Bank Liquidity, Bank Failure Risk and Bank Size

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ABSTRACT

The literature of the effect of bank liquidity on bank failure risk is large. The moral hazard view predicts that bank liquidity and failure risk are negatively correlated, while the precautionary motive view argues that they should be positively related. The empirical evidences are mixed and inconclusive. We argue and develop hypotheses that the relationship depends on bank size. Using the comprehensive measure of bank liquidity developed by Berger & Bouwman (2009), this paper finds evidence consistent with this view. In particular, for large banks, the relationship between bank liquidity and failure risk is negative; for small banks, the relationship between bank liquidity and failure risk is positive. The results are robust.

Keywords: Bank liquidity, Failure risk, Bank size, Precautionary motive, Moral hazard effect

1. INTRODUCTION

A well-functioning interbank market provides effective liquidity coinsurance by channelling liquidity between banks with surpluses and shortages (Allen, Carletti & Gale, 2009), which in turn minimizes banks' holding of costly liquid assets as these assets earn very low returns. In fact, interbank market funding has, until the start of the global financial crises, been the primary source of liquidity for banks and one of the most liquid sources in the financial sector (Heider, Hoerova & Holthausen, 2009). However, there is clear evidence that the interbank lending market became disrupted since 2008. In the wake of the Lehman Brothers episode, the interbank market started showing sensitivity to borrower characteristics and particularly limited the lending to large banks with high levels of nonperforming loans (Afonso, Kovner & Schoar, 2011). In this regard the interbank loans decreased from around USD 500 billion in early 2008 to about USD 100 billion in late 2011 (remaining about the same level to 2014).¹ During this interbank lending crunch, the spread between the London Interbank Offer Rate (LIBOR) and the Overnight Index Swap (OIS) rate, a primary indicator of stress in the banking sector (Sengupta & Tam, 2008; Thornton, 2009; Acharya & Skeie, 2011), increased to more than 350 basis points (bps) during October 2008, compared to its level of less than 10 bps in early 2007. The increased LIBOR-OIS spread, in addition to the decrease in the availability of interbank loans, reflected the increases in counterparty credit and liquidity risk (Christensen, Lopez &

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¹ See <u>http://research.stlouisfed.org/fred2/series/IBLACBW027NBOG</u>

Rudebusch, 2013; Hesse & Frank, 2009; Michaud & Upper, 2008; Acharya & Skeie, 2011; McAndrews, Sarkar & Wang, 2008; Hesse, Frank & Hermosillo, 2008).²

As a result of the interbank market disruption, banks started hoarding liquidity for two reasons: selfinsurance and indiscriminating distrust of counterparty bank repayment ability (Castiglionesi, Feriozzi, Loranth & Pelizzon, 2014). Banks with liquidity surpluses withheld their interbank lending due to uncertainty about counterparty solvency, whilst banks with liquidity deficits increased their liquidity holdings to cover themselves against liquidity shocks, such as credit line drawdowns and unexpected demand deposit withdrawals. Deficit banks predominantly attempted to attract funding by raising interest rates (Acharya & Mora, 2015). For expositional ease, these liquidity holding actions of banks can be referred to as "precautionary motive".³

Simultaneously, bank failures were very prominent.⁴ Intuitively, the failure of a bank to meet its deposit withdrawals or credit line drawdowns (let alone the inability to service its debt) is considered a default. Having been theoretically studied (e.g., Diamond & Rajan (2005)), bank failures induced by systematic liquidity shortages were not deemed very likely before the interbank lending crunch with the interbank market offering readily effective liquidity coinsurance. However, in the wake of the interbank lending crunch, bank failures increased dramatically.⁵ In this regard, Wu & Hong (2012) found that systematic liquidity risk explains 70% of the bank failure in 2008 and 80% in 2009.

In response to the interbank market disruption and the massive number of bank failures, the U.S. government used a variety of rescue tools, such as the Fed's Term Auction Facility and the Treasury's Troubled Asset Relief Program (TARP), to restore the U.S. banking industry. For example, Li (2013) found that TARP investments improved the annualized bank loan supply of banks that had low Tier 1 capital ratios by 6.36% during the 2007-2009 financial crisis. Bailouts of troubled banks were also conducted to prevent or curtail financial contagion risks (Goodhart & Huang, 2005; Flannery, 2010); systemic meltdown (Fischer, Hainz, Rocholl & Steffen, 2014) and the risk of bank runs (Goldsmith-Pinkham & Yorulmazer, 2010). However, such government support for banks may have created incentives for moral hazard (Mailath & Mester, 1994; Acharya & Yorulmazer, 2007; Gale & Yorulmazer, 2013), triggering banks to take on excessive risk, engage in risk shifting, and fund/finance their activities with lower levels of liquidity than they would do otherwise. These effects on the liquidity holding actions of banks can be referred to as "moral hazard effect".

