Banks' liquidity management dynamics: evidence from Indonesia

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Abstract

Purpose – This study aims to cover an important yet largely under-explored topic: the dynamic process of bank liquidity management in a vast developing economy by considering pool of funds hypothesis, signaling hypothesis and risk management hypothesis.

Design/methodology/approach – The authors apply the dynamic common correlated effect (DCCE) method with an error correction model format to a long panel datasets of 84 Indonesian banks from January 2003 to August 2019, resulting in 16,800 observations.

Findings – The authors obtain convincing evidence of dynamic liquidity management with an error correction mechanism. The time needed to adjust to a liquidity shock ranges from 2.5 to 3.5 months. The empirical results strongly support the pool of funds and signaling hypotheses, whereas risk management motive appears to have secondary importance.

Practical implications – The regulator should also encourage banks to diversify liquidity management to include interbank money market and off-balance-sheet instruments. The current condition shows that bank liquidity management is strongly correlated with intermediation dynamics and thus is contracyclical. Banks could end up with tight liquidity in a booming economy, which would pose a severe risk to their financial standing.

Originality/value – To authors' knowledge, this study is the first to analyze bank liquidity management behavior empirically using a panel error correction mechanism. Here, the authors also try to combine a practitioner perspective with a scientific one.

Keywords Liquidity management, Pool of funds, Signaling, Risk management, Error correction model

Paper type Research paper

1. Introduction

Banking is a business that deals with maturity transformation, borrowing short and lending long (Freixas and Rochet, 2008; Greenbaum *et al.*, 2019). In doing so, banks expose themselves to maturity mismatch, hence the presence of liquidity risk [1]. Banks must be able to secure sustainable funding to finance their mostly longer-duration assets. Further complicating the matter, a substantial portion of banks' funding is withdrawable on demand. On the other hand, the use of this funding cannot be readily liquidated, at least without severe penalty. Holding too many assets in reserve is undesirable because that means banks are losing potential opportunities for return from placing the money in higher-yielding assets, such as

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loans or securities. Therefore, liquidity management is an essential part of the bank business model.

Bankers try to maintain adequate cash on hand by striking a balance between forecasted cash inflow and outflow (also known as funding gap analysis; Koch *et al.*, 2014). In doing so, banks have a target liquidity reserve. This target is not static; instead, it responds dynamically to internal and external factors. Liquidity management has two components: long-term target and short-run adjustment mechanism (Koch *et al.*, 2014, pp. 437–441). The long-term element is a component that a bank tries to maintain a stable (and perceived optimal) relationship of liquid assets with various key variables. We can consider it as a liquidity reserve for anticipated needs. Should there exist significant deviation perhaps due to random shocks, the bank would try to rebalance by adjusting the level of reserves. Therefore; an error correction mechanism should be at work for liquidity management.

Our study attempts to cover an important yet underexplored topic: the dynamic process of bank liquidity management in a large developing economy (Wilson *et al.*, 2010). We hope to contribute three important value added to existing literature. First, our empirical design tries to combine a practitioner perspective with a scientific one in expectation to shed light for unified theory. For decades, banks have conducted regular liquidity management, which academics largely overlook, especially in terms of the unified theory (Allen and Gale, 2014; DeYoung and Jang, 2016). In our view, the existence of long-term target and error correction mechanism: a practice long prevailed in the banking industry, constitute a unified core liquidity theory. Proper identification of both elements also informs us about (1) the style of liquidity management and (2) the extent of liquidity risk management, i.e. as substitute of capital or signaling. It is in this sense that we consider our empirical study as a vanguard for developing a unified theory. Our study attempts to provide key empirical findings for further theoretical rationalization. To the best of our knowledge, DeYoung and Jang (2016) and DeYoung *et al.* (2018) are the only empirical works that have similar spirit with ours. However, both studies are based on a developed economy (US banks) and using an annual frequency panel. We hope by using long panel higher-frequency (monthly) data better insights could be obtained, especially because liquidity is a "somewhat" fast-paced behavior.

Second, using Indonesia as object of study should bring substantial scientific value. Indonesia is a big emerging country (a member of G20; a world biggest economy club). It was also a nation hit hardest by the 1997 Asian financial crisis. The banking system was nationalized with impact of highly liquid profile for some years following the crisis. Today, the situation has normalized, but the transition makes for remarkably interesting "natural laboratory" study. Indonesia is also a bank-based economy; hence, many important lessons could be used for policy design in various similar large emerging countries. Third, we employ a novel econometric method: the dynamic common correlated effect (DCCE; Chudik and Pesaran, 2015). This method relaxes several strong (and often inappropriate) assumptions for long panel data, namely, slope homogeneity, cross-section independence and stationary-cointegrated variables [2]. To the best of our knowledge, we are the first to analyze bank liquidity management behavior using this method. To support our empirical strategy, we carefully construct an extensive balanced panel dataset composed of 84 Indonesian banks from January 2003 to August 2019 (200 months) [3].

Liquidity management in a banking firm is not only crucial from a micro perspective but even more so in the macro view. A bank's failure to meet its depositors' withdrawals could signal that another bank may be in a comparable situation. As shown by Tirole (2011), joint illiquidity of banks is a non-remote equilibrium. Therefore, bank liquidity management is subject to heavy regulation. Understanding how well bankers manage liquidity is one of the key regulatory themes (Barth *et al.*, 2008).

After the introduction (Section 1), the paper proceeds as follows. We briefly describe bank liquidity management in Indonesia in Section 2. In Section 3, literature study, we present some relevant and recent theoretical and empirical studies. This section provides required inputs on structuring the research design, which we present in the methodology section (Section 4). In Section 5, we present our results and discuss the findings, and Section 6 concludes.

2. Bank liquidity management in Indonesia

Indonesia's banking Industry is a two-tier system. The first tier consists of commercial banks that have a full license and thus can participate in the national payment system. As of August 2019, 112 banks are operating in the first tier. The second tier consists of community rural banks that are restricted by business area (permitted to operate only in certain provinces), and they are not allowed to participate in the national payment system.

Following the 1997 financial crisis, Indonesia's government effectively recapitalized its banking system by taking out bank bad assets and replacing them with government bonds (also known as recap bonds). The recapitalized banks could then sell the bonds to the market to obtain liquidity or for business expansion. In practice, most banks kept the bonds on their balance sheets because the bonds had good yields. Therefore, the initial years of the sample period show banks as mostly liquid (Figure 1).

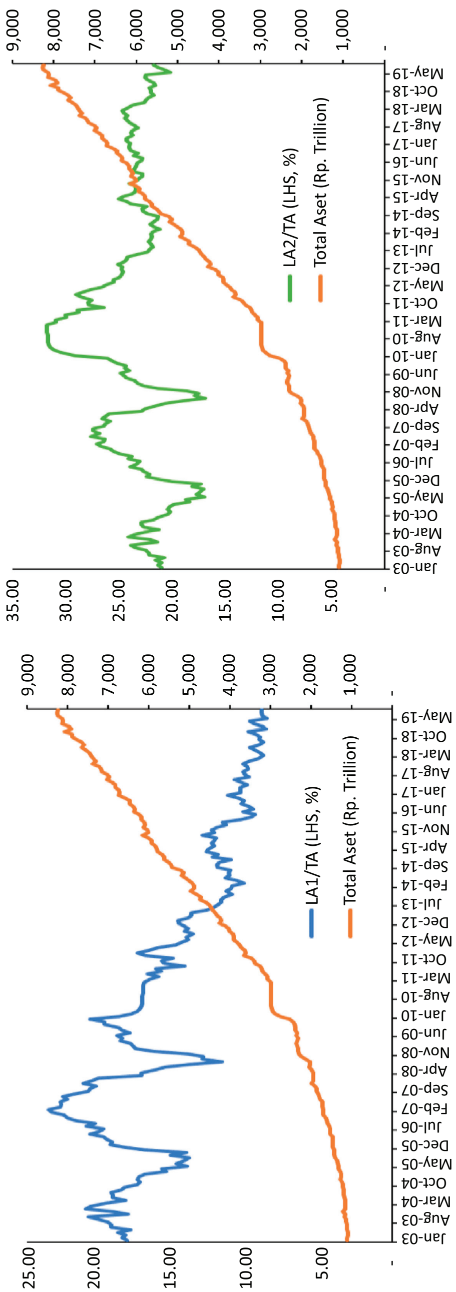
The banking industry liquid asset ratio to total assets (LA1, or Type 1 – see the methodology section for the full definition) hovered around 15–25% until the end of 2012. Subsequently, the movement of Type 1 liquid assets is a lot tighter until recently. If we use a broader measure of liquidity (Type 2), however, a different picture emerges. Here, the movement was volatile for the initial part of the period, with a slight uptrend, whereas the second half shows a much more stable and stagnant level.

Figure 2 depicts the movement of the loan to deposit ratio (LDR) and net off-balance-sheet ratio to total assets (OBS/TA). LDR started at a very low level (44.08) in January 2003, rising quite sharply to 74.07 in July 2009, before increasing at a much slower rate and becoming stagnant in December 2012. In the second half of the period, LDR hovered around the 84–94 range. The off-balance-sheet chart shows an interesting switching mode. Until June 2007, the OBS/TA tended to be positive, but it switched to negative thereafter. We think there is a fundamental reason for this phenomenon. Most of the off-balance-sheet transactions consist of a line of credit, bank guarantee or foreign exchange forward contract sold to customers. Because of highly precautionary sentiments post-recapitalization in the earlier period, these businesses were timid. Nevertheless, there has been a significant risk appetite shift in conducting off-balance-sheet business that prevailed until today.

Indonesian banks are conservative. They depend heavily on customer deposits to fund their lending (and other interest-earning assets). Table 1 shows that customer deposits account for almost 70% of system sources of funds. Banks subsequently channeled the funds into loans (which account for nearly 70% of the use of funds). Banks use the interbank money market and capital markets as secondary sources of funds. A handful of large banks usually uses the interbank money market for short-term borrowing or placement, generally because of unexpected shocks to their customers' cash flow forecast. The capital market is usually used by large banks to fund substantial long-term financing.

