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Performance Analysis of Liquidity Indicators as Early Warning Signals*

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Abstract

This study compares the performance of an old liquidity ratio (LiqR) and two new liquidity indicators, namely, liquidity creation (LiqC) and net stable funding difference (NSFD), in sending early warning signals for distressed banks. Recent evidence shows that the old indicator appears incapable of measuring the liquidity condition of banks. However, the two new indicators have not yet been fully examined in terms of their possible role as indicators. We classify distressed banks into banks that have experienced a bank run, bailout, and failure. Sample data are collected from the United States and the European Union from before and after the crisis (2005-2009). We estimate a model using a sample before the crisis to predict liquidity shortages in 2008 and 2009. Evidence shows that the academic (LiqC) and officially recommended indicators (NSFD) outperform LiqR as early warning signal. Furthermore, LiqC is superior when banks actively engage in income diversification but not when banks engage in fund diversification. Therefore, a well income-diversified bank with a high LiqC tends to have a high distress probability in subsequent periods.

Keywords: Liquidity Creation, Net Stable Funding Difference, Liquidity Ratio, Funding Diversification, Income Diversification

JEL Classifications: C23, G21, G32

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1. Introduction

Since August 2007, the subprime mortgage crisis in the United States has re-ignited the issue of liquidity risk and has underscored improper liquidity management of banks. The Basel Committee on Banking Supervision (2009) identifies ineffective liquidity management as one of the key characteristics of the crisis and highlights the lack of attention that liquidity risk received relative to other risks prior to the crisis. Ineffective liquidity management includes qualitative and quantitative oversight. It is argued that regulatory liquidity indicators, such as the liquidity ratio (LiqR) measured as liquid assets to total asset or total liabilities, should have but did not signal a shortage of bank illiquidity. For example, before the crisis, neither on- nor off-site supervision reports regarding the lack of liquidity across banks were announced.[1] However, it is widely believed that the crisis erupted mainly because of a shortage of liquidity. Higher liquidity helps to insulate stronger banks from the strains faced by the weaker ones but, it has been suggested that, the conventional LiqR is incapable of signaling which banks have insufficient liquidity.[2]

Recognizing the ineffectiveness of existing regulatory liquidity indicators, the Basel Committee (2008) suggested two new liquidity standards, namely, a liquidity coverage ratio (LCR) and a net stable funding ratio (NSFR). LCR and NSFR respectively evaluate short- and long-term liquidity adequacy. The two measures adopt a weighted sum concept, which is the sum liquid assets and liabilities weighted by the credit rating or the degree of liquidity.

In addition to the Basel Committee, Berger and Bouwman (2009a) propose a new liquidity measure termed “liquidity creation” (LiqC) to explore the relationship between LiqC and the financial crisis. In LiqC, banks provide liquidity by funding long-term, illiquidity assets with short-term, liquidity liabilities. Thus, banks hold illiquid assets and provide cash to the rest of the world. Therefore, banks face risk if some liabilities invested in illiquid assets are claimed as short notice. As liquidity creation exposes banks to liquidity risks, a higher LiqC indicates greater likelihood and severity of losses. However, although Berger and Bouwman (2009a) propose this new liquidity indicator, they do not use it to examine bank-level liquidity conditions instead they estimate the financial crisis at the country level. Therefore, the appropriateness of LiqC as an indicator for bank liquidity adequacy remains an issue.

This study examines the performance of the old regulatory liquidity indicator (LiqR) and two new indicators (LiqC and NSFR) as indicators of the liquidity adequacy of individual banks. LiqC and NSFR are rarely used in the literature because these indicators are new and their measurement requires information on banks’ balance sheets. Thus, given that the old indicator appears incapable of measuring liquidity conditions and the two new indicators have not yet been fully examined, this study

1 We examine the news through Fativa database and find no news reporting the liquidity shortage. At the country level, the interest rates of interbank market operate as normal, suggesting no massive liquidity shortage.

2 For example, the liquidity ratio of the Northern Rock Bank, a British entity established nearly 150 years ago, was 25% far exceeding the standard requirement before 2007. However, Northern Rock Bank was soon influenced by the magnitude of liquidity squeezes and was forced into a bailout by the Bank of England. Northern Rock Bank consequently suffered a bank run.

fills this gap by investigating the ability of the three indicators to monitor a bank's liquidity condition.

We employ data on 855 European and 359 US banks between 2005 and 2009 and classify the sample into two periods, the normal period (2005–2007) and the crisis period (2008–2009). Banks are classified into normal and distressed banks, with the latter having experienced a bank run, bailout, and failure. We estimate a model using the data from the normal period and the resulting parameters are used to predict distress in banks during the crisis.

Our study complements existing studies by adopting a liquidity indicator to predict a bank crisis at the country level. For example, Berger and Bouwman (2009a) employ LiqC to analyze five major financial crises in the United States.[3] Barrell, Davis, Karim, and Liadze (2010) suggest that bank liquidity ratios provide additional explanatory power in the presence of other well-known early warning indicators of a banking crisis. The Basel Committee (2010) shows graphically that liquidity ratios reduce the severity of a banking crisis. These studies examine whether or LiqC can enhance the predictably of a banking crisis but do not focus on individual banks' liquidity adequacy.

This work proposes two conceptual requirements given the absence of criteria to identify good liquidity indicators. The first requirement suggests that a good indicator should be sensitive to a change of bank liquidity conditions (Poorman and Blake, 2005). With respect to an individual bank, a liquidity indicator is insensitive if its graphic plot is flat or statistically insignificant before and after the bank is in distress. With respect to cross-bank comparisons, the magnitude of liquidity indicators should be unequal for distressed and normal banks. In this study, LiqR fluctuates little for distressed banks over the sample period, failing to meet the sensitivity requirement compared with LiqC and NSFR, which fulfill the requirement. Similarly, the graphic patterns of LiqR are almost the same for normal and distressed banks, thus, LiqR is insensitive to changes in the liquidity condition and cannot function as good liquidity indicator. Poorman and Blake (2005) obtain similar results for LiqR and suggest that conventional LiqRs, such as liquidity assets/liquidity liabilities and liquidity asset/total assets, are not sensitive enough to measure bank liquidity. They illustrate this insensitivity in the case of Southeast Bank, which has used over 30 different definitions of liquidity ratios to monitor liquidity adequacy, but failed because of liquidity risk. Therefore, a good liquidity indicator should be sensitive to liquidity conditions. This sensitivity requirement is one criteria to evaluate the three indicators.

The second requirement stresses the need for indicators to timely, correctly, and significantly separate banks with sufficient liquidity from banks with weak liquidity. We conduct a regression analysis to examine this requirement. For timely prediction, a one-year lagged liquidity indicator is used as a core explanatory variable to predict a bank's liquidity conditions. To achieve a correct prediction, we assume that the coefficients on the three liquidity indicators (LiqR, LiqC, and NSFR) are significantly negative, positive, and positive, respectively, because a higher LiqR has opposite implications than a higher LiqC and NSFR.

3 The five major financial crises include the stock market crash in 1987, the credit crunch in 1990, the Russian debt crisis/LTCM bailout in 1998, the dot.com bubble in 2000, and the subprime crisis in 2007.

Our study differs from previous studies in four aspects. First, Poghosyan and Čihák (2009) view liquidity ratios[4] as a determinant factor in measuring EU bank distress. Angora and Roulet (2011) compare liqC and NSFD[5] in explaining the default probability of US and European banks but they do not investigate the predictive ability of the three liquidity indicators. Because this issue is relatively new, few studies have focused on it.

Second, as we have large set of distressed banks, we are able to classify them into three types, namely those that have experienced a bank run, bailout, or failure. Each category contains a sufficient sample of banks. Previous studies consider only default and non-default banks without distinguishing patterns of failure. However, pooling different types of distressed banks may be misleading because some distressed banks may not necessarily fail altogether. For example, governments often inject funds prior to liquidation. Thus, there are differences between bailout and bank run banks. For each type of distressed banks, we match one normal bank with similar assets in the same country and use a multinomial logit model to analyse it.

Third, given that the number of distressed banks is quite small, we expand our sample to include 1,214 European and US banks to ensure that our results are not affected by too small a sample size. To do so, we first follow the approach of Angora and Roulet (2011) in collating distressed banks from Bloomberg during 2007 to 2009. They find a limited number of banks in distress (in total 45, of which 25 are US banks and 20 are European banks). Poghosyan and Čihák (2009) provide a high number of EU distressed banks (54 banks) from the mid-1990s to 2008. We conduct a comprehensive search over Factiva, the Federal Deposit Insurance Corporation, the *Wall Street Journal*, official supervisory websites, and the BankScope database. This wide-range collection expands our sample of distressed banks to 289. Our sample population contains many well-known failed banks not identified by Angora and Roulet (2011).[6] As such, the sample of banks in our study outnumbers that in Angora and Roulet's (2011) by a multiple of six. The large number of distressed banks renders our study robust in terms of different specifications and changes in the sample countries.[7]

Finally, we propose a *diversification effect* to posit that the performance of the above liquidity indicators is better when banks are diversified in funding or income. If a bank adopts a more diversified strategy, such as diversifying in its funding sources, the spectrum and structure of assets and liabilities differs from that of banks which do not diversify (Demirgüç-Kunt and Huizinga, 2010a). We postulate that diversification weakens the predictive ability of liquidity indicators because banks

[4] These authors compare two ratios as proxies for liquidity: liquid assets to deposits and short-term funding and wholesale financing to total liabilities.

[5] Angora and Roulet (2011) define NSFD as the difference between available stable funding and required stable funding as a percentage of total assets. We use the difference between required stable funding and available stable funding to provide consistency with the concept of LiqC. Therefore, Angora and Roulet expect a negative sign of NSFD, but we expect a positive sign of NSFD for the associated coefficient on bank vulnerability.

[6] Northern Rock Bank is an effective example in this study. It experienced a bank run in 2007 and was not included in the previous studies.

[7] Männasoo and Mayes (2009) use LiqC to study East European countries for the sample from 1995 to 2004. The list of failed banks is collected from BankScope only.

can easily find another funding source. For example, when deposit withdrawals occur, a fully diversified bank can obtain additional funds in the wholesale market, for example, by issuing bank debenture. By contrast, a less diversified (concentrated) bank must sell liquidity assets to finance lost deposits. Thus, the predictive ability of liquidity indicators is reduced in diversified banks but strengthened in concentrated banks.

The different diversification strategies may affect LiqC and NSFR more than LiqR because the sensitivity of LiqC and NSFR is based on changes in the whole spectrum of assets and liabilities. LiqR is mainly based on liquid assets, and LiqR's sensitiveness may not change significantly. In this situation, LiqC and NSFR may be even better in predicting liquidity risk for diversified banks in terms of sensitivities.

The remainder of this paper is organized as follows. Section 2 reviews three liquidity indicators. Section 3 introduces our research model. Section 4 presents sources of data and basic statistics. Section 5 presents empirical results concerning the role of liqR, LiqC, and NSFD in signaling a distressed bank and Section 6 concludes.

