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## **Macprudential Liquidity Stress Test: An Application to Indonesian Banks**

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**Abstract:** This paper develops a macroprudential liquidity stress test model for Indonesian banks. Our model incorporates two factors driving liquidity runs: (i) idiosyncratic factors; and (ii) macroeconomic factors. We estimate this model using a sample of 113 banks over the period of January 2011 to June 2018, and dynamic panel data estimators. We establish significant transmission channels from macroeconomic and idiosyncratic (bank idiosyncratic risks) factors to liquidity runs. By using the macroeconomic scenario transmission, we find the liquidity stress test to be more consistent with the solvency stress test.

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**JEL Classification:** G21; G33.

### **1. Introduction**

This paper develops a macroprudential liquidity stress test (LST) model for Indonesian banks. The global financial crisis (GFC) of 2008 shifted attention towards the management of liquidity risks in the financial industry (especially in the banking sector), since many views global liquidity stress as having triggered the financial market meltdown. One major improvement in the global financial regulatory reform for banks is the addition of requirements on liquidity ratios.

Since the crisis, Basel Committee for Bank Supervision (BCBS) has prescribed two relatively new instruments: liquidity coverage ratio (LCR) for short term liquidity needs and net stable funding ratio (NSFR) for structural funding requirement (BCBS, 2013). Although the design of the liquidity ratios incorporates the capacity of banks to face liquidity stress, it has not given any information on how banks should react, when they face the dynamic market-wide stress. This implies, without a clear way of dynamic market-wide stress, the possibility of dry-up of market liquidity, and consequently the loss of values in liquid assets because of fire sale, and the disappearance of contingent credit lines.

In order to assess the financial system resilience, financial authorities use stress tests to measure the loss absorbing capacity of banks in facing various macroeconomic scenarios (Schuermann, 2014). Although various stress tests typically extend to assess the solvency of banks during market-wide and idiosyncratic stress, generating a consistent scenario for all credit, market, and liquidity risks remains a challenge (Schmieder et al, 2012; Melecky and Podpiera, 2012). In most cases, the liquidity stress tests employ scenarios that are independent of the solvency stress tests, which measure credit and market risks. Therefore, it is important to develop a liquidity stress test that does not only gather information on the resilience of the banking system in the presence of both system-wide and idiosyncratic liquidity stress but also implement consistent macro scenarios that are contained in the solvency stress tests.

In addition to the need for a consistent scenario, a stress test should also establish the amplification and propagation mechanisms in order to present a complete picture of the impact of certain macroeconomic developments on the banking system. The impact of a system-wide stress can be easily detected in the first round of impact using the exposure data at the point of impact (*common exposure*) (Clerc et al, 2016). However, as the stress continues, the banking system is not out of the woods yet. Systemic risks may still amplify and propagate through the transmission channels of financial and information linkages (Dang et al, 2015)<sup>1</sup>. In the second round, anything can happen. For instance, a troubled bank may provide additional stress to the other banks (especially if the bank is systemically-important) (Hałaj, 2013). Panicking depositors may exacerbate the stress (Diamond & Dybvig, 1983). Banks may reduce credit that can cause a decline in real sector activities, which may reduce the repayment capacity of debtor corporations (Stiglitz & Weiss, 1981). In defense, banks may start to hoard liquidity, which dries up alternative funding from interbank loans (Heider et al, 2009). Hence, implementing each scenario in a stress test model is a daunting task. In this sense, some degree of effort to capture the impacts from various sources can help authorities assess the banking system's resilience more objectively.

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<sup>1</sup> In Dang et al (2015), they pointed out that the information contained in an asset will affect its price – tail risk. In this paper, we consider systemic risk as tail risk, since it reflects tail risk characteristics.

Our paper takes this seriously when developing a macroprudential liquidity stress test model for Indonesian banks. As mentioned above, a LST becomes very important especially nowadays since the GFC was characterized by global liquidity squeeze that eventually create contagion channels to banking systems all over the world. Most banking problems originate and amplified through liquidity risk (see Tirole, 2011). Banks face two different liquidity risks: funding liquidity risk, since they have to match their long-term assets to long-term liabilities; and market liquidity risk, since they need to be aware of prices, interest rates, and exchange rates that may affect the value of their counterbalancing capacity during a system-wide liquidity stress (Brunnermeier & Pedersen, 2008). Furthermore, they argued that during a system-wide stress, these two types of liquidity risks may reinforce each other. Therefore, it is important to capture both risks in the liquidity stress test, in addition to capturing the reinforcing factors.

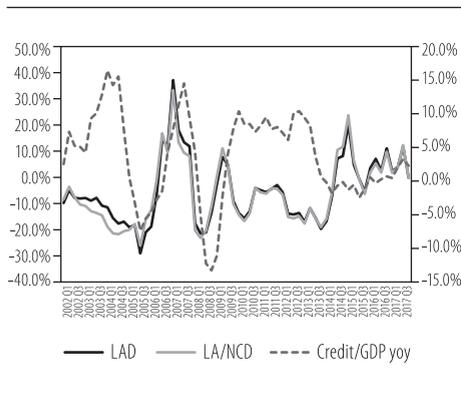
Prior to the GFC 2008, banks or financial authorities conduct LST by mostly focusing on idiosyncratic risks, and generating liquidity shock scenarios that are based on the historical liquidity shocks in the form of deposit withdrawal. This has become the standard liquidity stress test scenario in many central banks or bank supervisors that lead to the design of the liquidity requirement called Liquidity Coverage Ratio (BCBS 2008). Subsequent LSTs incorporate the additional scenario of reduced value of counterbalancing assets, in response to the GFC believed to be triggered by the loss of asset value (Tirole, 2011). Since banks are interconnected, idiosyncratic shocks (or liquidity stress among certain banks) may spillover to the global financial market. For instance, Diamond and Rajan (2005) find that banking crisis can be caused not only by bank runs, but also by contagious banking failure. An LST test that only captures liquidity stress of a certain group of banks—the banks exposed to the subprime mortgage products—ignores the macro-financial environment and global banking interconnectedness (Jobst et al, 2017).

