bank credit allocation would look like on the backdrop of a given monetary policy scenario in the recovery period. The rationale here is that during the pandemic, the decline on the banking industry asset quality posed inherent risks in the bank's balance sheet by undermining the banks' ability to intermediate credit and offer the possible support for recovery in post covid times. In addition, the simulated credit allocation in post covid era under existing monetary policy scenario is undertaken in the study. The simulations are based on the assumption that extensive monetary support is crucial in obviating some of the inherent risks and uncertainties likely to affect credit allocation in post covid times.

A review of the state of the banking industry in the Covid, Covid and post Covid pandemic indicates that Kenya's banking industry entered the Covid era in a largely stable and resilient state. Its notable that the industry remained resilient to the pandemic in 2020, supported by strong capital and liquidity buffers, reforms undertaken since 2015, leveraging on modern innovative financial technologies and business models, repeal of the interest rates capping law and Covid–19 policy measures (CBK Financial Stability Report, 2021). The policy support by the regulator, saw the industry restructure Ksh 1.7 trillion loans translating to 54 percent of the total gross loans by March 2021. During this period, banks got an opportunity to re-adjust and build their capital and liquidity buffers, contributing to stability of the industry.

In terms of credit allocations, the banks risk taking appetite slowed down with a shift towards less risky assets. In fact, the industry loans and advances and investments in Government securities accounted for 50 percent and 30 percent of net assets in December 2020, compared to 54.8 percent and 31 percent in June 2021. Since the fourth quarter of 2015, growth rate of government securities have outpaced growth in loans and advances, highlighting the risk aversion of banks during the pandemic period. Increased appetite for government securities, accumulation foreign denominated assets and skewed lending to large firms was a good reflection of the industry's flight to safety during the pandemic as credit risk increased.

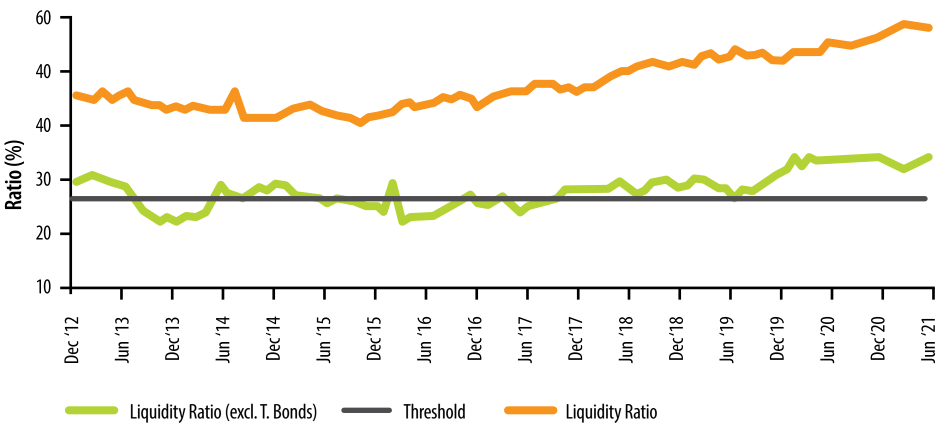
A review of the industry's liquidity levels reveals that the liquidity ratios stood above the minimum statutory level of 20 percent at an average liquidity ratio of 56.2 percent in the same period. Further, the core capital and total capital to total risk weighted assets ratios averaged 16.5 percent and 18.9 percent in the year to June 2021, compared to an average of 16.4 percent and 18.4 percent, respectively, since December 2016, against the minimum statutory core and total capital requirement of 10.5 percent and 14.5 percent, respectively (CBK Financial Stability Report, 2021).

**Figure 1: Trends in industry asset quality, liquidity levels and nonperforming exposure**




Further, review of the current years' banking industry liquidity levels indicates banks' liquidity remains high, averaging above 20 percent minimum regulatory requirement, hence no immediate liquidity risk. Liquid assets increased from KSh 1,746 billion in December 2019, to KSh 2,131 billion in December 2020, and KSh 2,326 billion in June 2021, with liquidity ratio averaging 56.8 percent in June 2021.

**Figure 2: Trends on banking industry liquidity ratio against requirement threshold**




Source: CBK, Monthly economic indicators

The novelty of this study is hinged on the quest why is bank credit allocation in pre and post Covid era important?. To answer this quest, the study cross examine the existing empirical works in this area of study. Its evident that the advent of Covid 19 occasioned a "new normal" globally. Further, we note that the new normal came with market disruptions that affected markets at large. One of such markets was the credit markets whereby new normal presented some inherent market risks that affected market credit supply. Further, we note that this being a new global crisis, the response measures put in play are expected to have had unique effects in the credit market. Therefore, the generalization of the effects of other past crises on credit markets would be misleading given the unique nature of the Covid 19 pandemic.

Further, this study notes that the effects of the pandemic on the real economy was a sufficient ground for the for constrained bank lending due to the possible credit risk. Further, this having been a unique pandemic, its possible that the lender adopted a wait and see scenario and the crisis unfolded. Though one of the outright risk is the credit risks, the question posed by this study is are there other risks that could have been eminent in this crisis beyond the credit risk that are likely to have had an effect on banking industry's credit allocation? This question is necessitated be the very measures implemented targeting the industry. It is very clear that much of the measures to the industry majorly focused on credit risk such as bank loan reclassification. Therefore, an examination into other possible risks beyond credit risks would be of great addition into the empirical work in this area.

Acharya et al (2017) asserts that banks' credit allocation is procyclical in nature thus its influenced by shocks in the economy. Therefore, covid being one of the shocks to the world, its expected that the bank credit allocation. During the pandemic, financial institutions such as banking sector has suffered an immediate exogenous shock (Elnahass, Trinh & Li, 2021). Existing studies in this area unanimously agree that during the pandemic, the banking industry's asset quality deteriorated considerably. Colak and Öztekin (2021) assert that during the crisis, financial intermediaries, bank loan, and credit markets are significantly negatively affected leading to credit supply constraints. Similarly, Ari ***et al*** (2021) assert that deep recession associated with the Covid-19 crisis inevitably led to high non-performing loans and weaken bank balance sheets.

However, despite this evidence, it is eminent that scanty empirical work in less developed markets does exist. In addition, majority of the existing empirical work is more biased towards credit risk arising from deteriorating banks assets quality hence being mute on other inherent risks likely to have rose from the Covid pandemic. Moreover, the empirical work in this area are short of offering the linkage between the market risks associated with Covid and the bank credit allocation more so the sectoral credit allocation. Moreover, studies in this area shy away from undertaking simulations of bank credit allocation in post covid / recovery period on the backdrop of supportive monetary policy which is key in supporting economy's post covid recovery process. This study seeks to fill in all these research gaps, hence its timeliness and worth. Therefore, by undertaking this study, the study sought to answer two pertinent questions. First is to what extent did the bank credit risk, liquidity risk, bank competition level affect credit allocation in pre - covid and covid era and secondly how would banking industry credit allocation look like in the recovery period under the existing monetary policy scenario?

Further, an investigation into bank credit allocation in covid and post covid era in so far as the power of the inherent risks is concerned is crucial given the role that bank credit stand to play in supporting economic growth in the recovery period. Further, the importance of undertaking an assessment of bank credit allocation in covid and post covid era is informed by the assertion that crises offer best opportunity to learn what works in economics, finance, or any field of research. As pointed out by Rajan (1994); Berger and Udell (2004); Thakor (2005); Acharya and Naqvi (2012) just like seeds of future crises are sown during booms, crisis and downturns provide a ground to evaluate what works and what does not as well as offering opportune time for corrective policies / measures to support recovery.

However, despite this evidence, it is eminent that scanty empirical work in less developed markets does exist. In addition, majority of the existing empirical work is more biased towards credit risk arising from deteriorating banks assert quality hence being mute on other inherent risks likely to have rose from the Covid pandemic. Moreover, the empirical work in this area are short of offering the linkage between the market risks associated with Covid and the bank credit allocation more so the sectoral credit allocation. Moreover, studies in this area shy away from undertaking simulations of bank credit allocation in post covid / recovery period on the backdrop of supportive monetary policy which is key in supporting economy's post covid recovery process. This study seeks to fill in all these research gaps, hence its timeliness and worth. Therefore, by undertaking this study, the study sought to answer two pertinent questions. First is to what extent did the bank credit risk, liquidity risk, bank competition level affect credit allocation in pre - covid and covid era and secondly how would banking industry credit allocation look like in the recovery period under the existing monetary policy scenario?

A quest to answer these two questions would be of significance in three-fold. First, is the significance in the banking industry players majorly the commercial banks. The study findings would elicit understanding on how the market risk and other associated risks affect bank credit allocation during crisis thus informing players reassessment of their respective credit models in post crisis era to support recovery. In addition, would be the informing of the players preparedness in possible future crisis. Secondly, is the significance to the policy development especially in so far as monetary policy stance pronouncement is concerned. By simulating how credit allocation on the backdrop of the monetary stance, the study findings would be key in invoking policy discussion on how the authority would tweak the policy rate in a manner that it supports bank's credit allocation to the sectors that were hardly hit by the pandemic. Further is the importance in eliciting the linkage between monetary policy and private sector credit growth majorly via the quantity channel whereby a conducive monetary policy would incentivise commercial banks to grow their loan book by lending more funds to borrowers.