 $^{^{2}}$ Liquidity risk addressed in the referenced research papers is defined as exposure to drawdowns of off-balance sheet loan commitments and unexpected demand deposit withdrawals.

³ Gale & Yorulmazer (2013) argue that banks have two reasons for hoarding liquidity. One is the precautionary motive and the other one is the speculative motive.

⁴ FDIC reported that it closed 140, 157 and 92 financial institutions in 2009, 2010 and 2011, respectively. For example, Lehman Brothers collapsed in mid-September 2008; Wachovia agreed to merge with Well Fargo in October 2008; Washington Mutual became the largest U.S. bank ever to fail, with most of its assets and liabilities purchased from the FDIC by J.P. Morgan Chase in September 2008; and Bank of America completed the acquisition of Merrill Lynch in January 2009.

⁵ See <u>https://www.fdic.gov/bank/individual/failed/banklist.html</u>

Substantial theoretical and empirical work has been done about banks' liquidity hoarding and its reasons (Gale & Yorulmazer, 2013; Berrospide, 2013; Acharya & Merrouche, 2013; Afonso, Kovner & Schoar, 2011; Heider, Hoerova & Holthausen, 2009; Gai & Kapadia, 2010) and the connection between bank capital management and failure risk (Berger & Bouwman, 2013). Recent attention has been given to how banks' liquidity management can be associated with failure risk based on size differences among banks. There is ample evidence that in the wake of the recent financial crisis (or more precisely, when the interbank market stopped functioning as an effective channel for liquidity reallocation among banks), banks with higher propensity to fail started hoarding liquidity (Iyer, Peydro, da-Rocha-Lopes & Schoar, 2014). Most intuitively, once hoarded, liquidity should bring down the failure propensity. However, it remains unknown yet how the increased liquidity holdings of banks mitigated their failure risk. In fact, bank failure is a rare event before the breakdown of the interbank market⁶. The massive number of bank failures during the recent financial crisis offers a valuable opportunity to learn about the effect of bank liquidity on failure risk. Although limited compared to before the crisis, the interbank market was not completely frozen and still working for some banks (Afonso, Kovner & Schoar, 2011), and therefore cannot be ruled out. Hence, the interbank market disruption, which is a systematic liquidity shortage and exogenous shock, provides a plausible test setting for us to re-examine the relationship between bank liquidity holding and failure risk. Recently, Wu & Hong (2012) find that systematic liquidity risk was a major predictor of bank failures in 2008 and 2009. However, bank size is not taken into account in their paper. We argue and develop hypotheses that the relationship between liquidity and failure risk depends on bank size.

The objective of this research is to empirically examine the relationship between bank liquidity and failure risk predicted by two opposing effects (precautionary motive and moral hazard effect) with specific consideration of the different sizes of banks. Using the comprehensive measure of bank liquidity developed by Berger & Bouwman (2009), this paper finds evidence consistent with this view. In particular, for large banks, the relationship between bank liquidity and failure risk is negative; for small banks, the relationship between bank liquidity and failure risk is positive.

This paper contributes significantly in three ways to existing research. First, it enhances the empirical findings and the resulting literature about bank liquidity and failure risk. Almost all previous empirical studies related to bank failures control for bank liquidity, but their findings concerning the effect of bank liquidity on failure risk is mixed and inconclusive. Ng & Roychowdhury (2014) find that liquidity is negatively and significantly related to bank failure, while Almanidis & Sickles (2012) and Cleary & Hebb (2016) find that liquidity is positively and significantly related to bank failure. Four other studies find liquidity to be insignificant (e.g., Cole & White, 2012; Berger & Bouwman,

⁶ FDIC reported that there were 3, 4, 0, 0 and 3 bank failure cases in 2003, 2004, 2005, 2006 and 2007, respectively. See https://www.fdic.gov/bank/individual/failed/banklist.html

2013; De Jonghe, 2010; DeYoung & Torna, 2013). This is the first study that integrates bank size as a primary component in the analysis of the effect of bank liquidity on failure risk. For large banks, the relationship between bank liquidity and failure risk is significantly negative. For small banks, the relationship between bank liquidity and failure risk is significantly positive. These findings are aligned with the literature research and hypotheses statements about precautionary motive and moral hazard effects in this paper.

Secondly, this paper re-examines the relationship between bank failure risk and bank liquidity with a new liquidity measure developed by Berger & Bouwman (2009) (hereafter called BB measure). BB measure is a comprehensive single measure of bank liquidity since it considers all the bank's on-balance sheet and off-balance sheet activities. Traditional bank liquidity proxies mostly focus on the CAMEL-based asset-side liquidity (i.e. the relationship of short-term to long-term assets, such as the cash-to-assets ratio) or the general funding liquidity ratio (such as the ratio of short-term to long-term deposits).

