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The Nexus between Bank Capital, Liquidity and the Business Cycles: Empirical Evidence from the UK Banking Sector

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Abstract

Financial stability and liquidity creation are fundamental to economic growth. As a result of the recent financial crisis, there has been a huge debate on the minimum capital level that is able to absorb credit risk, especially during a downturn. Using 10 largest banks in the UK, with the annual data from 2004 to 2013, this research examines the linkage among bank capital, bank liquidity, and the business cycle. Employing both dynamic and static models in line with other previous work,[1] the literature gives evidence that financial institution health is profoundly affected by its capital-asset ratio, its liquidity, and business-cycle variables. The results show that adequate capital level will mitigate the extent of the financial shocks. The positive association between loan to deposit and changes in the gross domestic product implies that credit extension falls as the economy contracts.

Keywords: business cycle; liquidity; solvency; capital

1. Introduction

The UK banking sector entered the global financial crisis whilst it was believed to have been in a relatively sound state. In light of the rapid and sharp worsening of the fiscal situation in America, as a result of sublime mortgage, financial turmoil spread to the UK and then to the rest of the world, more pronounced in the financial markets that are interconnected. What followed was an utter disaster, as the entire banking edifice was on the brink of collapse, rendering banks almost insolvent prompting governments to step in. Rapidly, the financial crisis spilled over into banks' fundamentals, and banks sought emergency capital and liquidity assistance, initially from the government.

Undoubtedly, comprehending fully the mechanism through which economic crises affect the process of financial intermediation through the banking sector remains a key challenge (Gorton, 2012). Basel III has proposed new guidelines on capital regulation on the premise that the financial crisis was rooted in the low solvency levels of the bank statement of financial position. One of the criticisms of the UK regulators in the last few years is that at the expense of the general economy, they rushed to build a new liquidity regime post-crisis the regulators on strait-jacketing banks and building societies. As pointed by Litan (1984), government policy changes have interacts with market-driven changes in various ways. For example, wider access to financial markets put competitive pressure on banks, which led the government to relax regulatory restrictions on the banks' activities.

The Basel Committee does not only emphasise bank solvency, but also liquidity creation, as this is the engine of the economy. Therefore, there needs to be a trade-off between financial stability and the cost of lower liquidity creation. However, Rogoff (2008) and Reinhart and Rogoff (2009) argue that lending boom emanating from too much liquidity is associated with business cycles that have been in existence for many centuries.

This study, by utilizing a panel of the UK's 10 largest banks attempts to shed some light on the relationship of liquidity and the business cycle. This work is limited to a one country data in order to have detailed data as demonstrated by Fiordelisi et al. (2011). UK is an interesting case to examine as it has large banks that operate globally.

Hypothesis

The 2008 global financial crisis illustrated a market failure as a result of illiquidity in banks that spread across most sectors in the economy. Therefore, we expect that there is a positive relationship between the liquidity position of the banks and the business cycles.

In addition, this work investigates how liquidity and solvency, the twins of banking, interact with each other in the period between 2006 and 2013. In particular, Section 2 very succinctly reviews the existing literature in the specific area whilst Section 3 touches upon the empirical methodology used, providing the evidence generated from the estimation process. Finally, Section 4 provides some concluding remarks.

[1] Barth, (1991) and Cebula and Hung, (1992)

2. Literature Review on Business Cycle and Liquidity-capital

Benston et al. (1991) noted that before the well-known Great Depression of 1930, savings and loan associations (S & Ls) financed their mortgage holdings mainly with share capital which could not be readily withdrawn. This precipitate the need to assess the form of funding in financial institutions. There are concerns that some banks rely too heavily on wholesale market funding and there are also broader concerns that firms (incorrectly) assume that assets can always be easily and immediately financed through the repo market. The recent financial crisis demonstrated the interrelationship between firm liquidity, asset market liquidity and solvency. This section provides a critical review of the literature on the association between banks' liquidity and the business cycle, emphasizing the role of bank capital in the equation. Other scholars have suggested that rises in the commodity prices have fuelled expectations of rise in inflation, leading to monetary policy tightening and increases in interest rates. Interest rates affect commodity returns and volatility through multiple macroeconomic channels. Interest rates also affect corporate investments (Hammoudeh & Yuan, 2008). Therefore, it is important that we understand how daily macroeconomic variables such as changes in interest rates affect daily commodity volatilities and make recommendations to both investors and policy makers. Song and Thakor (2010) noted the interaction between banks and markets is based not only on competition, but also on complementary and co-evolution. In addition, the section examines the main methodology and relevant variables that are worth testing.