Our paper develops a LST test, which incorporates consistent macroeconomic, idiosyncratic, system-wide, and unknown scenarios. The unknown aspect can be interpreted as the possibility of panic in the market that impacts on the banking system non-linearly. The test is specifically developed for the Indonesian banking system, which mostly practices a traditional banking business, as found in most emerging markets.<sup>2</sup> We employ this test to measure the liquidity-risk-absorbing capacity of the Indonesian banking system in the face of severe but plausible stress test sce-

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<sup>2</sup> Traditional banking business includes only collecting short-term debt and convert it into long-term asset. Non-traditional banking business expands the business to dealing with derivatives, and later explore the use of financial technology (Edwards & Mishkin, 1995, and King, 2018). Other studies on Indonesian banking system include Ashraf et al (2019), Ekananda (2017), Hidayati et al (2017), Ibrahim (2019), Ibrahim and Law (2019), Karim et al (2016), Mulyaningsih et al (2016), Purwono and Yasin (2019), Sakti et al (2018), Sunarmo (2018).

**Figure 1: Liquidity Procyclicality in Indonesian Banking System**



narios, namely GDP growth decline to a value close to Asian Financial Crisis.<sup>3</sup> The resulting insights from our LST can be useful for enhancing the Bank Indonesia's macroprudential liquidity instrument, thereby helping to mitigate system-wide liquidity stress. Macroprudential policy is needed to provide discipline in banking systems with procyclical behavior (Levy-Yeyati, Martinez Peria, and Schmukler, 2010; Cho and Hahm, 2014; Lee, Asuncion, and Kim, 2016; Jung, Kim, and Yang, 2017; Yang and Yi, 2019). The Indonesia banking system is prone to procyclical behavior, and therefore merits our attention (Figure 1).

The LST framework developed in the paper is a part of the overall macroprudential stress test for Indonesian banking system that is initiated in Taruna and Harun (2016a), and continued in Taruna and Harun (2016b), and Taruna and Harun (2017).<sup>4</sup> This LST framework follows the conceptual framework in the previous setup of LST, but increases the consistency of the macro scenario to the solvency stress test by incorporating the impact of the idiosyncratic, macroeconomic variables, and unknown factors to estimate the run-off/haircut for each liquidity instruments.<sup>5</sup> We apply the test to a dataset covering the 113 banks over the period of January 2011 to June 2018 and unravel the following findings. In general, the macroeconomic conditions do not trigger bank run on market liquidity in the short run. In the long term, liquidity runs are largely influenced by combined idiosyncratic and macroeconomic conditions. In terms of funding liquidity risk, the run on customer deposits is heavily triggered by the lagged variables of the deposit portfolios, suggesting a persistent impact of idiosyncratic conditions on liquidity risk. Overall, the run on customer deposits is influenced by banks' idiosyncratic conditions and unknown factors. Macroeconomic conditions do not affect liquidity run within short and medium term. Our results survive a number of robustness tests.

<sup>3</sup> Further explanation on the scenario, please refer to IMF Indonesia FSSA (2017).

<sup>4</sup> The work is inspired by the Bank of Korea's Systemic Risk Assessment for Macroprudential Policy (Seung et al, 2013).

<sup>5</sup> We refer to Schmieder et al (2012) definition on run-off/haircut rates. He defines run-off rates as a portion of bank's liquidity funding which does not rolled over. Whereas haircuts rate is a percentage of capital market assets indicate that it is sold at fire price.

The rest of the paper is organized as follows. Section II outlines the three main liquidity stress tests, explains liquidity testing in Indonesia, and presents some stylized facts about liquidity in the Indonesian banking system. Section III describes the LST model and data. Section IV presents the results. Section V concludes.

## 2. Liquidity Stress Tests and Stylized Facts

### 2.1 Liquidity Stress Tests

Basel Committee for Banking Supervision (BCBS, 2013) classifies stress testing into three groups, namely bottom up macro test, top down, and combined approaches. The bottom up stress test is usually carried out by financial institutions using scenarios or assumptions instructed by the authority. It may also be performed by authorities and consists of regular liquidity risk reports and occasional horizontal exercised using common stress assumptions. Top down stress test is regularly performed by authorities to measure the banking system resilience. One way to assess top down stress test is using balance sheet data. Scenario shocks are manifested through haircuts on assets and run-off rates of liabilities applied to balance sheet positions. According to BCBS (2013), this method is able to identify the source of individual vulnerabilities yet backward-looking, static, and limited to the first-round of impact of liquidity stress. Beside the balance sheet approach, several central banks employ a top-down approach with the methodology varying from basic simulation to a more complex integrated framework. The combined approach typically incorporates second-round effects into liquidity stress tests by adding behavioral reactions into a bottom-up stress test design. The benefit of the combined test is that it allows a cash-flow rather than a stock approach and weigh market liquidity shocks against the counterbalancing capacity (see BCBS, 2003).

We explored the practices of LST in several central banks and financial authority, including China, European Union, Italy, Japan, Brazil, Sweden, the Netherlands, Austria, Canada and England, and find that, although most of them have the same objective of producing a measurement of liquidity risk of the banking system, the results of the test vary.<sup>6</sup>

### 2.2. Liquidity Risk Measurements in Indonesia

Indonesia complied with the BASEL III requirements for the implementation of liquidity coverage ratio (LCR), and net stable funding ratio (NSFR) (BCBS 2013a & BCBS 2016). These ratios together with other liquidity indicators (e.g. the ratio of liq-

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<sup>6</sup> References for the practices of LST in these countries are listed in the bibliography.

uid asset to total asset) are used to measure liquidity risk in the banking system. To ensure bank resilience against liquidity risk, Bank Indonesia performs the Granular (bottom up) Liquidity Stress Test (GLST) to assess individual bank liquidity.<sup>7</sup> GLST is calculated using data from banks regulatory reports such as balance sheet, and other information such as on-site bank examination.<sup>8</sup> Scenarios used must be extreme but plausible (IMF, 2015). The scenarios employed are idiosyncratic stemming from liquidity pressure within the internal bank and system-wide stress stemming from global and domestic shocks. The methodology employed is cash-flow based analysis with three distinct components: counterbalancing, inflow, and outflow (IMF, 2017). This analysis assesses banks resilience based on the net cash balance after funding outflow shocks in two currencies—Indonesian rupiah and foreign currency (e.g. US dollar) and in several time buckets.