Thirdly, and perhaps most importantly, this paper provides additional insight about bank liquidity regulation appropriateness (i.e., the applicability of it to banks of different sizes). In this regard, the findings of the study shows that higher liquidity makes large banks safer, whilst small banks with higher liquidity buffers are exposed to higher failure risk. It is well known that regulators impose and adjust liquidity requirements of banks for safety and soundness reasons. As such, there has been significant debate about prudential regulation and supervision of the banking sector. As part of this debate, questions have been raised about new liquidity requirements, such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), which have been proposed under Basel III in December 2010. The findings in this study suggest that regulators may have to consider bank sizes as part of base criteria for liquidity requirements to enhance regulation efficiency.

The rest of the paper is structured as follows: Section 2 presents the related literature and hypothesis development; Section 3 describes the data and model specification; Section 4 provides the main empirical findings; Section 5 addresses robustness issues, and Section 6 contains the conclusion.

2. RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

In the context of non-financial firms, Acharya, Davydenko & Stebulaev (2012) find that, contrary to the common intuition, endogenously determined liquidity is driven by the precautionary motive for saving cash, and the long-term default probability is positively correlated with liquidity. In the context of financial institutions, Garleanu & Pedersen (2007) point out that liquidity hoarding of individual banks can have negative externality effects, leading to market illiquidity at the aggregate level. If the negative externality effects outweigh the beneficial liquidity buffer effect, then a positive relationship between liquidity buffer and bank failure may be observed. Therefore, precautionary motive predicts that bank liquidity is positively associated with failure risk.

This line of argument is well supported by liquidity hoarding phenomena during the recent financial crisis. Banks started to build up cash reserves rapidly since September 2008 following the collapse of Lehman Brothers. The drying up of liquidity in the interbank market is attributed to liquidity hoarding by banks to counter the increased uncertainty over aggregate liquidity demand and their fear of lending to other banks (Acharya & Merrouche, 2013; Allen & Carletti, 2008). With liquidity exchange withheld by banks, the interbank lending crunch further exacerbated. This accounts for the observation that, despite the trillion dollars of liquidity injection into the banking system, the interbank market still remained impaired. In other words, banks tended to hold high levels of precautionary liquidity, rendering the government's liquidity injection somewhat less effective in assisting economic recovery. As noted previously, in the wake of the interbank market disruption, bank failures increased dramatically. Thus, it suggests a positive relationship between bank liquidity and failure risk during that period of time.

On the other hand, liquidity holdings, based on moral hazard effect, are negatively associated with failure risk. Government support of banking firms in distress may incentivize banks to engage in risk-shifting and risk-taking behaviour associated with moral hazard effect. Duchin & Sosyura (2014) find that bailed-out banks initiate riskier loans and shift assets toward riskier securities after receiving government support. In addition to actual bailout, moral hazard effect is driven by bailout expectations since such expectations disrupt the cautionary behaviour to prevent bankruptcy of banks: they have little reason to constrain risk-taking in search for high returns if expected government guarantees limit downside risk (Forssbaeck & Nielsen, 2015). Kim (2013) finds that banks with beliefs of a higher bailout probability rely more heavily on risky debt and higher-risk investments, especially when they are very close to bankruptcy. As a result, excessive risk-taking makes banks susceptible to distress and failure. In the meanwhile, government intervention may discourage banks may keep too low a level of liquidity to meet deposit withdrawal and loan commitments drawdowns. Therefore, moral hazard effect suggests that a negative relationship may exist between bank liquidity and failure risk.

It is evident from the aforementioned research about the precautionary motive and the moral hazard effect that they may provide opposing findings about the relationship between bank liquidity and failure risk. Moreover, bank liquidity varies greatly by bank size (Berger & Bouwman, 2009). They find that liquidity creation differs considerably among large banks (GTA⁷ exceeding \$3 billion), medium banks (GTA \$1 billion-\$3 billion), and small banks (GTA up to \$1 billion). Therefore, the main objective of this research is to empirically examine the relationship between bank liquidity and

⁷ GTA (gross total assets) equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve.

failure risk predicted by two opposing effects (precautionary motive and moral hazard effect) with specific consideration of the different sizes of banks.