Lastly is the contribution to literature. It's notable that much of the empirical work in this area has been around crises such as global financial crisis of 2007/2008, as well as other country specific crises. Therefore, limited empirical literature dose exist on banks credit allocation in Covid crisis. This could however be informed by the fact that Covid pandemic is a recent global development hence research in this area is crucial in adding to existing body of empirical literature in this area. Undertaking this study is therefore timely in empirical literature contribution.

# 2.0 Literature Review

## 2.1 Theoretical perspective

There exists several theories on credit allocation by the financial service providers. This section reviews these theories upon which the study was anchored on. According to Werner (2014), three typical banking theories are eminent which explain the credit allocation within the banking industry. These include the credit creation, the financial reserve, and the intermediation theories. Credit creation theory emphasizes on the role of money creation in the loans disbursement and accounting operations. On the other hand, financial reserve theory explains how the banking system creates money collectively, whereas in the financial intermediation theory, banks being the intermediaries, function as a medium to collect deposits and lend out those deposits to benefit from the interest spread (Ravn, 2019; Werner, 2016).

According to the credit creation theory, banks create credit by advancing loans and purchasing securities. They lend money to individuals and businesses out of deposits accepted from the public. However, it's notable that the customer deposits are limited in meeting all the banking lending obligations. Therefore, banks do not solely lend customer deposits but they can create money. Consequently, bank creates bank deposits as a results of bank lending. The idea of credit creation process by the bank is to overcome the constraint of relying on customer deposits for lending. Therefore, according to the theory, banks' ability to create credit money arises from combining lending and deposit taking activities. The relevance of this theory to the study is the during crisis, credit creation is likely to be halted. Risks averse behaviour amid credit risk in crisis times are likely to adversely affect bank lending activities. However, on the other hand, the Risks averse behaviour in crisis times are likely to push banks to engage in the purchase of the securities perceived to be less risky. These two dimensions results into credit reallocation in the long run. Therefore, the overall credit creation would be determined by the net of advancing loans and purchasing securities.

The financial intermediation theory by Gurley and Shaw (1960) asserts that banks being intermediaries play a crucial role in reducing transaction costs and informational asymmetries in the financial markets. However, during the crisis period such as one witnessed in the Covid era, market information asymmetry transaction costs rises substantially due to high credit risks. The uncertainties posed by the pandemic coupled with the inherent risks made it difficult for the banks to ascertain the true market risk level thus hindering efficient financial resources allocation. This could in return have resulted into some element of credit misallocation during the crisis (World Bank, 2020). In addition, it's notable that during the covid crises, government put a number of borrower relief measures to cushion borrower. One of the key measure was the loan restructuring. However, in this study we note that while the borrower relief measures help to reduce pressures on banks' capital, their extension can be associated with a negative impact on banks' liquidity, as the relief measures translate into a potentially significant reduction on cash flows and overall earnings on banks' loan books.

In addition, the extension of measures can feed into borrowers' expectations that moratoria constitute a new normal, impeding a reversal to the status quo pre-COVID-19, and exacerbating moral hazard due to their deleterious effect on credit culture and repayment discipline. Lastly, prolonging the borrower relief measures may also be associated with a misallocation of capital. Zombie borrowers, whose financial difficulties predate COVID-19, will exert considerable pressure to benefit from the borrower relief measures. This can effectively lock up the credit stock in underperforming economic sectors and crowd out the financing needs of more dynamic borrowers. This explains the application of the financial intermediation theory in this study.

In fact, World Bank (2020) Policy note asserts that during the crisis, the non-viable borrowers were kept afloat and lingered around though still financially distressed. However, on the contrary, the viable borrowers did not get the depth and quality of long-term restructuring measures they needed to fully recover. Consequently, banks' credit stock got stuck in underperforming sectors, at the expense of newer more dynamic sectors thus piling downward pressures on banks asset quality. This was an indication of credit misallocation.

## 2.2 Empirical literature review

A review of literature in this area of research reveals that sizeable body of literature exists regarding banks' credit allocation in crises periods. However, it's notable that much of the empirical work in this area has been around crises such as global financial crisis of 2007/2008, as well as other country specific crises. Therefore, limited empirical literature dose exist on banks credit allocation in Covid crisis. This could however be informed by the fact that Covid pandemic is a recent global development hence research in this area is crucial in adding to existing body of empirical literature in this area. However, despite this scenario, its noteworthy that review of such studies are core in info0rming banks' response to any form of crisis and how the inherent uncertainties and risks posed by the crisis feed into credit allocation dynamics.

Bolton *et al*, (2013) studied credit allocation among Italian banks during crisis by examining how relationship and transaction-banks respond to the crisis. The study found that in line with the basic predictions, relationship banks charged a higher spread before the crisis, offer more favourable continuation-lending terms in response to the crisis, and suffer fewer defaults. This finding confirms informational advantage of relationship banking in the sense that relationship banks gather information on their borrowers, which allows them to provide loans for profitable during a crisis. For this reason, relationship banks are capable of cushioning themselves from extending new credit facilities or even prolonging the existing credit facility to low-productivity firms in times of crisis. Therefore it can be concluded that relationship banks shift their credit allocation in favour of profitable firms in times of crisis at the expense of low-productive firms hence likely to register less defaults.

Demirguc-Kunt et al (2020) examined the banking sector performance during the covid-19 crisis. The study investigated how the banks performed in the pandemic era as well as how different policy interventions shaped the industry performance. The study postulates that during the first phase of the pandemic, the banking industry was faced with liquidity shortages that were aggravated by high volatilities in the security markets and forex markets. During this period the interbank liquidity premium rose substantially worsening the liquidity risk in the industry. Moreover, the bank level analysis indicated that banks with lower pre-crisis liquidity and oil sector exposure also suffered greater reduction in returns, consistent with their greater vulnerability to such a shock.

Dung (2020) evaluated the role of funding liquidity on bank credit allocation among the United States commercial banks. The study reveals that banks that rely more on deposits for lending tend to register lower growth in their loan books. Therefore, the study found that the leveraged effect of funding liquidity is larger among the high-loan growth banks. An examination into the role of funding liquidity on bank credit allocation in 2007 / 2008 financial crisis period indicates that the negative effects of funding liquidity on lending seem to be clearer before the crisis and especially for large banks. However, the study reports no relationship between lending and funding liquidity after the crisis period.

Still on liquidity risk and banks credit allocation, several studies report a negative effect on the bank risk-taking. According to Dahir, Fauziah, and Noor Azman (2018), a reduction in the liquidity risk leads to increased banks risk taking appetite. The same argument is upheld by Khan et al. (2017). In addition, banks with weaker structural liquidity and highly levered in a pre- crisis period have a high likelihood for failure (Vazquez and Federico, 2015). Therefore, in this regard, liquidity abundance is likely to increase banks risk taking appetite which in turn leads to moral hazard. The end result is excessive lending arising from relaxed credit standards which could lead to asset bubble (Acharya and Naqvi, 2012). Based on these studies, its evident that upon the global financial crisis, the banking industry regulators were cognisant of the importance of strengthening liquidity management and financial stability of banks developing frameworks for assessing liquidity in banking in addition to more stringent capital adequacy rules. This holds even in post Covid – 19 era.

The effect of liquidity risk on the bank credit allocation asserts the need for the banks to restructure their balance sheet in preparation for crisis or in the post crisis periods. Therefore, any adjustment towards increasing capital and liquidity buffers is a welcome move in cushioning the bank against liquidity crunches in crises period. A shift from reliance on deposit for lending is core in cushioning the bank from ex-post withdraw of funds by depositors (Tran and Nguyen, 2018). During crisis, banks may experience further difficulties and higher probabilities of failure. The emphasis of the banks to reduce reliance on deposits for lending is premised on the assertion that during crisis, depositors become more aware of the risk of losing their deposits, and then they increase market discipline during the crisis by withdrawing their deposits (Tran and Nguyen, 2018).

Cyril ***et al*** (2022) examined bank capital buffers and credit allocation in Covid – 19 times among the European banks. The study motivation was underpinned on the premises that banks would deploy their capital buffers accumulated in pre Covid times to absorb for loses during the crisis as well as continue extending credit facilities to borrowers in the crisis period. However, such risk taking is subject to the bank's capital buffers proximity to the maximum distributable assets levels. The study found that proximity to the maximum distributable assets trigger results in lower lending. Specifically, we find that in addition, lower lending from banks in proximity of the MDA trigger resulted in credit constraints to firms exposed to these banks as lost loans were not fully replaced. In particular, firms that prior to the pandemic received most of their borrowing from banks closer to the MDA trigger experienced about 2.5% lower borrowing during the pandemic in comparison to firms that borrowed mostly from other banks. The study document that this lack of perfect credit substitution led to firms cutting down their headcounts by close to 1% in comparison to other firms.