It is the role of bank prudential regulation to ensure the safety and soundness of banks, for example by ensuring that they have sufficient capital and liquidity resources to avoid a disruption on liquidity creation that is vital for the growth of the economy. The existing empirical literature provides conflicting assumptions about the relationship between capital and liquidity creation, both in terms of its magnitude and of the nature of its causality. Diamond and Rajan (2001) maintained that tightening capital requirements hampers liquidity creation. Likewise, when Horvath et al. (2012) applied Granger causality tests in a dynamic panel framework, they found that capital negatively Granger-causes liquidity creation in the Czech banking sector, where the majority of banks are small. However, they also reported that liquidity creation Granger-causes capital reduction, hence a bi-causational relationship. On the other hand, Berger and Bouwman (2009), in a pioneering article, discussed the causal link that moves from banks' capital to liquidity creation. The authors' "risk absorption hypothesis" suggests that increased capital enhances the ability of banks to create liquidity. The framework proposed by the Basel Committee on Banking Supervision (BCBS) incorporates measures to reduce procyclicality, which require banks to build up capital defenses and moderate excessive credit growth when economic and financial conditions are buoyant, so that the flow of credit in the economy is maintained when the broader financial system experiences stress. These measures include a countercyclical capital buffer above the minimum 4.5% core Tier 1 requirement. This argument stems from the theoretical literature concerning the role of banks as risk transformers (Allen & Gale, 2004). Using an unbalanced panel of SEE banks from 2001 to 2009, Athanasoglou (2011) explores the role of liquidity on capital and posits a positive, significant, and robust effect. A previous study by Bollerslev, Chou and Kroner (1992) using GARCH models captured the volatility of short-term interest rates predominately during the financial crisis.

Financial intermediation is the main reason as to why banks exist. Based on this a healthy financial system is a key ingredient for stable and sustainable economic growth. Following this train of thought, Westerlund's (2003) findings suggest that loan growth falls significantly following a monetary contraction, while the fall is pronounced among illiquid and under-capitalised banks. Consistent with this theory, well-capitalised and liquid banks are expected to supply more credit (Kashyap & Stein, 1995). Based on Westerlund's (2003) findings, one argument is that during the financial crisis instead of bailing out, there need to "bail-in", whereby subordinated debt may be written down or converted into equity when there is a broader systemic need to bolster capital.

Many banking system crises, especially in developing countries, display a recurrent pattern of distress, with insolvency and illiquidity usually traceable to pervasive government involvement, while other countries have experienced macroeconomic collapses before the crisis (Honohan, 1997). Studies by Hedge (1982), Barth (1991), and Salts (1996) reported that increased interest rate volatility also contributes to the financial problem because the variability of interest rates affects investors' decisions about how to save and invest. Investors differ in their willingness to hold risky assets such as stocks and bonds. In other words, volatility affects the output, consumption and investments. In general, empirical studies concur that good economic conditions positively affect the quality of banks' fundamentals, whereas disturbances anywhere in the business cycle and the macro-economy are likely to have repercussions on the banking system (Quagliariello, 2004). The recent financial crisis powerfully demonstrated the instability that can result from banks having insufficient capital or liquidity. The optimal banking system is very significant in economic growth. Countries that choose ''loose'' banking system take on the risk of short run output losses of crisis to enjoy the higher liquidity insurance and possible abnormal returns. Models of banks' pro-cyclical behaviour aim to answer whether the business cycle affects banks' finance and if banks' behaviour reinforces fluctuations in the business cycle. Furthermore, models that include macroeconomic variables as regressors perform better than those that employ solely bank-specific variables (Demirgüç-Kunt & Detragiache, 1997).

During the crisis a number of banks faced the process of having to raise fresh capital to cover write-downs during an economic downturn. The quality of market capital is also a cause for concern; hybrid/subordinated debt used to meet capital requirements was not effective in absorbing losses during the recent economic downturn – there is a need for more common equity. Nevertheless, the empirical evidence on the liquidity-capital nexus appears mixed, the theory of liquidity points to a correlation between banks' liquidity, capital, and the business cycle that is worth testing empirically. While most economists may consider that a 'trivially true' relationship exists between macroeconomic conditions and banks' balance sheets (Jacobson et al., 2005), in practice it is challenging to quantify these linkages, given the idiosyncratic features of the UK banks and the timeline of the research. This work differs from previous works by jointly explaining the evolution of financial architecture and of the bank asset portfolios within the context of macroeconomic factors. Specifically, this work embeds a standard micro-founded model of banking into an equally standard neoclassical growth model. This is based on the work of Resende et al. (2011), who argued that the countercyclical capital requirements have a significant stabilizing effect on key macroeconomic variables, and mostly after financial shocks.