Based on the GLST, a bank is experiencing a liquidity shortfall when there is any threshold exceeded in any time bucket calculations in both rupiah and foreign currency. The GLST uses two difference scenarios, (i) idiosyncratic risk; and (ii) market-wide stress. In idiosyncratic scenario, GLST estimates run-off/haircut rates on each liquidity instrument by estimating a percentile 5% of historical data. The rates will indicate the stress condition which is unique to each bank. Different from idiosyncratic scenario, market-wide stress defined as a stress that cause a huge loss to bank's counterbalancing capacity and worse liquidity run. In order to create this scenario, the GLST approaches two risk channels, which are: (i) Capital markets (counterbalancing instruments) run, which is reflected by increase in run-off/haircut rate<sup>9</sup>; and (ii) government bond price drop, which is calculated based on two approaches.<sup>10</sup>

Similar to other balance sheet approaches, the GLST is able to reveal individual vulnerabilities based on their historical performance, and yet it fails to directly connect with the macroeconomic state (author's interpretation on Cihak 2007, Basel, 2013a, & Jobst, 2017).<sup>11</sup> We are also aware that individual vulnerabilities may have noth-

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<sup>7</sup> Granular ST is a form of top-down ST which enriched by using individual bank data. The data tries to capture bank specific behavior by combining bank's individual model with financial authority view on the bank. Further information please contact Financial System Surveilans Department (widi, email: Wahyu\_w@bi.go.id).

<sup>8</sup> Please see footnote no 7 (above).

<sup>9</sup> The rates are calculated using tail-risk of DSIB (domestic systemically important bank) run-off/haircut rates which calculated using past historical data. The rates are estimated to replicate Global Financial Crisis effect to liquidity run in Indonesia banking system. The approach is applied to all banks (see footnote no. 7).

<sup>10</sup> The Mathematical expression of both approaches are in the appendix.

<sup>11</sup> The common practice in liquidity stress is using historical highest run-off/haircuts rate as the stress scenario. While the rates might be the result, but in stress testing framework, it is hard to explain which macroeconomic scenario caused the rates.

ing to do with the system-wide condition, so it can generate either too mild or too severe scenario for the particular banks during system-wide stress. The focus of this paper is to make improvements in terms of the transmission of the macroeconomic scenario toward the liquidity shock. This improvement is very important to conduct the macroprudential surveillance and help in calibrating any macroprudential buffer before a shock happens.

### 2.3. Stylized Facts of Indonesian Banking System

Harun et al (2016) point out the existence of liquidity procyclicality in the Indonesian banking system. Figure 1 is an illustration of liquidity procyclicality in the Indonesian banking system. The ratio of liquid asset to non-core deposits and the ratio of liquid asset to deposits, which serve as the proxy of Indonesian banking liquidity, move in opposite direction with the ratio of credit to gross domestic product (GDP), which serves as the proxy of economic performance. This means when the economy is doing well, banking liquidity is decreasing, indicating the shift in banks' preference towards lending in order to generate bigger profits. That is, during such times, most banks believe the market is able to supply banks liquidity at reasonable interest rates. Duijm and Wiert (2014) find similar liquidity procyclicality in the Netherland.

## 3. Model and Data

### 3.1. Model

We argue that macroeconomics conditions, together with idiosyncratic factors contribute to liquidity runs. Hence, model liquidity runs function of macroeconomic and idiosyncratic factors in an ARDL specification. The specification is as follows:

$$y_{i,t} = \alpha_i + \sum_{n=0}^L \beta_{i,n,z} X_{i,t-n,z} + \sum_{n=1}^L \gamma_{i,n} y_{i,t-n} + \sum_{n=1}^L \vartheta_{i,n} CAR_{i,t-n} \varepsilon_{i,t} \quad (1)$$

where  $y_{i,t}$  is month-to-month rates of liquidity instrument for each bank,  $i$  and time  $t$ ;  $\alpha_i$  is fixed-effect coefficient;  $\beta_z$  is the coefficient of the macroeconomic variables;  $CAR$  is capital adequacy ratio;  $X_{i,t-n,z}$  is the vector of macroeconomic variables;  $z$  denotes GDP and CPI;  $\gamma_i$  is the coefficients of the lagged liquidity instrument;  $y_{i,t-n}$  lagged month-to-month rates of liquidity instrument;  $L$  is the maximum lags in the model; and  $\varepsilon_{i,t}$  is the residual for each  $i$  and  $t$ .

We use three different maximum lags: no lag, up to 6 months, and from 6 to 12 months to represent contemporaneous or short-term, medium-term and long-term

phases. We presume within the shorter term that most runs are caused by idiosyncratic and unknown factors, while macroeconomic conditions should have the biggest impact to cause a persistent liquidity run. The idiosyncratic factors are captured by the lagged dependent variable, macroeconomic variables reflect system-wide factors, and residual reflect the unknown factors. We control for other conditions using capital adequacy ratios (CAR). CAR is suitable because it captures liquidity interaction with the triggering factors. What we meant by triggering factors here are all the changes in the macro variables that may have impacts to the liquidity ratios. We do not use any liquidity ratios as control variables because most liquidity instruments are strongly correlated with the dependent variable.

### 3.2. Data

Based on the structure of the money market of Indonesia and according to the characteristic of HQLA (BCBS 2013a), we use the following liquidity instruments: Corp bond rated AA- (both Rupiah and foreign currency) run-off rates; Corp bond rated A+ to BBB (both Rupiah and foreign currency) run-off rates. For customer deposits, we used the classification in practice. They are: (i) depositor: individual, non-financial agent entities, non-residence, government, other financial institution, and inter-bank; (ii) currency denominations: Rupiah and foreign exchange (as a total nominal of available foreign currency deposit in Indonesia); (iii) guaranteed by Indonesia Deposit Insurance Company: insured and uninsured; (iv) time horizons: within 1 day, within 1 month, within 3 months, within 6 months, and beyond 6 months. Government securities are excluded because they are stable and backed by the government. Unless the issuer, government, defaulted, then the securities are secured. In addition, it is common that Bank Indonesia's open market operation uses government securities to influence market liquidity, thereby making the price biased. MBS and other securities are excluded due to their small outstanding value.

All bank data are taken from monthly bank reports. The data sample ranges from January 2011 to June 2018 and includes 113 banks. In total, we used four liquidity instruments from counterbalancing (high-quality liquid assets, HQLA) and 18 instruments from customer deposits, and therefore we run 22 panel data regressions. We used yearly GDP growth and inflation rate to measure macroeconomic conditions, as suggested by Drehmaan and Juselius (2013). All macroeconomic data are from CEIC database. We interpolated the data from quarterly basis into monthly basis in order to match the bank data.

## 4. Results

### 4.1. Baseline Results

We are mainly interested in what triggers a liquidity run. Hence, we only focus on the statistical significance level of each triggering factor. We do not report the coefficients of the variables, since whether they are large or small is irrelevant, as long as they are significant, and therefore impact on liquidity runs.