A review of the monetary policy effect in credit allocation amid the inherent risks posits that an adoption of an expansionary monetary policy increases the loanable funds available in the banking industry which in turn could trigger a reduction in the cost of credit. However, it's notable that the response by different sectors or firms to this outcome is dependent on the sector or firm heterogeneous in so far as the inherent risks facing the sectors of firms is concerned. First, the expansionary monetary policy will stimulate all the sectors / firms with productivity higher than the cut-off level because of reduced borrowing costs. As a result, the sectors and firms with productivity near the cut-off will expand their financing and investment activities.

Early empirical works by Kashyap, Lamont, and Stein (1994) and Gertler and Gilchrist (1994) asserts that the financially constrained firms are more responsive to monetary policy. Further, Ottonello and Winberry (2018) showed that firms with low leverage are the most responsive to monetary policy shocks. Therefore, emanating from this finding, we could expect the same to apply to the financially constrained sectors. However, a send strand of literature points out towards monetary policy expansion causing credit misallocation. Gopinath et al. (2017) found that, following the imbalances emerging across Europe, capital inflows into southern Europe lowered interest rates, which in turn resulted in an increase in credit misallocation across firms. It's therefore clear that credit expansion through the monetary policy stance plays a crucial role in alleviating financing constraints and promoting resource allocation efficiency. This informs the basis of undertaking a forecast on how bank credit allocation would be on the wake of monetary policy stance.

# 3.0 Methodology

## 3.1 Conceptual framework

**The financial intermediation theory by Gurley and Shaw (1960) asserts that banks being intermediaries play a crucial role in reducing transaction costs and informational asymmetries in the financial markets.** However, during the crisis period such as one witnessed in the Covid era, market information asymmetry transaction costs rises substantially due to high credit risks. The uncertainties posed by the pandemic coupled with the inherent risks made it difficult for the banks to ascertain the true market risk level thus hindering efficient financial resources allocation. This could in return have resulted into some element of credit misallocation during the crisis (World Bank, 2020). Given this scenario we model credit allocation as being determined by market risks. Since we note that market risks have always existed way before even the covid pandemic, in addition to modelling credit allocation as a function of market risks, we introduce the interactions between the market risks and the covid pandemic dummy. These interactions will enable the examination of how the effects of the risks on the credit allocation have evolved in the covid era.

## 3.2 Empirical model

The study applied the ARDL model in estimating the effect of inherent risks and uncertainties on bank credit allocation. First, the ARDL model was estimated for the entire banking industry for 2010 – 2021 period using the bank level data. Secondly, the ARDL models for the respective top 5 sectors bank credit allocation were estimated. Within the models, the Covid era dummy will be included to account for the effect the crisis had on the bank credit allocation.

The general ARDL model was defined as follows:

$$\Delta y_{it} = \phi i(y_i - \gamma X_{it}) + \sum_{j=1}^{p-1} \S_{i,j}\, \Delta y_{t-j} + \sum_{j=0} \beta_{i,j} \Delta X_{it-j} + \phi i + \varepsilon_{it} \quad \ldots.. (1)$$

The specific regression model for the study is defined as follows:

$$CA_{it}=f(CA_{it-1}, \text{Credit risk}_{it}, \text{Liquidity risk}_{it}, \text{Market competition}_{it}, \text{Bank efficiency}_{it}, \text{Covid Dummy}_{t}, \varepsilon_{it})\ldots\ldots(2)$$

Where **CA** is bank credit allocation,

Regarding the banking level analysis, the study applied the panel ARDL. This is supported by the fact that the bank level analysis entailed analysis using the bank level data over a period of 2010 – 2021 hence resulting into panel data. For the sectoral analysis, the rationale for using the ARDL model was informed by the order of integration of the model variables whereby the model variables were integrated of order 0 and order 1, thus supporting the application of the ARDL model. Regarding the effect of the existing monetary policy stance, the study undertook a simple dynamic forecast of the sectoral credit allocation in post covid era. This was done for the 12 months spanning from January 2022 to December 2022. To undertake the dynamic forecasts at sectoral level, the forecast model relied on the ARDL model estimates for the respective sectors. Further to ensure bank heterogeneity, the study ignored controlling the banks heterogeneity as depicted by bank size or bank tier categorization. This is supported by the fact that inclusion of industry competition captured by competition index indirectly controls for banks heterogeneity since the index is computed from bank asset to total industry assets. In addition to panel ARDL, the panel GMM regression model was applied for robustness check. When running the panel GMM model, the industry competition, covid dummy and the interactions between the covid dummy with credit and liquidity risks were used as the instrumental variables. Specifically, the two – step difference GMM was estimated

## 3.3 Definition and measurement of variables:

Within the study, the variables to the model were defined and measured as follows:

**Table 3.1: Definition and measurement of the variables**

| Variable | Definition | Measurement |
|---|---|---|
| Credit allocation (bank level) | Refers to the amount of loans and advances by the bank on year – on – year basis | Year – on – year growth in total loans and advances, $CA_{bank}= (TL_t - TL_{t-1})/TL_{t-1}$ **TL** is the bank total loans, **t** stands for the time aspect in years |

| Variable | Definition | Measurement |
|---|---|---|
| Sectoral credit allocation | Refers to the total loans and advances to the sector | total loans and advances to the sector as a proportion of industry total loans and advances in a given month $\text{Sector CA} = TL_{si}/TL$ |
| Credit risk | Refers to the bank risk arising from the borrower's inability to service their loan facility | Ratio of non – performing loans to total loans and advances in a given period |
| Liquidity risk | Refers to state of bank's inability to access sufficient funds at a reasonable cost to meet potential demands from both funds providers and borrowers | Ratio of bank total loans to total deposits at a given period of time |
| Market competition | Refers to competition within the banking industry in a given period of time mainly annual | Hirschman-Herfindahl Index (HHI) as an indicator of industry competition. HHI was measured as the sum of square of the market shares of all firms in industry j for year t, the market share of each bank is the ratio of total asset (ta) the $i^{th}$ bank to the industry's total asset (TA) $HHI_t = \sum_{i=1}^{n_{jt}} S_{it}^2 = \sum_{i=1}^{n_{jt}} \left(\frac{ta_{it}}{TA_t}\right)$ |
| Bank efficiency | Refers to bank's ability to produced more output at least cost possible | Efficiency ratio calculated as a ratio of bank's noninterest expenses by their net income in a given time period |
| Covid Dummy | Refers to a time dummy measuring the declaration of covid pandemic in Kenya | Time dummy taking value 1 from January 2020 to December 2021 and 0 for December 2019 backwards |

### 3.4 Econometric approach:

To analyse the bank credit portfolio allocation in the pre and post covid era in the context of the inherent risks and uncertainties, the study utilized detailed econometric approach. To start with, a bank level analysis was undertaken whereby bank level data was applied to investigate how bank credit allocation is influenced by the evolutions of credit and liquidity risks in pre and post covid era. To undertake this analysis, a Panel ARDL model was used. Within the model, the industry competition level was factor in. This is informed by the fact that during the covid era, banks resulted in leveraging on the technology and other digital platforms to offer financial services in the wake of physical containment measures. This move definitely had a bearing on the industry competition level. However, in estimating the Panel ARDL model, we control for the effect of industry competition. The rationale for controlling for the effect of industry competition is informed by the fact that large banks are likely to have large capital buffers and therefore likely to advance more loans in crisis period as compared to medium and small banks. In this case, it can be argued that large banks are likely to use their capital buffers to absorb inherent risks and uncertainties during crisis albeit for a given period compared to medium and small banks. In addition, large banks are more likely to have liquidity levels was much above the required threshold hence, the liquidity risk is crisis era is likely to have lesser effect on their credit allocation compared to medium and small banks. To undertake analysis, model 3 was estimated.

In estimating the panel ARDL model for bank level analysis, the study applied two panel ARDL estimation techniques: - Pooled Mean Group (PMG) and Mean Group (MG) estimation techniques. The application of these techniques is anchored on Pesaran, Shin, and Smith (1999) who propose the two-estimating procedure for the panel ARDL model in the sense that the Mean Group and the Pooled Mean Group allow for a higher degree of parameter heterogeneity in growth regressions than the other estimators for panel data.

Further, we note that the Pooled Mean Group (PMG) estimator considers a lower degree of heterogeneity since it imposes homogeneity in the long run coefficients while still allowing for heterogeneity in the short run coefficients and the error variances. The basic assumptions of the PMG estimator include: - the error terms are serially uncorrelated and are distributed independently of the regressors; there is a long run relationship between the dependent and explanatory variables and the long run parameters are the same across groups. This estimator is also flexible enough to allow for long run coefficient homogeneity over a single subset of regressors and/or countries (Pesaran, Shin, and Smith, 1999).