3. Empirical investigation

Using the two metrics of liquidity, we investigate the liquidity-capital nexus and the impact of the business cycle. It is expected that banks' capital buffers can absorb the materializing credit risk. Therefore, the modelling exercise employs the liquid asset ratio (LAR) that serves as a proxy for market liquidity and the loan-to-deposit ratio (LD) as a measure of funding liquidity. Both ratios are simple yet transparent measures of banks' liquidity positions. A similar notion applies to the banks' solvency that is approximated by the equity to assets ratio, known as capital ratio. Estrella et al. (2000) point out that simple capital ratios which are virtually costless to implement are as effective in predicting banking failures as more complex ratios.

Table 4 (see appendix) reports on the correlation coefficients between the liquidity measures and a set of explanatory variables between 2004 and 2013. The results show that there is no concern with multicollinearity. In passing note, multicollinearity refers to the linear relationships among the variables but does not rule out the nonlinear association. Between them the liquidity measures exhibit a positive association with the changes in the gross domestic product. The market liquidity proxy is positively related to capital and credit growth, providing some preliminary evidence in line with expectations.

4. Methodology

For the empirical investigation both static and dynamic panel data analysis are utilized and effectively applied to a dataset consisting of 10 UK banks spanning the period from 2004 to 2013. The term 'panel data' refers to the pooling of time series and cross-sectional observations of banks on the same individual variables over several time periods (Baltagi, 2003). Panel data allow one to account for heterogeneity of the entities being observed. In addition, because of ''huge data set'' there is more variability and hence less collinearity among the variables.

4.1 The static model

The use of pooled time series and cross sections allows us to take into account the unobserved and time invariant heterogeneity across different banks. For the estimation of the models we use a dataset which consists of N is spartial units, denoted i = 1,…,N observed at T time periods, denoted t = 1,…,T. Therefore the total number of observations is T × N. Then, y is a (TN × 1) vector of endogenous variables, X is a (TN × k) matrix of exogenous variables, which does not include a column of units for the constant term. In the context of the research, N = 17 and T = 7. Given this, we can write a generic pooled linear regression model by ordinary least square procedure as.

$$y_{it} = \beta_0 + \sum_{N=1}^{N} \beta_1 X_{it} + \varepsilon_{it} \qquad (1)$$

where y_{it} is the dependent variable, β0 is the intercept term, β_i is a k×1 vector of parameters to be estimated on the explanatory variables, and x_{it} is a 1×k vector of observations on the explanatory variables, t = 1, . . . , T, i = 1, . . . , N and **Error! Bookmark not defined.**is random error term. Pooled OLS enables the researcher to capture the variation of what emerges through time or space simultaneously.

The specification in equation (1) suggests a linear panel data model. The associated assumptions to the model that we take into account are:

- The error term is normally distributed and have zero mean and standard deviation s_i^2, it ~ i.i.d. (0, s_i^2)
- Similar variances among banks, $s_i^2 = s_e^2$ "i
- Zero covariances among banks, Cov(e_{it} ,e_{js}) = 0 for i ≠ j

If the homogeneity hypothesis is rejected, the estimates based on the pooled model will lack meaning:

$$\begin{matrix} Y_1 \\ Y_2 \\ . \\ . \\ Y_N \end{matrix} = \begin{matrix} X_1 \\ X_2 \\ . \\ . \\ X_N \end{matrix} \beta + \begin{matrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ \varepsilon_N \end{matrix} = X\beta + \varepsilon \qquad (2)$$

However, if the difference between β's though significant is thought to be small, then one could consider a trade-off of accepting some bias in order to reduce variances. If the departure of homogeneity is so great, then this could result in serious distortion in the conclusion, hence we then proceed with the choice of the best alternative static specification that links to the pros and cons of each specification. The fixed effect model assumes that despite the intercept may vary across the banks, each individual intercept does not vary from time to time. Therefore, the intercept β_{1it} means that it is time invariant. Therefore the fixed effect model can be expressed as:

$$y_{it} = \beta_{1it} + \sum_{N=1}^{N} \beta_1 X_{it} + \varepsilon_{it} \qquad (3)$$

