Keeping up with the Joneses? Evidence from Peer Performance in the Banking Industry

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Abstract

Using a vector autoregressive regression (VAR) model, this paper provides an empirical analysis of the reaction of US banks to failure to meet the Return on Equity (ROE) of peers. A complementary analysis that reexamines the determinants of bank profitability using dynamic panel regressions suggests that large and medium sized banks rely on off-balance sheet liquidity creation as a main source of profitability while small sized banks rely on on-balance sheet liquidity creation activities. The VAR results suggest that banks react differently to underperformance across size groups. More specifically, all banks reassess their credit risk and opt to increase their non-discretionary loan loss provisions to face expected credit losses. The ability of small banks to build up their capital to face unexpected risk seems to be affected by the deterioration of earnings. Also, small and medium-sized banks tend to increase their off-balance sheet at the expense of on-balance sheet liquidity creation, implying greater reliance on commission and fees at the expense of interest margins in income generation. Finally, except large banks that are most likely subject to great scrutiny as a consequence of their systematic risk, small and medium-sized banks tend to rely on earnings management to mitigate their underperformance through discretionary loan loss provisions.

Keywords: *Liquidity creation, Earnings management, Financial performance, Risk management*

JEL Classification: G20, G21, G32, M41

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1. Introduction

Profitability plays an essential role in the banking sector as a major component of stocks' total return, a crucial determinant of executive compensation, a key element in determining banks' future plans, and a leading indicator of banks' competitive position. Financial markets and regulatory forces employ profitability as a measurement tool to evaluate banks' performance and identify the efficiency of their competitive strategies and management plans. Particularly, profitability ratios such as return on equity (ROE) and return on assets (ROA) are closely followed performance measures in the banking industry (Klaassen and Van Eeghen, 2015; Massari et al., 2014). If inadequate profits are earned, involved shareholders, whether individual or collective investors are alarmed. Specifically, banks that lend to the underperforming bank, depositors (especially large corporate depositors), holders of long-term debt capital, bank stockholders, potential investors, and regulators would be concerned. Subsequently, funding costs will grow for underperforming banks, which could further erode their future profitability if they do not bounce back promptly. Therefore, it becomes of utmost importance for bank management to react quickly to any signs of underperformance which might affect an underperforming bank's future strategy and risk levels. Hence, the main premise of this paper is to investigate how underperforming banks are dynamically modifying their asset and liability management and risk management strategies in their attempt to recover from their losses.

While there is an abundant literature that has focused on the determinants of banks' profitability (e.g, Athanasoglou et al., 2008; Bikker and Vervliet, 2017; Delis and Kouretas, 2011; Dietrich and Wanzenried, 2011; Dietrich et al., 2014; García-Herrero et al., 2009; Trujillo-Ponce, 2013), the objective of this paper is to investigate the impact of profitability underperformance in relation to peers on the liquidity creation (LC) of banks. Banks can pursue to offset lost margin income by either seeking higher net interest income through on-balance sheet activities or higher fee income through increased off-balance sheet activities. Following this reasoning, we further decompose the dynamics of LC to separately study on-balance sheet and off-balance sheet dynamics following underperformance using the LC measure developed by Berger and Bouwman (2009). Giving it further advantage, the LC decomposition can show the relative importance of each component in generating profitability for banks of different size groups. For instance, research by Hassan and Soula (2017) recognizes that size influences the decision to create on-balance sheet or off-balance sheet liquidity. Small-sized banks, usually experienced in processing soft information and relationship-lending, depend on on-balance sheet LC. In opposition, large banks, mainly experienced in hard information and transaction-lending, find off-balance sheet LC to be more potent. Therefore, it would be of considerable interest to see which LC component for each size group has the greatest effect on ROE and to also monitor how these banks dynamically alter their LC structure when they underperform and show signs of weakened competitive advantage. On one hand, underperforming banks might seek to increase their LC and target a higher income. On the other hand, underperforming banks might endure risk, failing to realize their primary objective, namely the ROE; they will then seek to reduce their risk exposure by decreasing their LC and increasing their capital and provisions. We believe that posing these significant questions will lead to a better understanding of the dynamics of LC and its correlation to profitability and market competition.

The second objective of the paper is to examine the impact of underperformance on the risk of banks. LC is closely associated with risk since it quantifies the liquidity transformation of banks that makes banks illiquid in the process. Therefore, excessive bank LC could increase the probability of failure merely due to higher liquidity risk. Also, higher LC might entail greater credit risk because loan growth tends to be associated with higher credit risk (Foos et al., 2010). Accordingly, the increase in LC could be coupled with an additional credit risk that significantly increases the total risk of the underperforming bank. In this paper, we investigate whether underperforming banks reassess their ability to manage their total risk following underperformance. We first examine whether the banks' capital, which works as a protection against failure and unexpected risk, is affected following underperformance, particularly considering how the affected banks will have a lower ability to build capital internally through retained earnings. This question is crucial for medium and small size banks as they are not perceived to be too big to fail.

Moreover, since one of the key managerial challenges is to control asset quality and the resulting loan loss, we also study the risk of banks by examining the impact of underperformance on loan loss provisions (LLP). Provisions and capital requirements are closely linked since both aim to handle credit risk; expected losses have to be covered by LLP while unexpected losses have to be covered by bank capital (Bouvatier & Petit, 2012). In order to properly assess the effect of underperformance on provisions related to loan quality, we separate loan loss provision to total loan ratio (LLP ratio) between discretionary (DLLP ratio) and non-discretionary (NDLLP ratio) components since DLLP is under the control of bank managers and will most likely drop following underperformance in order to smooth the income. NDLLP, in contrast, is associated with the fundamental credit risk of the outstanding loan portfolio.

To address these practical issues, the paper reexamines the determinants of profitability, captured by ROE, through the introduction of bank on and off-balance sheet LC and the partitioning of the LLP ratio to DLLP and NDLLP ratio. We use quarterly call report data on commercial banks for the period 1996-2014. Dynamic panel models with system GMM estimator

(Arellano and Bover, 1995; Blundell and Bond, 1998) are employed to analyze the ROE determinants. This is mainly due to the bidirectional nature of decisions in banking: the bank's specific factors influence profitability; simultaneously, these same factors are altered based on profitability. By decomposing our sample to large, medium, and small-sized banks, the paper validates that small banks impact their profitability through on-balance sheet activities while large and medium-sized banks derive their profitability from off-balance sheet activities. This shows that banks have disparate profitability determinants based on size. It also implies that banks could have different strategies to reach a target profitability level. The results also demonstrate that the equity capital has a negative impact on banks' profitability, which supports the conventional risk-return hypothesis that investors of safer banks should ask for a lower ROE. Unsurprisingly, the results show that DLLP and NDDLP ratios impact ROE negatively since additional LLP expenses directly reduce the net income.

To complement the analysis, this paper examines the impact of ROE underperformance on LC, capital, and LLP decisions over time using a panel data VAR model. Results show that large banks generally remain unfazed by ROE underperformance, reacting only by reassessing the risk of their loan portfolio and increasing the NDLLP ratio. On the other hand, medium and small-sized banks show a somehow different effect as they tend to cut their on-balance sheet LC. However, these banks tend to increase their off-balance sheet LC on the short-run, implying greater reliance on commission and fees at the expense of interest margins in income generation.

In terms of risk, the VAR model shows that all banks increase their NDLLP ratio, which denotes that banks reassess their risk following underperformance and become more risk-averse in terms of assessing the anticipated loss. The VAR analysis also supports the income smoothing hypothesis and the negative correlation between bank size and DLLP. Large banks do not alter DLLP ratio following underperformance, whereas medium and small size banks decrease their DLLP ratio to boost their ROE.

This study contributes to the literature in diverse ways. First, it examines the significant role that each of LC components, capital, and LLP ratio components plays in order to determine the reported profitability. In addition, the study shows that profitability underperformance can create a pressuring force on the bank to restructure its on-balance and off-balance sheet activities, inspect its capital needs, and reassess its credit risk to bounce back.

Understanding the reaction of underperforming banks relative to peers of a comparable size group is of practical importance and policy-making interest. Mainly, resorting to additional LC to rapidly amplify the reported profitability exposes the bank to further risks, especially a liquidity risk. This risk-taking approach, usually motivated by regulatory safety nets, could lead to poor asset quality and bank runs (e.g., Gorton, 1988) or result in asset bubbles that possibly burst financial crises due to poor lending policies (Acharya and Naqvi, 2012; Rajan, 1994). Therefore, it is crucial to investigate whether banks seek to increase their LC and risk to upturn their ROE or engage in more prudent practices such as higher provisioning to limit their risk exposure. In addition to the above enquiry, this study helps to predict the potential behavior of underperforming banks and to consequently enhance their transparency. Nevertheless, improving the transparency of underperforming banks is a task made difficult by the fact that bank profit components are observed only at low frequencies; the latter makes the monitoring process a challenging one (Albertazzi and Gambacorta, 2009). Therefore, this study aids in assessing whether or not bank regulators need to impose more restrictive regulations to limit risk-taking behavior. This step is also necessary because many of the present studies suggest that the deterioration of asset quality, credit growth (e.g., Gavin and Hausman, 1996), and excess LC (Berger and Bouwman, 2015) indicate the presence of a problem at the macro-level. Finally, GAAP allows management to shift the recognition of accruals in order to improve the reliability of the financial performance measures. Management, however, might deliberately exercise this accounting judgement to incur benefits in earnings management (Wall and Koch, 2000). By analyzing how banks manage their earnings following underperformance, we help to understand not only how banks administer their earnings, but also why they engage in this behavior in the first place.

In the next section, we examine different literature streams and develop the hypotheses in more detail. Section three discusses the data. Sections four and five deal with the estimation methodology and report the empirical results respectively. Section six concludes the paper.

2. Literature Review and Hypothesis Tested

2.1. Underperformance and the liquidity creation determinant

According to the LC hypothesis, banks create liquidity by transforming a comparable amount of liquid liability to a relatively illiquid asset through both on and off-balance sheet activities (e.g., Diamond and Dybvig, 1983; Kashyap et al., 2002). How banks manage their LC has not been fully explored largely because of the absence of newly developed comprehensive LC measures. Some leading LC measures that were recently introduced are the liquidity transformation gap (Deep and Schaefer, 2004), the Berger-

Bouwman LC measures (Berger and Bouwman, 2009), and the liquidity mismatch index (Brunnermeier et al., 2013). Prior to these measures, the banking literature mainly focused on the ability of banks to meet the withdrawals of deposits while considering the asset side to be passive since banks invest in assets with a given payoff. Instead, the recent theory emphasizes the importance of LC from both assets and liability sides because banks play an active rather than a passive role in meeting credit demands in the economy.