The second analysis level entailed the sectoral credit allocation. This analysis was done at industry level analysis given that granular bank level sectoral lending was not available. However for the sectoral credit allocation models, the study used credit risk given the liquidity risk data was not feasible on

$$\text{Bank CA}_{it} = \alpha_1 + \beta 1\ \text{Bank CA}_{it-1} + \beta_2\ \text{Credit risk}_{it} + \beta_3\ \text{Liquidity risk}_{it} + \beta\__4\ \text{Industry competition}_{it} + \beta_5\ \text{Covid Dummy}_t + \beta_6\ \text{Credit risk}_{it} {*} \text{Covid Dummy}_t + \beta_7\ \text{Liquidity risk}_{it} {*} \text{Covid Dummy}_t + \varepsilon_{it} \quad \ldots\ldots(3)$$

monthly basis. First, the unit root for the variables was determined as well as the maximum lag to inform the number of maximum lags to be applied in estimating the ARDL model.

Third level analysis entailed forecasting the expected bank credit allocation in post Covid era. To do so, the forecasts were anchored on the monetary policy stance pronouncement by the Central Bank of Kenya. The rationale behind anchoring forecasts on the monetary policy stance is underpinned on the understanding that the monetary policy impacts risk perception of commercial banks and encourages risk taking by banks when interest rates are low. If this channel is effective before the crisis banks tend to flight to liquidity just after the crisis even if interest rates are maintained low because of a high risk aversion. Secondly, the simulation of bank credit based on the monetary policy stance is hinged on the relationship between inherent bank risk (credit risk) and the effectiveness of the monetary policy. Notably, the high non-performing loan stocks can impair the monetary policy transmission mechanism by limiting banks' lending ability, the forecasting of bank credit on the back drop of monetary policy stance is considered.

To undertake the forecast, the study applied the existing CBR of 7 percent. The study therefore forecast what would be the expected sectoral credit allocation given that the Central Bank of Kenya maintained the CBR at 7 percent throughout the 2022 year. The forecast of the credit allocation to the 5 sectors were then graphed against the CBR ranging from February 2020 to December 2022. It's however notable that forecasts were only done for 12 months (Jan 2022 to Dec 2022). The rest of the credit allocation for February 2010 to December 2021 were the actual allocations. The forecasts model relied on the ARLD estimates for then sector models.

### 3.5 Study Data:

The study utilised bank level data for banks operating in Kenya in the period between 2010 – 2021. For the bank level analysis, annual bank data for 2010 – 2021. The banks level data was obtained from the audited financial statements over years from Kenya Bankers Association database. However, for sectoral analysis, monthly data for January 2010 – March 2022 was used. The sectoral lending data was obtained for the Central Bank of Kenya publications and releases for various months and quarters within 2010 to 2022.

# 4.0 Empirical Findings

## 4.1 Bank level analysis of credit allocation

### *Descriptive statistics*

**The bank level data descriptive statistics indicate that the mean credit allocation over that study period was 0.168 representing 16.8 percent growth in loans and advances over the period with the minimum being -0.087 and maximum being 0.710.** The liquidity risk averaged at 0.775 with a minimum of 0.09 and maximum of 2.2 implying relatively high level of liquidity. The mean credit risk was 0.133 with a minimum of 0.01 and maximum of 0.68. This indicates a substantial level of credit risk measured from non – performing loans point of view. The mean industry competition was 0.02 indicating market concentration. The bank level efficiency averaged at 0.08.

**Table 4.1: Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Credit allocation | 420 | 0.168 | 0.451 | -0.087 | 0.710 |
| Liquidity risk | 420 | 0.775 | 0.260 | 0.09 | 2.2 |
| Credit risk | 420 | 0.133 | 0.120 | 0.01 | 0.68 |
| hhi | 420 | 0.002 | 0.005 | 0.001 | 0.027 |
| eff | 420 | 0.081 | 0.614 | -8.904 | 0.99 |
| Covid dummy | 420 | 0.167 | 0.373 | 0.0 | 1.0 |
| Dummy liquidity risk | 420 | 0.123 | 0.301 | 0.0 | 2.02 |
| Dummy credit risk | 420 | 0.033 | 0.094 | 0.0 | 0.68 |

### *Correlation matrix*

The correlation coefficient matrix indicates that credit allocation is weakly correlated to liquidity risk, credit risk, industry competition, bank efficiency, covid dummy and the interactions between the covid dummy and risks. Strong correlations are reported between the two interactions of liquidity risks and credit risk with the covid dummy.

**Table 4.2: Matrix of correlations**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) ca | 1.000 | | | | | | | |
| (2) liquidity risk | 0.025 | 1.000 | | | | | | |
| (3) credit risk | -0.184 | 0.308 | 1.000 | | | | | |
| (4) hhi | -0.024 | 0.056 | -0.213 | 1.000 | | | | |
| (5) eff | 0.049 | 0.133 | 0.037 | 0.156 | 1.000 | | | |
| (6) covid dummy | -0.113 | -0.066 | 0.245 | 0.016 | -0.038 | 1.000 | | |
| (7) dummy *liquidity risk | -0.098 | 0.135 | 0.318 | 0.022 | 0.039 | 0.912 | 1.000 | |
| (8) dummy * credit risk | -0.106 | 0.087 | 0.490 | -0.048 | -0.135 | 0.789 | 0.840 | 1.000 |

***Unit root test***

Prior to running the regressions, unit root test was conducted to determine the order of integration among the model variables. The Levin-Lin-Chu unit - root test was applied to conduct the unit root test. The results indicate that under the Levin-Lin-Chu unit - root test based on the adjusted t – statistics, credit allocation, liquidity risk and bank efficiency are stationary at level at 5 percent significance level. This is because their respective p – values are less than 5 percent significance level. However, credit risk and industry competition were found to have one unit root hence stationary upon the first differencing.

**Table 4.3: Unit root test**

| | Levin-Lin-Chu unit-root test | | | Levin-Lin-Chu unit-root test | | | Order of integration |
|---|---|---|---|---|---|---|---|
| Variables | Unadjusted t statistic | Adjusted t* statistic | P - value | Unadjusted t statistic | Adjusted t* statistic | P - value | |
| CA | -13.5536 | -6.4419 | 0.000 | | | | I(0) |
| Liquidity risk | -8.8035 | -2.6502 | 0.004 | | | | I(0) |
| Credit risk | -4.5559 | 0.5909 | 0.7227 | -13.0050 | -4.5182 | 0.000 | I(1) |
| HHI | -7.2060 | -0.6006 | 0.2741 | -13.4462 | -2.2745 | 0.0115 | I(1) |
| Bank efficiency | -14.7982 | -7.6823 | 0.000 | | | | I(0) |

### *Panel ARDL Model*

In undertaking the bank level – analysis, the study estimated the panel ARDL model. To do this the study applied to estimation techniques namely the Pooled mean group model (PMG) and the Mean Group model (MG). We note that the Pooled Mean Group model is an intermediate estimator that allows the short-term parameters to differ between groups while imposing equality of the long-term coefficients between groups. In this study, the choice to apply the PMG estimator rests on the fact that the PMG estimator allows a greater degree of parameter heterogeneity than the usual estimator procedures by imposing common long run relationships across groups while allowing for heterogeneity in the short run responses and intercepts.

Further, the application of these two estimation techniques is rooted in the theoretical perspective by Pesaran, Shin, and Smith (1999) who postulate that the use of Mean Group and the Pooled Mean Group allow for a higher degree of parameter heterogeneity in regressions than the other estimators arising from other panel models regression techniques. Pesaran, Shin, and Smith (1999) asserts that the MG estimator allows for heterogeneity of all coefficients, intercepts and slopes, by estimating a separate equation for each group.