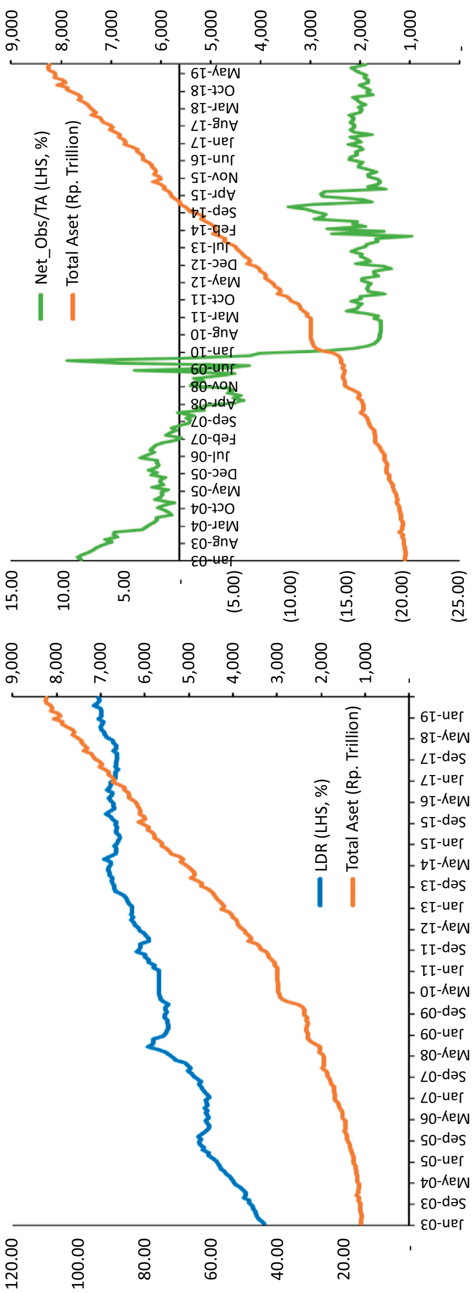
3. Literature review

Despite the key role of liquidity management in banks' business and financial stability, there is still limited theory of liquid assets holding, let alone its unified version (Tirole, 2011; Allen and Gale, 2014). Bank liquidity theories are mostly developed in partial perspectives, e.g. crisis context (Acharya *et al.*, 2011; Dijk, 2017), the role of transparency (Ratnovski, 2013), relationship with money market (Heider *et al.*, 2015) and impact to financial stability



Source(s): Website of the Indonesia Financial Services Authority (OJK)

Figure 1.
Liquid assets (LA1s and LA2) to total assets ratio



Source(s): Website of the Indonesia Financial Services Authority (OJK)

Figure 2.
LDR and OBS/TA

No	Variables	Proxy	Expected sign (hypothesis)
Long- and short-run equations			
1	Liquidity reserves: Dependent variable	Liquid assets type 1 to total assets ratio (*LA1TOTA*) Ratio liquid assets type 2 to total assets (*LAs2TOTA*)	
2	On-balance-sheet funding need	Loan to deposit ratio (*LDR*)	Negative
3	Off-balance-sheet funding need	(Net commitment + net contingent)/total assets (*OBS_AST*)	Positive
4	Extra funding capacity	Z_Score ($\mu^{i}_{\mathrm{ROA}} + \mathrm{CAR}_{\mathrm{it}}/\sigma^{i}_{\mathrm{ROA}}$) (*Z_SCORE*)	Negative (financial fragility hypothesis)/positive (signaling hypothesis)
Short-run equations			
5	Error correction term	Lagged one of long-run equation residual (*ECT*)	Negative with absolute value less than one
5	Size	Log of bank asset (*ASSET_L*)	Positive
6	Financial system stability	Interest rate of Overnight Jakarta Interbank Offered Rate (*JIBON*) Exchange rate: IDR per USD (*USDIDR*)	Positive Positive

Note(s): This table reports the definition of the variables used in the study and research hypotheses. The research hypotheses are given as expected impact sign against the dependent variable

Table 1.
Variable and hypotheses description

(Diamond and Kashyap, 2016). A simple general theory of bank liquidity recently has been proposed by Tirole (2011), and another is under development by Calomiris *et al.* (2015).

One long-standing perspective is a practitioner's point of view in which liquidity management has three major approaches: pool of funds, asset allocation and funding management (Sinkey, 2002). In the pool of funds approach, a bank pools all the funding and subsequently channels it into the desired asset structure. In asset allocation, banks try to match the duration of each item in their asset structure with their liabilities. Lastly, in funding management, banks actively manage their liabilities to keep up with profit opportunities present. That is, they will search for lending opportunities first, then obtain optimal funding to finance those opportunities (or "finance as you go" in a jargon of Tirole, 2011).

From this perspective, we could derive a hypothesis about a bank's liquidity management. If the bank follows a pool of funds approach, its liquid assets position should be aligned with the movement of loan and deposits. LDR would correlate negatively with the level of liquid assets. As a bank accumulates more funds (shown by decreasing LDR); the pressure to channel them rises. The opposite happens when LDR is already high (according to specific management measure); the move is toward relaxing LDR either by gathering more funds or cutting loan. If the bank uses another approach, we should see a low or insignificant relationship between LDR and liquid assets. We call this the pool of funds hypothesis.

Pool of fund hypothesis could also manifest in off-balance-sheet activities. However, off-balance-sheet posts have different treatment from perspective uses or sources of fund. Unlike its on-balance-sheet counterpart, which is actual uses or sources of funds, off-balance sheets are scheduled (commitment) or dependent upon realization of particular events (contingent) uses or sources of funds. The expansion of off-balance sheet does not mean liquidity irrelevant either; for example, banks still have to reserve for some amount of cash as a result of expansion of line of credit (i.e. their off-balance-sheet asset). Therefore, a positive relationship is expected to exist between liquid asset and off-balance-sheet activities. DeYoung and Jang (2016) and Al-Harbi (2017) provide empirical evidence for this conjecture.

Calomiris and Kahn (1991) developed a model based on Diamond and Dybvig's (1983) work in which a bank holds a liquidity reserve for the need of "misinformed" withdrawal by depositors. The word "misinformed" stems from the assumption that depositors could not observe the actual state of the bank and the economy. The reserves would reduce the risk and cost of having to liquidate assets earlier to repay withdrawals. Ratnovski (2013) emphasizes this notion through a theoretical model in which liquidity reserve and assets transparency (a form of signaling) could synergize. He acknowledges, however, transparency is not a substitute for liquidity reserve and without regulatory requirement; banks could end up in bad equilibrium: inadequate amount of both reserve and transparency.

In the regular course of a bank's daily business, sudden large cash flows can occur not only because of changing depositor perceptions with respect to the bank or economic condition but also because of the customer business itself. De Haan and van den End (2013) using unique Dutch banks' data provide empirical support in which banks do cascading of liquidity assets according to the projected customer related cash flows. Therefore, contingency plans must be ready. One such plan involves maintaining access to the interbank market. In this regard, liquidity management is like inventory management with multiple layers of protection. Managing this mechanism has a cost, which is passed through to the bank's customers as a component of interest margin (Ho and Saunders, 1981; Prisman *et al.*, 1986); see Al-Muharrami and Murthy (2017) for recent empirical evidence. Heider *et al.* (2015) developed a model in which liquidity reserve is endogenous (with regard to bank risk characteristics) and influenced by money market condition. They show how deteriorated information distribution among participant banks could lead to excessively high interest rate that subsequently trigger liquidity hoarding.

Tirole (2011) proposes a general theory of bank liquidity reserve that developed from the corporate finance literature (Holmstrom and Tirole, 1998). He postulates two styles of liquidity management: "finance as you go" and liquidity hoarding. Bank liquidity reserves are influenced by risk management, financial structure, reputation risk, corporate governance, external sources of funding and asset quality. From his model, he shows that there is a tradeoff between liquidity reserve and size. The model results in multiple equilibrium in which liquidity hoarding is optimal if it is cheap and shocks are not rare. Nevertheless, there could also be other inefficient equilibria, including under- or over-hoarding for non-zero subsets of banks and joint illiquid banks. Because of possible joint illiquid banks' equilibrium, there is an adverse phenomenon: deteriorating bank health reduces incentive for liquidity hoarding (in expectation, this behavior could attract regulatory intervention, i.e. economy-wide liquidity injection).

Calomiris *et al.* (2015) is an in-progress work attempting to build a unifying theory of banks' liquidity reserves based on works by Diamond and Dybvig (1983) and Calomiris and Kahn (1991). From the model, the authors propose three motives of banks holding liquidity reserves. First, the bank will increase its liquidity holding as a positive signal of risk management to depositors. Second, liquidity holding is a form of coinsurance of liquidity risk among peers in which bankers would require one another to maintain cash reserves to avoid the free-rider problem. Third, by allowing endogenous liquidity risk, liquidity reserves reduce insolvency risk by incentivizing efficient risk management. DeAngelo and Stulz (2015), using Modigliani and Miller (1958) paradigm and assuming material arbitrage cost (of intermediation between markets) and innate skill to manage the risk on the asset side, show that excessive leverage is a natural equilibrium for banks, which will fund the asset substantially using liquid claims (deposits). The unique ability possessed by banks to manage their risky assets would give them a liquidity discount to their cost of capital (arising from shifting depositor preferences).

There is an ample amount of recent empirical works casted in static perspective. In the financial fragility hypothesis, liquidity reserve acts as a substitute to bank health (i.e. they have a negative relationship). Al-Harbi (2017), Umar *et al.* (2018), Dahir *et al.* (2018), Tran *et al.* (2019), Jiang *et al.* (2019) provide empirical support for this hypothesis. Empirical support for signaling hypothesis (positive association between liquidity and riskiness) is shown by works of Horváth *et al.* (2014), Berger *et al.* (2016) and Díaz and Huang (2017). Existing empirical studies have yet to reach consensus of the relationship of liquidity reserve with size. Delechat *et al.* (2012), De Haan and van den End (2013), DeYoung *et al.* (2018) and Sahyouni *et al.* (2021) found the relationship to be negative. On the other hand, positive relationship was discovered by Berger *et al.* (2016), Díaz and Huang (2017) and Jiang *et al.* (2019).

De Young and Jang (2016) provide empirical work that closes in spirit with ours. They estimated empirical models using system GMM that incorporates dynamics of liquidity reserve adjustment using panel data of US banks. They found significant existence of liquidity target and reserve dynamic adjustment mechanism. The partial adjustment of liquidity reserve coefficients found are estimated to be 0.29 and 0.13 using a loan to core deposit (LTCD) proxy and net stable funding ratio (NSFR), respectively. This study was modified subsequently by DeYoung *et al.* (2018) to uncover the joint dynamics of liquidity and capital from a sample of pre-Basel III US banks. They also found that US banks treat liquidity and capital as substitutes, and liquidity reserve adjusts dynamically to capital target deficiency.