Table 1 shows all the significant variables in the HQLA equation. The results suggest that macroeconomic conditions (CPI), and the conditioning factor, CAR, influence changes in run-off/haircut rates in the short term. In the medium term, CPI and lagged liquidity (or idiosyncratic factors) affect changes in run-off/haircut rates. In the long term, changes in run-off/haircut rates are determined by idiosyncratic factors and macroeconomic conditions (CPI and GDP). Here, we find that macroeconomic conditions trigger run on liquidity in short term, which is counterintuitive with the our expectation that macroeconomic conditions would take effect more in the long run rather than in the short run, since macroeconomic variables usually deliver a lagged effect

**Table 1: Results of HQLA Panel Estimation**

	Short term	Medium term	Long term
Lagged y	0	3	3
CPI	1	1	2
GDP	0	0	2
CAR	2	0	0

Similar to the HQLA estimates, run on customer deposits are mostly affected by idiosyncratic factors and unknown factors.<sup>12</sup> From all estimation periods, macroeconomic conditions only trigger run on liquidity in the long term. Table 2 shows that that macroeconomic conditions influence liquidity runs in the short, medium, and long term. However, the coefficient estimates suggest that the influence of macroeconomic conditions on liquidity runs depends on the deposit portfolios. Unknown factors (herding behavior, reference bias, and narrative) tend to influence customer runs on bank's liquidity in short and medium term. Table 2 further suggest that idiosyncratic factors (captured by the lags of liquidity instruments) largely influence liquidity runs.

<sup>12</sup> We do not run the set of customer deposit regressions with the breakdown of unknown factors since without the unknown factors, the result already showed only a few of the deposit portfolios were affected by macroeconomic and idiosyncratic variables.

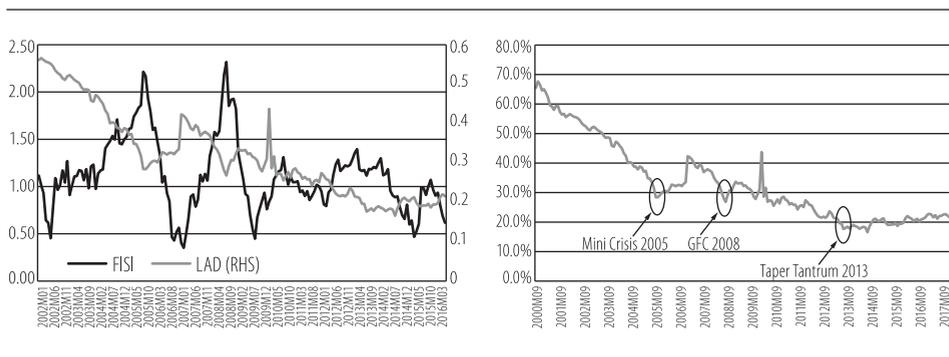
**Table 2. Customer Deposits Estimation Result**

	short	medium	long
CPI	4	4	8
GDP	5	4	4
CAR	1	1	2
Lagged	11	9	7

Historically, when a financial distress occurs, bank’s liquidity also experienced distress (Tirole 2011). Based on the results, liquidity distress is not only caused by macroeconomic conditions. It can be triggered by the idiosyncratic conditions and other unknown factors. Our findings are supported by previous research, for example, Tabak et al (2012), Gauthier et al (2014), and Wong & Hui (2009).

Figure 2 shows that when financial distress occurs (as a proxy by Bank Indonesia’s Financial Institution Stability Index), liquidity distress subsequently occurs (reflected by Liquid Asset to Deposit or LAD ratio). In all three cases of financial distress post-Asian Financial Crisis, the LAD ratio dropped. This confirms the propagation and amplification of financial distress through the liquidity distress channel.

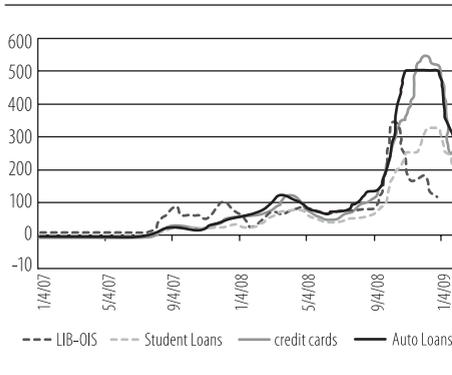
**Figure 2. Liquidity Distress Period in Indonesia**



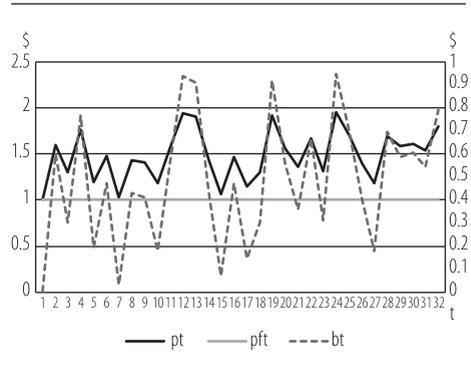
Other research that confirm our findings. Gorton and Metrick (2009a, 2009b, & 2012) point out that during the GFC, while mortgage-backed securities (MBS) suffered only 21 basis points of losses, they impact on the repurchase agreement (Repo) markets. The failure of Lehmann Brothers affected not only MBS but also other securities as can be seen as unknown factor in the liquidity run in Figure 3.

Barberis (2011) argues that wealth loss expectation triggered the runs leading to the GFC. This wealth loss expectation is interpreted as the unknown factor to the bank’s liquidity run in Figure 4, as shown by bt - bt stands for bubble price. Bubble price could mean possible wealth loss. It typically difficult to determine the triggering

**Figure 3. The Unknown Factor in the Liquidity Run**



**Figure 4. Bubble price and wealth expectation**



factors of a liquidity run happen. While liquidity stress testing frameworks can help financial authorities to grasp banks’ counterbalancing capacity, the authorities still have to consider worse scenarios. Furthermore, the tests may under/overestimate the loss and may cause irrelevant policy responses.<sup>13</sup>

**4.2. Further Analysis of HQLA**

The HQLA analysis can be classified into two categories: safe assets and investment grade assets. Corporate bonds with AA- rate fall into safe assets, whereas corporate bond with A+ to BBB are investment grade assets. Gorton and Metrick (2012) explain that safe assets and investment grade assets are information insensitive, which means investors do not require more information to value the price of these assets. These bonds should be stable over time. That is, unless there is a huge shock to the financial system, the value of these bonds does not change.