2. Three Liquidity Indicators

2.1 Conventional Liquidity Indicator: LiqR

No uniform prudential liquidity requirement is imposed across countries. In some countries, such as Italy and Spain, the liquidity regulations contain only qualitative requirements. In other countries, such as the United Kingdom and Germany, regulations specifying qualitative as well as quantitative requirements were introduced several years ago (Algorithmics 2007). In Asian countries and areas (China, India, Hong Kong, Singapore, Taiwan, and Thailand), there are no quantitative requirements were (*Asia Focus*, 2011).

Among various quantitative measures, the numerator of the liquidity ratio is commonly liquid assets but the denominator is usually proportional to a certain class of liability or asset size. These include a liquid assets to total assets ratio (e.g., Bourke, 1989; Molyneux and Thornton, 1992; Barth et al., 2003; Demirgüç-Kunt et al., 2003), a liquid assets to deposits ratio (Shen et al., 2001), and a liquid assets to customer and short-term funding (Kosmidou et al., 2005; Poghosyan and Čihák, 2009), to name a few. This study defines liqR as the ratio of liquid assets to total assets. An increase in liqR indicates that a bank has greater liquidity and is less vulnerable to a bank run.

Although liqR is widely employed as a regulatory liquidity measure, LiqR's usefulness as an early warning liquidity risk indicator is highly debateable. Padmalatha (2011, 397), in his textbook,[8] discusses an ironic case for liqR:

[8] Management of Banking and Financial Services.

"…For example, a large regional bank in US, Southeast Bank, used over 30 liquidity ratios to manage its liquidity. When it failed in 1991, the second largest failure of previous two decades in the US, the reason cited was "liquidity risk."

One of the plausible reasons for liqR's failure to detect a deterioration in liquidity conditions is the banks' ability to hold onto their liquid assets during liquidity shortages. For example, not all liquid assets can be sold in the market because of poor quality. This is particularly true during a crisis. Consequently, when liquidity shortages occur, liqR may change little.

Given these possible weaknesses in using liqR to detect liquidity risk, we examine whether liqC and NSFR can detect liquidity shortages.

2.2 Liquidity Creation

LiqC stresses the function of liquidity intermediation in the banking sector. Liquidity occurs when banks' transform liquid liabilities into illiquid assets. This liquidity transformation considers not only the pre-eminent function of banks but also the primary source of their vulnerability. Banks provide liquidity to the economic system by funding long-term illiquid assets with short-term, liquid liabilities.

To measure the degree of liquidity creation, Berger and Bouwman (2009b) classify a bank's assets, liabilities, equity, and off-balance sheet activities as liquid, semi-liquid, or illiquid and refer to their liquidity measure as liqC.[9]

$$\text{LiqC} = [\,(1/2\times\text{Illiquid assets}+0\times\text{Semi-liquid assets}-1/2\times\text{Liquid assets})+(1/2\times\text{Liquid liabilities}+0\times\text{Semi-liquid liabilities}-1/2\times\text{Illiquid liabilities})]/\text{Total assets},$$

where the weights of liquid, semi-liquid, and illiquid assets are −1/2, 0, and 1/2, respectively, and the weights of liquid, semi-liquid, and illiquid liabilities are 1/2, 0, and −1/2, respectively. LiqC measures liquidity mismatch between liquid liabilities and illiquid assets. The higher the LiqC the greater the liquidity transformation performed by the bank and the higher the liquidity maturity mismatch. Thus, a higher LiqC suggests greater liquidity transformation and therefore liquidity risk.

Our construction of liqC is slightly different from that of Berger and Bouwman (2009b) because of different data sources. We use the BankScope database, whereas they employ Call Reports from the United States. We use category as the criterion to classify items on and off the balance sheet (e.g., assets, liabilities, and equities) into three groups: liquid, semi-liquid, or illiquid groups. By contrast, Berger and Bouwman (2009b) use both category and maturity criteria. Maturity criteria are not used

[9] Studies considering LiqC include Matz and Neu (2007), who indicate that banks may apply the balance sheet liquidity analysis to assess liquidity risk. Choi, Park, and Ho (2009) measure the level of property and liability insurer LiqC and examine the factors relevant to insurer LiqC. Pana, Query, and Park (2010) find a positive effect of the merger activity on bank LiqC and document that equity capital and degree of revenue diversification have a limited effect on the LiqC around mergers.

because significant data are missing in BankScope. In addition, items in the off-balance sheet in BankScope have been available only recently and lack detail. Thus, we consider only total contingent liabilities to avoid excessive missing data. Table 1 tabulates the three groups of assets and liabilities.

2.3 Basel Liquidity Indicator: NSFD

In 2007, the Basel III Committee conducted liquidity ratio reform by substantially revising past liquidity ratios. Two measures, the LCR and NSFR, are proposed to examine the sufficiency of liquidity.[10] The LCR builds on traditional liquidity "coverage ratio" methodologies that are used internally by banks to assess their exposure to contingent liquidity events. The ratio can promote short-term resiliency of liquidity risk. NSFR is an extension of the traditional "net liquid asset" and "cash capital" methodologies used widely by internationally active banking organizations, bank analysts, and rating agencies. NSFR can promote resiliency over a longer-term horizon. These two ratios are complementary because both focus on short- (one month) and long-term (one year) liquidity adequacy. In particular, these two ratios focus on the quality of liquidity at each maturity and category. For example, high-quality liquid assets (e.g., AAA corporate bonds) increase more with the two ratios than with low-quality liquid assets (e.g., BBB corporate bonds). The exact calculation of both measures requires detailed information of components in assets and liabilities. For example, calculation of the LCR needs rating information on assets and liabilities, which are not available to outsiders.

Angora and Roulet (2011) propose the NSFD as an approximation to NSFR. Given the difficulty of collecting the maturities and ratings of assets and liabilities, they use the liquidity of "categories" to decide the weights of sub-aggregate items and to calculate the NSFD, which is the difference between weighted assets and liabilities, and to discuss the determinants of the NSFD.

The NSFD is the difference between required and available stable funding,[11] defined as follows:

$$\text{NSFD} = \frac{\text{Required amount of stable funding}}{\text{Total assets}} - \frac{\text{Available amount of stable funding}}{\text{Total assets}}.$$

Calculating the NSFD requires determination of the weights of the asset and liability components of required and available stable funding. Weights are smaller if components are more liquid. For instance, the weight of cash is zero and is unity for long-term fixed assets. Similarly, the weights of demand deposits are smaller than those of term deposits. Considering these basic principles, we assign weights to assets and liabilities in NSFD in accordance with the Basel III Committee. Thus, we can still assign weights based on these principles even when the terms used in NSFD are different from those presented by BankScope. Table 2 presents the weights of assets and liabilities for required

[10] See "Consultative Document: International framework for liquidity risk measurement, standards and monitoring," Basel Committee on Banking Supervision (2009).

[11] Although Basel III uses ratio and we use difference, the two calculations are basically the same.

and available stable funding. Angora and Roulet (2011) further detail the calculation of NSFD.

The concept of NSFD is similar to liqC so we expect the information shared by these liquidity indicators to be closely linked.

2.4 Comparison between LiqR, LiqC, and NSFD

We estimate correlation coefficients between each pair of these three liquidity measures. The estimated correlation coefficients of LiqC and NSFD, LiqR and NSFD, and LiqR and LiqC are 0.5, −0.4, and −0.13, respectively. LiqR appears to be less correlated with the other two measures. The correlation coefficient with liqC is only −0.13. Thus, liqR shares less information with the other two liquidity measures. As expected, liqC and NSFD are highly correlated up to 0.5 and share more information with each other.

The top, middle, and bottom panels of Figure 1 present the scatter plots between LiqC and NSFD, LiqR and NSFD, and LiqR and LiqC, respectively. The scatter plots show positive, negative, and negative relationships between the three paired liquidity risk measures. On the basis of the sign and size of correlation coefficients, the two new liquidity measures, LiqC and NSFD, are expected to yield similar results in regression analysis.

3. Econometric Model

3.1 Multinomial Logit Model

Our dependent variable is the status of the bank in stress (*Distress*) when the values assigned to the dependent variable are arbitrary. In our model, *Distress* ranges from 1 to 4, with 1 representing normal, 2 representing bank-run banks, 3 representing bailout banks, and 4 representing failed banks. The multinomial logit model (Babcock and Hennessy, 1995) is given as

$$p_1 = \mathrm{Prob}(Distress_{ijt} = s) = \frac{1}{\sum_{q=1}^{4} \exp(\mathbf{X}_{ijt-1}\mathbf{B}_s)} \tag{1}$$

$$p_q = \mathrm{Prob}(Distress_{ijt} = s) = \frac{\exp(\mathbf{X}_{ijt-1}\mathbf{B}_s)}{\sum_{q=1}^{4} \exp(\mathbf{X}_{ijt-1}\mathbf{B}_s)}; \; s = 2,\, 3, \text{ and } 4, \tag{2}$$

where subscripts *i*, *j*, and *t* denote the *i*th bank in *j*th country at time *t,* and *s* denotes the *s*th type of the distressed bank. The dependent variable *Distress* = *s* is the index denoting if a bank is the *s*th type in the bank quadrant, where *s* = 1, 2, 3, and 4. $\mathbf{X}$ is the vector of explanatory variables. All explanatory variables are lagged one period to alleviate the potential endogenous problem.

Notably, not all coefficients are subject to estimation through the maximum likelihood method. In practice, when estimating the model, the coefficients of the reference group are normalized to zero (Maddala, 1990; Greene, 2005; Kimhi, 1994).[12] The probabilities of all the choices must sum up to unity (Greene, 2005). Thus, with only four choices (i.e., 4 to 1), distinct sets of parameters may be identified and estimated. We select the first type of bank, that is, a normal bank, as the benchmark. The three sets of coefficients, which are $\mathbf{B}_s$ (*s* = 2, 3, and 4), are interpreted in relation to normal banks. The natural logarithms of the odd ratios of Equations (1) and (2) are expressed as

$$\log\left(\frac{p_s}{p_1}\right) = \mathbf{X}_{ijt-1}\mathbf{B}_s \qquad s = 2, 3, 4.$$

Thus, the coefficients denote the probability of the *s* group in relation to the *s* = 1 group. A significant positive coefficient on a variable for a particular group indicates that the variable is associated with a higher probability of being in that group in relation to the reference group. A negative significant coefficient has the opposite interpretation. We use White's (1980) heteroskedasticity-consistent standard errors and Petersen's (2009) approach to adjust the problem of heteroscedasticity and clustering at the firm level.[13]

Our vector of explanatory variables **X** includes a liquidity indicator (LiqR, LiqC, and NSFD) and three types of control variables, namely, bank-specific and country governance variables. A higher LiqR and lower LiqC and NSFD indicates a safer bank thus, their expected coefficients are negative, positive, and positive, respectively.

3.2 Control Variables

The first category of control variables are bank-specific variables, including capital, asset quality, management, earnings, and liquidity, which are referred to as CAMEL. These variables are common in the supervisory risk assessment and early warning system used by supervisory agencies worldwide. However, evidence shows that CAMEL grades have limits in predicting bank failure and should be complemented by other indicators (Rojas–Suarez, 2001). The proxies for CAMEL are capital adequacy (capital adequacy ratio, CAR), asset quality (non-performing loan, NPL), management for bank efficiency (cost to income ratio, CostInc), earnings (returns on assets, ROA), and liquidity (LiqR, LiqC and NSFD).