4. Methodology

We estimate an array of empirical liquid reserve models using DCCE with ECM format developed by Chudik and Pesaran (2015). This econometric method is preferred on long panel data with the assumption of weak exogeneity of explanatory variables (Eberhardt, 2011). The model comprises of two parts: (a) the long-run equation and (b) the short-run equation. We use two alternative proxies for liquidity reserve as the dependent variable. Liquid asset type 1 (LA1TA) is the commonly known "core" liquid assets of a bank, consisting of cash, reserves in the central bank and net interbank balance. The type 2 (LA2TA) consists of LA1TA assets plus net securities position (securities owned minus securities issued). Position in securities in times of volatile macroeconomic conditions might not be converted to cash without incurring an excessive cost. Therefore, a regulator treats this item as a secondary liquidity reserve. These liquidity measures were used by Delechat *et al.* (2012), Tran *et al.* (2019) and DeYoung *et al.* (2018), among others.

In modeling the long-run relationship, we hypothesize that the level of liquidity reserves would be influenced by liquidity management approach, bank health condition and size. The liquidity management approach is measured both on-balance sheet (proxied by LDR) and off-balance sheet (proxied by net commitment plus net contingent to total assets ratio; OBS_AST). Based on the pool of funds hypothesis, the estimates of LDR should be negative and OBS_AST should be positive [4]. Collectively, we call both proxies as intermediation activity. Bank health condition is proxied by Z_SCORE. Our Z_SCORE calculation follows a method proposed by Lepetit and Strobel (2013) and Lepetit and Strobel (2015). Based on the financial fragility hypothesis, a bank would use its liquid assets as a substitute of deteriorated financial health (i.e. increased riskiness). On the other hand, in the signaling hypothesis, the healthier bank would use higher liquid assets to signal its condition. Assets (in log form, ASSET_L) should account for bank-specific characteristics that are assumed to have a positive correlation with size but not include, specifically in our model. These characteristics include (among others): strength, perception on increasing systemic risk, volume of transactions, network and customer base.

In the short run, a bank's liquidity reserve should respond to deviation of (time variant) liquidity target, changes in long-run variables and financial system stability conditions. We expect a dynamic adjustment mechanism to exist; hence, the error coefficient term (lag one residual of long-run equation; ECT) should be negative with absolute value less than zero and significant. There are two proxies of financial system stability. The first is a proxy of market wide cost of funding, the Jakarta Interbank Overnight Interest Rate (JIBON). Second, we use a variable that would serve as a proxy of financial market volatility: exchange rate (IDR per USD; USDIDR). Allen and Carletti (2013) propose foreign exchange mismatch as one source of systemic risk, while Lang and Schmidt (2016) provide empirical support for the role of exchange rate pressure as early warning of bank crisis. Delechat *et al.* (2012) used exchange rate shock as a proxy of macroeconomic fundamental in a study of bank liquidity. Both proxies are expected to have a positive relation with liquid reserve. A summary of the variables, their definition and the hypotheses appear in Table 1.

As of August 2019, 97 commercial conventional banks were operational in Indonesia. We use these banks as unit of analysis, tracing their historical records back to January 2003. Some of these banks underwent mergers or acquisitions, and we address this issue by creating synthetic banks that combine the merged/acquired banks as if they were one bank since the beginning of the sample. Bank-level data are obtained from an individual bank financial report taken from the Financial Service Authority site. For financial system stability variables (USDIDR and JIBON), we collected data from Bank Indonesia.

We cleanse the data with the aim to preserve this balanced data panel structure. Initially, we have 19,400 bank-month observations from which we conducted a careful inspection. We use linear interpolation to fill in missing data if it happened in the middle of the time series. If it happened at one or both tails of the series, we use (moving) averaging year to date (the last one year). We dropped the bank if missing values or data defect reached more than 30% of the total. We do winsorizing at 1% and treat the data as missing if they are exceeding the threshold. To these data, we apply interpolation techniques, as described previously. After this process, we are left with a balanced panel structure of 16,800 observations, composed of 84 banks as cross-section units and 200 monthly time-series units (January 2003 to August 2019).

Because we are using long panel data, the standard assumption of cross-section independence would likely be violated (Pesaran, 2015a). The occurrence of cross-section dependence in panel data can have profound consequences in the form of bias standard error and even inconsistent estimates (Sarafidis *et al.*, 2009). Testing for stationarity should also be modified because the conventional tools would likely have substantial size distortions (O'Connell, 1998). We conduct testing for cross-section dependence using the method developed by Pesaran (2015b).

The panel data non-stationarity testing uses methods developed by Pesaran (2007; PESCADF) and Pesaran *et al.* (2013; CIPS). Both panel data unit root methods are designed to be robust to cross-section dependence (Pesaran, 2015b). For comparison, we will also perform panel unit root test using the methods proposed by Levin *et al.* (2002; LLC) and Im *et al.* (2003; IPS). We perform several modeling for each panel unit root test: PESCADF, CIPS, LLC and IPS. The modeling mainly considers the following aspects: (a) whether to include constant and trend or constant only and (b) the number of lags used. As for time-series variables, we perform unit root testing using the ADF (Dickey and Fuller, 1979), Phillips and Perron (1988, PP), and KPSS (Kwiatkowski *et al.*, 1992) methods.

The cointegration test is conducted using a method that accounts for cross-section dependence. The method proposed by Westerlund (2007) is based on following test regression model:

$$\Delta Y_{it} = \alpha_{0i} + \alpha_{1i}\Delta Y_{it-1} + \cdots + \alpha_{pi}\Delta Y_{it-p} + \beta_{0i}\Delta X_{it} + \beta_{1i}\Delta X_{it-1} + \cdots + \beta_{pi}\Delta X_{it-p} + \phi_i(Y_{i,t-1} - \beta_i\Delta X_{it-1}) + u_{it} \tag{1}$$

Test statistics Pt and Pa are used for "global" cointegration test with null hypothesis that all $\phi_i = 0$ versus all $\phi_i < 0$. Gt and Ga are test statistics for "non-zero subsets" cointegration test with null hypothesis that all $\phi_i = 0$ versus at least one i is less than zero. Rejection of null hypothesis is taken as evidence of cointegration. Persyn and Westerlund (2008) generalized the model to adopt various possible dynamic structure.

We conduct some specifications of the cointegration test that are based on (1) dependent variables used (LA1TA or LA2TA); (2) number of lags, leads and LR window; (3) whether using automatic lag selection (based on Akaike information criteria; AIC); and (4) whether using bootstrap method to obtain robust p-value (for inference). Blomquist and Westerlund (2014) proposed using a bootstrap method to obtain robust inference in a cointegration test of a panel data structure that suffers from cross-sectional dependence.

Another issue in long panel data is heterogeneity, which could arise from the slope in addition to component of residual (Eberhardt and Teal, 2011). It is doubtful that our data would meet slope homogeneity. We will test explicitly the assumption of slope heterogeneity using the method proposed by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) under various specifications. The specifications are based on (1) liquidity measures used (LA1TA and LA2TA), (2) whether using heteroscedasticity and autocorrelation consistent (HAC) standard error and (3) whether including cross-section averages of explanatory variables and number of lags (0 and 14).

We also assume the presence of a common factor and heterogenous factor loading. Following Ditzen (2016), the model is:

$$Y_{it} = \beta'_{ki} X_{it} + u_{it} \tag{2}$$

$$u_{it} = \lambda'_i F_t + e_{it} \tag{3}$$

where Y_{it} and X_{it} are possibly non-stationary vector-dependent variables and matrix of (weakly exogenous) explanatory variables, and u_{it} is a composite residual. The residual is composed of the unobserved common factor (F_t) and heterogenous (cross-section) factor loading (λ_i). Furthermore, the slopes are assumed to be randomly distributed around a common mean, $\beta_k = \beta + v_i, v_i \sim IID(0, \Omega_v)$.

Based on the result of slope heterogeneity test (see next subsection 5.2), we should use DCCE estimator that is a variant of mean group (MG) (Pesaran and Smith, 1995). To account for possible common factors, Pesaran (2004) suggested adding cross-section averages of $\bar{y}_t$ and $\overline{x_t}$ (collectively denotes as $\bar{z}_t$) in estimated regressions. The complete specification of the estimated model is as follows:

$$\Delta Y_{it} = \phi_i \left(Y_{i,t-1} - \beta'_k X^k_{i,t-1} \right) + \alpha_0 + \alpha'_{k,i} \Delta X^k_{i,t} + \delta_i \bar{z}_t + u_{it} \tag{4}$$

We estimate several specifications based on (1) whether to include no constant – no trend, constant only or constant and trend components in the short-run part of ECM (standard MG) and (2) including cross-section averages of explanatory variables (DCCE).

We do robustness check by splitting the sample into two subsamples (at a cut-off point of December 2012), assuming that each of them will characterize a different liquidity regime. The choice of December 2012 is made based on visual inspection. From Figure 1, we can see a somewhat different behavior of liquid asset ratio (in terms of level and volatility), which transitioned between 2012 and 2013.

Finally, we elaborate the analysis further by estimating regressions on restricted samples based on (1) bank size (large banks versus small banks, based on OJK classifications), (2) bank types (state-owned banks: SOE, regional development banks: DEV and private-owned: PRIV).

As cross-section dependence is present in our data (see subsection 5.3), both the robustness test and extended regressions will be performed only using fully specified DCCE estimators.

5. Results and discussion

This section presents the descriptive statistics, preliminary testing and regression results and accompanying discussions. The section is divided into three subsections: (5.1) descriptive analysis and correlation analysis of variables, (5.2) preliminary testing and (5.3) DCCE estimation.

5.1 Descriptive statistics and pairwise correlation

The averages and medians are all found somewhat close to each other, i.e. variables do not suffer excessive skewness (Table 2). A few variables perhaps warrant a notice; they are OBS_AST, Z_SCORE and ASSET. These variables have some degree of skewness. The OBS_AST mean is −0.112, while its median is −0.078, and Z_SCORE has a mean of 18.839 and median of 16.399. The skewness in ASSET is more substantial: The mean is (in Rp. million) 39,799,042, and the median is 6,294,628. After taking logs, however, this excessive skewness disappears. The same conclusion from descriptive analysis is found for time-series variables. The JIBON average is 6.226, while its median is 5.863. On the other hand, the USDIDR average is 10,759, while its median is 9,623 hence its distribution is somewhat skewed. This issue of skewed data is also handled by taking log to the variable.