It is expected that the precautionary motive is likely to be relatively strong for small banks and weak for large banks since Allen, Peristiani & Saunders (1989) find that small banks tend to act as lenders while large banks tend to act as borrowers in the interbank market. They argue that small banks face greater information asymmetry which makes it costly for them to access the interbank market, and thereby they have an incentive to keep some cash at hand. Also in corporate finance, small firms face more borrowing constraints and higher costs of external financing than large firms (Whited, 1992; Fazzari & Petersen, 1993; Kim, Mauer & Sherman, 1998). Opler, Pinkowitz, Stulz & Williamson (1999) find that small firms have restricted access to external capital markets. Along the same line, small banks are expected to have strong incentives of hoarding liquidity to avoid financing constraints and costly default. In contrast, large banks can more easily access funding from national or international capital markets and they are less likely to hoard cash. Thus, a negative relation should be expected between size and cash holdings.

It is expected that the "moral hazard effect" applies more strongly to large banks than to small banks since sufficiently large banks are deemed to be "too big to fail" and, in the event of distress, tend to receive government support. In this regard, Bayazitova & Shivdasani (2012) find that larger banks are more likely to receive capital injections than smaller banks because they pose greater systemic risk. Moral hazard from the "too big to fail" problem is pervasive in the financial system because of the interrelationship between the potential damage from a large bank's failure and government intervention possibility, which in turn erodes market discipline and creates incentives for increased risk-taking. Black & Hazelwood (2013) find that government support increases the loan origination risk of large banks but it decreases such risk of small bailed-out banks.

Based on the preceding literature review, the hypotheses for the relationship between bank liquidity and failure risk are:

Hypothesis 1. For small banks, the relationship between bank liquidity and failure risk is positive, consistent with the precautionary motive.

Sub-hypothesis 1.1 A positive relationship between bank liquidity and failure risk can be observed for small banks during the recent financial crisis of 2007-2009.

Hypothesis 2. For large banks, the relationship between bank liquidity and failure risk is negative, consistent with the moral hazard effect.

Hypothesis 3. Since medium size banks represent the grey area between small and large banks, either the moral hazard effect or the precautionary motive may apply to them, or these effects may simply offset each other.

3. SAMPLE, VARIABLES, AND ECONOMETRIC MODEL

3.1 Sample and data

The sample of banks in this paper consists of all Federal Deposit Insurance Corporation (FDIC) insured institutions over the period 2003-2014. The data is obtained from several sources. Quarterly financial data is sourced from Statistics on Depository Institutions (SDI) reports from the FDIC bank data and statistics. The sample of failed banks is obtained from the failed bank list of the FDIC (https://www.fdic.gov/bank/individual/failed/banklist.html). Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) is sourced from Federal Reserve System (https://www.federalreserve.gov/datadownload/Choose.aspx?rel=SLOOS), and federal funds rate data is taken from the Federal Reserve Bank of St. Louis. This study also makes use of the publicly available dataset of quarterly bank liquidity creation for U.S. commercial banks over the observation period that was compiled by Allen N. Berger and Christa Bouwman. It was downloaded from Christa Bouwman's personal website (https://sites.google.com/a/tamu.edu/bouwman/data). The composition of this dataset and calculations applied in it is described in Berger & Bouwman (2009). All the aforementioned data sources are merged together to construct the dataset for this study.

3.2 Variables and statistics

The relationship between failure risk and bank liquidity is the main focus area of this study. Therefore failure risk serves as the dependent variable and bank liquidity as the main independent variable. To analyse such relationship, a binary performance variable is used to indicate whether a bank fails within the next 12 months after a specific financial report date. If failure occurs, it is flagged as "bad" and is assigned the binary value of one. Otherwise, it is flagged as "good" and is assigned the binary value of zero.

As hypothesized, the relationship between liquidity and failure risk may vary depending on bank size, i.e., negative for large banks and positive for small banks. To test this relationship, the size criteria is the same as that used by Berger & Bouwman (2009), namely, large banks (GTA exceeding \$3 billion), medium banks (GTA \$1 billion-\$3 billion) and small banks (GTA up to \$1 billion). Berger & Bouwman's (2009) preferred liquidity creation measure (BB Measure) is used as a proxy for the main independent bank liquidity variable because the BB Measure is a comprehensive single measure of bank liquidity that considers all the bank's on-balance sheet and off-balance sheet activities. This BB "cat fat" liquidity creation measure considers both asset-side liquidity and liability-side liquidity, with product categories and maturities combined. It is therefore a much more comprehensive measure than

other traditional bank liquidity proxies mostly focus on the CAMEL-based asset-side liquidity (i.e. the relationship of short-term to long-term assets, such as the cash-to-assets ratio) or the general funding liquidity ratio (such as the ratio of short-term to long-term deposits). Maturity transformation risks are also largely ignored by traditional bank liquidity proxies.