In addition to the CAMEL variables, we control for the size effect by adding LAsset, which denotes the

[12] We must recall that the possibility of using the estimates in this manner relies on the validity of the independence of irreverent alternatives (IIA) assumption: the inclusion or exclusion of choices does not affect the odds ratios associated with the remaining choices.

[13] The goodness-of-fit is the pseudo-R^2 value, which is equal to $R^2 = 1 - L_u / L_R$, where L_u and L_R are the likelihood values under the unrestricted and restricted conditions, respectively.

log of total assets. The addition of LAsset can avoid the influence of “too big to fail.”

The second category of leading indicator of bank distress considers a country governance variable (InvestPro) as a control variable. InvestPro denotes investor protection and is often used as a proxy for governance. This index developed by Djankov et al. (2006) takes a value of 1 to 4, with higher values indicating greater investor protection.

The third category considers two macro-economic variables, GDPg and Infla, where GDPg is the real GDP growth rate and Infla is the inflation rate calculated by the consumer price index. Männasoo and Mayes (2009) also use these variables in their study. A higher GDPg enhances bank survival. Infla represents an increase in nominal interest rates and is likely to be associated with adverse effects on the banking system. Table 3 lists the detailed definitions of variables used.

3.3 Diversification Effect

We also examine whether diversification affects the choice of good liquidity indicators. Based on the discussion in Demirgüç-Kunt and Huizinga (2010a), we consider two types of diversification measures in the present study. The first type focuses on deposit and non-deposit funding sources (Div_Fund), as suggested by Demirgüç-Kunt and Huizinga (2010a). The main component of non-deposit funding is wholesale funding. However, wholesale funding has positive and negative effects on banks (Demirgüç-Kunt and Huizinga, 2010a; Huang and Ratnovski, 2011; Lopez-Espinosa, Moreno, Rubia, and Valderrama, 2012). On the positive side, wholesale funding provides banks with more funding sources in addition to deposits, as well as greater market supervision (Calomiris, 1999). On the negative side, wholesale lenders not only have short expected investment periods but also frequently refinance by using rollovers. Thus, wholesale lenders can easily trigger large-scale withdrawals because of market noise and may be at great risk (Demirgüç-Kunt and Huizinga, 2010a; Huang and Ratnovski, 2011). Therefore, the influence of diversification in funding on the effects of liqC on distressed banks remains uncertain. The second type of diversification is relates to income (Div_Inc), where income consists of net interest and non-interest incomes. Traditional banks focus on net interest income; thus, diversification in income suggests that banks shift away from lending activities and lean more toward fee-based activities (Stiroh and Rumble, 2006). Diversification enhances the influence of liquidity risk on distressed banks because income diversification encourages banks to conduct more non-traditional deposit/loan business.

The two diversifications are defined as follows:

$$\text{Div\_Fund}=\left(\frac{\text{Depoist}}{\text{NonDeposit}+\text{Deposit}}\right)^2+\left(\frac{\text{NonDeposit}}{\text{NonDeposit}+\text{Deposit}}\right)^2,$$

$$\text{Div\_Inc} = \left(\frac{\text{NII}}{\text{NII+NonII}}\right)^2 + \left(\frac{\text{NonII}}{\text{NII +NonII}}\right)^2$$

where NonDeposit is non-deposit funding, Deposit is deposit funding, NII is the net interest income, and NonII is the non-interest income.

Both diversification measures are in the range of 0.5 to 1.0, where 0.5 denotes full diversification and 1.0 denotes full specialization. For example, full diversification in funding suggests that the bank's total funding is equally obtained from deposit and non-deposit sectors allocated into Deposit and NonDeposit (i.e., Deposit=NonDeposit). Thus, Div_Fund = 0.5. By contrast, full specialization in Fund (Deposit or NonDeposit = 0) suggests that Div_Fund = 1. Therefore, a lower value indicates greater diversification.

In the introduction, we postulated that diversification weakens the predictive ability of liquidity indicators because of a banks' accessibility of other funding sources. For example, in a mild deposit withdrawal, a fully diversified bank can easily access additional funds by issuing bank debentures. By contrast, a non-diversified bank must sell liquid assets to finance the lost funding. Thus, the predictive ability of liquidity indicators is reduced in diversified banks but strengthened in non-diversified banks. We include two interaction terms, Liquidity × Div_Fund and Liquidity × Div_Inc, to examine the effects of diversification on the liquidity ratios predictive ability. The coefficients on the interaction variables LiqR × Div_Fund, LiqC × Div_Fund, and NSFD × Div_Fund are expected to be negative, positive, and positive, respectively.

Table 4 highlights the expected sign of the three liquidity indicators being considered. A higher LiqR is expected to decrease distress probabilities, whereas a higher LiqC and NSFD increase the probability. The expected sign of the three liquidity indicators with the two interaction terms are also reported.

4. Data Source and Basic Statistics

4.1 Data Source

We focus on commercial banks in the United States and European Union.[14] The bank-specific variables are obtained from BankScope, and the country-specific variables are drawn from World

[14] Our sample belongs to the following 27 European countries: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom. We exclude the non-crisis countries to ensure that our sample contains crisis and non-crisis commercial banks. The non-crisis countries are Bulgaria, Cyprus, Estonia, Finland, Greece, Lithuania, Malta, Romania, Slovenia, and Sweden.

Bank Indicators from 2005 to 2009. Furthermore, banks with no data before 2007 are removed.[15] However, not all countries have distressed banks; therefore, our sample countries include only bank data from 18 Organization for Economic Cooperation and Development countries.

4.2 Descriptive Statistics

Table 5 shows the number of normal, bank-run, bailout, and failed banks across 18 countries. The total number of banks is 1,214, of which 289 (~24%) have experienced distress. The number of bank-run, bailout, and failed banks totals 23, 145, and 121, respectively. Among the 18 countries, the United States had the largest number of distressed banks (190), according to the list of distressed banks disclosed by TARP. We also estimated the model by removing US banks to examine the robustness of the estimated results but the results were similar and so are not reported.

4.3 Sensitivity Examination

We consider the macro- and micro-views to examine the sensitivity of three liquidity indicators. This evaluation is simply based on the graphic evidence and basic statistics to provide intuitive evidence.

4.3.1 Graphic Evidence

We consider the micro-view by plotting three liquidity indicators for each type of bank (i.e., normal, bank-run, bailout, and failed) from 2005 to 2009. In Figure 2, the three liquidity indicators are flat for normal banks (Panel A). Thus, the three liquidity indicators have low Type II error (i.e., no false alarm). In the case of bank-run data (Panel B), liqR (dashed line) is again flat before 2008 and slightly dropped thereafter. In contrast to the flat LiqR, liqC (solid line) exhibits a significant increase in 2008, and NSFD (dotted line) shows a slight increase and decrease. Therefore, liqC appears to be responsive to the change in liquidity conditions. In the case of bailout data (Panel C), the results are similar to those of bank run banks. However, NSFD shows a flatter trend compared with liqC for bailout banks. For the failed bank cases, the three indicators slightly fluctuate. The three liquidity indicators are not very responsive to the liquidity conditions of failed banks because banks require years to reach the last step of liquidation, which is auction sale and merger. The above results suggest that liqR is the least sensitive and liqC is the most sensitive. This is particularly true in the case of bank run banks and bailout banks. LiqC appears to give a better early warning signal for bank-run banks but not for bailout and failed banks in terms of sensitivity.

We next use the macro view by graphing three liquidity indicators of each country. Figure 3 plots liqRs, LiqCs, and NSFDs of 18 countries from 2005 to 2009. We expect the shape of the curve to exhibit a turn around 2008 or 2009 to demonstrate sensitivity. LiqR (dotted line) exhibits a mixed pattern showing a slight V-shaped trend for some countries, a flat pattern some, and an inverse V-

[15] We exclude banks with capital adequacy ratios >30%, ROA >3%, or equity-to-assets ratio >20%. Banks with these ratios are unlikely to be commercial banks and are excluded from our sample.

shaped trend for the remaining countries. This suggests that liqR gives confusing signals on the basis of the graphic evidence alone. LiqC (solid line) peaked in 2008 and dropped thereafter in most of the countries. Thus, each country tends to show high liquidity risk before the subprime crisis, with risk diminishing afterwards. Therefore, liqC is sufficiently sensitive to reflect changes in liquidity during the subprime crisis. NSFD (dashed line) shows a pattern in-between the two other indicators. In summary, liqC indicates that the liquid condition of banks worsened in 2008 compared with earlier periods, and that liqR and NSFD show minimal responsiveness to changes in liquidity conditions.

Our intuitive evidence suggests that liqR is the most sensitive in distinguishing normal from distressed banks, followed by NSFD and liqR.

4.3.2 Basic Statistical Evidence

Our sensitivity analysis requires that the three liquidity indicators are different for normal and distressed banks. Table 6 presents descriptive statistics of bank characteristic variables across four types of banks. We use *F*-statistics to test the differences of these variables among the four types of banks. We also examine pairwise differences between normal banks and each type of distressed bank using *t*-tests. The median LiqC for normal, bank-run, bailout, and failed banks is 0.31. 0.38, 0.39, and 0.4, respectively. Therefore, liqC is sensitive because the three distressed banks showed a higher LiqC median than for normal banks. Moreover, the pairwise difference between normal banks and each type of distressed bank are significant. Thus, liqC is sensitive for distressed banks. By contrast, liqR is the lowest for bailout banks, followed by normal, bank-run, and failed banks. LiqR is not sensitive because it cannot distinguish between normal from distressed banks. NSFD shows a high sensitivity to bank-run and bailout banks and less so for normal and failed banks, and so is less sensitive than liqC.

4.4 Diversification Effect

The graphs in Figure 4 show that banks which are diversified in their funding have low liquidity risk. We divide banks into those with a high and low degree of diversification in their funding (Div_Fund) by using the median as a cutoff point. Panels A, B, and C in Figure 4 plot banks with high and low Div_Fund by using liqR, LiqC, and NSFD as liquidity measures, respectively. An increase in average Div_Fund has been observed in all three panels since 2007. When liqR is employed, Panel A, banks with lower Div_Fund (i.e., greater diversification) values exhibit a lower LiqR than banks with higher Div_Fund values. Banks with greater diversified funding tend to have lower liquidity risk, thereby fulfilling the diversification effect. The results using liqC and NSFR show similar results. Thus, the intuition provided by the graphic evidence supports our proposition.

Figure 5 shows that diversified banks in income have a higher liquidity risk. When liqC is employed as a liquidity measure in Panel B, banks with lower Div_Inc values exhibit a significantly higher LiqC than banks with higher Div_Inc values. Thus, banks with highly diversified income tend to have high liquidity risk. Similar results are found in Panel A when liqR is used as the liquidity measure. Banks with lower Div_Inc values exhibit a lower LiqR than banks with higher Div_Inc values. Banks with a low Div_Inc show a higher NSFD in Panel C since 2007. Thus, a bank with highly diversified income has more potential liquidity risk than banks with lower diversificatied income.