Looking at the results in Table 3, safe assets and investment grade bonds are unaffected by macroeconomic conditions. This is line with their characteristic—unless investors are required to put in effort to assess these assets, their value should stay the same. In the short and medium terms, run on these types of bonds is caused by unknown factors. If the financial turmoil lasts longer than 6 months, macroeconomic conditions make the liquidity run worse. If the financial turmoil persists, investors feel less confident about their investment prospect and fire sale their assets further, making the liquidity run worse.

<sup>13</sup> Lucas’s critique on how statistical estimations based on historical data may not be able to capture current conditions (Lucas, 1976).

**Table 3. HQLA Instrument Estimation Results**

Corp bond AA- Rp mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	t0	-	-9
GDP	-	-	-
CAR	-	-	-7,-9,-11,-12
Lagged	-	-	-
Corp bond AA- FX mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-3	-9
GDP	-	-	-4,-6,-7,-10,-11
CAR	-	-	-
Lagged	-	-1,-2,-4	-3
Corp bond A+ to BBB- Rp mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-	-
GDP	-	-	-
CAR	t0	-	-
Lagged	-1	-1,-2,-4,-5	-1,-2,-4,-7
Corp bond A+ to BBB- FX mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-	-
GDP	-	-	-4,-5,-6
CAR	t0	-	-
Lagged	-	-1,-2	-1,-2,-6,-12

### 4.3. Further Customer Deposit Analysis

Table 4 shows results for customer deposits regressions. The estimates for the customer deposit instruments are similar to HQLA estimates (see Table 3). Increasing claim on customer deposits are highly affected by the bank conditions (idiosyncratic factors) and other unknown factors. Macroeconomic conditions may worsen run on certain customer deposits (e.g. deposit sourced from interbank placement), although these conditions may not broadly influence liquidity run on customer deposits. As mentioned in the previous section, regardless of whether bonds are classified as

safe assets or investment grade bonds, run on HQLA might happen due to panic arising in the financial system and expectation of wealth loss.

When comparing local currency and foreign denominated customer deposit, we find that Rupiah denominated deposits are more susceptible to unknown factors. Historically, when a financial turmoil occurs, investors tend to buy foreign currency thereby pushing down the Rupiah value (Iriana & Sjolholm, 2002, and Hill, 2012). Arguably this investor behavior is embedded in the unknown factors. The triggering factors in corporate deposits, both Rupiah and foreign denominated, are the idiosyncratic conditions and unknown factors (Table 4). Similar to HQLA, macroeconomic conditions may worsen the run if the financial turmoil last more than 6 months (Table 4).

**Table 4. Selected Customer Deposits Estimation Results**

Interbank within 1 Mo Rp mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)	Interbank within 1 Mo FX mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-	-	CPI	t0	-4	-1,-2
GDP	-	-	-	GDP	-	-	-
CAR	-	-	-	CAR	-	-	-
Lagged	-	-	-	Lagged	-1	-1 to -6	-1 to -12

Interbank within 6 Mos Rp mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)	Interbank within 6 Mos FX mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-	-	CPI	-	-	-9,-11,-12
GDP	-	-	-7,-8,-9	GDP	t0	-	-
CAR	-	-	-	CAR	-	-	-
Lagged	-	-	-	Lagged	-1	-1 to -3,-5,-6	-1 to -3,-5 to -9,-11,-12

Corp deposit Rp insured mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)	Corp deposit FX insured mtm rate	Short Term (coincide w/ shock)	Medium Term (till 6 month)	Long Term (till 1 year)
CPI	-	-	-1	CPI	-	-3,-4	-3,-4,-8
GDP	-	-	-	GDP	-	-	-5
CAR	-	-1	-1,-3,-4,-6,-12	CAR	-	-	-
Lagged	-1	-1,-3,-4,-6	-1 to -9, -11,-12	Lagged	-1	-1,-5	-1,-5,-9 to -12

#### 4.4. Triggering Effect

Bagehot (as summarized by Goodhart, 1999, and Tucker, 2019) and former US Treasury Secretary Tim Geithner (2009) argue that the financial system should be flooded with liquidity during financial crisis. According to them, the source of liquidity is irrelevant, as long as it can shorten the liquidity run and calm the unknown factors circulating in the system. During the Great Depression, liquidity run occurred in the US repo market and subsequently trigger run in banking sector (Gorton & Metrick, 2009a).<sup>14</sup> Some banks experienced run although they were solvent. The loss of confidence caused investors to claim their deposit immediately (Gorton & Metrick, 2009b, Eichengreen, 2016, and Schmidt et al, 2016).

Our findings generally confirm that unknown factors, which can be expressed by fear of losing wealth and market perception of financial conditions are the primary triggering factors of a liquidity run. Macroeconomic conditions can worsen the run, if the financial crisis persists. These mechanisms should be considered when financial authorities are assessing the probability of a run, especially in doing liquidity stress testing.

#### 4.5. The existence of unknown factors in the linear regression

To check our hypothesis on liquidity risk triggering factors, we exercise several robustness checks to the model. The exercise was also done to check the existence of unknown factor in the system.

In theory, when we use residual as a regressor, we should get a perfect  $R^2$  and a residual coefficient equal to 1. The reason is as follows:

Suppose we have an equation of  $y = \alpha + \beta x + \varepsilon$ , where  $\varepsilon$  is the residual.

Now, we take  $\varepsilon$  and use it as another regressor:

$$y = \alpha + \beta x + \gamma \varepsilon.$$

Since  $\varepsilon$  is the residual in the first regression, we know that setting  $\gamma$  to 1 will give zero errors in the second regression.

Table 5 shows a simple OLS regression of a liquidity instrument. The dependent variable is a corporate bond rated AA- haircut rate (monthly change of its price).

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<sup>14</sup> To distinguish Global Financial Crisis with the Great Recession (stock market crisis) in 1930, scholar nicknamed it as Great Depression.