In this study, a wide range of bank-specific characteristics and macroeconomic variables are employed as control variables. Bank-specific characteristics may have significant relationships with bank performance in terms of success or failure and are selected from empirical bank failure-predicting models of Collier, Forbush, Nuxoll & O'Keefe, 2003; Morkoetter, Schaller & Westerfeld, 2014; and Betz, Oprica, Peltonen & Sarlin, 2014. The macroeconomic variables are used to control for loan demand that varies across banks and regions, as well as the effect of monetary policy.

Bank-specific characteristics

The CAMELS rating system, employed by regulators for off-site monitoring of bank failures, entails the assessment of the following six main areas: capital adequacy, asset quality, management capability, earnings, liquidity, and sensitivity to market risk. Because the BB liquidity measure is applied as the main independent test variable in this study, control variables are selected from the remaining five areas. These five key measures of bank failure are the common equity to total risk-weighted assets (for capital adequacy); non-performing assets to total assets (for asset quality); cost-to-income ratio (for management capability); the ratio of net income to total assets (for earnings); and loans-to-deposits ratio (for sensitivity to market risk).

Furthermore, this study employs the following ratios: the ratio of unused loan commitments to total loans as a proxy for the vulnerability of banks to a systemic liquidity crisis (Acharya & Mora, 2015); the ratio of non-interest income to total income as a measure of income diversification (DeYoung & Torna, 2013); the natural logarithm of total assets to control for bank size (Forssbaeck & Nielsen, 2015); and a dummy variable that equals one if the bank is a bank holding company and zero otherwise, to control for the bank holding company (BHC) status of banks (Berger & Bouwman, 2009).

Macroeconomic variables

Loan demand depends on regional and nation-wide economic conditions (Li, 2013) as well as individual bank conditions (Ashcraft, 2006). To control for varying levels of loan demand, this study employs the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). In addition, this study employs the federal funds rate to control for the effect of monetary policy (Ashcraft, 2006; Afonso, Kovner & Schoar, 2011; Engen, Laubach & Reifschneider, 2015; Labonte, 2013; Fawley & Juvenal, 2012).

The abbreviations used for the main variables are contained in Appendix 1, whilst the descriptive statistics of these variables (number of observations, mean, standard deviation, minimum figure and maximum figure) are reflected in Table 1. Table 2 shows the correlation of the main variables.

[Insert Appendix 1, Table 1 and 2 about here]

3.3 Econometric model

The following logit model is employed to determine the effect of bank liquidity on failure risk:

$$Prob(Bank \ Failure \ Indicator = 1|X, Z) = \Lambda \left(\alpha + \beta X + \sum_{j=1}^{J} \gamma_j Z_j \right), \tag{1}$$

where $\Lambda(Y) = \frac{e^Y}{1+e^Y} = \frac{\exp(Y)}{1+\exp(Y)}$, $Y = \alpha + \beta X + \sum_{j=1}^J \gamma_j Z_j$; Λ denotes the cumulative logistic distribution function; X is the main test variable, namely the BB measure; and Z represents the control variables. Two sets of control variables are used in this study. The first set controls for bank-specific characteristics, and consists of common equity to total risk-weighted assets (*ca*); non-performing assets to total assets (*aq*); cost-to-income ratio (*mc*); ratio of net income to total assets (*earn*); loan-to-deposit ratio (*ltdrt*); ratio of unused loan commitments to total loans (*ucrt*); ratio of non-interest income to total income (*noniirt*); natural logarithm of total assets (*banksize*); and bank holding company (BHC) status (*bhc*). The other set includes macro-economic variables, which are the fed funds rate (*fedfunds*) and SLOOS (*sloos*). Equation (1) is applied separately, in similar format, across large banks (GTA exceeding \$3 billion), medium banks (GTA \$1 billion-\$3 billion), and small banks (GTA up to \$1 billion).

4. EMPIRICAL ANALYSIS

In this section, the main regression results of the logit model as specified in Equation (1) are presented. Bank liquidity creation (*catfat_gta*) is the key explanatory variable and failure risk is the dependent variable. The regression is independently applied to small banks (GTA up to \$1 billion), medium banks (GTA \$1 billion-\$3 billion) and large banks (GTA exceeding \$3 billion) to determine whether bank size is relevant. In each year, if a bank fails within the next 12 months, it is assigned the binary value of one. Otherwise, it is assigned the binary value of zero. In all cases, it is determined whether the findings are consistent with the economic intuition discussed earlier and the hypotheses statements that emanated from it. In other words, whether for small banks, bank liquidity and failure risk are positively correlated; whether for large banks, bank liquidity and failure risk are negatively correlated, and whether for medium banks, the relationship is insignificantly positive or negative.