**Table 4.4: Panel ARDL Regression Results - Pooled Mean Group and Mean Group**

| Pooled Mean Group Model | | Mean Group Model | |
|---|---|---|---|
| **Variable** | **Coefficient** | **Variable** | **Coefficient** |
| **__ec** | | **_ec** | |
| Liquidity risk | -0.327*** (0.040) | Liquidity risk | -0.984** (0.476) |
| Credit risk | -0.738*** (0.059) | Credit risk | -5.972 (7.27) |
| HHI | -28.522** (2.795) | HHI | 575.251 (533.838) |
| Efficiency | 0.114*** (0.017) | Efficiency | 0.96 (0.732) |
| Covid dummy | -0.057** (0.092) | Covid dummy | -1.003 (0.882) |
| Covid dummy *liquidity risk | -0.404** (0.198) | Covid dummy *liquidity risk | -0.042 (0.044) |

| Pooled Mean Group Model | | Mean Group Model | |
|---|---|---|---|
| **Variable** | **Coefficient** | **Variable** | **Coefficient** |
| Covid dummy *credit risk | -0.517 (0.401) | Covid dummy *credit risk | -0.82 (7.51) |
| **SR** | | | |
| Error Correction term | -0.66** (0.33) | Error Correction term | -1.008 (0.063) |
| Liquidity risk | | Liquidity risk | |
| D1. | 1.574*** (0.436) | D1. | 1.238** (0.547) |
| **Credit risk** | | **Credit risk** | |
| D1. | 0.523 (0.546) | D1. | 0.269 (1.23) |
| **HHI** | | **HHI** | |
| D1. | 362.021** (143.419) | D1. | -684.968* (371.497) |
| **Efficiency** | | **Efficiency** | |
| D1. | -0.02** (0.14) | D1. | -0.016 (0.288) |
| **Covid dummy** | | **Covid dummy** | |
| D1. | 3.556 (3.84) | D1. | 0.083 (0.517) |
| **Dummy * liquidity risk** | | **Dummy * liquidity risk** | |
| D1. | 0.958* (1.093) | D1. | 0.058 (0.038) |
| **Dummy * credit risk** | | **Dummy * credit risk** | |
| D1. | 9.664 (9.156) | D1. | 0.128 (0.528) |
| Constant | 0.563 (0.047) | Constant | 0.255 (0.398) |

**Note:** Standard errors are in parenthesis; For significance levels: *** p<.01, ** p<.05, * p<.1

From the PMG model, it can be deduced that there exists a negative long run relationship between liquidity risk and banking industry credit allocation. In addition, the relationship was found to be significant at 1 percent significance level. Similar results are reported for the credit risk and industry competition. However, the bank efficiency coefficient was found to be positive and significant at 1 percent significant level. This implies that bank efficiency plays a crucial role in fostering optimal credit allocation thus trading off credit misallocation.

A further look into the covid pandemic dummy, results of the PMG model reveal a negative long run relationship between pandemic and banking industry credit allocation. The relationship was found to be significant at 5 percent significance level. This ascertains the adverse effect the pandemic had on banks' loans and advances growth. However, from the results, though credit risk, liquidity risk and covid pandemic were found to have a negative and significant long run effect on banks' credit allocation, interaction of the two risks with the pandemic dummy presents unique results. First, the interaction of the covid dummy and credit risk presents a negative but insignificant long run effect with banks' credit allocation. However, the interaction of the covid dummy and liquidity risk presents a negative long run effect with banks' credit allocation which is significant at 1 percent significance level. This implies that during the covid period the liquidity risk on credit allocation was more pronounced while the credit risk effect on credit allocation was more muted. This finding could implies two possible explanation. First is that the policy measures put in place during the pandemic weighed down on the credit risk effects as opposed to liquidity risk. In this case, measures such as bank loans reclassification traded – off credit risk in the market but the liquidity risks remained eminently presence. The second interpretation, though tied to the first interpretation is that the industry was faced with the liquidity distribution challenges in covid period as opposed to the credit challenges. As such the pronounced monetary policy stance during the pandemic period were futile in trading off the adverse effect of liquidity risk on bank credit allocation. This could therefore imply a weak pass-through effect of the monetary policy on the credit markets in terms of unlocking liquidity distribution challenges in the market.

Turning to the short run model, the PMG model results found that the convergence coefficient is negative and significant as expected, a necessary condition for the existence of a long run relationship between the variables. The error correction coefficient is -0.66 significant at 5 percent significance level. This convergence coefficient reveals that the short run disequilibrium are being corrected at the rate of 66 percent annually towards the long term equilibrium. Within the short run model, the negative relationship between credit and liquidity risk and bank credit allocation is evident though only the liquidity risk - bank credit allocation nexus was found to be significant at 1 percent significance level. Further, the covid dummy and the interactions with credit and liquidity risks were found to be negatively related to bank credit allocation though insignificant.

In addition to the PMG model, the study estimated the mean group model. The long run estimations for the MG model indicate that liquidity risk and bank credit allocation have a significant negative relationship significant at 5 percent significance level. Similar results are reported for credit risk - bank credit allocation relationship though insignificant. Industry competition and bank efficiency were found to have positive relationship with bank credit allocation but insignificant. Regarding the pandemic, a negative relationship was found between bank credit allocation and pandemic dummy. However, the relationship was insignificant. Interaction between pandemic dummy and liquidity risk found a negative relationship between the interaction and bank credit allocation albeit insignificant. The interaction between pandemic dummy and credit risk is dropped of from the model during estimation process.

Regarding the short run model, the PMG model results found that the convergence coefficient is negative and significant as expected, a necessary condition for the existence of a long run relationship between the variables. The error correction coefficient is -1.008 significant at 1 percent significance level indicating an overcorrection. Within the short run model, the negative relationship between credit and liquidity risk and bank credit allocation is evident though insignificant. Further, the covid dummy and the interactions with liquidity risks were found to be negatively related to bank credit allocation though insignificant.

In addition to estimating the PMG and the MG model, a Hausman test was conducted between the two model. The test results indicated a Chi-square test value of 209.15. The p – value of the test statistic was 17.28 percent. Using the 5 percent significance level, it's evident that the p- value was higher that 5 percent significance level. This leads to rejection of the MG model and acceptance of the PMG model as the best fit model.

**Table 4.5: Hausman (1978) specification test**

| | |
|---|---|
| Chi-square test value | 209.15 |
| P-value | 0.1728 |

### ***Panel GMM Model***

The Generalized Method of Moments results confirm the results of the PMG model. From the model estimation results, both liquidity and credit risks have a negative and significant effect on bank level credit allocation. Similar results are reported for the covid dummy. However, in terms of covid dummy interactions with the risks, the interaction between liquidity risk and covid dummy has a negative effect on credit allocation though significant at 10 percent significance level. Interaction between covid dummy and credit risk was found to have negative but insignificant effect. The model diagnostic test results for the GMM model indicate that the model results are valid. The Hansen test results posit that the used instruments in the estimation are valid, and therefore overidentification doesn't exit given the probability of the chi2 is greater than 5% significance level. For test of serial correlation, the Arellano-Bond test results for AR (2) indicates the absence of serially correlated in error terms given that the probability value of the z statistics is greater than 5% significance level.

**Table 4.6: GMM model results**

| CA | Coefficient |
|---|---|
| CA (-1) | -0.325*** (0.066) |
| Liquidity risk | -0.223** (0.368) |
| Credit risk | -2.955* (0.78) |
| HHI | 21.558 (33.622) |
| Efficiency | 0.096 (0.145) |
| Covid dummy | -0.37** (0.387) |
| Covid dummy * liquidity risk | -0.272* (0.316) |
| Covid dummy * credit risk | -0.932 (0.862) |

| | | | |
|---|---|---|---|
| Arellano-Bond test for AR(1) in first differences | z = -1.26 Pr > z | = | 0.209 |
| Arellano-Bond test for AR(2) in first differences | z = -1.37 Pr > z | = | 0.172 |
| Hansen test of overid. restrictions | chi2(40) = 32.95 Prob > chi2 | = | 0.778 |
| Hansen test excluding group: chi2(36) | chi2(36) = 31.08 Prob > chi2 | = | 0.701 |
| Difference (null H = exogenous): chi2(4) | chi2(4) = 1.87 Prob > chi2 | = | 0.760 |

**Note:** Standard errors are in parenthesis; For significance levels: *** p<.01, ** p<.05, * p<.1

## 4.2 Sectoral level credit allocation analysis

Turning to the sectoral credit allocation, the study used monthly data in its analysis. The sectoral credit allocation was computed by the proportion of credit allocated to the sector within the month to the total loans and advances by the industry within the month.

Within the analysis, credit risk was computed as a proportion of monthly industry non – performing loans to total monthly loans and advances. Similarly, liquidity risk was computed as a proportion of monthly industry loans and advances to total monthly industry bank deposits.

### *Maximum lag determination*

Prior to estimating the ARDL model, the maximum lag for the variables was determined. The study relied on AIC and SBIC in determining the maximum lag. The results indicate that the maximum lag for the variables is 4.

**Table 4.7: Maximum lag selection Results**

| Lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| **0** | 5132.51 | | | | 1.60E-48 | -73.1358 | -73.0248 | -72.8627 |
| **1** | 6544.81 | 2824.6 | 169 | 0 | 3.20E-56 | -90.8973 | -89.3433 | -87.0732 |
| **2** | 7563.73 | 2037.8 | 169 | 0 | 1.80E-61 | -103.039 | -100.042 | -95.6639 |
| **3** | 8270.77 | 1414.1 | 169 | 0 | 9.60E-65 | -110.725 | -106.285 | -99.7991 |
| **4** | 8928.32 | 1315.1* | 169 | 0 | 1.2e-67* | -117.705* | -111.822* | -103.227* |

### *Correlation matrix*

The correlation coefficient matrix indicates that strong correlation is reported among the sectoral credit allocation given that the credit allocation among the sectors is mutually exclusive. However, for each sector model variables, no strong correlation between sector credit allocation on one hand and risks and industry competition on the other side. However, its notable that some strong correlations are reported between some sector credit allocation such as trade credit and household credit. However, this possess no challenge since no empirical model includes two sectors since each sector model is estimated independently.