5. Regression Results

We determine whether liqR, LiqC, and NSFD can correctly predict distressed banks one year earlier. We also consider the influence of income and funding diversification on the performance of liqR, LiqC, and NSFD.

5.1 Three Liquidity Indicators and Diversification in Funding: Normal Period (2005~2007)

Table 7 shows the estimated results when the three liquidity measures are used in turn as a proxy for liquidity conditions and their joint influence in funding diversification (i.e., Div_Fund).

We first examine the effectiveness of liqR as a liquidity indicator (two columns on the left). Panel A of the liqR column shows that the coefficient on bank run and bailout banks is significantly negative at the 10% level when no interaction term is considered. This scenario indicates that an increase in liqR reduces the probability of a bank run and bailout in the following year. Thus, although the importance of liqR has been gradually downgraded in most countries, liqR still exhibits weak predictive power for bank run and bailout cases.

Panel B of the LiqR column shows the evaluation of the performance of liqR with interaction terms. The coefficients of liqR are significantly negative when distressed banks experience a bank run and bailout. The coefficient on $\mathrm{LiqR} \times \mathrm{Div\_Fund}$ is significantly positive for bank run and bailout banks but insignificant for failed banks. Thus, liqR is also an effective early warning signal, particularly for banks experiencing a bank run and bailout. The interaction term is negative; therefore, the predictive ability of liqR is reduced for diversified banks.

The middle part of Table 7 uses LiqC as a proxy of liquidity conditions (two columns in the middle part). Panel A of liqC column shows that when no interaction variables are considered, the coefficient is significant only for banks experiencing a bank run. Panel B of liqC column shows that the coefficients of LiqC are significantly positive for banks experiencing bank run and failure but insignificant for those experiencing a bailout. The coefficient on $\mathrm{LiqC} \times \mathrm{Div\_Fund}$ is significantly positive for bailout banks. Thus, liqC remains a good early warning signal. Funding diversification does not influence the adverse effect of liqC on bank runs and default banks but mitigates the adverse effect of liqC on banks experiencing bailout.

Our results are similar to those of Demirgüç-Kunt and Huizinga (2010a), who report that wholesale funding has a nonlinear U-shaped effect in affecting risk. Wholesale funding first reduces bank risk with a small amount of funding but increases risks with a large amount of funding. In our sample of banks, the percentage of wholesale funding is small;[16] thus, wholesale funding is similar to the left part of the U-shaped curve between wholesale funding and risk. Funding diversification may also reduce the adverse effect of liqC on distressed banks. Our results differ from those of Huang and Ratnovski (2010), who indicate that wholesale funding financiers are myopic and usually withdraw ahead of retail depositors following a negative signal. On the basis of this contradictory view, we denote that funding diversification should strengthen the adverse effect of liqC.

Finally, we examine the performance of NSFD in the last two columns of Table 7. In Panel A of NSFD, the coefficients on NSFD are significantly positive when distressed banks experience a bank run or bailout, which indicates that a larger NSFD tends to indicate a higher probability that a bank will experience a bank run or bailout. In Panel B, the coefficients of NSFD are significantly positive for bank run and bailout banks. The coefficient on $\text{NSFD} \times \text{Div\_Fund}$ is significantly positive for bailout banks only and significantly negative for bank run banks. Funding diversification does not influence the adverse effect of liqC on default banks but aggravates the adverse effect of liqC on banks experiencing a bailout.

5.2 Three Liquidity Indicators and Diversification in Income: Normal Periods (2005~2007)

We examine whether the results change when Div_Inc is used to replace Div_Fund. Table 8 shows the results with the interaction terms and Div_Inc.

The first column of Table 8 shows the estimated results using liqR and considers its interaction terms with income diversification. We add the interaction term LiqR × Div_Inc to the model, where the range of Div_Inc is between 0.5 and 1.0. We calculate the “net effects” of LiqR on the distressed banks by jointly using the coefficients of LiqR and LiqR × Div_Inc. We illustrate how to calculate the net effect by using the bank bailout case because coefficients are only significant in Panel B in this case. The net effect is expressed as (coefficient of LiqR + coefficient of LiqR × Div_Inc) = (12.65−22.12 × Div_Inc), which is 1.59 when Div_Inc = 0.5 (full diversified) and –9.47 when Div_Inc = 1.0 (specialized). Accordingly, the predictive power decreases for diversified banks and increases for specialized banks.

The performance of liqC is encouraging when the interaction term LiqC × Div_Inc is considered (the second column in Table 8). Coefficients of LiqC and the interaction terms are significantly positive for three types of distressed banks at the 1% level, whereas coefficients of the interaction term LiqC × Div_Inc are significantly negative. Two implications can be drawn from these results. First, a higher LiqC results in a greater tendency for banks to be in distress, which suggests that liqC may be an appropriate signal indicator for liquidity risk. This relationship is true for fully diversified banks. Second, the adverse effect of liqC is decreased when bank incomes become more specialized from

16 In our sample, most of the banks had small non-deposit funding shares that are close to zero. Few banks had large non-deposit funding share.

different sources (i.e., Div_Inc is higher). Therefore, specialization in income mitigates the adverse effect of liqC on distressed banks. If two banks have the same LiqC, the bank with higher income diversification should be concerned with the maturity mismatch implied by our estimated results using liqC. Accordingly, liqC is a useful early warning signal for distressed banks. A diversified income also intensifies this signal effect.

The three columns of Table 8 use NSFD as the liquidity indicator. When NSFD×Div_Inc is added, the predictive power of NSFD on distressed banks decreases because the coefficients of NSFD and NSFD×Div_Inc are significant only for bank run banks. The net effect values are 4.84 and 0.92 for fully diversified and specialized banks. A diversified income also decreases this signal effect.

Our intuition for the above results is as follows. The inferior performance of liqR is possibly due to the fact that it is a lump sum concept by aggregating the liquidity assets with equal weights. However, many assets are liquid in normal periods but become illiquid or discounted during crisis periods. Thus, banks with a high LiqR, which may have many “liquidity assets”, do not protect themselves from adverse effects during crisis periods. By contrast, liqC and NSFD consider the liquidity degree of each liquid asset, which correctly signals risk-taking behaviour and danger in the future distress.

5.3 Robustness Testing

5.3.1 Three Liquidity Indicators and Diversification in Funding and Income: Crisis Periods (2008~2009)

We re-examine the performance of the three liquidity indicators with and without interaction terms and with two diversification variables during the global financial crisis of 2008-9. In Tables 9 and 10, the estimated results using the three liquidity indicators taking account of fund and income diversification resembles the results presented in Tables 7 and 8. Hence, the early warning signal of liquidity creation or the net stable difference is robust even during the crisis period.

5.3.2 Removing US Data

We also examine whether our results are sensitive to the exclusion of US banks from our sample. To examine this, we estimate the models leaving out the US banks. Some coefficients become insignificant, but our results remain the same statistically except for the coefficients of the interaction terms between liquidity creation and fund diversification (or income diversification) for bailout banks.[17]

[17] Results are available upon request.

5.3.3 Does Ownership Matter?

We also consider the influence of ownership. We define domestically owned banks as banks where the ultimate owner is a local resident. Ownership is a dummy variable, which is equal to one if it is foreign owned bank and zero otherwise. The coefficients for the three liquidity indicators and their interaction terms (measuring diversification in funding or income) are robust to including an ownership control variable. The results are not reported but are available upon request.

The ownership variable enters these regressions with a significantly negative sign for bailout banks and a significantly positive one for failed banks. The results indicate that foreign owned banks have a higher probability of failure than bailout banks during the subprime crisis. Hence, local banks seem easily to be bailout than foreign banks. This is a important issue for future research

6. Conclusion

In contrast to the considerable efforts that have been exerted to examine capital adequacy, few empirical studies have investigated liquidity adequacy. Although liquidity risk is crucial in bank operations, studies have yet to reach a consensus on which liquidity measures are appropriate as early warning indicators for liquidity adequacy. The present study fills this gap by examining which liquidity measure among LiqR, LiqC, and NSFD is more reasonable as an early warning signal for distressed banks.

Our results demonstrate that the two novel liquidity ratios, namely, LiqC and NSFD, are more effective and stable than the conventional measure, LiqR, is in reflecting signals of bank weaknesses. Effectiveness test denotes that most coefficients of LiqC and NSFD are significant, whereas stability test denotes that signs are consistent with the expectation and are robust to different specifications. Although many coefficients of LiqR are also significant, their signs are sensitive to specifications and even become counter-intuitive. Thus, LiqR alone cannot be used as effective signal. LiqC and LiqR are negatively correlated to some extent and may function as complements rather than substitutes. Therefore, both officially recommended NSFD and academically recommended LiqC are useful as early warning indicators. Although the NSFD indicator is only an approximation, the probability of changes in results is less even when the exact NSFD is calculated.

We have also considered whether diversification in income and funding could alleviate the degree of liquidity risk. The two diversification types do not alleviate the adverse effect of LiqC on banks. Moreover, diversification in income intensifies the adverse effect of LiqC on banks. LiqC has a stronger signaling effect on liquidity risk for banks with diversified income compared with NSFD. Diversification in funding has a weak influence on the adverse effect of LiqC on distressed banks, which is consistent with previous findings in literature.

We conclude that LiqC and NSFD demonstrate a stronger signaling effect for banks in distress than

LiqR does, particularly for bank run. Diversification in income further strengthens this adverse signaling.

Future studies could use “exact” NSFD values to re-examine the same issues.

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Table 1. Definition of LiqC

Liquid Asset (weight = −1/2)	Semi-liquid Assets (weight = 0)	Illiquid Assets (weight = 1/2)
	Assets (Category)	
• Cash and Due from Banks • Deposits with Banks • Due from Central Banks • Due from Other Banks • Due from Other Credit Institutions • Treasury Bills and Other Bills • Government Securities and Trading Securities • CDs • Other Listed Securities, Non-Listed Securities, investment Securities, and Other Securities	• Loans to Municipalities / Government • Loans to Banks • Mortgages • Other Consumer/ Retail Loans	• Loans to Other Corporate • HP/Lease • Loans to Group Companies / Associates • Corporate & Commercial Loans • Trust Account Lending and other lending • Equity Investments and Other Investments • Bonds • Other Non Earning Assets • Intangible Assets • Total Fixed Assets
	Liabilities plus equity	
Liquid Liabilities (weight= 1/2)	**Semi-liquid Liabilities (weight = 0)**	**Illiquid Liabilities (weight = −1/2)**
• Deposits – Demand • Total Money Market Funding (Certificates of Deposit, Commercial Paper, Debt Securities, Securities Loaned, Other Securities, and Other Negotiable Instruments) • Municipalities / Government Deposits • Banks Deposits • Commercial Deposits • Other Deposits	• Customer Deposits – Term	• Total Other Funding (Convertible Bonds, Mortgage Bonds, Other Bonds, Subordinated Debt, Hybrid Capital, and Other Funding) • Other Liabilities • Equity
	Off-balance Sheet (Total Contingent Liabilities)	
Liquid Contingent Liabilities (weight = −1/2)		**Illiquid Contingent Liabilities (weight = 1/2)**
• Guarantees		• Committed Credit Lines • Other Contingent Liabilities