The LC management is motivated by the expected associated profits and risk. This is because the transformation of cheap funding to high return illiquid assets should generate a high net interest margin with a higher maturity mismatch of assets and liabilities. However, banks might manage to raise their profitability by increasing their liquid assets despite the fact that these liquid assets are expected to yield much lower returns relative to illiquid assets. For instance, Bordeleau and Graham (2010) proclaim that bank profitability does not need to be negatively affected by holding more liquid assets. Reducing default risk lowers the financing costs and can eventually increase bank profitability if the cost reduction outweighs the opportunity cost of investing in illiquid assets. Accordingly, the quantity of liquidity produced by a bank should generally be positively related to bank profitability (e.g., Goddard et al., 2010; Molyneux and Thornton, 1992) unless the cost of financial distress erodes this higher profitability. Therefore, while we generally expect to find a positive association between LC and profitability, there is a likelihood that increasing LC can lead to higher financing cost when banks underperform. Therefore, whether banks increase or decrease on-balance sheet LC following underperformance remains an empirical question to answer.

In addition, Curcio and Hasan (2015) notably discovered that large and medium size banks mainly rely on off-balance sheet activities while small size banks rely on on-balance sheet activities to generate profit. Based on their findings, we expect the impact of on-balance sheet LC on ROE to have a more prominent effect as the size group decreases. We further expect small banks to decrease their on-balance sheet LC following underperformance since they are not perceived to be too big to fail, which means that managing their financing and bankruptcy costs rather than profitability will be their main priority.

In this paper, we do not limit the analysis of LC to the total LC of banks. We separate on-balance sheet and off-balance sheet LC since the dynamics of off-balance sheet activities and the trade-off between them are still not well-understood (Berger and Bouwman, 2015). Even though off-balance sheet activities might constitute up to half of all US bank LC, off-balance sheet LC is still not vigorously investigated (Berger and Bouwman, 2009). It would be of great interest to see whether banks revert to on-balance sheet or off-balance sheet items to bounce back when their performance is not satisfactory.

Similar to the on-balance sheet LC argument, we expect off-balance sheet activities to increase bank profitability given the fees and commissions that they generate. Nonetheless, a negative impact of LC on profitability remains a possibility if granting more loans and commitments increases the probability of default for banks and the funding costs (Bordeleau and Graham, 2010), which entails that underperforming banks will reduce off-balance sheet activities in this case. However, as previously mentioned, the decision to increase or decrease off-balance sheet activities following underperformance would be an empirical question to answer. Notwithstanding, we expect a different behavior across different bank size groups since the role of off-balance sheet activities becomes more prominent as the size of the bank increases (Curcio and Hasan, 2015).

2.2. Underperformance and risk

2.2.1. Underperformance and the equity capital determinant

Banks often find themselves on the wrong side of the risk level. For instance, Taylor (2009) states that excessive risk-taking as well as the lack of balance sheet transparency and quality led to the 2008 subprime crisis. Therefore, in quest of a higher ROE, it is possible for banks to end up with excessive risk, especially for underperforming banks since their ability to build up internal capital through retained earnings will diminish.

Higher capital is often assumed to be costly for banks, indicating that it reduces their profitability (e.g., Altunbas et al., 2007). However, others refer to capital as the amount of funds available to support a bank's business; capital acts as a safety net in the case of adverse developments, enabling the bank to compete more efficiently for risky loans or achieve cost savings upon increasing the size of the bank (e.g., Athanasoglou et al., 2008; Berger, 1995; García-Herrero et al., 2009; Molyneux and Thornton, 1992). For instance, Berger (1995) and Athanasoglou et al. (2008) both argue that capital can mitigate bankruptcy costs and enable the bank to finance its assets at more favorable interest rates. In addition, the literature suggests that the effects of bank capital on profitability vary by size class. Banks that are relatively large tend to raise less expensive capital, and hence, appear more profitable (Athanasoglou et al., 2008). Given the opposite theoretical effects of capital on profitability, we cannot predict the impact of capital on profitability, particularly because the empirical evidence is mixed.

On the other hand, retained earnings seem to be used to increase the capital cushion for banks (e.g., Jacques and Nigro, 1997; Jokipii, and Milne 2008; Shim, 2013). Consequently, when banks underperform, their ability to build up their capital from internally generated funds would be weaker due to the lower returns. Therefore, we expect a bank's underperformance to lead to a lower equity capital relative to total assets, especially if underperforming banks expand their assets while increasing their LC in their attempt to bounce back. This is particularly the case for small size banks in which raising capital from external sources is costly. It is a matter of empirical investigation to see if banks of different sizes have similar abilities when they underperform, taking into consideration that small banks cannot raise equity easily.

2.2.2. Underperformance and LLP

The literature decomposes the LLP account into non-discretionary components that measure expected credit losses and discretionary ones that capture management objectives. The literature generally concludes that the market is able to differentiate between the two components (e.g., Beaver and Engel, 1996) although it makes assessing the risk of the balance sheet more opaque (Anandarajan et al., 2005).

Prior research mainly focuses on three managerial objectives behind DLLP: income smoothing, capital management, and signaling. The income smoothing theory claims that DLLP aims to stabilize the profitability over time to meet a firm-specific mean or the average benchmark of comparable firms (e.g., Kanagaretnam et al., 2005)[1]. Alternatively, the capital management theory posits that banks resort to DLLP in order to

[1] Taking large provisions when income is high and small provisions when income is low permits banks to shift income from good to bad periods. This allows the management to report earnings compliant to the stakeholders' expectations without being affected by any specific conditions. In addition, it helps the management meet its compensation target even during downturns.

boost their capital adequacy ratio and mitigate regulatory costs (e.g., Beatty et al., 1995)[2]. On the other hand, the signaling theory claims that DLLP could be used when dealing with investors to convey that a bank's expected earnings can easily absorb additional provisions (e.g., Beaver and Engel, 1996; Curcio and Hasan, 2015)[3].

If the primary focus of the bank is to bounce back its profitability, we expect to find a negative association between DLLP and ROE following underperformance in the context of the income smoothing theory. This is because lower DLLP could move ROE of the underperforming bank closer to that of peer banks.

However, our primary focus in this paper is on the NDLLP component since our main objective is to study the LC functionality of banks and the associated risk following underperformance, especially credit risk. NDLLP are used to absorb expected credit losses, which becomes of extreme importance when banks are poorly capitalized (Bouvatier & Lepetit, 2008). Consequently, the nature of NDLLP is dynamic and it is expected to change when the credit risk of an existing portfolio is unfolded. While it is difficult to foresee how many years are required till the credit risk of an existing loan is revealed, we claim that a profitability underperformance serves as a catalyst to reassess credit risk and increase NDLLP. We attribute this to two main reasons. First of all, with lower profitability, the dependence on retained earnings and internal capital will most

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[2] The evidence supporting this theory was robust prior to the introduction of the Basel accord since LLP were completely considered a source of capital. After the presentation of the Basel accord, LLP were not incorporated in the computations of Tier 1 capital; only a small portion was included as part of Tier 2 capital. For instance, under Basel II, if the bank uses a standard or internal-based approach, then LLP could be used as part of Tier 2 capital. Consequently, recent studies show the diminishing role of this theory (e.g., Ahmed et al., 1999; Curcio and Hasan, 2015).

[3] Liu and Ryan (1995) found that only banks with poor asset quality resort to signaling. Kanagaretnam et al. (2005) detected that the bank's size is negatively correlated with DLLP signaling while earnings variability, investment opportunities and undervaluation are positively correlated.

likely reduces the ability of banks to handle unexpected risk. Secondly, underperformance itself could be related to previous lending policies that failed to generate the desired income. Therefore, we expect banks to increase NDLLP following an underperformance shock. Also, we anticipate this effect to be most prominent for small size banks because they cannot raise capital easily.

3. **Data and Summary Statistics**

3.1. Data description

We obtained US individual commercial bank quarterly bulk data over the period of 1996 through 2010 from the Federal Reserve Bank of Chicago's website. We also obtained the bulk data for the 2011-2014 period from the website of the Federal Financial Institutions Examination Council (FFIEC).[4] We chose year 1996 as a starting year since the FFIEC website made the consolidated reports of condition and income for commercial banks (FFIEC forms) publicly available starting that year. We use quarterly data because a bank's management has incentives to reach a target ROE at each quarter when they release quarterly reports to regulators (call reports) and their investors. We follow the common practice in LC analysis and classify banks into three different size classes because banks of different sizes behave and perform differently (e.g., Berger and Bouwman, 2009; Berger et al., 2005; Kashyap et al., 2002)[5]. We follow the size classes defined by Berger and Bouwman (2009) and categorize each quarter banks with gross total assets (GTA) above $3 billion as large-sized banks, banks with GTA exceeding $1 billion and up to $3 billion

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[4] The Federal Reserve Bank of Chicago provides quarterly bulk SAS files of all Call Report items. These files are made available till the fourth quarter of year 2010. On the other hand, FFIEC provides bulk text files starting the first quarter of year 2001 to present.

[5] We retrieve the data frpm Christa Bouwman's website: https://sites.google.com/a/tamu.edu/bouwman/data

as medium-sized banks, and those with GTA less than $1 billion as small-sized banks (known as community banks). We eliminate bank observations with missing or unusable data. Specifically, we eliminate banks with negative equity capital or zero total loans. Moreover, we eliminate the smallest banks with a GTA less than $500 million because these banks tend to have a different structure than that of other banks. More importantly, including banks with less than 500 million GTA in the study resulted in a dynamic panel data model that failed to overcome Sargan/Hansen over-identification tests and the no second order serial autocorrelation of error terms needed to justify the stability of the model. In order to mitigate the influence of outliers, we winsorize all bank specific variables at the 1st and 99th percentiles. The resulting sample consists of 38,917 observations for 2,712 banks over the twenty-year period: 5,454 observations for 293 large-sized banks, 15,205 for 1,170 medium-sized banks and 18,285 observations for 1,269 small-sized banks. The regressions control for time trend using quarterly dummies and bank level heterogeneity. Robust standard errors are used to correct for heteroscedasticity.

3.2. Summary statistics

Table 1 provides an overview of the summary statistics of banks that underperformed the median of peer banks of the same size group in the same state as well as banks that matched or over-performed this median (achiever banks). A simple comparison between the two groups show that all reported banks' characteristics are different and significant at the 1% except the on – balance sheet LC for large and medium size banks.