**Table 4.8: Correlation matrix coefficient**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **(1) Man CA** | 1.0000 | | | | | | | | |
| **(2) HH CA** | 0.9165 | 1.0000 | | | | | | | |
| **(3) Trade CA** | 0.9322 | 0.9282 | 1.0000 | | | | | | |
| **(4) Transcom CA** | 0.8154 | 0.8819 | 0.7778 | 1.0000 | | | | | |
| **(5) Agri CA** | 0.3042 | 0.4146 | 0.3252 | 0.6179 | 1.0000 | | | | |
| **(6) Real estate CA** | -0.1674 | -0.0708 | -0.1424 | -0.2086 | -0.3314 | 1.0000 | | | |
| **(7) Credit risk** | 0.5544 | 0.4980 | 0.2250 | 0.1781 | 0.1725 | -0.1694 | 1.0000 | | |
| **(8) Liquidity risk** | -0.5405 | -0.4493 | -0.3663 | -0.4728 | 0.0354 | -0.0139 | -0.4070 | 1.0000 | |
| **(9) Industry HHI** | 0.2168 | 0.1347 | 0.2682 | 0.4396 | 0.1831 | -0.4250 | 0.4466 | -0.2961 | 1.0000 |

### *Unit root test*

Prior to running the regressions, unit root test was conducted in order to determine the order of integration among the model variables. The Augmented Dickey-Fuller test for unit root indicates that all the sector credit allocation variables have one unit root. This is ascertained by the fact that the manufacturing sector and private HH sector credit allocation become stationary upon the first differencing. The credit risk, liquidity risk, industry competition index and the covid dummy are stationary at level. It's therefore clear that for the sectoral credit allocation models, the model variables have mixed levels of integration comprising of order zero and order one. This justifies the use of ARDL model which is best suited when model variables are integrated of order 0 and order 1.

### *Sector Regression models results*

The ARDL model for the respective sectors were estimated accordingly. In each model, the sector credit allocation was regressed on credit risk, liquidity risk, industry competition index, covid dummy and the interactions between the covid dummy and the two risks: credit and liquidity risks. The sectoral models were estimated with the maximum lag of 4. The results for the sectoral models are reported in appendices 1 to 5. The sectoral model estimations indicate that in general the both the credit and liquidity risks have a negative effect on each sector's credit allocation. However, in terms of significance of the credit and liquidity risks effect, the significance levels vary across the sectors. Further, the significance levels also vary across the lags.

**Table 4.9: Unit root test results**

| Variable | At level | | | | At first difference | | | | Order of integration |
|---|---|---|---|---|---|---|---|---|---|
| | t statis-tic | 1% Critical value | 5% Critical value | 10% Critical value | t statis-tic | 1% Critical value | 5% Critical value | 10% Critical value | |
| Manufacturing CA | -3.029 | -4.026 | -3.444 | -3.144 | -13.147 | -4.026 | -3.444 | -3.144 | I(1) |
| Private HH CA | -3.270 | -4.026 | -3.444 | -3.144 | -10.927 | -4.026 | -3.444 | -3.144 | I(1) |
| Trade CA | -3.165 | -4.026 | -3.444 | -3.144 | -11.645 | -4.026 | -3.444 | -3.144 | I(0) |
| Transcom CA | -3.281 | -4.026 | -3.444 | -3.144 | -11.234 | -4.026 | -3.444 | -3.144 | I(0) |
| Real estate CA | -3.371 | -4.026 | -3.444 | -3.144 | -20.880 | -4.026 | -3.444 | -3.144 | I(0) |
| Credit risk | -4.595 | -4.026 | -3.444 | -3.144 | -10.255 | -4.026 | -3.444 | -3.144 | I(0) |
| Liquidity risk | -8.142 | -4.026 | -3.444 | -3.144 | -12.472 | -4.026 | -3.444 | -3.144 | I(0) |
| HHI | -5.418 | -4.026 | -3.444 | -3.144 | -13.176 | -4.026 | -3.444 | -3.144 | I(0) |
| Covid dummy | -7.408 | -4.026 | -3.444 | -3.144 | | -4.026 | -3.444 | -3.144 | I(0) |

However, one common finding is elicited that the liquidity risks affect is more pronounced in terms of their significance across all the sectors and across all the lags as opposed to the credit risk. Within the personal household sector, the current month liquidity risk and all the four months lags liquidity risk had negative and significant effect on credit allocation in this sector. Similar results are reported for real estate sector and transport sector though with some differences on the monthly lags effects and significance levels.

Turning to the effect of the covid pandemic on the sectoral credit allocation, results indicates that, the pandemic adversely affected sector credit allocation. From the analysis, the most hit sectors in credit allocation during the pandemic were the private household, real estate and the transport sectors where all the monthly lags effects had negative and significant effect on sector credit allocation at 1 percent significance level. Though the credit allocation in manufacturing and trade sectors were adversely affected by the pandemic, the effect seems to be insignificant at 5 percent significance level with all the lags being decayed off from the model. This scenario could be explained by the fact that amid the supply shocks in the global arena during the pandemic, manufacturing and trade sectors were highly relied upon to ease the supply constraints. In this case credit allocation towards local manufacturing could have been deemed essential. Further, amid people movement containment measures, movement of goods were largely unaffected to cushion against possible worse scenarios on supply side regarding essential goods. For this reason, extension of credit to trade sector could have been perceived essential hence the muted effect of the pandemic on trade sector credit allocation.

Interesting findings are reported for the interaction between the covid pandemic variable with the credit and liquidity risks. Sectoral dynamics here are evident. Within the manufacturing sector, credit risk was more pronounced in terms of both the effect and significance was the liquidity risk was largely muted. Similar finding is reported for the real estate and transport sector. However, for the trade sector, liquidity risk was more pronounced in terms of both the effect and significance was the credit risk was largely muted. Interestingly, regarding the personal household sector, the interaction of covid dummy with credit and liquidity risks reveal that the effects of both interactions were insignificant. This scenario could be explained by the loan reclassification undertaken by the industry whereby majority of the reclassified facilities could have been in the personal household sector in attempt to cushion the households with existing facilities. This therefore could perhaps explain the muted effect of the interaction of the covid pandemic dummy with the credit and liquidity risks.

### ***Credit allocation forecast in recovery period***

In addition to the bank level and sector level analysis, the study undertook a simple dynamic forecasts of what the credit allocation would look like during the recovery period. The forecasts were done at the sectoral level. In the forecast, the monetary policy stance was pegged at the 7 percent CBR. The forecast therefore projected what the sectoral credit allocation would look like for January 2022 to December 2022 if the CBR was maintained at 7 percent for the 12-month period. In the forecasts, the ARDL models estimates were used. The CBR was modelled as the exogenous variable in the forecast model. The graphical presentation for the respective sectoral forecasts are in appendices. The forecast results posit that with the CBR held at 7 percent for 2022m1 to 2022m12, sectoral differences in terms of credit allocation would still persist. From the forecast, the Private Household sector would register the highest allocation with the allocation surpassing all previous months allocations compared to others sectors followed by trade sector with manufacturing coming third. However, an interesting result is evident in transport and the real estate sector. First, regarding transport sector, a decline in the allocation would be evident with some rises being evident towards the last months of 2022. For the real estate sector allocations, forecasts reveal that credit allocation to this sector would decline to levels lower than all previous months allocations in the first months of 2022 then pick up in mid months of 2022 though with the rises below all the previous months allocations and then decline with the lowest allocation levels being registered towards the last months of 2022.

# 5.0 Conclusion

## 5.1 Conclusion and policy implication

**The study sought to examine the bank credit portfolio allocation in pre and post Covid times.** In so doing, the study sought to examine the of inherent risks during the pandemic periods. In undertaking the study, two risks were at the centre of the focus namely: - credit risk and liquidity risk. For the industry level analysis, the PMG model results, revealed a negative long run relationship between liquidity risk and banking industry credit allocation. Similar results are reported for the credit risk and industry competition. However, the bank efficiency was found to positively affect credit allocation.

A further look into the covid pandemic dummy, results of the PMG model reveal a negative long run relationship between pandemic and banking industry credit allocation. However, from the results, though credit risk, liquidity risk and covid pandemic were found to have a negative and significant long run effect on banks' credit allocation, interaction of the two risks with the pandemic dummy found that during the covid period the liquidity risk on credit allocation was more pronounced while the credit risk effect on credit allocation was more muted.

The short run model for the PMG model results found that the convergence coefficient is negative and significant as expected, a necessary condition for the existence of a long run relationship between the variables. The error correction coefficient is -0.66 significant at 5 percent significance level. This convergence coefficient reveals that the short run disequilibrium are being corrected at the rate of 66 percent annually towards the long term equilibrium. Within the short run model, the negative relationship between credit and liquidity risk and bank credit allocation is evident though only the liquidity risk - bank credit allocation nexus was found to be significant at 1 percent significance level. Further, the covid dummy and the interactions with credit and liquidity risks were found to be negatively related to bank credit allocation though insignificant.