Table 2. Definition of NSFD

Assets	Required Amount of Stable Funding Angora and Roulet (2011)	Basel III	Weights
● Cash and Due from Banks ● Deposits with Banks ● Due from Central Banks ● Due from Other Banks ● Due from Other Credit Institutions	Cash and near cash items	Cash	0 0
● Treasury Bills and Other Bills		Debt issued or guaranteed by sovereigns, central banks, BIS, IMF, EC, non-central government, multilateral development banks	0.05
● Government Securities and Trading Securities ● CDs	Marketable securities and other short-term investments	Short-term unsecured actively traded instruments (< 1 yr)	0
● Other Listed Securities, Non-Listed Securities, investment Securities, and Other Securities		Unencumbered listed equity securities or non-financial senior unsecured corporate bonds (or covered bonds) rated at least A-, maturity ≥ 1 yr	0.5
● Loans to Municipalities / Government			0
● Loans to Banks	Other loans	All other assets	0
● Mortgages		Mortgages	0.65
● Other Consumer/ Retail Loans	Consumer loans	Loans to retail clients having a maturity < 1 yr	0.85
● Loans to Other Corporate	Commercial loans	All other assets	1
● HP/Lease		All other assets	1
● Loans to Group Companies / Associates	Commercial loans	All other assets	1
● Corporate & Commercial Loans	Commercial loans	All other assets	1
● Trust Account Lending and other lending		All other assets	1
● Equity Investments and Other Investments ● Bonds	Long-term investment	Unencumbered listed equity securities or non-financial senior unsecured corporate bonds (or covered bonds) rated at least A-, maturity ≥ 1 yr	0.5
● Other Non Earning Assets	Other assets	All other assets	1
● Total Fixed Assets	Net fixed assets	All other assets	1

Table 2. Definition of NSFD (continued)

Liabilities	Available Amount of Stable Funding Angora and Roulet (2011)	Basel III	Weights
Deposits – Demand	Demand deposits	Less stable deposits of retail and small business customers (non-maturity or residual maturity < 1yr)	0.8
Total Money Market Funding (Certificates of Deposit, Commercial Paper, Debt Securities, Securities Loaned, Other Securities, and Other Negotiable Instruments)	Short-term borrowings	Wholesale funding provided by nonfinancial corporate customers (non maturity or residual maturity < 1yr)	0.5
Municipalities / Government Deposits Banks Deposits Commercial Deposits Other Deposits	Other term deposits	Other liabilities with an effective maturity of 1 year or greater	1 1 1 1
Customer Deposits – Term	Term deposits	Other liabilities with an effective maturity of 1 year or greater	1
Total Other Funding (Convertible Bonds, Mortgage Bonds, Other Bonds, Subordinated Debt, Hybrid Capital, and Other Funding)	Long-term borrowing	Other liabilities with an effective maturity of 1 year or greater	1
Other Liabilities		All other liabilities and equity not included above	0
Equity	Tier 1&2 capital instruments, other preferred shares and capital instruments in excess of Tier 2 allowable amount having an effective maturity of one year or greater	Tier 1 & 2 Capital Instruments, other preferred shares and capital instruments in excess of Tier 2 allowable amount having an effective maturity of one year or greater	1

Table 3. Definition of Variables

Mnemonics	Description	Definition	Source
Dependent Variable			
Distress	Banks are in distress	0:Normal ; 1:Bank-run; 2:Bailout 3:Fail	
Independent Variable			
LAsset	Size	Log (Total Assets)	BankScope
CAR	Capital adequacy ratio	Qualified capital / Risk weighted assets	BankScope
NPL	Non-performing loan	Nonperforming loans / Total loans	BankScope
CostInc	Cost to income	Total operation expenses / Total operation income	BankScope
ROA	Return on assets	Net income / Average total assets	BankScope
LiqR	Liquid ratio	Liquid assets / Total assets	BankScope
LiqC	Liquid creation	[(0.5 × Illiquid assets+0 × Semi-liquid assets-0.5 × Liquid assets)+(0.5 × Liquid liabilities +0 × Semi-liquid liabilities -0.5 × Illiquid liabilities)]/Total assets	BankScope
NSFD	Net stable funding difference	[Required stable funding-Available stable funding]/Total assets	BankScope
Div_Fund	Funding diversification	$(\frac{NonDep\_F}{NonDep\_F+Dep\_F})^2+(\frac{Dep\_F}{NonDep\_F+Dep\_F})^2$	BankScope
Div_Inc	Income diversification	$(\frac{NII}{NII+NonII})^2+(\frac{NonII}{NII+NonII})^2$	BankScope
GDPg	GDP growth rate	Annual percent change of gross domestic product, current prices	World Bank
Infla	Inflation rate	Annual change in CPI index	World Bank
InvestPro	Governance	A measure of legal protection of minority shareholders against insiders expropriation	DLSS

Notes: DLSS: Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2006)

Table 4. Expected Signs of the Coefficients of Liquidity Indicators

	LiqR	LiqC	NSFD
Expected Sign on the distressed banks	-	+	+
Expected Sign of interaction with:			
Fund diversification	-	+	+
Income diversification	+	-	-

Note: negative (positive) sign denotes the negative (positive) effect of liquidity indicator on the distress banks.

Table 5. Bank Categories in 18 Countries

		Normal	Bank-run	Bailout	Fail
1	**Austria**	45	1	1	0
2	**Belgium**	26	1	4	1
3	**Czech Republic**	16	0	0	1
4	**Denmark**	26	0	0	8
5	**France**	121	0	4	9
6	**Germany**	104	0	6	4
7	**Hungary**	15	0	1	0
8	**Ireland**	17	0	4	4
9	**Italy**	112	0	1	12
10	**Latvia**	8	1	0	0
11	**Luxembourg**	58	1	2	5
12	**Netherlands**	24	2	1	2
13	**Poland**	31	0	2	1
14	**Portugal**	15	0	0	1
15	**Slovakia**	12	0	0	1
16	**Spain**	47	0	0	6
17	**UK**	79	3	8	1
18	**US**	169	14	111	65
	Total	925	23	145	121

Notes:
1 Normal, bank-run, bailout, and fail denote banks that are normal, bank-run, bailout, and failed.
2 We collected these four types of banks from BankScope database, Factiva, government departments, and other relative websites.

Table 6. Descriptive Statistics

Variable (*t*−1)		Normal	Bank-run	Bailout	Fail	F-value
LiqR	Median	0.14	0.18	0.05	0.19	4.52
	Mean	0.23	0.20	0.12	0.21	
	Std.	0.24	0.12	0.17	0.18	
	Differ		0.03	0.10***	0.02	
	P−value		(0.69)	(0.00)	(0.57)	
	N	4162	22	139	118	
LiqC	Median	0.31	0.38	0.39	0.40	0.03
	Mean	0.32	0.33	0.33	0.30	
	Std.	0.68	0.19	0.18	0.38	
	Differ		−0.01	−0.01	0.02	
	P−value		(0.97)	(0.86)	(0.83)	
	N	4164	22	139	118	
NSFD	Median	−0.04	0.15	0.18	−0.11	12.74
	Mean	−0.09	0.21	0.14	−0.13	
	Std.	0.31	0.47	0.22	0.26	
	Differ		−0.30***	−0.23***	0.03	
	P−value		(0.00)	(0.00)	(0.45)	
	N	4164	22	139	118	
LAsset	Median	8.65	11.86	9.29	8.50	14.89
	Mean	9.05	11.62	9.98	9.05	
	Std.	1.68	2.30	2.17	1.79	
	Differ		−2.57***	−0.93***	−0.01	
	P−value		(0.00)	(0.00)	(0.99)	
	N	4165	22	139	118	
CAR (%)	Median	11.40	11.55	10.97	10.89	2.82
	Mean	12.27	12.85	11.39	11.06	
	Std.	3.27	4.61	1.77	2.63	
	Differ		−0.01	0.01**	0.01*	
	P−value		(0.56)	(0.03)	(0.07)	
	N	2407	21	126	96	
NPL (%)	Median	0.97	1.67	0.92	1.07	1.27
	Mean	2.21	1.70	1.53	2.67	
	Std.	3.33	1.06	1.52	3.01	
	Differ		0.01	0.01*	−0.01	
	P−value		(0.61)	(0.09)	(0.44)	
	N	2164	22	130	100	
CostInc (%)	Median	59.79	64.98	59.01	53.83	3.80
	Mean	60.00	75.12	61.61	53.77	
	Std.	19.02	31.27	20.28	21.72	
	Differ		−0.15***	−0.02	0.06**	
	P−value		(0.00)	(0.49)	(0.04)	
	N	4096	20	136	113	
ROA (%)	Median	0.81	0.04	0.99	0.85	4.36
	Mean	0.83	−0.04	0.77	0.79	
	Std.	0.80	1.45	0.92	0.88	
	Differ		0.01***	0.01	0.01	
	P−value		(0.00)	(0.50)	(0.76)	
	N	4156	22	138	118	
Div_Fund	Median	0.78	0.66	0.68	0.64	0.30
	Mean	0.83	0.70	0.95	0.72	
	Std.	1.37	0.15	2.28	0.18	
	Differ		−0.01	0.05**	−0.01	
	P−value		(0.97)	(0.04)	(0.80)	
	N	4019	22	137	116	
Div_Inc	Median	0.74	0.57	0.64	0.73	10.57
	Mean	0.75	0.61	0.66	0.74	
	Std.	0.15	0.14	0.11	0.16	
	Differ		0.14***	0.09***	0.01	
	P−value		(0.00)	(0.00)	(0.76)	
	N	3969	21	137	117	

Table 7. Performance of Three Liquidity Indicators: Funding Diversification (Normal Period, 2005~2007)