We do not observe any potential multicollinearity from explanatory variables. Table 3 shows that the bivariate correlation among independent variables is all well below 0.500. Simple correlation coefficients among liquid asset measures (LA1TA and LA2TA) both are high with LDR, at −0.689 and −0.695, respectively. These statistics give hints for the possible substantial and significant negative influence of LDR to liquid asset measures. In a nutshell, from our exploratory data analysis, we do not see the data profile would pose severe consequences for subsequent analysis.

5.2 Preliminary testing: unit root, cointegration and slope heterogeneity

Unlike its pure time-series counterpart, the inference of unit root test results of a panel data structure is harder (Pesaran, 2012). Existing panel data unit root tests have as the null hypothesis that cross-section units are all non-stationary (homogenous test). Nevertheless, Pesaran's (2012) analysis suggested that the rejection of the null hypothesis could mean there is a non-zero fraction of non-stationary. Therefore, at the current state of literature, we should treat the unit root test as a gauge of confidence of using regression based on the assumption of cointegration.

Table 4 presents the summary of unit root test of variables used in the study [5]. We find strong statistical evidence of rejection of homogenous non-stationary null hypotheses for variables LA1TA, LA2TA and LDR with all methods used. Other macro panel variables (OBS_AST, Z_SCORE and ASSET_L) are less clear-cut, depending on methods and specifications. If we use cross-section-dependent robust unit root test (CIPS and PESCADF), the results are similar with previously mentioned variables: rejection of the null hypothesis of homogenous non-stationary. However, when we use LLC and IPS, a substantially weakened conclusion is found. Unit root test results are clearer for time-series variable. JIBON has been tested as a stationary variable by all methods, while on the other hand, USDIDR is clearly non-stationary.

Table 5 reports Persyn and Westerlund (2008) cointegration test results for liquidity measures LA1TA and LA2TA against other explanatory variables. There are 12 specifications, of which eight specifications are performed with bootstrap to calculate robust variance in the presence of cross-section dependence (as suggested by Blomquist and

Table 2.
Descriptive statistics

	LA1TA	LA2TA	LDR	OBS_AST	Z_SCORE	ASSET	ASSET (LOG)	JIBON	USDIDR	USDIDR (LOG)
Avg	0.251	0.254	0.775	−0.112	18.839	3,97,99,042	6.825	6.226	10,759	4.024
Median	0.210	0.235	0.795	−0.078	16.399	6,294,628	6.799	5.863	9,623	3.983
Max	0.982	0.950	2.945	1.147	96.781	1,298,674,152	9.114	12.436	15,203	4.182
Min	(0.217)	(0.122)	0.001	−1.916	2.740	18,395	4.265	3.354	8,275	3.918
Stdev	0.170	0.123	0.246	0.143	9.174	112,937,339	0.845	1.947	2,051	0.080
Percentile										
1%	(0.022)	0.039	0.194	−0.726	6.261	94,957	4.978	3.569	8,394	3.924
99%	0.797	0.654	1.469	0.117	47.549	682,754,017	8.834	12.207	14,732	4.168
5%	0.055	0.093	0.346	−0.329	8.583	284,147	5.454	3.904	8,510	3.930
95%	0.605	0.496	1.154	0.007	38.714	175,758,976	8.245	10.261	14,242	4.154
No. of observations	16,800	16,800	16,800	16,800	16,800	16,800	16,800	200	200	200

Note(s): This table reports descriptive statistics variables used in the study. The variables are in numeric (up to three digits behind the comma) except Z_Score (in percentage) and asset (in million IDR). Descriptive statistics presented are average, median, maximum, minimum, standard deviation and percentiles. The statistics are calculated over the whole sample data

	LA1TA	LA2TA	LDR	OBS_AST	Z_SCORE	ASSET (LOG)	JIBON	USDIDR (LOG)
LA1TA	1.000							
LA2TA	0.839	1.000						
LDR	−0.689	−0.695	1.000					
OBS_AST	0.222	0.054	−0.197	1.000				
Z_SCORE	−0.120	−0.024	0.172	−0.178	1.000			
ASSET (LOG)	−0.370	−0.135	0.133	−0.220	0.127	1.000		
JIBON	0.235	0.115	−0.218	0.071	−0.072	−0.266	1.000	
USDIDR (LOG)	−0.324	−0.204	0.319	−0.055	0.122	0.362	−0.350	1.000

Note(s): This table reports simple bivariate correlation statistics (Pearson) between variables used in the study. Correlation statistics are calculated over the whole sample data. Correlations are presented as a half-triangle matrix

Table 3.
Correlation matrix

Westerlund, 2014). The calculated *p*-value and robust *p*-value for all test statistics (*Z*-value of Gt, Ga, Pt and Pa) are virtually zero. Therefore, the null hypotheses of no cointegration (both global and subsets) are strongly and uniformly rejected across various specifications. We still have to compare these results against the coefficients and inference of the error correction term obtained in the next section.

Finally, we perform slope heterogeneity tests. From Table 6, we can see the null hypotheses of slope homogeneity across cross-section are uniformly and strongly rejected, as shown by very high-test statistics and virtually zero corresponding calculated *p*-value. Considering this, estimation accounting for slope heterogeneity should be used. As a note, the estimation procedure we use in the next section also calculates the post-estimation cross-section dependence test, whose results are aligned with the *ex ante* procedure.

5.3 Dynamic common correlated error (DCCE) estimation

In this section, we present regression results of the DCCE-ECM format. We present the baseline models with their robustness check in the first and second subsections. In the third subsection, we present the extended model based on bank size and bank type.

5.3.1 Baseline model. Table 7 presents DCCE regressions (model 4–6) along with standard MG estimates (model 1–3) for comparison. We find strong and significant evidence of an error correction mechanism from the regressions. As hypothesized estimated parameters range from −0.142 (MG with no constant-trend) to −0.372 (DCCE with constant and trend), these ECT estimates correspond to 2.7 months (=1/0.372) to 7.0 months (= 1/0.142) time lag of the equilibrating process. From the long-run equation, as hypothesized, we find LDR to be negatively correlated (and highly significant) to the liquidity measure (LA1TA). We find OBS_AST estimates to be positive but only significant in models 2, 3 and 6. Z_SCORE estimates are positive and significant, although in much lower magnitude compared with LDR. The estimates of ASSET_L are significant only in models 1 and 2; however, they have different algebraic sign.

We find a qualitatively similar picture, albeit better statistical significance in the short-run equation. We find positive and (generally) better significance short-run estimates for OBS_AST. Therefore, it seems that off-balance-sheet impact to liquidity reserve is more short-term reaction rather long-term adjustment. Estimates of JIBON are only modestly significant in models 1–3. Once we account for possible cross-section dependence in DCCE, however, those coefficients lose magnitudes and inferences. Estimates on the other financial system stability variable, USDIDR, are not statistically significant.

No.	Variable	Method	Result
1.	LA1TA	CIPS	Reject homogenous non-stationary null hypothesis at 1% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Reject, all panels contain a unit root null hypothesis at 1% significance level
		IPS	Reject, all panels contain a unit root null hypothesis at 1% significance level
2.	LA2TA	CIPS	Reject homogenous non-stationary null hypothesis at 1% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Reject, all panels contain a unit root null hypothesis at 1% significance level
		IPS	Reject, all panels contain a unit root null hypothesis at 1% significance level
3.	LDR	CIPS	Reject homogenous non-stationary null hypothesis at 1% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Reject, all panels contain a unit root null hypothesis at 1% significance level
		IPS	Reject, all panels contain a unit root null hypothesis at 1% significance level
4.	OBS_AST	CIPS	Reject homogenous non-stationary null hypothesis at 1% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Cannot reject, all panels contain a unit root null hypothesis at significance level 10% at lag = 6, I(1)
		IPS	Reject, all panels contain a unit root null hypothesis at 1% significance level
5.	Z_Score	CIPS	Reject homogenous non-stationary null hypothesis at 1% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Cannot reject, all panels contain a unit root null hypothesis at significance level 10% at lag = 6, I(1)
		IPS	Reject, all panels contain a unit root null hypothesis at 1% significance level
6.	Asset_L	CIPS	Reject homogenous non-stationary null hypothesis at 5% significance level
		PESCADF	Reject heterogenous non-stationary null hypothesis at 1% significance level
		LLC	Cannot reject, all panels contain a unit root null hypothesis at significance level 10% at lag = 1
		IPS	Cannot reject, all panels contain a unit root null hypothesis at significance level 10% at lag = 1
7.	JIBON	ADF	Reject non-stationary null hypothesis at level at significance level 5% at lag = 6
		PP	Reject non-stationary null hypothesis at level at significance level 1%
		KPPS	Cannot reject stationary null hypothesis at level at significance level 1%
9.	USDIDR	ADF	Cannot reject non-stationary null hypothesis at level. Reject null hypothesis at 1st difference at significance level 1%
		PP	Cannot reject non-stationary null hypothesis at level. Reject null hypothesis at 1st difference at significance level 1%
		KPPS	Reject stationary null hypothesis at level. Cannot reject null hypothesis at 1st difference at significance level 1%

Note(s): This table reports summary of some selected unit root tests performed on variables used in the study. The report covers only (1) name of variables, (2) name of corresponding unit root test method used and (3) conclusion of the test (reject or cannot reject the null hypothesis). See Section 4 for an overview of unit root test methods. The levels of significance used as a rule for null hypothesis rejection are 1%, 5% and 10%

Table 4.
Summary of unit root test

A qualitatively similar picture is obtained when we replace the dependent variable proxy to from LA1TA to LA2TA (Table 8). The ECTs are all negative and highly significant, ranging from −0.156 to −0.328. These ECT estimates correspond to 3.0 months (=1/0.328) to 6.4 months (= 1/0.156) time lag of the equilibrating process. The CD test reports significant statistics for all models, showing that cross-section dependence is present and important. Therefore, estimates using DCCE (models 4–6 in LA1TA and model 10–12 in LA2TA) are preferred.