Sectoral credit allocation analysis indicate that the both the credit and liquidity risks have a negative effect on each sector's credit allocation. However, in terms of significance of the credit and liquidity risks effect, the significance levels varies across the sectors. Further, the significance levels also varies across the lags. However, the liquidity risks affect is more pronounced in terms of their significance across all the sectors and across all the lags as opposed to the credit risk a finding similar to the bank level analysis for panel ARDL for the industry level analysis.

Based on the findings, the study calls on the need for the banking industry players to be vigilant in the post pandemic times on issues of the credit risk. The muted effect of the credit risk could be because of the loan reclassification undertaken by the banks during the pandemic period. Therefore, we deduce the delayed reporting of NPLs is feasible in covid era. Therefore, a rise in NPLs is likely to be revealed in post pandemic period owing to relaxation of reclassification. Further, the muted effects of credit risk on credit allocation could be informed by the initial conditions that the industry entered the covid era as evidenced by rise in non – performing loans as well as subdued loans and advances following the enactment of interest rate capping in the previous years. In this light, the players should not be quick in relaxing the credit standards in post covid error to extend more facilities but rather should do so with caution.

Secondly, the pronounced effect of liquidity risks points to the inefficiency of the existing monetary policy to unlock liquidity distribution challenges in the market. Therefore, there is the need for the monetary policy authority to review the policy stance in cognisant with the liquidity distribution challenges in the credit market. There is a need for the policy to consider of how to effectively address this challenge beyond the core objective of anchoring inflation to unlocking liquidity distribution challenges in the market.

Third, is the need for the regulatory institution to consider the effect of the pandemic shock on credit allocation when designing macroeconomic policies. Based on the study findings, the sectoral level analysis indicated that different sectors were affected differently by the pandemic when it came to credit allocation. Further, the sectoral credit allocation proved to have been affected differently by the liquidity and credit risks in pre – covid and covid periods. Such sectoral dynamics ought to be accounted for when pronouncing post recovery macroeconomic policies.

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# Appendices

## Appendix 1: Manufacturing sector ARDL Model

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Manufacturing ca** | | | | | | |
| L1. | -0.280 | 0.072 | -3.900 | 0.000 | -0.422 | -0.138 |
| L2. | 0.072 | 0.077 | 0.920 | 0.357 | -0.082 | 0.225 |
| L3. | 0.075 | 0.072 | 1.040 | 0.299 | -0.067 | 0.217 |
| L4. | 0.298 | 0.088 | 3.390 | 0.001 | 0.124 | 0.472 |
| **Credit risk** | | | | | | |
| --. | -0.197 | 0.072 | -2.730 | 0.007 | -0.339 | -0.054 |
| L1. | -0.029 | 0.064 | -0.450 | 0.655 | -0.155 | 0.098 |
| L2. | -0.432 | 0.077 | -5.640 | 0.000 | 0.280 | 0.584 |
| **Liquidity risk** | | | | | | |
| --. | -0.021 | 0.008 | -2.560 | 0.012 | -0.037 | -0.005 |
| L1. | -0.007 | 0.008 | -0.890 | 0.375 | -0.023 | 0.009 |
| L2. | -0.031 | 0.007 | -4.250 | 0.000 | 0.016 | 0.045 |
| **Industry hhi** | | | | | | |
| --. | 0.528 | 0.911 | 0.580 | 0.563 | -1.277 | 2.333 |
| L1. | 3.708 | 0.771 | 4.810 | 0.000 | 2.182 | 5.235 |
| L2. | 0.354 | 0.459 | 0.770 | 0.442 | -0.554 | 1.262 |
| L3. | -4.346 | 0.715 | -6.080 | 0.000 | -5.762 | -2.930 |
| **Covid dummy** | -0.184 | 0.105 | -1.740 | 0.084 | -0.393 | 0.025 |
| **Dummy credit risk** | | | | | | |
| --. | -0.584 | 0.291 | -2.000 | 0.047 | 0.007 | 1.161 |
| L1. | -0.018 | 0.036 | -0.510 | 0.614 | -0.090 | 0.053 |

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| L2. | -0.497 | 0.077 | -6.480 | 0.000 | -0.649 | -0.345 |
| L3. | -0.216 | 0.054 | -4.010 | 0.000 | 0.109 | 0.323 |
| L4. | -0.484 | 0.065 | -7.490 | 0.000 | -0.611 | -0.356 |
| | | | | | | |
| **Dummy liquidity risk** | -0.135 | 0.103 | -1.310 | 0.192 | -0.069 | 0.339 |
| **Constant** | 0.077 | 0.119 | 0.650 | 0.520 | -0.159 | 0.313 |

## Appendix 2: Private Household sector ARDL Model

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **hhca** | | | | | | |
| L1. | -0.145 | 0.085 | -1.710 | 0.091 | -0.313 | 0.023 |
| L2. | 0.288 | 0.087 | 3.310 | 0.001 | 0.116 | 0.459 |
| **Credit risk** | | | | | | |
| --. | -0.037 | 0.078 | -0.470 | 0.637 | -0.117 | 0.191 |
| L1. | -0.099 | 0.066 | -1.490 | 0.138 | -0.229 | 0.032 |
| L2. | -0.106 | 0.069 | -1.540 | 0.125 | -0.242 | 0.030 |
| L3. | -0.117 | 0.070 | -1.670 | 0.098 | -0.257 | 0.022 |
| L4. | -0.236 | 0.079 | -2.970 | 0.004 | -0.393 | -0.079 |
| **Liquidity risk** | | | | | | |
| --. | -0.025 | 0.009 | -2.860 | 0.005 | -0.043 | -0.008 |
| L1. | -0.015 | 0.008 | -1.860 | 0.065 | -0.032 | 0.001 |
| L2. | -0.028 | 0.008 | -3.680 | 0.000 | -0.043 | -0.013 |
| L3. | -0.030 | 0.009 | -3.440 | 0.001 | -0.047 | -0.013 |
| **Industry hhi** | | | | | | |
| --. | -7.198 | 2.231 | -3.230 | 0.002 | -11.616 | -2.780 |
| L1. | 10.222 | 1.016 | 10.060 | 0.000 | 8.210 | 12.234 |

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| L2. | 4.183 | 1.141 | 3.660 | 0.000 | 1.923 | 6.444 |
| L3. | -10.606 | 1.351 | -7.850 | 0.000 | -13.281 | -7.931 |
| L4. | 4.101 | 0.680 | 6.030 | 0.000 | 2.753 | 5.448 |
| **Covid dummy** | | | | | | |
| --. | 0.022 | 0.092 | 0.230 | 0.815 | -0.160 | 0.204 |
| L1. | 0.006 | 0.008 | 0.690 | 0.489 | -0.010 | 0.022 |
| L2. | -0.108 | 0.019 | -5.690 | 0.000 | -0.146 | -0.070 |
| L3. | 0.109 | 0.016 | 6.670 | 0.000 | 0.076 | 0.141 |
| L4. | -0.044 | 0.011 | -3.900 | 0.000 | -0.066 | -0.021 |
| | | | | | | |
| Dummy credit risk | -0.050 | 0.247 | -0.200 | 0.840 | -0.539 | 0.439 |
| Dummy liquidity risk | 0.002 | 0.097 | 0.020 | 0.983 | -0.190 | 0.195 |
| Constant | 0.210 | 0.184 | 1.140 | 0.257 | -0.155 | 0.575 |

## Appendix 3: Trade sector ARDL Model

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Trade ca** | | | | | | |
| L1. | 0.072 | 0.072 | 0.990 | 0.323 | -0.072 | 0.215 |
| L2. | 0.314 | 0.073 | 4.290 | 0.000 | 0.169 | 0.459 |
| Credit risk | -0.113 | 0.078 | -1.460 | 0.147 | -0.040 | 0.267 |
| **Liquidity risk** | | | | | | |
| --. | -0.000 | 0.009 | -0.000 | 1.000 | -0.018 | 0.018 |
| L1. | -0.036 | 0.009 | -4.020 | 0.000 | 0.018 | 0.054 |
| **Industry hhi** | | | | | | |
| --. | -4.489 | 0.913 | -4.920 | 0.000 | -6.297 | -2.682 |
| L1. | 9.090 | 0.847 | 10.740 | 0.000 | 7.414 | 10.766 |
| L2. | 2.151 | 0.413 | 5.210 | 0.000 | 1.334 | 2.969 |