Variables	LiqR						LiqC						NSFD					
	Panel A			Panel B			Panel A			Panel B			Panel A			Panel B		
	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail
CON	−17.5724***	−3.4019*	0.9990	−17.6230***	−3.4725**	1.0517	−15.2414***	−2.5584	0.2843	−15.1238***	−2.5726	0.3370	−11.2325***	−0.8599	4.8342*	−12.9704***	−5.1991***	2.8100
	(−3.98)	(−1.96)	(0.36)	(−4.02)	(−2.00)	(0.38)	(−4.25)	(−1.56)	(0.11)	(−4.31)	(−1.57)	(0.13)	(−2.92)	(−0.50)	(1.93)	(−3.05)	(−3.44)	(1.07)
LAsset	0.7773***	0.1602**	−0.1127	0.7991***	0.1681**	−0.1170	0.5950***	0.0867	−0.0925	0.5938***	0.0886	−0.0957	0.6634***	0.1204*	−0.4076**	0.7788***	0.0996	−0.1492
	(3.62)	(2.25)	(−0.63)	(3.81)	(2.36)	(−0.65)	(4.43)	(1.18)	(−0.55)	(4.49)	(1.20)	(−0.58)	(4.80)	(1.71)	(−2.22)	(5.09)	(1.41)	(−0.85)
Liq	−4.0183*	−2.1763*	−0.0468	−5.1254**	−2.7342**	0.2125	0.6111**	0.1580	0.6451	0.6288**	0.1335	0.7390**	2.5750*	1.3841**	−0.7409	10.1420***	2.2886***	−0.7344
	(−1.73)	(−1.68)	(−0.04)	(−2.27)	(−2.22)	(0.12)	(2.10)	(0.63)	(1.58)	(2.12)	(0.52)	(2.04)	(1.93)	(2.25)	(−0.91)	(3.79)	(4.17)	(−0.70)
Liq × Div_Fund				1.6956**	0.8733***	−0.3680				−0.0380	0.0321**	−0.1365				−8.8949***	0.1288**	−0.0645
				(2.15)	(4.04)	(−0.20)				(−0.38)	(2.48)	(−0.71)				(−2.97)	(2.45)	(−0.17)
CAR	12.9898	−23.9773***	−25.8135*	13.9985	−23.2034***	−25.8126*	11.0820	−25.5582***	−24.0110*	11.6547	−24.985***	−24.2124*	12.8717*	−7.8788	−31.6859**	20.5834***	−23.9579***	−26.5040**
	(1.17)	(−3.59)	(−1.86)	(1.31)	(−3.36)	(−1.80)	(0.82)	(−3.77)	(−1.82)	(0.89)	(−3.60)	(−1.79)	(1.79)	(−0.88)	(−2.55)	(3.48)	(−2.76)	(−2.11)
NPL	−20.6002	−4.0857	8.4936	−21.2167	−4.4772	8.2812	−22.9576	−7.8876	7.9713	−22.9021	−8.0623	7.8381	−21.5995	−5.4401	5.2415	−22.02029	1.6197	6.6665
	(−0.99)	(−0.54)	(1.35)	(−1.00)	(−0.58)	(1.30)	(−1.08)	(−1.07)	(1.32)	(−1.08)	(−1.08)	(1.28)	(−0.84)	(−0.84)	(0.92)	(−0.81)	(0.27)	(1.16)
CostInc	7.7510*	1.2043	−3.8836	7.0721*	1.0845	−4.0478	5.7071	0.7860	−3.4722	5.2927	0.7019	−3.6282	−2.0389	0.0491	−4.0644	−3.5381*	3.6176	−5.3100**
	(1.88)	(0.52)	(−1.29)	(1.77)	(0.46)	(−1.35)	(1.41)	(0.35)	(−1.14)	(1.36)	(0.31)	(−1.20)	(−0.85)	(0.03)	(−1.49)	(−1.86)	(1.63)	(−2.10)
$CostInc^2$	−2.9796	−0.6314	1.1865	−2.6646	−0.5637	1.2608	−2.3419	−0.5446	0.9500	−2.1525	−0.5102	1.0112	1.1786	−0.5290	1.2132	1.7708*	−2.1716	1.7909
	(−1.28)	(−0.69)	(0.84)	(−1.21)	(−0.61)	(0.89)	(−0.95)	(−0.61)	(0.6)	(−0.92)	(−0.57)	(0.64)	(1.14)	(−0.63)	(0.92)	(1.75)	(−1.41)	(1.42)
ROA	−38.2710	−22.6447	−66.0504**	−38.4691	−21.6755	−65.6904**	−49.3571	−27.59619	−69.8055**	−49.6146	−27.7432	−69.8960**	−38.1327	−24.6592	−72.6828***	−46.0761	−12.5246	−70.9211**
	(−1.39)	(−0.98)	(−2.34)	(−1.40)	(−0.97)	(−2.34)	(−1.48)	(−1.17)	(−2.09)	(−1.47)	(−1.19)	(−2.06)	(−1.50)	(−1.29)	(−3.08)	(−1.40)	(−0.53)	(−2.05)
GDPg	12.3972	−16.7234	38.3967***	13.3311	−16.9410	39.4495***	9.7939	−17.5204	40.8524***	10.7644	−17.5009	41.8554***	−16.6510	−36.7097*	32.5043***	−10.1229	−17.3713	34.7919***
	(0.54)	(−1.27)	(3.83)	(0.57)	(−1.26)	(3.95)	(0.47)	(−1.36)	(3.76)	(0.51)	(−1.34)	(3.88)	(−0.28)	(−1.91)	(3.82)	(−0.17)	(−1.16)	(3.76)
Infla	41.1793***	−12.9522	−25.4504	41.9415***	−13.0749	−21.5728	37.4797***	−10.3021	−27.1263	38.0320***	−10.1455	−23.0211	27.5210	−38.3014	−32.7125**	32.7414	−11.7081	−26.9140*
	(2.79)	(−0.67)	(−1.39)	(2.77)	(−0.66)	(−1.25)	(2.97)	(−0.64)	(−1.4)	(2.96)	(−0.63)	(−1.27)	(0.83)	(−0.74)	(−2.21)	(0.89)	(−0.42)	(−1.76)
InvestPro	−1.4552	4.5384***	1.7213	−1.5376	4.4551***	1.5796	−0.8685	4.5075***	1.6568	−0.8971	4.4529***	1.5407	−1.7387	6.3257***	2.2875	−2.0822	5.9179***	0.5735
	(−0.90)	(3.25)	(1.14)	(−0.94)	(3.17)	(1.04)	(−0.51)	(3.63)	(1.09)	(−0.52)	(3.57)	(1.01)	(−1.06)	(2.98)	(1.29)	(−1.19)	(3.83)	(0.33)
Pseudo R^2		0.12			0.12			0.12			0.12			0.15			0.16	
N		2065			1032			2065			2041			2065			2041	

Notes:
1. The model is estimated by using the multinomial logit method.
2. Pseudo R^2 denotes the goodness-of-fit test.
3. *t*-statistics are placed in parentheses.
4. N: number of bank-year observations
5. The models are estimated with robust standard errors clustered by bank.
6. ***, **, and* denotes the significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Performance of Three Liquidity Indicators: Income Diversification (Normal Period, 2005-2007)

Variables	Panel A (LiqR)			Panel B (LiqC)			Panel C (NSFD)		
	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail
CON	−17.0482***	−2.5552	1.5551	−14.5311***	−2.1289	3.2782	−10.9896***	−0.7900	4.8389*
	(−3.82)	(−1.49)	(0.57)	(−3.98)	(−1.25)	(1.12)	(−2.82)	(−0.44)	(1.94)
LAsset	0.7728***	0.1177	−0.1269	0.5971***	0.0768	−0.1641	0.7014***	2.2640	−0.4053**
	(3.41)	(1.57)	(−0.73)	(4.02)	(1.07)	(−0.93)	(4.95)	(0.86)	(−2.2)
Liq	9.6596	12.6531***	5.6098	11.7888***	3.4430***	5.0465*	8.7546***	−1.1481	0.5824
	(1.00)	(3.94)	(1.27)	(3.69)	(2.63)	(1.68)	(2.61)	(−0.38)	(0.15)
Liq × Div_Inc	−22.3147	−22.1220***	−7.9947	−19.4106***	−5.4229**	−7.5760*	−7.8336*	−7.5599	−1.7612
	(−1.34)	(−4.29)	(−1.3)	(−3.54)	(−2.58)	(−1.66)	(−1.84)	(−0.82)	(−0.34)
CAR	14.8452*	−26.8272***	−29.0868*	4.6320	−21.3248***	−24.9869**	16.0101***	−5.5275	−31.2858**
	(1.70)	(−3.64)	(−1.77)	(0.36)	(−2.82)	(−2.05)	(3.16)	(−0.84)	(−2.46)
NPL	−15.3666	1.4894	8.9793	−17.5678	−1.9665	9.9498	−22.2963	−0.0997	5.1412
	(−0.68)	(0.24)	(1.58)	(−0.84)	(−0.31)	(1.63)	(−0.78)	(−0.06)	(0.89)
CostInc	7.3646*	0.4949	−4.0447	5.7780	−1.0436	−6.4578***	−4.3348*	−0.4646	−4.0892
	(1.74)	(0.22)	(−1.36)	(1.46)	(−0.48)	(−2.82)	(−1.66)	(−0.54)	(−1.52)
$CostInc^2$	−3.1873	−0.4708	1.1341	−2.600375	0.1195	1.9750	2.0954**	−25.6942	1.2025
	(−1.32)	(−0.54)	(0.80)	(−1.22)	(0.14)	(1.48)	(2.01)	(−1.30)	(0.90)
ROA	−54.5167**	−24.6459	−70.6010***	−74.3996**	−30.2458	−82.3043**	−45.8822	−36.7043*	−74.6500***
	(−2.06)	(−1.02)	(−2.77)	(−2.54)	(−1.31)	(−2.38)	(−1.61)	(−1.92)	(−2.90)
GDPg	15.3122	−19.1133	40.1307***	12.20864	−17.7897	38.2259***	−15.6160	−38.6329	32.3850***
	(0.62)	(−1.22)	(3.87)	(0.45)	(−1.44)	(3.67)	(−0.26)	(−0.73)	(3.67)
Infla	42.0134***	−15.9837	−26.0868	41.36749***	−9.0152	−27.8481	28.3445	6.2806***	−32.9207**
	(2.87)	(−0.69)	(−1.42)	(3.16)	(−0.54)	(−1.61)	(0.82)	(3.00)	(−2.23)
InvestPro	−2.0230	5.0641***	1.8315	−0.71381	4.6514***	0.9586	−1.9732	−0.7900	2.2330
	(−1.21)	(2.96)	(1.19)	(−0.4)	(3.95)	(0.59)	(−1.14)	(−0.44)	(1.23)
Pseudo R^2		0.14			0.14			0.15	
N		2045			2045			2045	

Notes:
1. The model is estimated by using multinomial logit method.
2. Pseudo R^2 denotes the goodness-of-fit test.
3. *t*-statistics are placed in parentheses.
4. N: number of bank-year observations
5. The models are estimated with robust standard errors clustered by bank.
6. ***, **, and* denotes the significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Performance of Three Liquidity Indicators: Funding Diversification (Crisis Period, 2008-2009)