Columns (1), (2) and (3) of Table 3 contain the regression results for small banks (GTA up to \$1 billion), medium banks (GTA \$1 billion-\$3 billion), and large banks (GTA exceeding \$3 billion), respectively. All of the regressions include the full set of control variables and have time fixed effects.

[Insert Table 3 about here]

The results in Column (1) of Table 3 show that the relationship between small bank liquidity and failure risk is positive and significant. The economic significance of the result is reflected by the magnitude of the coefficient of 2.764 on *catfat_gta*. It suggests that if the small bank liquidity is 1 percent higher, then the small bank's failure risk is predicted to be around 2.7 percent higher at the 1% significance level. Column (2) of Table 3 reports the regression results for medium banks. For these banks, the relationship between bank liquidity and failure risk is positive but not significant. The results in Column (3) of Table 3 show that the relationship between large bank liquidity and failure risk is negative and significant at the 1% level. The contrast is sharp compared to the positive relationship found for small banks. The magnitude of the coefficient of -2.879 on *catfat_gta* suggests that if the large bank liquidity is 1 percent higher, then the large bank's failure risk is predicted to be around 2.8 percent lower. In fact, the *catfat_gta* coefficients for the small and large banks are of similar magnitude but in opposite direction.

In essence, for small banks, bank liquidity and failure risk are positively correlated. For large banks, bank liquidity and failure risk are negatively correlated. For medium size banks, the two effects largely offset each other, therefore, the correlation between bank liquidity and failure risk is statistically insignificant. Thus, the data suggests that, consistent with the economic intuition, the "precautionary motive" hypothesis strongly dominates for small banks and the "moral hazard effect" hypothesis strongly dominates for large banks.

Table 3 also presents the coefficients for each of the control variables included in the model. The coefficients of common equity to total risk-weighted assets (*ca*) and ROA (*earn*) are negative and statistically significant for all banks, suggesting that banks with higher capital buffers and higher earning power are less likely to fail; the coefficient of non-performing assets to total assets (*aq*) is positive and statistically significant for all banks, confirming the relationship between asset quality and failure risks; banks with higher cost-to-income ratios (*mc*) are more likely to fail, but only significant for small banks; consistent with the finding of Almanidis & Sickles (2012), the loan-to-deposit ratio (*ltdrt*) is negatively related to failure, but only significant for small banks; the coefficient of non-interest income to total income (*noniirt*) shows no effect for small and medium banks but it is negative and statistically significant for large banks, indicating that the more the income of large banks is diversified, the lower chance of failure; the coefficient of the natural logarithm of total assets

(*banksize*) is negative and statistically significant for large banks, whilst positive and statistically significant for small banks; loan demand proxy (*sloos*) has a significant and negative coefficient for small banks showing that small banks with higher loan demand are less likely to fail, whilst it is insignificant positive for medium banks and insignificant negative for large banks. Contrary to expectations, the ratio of unused loan commitments to total loans (*ucrt*) has a negative and significant coefficient for small banks. This also contradicts the result of Mora (2010) who finds that the more commitments a bank has outstanding, the more exposed it will be to a drawdown of commitments when market conditions tighten. On the other hand, the coefficients for both medium and large banks are positive although not significant. Finally, bank holding company (BHC) status (*bhc*) is positively and significantly related to failure for medium banks, insignificant for small banks and has no effect for large banks⁸, and the monetary policy proxy (*fedfunds*) is insignificant across all bank sizes.

5. ROBUSTNESS CHECKS

In Section 4, the main findings show that, the relationship between bank liquidity and failure risk is positive and significant for small banks, insignificant for medium banks, and negative and significant for large banks. To substantiate the main empirical analysis findings, this section now examines the robustness of these main findings to (1) using a two-stage residual inclusion (2SRI) approach to control for endogeneity; (2) using alternative time-span to define bank failure risk; (3) using an alternative measure of bank size; and (4) focusing on the recent financial crisis of 2007-2009 to verify the prevalence of the findings in what can be described as a bank crisis period of time.

5.1 Using two-stage residual inclusion (2SRI) approach to control for endogeneity

The main objective of this paper is to study the effect of bank liquidity on failure risk. In doing so, liquidity is treated as exogenously given. Essentially, banks may choose their liquidity policy endogenously, therefore, this study controls for the potential endogeneity problem. Two main causes can give rise to endogeneity issues in this study. First, omitted variables can lead to endogenously determined liquidity. Omitted variables refer to those variables not used but should have been included in the vector of explanatory variables, because they may be correlated with liquidity and other explanatory variables. In this regard, a number of bank governance factors are relevant but unobservable, for example, bank CEO compensation depends on executive abilities, which are difficult to quantify and observe. Secondly, simultaneity bias occurs when the dependent variable and one or more of the independent variables are determined in equilibrium resulting in uncertainty whether the independent variables. While the theories predict a causal relationship from bank liquidity to failure risk, in practice both may be jointly determined. This makes it challenging to establish

⁸ The coefficient on *bhc* is zero and standard error is omitted because of perfect prediction. In other words, "*bhc*" predicts failure perfectly in this case.

causation. For example, banks with a higher likelihood of failure to meet credit line drawdowns and unexpected demand deposit withdrawals, caused by the lack of interbank lending coinsurance, tend to hoard large piles of liquidity for self-insurance purposes (Castiglionesi, Feriozzi, Loranth & Pelizzon, 2014).