Our results confirm a similar pattern identified by DeYoung and Jang (2016) and DeYoung *et al.* (2018). This finding is especially important in following regards. First, as our study object is a large emerging country (Indonesia), it is highly possible that the behavior could be

No.	Specification	Statistic; p-value	Gt	Ga	Pt	Pa
1.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags: 1–6, leads: 1–6, LR window: 6, selection: AIC (lag: 1.54; lead: 1.42)	Z value p-value	−12.621 0.000	−14.404 0.000	−13.793 0.000	−18.295 0.000
2.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant-trend, lags: 1–6, leads: 1–6, LR window: 6, selection: AIC (lag: 1.54; lead: 1.39)	Z value p-value	−11.491 0.000	−11.205 0.000	−12.303 0.000	−14.003 0.000
3.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags: 1, leads: 1, LR window: 1, bootstrap	Z value Robust p-value	−13.260 0.000	−20.168 0.000	−13.957 0.000	−23.052 0.000
4.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags:2, leads: 2, LR window: 2, bootstrap	Z value Robust p-value	−10.304 0.000	−16.307 0.000	−10.736 0.000	−18.016 0.000
5.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, trend, lags: 1, leads: 1, LR window: 1, bootstrap	Z value Robust p-value	−11.826 0.000	−16.590 0.000	−12.488 0.000	−18.906 0.000
6.	LA1TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, trend, lags: 1, leads: 1, LR window: 1, bootstrap	Z value Robust p-value	−8.632 0.000	−13.065 0.000	−9.036 0.000	−14.267 0.000
7.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags: 1–6, leads: 1–6, LR window: 6, selection: AIC (lag: 1.50; lead: 1.29)	Z value p-value	−12.524 0.000	−16.336 0.000	−13.115 0.000	−17.157 0.000
8.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant-trend, lags: 1–6, leads: 1–6, LR window: 6, selection: AIC (lag: 1.54; lead: 1.31)	Z value p-value	−11.548 0.000	−13.319 0.000	−11.407 0.000	−12.856 0.000
9.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags: 1, leads: 1, LR window: 1, bootstrap	p-value Robust p-value	−12.636 0.000	−21.408 0.000	−13.412 0.000	−21.751 0.000
10.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, lags:2, leads: 2, LR window: 2, bootstrap	Z value Robust p-value	−9.975 0.000	−17.122 0.000	−11.160 0.000	−17.932 0.000
11.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, trend, lags: 1, leads: 1, LR window: 1, bootstrap	Z value Robust p-value	−11.106 0.000	−18.009 0.000	−11.747 0.000	−17.527 0.000
12.	LA2TA; LDR, OBS_AST, Z_SCORE, ASSET_L, constant, trend, lags: 1, leads: 1, LR window: 1, bootstrap	Z value Robust p-value	−8.084 0.000	−14.050 0.000	−8.911 0.000	−13.763 0.000

Note(s): This table reports the results of cointegration test based on Westerlund (2007), Persyn and Westerlund (2008) and Blomquist and Westerlund's (2014) methods. Cointegration is based on various specifications: with LA1TA and LA2TA as the dependent variable. Null hypotheses are (1) global no cointegration (using Pt and Pa test statistics) and (2) subsets cointegration (using Gt and Ga) for all specifications

Table 5.
Cointegration test

"somewhat" generalized. Second, we use higher-frequency data (monthly), which, in our view, better reflect liquidity response, i.e. it should be rapid.

Assessing long- and short-run estimates, we find several important results. First, LDR estimates are consistent with the pool of funds hypothesis: liquid asset position responds primarily to serving customer financing need (De Haan and van den End, 2013, Al-Muharrami and Murthy, 2017; Tran *et al.*, 2019). Second, from the estimates of Z score, we find support for the signaling hypothesis. Healthy banks use liquidity to signal their

Table 6.
Slope heterogeneity test

No	Specification	Unadjusted delta Stats	Unadjusted delta p-value	Adjusted delta Stats	Adjusted delta p-value
1.	LA1TA; LDR OBS_AST Z_SCORE, ASSET_L; HAC	33.695	0.000	33.868	0.000
2.	LA1TA; LDR OBS_AST Z_SCORE, ASSET_L; cross-section average, CR Lags = 0, HAC	16.587	0.000	16.674	0.000
3.	LA1TA; LDR OBS_AST Z_SCORE, ASSET_L; cross-section average, CR Lags = 14, HAC	14.292	0.000	14.428	0.000
4.	LA2TA; LDR OBS_AST Z_SCORE, ASSET_L; HAC	38.063	0.000	38.259	0.000
5.	LA2TA; LDR OBS_AST Z_SCORE, ASSET_L; cross-section average, CR Lags = 0, HAC	16.587	0.000	16.674	0.000
6.	LA2TA; LDR OBS_AST Z_SCORE, ASSET_L; cross-section average, CR Lags = 14, HAC	14.292	0.000	14.428	0.000

Note(s): This table reports the slope heterogeneity test using the method proposed by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013). There are several specifications based on (1) whether LA1TA and LA2TA as dependent variables, (2) inclusion of cross-section average and (3) heteroscedasticity treatment. Null hypotheses are slope homogeneity for all specifications

condition to the public, as also found by the empirical works of Horváth *et al.* (2014), Berger *et al.* (2016) and Díaz and Huang (2017) and Umar *et al.* (2018). Third, estimates of OBS_AST support generally positive association of liquidity reserve with off-balance-sheet (as found by DeYoung and Jang, 2016, Berger *et al.*, 2016; Al-Harbi, 2017, Sahyouni *et al.*, 2021). Fourth, empirical estimates on ASSET_L are generally aligned with the transaction banking hypothesis and signaling hypothesis. This finding supports empirical results from Berger *et al.* (2016), Díaz and Huang (2017), Dahir *et al.* (2018) and Jiang *et al.* (2019). Fifth, we find rather limited role of financial stability variables (JIBON and USDIDR) in influencing liquidity behavior. Positive correlation of JIBON and liquidity measure supports Heider *et al.* (2015) theoretical conjecture that tightening in money market condition trigger liquidity hoarding behavior.

5.3.2 Robustness check. The estimates of ECT could be considered as qualitatively similar in robustness check regression using LA1TA (Table 9). Nevertheless, we obtain a somewhat different result when we replace LA1TA with LA2TA as dependent variable (Table 10). Coefficients of ECT are lower in the subsample “before Dec 2012” compared with “after Dec 2012.” The estimates correspond to the idea that banks’ adjustment to liquidity shocks is faster in the period after December 2012, with broader measure of liquidity (LA2TA).

The robustness check exercises show that our previously reported findings remain unaltered with splitting sample design. All long-run LDR estimates are negative and highly significant in both subsamples (“before Dec 2012” and “after Dec 2012”). Similar qualitative conclusion is also obtained for long-run Z_SCORE estimates, which again are positive and highly significant regardless sample set. Estimates of ASSET_L are not significant in the long-run equation for both subsamples. Interestingly, unlike the LA1TA model, the coefficients of ASSET_L in the short-run equation are significant only in the subsample "before Dec 2012." In the subsample “after Dec 2012,” ASSET_L estimates lose significance. It seems that the signaling hypothesis using liquid assets is valid only for narrow liquidity measure (LA1TA); the broader liquidity measure (LA2TA) lost its role after December 2012. Lastly, we find that JIBON has a positive and significant impact on LA2TA for the subsample “after Dec 2012.”

We find modest significance for OBS_AST in the subsample “after Dec 2012” (models 4b and 5b). Nevertheless, in the short-run equation, the coefficients of OBS_AST are all

Table 7. Baseline ECM, dependent variable: D.LA1TA

Variables	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Dep. Var: D.LA1TA	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Long run												
LDR	−0.491***	0.039	−0.450***	0.035	−0.451***	0.033	−0.504***	0.028	−0.539***	0.027	−0.549***	0.027
OBS_AST	0.079	0.087	0.168***	0.071	0.201***	0.074	0.100	0.072	0.104	0.069	0.119*	0.063
Z_SCORE	0.007***	0.002	0.003**	0.001	0.004***	0.001	0.005***	0.001	0.006***	0.001	0.005***	0.001
ASSET_L	0.027***	0.002	−0.029***	0.007	0.002	0.016	−0.012	0.014	0.013	0.019	0.011	0.021
Short run												
ECT	−0.142***	0.010	−0.187***	0.011	−0.206***	0.011	−0.307***	0.014	−0.337***	0.014	−0.372***	0.015
D.LDR	−0.594***	0.020	−0.596***	0.020	−0.595***	0.020	−0.601***	0.019	−0.607***	0.020	−0.606***	0.020
D.OBS_AST	0.045**	0.021	0.050**	0.020	0.055***	0.021	0.039*	0.021	0.040*	0.021	0.044**	0.022
D.Z_SCORE	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001
D.ASSET_L	0.086***	0.018	0.077***	0.018	0.079***	0.018	0.071***	0.018	0.075***	0.018	0.076***	0.019
JIBON	0.158***	0.021	0.058***	0.020	0.066***	0.019	0.005	0.025	0.015	0.026	0.008	0.027
D.USDIDR	−0.002	0.010	−0.003	0.010	−0.004	0.010	−0.005	0.010	−0.003	0.011	−0.001	0.010
Trend					0.000	0.000					0.000	0.000
Constant			0.172***	0.019	0.096**	0.043			−0.026	0.050	0.296*	0.156
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Cross section average	N		N		N		Y		Y		Y	
Observations	16,716		16,716		16,716		16,716		16,716		16,716	
F statistic	27.530	0.000	26.330	0.000	24.550	0.000	23.210	0.000	22.400	0.000	22.010	0.000
CD test	94.610	0.000	94.040	0.000	94.760	0.000	51.060	0.000	47.840	0.000	43.180	0.000

Note(s): This table reports estimations of the baseline model with dependent variable: first difference of LA1TA (D.LA1TA) using MG (models 1–3) and DCCE technique (models 4–6) with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by number in the first line of each column heading) corresponds to specific specifications described by (1) inclusion of constant and/or trend and (2) application of cross-section average (DCCE class estimators). Estimations are applied to the full sample. Statistical significance is denoted as * at the 10% level, ** at the 5% level and *** at the 1% level