Variables	Panel A (LiqR)			Panel B (LiqC)			Panel C (NSFD)		
	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail
CON	-17.5038***	-3.6875*	-7.5624**	-9.6096***	-2.9487*	-0.4275	-13.2483***	-5.0289***	-1.6984
	(-3.86)	(-1.80)	(-1.98)	(-3.62)	(-1.74)	(-0.12)	(-3.47)	(-3.2)	(-0.47)
LAsset	0.8152***	0.1579**	0.1695	0.5239***	0.0625	-0.0224	0.7515***	0.0523	0.0696
	(3.97)	(2.00)	(0.61)	(5.01)	(0.85)	(-0.11)	(5.36)	(0.66)	(0.32)
Liq	-6.4104**	-3.5147**	4.7181	0.5770**	-0.04720	-2.683	10.7413***	2.1361***	-1.5273
	(-2.43)	(-2.28)	(0.27)	(2.30)	(-0.16)	(-1.1)	(3.66)	(3.37)	(-0.88)
Liq × Div_Fund	2.2267***	1.7291***	-15.6443	0.0415	0.0544***	0.0024	-10.1828***	0.2578***	0.1746
	(2.77)	(4.04)	(-0.49)	(0.39)	(2.78)	(0.02)	(-3.16)	(2.77)	(0.38)
CAR	18.2194	-22.8725***	-16.2087	19.9093**	-20.8977**	-22.9622	28.7648***	-23.2517***	-25.5509
	(0.90)	(-3.17)	(-1.00)	(2.48)	(-2.57)	(-1.62)	(2.95)	(-2.61)	(-1.1)
NPL	-30.4902	-6.2741	26.4547***	-26.3629	-5.2615	11.8966*	-36.8773	0.2821	12.3630
	(-1.34)	(-0.70)	(2.86)	(-1.35)	(-0.74)	(1.92)	(-1.54)	(0.05)	(1.16)
CostInc	7.2617*	1.0676	-2.6254	-4.4331**	0.4148	-7.6893**	-3.9421*	3.3181	-6.0813
	(1.74)	(0.37)	(-0.57)	(-2.19)	(0.16)	(-2.56)	(-1.78)	(1.45)	(-1.36)
$\mathrm{CostInc}^2$	-2.929	-0.4821	0.3432	1.7601*	-0.2595	2.2714*	1.8728*	-1.7077	1.8819
	(-1.19)	(-0.45)	(0.17)	(1.81)	(-0.25)	(1.86)	(1.84)	(-1.34)	(1.11)
ROA	-22.2841	0.7887	-68.2802***	-45.8997	-0.6677	-91.1692**	-39.6520	11.1410	-78.9759**
	(-1.08)	(0.03)	(-2.81)	(-1.38)	(-0.03)	(-2.49)	(-1.08)	(0.44)	(-2.07)
GDPg	22.8729*	24.8616**	86.0934***	3.905679	21.5554***	67.4364***	15.8830	31.3000***	62.4107***
	(1.83)	(2.55)	(3.71)	(0.19)	(2.67)	(3.55)	(0.91)	(3.34)	(3.33)
Infla	36.3293**	-16.75372	-29.1167	25.01669*	-20.2559	-33.9743	36.2793**	-15.27867	-36.8909*
	(2.42)	(-0.88)	(-1.35)	(1.82)	(-1.17)	(-1.56)	(2.18)	(-0.88)	(-1.82)
InvestPro	-0.8917	5.1937***	7.5251***	-0.2632	5.4950***	6.0196***	-1.8655	6.2020***	4.6637*
	(-0.57)	(3.61)	(3.3)	(-0.19)	(4.21)	(3.07)	(-1.13)	(4.48)	(1.83)
Pseudo R^2		0.18			0.17			0.21	
N		1009			1009			1009	

Notes:
1. The model is estimated by using the multinomial logit method.
2. Pseudo R^2 denotes the goodness-of-fit test.
3. *t*-statistics are placed in parentheses.
4. N: number of bank-year observations
5. The models are estimated with robust standard errors clustered by bank.
6. ***, **, and* denotes the significance at the 1%, 5%, and 10% levels, respectively.

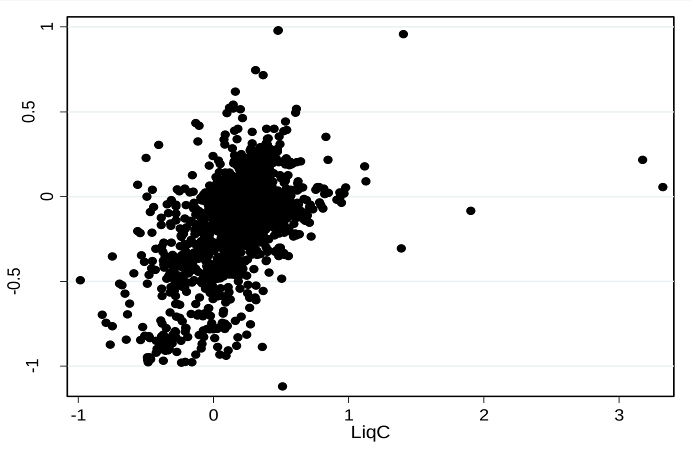
Table 10. Performance of Three Liquidity Indicators: Income Diversification (Crisis Period, 2008-2009)

Variables	Panel A (LiqR)			Panel B (LiqC)			Panel C (NSFD)		
	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail	Bank−run	Bailout	Fail
CON	-17.4149***	-1.7963	-4.6627	-16.3528***	-0.2239	0.2411	-11.7730***	-5.1353***	-3.3494
	(-3.86)	(-0.82)	(-1.02)	(-3.68)	(-0.1)	(0.04)	(-3.27)	(-3.17)	(-0.88)
LAsset	0.7886***	0.0548	0.1223	0.7498***	0.0180	-0.0549	0.6969***	0.0482	0.1654
	(3.48)	(0.62)	(0.55)	(4.08)	(0.22)	(-0.21)	(5.31)	(0.60)	(0.72)
Liq	12.2109	18.6381***	15.0889	27.9465***	4.8287***	19.9720**	9.9843***	1.167956	8.6989
	(1.02)	(4.81)	(1.58)	(3.35)	(2.68)	(2.04)	(2.95)	(0.43)	(1.2)
Liq × Div_Inc	-27.5630	-30.3895***	-29.3255**	-45.4514***	-7.9811***	-31.7297**	-9.8814**	1.5138	-13.9937
	(-1.28)	(-5.08)	(-2.09)	(-3.27)	(-2.74)	(-1.96)	(-2.29)	(0.43)	(-1.43)
CAR	19.4697	-30.3429***	-35.5156	14.859	-30.1269***	-51.8398	26.5333***	-25.1976***	-22.6737
	(1.1)	(-3.69)	(-1.43)	(0.90)	(-3.76)	(-1.64)	(2.68)	(-2.69)	(-1.02)
NPL	-23.6308	-0.3057	21.9321***	-21.2888	-3.5883	29.3788***	-35.3480	1.5255	18.3778**
	(-0.96)	(-0.05)	(2.92)	(-0.83)	(-0.48)	(2.65)	(-1.44)	(0.25)	(2.23)
CostInc	7.8012*	-0.9740	-5.0593	4.622781	-1.5615	-9.3128	-4.5958	3.8911	-5.5060
	(1.77)	(-0.34)	(-0.93)	(1.09)	(-0.54)	(-1.50)	(-1.51)	(1.50)	(-1.35)
CostInc^2	-3.7187	-0.0097	1.0684	-2.6051	0.2407	2.3257	2.0704*	-1.9837	1.7791
	(-1.44)	(-0.01)	(0.49)	(-1.12)	(0.23)	(1.02)	(1.79)	(-1.33)	(1.09)
ROA	-47.1988*	-18.3926	-109.336***	-88.9253***	-22.2938	-125.1967***	-40.9162	13.5999	-75.8303**
	(-1.77)	(-0.69)	(-3.4)	(-3.42)	(-0.9)	(-3.23)	(-1.09)	(0.52)	(-2.04)
GDPg	29.0888**	33.9236***	110.4631***	28.2718*	23.4503**	98.2422**	10.0593	30.6345***	57.6958***
	(2.06)	(2.98)	(4.03)	(1.77)	(2.54)	(2.54)	(0.54)	(3.26)	(3.05)
Infla	39.2512**	-15.6641	-53.1619*	51.6014***	-20.20995	-42.7451	31.5039**	-16.3514	-34.9552*
	(2.45)	(-0.84)	(-1.72)	(3.16)	(-1.1)	(-1.03)	(2.04)	(-0.95)	(-1.75)
InvestPro	-0.9524	6.5050***	9.718***	-1.4773	5.5714***	9.9773***	-1.8520	6.4385***	4.2513*
	(-0.58)	(3.85)	(3.26)	(-0.77)	(4.02)	(2.91)	(-1.11)	(4.57)	(1.68)
Pseudo R^2		0.14			0.22			0.20	
N		1008			1008			1008	

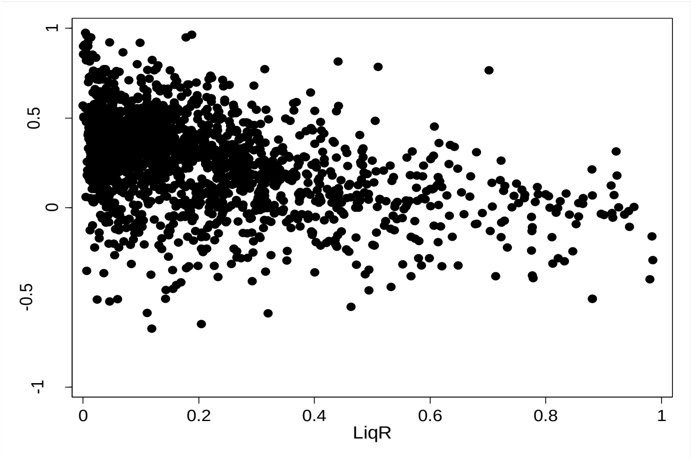
Notes:
1. The model is estimated by using the multinomial logit method.
2. Pseudo R^2 denotes the goodness-of-fit test.
3. *t*-statistics are placed in parentheses.
4. N: number of bank-year observations
5. The models are estimated with robust standard errors clustered by bank.
6. ***, **, and* denotes the significance at the 1%, 5%, and 10% levels, respectively.

Figure 1. Scatter Plot between LiqC (LiqR) and NSFD

Panel A: LiqC and NSFD



Panel B: LiqR and NSFD



Panel C: LiqR and LiqC

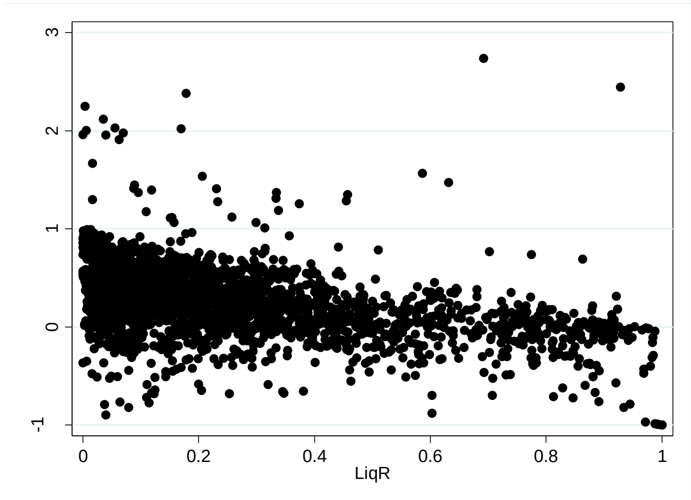


Figure 2. LiqR, LiqC and NSFD in Four Types of Banks (LiqR: Dashed Line; LiqC: Solid Line NSFD: Dotted Line)