A two-stage residual inclusion (2SRI) estimation method to control for endogeneity bias in the nonlinear regression model, i.e. logit model is applied. 2SRI is an applied instrumental variable (IV)-based approach which is the rote extension to nonlinear models of the popular linear two-stage least squares (2SLS) estimator. Terza, Basu & Rathouz (2008) demonstrate the superiority of the 2SRI method over the two-stage predictor substitution (2SPS) method, and find that the 2SRI estimator is consistent in addressing endogeneity in nonlinear models. This method is applied in this study to determine the causal effects between liquidity and failure risk for the different bank sizes.

Under the 2SRI approach, the first stage model yields the predicted residual value for the endogenous variable (*catfat_gta*) as a function of an instrument and other exogenous variables. In the second stage regression, the residual term of the first stage regression is added as an additional regressor along with the endogenous variable. In this study, three-year lagged average values of bank liquidity creation (*catfat_gta_average*) are used as the instrumental variable, as lagged values are more likely to reflect bank earlier decisions and may not directly affect the contemporaneous failure risk. The use of three-year averages, rather than a single lagged year, may reduce the effects of short-term fluctuations and problems with the use of accounting data (Berger & Bouwman, 2009). The two-stage residual inclusion (2SRI) model entails the following equations:

First stage regression,

$$E(Y|X, Z) = \alpha + \beta_1 X_1 + \beta_2 Z_2 + \beta_3 Z_3 + \dots + \beta_p Z_p + \varepsilon,$$
(2)

Where Y is the endogenous variable, *catfat_gta*; X is the instrumental variable, *catfat_gta_average* and Z_2 Z_p are control variables, as defined in the baseline specification.

Second stage regression,

$$Prob(Bank \ Failure \ Indicator = 1|X, Z, R) = \Lambda(\alpha + \beta X + \sum_{j=1}^{J} \gamma_j Z_j + \Phi R), \quad (3)$$

where $\Lambda(Y) = \frac{e^Y}{1+e^Y} = \frac{\exp(Y)}{1+\exp(Y)}$, $Y = \alpha + \beta X + \sum_{j=1}^J \gamma_j Z_j + \Phi R$; Λ denotes the cumulative logistic distribution function; X is the main test variable (endogenous variable), *catfat_gta*; Z's are control variables, as defined in the baseline specification, and R is the residual from the first stage regression, which is then included as an additional regressor in the second-stage estimation.

The output from the 2SRI model above includes the naive standard error, which assumes that there is no error in the generation of the "residual" in the first-stage regression model. The fact that "residual"

is a "generated" regressor (i.e., with estimation errors) affects how the standard error of the regression coefficient in the second-stage regression is computed. Thus, bootstrapping is used to deal with this issue.

[Insert Table 4 about here]

Column (1), (2) and (3) of Table 4 reports the regression results using the two-stage residual inclusion (2SRI) approach across different sizes of banks. As can be seen from the table, the results are in line with the earlier main estimation findings. Consistent with the "precautionary motive" and "moral hazard effect" hypotheses, the effect of bank liquidity on failure risk is statistically positive significant for small banks, statistically negative significant for large banks, and insignificant for medium banks. The coefficient on *catfat_gta* is 2.990 and -3.593 for small and large banks, respectively. The magnitude is also economically important, implying that for small banks, an increase in bank liquidity of 1% translates into a 3% increase in failure risk; in sharp contrast, for large banks, a 1% increase in bank liquidity predicts a 3.6% decrease in failure risk. The coefficients on most of the control variables (*aq, mc, earn, ltdrt, ucrt, noniirt, bhc, banksize*) have the predicted consistent signs and significance as shown in Table 3, except for the capital adequacy (*ca*) proxy and macroeconomic variables (*fedfunds and sloos*). It is interesting that the coefficient of *ca* becomes insignificant for medium banks and the coefficient of *fedfunds* turns significant for small banks. Loan demand proxy - *sloos* is significantly negative correlated with failure risk for both small and large banks when the 2SRI approach is employed.