Table 8.
Baseline ECM: D.LA2TA

Variables	Model 7		Model 8		Model 9		Model 10		Model 11		Model 12	
Dep. Var: D.LA2TA	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run												
LDR	−0.489***	0.025	−0.468***	0.028	−0.494***	0.027	−0.476***	0.028	−0.500***	0.024	−0.493***	0.026
OBS_AST	0.022	0.071	0.110	0.077	0.091	0.055	0.045	0.043	0.027	0.040	0.043	0.040
Z_SCORE	0.008***	0.002	0.007**	0.003	0.005***	0.001	0.005***	0.001	0.005***	0.001	0.005***	0.001
ASSET_L	0.032***	0.002	0.018**	0.008	0.004	0.016	−0.015	0.012	0.003	0.016	0.000	0.016
Short run												
ECT	−0.156***	0.012	−0.212***	0.014	−0.236***	0.015	−0.258***	0.014	−0.303***	0.016	−0.328***	0.016
D.LDR	−0.523***	0.019	−0.523***	0.019	−0.523***	0.019	−0.518***	0.019	−0.517***	0.019	−0.516***	0.018
D.OBS_AST	0.003	0.014	0.009	0.015	0.012	0.015	0.008	0.015	0.010	0.015	0.012	0.015
D.Z_SCORE	0.004***	0.000	0.004***	0.000	0.004***	0.000	0.004***	0.000	0.004***	0.000	0.004***	0.000
D.ASSET_L	0.029**	0.014	0.028**	0.014	0.027**	0.014	0.022	0.014	0.025*	0.014	0.025*	0.014
JIBON	0.055***	0.014	0.003	0.014	0.009	0.015	0.001	0.017	0.010	0.017	0.009	0.017
D.USDIDR	0.007	0.009	0.005	0.009	0.005	0.008	0.013	0.009	0.014	0.009	0.015*	0.009
Trend					0.000	0.000					0.000	0.000
Constant			0.065***	0.022	0.103***	0.039			−0.036	0.040	0.044	0.077
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Cross section average	N		N		N		Y		Y		Y	
Observations	16,716		16,716		16,716		16,716		16,716		16,716	
F statistic	38.110	0.000	36.130	0.000	33.890	0.000	28.420	0.000	27.780	0.000	26.650	0.000
CD test	23.320	0.000	22.260	0.000	22.150	0.000	9.400	0.000	8.020	0.000	7.670	0.000

Note(s): This table reports estimations of the baseline model with dependent variable: first difference of LA2TA (D.LA2TA) using MG (models 1–3) and DCCE technique (models 4–6) with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by number in the first line of each column heading) corresponds to specific specifications described by (1) inclusion of constant and/or trend and (2) application of cross-section average (DCCE class estimators). Estimations are applied to the full sample. Statistical significance is denoted as * at the 10% level, ** at the 5% level and *** at the 1% level

Table 9. Robustness test: splitting samples, D.LA1TA

Variables	≤ Dec 2012						> Dec 2012					
Dep. Var: D.LA1TA	Model 4a		Model 5a		Model 6a		Model 4b		Model 5b		Model 6b	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run												
LDR	−0.619***	0.030	−0.649***	0.031	−0.647***	0.031	−0.468***	0.037	−0.449***	0.047	−0.226***	0.214
OBS_AST	−0.079	0.077	−0.067	0.067	−0.045	0.066	0.167*	0.091	0.143*	0.076	0.405	0.404
Z_SCORE	0.007***	0.001	0.007***	0.001	0.006***	0.001	0.004***	0.001	0.006***	0.002	0.001	0.004
ASSET_L	0.025	0.019	0.020	0.020	0.016	0.021	0.013	0.023	0.046	0.037	0.745	0.705
Short run												
ECT	−0.430***	0.021	−0.475***	0.021	−0.501***	0.021	−0.436***	0.022	−0.468***	0.022	−0.529***	0.022
D.LDR	−0.670***	0.021	−0.676***	0.021	−0.674***	0.021	−0.584***	0.023	−0.590***	0.024	−0.588***	0.023
D.OBS_AST	0.000	0.026	0.009	0.027	0.012	0.027	0.042	0.035	0.041	0.038	0.020	0.035
D.Z_SCORE	0.005***	0.001	0.005***	0.001	0.005***	0.001	0.005***	0.001	0.005***	0.001	0.005***	0.001
D.ASSET_L	0.080***	0.018	0.077***	0.019	0.078***	0.019	0.065***	0.020	0.065***	0.020	0.070***	0.021
JIBON	0.004	0.027	−0.030	0.031	0.003	0.032	0.049	0.067	0.025	0.065	0.015	0.065
D.USDIDR	−0.018	0.012	−0.028	0.012	−0.017	0.013	−0.001	0.014	−0.002	0.014	−0.002	0.013
Trend					0.001*	0.001					0.000	0.000
Constant			0.215*	0.112	1.209**	0.518			−0.190	0.165	0.098	0.289
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Observations	9,996		9,996		9,996		6,720		6,720		6,720	
F statistic	14.390	0.000	14.200	0.000	13.950	0.000	18.090	0.000	17.750	0.000	17.700	0.000
CD test	34.120	0.000	30.280	0.000	27.630	0.000	7.770	0.000	6.810	0.000	5.520	0.000

Note(s): This table reports estimation of robustness check regression with dependent variable:D.LA1TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the first line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to split samples ("before Dec 2012" and "after Dec 2012"). Statistical significance is denoted as * at the 10% level, ** at the 5% level and *** at the 1% level

Table 10. Robustness test: splitting samples, D.LA2TA

Variables	≤ Dec 2012						> Dec 2012					
Dep. Var: D.LA2TA	Model 10a		Model 11a		Model 12a		Model 10b		Model 11b		Model 12b	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run												
LDR	−0.543***	0.025	−0.553***	0.024	−0.554***	0.022	−0.477***	0.024	−0.477***	0.025	−0.495***	0.025
OBS_AST	−0.041	0.058	−0.074	0.051	−0.036	0.042	0.040	0.066	0.012	0.051	−0.019	0.049
Z_SCORE	0.006***	0.001	0.005***	0.001	0.005***	0.001	0.004***	0.001	0.004***	0.001	0.003***	0.001
ASSET_L	−0.001	0.021	0.002	0.019	−0.005	0.021	0.021	0.016	0.026	0.022	0.008	0.025
Short run												
ECT	−0.359***	0.017	−0.417***	0.018	−0.450***	0.018	−0.514***	0.030	−0.596***	0.029	−0.672***	0.029
D.LDR	−0.563***	0.020	−0.563***	0.020	−0.558***	0.019	−0.510***	0.019	−0.512***	0.020	−0.514***	0.020
D.OBS_AST	−0.017	0.018	−0.013	0.019	−0.013	0.019	0.023	0.026	0.016	0.028	0.010	0.026
D.Z_SCORE	0.005***	0.001	0.005***	0.001	0.005***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001
D.ASSET_L	0.040***	0.015	0.038***	0.015	0.042***	0.015	−0.014	0.015	−0.013	0.016	−0.014	0.017
JIBON	0.008	0.021	0.000	0.019	0.016	0.024	0.070*	0.040	0.087**	0.042	0.092*	0.048
D.USDIDR	0.004	0.010	0.001	0.009	0.006	0.009	0.008	0.008	0.006	0.009	0.004	0.008
Trend					0.001	0.000					0.000	0.000
Constant			0.079	0.068	0.582	0.344			−0.103	0.127	0.276	0.315
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Observations	9,996		9,996		9,996		6,720		6,720		6,720	
F statistics	16.990	0.000	16.590	0.000	16.100	0.000	24.770	0.000	24.490	0.000	24.980	0.000
CD test	4.360	0.000	3.350	0.001	3.220	0.001	6.120	0.000	5.930	0.000	5.540	0.000

Note(s): This table reports estimation of robustness check regression with dependent variable:D.LA2TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the first line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to split samples ("before Dec 2012" and "after Dec 2012"). Statistical significance is denoted by * at the 10% level, ** at the 5% level and *** at the 1% level

Table 11. Extended model, D.LA1TA, bank size

Variables	Small						Large					
Dep. Var: D.LA1TA	Model 13		Model 14		Model 15		Model 16		Model 17		Model 18	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run												
LDR	−0.500***	0.032	−0.536***	0.032	−0.543***	0.032	−0.512***	0.053	−0.550***	0.049	−0.576***	0.047
OBS_AST	0.065	0.089	0.092	0.089	0.086	0.080	−0.037	0.053	−0.042	0.041	−0.017	0.050
Z_SCORE	0.005***	0.001	0.006***	0.001	0.005***	0.001	0.009***	0.003	0.010***	0.002	0.011***	0.002
ASSET_L	0.013	0.013	0.021	0.021	0.017	0.021	0.009	0.033	0.023	0.033	0.028	0.046
Short run												
ECT	−0.316***	0.017	−0.351***	0.018	−0.387***	0.019	−0.303***	0.026	−0.339***	0.026	−0.359***	0.025
D.LDR	−0.603***	0.025	−0.606***	0.025	−0.603***	0.025	−0.606***	0.027	−0.613***	0.027	−0.619***	0.025
D.OBS_AST	0.022	0.027	0.026	0.027	0.026	0.028	0.040	0.030	0.035	0.030	0.039	0.030
D.Z_SCORE	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.005***	0.001
D.ASSET_L	0.072***	0.022	0.073***	0.022	0.075***	0.023	0.079***	0.028	0.082***	0.027	0.082***	0.028
JIBON	0.007	0.035	0.025	0.030	0.021	0.032	0.032	0.040	0.022	0.050	0.006	0.046
D.USDIDR	0.002	0.012	0.005	0.012	0.007	0.012	−0.015	0.021	−0.016	0.021	−0.016	0.021
Trend					0.000	0.000					0.000	0.000
Constant			−0.052	0.058	0.245	0.151			0.012	0.107	0.106	0.290
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Observations	12,338		12,338		12,338		4,378		4,378		4,378	
F statistics	24.220	0.000	23.560	0.000	23.190	0.000	20.270	0.000	19.650	0.000	19.000	0.000
CD test	29.850	0.000	27.990	0.000	25.410	0.000	21.130	0.000	19.390	0.000	18.020	0.000

Note(s): This table reports estimation of the extended model: bank size regressions with dependent variable:D.LA1TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the second line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to subsamples based on bank size ("Large" and "Small"). Statistical significance is denoted by *** at the 1% level insignificant. Z_SCORE estimates are significant in the subsample "before Dec 2012" but not in the subsample "after Dec. 2012." In the short-run equation, coefficients for Z_SCORE are identical and highly significant. Estimates of ASSET_L in the short-run equation are higher in the subsample "before Dec 2012." Financial stability variables: JIBON and USDIDR are not significant in either subsample.

5.3.3 Extended model. Using LA1TA as the dependent variable (Table 11), qualitatively, we do not think there is a fundamental difference between ECT coefficients of small banks versus large banks. The ECT estimates are between −0.387 and −0.303 and significant at the 1% level. These estimates correspond to 2.6 months–3.3 months of time response of the equilibrating process. When we replace LA1TA with LA2TA as the dependent variable, different results emerge (Table 12). Now the ECT estimates are slightly higher (in absolute terms) for small banks. The estimates range from −0.339 to −0.279, versus −0.309 to −0.270 for large banks. Adjustment to liquidity shock is slightly quicker in small banks than large banks.