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| L3. | -9.576 | 0.859 | -11.140 | 0.000 | -11.277 | -7.874 |
| L4. | 1.530 | 0.610 | 2.510 | 0.013 | 0.323 | 2.738 |
| **Covid dummy** | -0.153 | 0.102 | -1.500 | 0.137 | -0.049 | 0.354 |
| **Dummy credit risk** | -0.702 | 0.261 | -2.690 | 0.008 | -1.219 | -0.184 |
| **Dummy liquidity risk** | | | | | | |
| --. | -0.063 | 0.101 | -0.630 | 0.532 | -0.263 | 0.136 |
| L1. | 0.007 | 0.006 | 1.180 | 0.242 | -0.005 | 0.018 |
| L2. | -0.141 | 0.014 | -10.080 | 0.000 | -0.168 | -0.113 |
| L3. | 0.093 | 0.013 | 7.350 | 0.000 | 0.068 | 0.118 |
| L4. | -0.064 | 0.010 | -6.530 | 0.000 | -0.084 | -0.045 |
| Constant | 0.156 | 0.094 | 1.660 | 0.099 | -0.030 | 0.342 |

## Appendix 4: Transport & Communication sector ARDL Model

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **transcomca** | | | | | | |
| L1. | -0.134 | 0.080 | -1.680 | 0.095 | -0.293 | 0.024 |
| **Credit risk** | | | | | | |
| --. | 0.016 | 0.056 | 0.280 | 0.779 | -0.095 | 0.126 |
| L1. | -0.131 | 0.055 | -2.370 | 0.019 | -0.241 | -0.022 |
| **Liquidity** risk | | | | | | |
| --. | -0.005 | 0.008 | -0.680 | 0.500 | -0.021 | 0.010 |
| L1. | -0.036 | 0.007 | -5.580 | 0.000 | 0.023 | 0.049 |
| **Industry hhi** | | | | | | |
| --. | -0.912 | 0.745 | -1.220 | 0.224 | -2.387 | 0.564 |
| L1. | 7.356 | 0.770 | 9.550 | 0.000 | 5.831 | 8.881 |
| L2. | -1.830 | 0.291 | -6.300 | 0.000 | -2.405 | -1.255 |
| L3. | -5.593 | 0.427 | -13.110 | 0.000 | -6.437 | -4.748 |

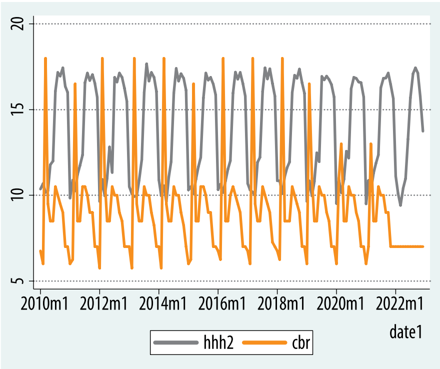
| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| L4. | 2.560 | 0.519 | 4.930 | 0.000 | 1.531 | 3.588 |
| **Covid dummy** | | | | | | |
| --. | -0.069 | 0.103 | -0.670 | 0.506 | -0.135 | 0.273 |
| L1. | -0.084 | 0.027 | -3.060 | 0.003 | -0.139 | -0.030 |
| L2. | -0.036 | 0.007 | -4.950 | 0.000 | -0.050 | -0.022 |
| L3. | -0.025 | 0.006 | -3.930 | 0.000 | 0.012 | 0.038 |
| L4. | -0.054 | 0.007 | -7.210 | 0.000 | -0.068 | -0.039 |
| **Dummy credit risk** | | | | | | |
| --. | -0.171 | 0.246 | -0.690 | 0.489 | -0.316 | 0.657 |
| L1. | -0.597 | 0.205 | -2.920 | 0.004 | 0.192 | 1.002 |
| | | | | | | |
| Dummy liquidity risk | -0.108 | 0.102 | -1.060 | 0.289 | -0.310 | 0.093 |
| Constant | -0.064 | 0.082 | -0.770 | 0.441 | -0.226 | 0.099 |

## Appendix 5: Real estate sector ARDL Model

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Real estate ca** | | | | | | |
| L1. | 0.064 | 0.069 | 0.920 | 0.357 | -0.073 | 0.200 |
| L2. | 0.179 | 0.072 | 2.470 | 0.015 | 0.035 | 0.322 |
| L3. | 0.250 | 0.061 | 4.070 | 0.000 | 0.128 | 0.372 |
| L4. | 0.312 | 0.059 | 5.260 | 0.000 | 0.195 | 0.430 |
| **Credit risk** | -0.931 | 0.245 | -3.800 | 0.000 | -1.416 | -0.446 |
| **Liquidity risk** | | | | | | |
| --. | -0.018 | 0.023 | -0.790 | 0.433 | -0.065 | 0.028 |
| L1. | -0.063 | 0.025 | -2.520 | 0.013 | 0.014 | 0.113 |
| L2. | -0.019 | 0.024 | -0.770 | 0.443 | -0.066 | 0.029 |
| L3. | -0.151 | 0.024 | -6.250 | 0.000 | -0.199 | -0.103 |

| | Coef. | Std.Err. | t | P>t | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Industry hhi** | | | | | | |
| --. | -230.129 | 18.138 | -12.690 | 0.000 | -266.047 | -194.212 |
| L1. | 124.771 | 23.266 | 5.360 | 0.000 | 78.698 | 170.845 |
| L2. | 121.666 | 10.051 | 12.110 | 0.000 | 101.763 | 141.569 |
| L3. | -72.240 | 19.898 | -3.630 | 0.000 | -111.644 | -32.837 |
| L4. | 69.627 | 20.888 | 3.330 | 0.001 | 28.263 | 110.991 |
| **Covid dummy** | | | | | | |
| --. | -0.240 | 0.259 | -0.920 | 0.357 | -0.753 | 0.274 |
| L1. | -0.484 | 0.052 | -9.240 | 0.000 | 0.380 | 0.587 |
| L2. | -2.733 | 0.225 | -12.130 | 0.000 | -3.179 | -2.287 |
| L3. | 1.292 | 0.249 | 5.190 | 0.000 | 0.799 | 1.785 |
| L4. | -1.850 | 0.242 | -7.640 | 0.000 | -2.329 | -1.371 |
| | | | | | | |
| **Dummy credit risk** | 0.896 | 0.670 | 1.340 | 0.184 | -0.431 | 2.223 |
| **Dummy liquidity risk** | 0.351 | 0.259 | 1.360 | 0.177 | -0.161 | 0.864 |
| **Constant** | -0.382 | 1.588 | -0.240 | 0.810 | -3.527 | 2.763 |

## Appendix 6: Forecast plots for 2022m1 – 2022m12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2010m1 2012m1 2014m1 2016m1 2018m1 2020m1 2022m1
date1
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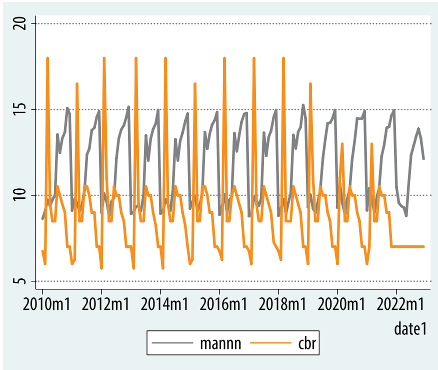
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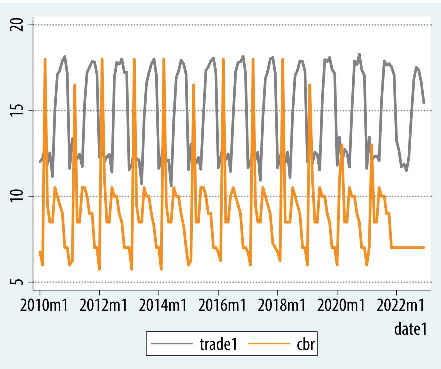
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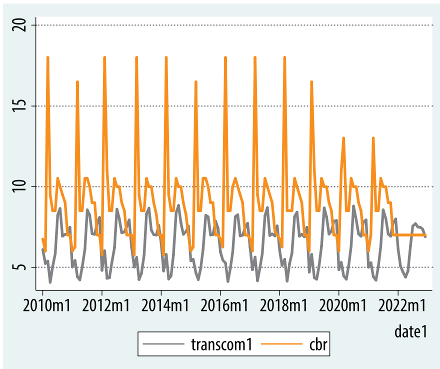
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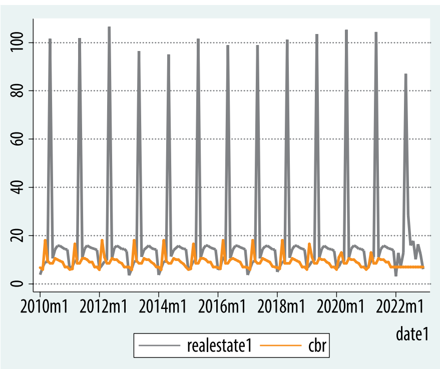
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2010m1 2012m1 2014m1 2016m1 2018m1 2020m1 2022m1
date1
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**Kenya Bankers Association**
13th Floor, International House, Mama Ngina Street
P.O. Box 73100– 00200 NAIROBI
Telephone: 254 20 2221704/2217757/2224014/5
Cell: 0733 812770/0711 562910
Fax: 254 20 2221792
Email: research@kba.co.ke
Website: www.kba.co.ke

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