Also the common slope coefficients and constants may not be fixed but random. In this case the random effects model would be appropriate. In a nutshell, random effect is a compromise between pooling under complete homogeneity and pooling with common slope coefficient, but with the intercept, which may vary by the cross section. That is, all of the elements in the coefficient vector, slopes as well as intercepts, are random variable rather than fixed parameters. Under the assumption of intercepts for the cross-section which are random variables and slope coefficients which are fixed parameters, the vector would represent slopes only while the random error term would have two components. Thus:

$$\varepsilon_i = \begin{matrix} \mu_i \\ \mu_i \\ . \\ . \\ \mu i \end{matrix} + \begin{matrix} \eta_{i1} \\ \eta_{i2} \\ . \\ . \\ \eta_{iT} \end{matrix} \qquad (4)$$

The μ_i represents randomness which is due to the choice of the cross section, while η_{it} represents the randomness stemming from cross section and time period.

The argument in favour of the random effects model is that the fixed effects model often results in a loss of a large number of degrees of freedom and also eliminates a large portion of the total variation in the panel. Another argument is that β_i combine a total of several factors specific to the cross-sectional units and as such they represent 'specific ignorance' (Maddala, 2001). Hence, β_i can be treated as random variables by much the same argument that ${}_{it}$ representing 'general ignorance' can be treated as random variables. On the other hand, there are two arguments in favour of the use of the fixed effects model. The first, common in the analysis of variance literature, is that if the analysis wants to make inferences about only this set of cross -sectional units, then we should treat β_i as fixed. On the other hand, if we want to make inferences about the population from which these cross-sectional data come, then β_i should be treated as random. We can conduct a formal test to identify the best model using the restricted F test which can be expressed as:

$$F = \frac{(R_{UR}^2 - R_R^2)/m}{(1 - R_{UR}^2)/(n-k)} \qquad (5)$$

Where R_{UR}^2 and R_R^2 are respectively the values obtained from the unrestricted and unrestricted regressions.

4.2 The dynamic model

The dynamic panel data specifications are used in this study in an attempt to capture the time path of the dependent variable in relation to its past values. Many related studies provide evidence that bank-specific or economic variables are dynamic in nature (Louzis et al., 2012). A body of literature indicates that in typical micro-panels with large N and small T, the fixed effect (FE) estimator is biased and inconsistent when the model is dynamic. Similarly, the random effects GLS estimator is also biased in a dynamic panel data model (Baltagi, 2003). Yet many economic relationships are dynamic in nature and should be modelled as such (Asteriou & Hall, 2007). In view of these arguments, our approach involves the estimation of dynamic panel data models using the Generalized Method of Moments (GMM) framework proposed by Holtz-Eakin et al. (1988) and developed by Arellano and Bond (1991) and Arellano and Bover (1995). According to Pesaran et al. (1999), even if the dynamic specification is unlikely to be the same in all cross sections, it is still possible to pool the estimates treating the model as a system since. This is because, the efficiency gained from pooling the data outweighs the losses from the bias introduced by heterogeneity. Empirical literature suggests that Arellano and Bond's (1991) framework suits cases with small T and bigger N (but N>T), especially when samples are small, as with the undertaken research, and the model is of dynamic form as emphasized by a number of authors (Quagliariello, 2004; Louzis et al., 2012). Also, the need to validate the static models' results – triangulation of methods – justifies the use of Arellano and Bond's (1991) framework.

5. The Results

5.1 Descriptive statistics

We conducted a number of diagnostic tests on the data before conducting any statistical analysis. First, we tested the data to make sure it is normally distributed and also tested stationality using Argumented Dickey-Fuller test. Non-stationality of the variables exhibits unfortunate property that the previous values of the error term have non-declining effects on the current value of the dependent value as time progresses. As shown in the Table 5 (see appendix), the Levin, Lin and Chu t statistic are less than the Pesaran and Shin statistics, hence we reject the null hypothesis of a unit root. We then tested whether there is any cointegration between bank's liquidity and solvency. The results on cointegration as shown in Table 6 (see appendix) point out that the variables used to proxy banks' liquidity (LAR) and solvency (EA) are integrated of order 1, i.e., I (1). Subsequently, the Pedroni panel cointegration results suggest that the null hypothesis of no cointegration can be rejected in three out of seven cases at all significance levels. Hence, the outcome seems to advocate a positive link between liquidity and capital in concert with expectations arising from theoretical standpoints. Then, we model the banks' liquidity as a function of a number of exogenous variables and banks' solvency, using the general to the specific approach. This is in line with Covas and Fujita (2009) that use a general equilibrium model to show that output is more volatile, and household welfare is reduced, when capital requirements are procyclical. The estimated static and dynamic models are couched in the following manner:

$$LAR_{it} = \beta_0 + \beta_1 EA_{it} + \beta_2 DGDP_t + \beta_3 REED_t + \varepsilon_{it} \quad (6)$$

where LAR_{it} denotes the ratio of liquid assets to total assets for bank i at time t, and EA_{it} is the capital to assets ratio for bank i at time t. The business cycle is reflected in $DGDP_t$, the growth rate of GDP, $REED_t$, is the growth rate of the real effective exchange rate in terms of unit labour costs that serves as a proxy for the country's competitiveness. The panel regression results are summarized in table 1. The Akaike Information Criteria (AIC) for pooled OLS is lower than that of fixed effects. We also tested the fixed effects and found them be not significant individually and as a group. In other words, the static modelling framework, the tests for redundant fixed effects, and the likelihood ratio reject the null hypothesis that the cross-sectional effects are unnecessary. Nevertheless, we estimated the fixed effects, random effect and pooled OLS for triangulation and in order to make meaningful comparisons.

The pooled OLS model maintains that about 18% of the variation in LAR over the period from 2006 to 2013 is explained by the model's variables. Banks' solvency and GDP have a positive 5% significant and contemporaneous effect on liquidity. Likewise, the Pearson correlation coefficient shows a positive association between the two. On the other hand, REED has a clear negative association with liquidity.

Table 1. The dependent variable is LAR and the LAR (-1), EA, DGDP, REED, GLG LD are the independent variables. The regression equation is estimated by pooled ordinary least square, the fixed effects, random effect and Generalized Moment of Method.

Variable	Pooled OLS	FE	RE	GMM
Intercept	0.3536*** (0.0312)	0.8407** (0.1442)	0.3536*** (0.0712)	0.3536** (0.0712)
LAR(-1)	0.1507** (0.0511)	0.2594* (0.1446)	0.15077 (0.1165)	0.1508 (0.1165)
EA	0.2301* (0.1140)	1.9276** (0.6797)	0.2302 (0.2659)	0.2301* (0.2659)
DGDP	0.3928** (0.0631)	0.0660 (1.0655)	0.3928 (1.0481)	0.3928* (0.0651)
REED	-0.0994 (0.4312)	-0.3702 (0.9832)	-0.0998 (0.9748)	-0.0998 (0.9748)
GLG	-0.0276 (0.0187)	-0.0033 (0.0461)	-0.0276 (0.0424)	-0.0276 (0.0423)
LD	-0.1330*** (0.0210)	-0.3292** (0.0725)	-0.1330** (0.0476)	-0.1330** (0.0476)
R Squared	18%	28%	18%	18%
F Statistic	13.5091***	3.0091**	2.0392*	
AIC	-1.5112	-1.4922		
SC	-1.4385	-1.0159		
Durbin Watson	2.1451	1.9699	2.0221	2.1228
Hausman Test		ChiSq 7.264 p.value. 0.2017		

The dependent variable, LAR is defined as liquid assets to total assets and LD is measured loans to deposit. While EA is equity to total assets, DGDP is percentage change in gross domestic product, GLG is percentage change in gross loans, PUDP is the public debt as percentage of GDP and REED is real Effective Exchange rate measured as percentage change of unit labour costs

A major hypothesis under investigation remains the interaction between banks' liquidity and solvency. In the light of the UK financial crisis, the results provide evidence of a clear-cut nexus between liquidity and capital, in agreement with theory and other empirical studies (Berger & Bouwman, 2009). A high leverage ratio, or alternatively a weak capital position, is critical in the propagation of banks' liquidity shocks. The importance of these results relates to the theory that maintains that well capitalised and liquid banks are able to provide credit in the economy (Westerlund, 2003). Contrary to Horvath et al.'s (2012) study on Czech banks, but broadly in line with the framework of new capital rules known as Basel III and Berger and Bouwman's (2009), the modelling outcome suggests that solvency increases liquidity creation as depicted by a positive coefficient of equity to total assets and liquidity. On the other hand, the results support a negative association of REED, a leading crisis indicator, with market liquidity. Previous research (e.g., Allen, 1990; Cebula, 1991; Al-Saji, 1992; Liargovas et al., 1997) has demonstrated that liquidity could be caused by the government's budget deficit. That is, forcing the government to borrow domestically could lead to crowding out which could also result in high interest rates.