From Tables 13 and 14, we can see that SOE banks have the quickest response in the event of a liquidity shock. For example, using LA1TA as liquidity measure, the ECT estimates are in the range of −0.554 to −0.511 (1.8–2 months shock adjustment) for SOE banks, higher than DEV banks (ranging from −0.385 to −0.331; 2.6–3.0 months shock adjustment) and PRIV banks (−0.372 to −0.321; 2.7–3.1 months shock adjustment). This phenomenon might result from exceptional reputation or credibility that allows SOE banks to obtain or release liquidity more easily. If we replace the dependent variable with LA2TA, we obtain a similar picture.

Long-run estimates of LDR are negative and highly significant irrespective of types and liquidity proxies, consistent with baseline finding. Long-run OBS_AST estimates for SOE banks are all negative and highly significant in regression using narrow liquidity measure. We think this might be caused by different off-balance-sheet business model adopted by SOE compared to the rest of the industry. It seems SOE banks have off-balance-sheet activities geared toward financing customers. Therefore, its behavior closely resembles a pool of funds hypothesis. Z_SCORE long-run equation estimates are positive but significant only for PRIV banks. It seems that the signaling hypothesis is most applicable to DEV banks and PRIV banks.

Aligned with the previous finding, LDR short-run estimates are negative and highly significant, irrespective of bank types and liquidity measures. We find Z_SCORE short-run estimates significant for both DEV banks and PRIV banks, irrespective of liquidity measures. Using narrow liquidity measure, short-run ASSET_L estimates are positive and significant, irrespective of bank types. The role of ASSET_L is largely insignificant when we use broader liquidity measure. We do not find significant role of financial stability variables (JIBON and USDIDR) in any model.

6. Conclusion and policy recommendation

In this study, we collect and synthesize several key insights of recent bank's liquidity management literature from both theoretical and practitioner's perspective. We estimate the empirical model using novel econometric methods: DCCE in ECM format. Below are several key results. First, we find convincing evidence of a time-variant liquidity target and a dynamic adjustment mechanism in liquidity management being practiced in banks. Second, the estimates show that the time needed to adjust to liquidity shock ranges from 1.5 months (= 1/0.67, the highest ECT found in model 12b) to 7.0 months (=1/0.142, the lowest ECT found in model 1). The most common (mode) equilibrating process time is around 2.5–3.5 months. Third, the data support a pool of funds hypothesis driven by intermediation activity. On-balance-sheet intermediation appears much more significant than off-balance-sheet

Table 12. Extended model: D.LA2TA, bank size

Variables	Small						Large					
Dep. Var: D.LA2TA	Model 19		Model 20		Model 21		Model 22		Model 23		Model 24	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run												
LDR	−0.449***	0.027	−0.465***	0.024	−0.464***	0.024	−0.522***	0.043	−0.539***	0.046	−0.552***	0.045
OBS_AST	0.055	0.046	0.014	0.048	0.032	0.046	−0.169***	0.069	−0.163***	0.066	−0.131***	0.065
Z_SCORE	0.004***	0.001	0.005***	0.001	0.004***	0.001	0.006***	0.002	0.006***	0.002	0.006***	0.002
ASSET_L	0.010	0.013	0.016	0.017	0.012	0.017	0.016	0.035	0.023	0.037	0.024	0.041
Short run												
ECT	−0.279***	0.017	−0.310***	0.018	−0.339***	0.019	−0.270***	0.028	−0.294***	0.027	−0.309***	0.026
D.LDR	−0.473***	0.019	−0.474***	0.020	−0.473***	0.020	−0.642***	0.031	−0.644***	0.030	−0.642***	0.029
D.OBS_AST	0.005	0.019	0.001	0.019	0.002	0.019	0.006	0.019	0.005	0.019	0.009	0.019
D.Z_SCORE	0.004***	0.001	0.004***	0.001	0.004***	0.001	0.005***	0.001	0.005***	0.001	0.004***	0.001
D.ASSET_L	0.040**	0.016	0.039**	0.017	0.039**	0.017	−0.013	0.023	−0.011	0.024	−0.011	0.023
JIBON	0.010	0.019	0.015	0.018	0.015	0.018	0.001	0.037	0.002	0.038	0.000	0.039
D.USDIDR	0.010	0.011	0.010	0.011	0.012	0.011	0.019	0.016	0.019	0.016	0.016	0.016
Trend					0.000	0.000					0.000	0.000
Constant			−0.027	0.040	0.058	0.081			0.017	0.061	−0.147	0.164
ECM specifications												
Constant	N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y	
Cross-section average	Y		Y		Y		Y		Y		Y	
Observations	12,338		12,338		12,338		4,378		4,378		4,378	
F statistics	31.450	0.000	30.230	0.000	29.170	0.000	22.680	0.000	21.460	0.000	20.500	0.000
CD test	5.050	0.000	4.990	0.000	4.960	0.000	5.600	0.000	5.260	0.000	4.730	0.000

Note(s): This table reports estimation of the extended model: bank size regressions with dependent variable:D.LA2TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the second line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to subsamples based on bank size ("Large" and "Small"). Statistical significance is denoted by ** at the 5% level and *** at the 1% level

Table 13. Extended model: D.LA1TA, bank types

Variables	SOE						DEV						PRIV					
Dep. Var: D.LA1TA	Model 25		Model 26		Model 27		Model 28		Model 29		Model 30		Model 31		Model 32		Model 33	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run																		
LDR	−0.495***	0.122	−0.569***	0.107	−0.595***	0.119	−0.662***	0.056	−0.697***	0.052	−0.680***	0.054	−0.446***	0.030	−0.477***	0.030	−0.485***	0.029
OBS_AST	−0.075**	0.030	−0.103***	0.003	−0.080***	0.017	0.337***	0.201	0.347***	0.182	0.280*	0.156	−0.034	0.054	−0.004	0.048	0.006	0.049
Z_SCORE	0.001	0.001	0.001	0.001	0.002**	0.001	0.002	0.003	0.004	0.003	0.003	0.003	0.005***	0.001	0.006***	0.001	0.006***	0.001
ASSET_L	0.020	0.019	0.068	0.050	0.071***	0.025	−0.021	0.032	−0.022	0.032	−0.010	0.028	−0.013	0.015	0.012	0.021	0.011	0.022
Short run																		
ECT	−0.511***	0.032	−0.546***	0.035	−0.554***	0.038	−0.331***	0.029	−0.356***	0.029	−0.385***	0.032	−0.321***	0.017	−0.348***	0.017	−0.372***	0.017
D.LDR	−0.561***	0.067	−0.572***	0.067	−0.584***	0.064	−0.641***	0.039	−0.645***	0.040	−0.631***	0.038	−0.589***	0.025	−0.595***	0.025	−0.593***	0.025
D.OBS_AST	0.025	0.036	0.004	0.026	0.011	0.031	0.074	0.054	0.074	0.052	0.076	0.051	0.015	0.018	0.017	0.018	0.017	0.019
D.Z_SCORE	0.001	0.001	0.001	0.001	0.001*	0.001	0.003***	0.001	0.003***	0.001	0.003***	0.001	0.004***	0.001	0.005***	0.001	0.005***	0.001
D.ASSET_L	0.139**	0.060	0.160***	0.051	0.150***	0.054	0.063**	0.029	0.056*	0.031	0.066**	0.030	0.061***	0.024	0.067***	0.024	0.067***	0.024
JIBON	0.007	0.049	−0.021	0.049	−0.023	0.050	0.026	0.032	0.049	0.035	0.039	0.035	0.018	0.034	0.031	0.038	0.037	0.039
D.USDIDR	−0.003	0.022	−0.004	0.024	−0.005	0.025	0.000	0.017	0.004	0.017	0.005	0.017	0.001	0.014	0.001	0.014	0.004	0.014
Trend					0.000	0.000					0.000	0.000					0.000	0.000
Constant			−0.146	0.294	−0.586	0.637			−0.164**	0.079	0.092	0.208			−0.045	0.067	0.237	0.172
ECM specifications																		
Constant	N		Y		Y		N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y		N		N		Y	
Cross-section average	Y		Y		Y		Y		Y		Y		Y		Y		Y	
Observations	796		796		796		5,174		5,174		5,174		10,746		10,746		10,746	
F statistics	30.130	0.000	30.020	0.000	29.050	0.000	40.130	0.000	39.330	0.000	38.540	0.000	18.210	0.000	17.590	0.000	17.090	0.000
CD test	−3.060	0.002	−4.250	0.000	−4.270	0.000	4.850	0.000	3.850	0.000	3.140	0.002	43.780	0.000	41.240	0.000	38.580	0.000

Note(s): This table reports estimation of the extended model: bank type regressions with dependent variable:D.LA1TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the second line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to subsamples based on bank types ("SOE," "DEV" and "PRIV"). Statistical significance is denoted by * at the 10% level, ** at the 5% level and *** at the 1% level

Table 14. Extended model, D.LA2TA, bank types

Variables Dep. Var: D.LA2TA	SOE						DEV						PRIV					
	Model 34		Model 35		Model 36		Model 37		Model 38		Model 39		Model 40		Model 41		Model 42	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Long run																		
LDR	−0.635***	0.112	−0.748***	0.086	−0.750***	0.077	−0.497***	0.045	−0.531***	0.037	−0.507***	0.046	−0.449***	0.028	−0.457***	0.025	−0.459***	0.024
OBS_AST	−0.010	0.075	−0.046	0.099	−0.036	0.100	0.139	0.103	0.081	0.089	0.082	0.084	−0.019	0.041	0.001	0.040	0.008	0.039
Z_SCORE	0.000	0.003	0.001	0.003	0.001	0.002	0.000	0.002	0.001	0.001	0.000	0.001	0.005***	0.001	0.006***	0.001	0.005***	0.001
ASSET_L	−0.068***	0.016	−0.029	0.079	−0.042	0.045	0.001	0.020	−0.011	0.017	−0.007	0.021	−0.008	0.013	0.011	0.020	0.008	0.018
Short run																		
ECT	−0.482***	0.059	−0.511***	0.067	−0.523***	0.068	−0.330***	0.031	−0.364***	0.029	−0.383***	0.031	−0.267***	0.017	−0.316***	0.018	−0.341***	0.019
D.LDR	−0.657***	0.054	−0.672***	0.059	−0.673***	0.058	−0.488***	0.029	−0.493***	0.029	−0.489***	0.029	−0.520***	0.024	−0.517***	0.023	−0.516***	0.023
D.OBS_AST	0.042	0.055	0.017	0.066	0.019	0.067	0.039	0.034	0.035	0.036	0.038	0.035	−0.015	0.013	−0.011	0.014	−0.009	0.014
D.Z_SCORE	0.002*	0.001	0.002	0.001	0.002*	0.001	0.002***	0.001	0.002***	0.001	0.002***	0.001	0.005***	0.001	0.005***	0.001	0.005***	0.001
D.ASSET_L	−0.012	0.040	0.013	0.025	−0.004	0.035	0.038*	0.023	0.032	0.024	0.032	0.024	0.016	0.018	0.020	0.018	0.020	0.018
JIBON	−0.013	0.039	−0.037	0.033	−0.041	0.031	0.000	0.020	0.010	0.022	0.011	0.023	0.007	0.022	0.026	0.023	0.032	0.023
D.USDIDR	0.007	0.018	0.005	0.019	0.007	0.018	0.005	0.010	0.006	0.010	0.006	0.010	0.015	0.013	0.018	0.013	0.019	0.012
Trend					−0.001	0.000					0.000	0.000					0.000	0.000
Constant			−0.301	0.345	−0.885	0.825			−0.067	0.054	0.016	0.084			−0.059	0.053	0.019	0.108
ECM specifications																		
Constant	N		Y		Y		N		Y		Y		N		Y		Y	
Trend	N		N		Y		N		N		Y		N		N		Y	
Cross-section average	Y		Y		Y		Y		Y		Y		Y		Y		Y	
Observations	796		796		796		5,174		5,174		5,174		10,746		10,746		10,746	
F statistics	25.440	0.000	27.370	0.000	26.970	0.000	60.510	0.000	59.460	0.000	56.600	0.000	21.84	0.00	21.44	0.00	20.70	0.00
CD test	−3.450	0.001	−4.450	0.000	−4.870	0.000	−0.860	0.391	−1.330	0.185	−1.270	0.205	5.14	0.00	4.23	0.00	3.84	0.00