ROE and ROA of underperforming banks is much below the ROE of achiever banks. As expected, achiever banks create more off-balance liquidity than underperforming banks with higher off-balance sheet LC over GTA. Also, the cost-income structure for achievers is lower than that of underperformers, indicating that managerial efficiency in dealing with the cost structure is strongly associated with the overall performance of the bank. Particularly, large banks show economies of scale as they report a cost structure below those of medium and small size banks. Notably, LLP ratio in our sample reaches less than the double for underperformers compared to achievers for large banks and more than the double for medium and small size banks although total loans over GTA are higher for achievers. Remarkably, equity over GTA is higher for underperformers than that for achievers, which reflects the need for a higher protection against risk. As noted earlier, in the presence of close regulatory supervision in the US, one would expect underperforming banks to have higher equity capital.

[Insert Table 1 about here]

4. Estimation Methodology

4.1. A Dynamic Panel System GMM

The bank performance literature has broadly recognized that profitability persists and depends on a bank performance's lagged value (e.g., Berger et al., 2000) since the structure of the balance sheet cannot be altered quickly. Consequently, the intertemporal rigidities in some of the model variables imply that bank profits are serially correlated. Also, in practice, our dependent and independent variables could be jointly determined because a bank's profitability can impact its choices for LC, risk levels, and discretionary accounting choices. Therefore, in order to ensure that we are capturing causality and not mere correlation, we develop a dynamic profitability model with system GMM estimator as suggested by Arellano and Bover (1995) and Blundell and Bond (1998). This model specification is suitable for the study for many reasons. Firstly, some of the profitability determinants are conceivably endogenous and might be correlated with the error term. This could be due to an omitted variable bias or a loop in causality between the dependent and independent variables. Indeed, in our model, many variables could be caused by ROE. To illustrate, banks with higher ROE can afford to increase their on-balance and off-balance sheet LC due to their competitive advantage in the market. Similarly, banks with higher ROE could take more risk because they can absorb its negative outcome. Also, banks with high ROE can afford to spend more on operations to gain market share. For instance, they have the ability to spend on advertising or introduce new products. Likewise, profitability would probably affect the discretionary accounting choices of the bank.

In addition to that, unobserved bank heterogeneity that is not captured by the model could affect ROE. For example, the role of bank management or its clientele in determining ROE could differ from one bank to another. The system GMM estimator from Arellano and Bover (1995) and Blundell and Bond (1998) is used to overcome the issues of endogeneity, unobserved heterogeneity, and the persistence of ROE. The methodological instruments used for system GMM estimator include the lagged values, in levels and in differences, of both the dependent variables as well as the predetermined endogenous independent variables. Surely, the recent empirical literature on bank profitability has broadly used similar specifications: Athanasoglou et al. (2008) and Delis and Kouretas (2011) for the Greek banking sector, Dietrich and Wanzenried (2011) for Swiss banks, García-Herrero et al. (2009) for Chinese banks, Trujillo-Ponce (2013) for Spanish banks, Dietrich et al. (2014) for Western European banks, Bikker and Vervliet

(2017) for US banks.

The first model that we use in this study is based on the aforementioned bank profitability literature. The used model shows the main determinants of bank profitability; these same determinants are later used as dependent variables in subsequent models to reflect their causal relationship with underperformance. The model is as follows:

$$ROE_{it} = cst + \alpha ROE_{it-1} + \beta X_{it}^{Specific} + \gamma X_{it}^{Macro} + \delta X_{it}^{Industry} + \varepsilon_{it} \quad (1)$$

where,

cst is the intercept.

$X_{it}^{Specific}$ are the bank specific variables. These variables are listed below:

1. $LCon_{it}$: On-balance sheet LC scaled by gross total assets. As previously discussed, in general, the expected sign is positive, but it is possible that financing costs might outweigh lending benefits. Therefore, the sign is ambiguous.

2. $LCoff_{it}$: off-balance sheet LC scaled by gross total assets. Same as on-balance sheet LC argument. The sign is ambiguous.

3. EqC_{it}: is the equity capital to gross total asset ratio. The expected sign is negative unless the benefit from reducing default probabilities is significant, which then makes the sign theoretically undetermined.

4. $DLLP_{it}$ is the DLLP ratio defined as the discretionary loan loss provision as a fraction of total loans. The expected sign is negative given its direct impact on banks' income statements. Similar to Cohen et al. (2014) and Beatty et al. (2002), we separate the discretionary from the non-discretionary NDLLP ratios using the following regression:

$$Loss_{it} = \alpha_0 + \beta_1 Size_{it-1} + \beta_2 \Delta NPL_{it} + \beta_3 ALL_{it} + \beta_4 RE_{it} + \beta_5 CI_{it} +$$

$$\beta_6 Depository_{it} + \beta_7 Consumer_{it} + z_{it} \qquad (2)$$

where Loss is the LLP ratio measured as LLP as a fraction of total loans. Size is the lagged natural logarithm of total assets; ΔNPL is the change in non-performing loans as a percentage of the average quarterly total loans; ALL is the allowance for loan loss as a percentage of total loans at the beginning of the quarter; RE is the real estate loans as a percentage of total loans; CI is the commercial and industrial loans as a percentage of total loans; Depository is the loans to depository institutions as a percentage of total loans; Consumer is loans to individuals as a percentage of total loans; z is DLLP scaled by total loans and represents the DLLP ratio variable in equation (1) . The specification of equation (6) implies that z is scaled by total loans (Cohen et al., 2014). Note that higher levels of DLLP ratio decrease net income, and subsequently, the ROE.[6]

5. $NDLLP_{it}$ is the NDLLP ratio defined as the non-discretionary loan loss provision as a fraction of total loans. It is measured as the difference between the LLP ratio and DLLP ratio in equation (2). Similar to DLLP ratio the expected sign is negative.
6. Costincome_{it}: is the cost–income ratio defined as the operating costs' net of interest expense over operating income[7]. This ratio measures the management efficiency in handling the costs of banks. It is also frequently used to assess the performance of banks (Hasan et al., 2009).

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6 We investigated the role of the discretionary realized security gains and losses (DRSGL) as ROE determinants. Following the methodology from Beatty et al. (2002), we separated the discretionary from the non-discretionary realizations of security gains or losses using the residuals. Across all regressions, DRSGL was insignificant.

7 Specifically, we use the following items from the call report: Expenses of Premises and Fixed Assets (RIAD 4217) + RIAD 4135 ("Salaries and Employee Benefits") + "Other" non-interest expenses (RIAD 4092) divided by operating income (RIAD 4000).

Therefore, we expect a negative sign since higher cost as a percentage of income would depress the profitability of a bank[8].

X_t^{Macro} are the macro control variables. Based on the literature, we include the following variables:

1. GDPg_t is the real GDP growth rate. The expected sign is positive since higher GDP increases the demand for lending.
2. $\mathrm{Inflation}_t$ is the inflation rate. The expected sign is ambiguous. On one hand, inflation will increase banks' costs. On the other hand, banks can increase their revenue at a faster rate than costs would if the inflation is fully anticipated (e.g., Molyneux and Thornton, 1992).
3. ST_t is the short term (90 day T-bill) interest rate. The expected sign is negative since the monetary policy literature shows that low interest rates are the main tool that central banks use to stimulate the economy.
4. LT_t is the long term (10 year) interest rate. The expected sign is positive since long-term lending rates would increase in the net interest margin of the bank (Bikker and Vervliet, 2017).

$X_t^{Industry}$ is the Herfindahl-Hirschman Index (HH_t), which is calculated as the sum of the squares of all banks' market shares in terms of total assets in percentage. We expect a negative association between HH and ROE since more concentration as a result of competition is likely to erode bank profitability.

$\varepsilon_{it} = \eta_i + \mu_{it}$, where η_i is the time-invariant unobserved bank specific effect and μ_{it} is the idiosyncratic error.

4.2. A VAR Model

To examine how the ROE underperformance shock affects banks strategies and structures, we use a panel vector auto regression (VAR) model whereby each variable in the model is simply

8 Since lower income that leads to a lower ROE would automatically drive up the ratio, we do not look at the dynamics of this ratio following underperformance.

a linear function of lags of all variables.[9] Several models were run, and the ordering of the variables turned out to be irrelevant. This model allows us to estimate the impact of banks' underperformance (Lmiss) of the previous quarter on the LC, risk, and other endogenous variables (i.e., LCon, LCoff, EqC, DLL, and NDLL variables). Thus, we end up with the following model:

$$ROE_{it} = cst + \alpha Lmiss_{it-1} + \beta X_{it}^{Specific} + \gamma X_{it}^{Macro} + \delta X_{it}^{Industry} + \varepsilon_{it}$$

where "Lmiss" is a one-period lagged dummy variable that equals 1 if ROE of the banks underperformed the median of its peer banks. We define peers as banks of the same size group headquartered in the same state.

In general, in a VAR model, the most useful analysis is not the analysis of VAR coefficients, but rather the impulse response function (IRF). The IRF enables us to examine the direction, size and speed with which ROE determinants change due to a unit shock to the dummy Lmiss that takes a value of 1 if banks underperform in the previous quarter; otherwise, it takes a value of zero.

5. Results

5.1. The Determinants of Profitability

In Table 2, we report the results of the core model for various size samples using ROE as the dependent variable. Most importantly, to determine the appropriate lag structure, we use three information criteria: The Akaike Information Criterion, Schwartz Bayesian Information Criterion, and the Hannan-Quinn Information Criterion. Accordingly, a two lag-order selection criteria is used for all endogenous (firm-specific) variables for all size

[9] The unit root tests, Im, Pearson and Shin W-stat and Augmented Dickey Fuller and Phillips–Perron test, show that the data is stationary.

group models. We employ one lag level variable for all exogenous (macroeconomic and industry specific) variables.

Table 2 shows the relevant specification tests that support the stability of the model. Specifically, we report the p-value of the Arellano–Bond tests for autocorrelation of orders 1 and 2 (henceforth, AR(1) and AR(2) tests, respectively) as well as that for the Hansen J-test for over-identifying restrictions.

The dynamic panel model specification tests indicate that the model produces stable coefficients. The AR(1) tests reflect the presence of first-order autocorrelation which does not indicate inconsistent estimates. AR(2) tests, on the other hand, reject the second order autocorrelation, suggesting that the model coefficient are consistent. In addition, the p values of the Hansen J-test show that the instruments used are valid and not weak. Above all, the model demonstrates very high significance for the lagged dependent variable (ROE or ROA) with coefficients that indicate persistence between 0 and 1, which is the key characteristic of dynamic panel models. However, the coefficient of the lagged dependent variable indicates moderate persistence level for large and medium-sized banks. This result is consistent with studies that reported moderate persistence level for their bank samples, signifying a departure from a perfectly competitive market structure (e.g., Athanasoglou et al., 2008; Dietrich and Wanzenried, 2011). Yet, for small banks, a low persistence level was observed, which implies a high level of competition among these banks. The macro and industry variables are generally in accordance with the signs predicted by the theory, making them another indicator for the validity of the model.