**Table 5. An Example of OLS Regression Residual Coefficient Value**

Dependent Variable: DAAMINRP				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.91	5.76	-2.24	0.03
CAR	0.28	0.13	2.18	0.03
GDP	1.18	0.60	1.97	0.05
CPI	0.29	0.10	2.83	0.01
DAAMINRP(-1)	-0.14	0.11	-1.26	0.21

Statistics			
R-squared	0.11	Mean dependent var	0.18
Adjusted R-squared	0.06	S.D. dependent var	1.36
S.E. of regression	1.32	Akaike info criterion	3.45
Sum squared resid	137.36	Schwarz criterion	3.59
Log likelihood	-139.85	Hannan-Quinn criter.	3.51
F-statistic	2.35	Durbin-Watson stat	1.97
Prob(F-statistic)	0.06		

The residual consists of all other unobserved (unknown) factor that can explain the dependent variable. Let  $\epsilon$  be RESIDTRUE, we have a new estimation result:

**Table 6. Residual as Regressor**

Dependent Variable: DAAMINRP				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.91	0.00	-108E+8	0.00
CAR	0.28	0.00	105E+8	0.00
GDP	1.18	0.00	95E+8	0.00
CPI	0.29	0.00	137E+8	0.00
DAAMINRP(-1)	-0.14	0.00	-609E+7	0.00
RESIDTRUE	1.00	0.00	430E+8	

Statistics			
R-squared	1	Mean dependent var	0.18
Adjusted R-squared	1	S.D. dependent var	1.36
S.E. of regression	0	Akaike info criterion	-41.14
Sum squared resid	0	Schwarz criterion	-40.96
Log likelihood	1733.77	Hannan-Quinn criter.	-41.07
F-statistic	413E+18	Durbin-Watson stat	1.98
Prob(F-statistic)	0.00		

As shown by Table 6, the residual coefficient is equal to 1. This estimation result is true to the theoretical approach on ordinary least square.

#### 4.6. Unknown factors in liquidity instruments

The second HQLA estimation, using residual as a regressor, we got a residual coefficient which was not equal to 1. As previously mentioned, the residual coefficient should be 1 when we use it as a regressor. Based on this contradiction fact, we did several test to check if the estimation result were correct, which are:

- Check all the residual data quality, this includes sample period, re-extracting the residual from each estimation;
- Re-estimate the regression using residual as a regressor. This process involves:
  - Using exactly the same model with the model that did not include the residual;
  - Using the same sample period with the model without the residual;
  - Using regressor which mirror the model without the residual.

All robustness checks indicated that the unknown factor had an impact to the change in liquidity instruments, the coefficient of all residuals did not equal to 1 (as shown by Table 7). One possibility than can create this condition is that the regressions re-estimate the fixed effect coefficient which represents the idiosyncrasy of each bank, thus treat the residual as a new variable instead of just residual. While this finding did not satisfy the original claim, this finding points that the existence of unknown driving factors that may influence the estimation via the dynamics with the idiosyncrasy of each bank.

**Table 7. Robustness Check Using Different Set-ups**

Dependent Variable: DAAMINRP				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.84	5.98	-2.32	0.02
CAR	0.29	0.13	2.23	0.03
GDP	1.25	0.62	2.02	0.05
CPI	0.33	0.11	3.02	0.00
DAAMINRP(-1)	-0.17	0.11	-1.45	0.15
RESIDUAL	-0.24	0.12	-2.10	0.04
Statistics				
R-squared	0.16	Mean dependent var	0.20	
Adjusted R-squared	0.10	S.D. dependent var	1.41	
S.E. of regression	1.34	Akaike info criterion	3.49	
Sum squared resid	129.00	Schwarz criterion	3.68	
Log likelihood	-130.30	Hannan-Quinn criter.	3.57	
F-statistic	2.71	Durbin-Watson stat	2.07	
Prob(F-statistic)	0.03			

## 5. Conclusion

The LST framework plays a huge role in assessing the conditions of banks. At present, the test is run separately from solvency stress test. While, an island-by-island run test may be proper when the policymaker is interest in specific conditions of banks (e.g. liquidity), it does not provide a complete picture of the general development in the banking system.

We provide a more complete framework for assessing the banking system by integrating solvency and liquidity tests. Specifically, we expand the standard LST to capture the impact of the idiosyncratic, macroeconomic, and unknown factors on haircuts/run-off rates. Within our LST framework, the impact of these conditions is transmitted dynamically. We show that both idiosyncratic and macroeconomic conditions influence run-off/haircut rates. In the short run, the macroeconomic conditions do not trigger run on liquidity. By incorporating the unknown factors—(interpreted as herding behavior, reference bias and narrative) — we find that macroeconomic conditions affect the run-off of corporate bonds with higher rating. In the medium term, unknown factors drive the run-off of foreign currency denominated corporate bonds, whereas, in the long term, most liquidity runs are influenced by idiosyncratic and macroeconomic conditions. In addition, we show that run on customer deposits is heavily triggered by the idiosyncratic and unknown factors. Macroeconomic conditions do affect run on customer deposits within the short and medium terms; but this is contingent on the type of instruments.

Our findings imply that financial authorities should consider unknown factors, when assessing the soundness of banking systems. Idiosyncratic and macroeconomic factors are very important and should be used as leading indicators of liquidity runs.

## References

1. Adrian and Shin. (2007). Financial System and Macroeconomic Resilience, Liquidity and Financial Cycles. 6th BIS Annual Conference, June 2007, Brunnen.
2. Ashraf, A., Hassan, M., Putnam, K., Turunen-Red, A., (2019) Prudential regulatory regimes, accounting standards, and earnings management in the banking industry, *Bulletin of Monetary Economics and Banking*, 21, 367-394.
3. Barberis, Nicolas. (2011). Psychology and the Financial Crisis of 2007-2008. Michael Haliassos ed., MIT Press, 2013.
4. \_\_\_\_\_. (2018). Psychology-based Models of Asset Prices and Trading Volume. *Handbook of Behavioral Economics*.
5. Basel Committee for Bank Supervision (2008). Principles for Sound Liquidity Risk Management and Supervision. Bank for International Settlements Working Paper, September.
6. \_\_\_\_\_. (2013a). Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools. Bank for International Settlements, January
7. \_\_\_\_\_. (2013b). Liquidity Stress Testing: A Survey of Theory, Empirics and Current Industry and Supervisory Practices. Bank for International Settlements Working Paper, No. 24, October.
8. \_\_\_\_\_. (2014). Basel III: The Net Stable Funding Ratio. Bank for International Settlements Working Paper, October.
9. \_\_\_\_\_. (2016). Regulatory Consistency Assessment Programme (RCAP): Assessment of Basel III LCR regulations – Indonesia. Basel Committee on Banking Supervision.
10. Blancer, Nicolas, Mitra, Srobona., Morsy, Hanan., Otani, Akira., Severo, Tiago., & Valderrama, Laura. (2013). Systemic Risk Monitoring (“SysMo”) Toolkit – A User Guide. *IMF Working Paper*, July.
11. Breuer, Thomas, Jandačka, Martin, Rheinberger, Klaus, & Summer, Martin. (2009). How to Find Plausible, Severe, and Useful Stress Scenario. *International Journal of Central Banking*, September.
12. Brunnermeier, M. K., & Pedersen, L.H. (2008). Market Liquidity and Funding Liquidity. *The Review of Financial Studies*, 22 (6) : 2201–2238.
13. Borio, Claudio. (2009). Ten Propositions about Liquidity Crises. *BIS Working Papers*: 293.
14. Clerc, Laurent, Giovannini, Alberto, Langfield, Sam, Peltonen, Portes, Richard, & Scheicher, Martin. (2016). Indirect Contagion: The Policy Problem. European Systemic Risk Board Occasional Paper Series.
15. Cho, S., & Hahm, J. H. (2014). Foreign Currency Noncore Bank Liabilities and Macroprudential Levy in Korea. *Emerging Markets Finance and Trade*, 50(6), 5-18.
16. Čihák, Martin. (2007). Introduction to Applied Stress Test. *IMF Working Paper* WP/07/59.