Overall, the role of capital and cyclical movements in macroeconomic variables are valuable indicators in explaining the UK banks' market liquidity in the crisis period. The results also show a negative association between bank capital and growth in the GDP. This resonates with Ayuso et al. (2004) who found a negative effect of the business cycle on the capital buffers of Spanish banks, which they interpreted as short sightedness of banks. This is in contrast to Lindquist's (2003) findings of a positive effect of the business cycle on the capital buffer of Norwegian banks. The positive association can be attributed to the fact that banks build up their capital buffers in a boom possibly in anticipation of rising losses during a downturn. Improving banks' liquidity so that they fund themselves without relying on rescue funds will depend on the quality of the assets sitting in their balance sheets.

6. Concluding remarks

Employing the use of correlation analysis, cointegrating techniques, and one -way static and dynamic panel models we examined the presence as well as the strength of the relationship between banks' liquidity with the business cycle in the UK, while allowing for the role of solvency.

We carried a number of diagnostic tests to ensure that the coefficients are best linear and unbiased. These include the serial correlation of errors and heteroskedasticity as shown in Tables 7 and 8 (see appendix). The modelling framework used identified several significant relationships between the variables of interest. In all modelling cases, the static and dynamic framework presented an adequate fit of the data confining the relationship under investigation, as the results produced by the two methods were very close. We assessed this using Ramsey reset as shown in Table 9 (see appendix). Broadly speaking, business cycle variables were found to be semantic in explaining the UK banks' liquidity over the period from 2006 to 2013. In line with this theory, the business cycle reflected in the growth in real GDP and the real effective exchange rate in labour costs - also a leading crisis indicator - exerts a significant effect on UK banks' market liquidity. Also, the results pinpoint a clear-cut nexus between market liquidity and solvency. Economic growth is liquidity-friendly, but macroeconomic imbalances reflected in the real exchange rate weaken banks' liquid positions. The results also show a positive association between loan to deposit and changes in the GDP. This implies that credit extended by banks falls as the economy contracts. The modelling outcome contributes to the research agenda of UK banks and provides the basis for policy recommendations. Adequate capital positions are important during prosperous but also during troubled economic periods. This echoes well with the Basel capital requirement that has been at the forefront of campaigning increased minimum bank capital requirement that has seen the increase of tier 1 from 4.5 to 7%. The result also shows that solvency shocks can induce liquidity problems and constrain significantly the bank's intermediation role. Addressing banks' liquidity is a pressing issue that can be solved through stronger capital bases and restoring competitiveness in the economy. However, it is worth noting that to increase its capital-asset ratio, a bank can shrink assets (mainly loans and securities) or raise more capital, or do a mix of both hence reducing private credit to GDP.

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Appendices

Table 1. The dataset of the bank-specific variables

Variable	Definition	Measures or Proxies
EA	Equity to assets	Capital – Solvency
GLG	Gross loans (% change pa)	Growth in loans
LAR	Liquid assets to total assets	Liquidity
LD	Loans to deposits	Liquidity

Sources: Bankscope, Banks' IFRS audited annual reports.
All ratios expressed in percentage point

Table 2. The set of macroeconomic variables

Variable	Definition
DGDP	Gross domestic product, real (% change pa)
PUDP	Public debt (% of GDP)
REED	Real Effective Exchange Rate (unit labour costs, % change pa)

Sources: IMF Statistics.

Table 3. Descriptive Statistics of the bank-specific variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
EA	12.19	12.44	20.60	0.10	0.49
GLG	9.24	1.66	197.68	-37.97	33.74
DGDP	1.39	1.40	3.40	-0.01	1.55
LAR	24.40	23.20	79.87	2.85	12.32
REED	0.30	-0.01	3.90	-0.14	1.62
PUDP	67.56	59.05	102.60	43.50	1.55
LD	90.15	85.05	161.96	18.66	30.45

Source: Authors calculations.