Analogous to Dietriech and Wanzenried's (2011) approach, to test for the stability of our parameter estimates, we reexamined the study's progression while eliminating the individual variables. There was no change upon the omission of each variable in the equation after every trial.

Considering that the collinear nature of the independent variables does not cause hindrance to the study's method, we kept all the variables in the model.

The LCon coefficients show an intriguing pattern. We generally expect on-LC to positively affect ROE because higher LC indicates riskier balance sheets, which in turn results in higher profitability, given the positive association between risk and expected return. Indeed, small banks show that more LC leads to higher profitability. The LCon coefficient for large banks is negative, showing that large banks create liquidity beyond the optimal level. Large banks might be willing to go beyond the optimal LC levels since by winning an additional market share, they might aim to benefit from other fee-based non-lending products and financial services. For example, De La Torre et al. (2010) point out that large banks aspire to become the principal bank involved with the SMEs. In its ability to become the main bank, the large banks would provide special products as part of a larger overall package such as asset-based lending, factoring, and fixed-asset lending, all of which small banks cannot offer. At the same time, the large banks can offer leasing to finance SMEs.

The LCoff coefficient shows complementary results to the LCon coefficients. The main source of profitability for large banks from LC activities comes from off-balance sheet activities rather than on-balance sheet activities. This would explain why large banks work beyond optimal levels for on-balance sheet LC activities. Lcoff coefficients confirm the previous findings (Hassan and Soula, 2017), claiming that small banks do not rely on off-balance sheet activities—unlike large and medium banks that use off-balance sheet activities to generate profits.

[Insert table 2 about here]

For robustness, we report the empirical results of the core model in Table 3. The data in the period ranging from the third quarter of year 2007 until the last quarter of year 2009 is excluded because banks might have behaved differently during the subprime financial crisis, mainly focusing on risk management rather than on ROE maximization. An additional robustness test is reported in Table 4, where we used ROA as an alternative bank profitability measure.

[Insert tables 3 and 4 about here]

In general, the LC inferences remain the same with the large and medium banks' reliance on off-balance sheet activities to generate profit. Small banks rely on on-balance sheet activities.

The role of equity capital in determining profitability is well-supported in our results. On one hand, equity capital has a negative effect on ROE for large and medium banks and incurs a positive effect on ROA for all bank sizes, as reported in Table 4. These opposite results suggest that when ROA is the dependent variable, the relationship between capital and profitability is positive. This finding is quite plausible and in line with many papers in the literature (e.g., Athanasoglou et al., 2008; Berger, 1995; García-Herrero et al., 2009; Molyneux and Thornton, 1992) because higher equity capital allows banks to rely less on deposits and borrowings to finance its assets. Consequently, the lower interest expenses and higher margins lead to a higher ROA. When the dependent variable is ROE, higher equity capital can lead to a lower ROE; this correlation suggests a dilution effect to equity holders since earnings will be distributed over a larger base number of shares.

Table 2 shows that, in general, LLP negatively impact profitability measures. This is not surprising given that LLP (both discretionary and non-discretionary) directly impact expenses and subsequently affect earnings. Interestingly, the results show that the discretionary loan loss provisions are an important determinant of profitability for medium and small banks. Table 2 shows that DLLP ratio does not seem to influence the profitability of large banks due to the fact that large banks are frequently under close prudent surveillance from regulators. This reasoning is accentuated when observing how the DLLP ratio for large banks prior to the crisis becomes significant at the 10% level, as shown in Table 3. Table 4, on the other hand, shows a lower significance of DLLP ratio on ROA; it is only significant for small banks. This supports the notion that bank managements give priority to ROE targeting in their decision-making instead of ROA because DLLP decisions are driven by managerial incentives.

The literature has strongly identified managerial cost efficiency as a source of profitability (e.g. Athanasoglou et al. 2008; Dietrich et al., 2014). However, the literature has not investigated the impact of cost efficiency on different size groups. Indeed, our results indicate that the cost-income ratio has a strong negative impact on profitability. Most importantly, the results across Tables 2, 3, and 4 indicate that as the impact of the cost-income ratio magnifies, the smaller the bank size becomes.

5.2. VAR Simulation Results

Figures 1, 2 and 3 show the response of ROE determinants to bank underperformance for large, medium and small banks respectively. Panel A of each figure presents the IRF of the VAR model for each category in which underperformance is computed based on the median of peers. For robustness, we report the IRF of a VAR model in Panel B where underperformance is measured relative to the 25^{th} percentile as an alternative to the median.

[Insert figures 1, 2, and 3 about here]

For large banks (Figure 1, Panel A), underperformance has a significant impact on ROE. ROE levels immediately and sharply deteriorate in the first two quarters and then become fairly flat after the fourth quarter. Hence, the impact of underperformance on ROE is short-termed. As for equity capital, on-balance sheet LC, and off-balance sheet LC, their impulse is relatively flat over the phase along with insignificant results, which implies that the aforementioned variables carry no substantial reaction to underperformance. With regard to the impact on DLLP ratio, though insignificant at 5% level, it is worth noting that DLLP sharply drops in the first two quarters. DLLP then recovers by quarter 4, where it fairly flattens afterwards. Due to underperformance, large banks would increase the NDLLP ratio levels in the first two quarters after which the levels fairly flatten. This implies that large banks become more risk-averse in assessing their portfolio risk following underperformance in order to alleviate credit risk and contain the anticipated financial loss on their loan portfolio. Overall, the impact of underperformance for large banks is short-termed and limited to risk mitigation through provisioning for bad debt. The robustness VAR test (Figure 1, Panel B) leads to the same results as in the original VAR test.

For medium banks (Figure 2, Panel A), all the chosen ROE determinants respond significantly to underperformance except for equity capital. Starting with the impact of underperformance on ROE, medium banks witness an immediate drop in ROE in the first two quarters after which the level increases back to its original level smoothly. Thus, the impact on ROE is short-termed and limited to two quarters. Medium banks drop down the on-balance sheet LC levels in response to underperformance and the effect is rather long-termed as the trend never recovers and continues to slope down. This shows that medium banks take drastic measures following underperformance by cutting back their on-balance sheet LC activities, which in turn reduces the risk exposure. Off-balance sheet LC, on the other hand, increases in the first quarter after which it drops back and flattens, but does not recover to its previous level prior to the shock. This is consistent with the findings of Thakor (2005) which claim that banks facing uncertain conditions tend to revoke the commitments. Furthermore, similar to the case of large banks, NDLLP ratio for medium banks increase sharply in the first two quarters to flatten down afterwards, indicating an immediate provisioning for bad loans as a way to reduce risk. Interestingly, medium banks drop immediately following underperformance in their DLLP ratio. DLLP ratio picks up in the end of the first quarter to flatten fairly afterwards; this again is a short-termed effect of underperformance on DLLP that aims to positively impact ROE. The robustness VAR model (Panel B, Figure 2) shows the same trends and conclusions.

With regard to small banks (Figure 3, Panel A), ROE along with its determinants react considerably to underperformance. Similar to the case of medium banks, discretionary loan loss provisions are used following underperformance. DLLP ratio drops very sharply in the first two quarters to recover in the same speed by the fourth quarter after which it flattens up to its original level prior to the shock. Again here, small banks reduce their risk by increasing their NDDLP ratio, which increases in response to underperformance in the first two quarters and drops down smoothly afterwards. In view of that, there is an immediate yet short-term impact of underperformance on all of ROE, DLLP and NDLLP. With respect to equity capital and on-balance sheet LC, the levels drop down in the first five quarters, where they pick up again to flatten slowly. However, underperformance leads to lower equity capital for small banks only. This might indicate lower ability for small banks to manage their interest rate risk as unrealized losses can act to reduce equity capital under generally accepted accounting principles. Off-balance sheet LC, nonetheless, reacts differently; it increases considerably in the first quarters. LCoff consequently continues to rise afterwards at a slower pace and flattens ultimately at a level higher than that of its original, signifying a rather long-term effect of underperformance on LCoff. However, given that small banks do not rely on off-balance sheet activities to generate profitability, it is probable that this increase is due to greater reliance on risk management instruments. One instrument is the derivatives for hedging purposes to compensate for the decrease in equity capital, which would be consistent with the decline in on-balance sheet activities as well. The robustness VAR model (Figure 3, Panel B) revealed the same results.

6. Conclusion

In this paper, we reinvestigate the determinants of bank profitability using dynamic panel regression by introducing on-balance sheet and off-balance sheet LC as in Berger and Bouwman (2009). Since LC relies on the synergy between the asset and liability sides of the balance sheet, we argue that using this measure is more efficient than using an asset side measure such as loans or a liability side measure such as deposits to investigate profitability determinants. Furthermore, this measure captures off-balance sheet activities and the liquidity of the balance sheet. Indeed, the results support the fact that on and off-balance sheets are major determinants of profitability despite the fact that small banks do not rely on off-balance sheet activities. The results prove that as banks become larger, their dependence on off-balance sheet LC activities to generate return outweighs that of on-balance sheet activities.

The paper then uses a complementary panel vector autoregressive model to study the impact of underperformance on ROE determinants. The results show that banks tend to cut their LC exposure following underperformance. This is not the case for large banks that seem unfazed by the underperformance in terms of LC, possibly because the banks are too big to fail and need to keep their market share. However, all banks account for risk following underperformance and opt to reduce this risk by increasing their NDLLP ratio. Except large banks that are most probably subject to great scrutiny due to their systematic risk, banks tend to rely on earnings management following underperformance to smoothen their return through discretionary loan loss provision. Rising equity capital does not seem to be an immediate reaction to underperformance, which could be due to its dilutive effect and its costly form of financing. Interestingly, we show that non-discretionary loan loss provisions keep on increasing following underperformance, which reflects a more risk averse attitude from banks.

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Table 1. Descriptive Statistics. This table presents descriptive statistics for banks that achieved an ROE above the median ROE of peer banks (Achiever banks) as well as for underperforming banks with a ROE below the median ROE of peers. We also report the difference in mean of achievers and underperformers. On balance sheet liquidity creation (LCon), off-balance sheet liquidity creation (LCoff) , and equity capital (EqC) are normalized by GTA. Loan loss provisions (LLP) are normalized by total loans whereas the cost income ratio (Costincome) represents operating costs normalized by operating income. All values are reported in percent. N is the sample size. * p<0.1, ** p<0.05, *** p<0.01.