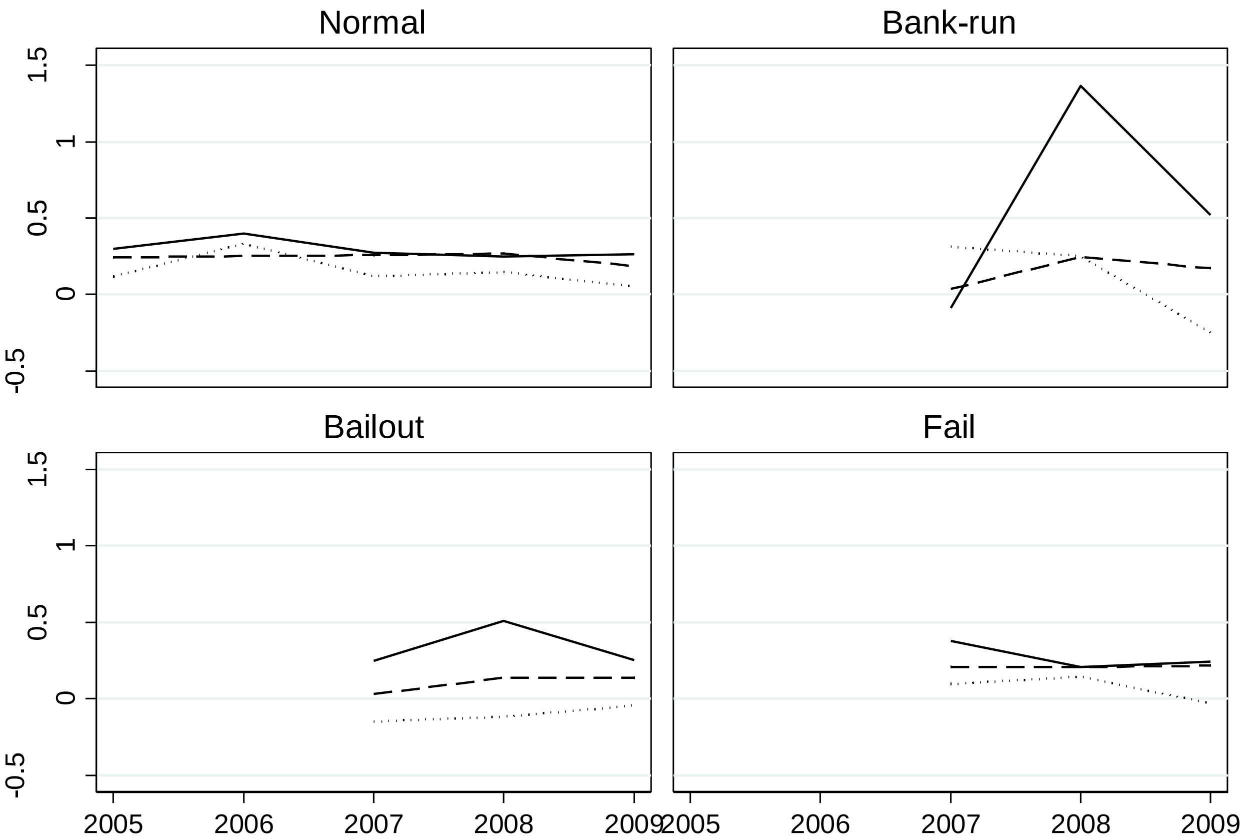
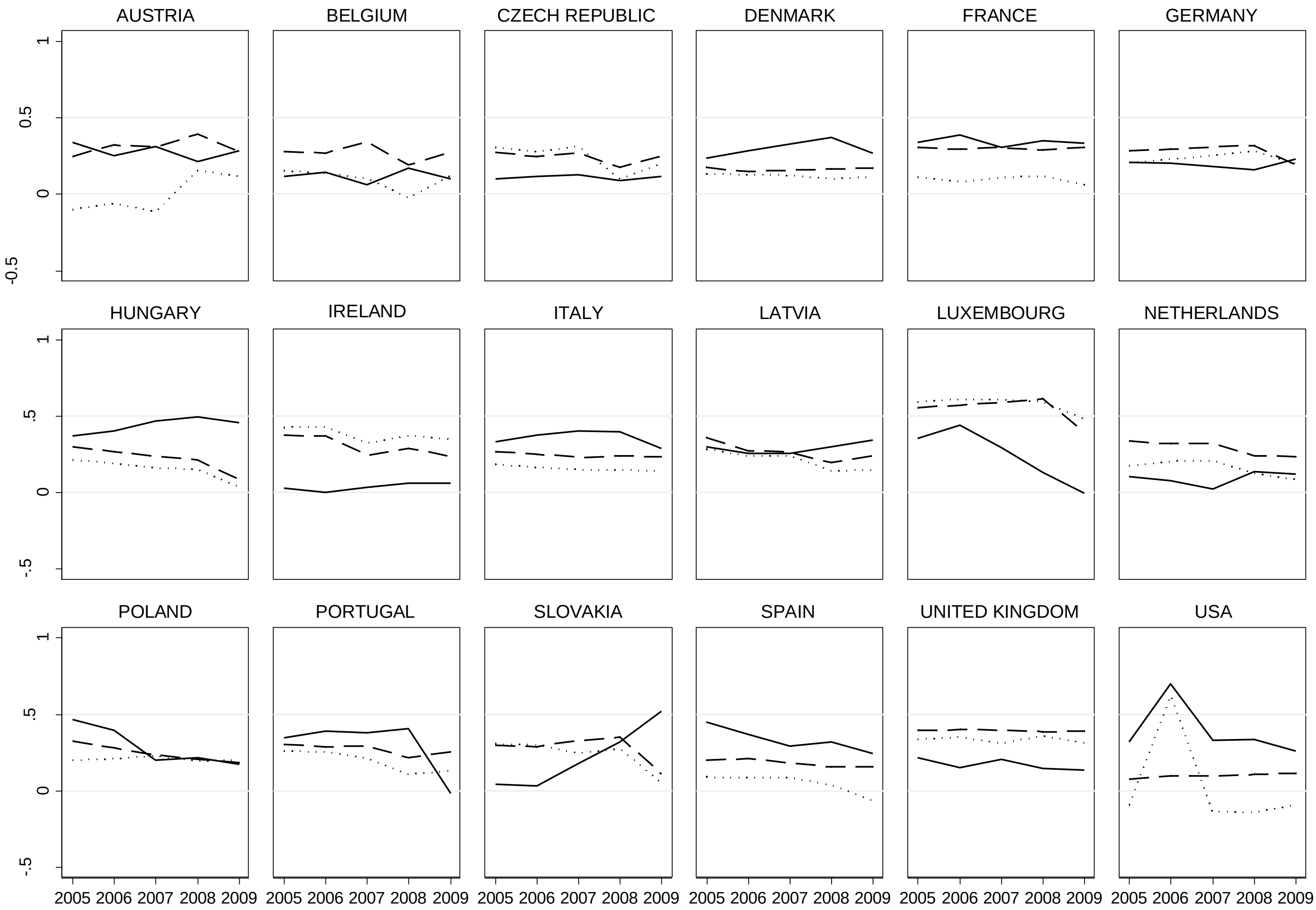
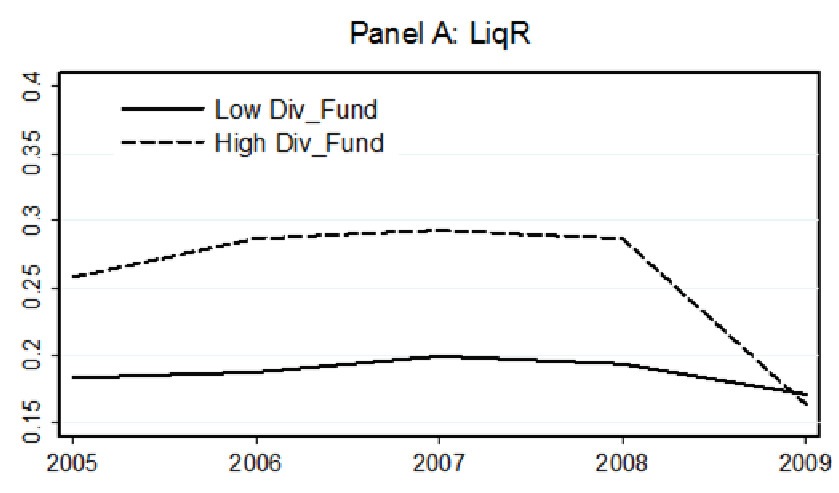


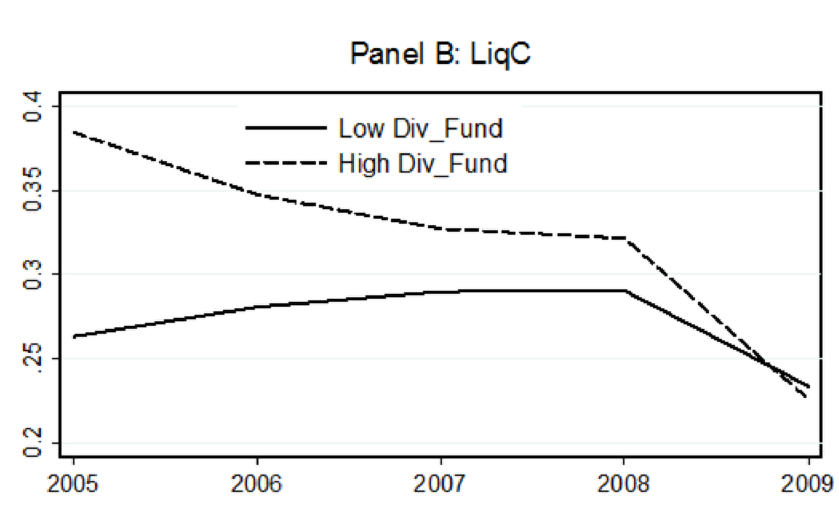
Figure 3. Trend of LiqR, LiqC and NSFD in Each Country (LiqR: Dashed Line; LiqC: Solid Line NSFD: Dotted Line)



Notes: This plot shows the trend of LiqC and LiqR in 18 crisis countries from 2005 to 2009. LiqC is defined as liquidity creation divided by total assets. LiqR is defined as liquid assets divided by total assets. NSRD is net stable funding difference.

Figure 4. High and Low Div_Fund in LiqR, LiqC, and NSFD (High Div_Fund and Low Div_Fund are divided by median)





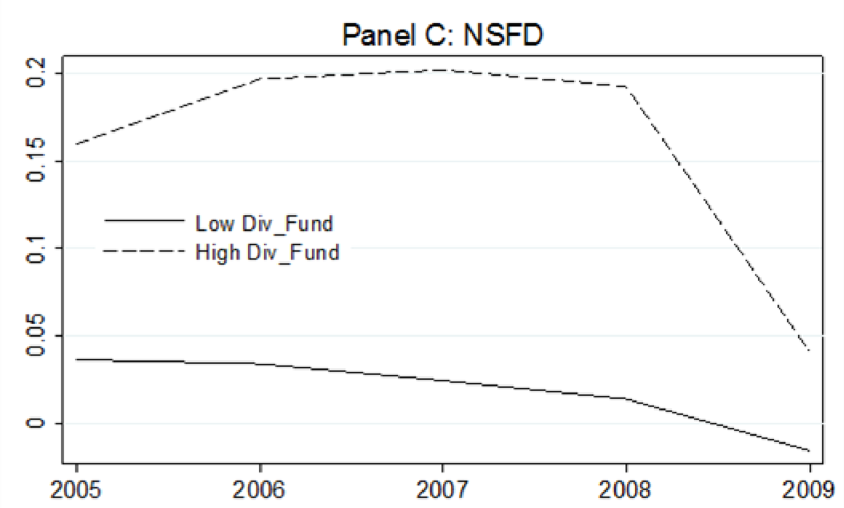


Figure 5. High and Low Div_Inc in LiqR, LiqC, and NSFD (High Div_Inc and Low Div_Inc are divided by median)