Note(s): This table reports estimation of the extended model: bank type regressions with dependent variable:D.LA2TA using the DCCE technique with ECM format. The table presents the estimated coefficients and standard error in each column. Each regression model (denoted by a number in the second line of each column heading) corresponds to specific specifications described by inclusion of constant and/or trend. Estimations are applied to subsamples based on bank types ("SOE," "DEV" and "PRIV"). Statistical significance is denoted by * at the 10% level and *** at the 1% level intermediation. Fourth, we found that banks use liquid assets as a signaling device. The use of liquid assets as a signaling device is more important for large banks and private banks.

The adjustment mechanism takes around 2.5–3.5 months to complete. In our view, it is quite adequate because it is obtained from full data set comprised of both normal and turbulence period. Nevertheless, Basel III recommends that the liquidity coverage ratio provides liquidity protection for up to 30 days. Therefore, further study using our approach to higher frequency data (i.e. daily or weekly) and two states of economy: stable and turbulence is highly desired.

The bank liquidity management mechanism has strong contra-cyclical feature, as shown by large and negative correlation between liquidity measures with LDR. Banks could end up with tight liquidity (under hoarding) in a booming economy, which would pose a severe risk to their financial standing. To mitigate this risk, banks should be encouraged to do more diversification on liquidity management using interbank money market and off-balance-sheet instruments. As our empirical results have shown, the role of both instruments in liquidity management are still inadequate.

Our study shows strong support for the existence of a target liquidity and its equilibrating mechanism. We hope these empirical contributions could encourage scientific endeavor to explain the phenomenon from a (a) theoretical perspective-casted in dynamic setting and (b) more empirical generalization: extensive long panel cross-country study, including both developed and emerging countries.

Notes

1. This paper studies liquidity funding risk – i.e. the inability of a bank to meet cash withdrawals. Another type of liquidity risk is market liquidity risk – i.e. the inability to sell assets at a fair price (Greenbaum *et al.*, 2019). The latter liquidity risk is not our focus.
2. See Pesaran (2015b) for a recent comprehensive textbook on the evolution of panel data econometrics.
3. In this study, we focus only on conventional banks (whose business model is based on the interest rate) and exclude banks that are well known to have inactive intermediation business (i.e. an LDR > 300%).
4. This is not a contradiction, because an (on-balance sheet) asset is realized use of fund, while an off-balance-sheet asset is scheduled or contingent upon event use of fund.
5. We do not report unit root regressions result here for the sake of efficiency. Results are available upon request.

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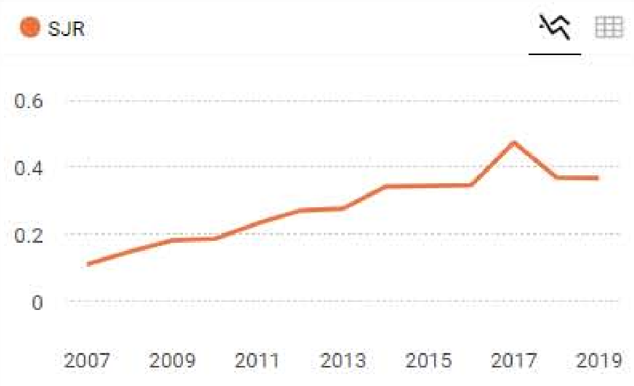

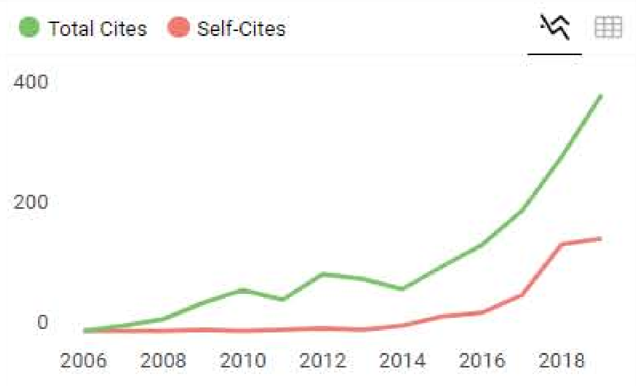

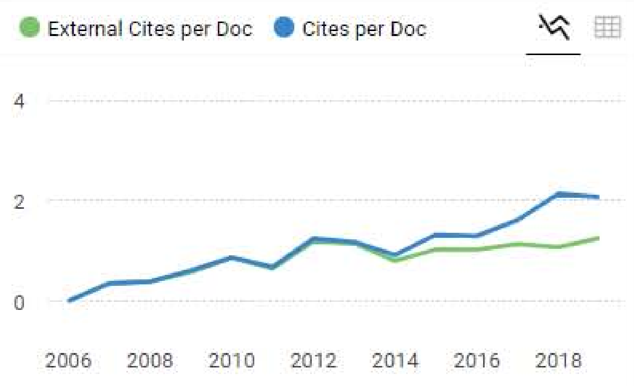

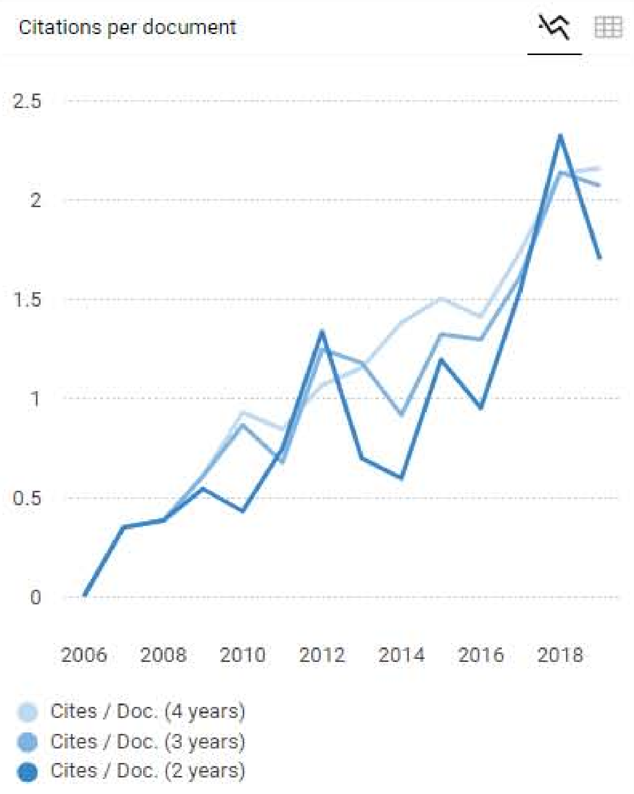

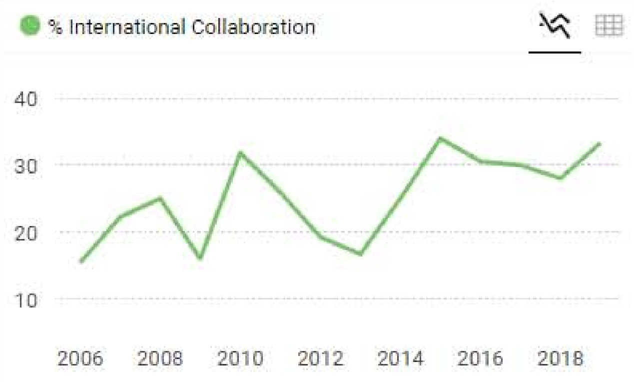

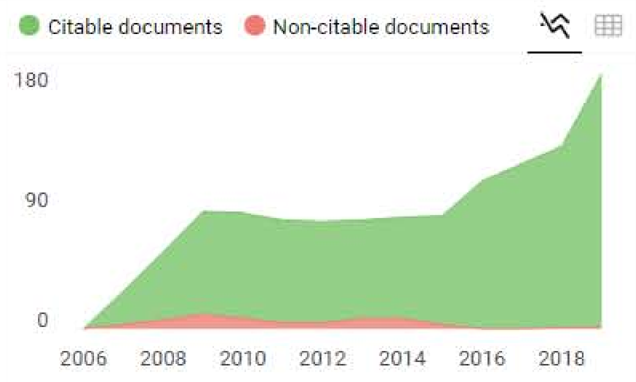

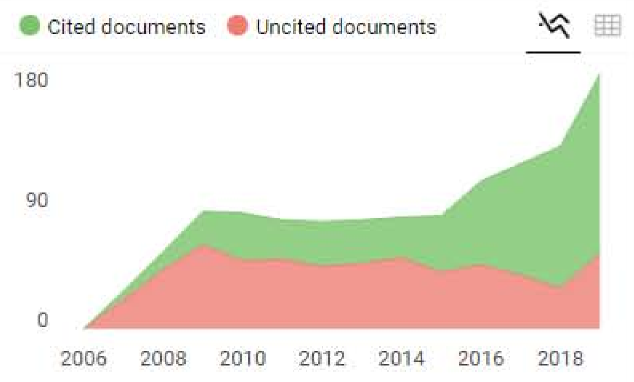

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