Panel A: Large Banks	**Achievers**					**Underperformers**						
	Mean	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Mean**	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Difference in Mean**	**t test**
ROE	9.95	8.84	5.9	1.94	26.53	1.29	2.98	9.33	-34.58	12.17	8.66***	-40.91
ROA	0.91	0.82	0.56	0.18	2.51	0.24	0.34	0.78	-2.36	1.58	0.68***	-36.72
LCon	29.66	30.44	13.19	-5.92	57.26	30.04	31.93	14.24	-14.40	57.46	-0.38	-1.01
Lcoff	18.41	9.95	30.69	0.58	150.71	12.47	8.84	20.33	0.58	150.71	5.94***	-8.44
LLP	0.41	0.20	0.70	-0.30	4.59	0.70	0.25	1.09	-0.24	4.59	-0.29***	-11.78
EqC	9.58	9.15	2.55	5.42	18.58	11.47	10.86	3.85	4.88	21.97	-1.89***	-21.35
Costincome	42.15	41.55	12.13	19.62	74.21	49.54	47.71	15.71	19.62	94.12	-7.385***	(-18.60)
N	2749					2707					5454	
Panel B: Medium Banks	**Achievers**					**Underperformers**						
	Mean	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Mean**	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Difference in Mean**	**t test**
ROE	9.32	8.49	5.35	1.88	26.53	1.23	2.94	9.35	-34.58	12.32	8.10***	-65.02
ROA	0.84	0.77	0.50	0.17	2.51	0.19	0.3	0.74	-2.36	1.33	0.65***	-62.94
LCon	32.46	33.43	12.73	-1.94	57.46	32.41	33.21	12.11	-1.19	57.46	0.06	-0.29
Lcoff	9.60	8.24	9.12	1.09	33.75	8.91	7.82	7.91	1.09	28.42	0.69***	-4.96
LLP	0.29	0.16	0.48	-0.20	2.31	0.65	0.25	1.01	-0.17	4.59	-0.37***	-28.28
EqC	9.27	8.98	2.02	5.95	16.87	10.12	9.57	3.04	4.88	21.97	-0.84***	-19.96
Costincome	43.78	42.83	12.03	19.62	75.09	52.18	50.04	15.75	20.48	103.94	-8.402***	(-35.19)
N	7836					7369					15205	
Panel C: Small Banks	**Achievers**					**Underperformers**						
	Mean	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Mean**	**Median**	**SD**	**1% Percentile**	**99% Percentile**	**Difference in Mean**	**t test**
ROE	9.05	8.11	5.29	1.74	26.53	1.46	2.79	8.45	-34.58	12.25	7.59***	-72.66
ROA	0.83	0.75	0.50	0.15	2.51	0.21	0.28	0.66	-2.36	1.29	0.62***	-71.42
LCon	31.89	32.87	13.46	-9.92	57.46	30.83	31.7	12.04	-2.83	55.82	1.06***	-5.62
Lcoff	8.09	7.20	6.64	0.59	22.41	7.40	6.42	6.57	0.85	22.94	0.69***	-7.07
LLP	0.27	0.15	0.45	-0.12	2.02	0.59	0.24	0.90	-0.18	4.59	-0.32***	-30.33
EqC	9.43	9.02	2.19	5.62	17.1	10.08	9.55	2.87	4.88	21.21	-0.65***	-17.26
Costincome	44.45	43.70	11.52	19.62	72.97	53.91	52.53	15.28	22.11	101.47	-9.463***	(-47.24)
N	9150					9108					18258	

Table 2: ROE Determinants Based on Bank Group Size

This table reports the results of system GMM dynamic models for the 1996-2014 period. The model regresses return on equity (ROE) on its lagged value ROE(-1), balance sheet liquidity creation (LCon), off-balance sheet liquidity creation (LCoff), discretionary loan loss provisions (DLLP), non-discretionary loan loss provision (NDLL), GDP growth (GDPg), Herfindahl-Hirschman Index (HH), inflation, the 90-day interest rate (ST), and the 10-year interest rate (LT). LCon, LCoff, and EqC are normalized by GTA. DLLP and NDLLP are normalized by total loans. The cost income ratio (Costincome) represents operating costs normalized by operating income. All variables except HH are in percent. Standard errors are clustered at the bank level. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Large		Medium		Small	
ROE(-1)	0.450***	(0.000)	0.467***	(0.000)	0.245***	(0.000)
LCon	-0.059***	(0.000)	0.083	(0.301)	0.059**	(0.045)
LCoff	0.182***	(0.000)	0.235**	(0.035)	0.086	(0.261)
DLLP	-1.086	(0.288)	-9.561***	(0.000)	-5.958***	(0.000)
Costincome	-0.063***	(0.002)	-0.136***	(0.001)	-0.173***	(0.000)
EqC	-0.094**	(0.037)	-0.194**	(0.015)	0.015	(0.915)
NDLLP	-6.278***	(0.000)	-2.580***	(0.000)	-10.840***	(0.000)
GDPg	0.140**	(0.044)	0.334*	(0.056)	0.085	(0.419)
HH	0.000**	(0.035)	-0.000	(0.390)	0.000	(0.697)
Inflation	-1.183***	(0.000)	-1.667***	(0.000)	-1.421***	(0.000)
ST	-0.313	(0.245)	-1.088***	(0.000)	-1.169***	(0.007)
LT	1.178***	(0.006)	1.164	(0.107)	1.918***	(0.001)
Observations	5,454		15,205		18,285	
Number of groups	293		1,170		1,269	
AR(1)	0		0		0	
AR(2)	0.152		0.203		19.901	
Hansen test (p-value)	0.246		0.368		0.281	

Table 3: ROE Determinants Based on Bank Group Size excluding the 2007-2009 crisis quarters

This table reports the results of system GMM dynamic models for the 1996-2014 period excluding the 2007q3-2009q4 crisis quarters. The model regresses return on equity (ROE) on its lagged value ROE(-1), balance sheet liquidity creation (LCon), off-balance sheet liquidity creation (LCoff), discretionary loan loss provisions (DLLP), non-discretionary loan loss provision (NDLL), GDP growth (GDPg), Herfindahl-Hirschman Index (HH), inflation , the 90-day interest rate (ST), and the 10-year interest rate (LT). LCon , LCoff, and EqC are normalized by GTA. DLLP and NDLLP are normalized by total loans. The cost income ratio (Costincome) represents operating costs normalized by operating income. All variables except HH are in percent. Standard errors are clustered at the bank level. p-values are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Large		Medium		Small	
ROE(-1)	0.484***	(0.000)	0.516***	(0.000)	0.228***	(0.000)
LCon	-0.025	(0.595)	-0.097**	(0.040)	0.095**	(0.022)
LCoff	0.213**	(0.012)	0.577***	(0.007)	-0.079	(0.322)
DLLP	-8.484*	(0.081)	-5.756**	(0.018)	-11.002***	(0.000)
Costincome	-.045**	(0.029)	-0.119***	(0.007)	-.169***	(0.000)
EqC	-0.034	(0.839)	-0.282***	(0.000)	0.007	(0.966)
NDLLP	-4.525***	(0.000)	-2.615***	(0.000)	-9.864***	(0.000)
GDPg	0.436***	(0.002)	0.173	(0.108)	0.236***	(0.003)
HH	0.000	(0.121)	-0.000	(0.850)	0.000	(0.576)
Inflation	-1.226***	(0.000)	-1.095***	(0.000)	-1.686***	(0.000)
ST	-2.193***	(0.000)	-2.184***	(0.000)	-1.269***	(0.001)
LT	2.217**	(0.016)	2.352***	(0.004)	2.341***	(0.001)
Observations	3,884		9,812		14,735	
Number of groups	279		1,112		1,209	
AR(1)	0		0		0	
AR(2)	0.245		0.139		0.181	
Hansen test (p-value)	0.206		0.328		0.262	

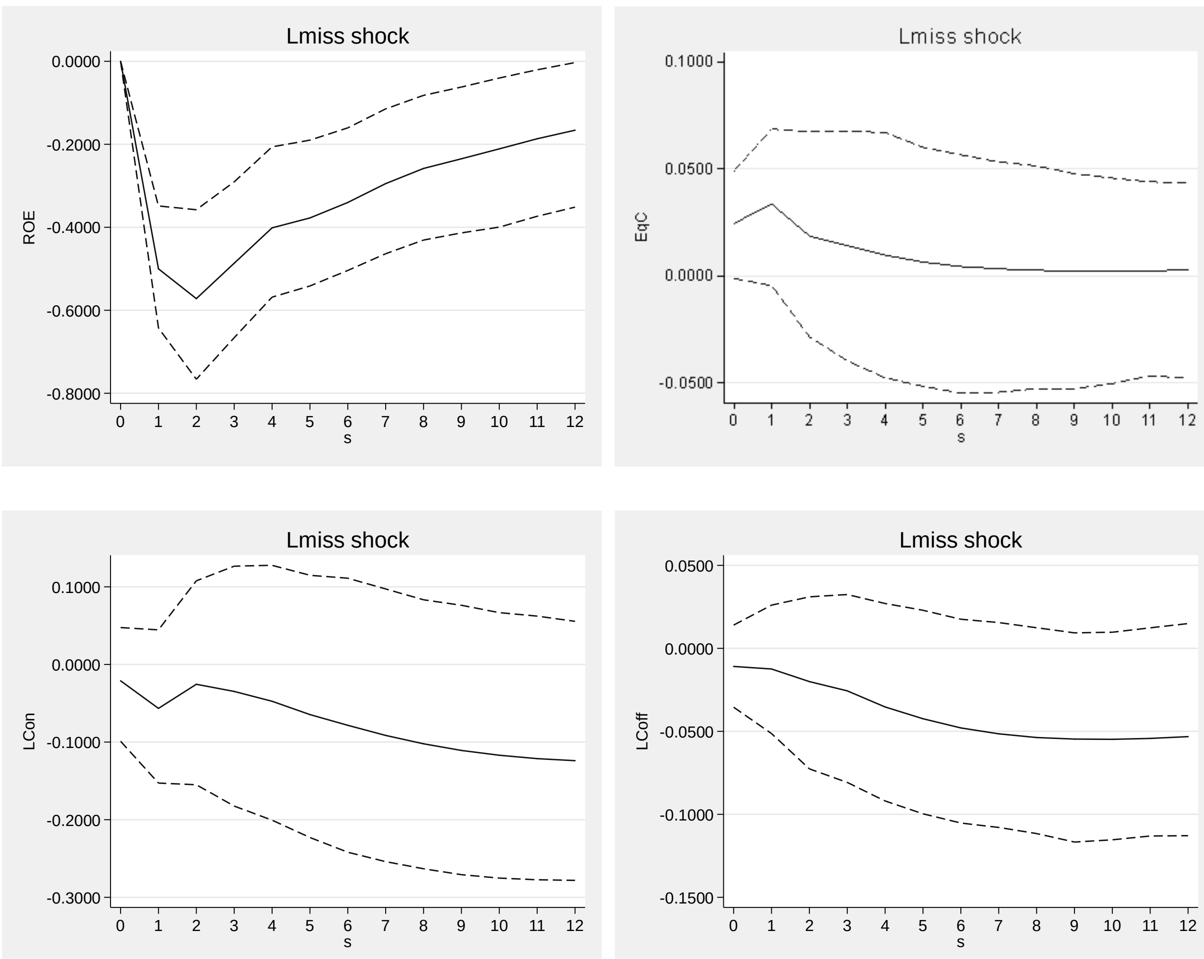
Table 4: ROA Determinants Based on Bank Group Size