17. Dang, Tri Vi, Gorton, Gary, & Holmström, Bengt. (2015). The Information Insensitivity of Security. *Columbia University Working Paper*. Deutsche Bank. (2016), Annual report 2016.
18. De Bandt, Oliver., & Hartmann, Philipp. (2000). Systemic Risk: A Survey. *European Central Bank Working Paper* No. 35, November.
19. Drehmann, Mathias & Juselius, Mikael (2013) Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements. *Bank for International Settlement Working Paper*.
20. Diamond, Douglas W. & Dybvig, Philip H. (1983) Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, Vol. 91, No. 3, June, pp. 401-419.
21. Diamond, Douglas W. & Rajan, Raghuram (2001). Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking. *Journal of Political Economy*, Vol. 109, No. 2 (April 2001), pp. 287-327.
22. \_\_\_\_ (2005). Liquidity Shortage and Banking Crises. *The Journal of Finance*, Vol. LX, No. 2 (April 2005), pp. 615 – 647.
23. Duijm, Patty, & Wierds, Peter. (2014). The Effects of Liquidity Regulation on Bank Assets and Liabilities. *Duisenberg School of finance - Tinbergen Institute Discussion Paper*
24. Edwards, Franklin R., & Mishkin, Frederic S. (1995). The Decline of Traditional Banking: Implications for Financial Stability and Regulatory Policy. *NBER Working Paper Series*.
25. Eichengreen, Barry. (2016). Hall of Mirrors: The Great Depression, the Great Recession, and the Uses-and Misuses-of History. Oxford University Press; Reprint edition (October 1, 2016).
26. Ekananda, M., (2017) Macroeconomic condition and banking industry performance in Indonesia, *Bulletin of Monetary Economics and Banking*, 20, 71-98.
27. European Central Bank. (2008). EU Banks' Liquidity Testing and Contingency Funding Plans. November.
28. Gauthier, C., Souissi, M., & Liu, X. (2014). Introducing Funding Liquidity Risk in A Macro Stress-testing Framework. *International Journal of Central Banking*, 10(4), 105-141.
29. Geithner, Timothy F. Final Written Testimony on Global Financial Crisis. Testimony to House of Financial Services Committee.
30. Goodhart, Charles. (1999). Myths about the Lender of the Last Resort. *International Finance* 2:3, pp. 339-60.
31. Gorton, Gary & Metrick, Andrew. (2009a). Haircut. National Bureau of Economic Research Working Paper Series.
32. Gorton, Gary & Metrick, Andrew. (2009b). Securitized Banking and the Run on Repo. National Bureau of Economic Research Working Paper Series.
33. \_\_\_\_ (2012). Getting up to Speed on the Financial Crisis: A One-Weekend-Reader's Guide. NBER Working Paper No. 17778.

34. \_\_\_\_ (2018). Global Financial Crisis and Capital Markets. Yale School of Management Lecture Material.
35. Hałaj, Grzegorz, & Kok, Christoffer. (2013). Assessing Interbank Contagion Using Simulated Networks. European Central Bank Working Paper.
36. Harun, Cicilia A., Wijayanti, Rani., Rachmanira, Sagita., & Nattan, R. Renanda., (2016). Macroprudential Liquidity Instrument: The Case of Indonesia. Bank Indonesia Working Paper, September.
37. Heider, Florian, & Hoerova, Marie. (2009). Interbank Lending, Credit Risk Premia and Collateral. *International Journal of Central Banking*, Vol. 5, pp. 1-39
38. Hidayati, N., Siregar, H., Pasaribu, S., (2017) Determinant of efficiency of the Islamic banking in Indonesia, *Bulletin of Monetary Economics and Banking*, 20, 29-48.
39. Hill, Hal. (2012). The Best of Times and the Worst of Times: Indonesia and Economic Crises. Australia National University Working Paper in Trade and Development No. 2012/13.
40. Ibrahim, M., (2019) Capital regulation and Islamic banking performance: A panel evidence, *Bulletin of Monetary Economics and Banking*, 22, 47-68.
41. Ibrahim, M.H., and Law, S.H., (2019) Financial intermediation costs in a dual banking system: The role of Islamic banking, *Bulletin of Monetary Economics and Banking*, 22, 531-552.
42. International Monetary Fund. (2014). Bank Size and Systemic Risk. IMF Staff Discussion Note SDN 14/04, May.
43. \_\_\_\_ (2017). Indoensia: Financial System Stability Assessment — Press Release and Statement by the Executive Director for Indonesia. IMF Country Report No. 17/152.
44. Iriana, Reiny, & Sjolholm, Fredrik. (2002). Indonesia's Economic Crisis: Contagion and Fundamentals. *The Developin Economics*, XL-2 (June 2002): 135-51.
45. Jobst, Andreas A., Ong, Li Lian, & Schmieder, Christian. (2017). Macroprudential Liquidity Stress Testing in FSAPs for Systemically Important Financial Systems. IMF Working Paper.
46. Jung, Y., Kim, S., & Yang, D. Y. (2017). Optimal macroprudential policies and house prices in Korea. *Emerging Markets Finance and Trade*, 53(11), 2419-2439.
47. Karim, N., Al-Habshi, S., Abduh, M., (2016) Macroeconomics indicators and bank stability: A case of banking in Indonesia, *Bulletin of Monetary Economics and Banking*, 18, 431-448.
48. King, Brett. (2018). Bank 4.0: Banking Everywhere, Never at a Bank. Marshall Cavendish Business.
49. Lee, M., Asuncion, R. C., & Kim, J. (2016). Effectiveness of macroprudential policies in developing Asia: an empirical analysis. *Emerging Markets Finance and Trade*, 52(4), 923-937.