Table 4. Correlation Coefficients of the bank and Macroeconomic variables.

	LAR	LD	DGDP	PUDP	REED	EA	GLG	Collinearity	
								Tolerance	VIF[2]
LAR	1.000							0.839	1.192
LD	0.379	1.000						0.814	1.229
DGDP	0.019	0.151	1.000					0.577	1.734
PUDP	0.046	-0.076	-0.412	1.000				0.793	1.262
REED	-0.059	0.001	-0.509	0.051	1.000			0.708	1.412
EA	0.083	0.051	-0.018	0.004	0.017	1.000		0.985	1.015
GLG	0.391	0.252	-0.151	0.218	0.258	-0.013	1.000	0.815	1.227

[2] The speed with which the variance and converiance increases can be captured by the variance inflation factors (VIF) which is a reciprocal of tolerance defined as: $\frac{1}{1-R^2}$ if the VIF is greater than 5 then multicollinearity is high.

Table 5. Group unit root test: Summary

Series: EA, GLG, LAR, LD, DGDP, PUDP, REED
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-Sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.72292	0.0001	4	269
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.27553	0.0000	4	269
ADF - Fisher Chi-square	71.4555	0.0000	4	269
PP - Fisher Chi-square	73.6986	0.0000	4	269

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 6. Pedroni panel cointegration test for liquidity (LAR) and solvency (EA)

	Statistic	p-value
Panel v-Statistic	0.624	0.2660
Panel rho-Statistic	-25.118	0.000
Panel PP-Statistic	-13.807	0.000
Panel ADF-Statistic	-7.952	0.000
Group rho-Statistic	-22.080	0.000
Group PP-Statistic	-15.413	0.000
Group ADF-Statistic	-8.462	0.000

Note: The Pedroni test is an Engle-Granger type test where the null hypothesis suggests no cointegration and the decision is based on seven statistics – panel and group.

Table 7. Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.475960	Prob. F(2,56)	0.6238
Obs*R-squared	1.069724	Prob. Chi-Square(2)	0.5858

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000234	0.062636	-0.003737	0.9970
EA	0.007542	0.302263	0.024951	0.9802
DGDP	0.254407	1.170220	0.217401	0.8287
REED	0.089754	1.107644	0.081031	0.9357
GLG	-0.005998	0.048112	-0.124664	0.9012
LD	-0.004492	0.052334	-0.085832	0.9319
RESID(-1)	0.123841	0.140695	0.880206	0.3825
RESID(-2)	0.040646	0.136950	0.296792	0.7677

R-squared	0.016714	Mean dependent var	-1.95E-17
Adjusted R-squared	-0.106196	S.D. dependent var	0.112950
S.E. of regression	0.118796	Akaike info criterion	-1.306351
Sum squared resid	0.790298	Schwarz criterion	-1.036491
Log likelihood	49.80324	Hannan-Quinn criter.	-1.200040
F-statistic	0.135988	Durbin-Watson stat	2.102338
Prob(F-statistic)	0.995060		

Table 8. Heteroskedasticity Test: ARCH

F-statistic	2.035605	Prob. F(1,54)		0.1594
Obs*R-squared	2.034311	Prob. Chi-Square(1)		0.1538
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.010086	0.005176	1.948779	0.0565
RESID^2(-1)	0.191498	0.134220	1.426746	0.1594
R-squared	0.036327	Mean dependent var		0.012756
Adjusted R-squared	0.018481	S.D. dependent var		0.036450
S.E. of regression	0.036111	Akaike info criterion		-3.769362
Sum squared resid	0.070417	Schwarz criterion		-3.697028
Log likelihood	107.5421	Hannan-Quinn criter.		-3.741319
F-statistic	2.035605	Durbin-Watson stat		2.056749
Prob(F-statistic)	0.159410			

Table 9. Ramsey RESET Test
Specification: LAR C EA REED GLG PUDP DGDP LD
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.843345	56	0.4026
F-statistic	0.711231	(1, 56)	0.4026
Likelihood ratio	0.807718	1	0.3688

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.010062	1	0.010062
Restricted SSR	0.802292	57	0.014075
Unrestricted SSR	0.792230	56	0.014147
Unrestricted SSR	0.792230	56	0.014147

LR test summary:

	Value	df
Restricted LogL	49.32125	57
Unrestricted LogL	49.72511	56