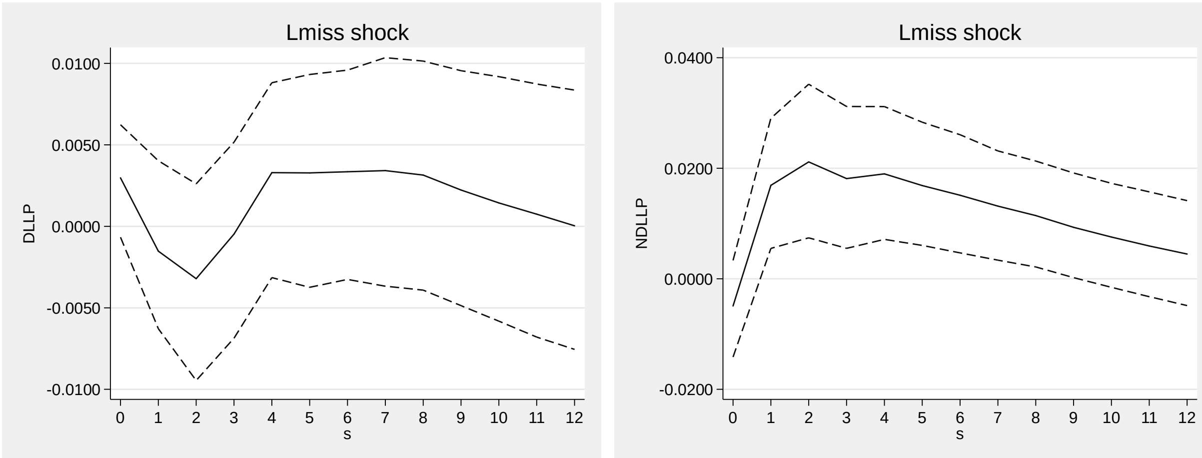
This table reports the results of system GMM dynamic models for the 1996-2014 period. The model regresses return on asset (ROA) on its lagged value ROA(-1), balance sheet liquidity creation (LCon), off-balance sheet liquidity creation (LCoff), discretionary loan loss provisions (DLLP), non-discretionary loan loss provision (NDLL), GDP growth (GDPg), Herfindahl-Hirschman Index (HH), inflation, the 90-day interest rate (ST), and the 10-year interest rate (LT). LCon, LCoff, and EqC are normalized by GTA. DLLP and NDLLP are normalized by total loans.
The cost income ratio (Costincome) represents operating costs normalized by operating income. All variables except HH are in percent. Standard errors are clustered at the bank level. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Large		Medium		Small	
ROA(-1)	0.460***	(0.000)	0.458***	(0.000)	0.191***	(0.000)
LCon	-0.006***	(0.000)	-0.005***	(0.000)	0.063*	(0.088)
LCoff	0.017***	(0.000)	0.018***	(0.000)	0.076	(0.429)
DLLP	-0.074	(0.412)	-0.063	(0.495)	-6.608***	(0.000)
Costincome	-0.006***	(0.002)	-0.006***	(0.001)	-0.007***	(0.001)
EqC	0.014***	(0.004)	0.014***	(0.004)	0.308**	(0.045)
NDLLP	-0.628***	(0.000)	-6.220***	(0.000)	-10.580***	(0.000)
GDPg	0.018***	(0.008)	0.017***	(0.009)	0.102	(0.123)
HH	0.000*	(0.072)	0.000*	(0.075)	0.000	(0.297)
Inflation	-0.111***	(0.000)	-0.109***	(0.000)	-1.196***	(0.000)
ST	-0.022	(0.397)	-0.009	(0.688)	-1.353***	(0.000)
LT	0.053	(0.182)	0.036	(0.323)	1.895**	(0.014)
Observations	5,454		15,205		18,285	
Number of groups	293		1,170		1,269	
AR(1)	0		0		0	
AR(2)	0.127		0.222		0.237	
Hansen test (p-value)	0.247		0.312		0.348	

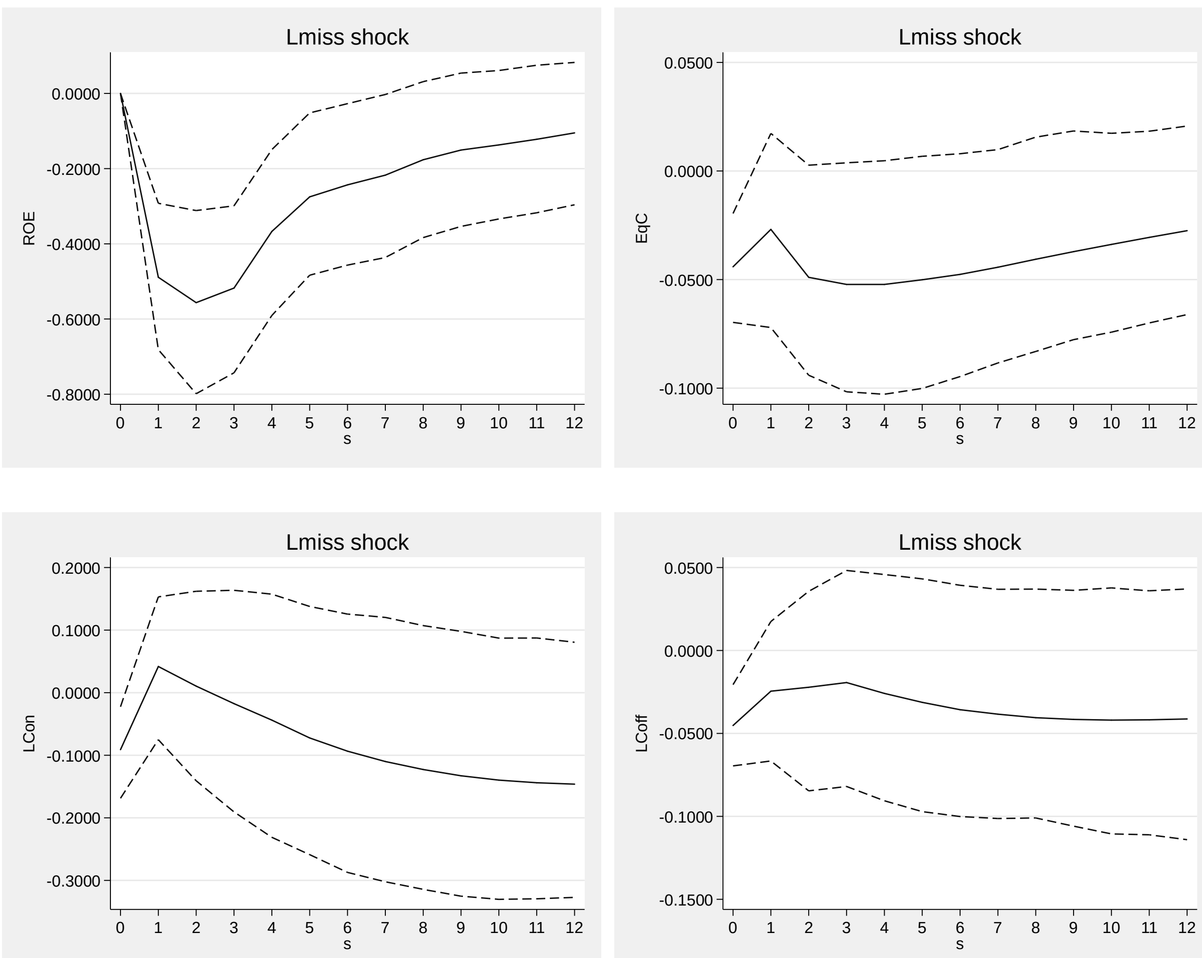
Figure 1: The Effect of large banks underperformance on ROE determinants (VAR model)
This figure shows the impulse responses of ROE determinants of large banks to underperformance together with a 95% confidence interval, using the panel vector autoregressive (VAR) model. Panel A reports the impulse response function of ROE determinants to underperformance when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the median ROE of its peers. Panel B reports the robustness test when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the 25th percentile of peers.

Panel A:





Panel B: Robustness VAR model for large banks



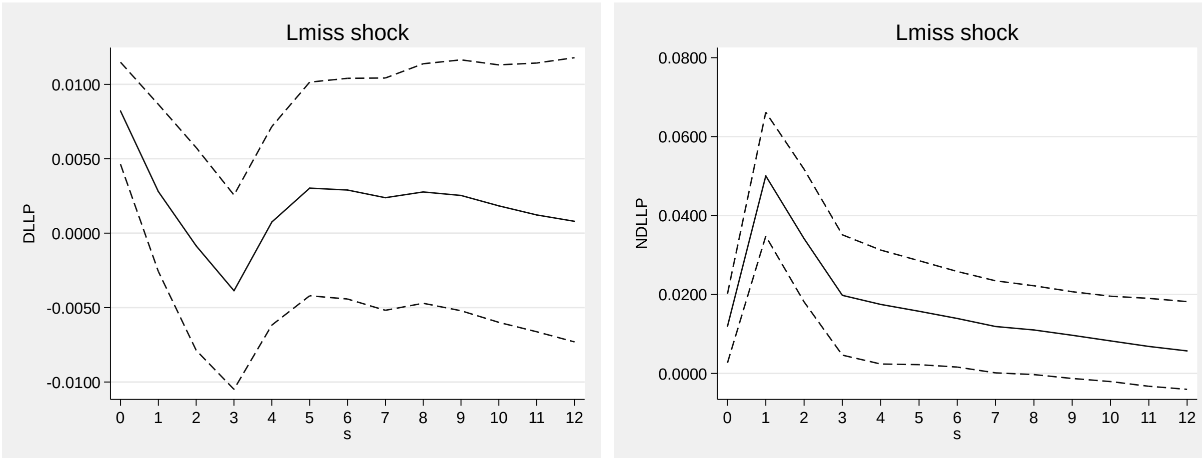
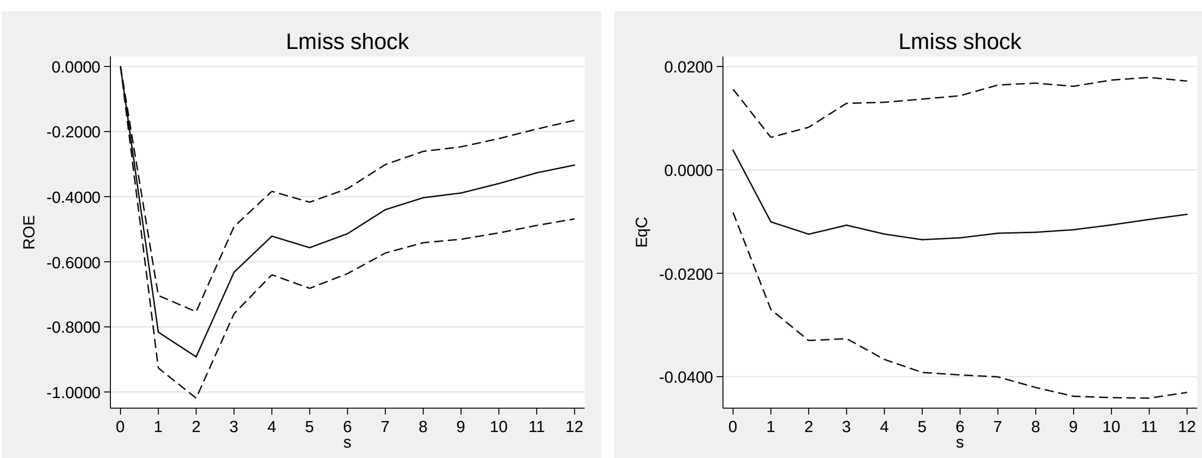
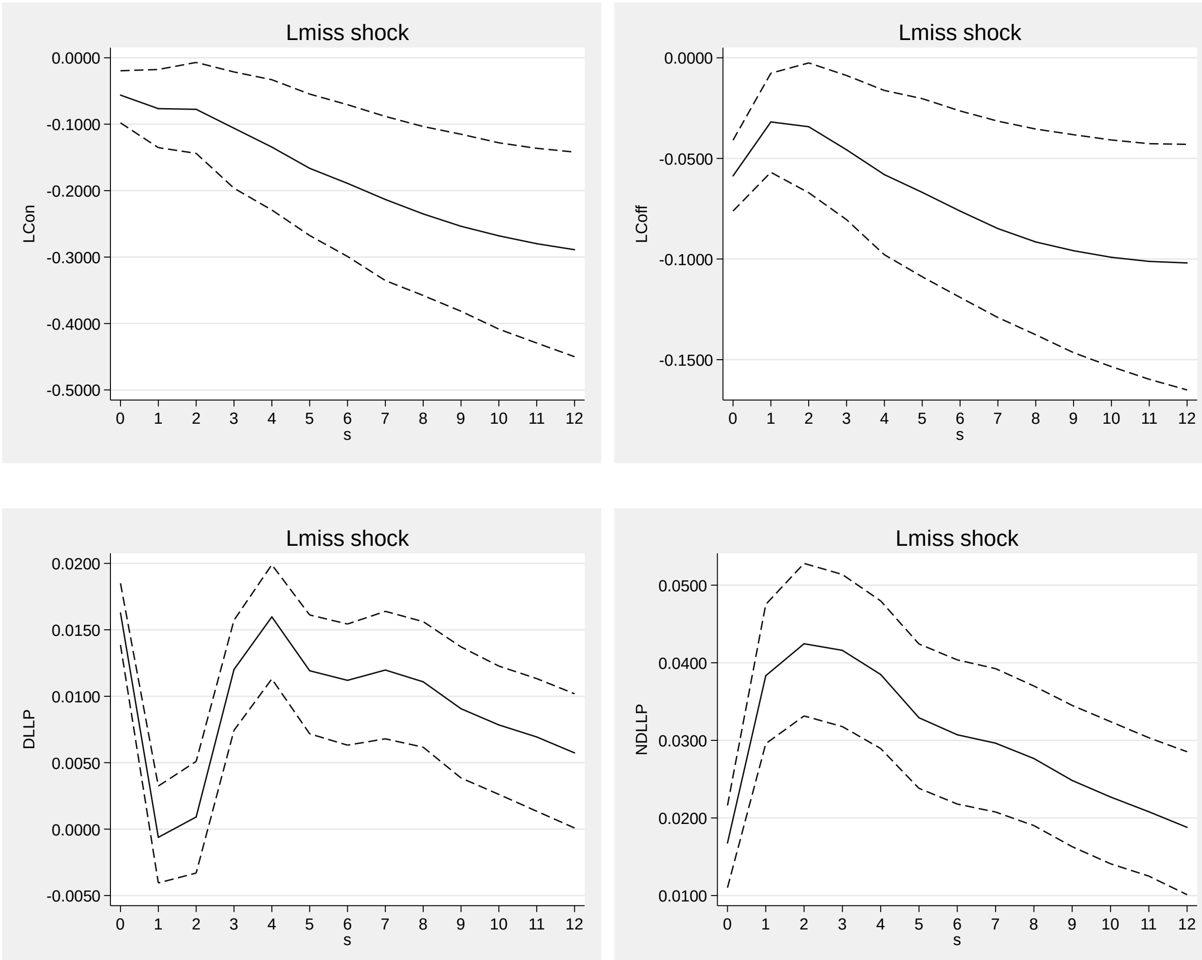


Figure 2: The Effect of medium banks underperformance on ROE determinants (VAR model)

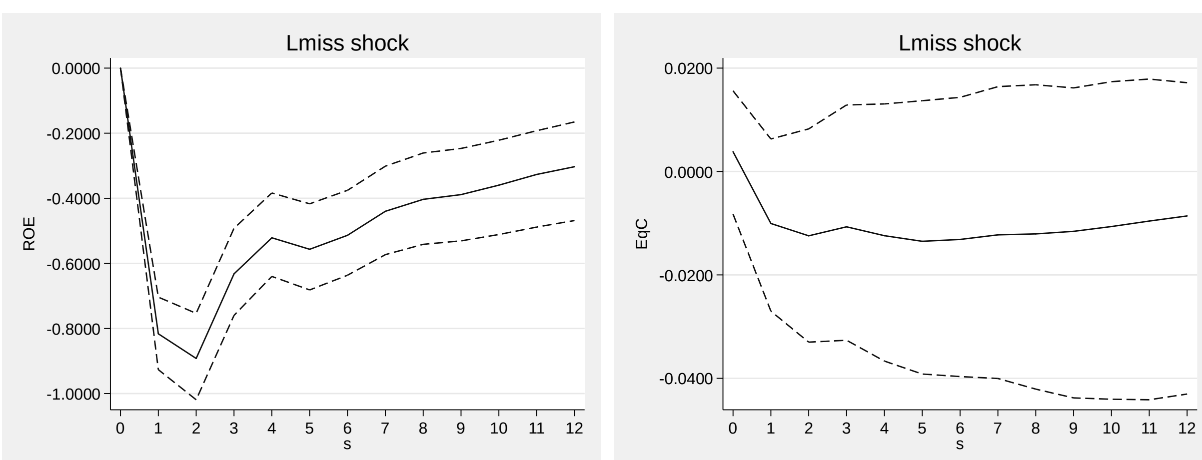
This figure shows the impulse responses of ROE determinants of medium banks to underperformance together with a 95% confidence interval, using the panel vector autoregressive (VAR) model. Panel A reports the impulse response function of ROE determinants to underperformance when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the median ROE of its peers. Panel B reports the robustness test when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the 25th percentile of peers.

Panel A:




Lmiss shock
LCon
s
Lmiss shock
LCoff
s
Lmiss shock
DLLP
s
Lmiss shock
NDLLP
s

Panel B:


Lmiss shock
ROE
s
Lmiss shock
EqC
s

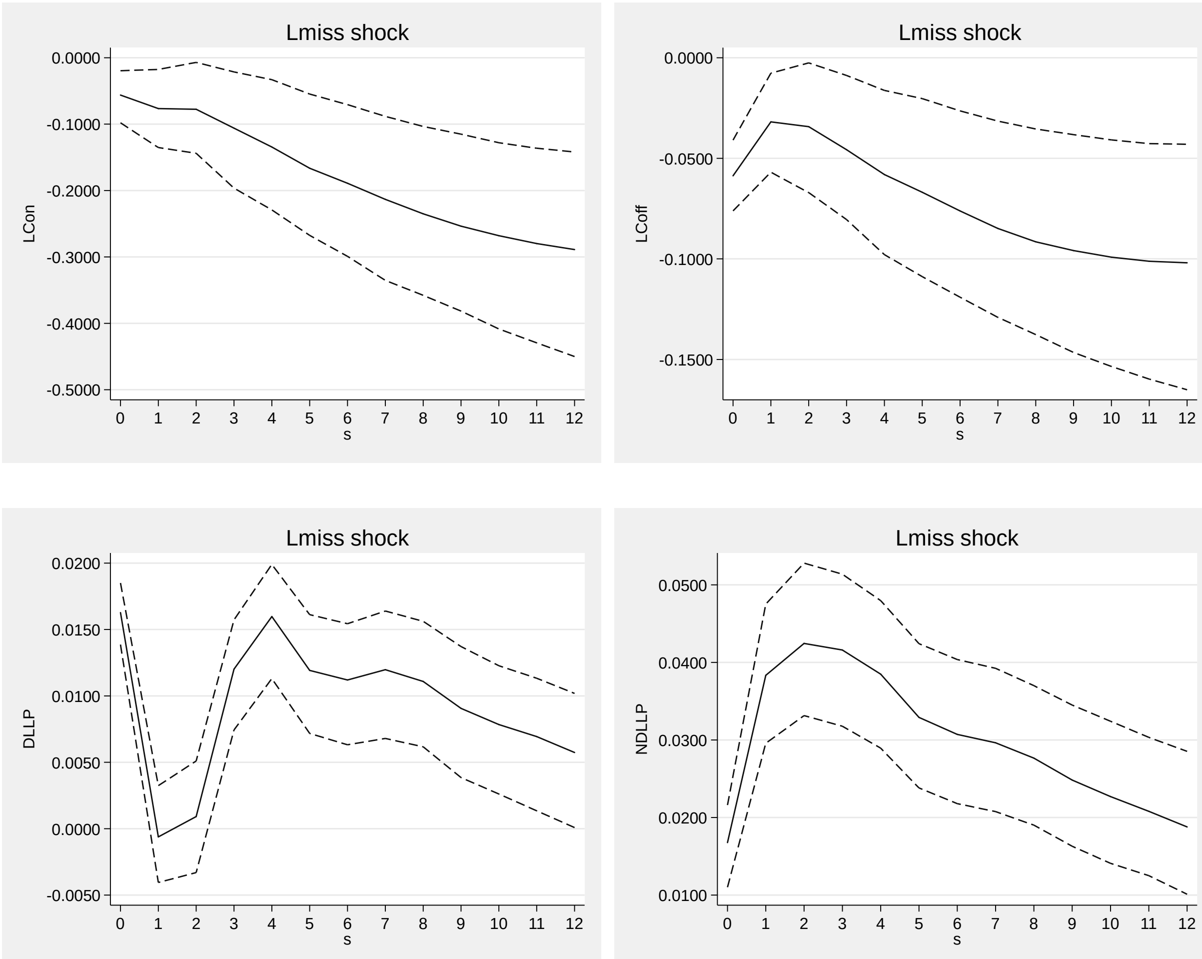
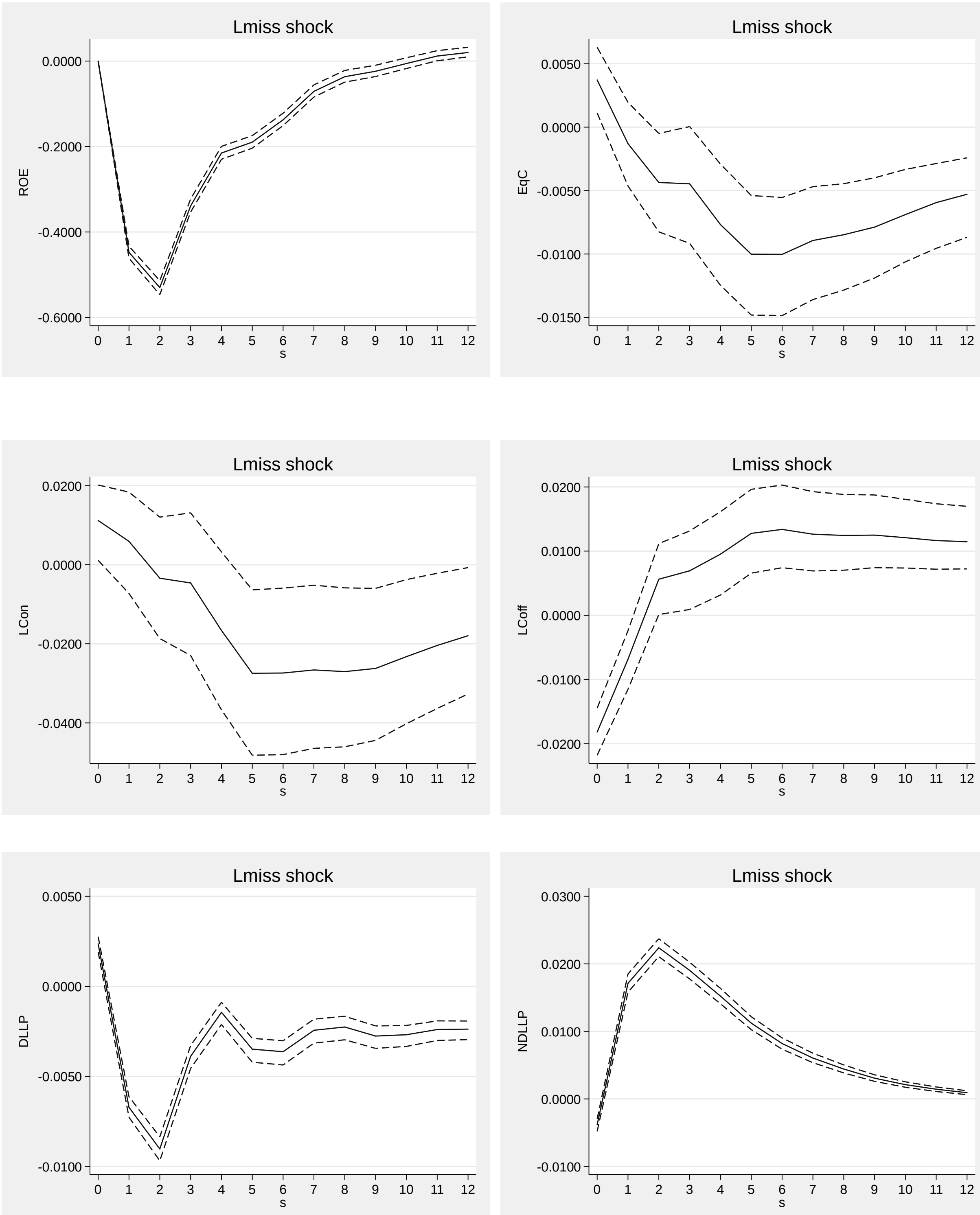
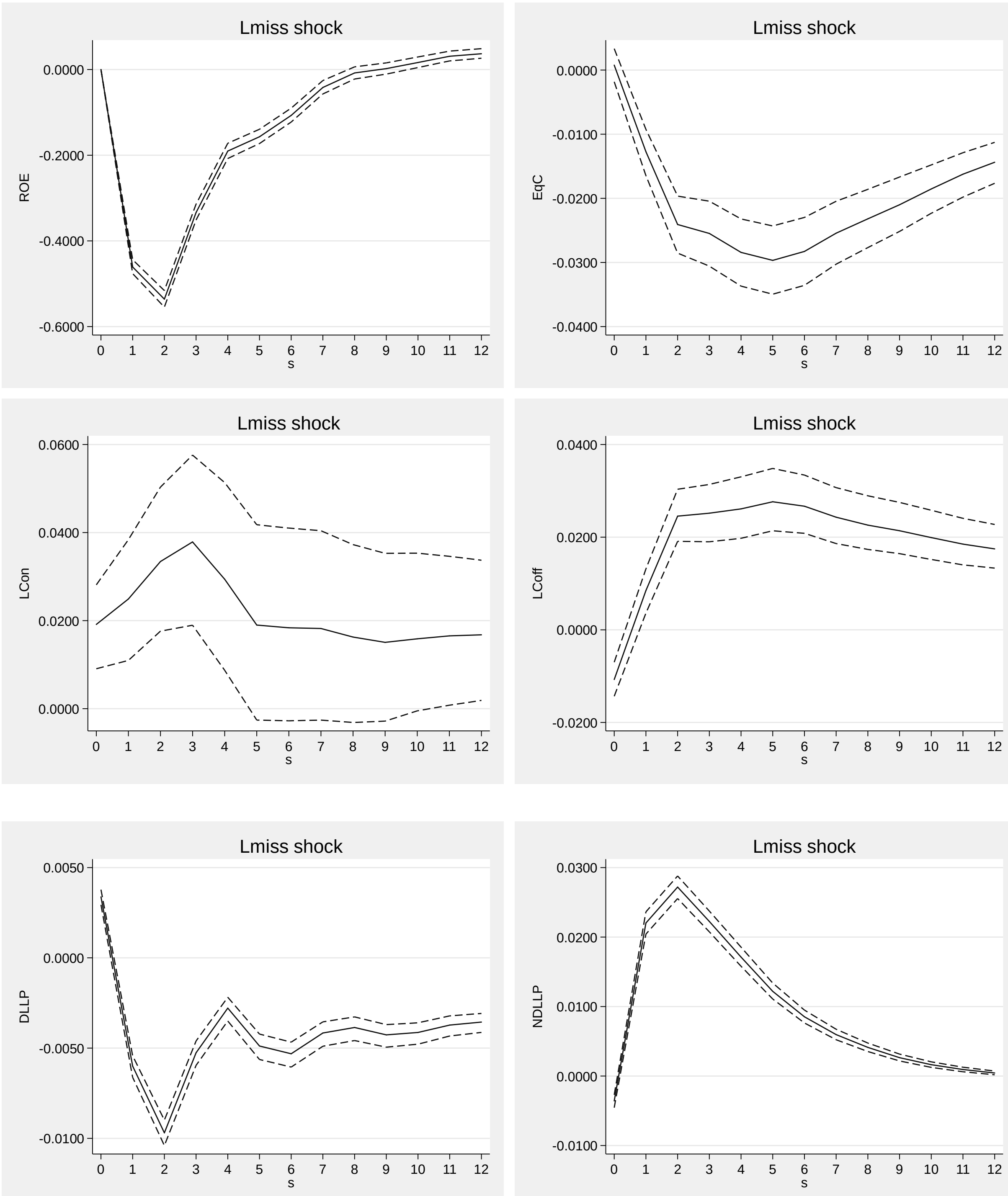


Figure 3: The Effect of small banks underperformance on ROE determinants (VAR model)
This figure shows the impulse responses of ROE determinants in small banks to underperformance together with a 95% confidence interval, using the panel vector autoregressive (VAR) model. Panel A reports the impulse response function of ROE determinants to underperformance when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the median ROE of its peers. Panel B reports the robustness test when underperformance is measured as a dummy variable that takes a value of 1 if ROE of the bank is below the 25th percentile of peers

Panel A:


Lmiss shock
ROE
0.0000
-0.2000
-0.4000
-0.6000
0 1 2 3 4 5 6 7 8 9 10 11 12
s
Lmiss shock
EqC
0.0050
0.0000
-0.0050
-0.0100
-0.0150
0 1 2 3 4 5 6 7 8 9 10 11 12
s
Lmiss shock
LCon
0.0200
0.0000
-0.0200
-0.0400
0 1 2 3 4 5 6 7 8 9 10 11 12
s
Lmiss shock
LCoff
0.0200
0.0100
0.0000
-0.0100
-0.0200
0 1 2 3 4 5 6 7 8 9 10 11 12
s
Lmiss shock
DLLP
0.0050
0.0000
-0.0050
-0.0100
0 1 2 3 4 5 6 7 8 9 10 11 12
s
Lmiss shock
NDLLP
0.0300
0.0200
0.0100
0.0000
-0.0100
0 1 2 3 4 5 6 7 8 9 10 11 12
s

Panel B:


Lmiss shock
ROE
0.0000
-0.2000
-0.4000
-0.6000
s
Lmiss shock
EqC
0.0000
-0.0100
-0.0200
-0.0300
-0.0400
s
Lmiss shock
LCon
0.0600
0.0400
0.0200
0.0000
s
Lmiss shock
LCoff
0.0400
0.0200
0.0000
-0.0200
s
Lmiss shock
DLLP
0.0050
0.0000
-0.0050
-0.0100
s
Lmiss shock
NDLLP
0.0300
0.0200
0.0100
0.0000
-0.0100
s
0 1 2 3 4 5 6 7 8 9 10 11 12