50. Levy-Yeyati, E., Martinez Peria, M. S., & Schmukler, S. L. (2010). Depositor behavior under macroeconomic risk: evidence from bank runs in emerging economies. *Journal of Money, Credit and Banking*, 42(4), 585-614.
51. Lucas, R. E. (1976, January). Econometric policy evaluation: A critique. In Carnegie-Rochester conference series on public policy (Vol. 1, pp. 19-46). North-Holland.
52. Melecky, M., & Podpiera, A. M. (2012). Macroprudential stress-testing practices of central banks in central and southeastern Europe: Comparison and challenges ahead. *Emerging Markets Finance and Trade*, 48(4), 118-134.
53. Muljawan, Dadang, Taruna, Aditya A. & Harun, Cicilia A. (2013). Banking Liquidity Redux. Bank Indonesia working paper.
54. Mulyaningsih, T., Daly, A., Miranti, R., (2016) Nexus of competition and stability: Case of banking in Indonesia, *Bulletin of Monetary Economics and Banking*, 18, 333-350.
55. Purwono, R., Yasin, M., (2019) The convergence test of Indonesia banking inefficiency: Do macroeconomic indicators matter? *Bulletin of Monetary Economics and Banking*, 21, 123-137.
56. Sakti, M., Achsani, N., Syarifuddin, F., (2018) Online banking implementation: Risk mapping using ERM approach, *Bulletin of Monetary Economics and Banking*, 20, 279-306.
57. Schmieder, Christian, Hesse, Heiko, Neudorfer, Benjamin, Pühr, Claus, & Schmitz, Stefan W. (2012). Next Generation System-Wide Liquidity Stress Testing. IMF Working Paper.
58. Schmidt, Lawrence, Timmermann, Allan, & Wermers, Russ. (2011). Runs on Money Market Mutual Funds. *The American Economic Review*, Vol. 106, No. 9 (September 2016), pp. 2625-265.
59. Schuermann, Til. (2014). Stress Testing Banks. *International Journal of Forecasting*.
60. Seung, H.L., Ho, S.M., Jong, H.L., Ji, H. B., Sejin, Y., & Dongkyu, C. (2013). Systemic Risk Assessment Model for Macroprudential Policy. Macroprudential Analysis Department, Bank of Korea.
61. Stiglitz, Joseph E. and Andrew Weiss (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, Vol. 71, No. 3 (Jun., 1981), pp. 393-410.
62. Sunarmo, (2018) Market structure and competition of Islamic banking in Indonesia, *Bulletin of Monetary Economics and Banking*, 20, 307-324.
63. Tabak, B. M., Guerra, S. M., Miranda, R. C., & de Souza, S. R. S. (2012). Stress Testing Liquidity Risk: The Case of the Brazilian Banking System (No. 302).
64. Taruna, Aditya A. & Harun, Cicilia A. (2016a). The Gap Identification of Bank Indonesia's Stress Testing Framework and Bank of Korea' System Risk Assessment: Diagnostic. Bank Indonesia Working Paper.
65. Taruna, Aditya A. & Harun, Cicilia A. (2016b). The Estimation of Systemic Risk Indicators Using Threshold Logic. Bank Indonesia Working Paper.

66. Taruna, Aditya A. & Harun, Cicilia A. (2017). Credit Risk Estimation Using Micro Risk Component. Bank Indonesia Working Paper.
67. Tucker, Paul. (2019). Is the Financial System Sufficiently Resilient: A Research Programme and Policy Agenda. BIS Working Paper No. 792.
68. Tirole, Jean. (2011). Illiquidity and All Its Friends. *Journal of Economic Literature*, Vol. 49, No. 2 (June 2011), pp. 287-325.
69. Wong, T. C., & Hui, C. H. (2009). A liquidity Risk Stress-testing Framework with Interaction between Market and Credit Risks. Available at SSRN 1370826.
70. Yang, L., & Yi, Y. (2019). Effectiveness of macroprudential policies under maturity mismatch. *Emerging Markets Finance and Trade*, 1-26.

## Appendix 1 – Bond Pricing Methods, Mathematical Expression

### Modified Duration Mathematical Expression

$$\text{Mod Dur} = \left[ \frac{\text{Macaulay Duration}}{(1+y_tM)} \right]$$

$$\text{Mac Dur} = \sum_{t=1}^n \frac{PV(C) \times t}{\text{Market Price Bond}} + \dots + \frac{PV(C+F_t) \times n}{\text{Market Price Bond}}$$

Let's rewrite the formula:

$$\text{Mod Dur} = \left( \sum_{t=1}^n \frac{PV(C) \times t}{PV(C+F_t)} + \frac{PV(C+F_t) \times n}{PV(C+F_t)} \right) \cdot \frac{1}{(1+y_tM)}$$

$$\text{Mod Dur} = \frac{1}{PV(C+F_t)} \left( \sum_{t=1}^n PV(C) \times t + PV(C+F_t) \times n \right) \cdot \frac{1}{(1+y_tM)}$$

Where  $(\sum_{t=1}^n PV(C) \times t + PV(C+F_t) \times n)$  is the remaining cashflow.

Let X be Mod Dur and H be adjusted cash flow, above formula can be rewritten into

$$X = \frac{1}{PV(C+F_t)}; \quad H = \frac{1}{(1+y_tM)}$$

Rearranging the formula

$$PV(C+F) = \frac{H}{X} \frac{1}{(1+y_tM)} \quad \text{or} \quad PV(C+F) = \frac{H}{X} Z$$

Here we have PV of a bond as a function of discount factor and its adjusted cash flow  $(\frac{H}{X})$ . The adjustment comes from change in interest rate or yield to bond price.

### Present Value with Stressed Yield

$$PV = \frac{C}{(1+y_t+x+s_t)^t} + \dots + \frac{C+F}{(1+y_t+x+s_{t+n})^{t+n}}$$

Where  $x + s_t$  and  $x + s_{t+n}$  are additional factors to yield.

Let's rewrite the additional factors:

$$x + s_t = \delta_t$$

Now we have:

$$PV(C+F) = \frac{C}{(1+y_t+\delta_t)^t} + \dots + \frac{C+F}{(1+y_t+\delta_n)^{t+n}}$$

Simplifying the formula, we have:

$$PV(C+F) = CZ'_t + \dots + (C+F)Z'_{t+n}$$

Here we have PV of a bond as a function of its cash flow and adjusted discount factor. The adjustment considers yield changes in all tenure.