5.2 Using alternative time-span to define bank failure risk

In the baseline model, if a bank fails within the next 12 months of the financial report date, it is assigned the binary value of one. Otherwise, it is assigned the binary value of zero. The robustness of these main findings is examined by using alternative time periods to measure bank failure risk. In the robustness test, a bank is assigned the binary value of one if it fails within the next two, three, and five years of the financial report date. Otherwise, it is assigned the binary value of zero. The regression results presented in Table 5, 6, 7 reinforce the prior findings for small and large banks. That is, for large banks, the relationship between bank liquidity and failure risk is negative and significant. For small banks, the relationship between bank liquidity and failure risk is positive and significant. However, for medium banks, the relationship turns positive and statistically significant from the prior positive and insignificant relationship, suggesting that precautionary motive for liquidity holdings dominates when the time horizon for predicting failure risk is more than one year.

[Insert Table 5, 6, 7 about here]

5.3 Using an alternative measure of bank size

In the main analysis, the sample is split into large banks (GTA exceeding \$3 billion), medium banks (GTA \$1 billion-\$3 billion), and small banks (GTA up to \$1 billion)⁹. The percentile distribution of bank size as the key bank characteristic is computed to verify the significance of the bank size grouping in the analysis of the findings. Large banks are measured by the 80th percentile of the GTA distribution, small banks are measured by the 20th percentile of the GTA distribution and medium banks are measured between the 20th percentile and the 80th percentile of the GTA distribution. Using the aforementioned percentile of the sample distribution, small banks are defined as GTA less than \$67,234,000, medium banks as GTA between \$67,234,000 and \$418,201,000, and large banks as GTA more than \$418,201,000.

Results of applying the alternative measure of the percentile distribution of bank size are shown in Table 8. It supports the main research findings. In the case of small banks, the effect of bank liquidity on failure risk is still positive and statistically significant at the 1% level, but the coefficient significantly increases from 2.764 to 7.030. In terms of economic magnitudes, a 1% increase in bank liquidity results in a 7% increase in failure risk for small banks, which appears to be a substantial increase in the effect. The relationship between the liquidity and failure risk for medium banks becomes statistically significant in contrast with the original finding that no significance exist. The reason is that all medium banks now fall under the size category of originally classified small banks. Due to the inclusion of the larger number of additional small than large banks and the resulting skewness to small bank representation, it shows a positive relationship between medium bank liquidity and failure risk. For large banks, the effect of bank liquidity on failure risk is negative and statistically significant, and the magnitude is slightly smaller than that reported in the main findings. All in all, this alternative measure of bank size suggests that "precautionary motive" strongly dominates for small and medium banks and "moral hazard effect" dominates for large banks. The finding regarding medium banks is not regarded as contrary to the original findings since the skewness to small bank representation in the percentile broadening of this bank size contributes to it.

[Insert Table 8 about here]

5.4 The effect of the recent financial crisis of 2007-2009

The global financial crisis (GFC) is commonly believed to have started with the credit crunch in July 2007, when a loss of confidence by U.S. investors in the value of sub-prime mortgages caused a liquidity crisis. Illiquidity peaked in the fourth quarter of 2008 after the failure of Lehman Brothers and the AIG bailout. Following the Lehman failure on September 15, 2008, a significant, but relatively mild, financial disruption was transformed into a full-fledged financial crisis with the Lehman bankruptcy that led to a large increase in uncertainty and a wave of distressed selling of

⁹ The size categories are aligned with the FDIC and Federal Reserve Guidelines on bank size group.

securities that caused a collapse in asset prices. However, with the implementation of conventional and unconventional monetary policies, and bailouts of some banks and financial institutions by the U.S. Federal Reserve and Treasury, financial markets began to recover in the first half of 2009. For example, the "TED spread"¹⁰ began to fall from its peak of over 400 basis points in October 2008 to below 100 basis points in January 2009. This spread fell to below pre-crisis levels (less than 20 basis points) by May 2009. Therefore, this check intends to examine how the relationship between bank liquidity and failure risk differed over the period 2007:Q3 to 2009:Q2. Compared to the total research period from 2003:Q1 to 2014:Q4, Table 9 reports the results over the 2007:Q3 to 2009:Q2 period of the recent financial crisis. As the results show in Table 9, the effect of bank liquidity on failure risk is only significant for small banks, confirming that the "precautionary motive" is a dominating factor for small banks during the GFC period. This is in line with the total period findings. However, for medium and large banks, the relationship between bank liquidity and failure risk remains positive and negative, similar to the main findings, but is insignificant during this period of time. Especially in the case of large banks, the difference from the original findings, that a significant and negative relationship exists over the total time period from 2003:Q1 to 2014:Q4 between liquidity and failure risk, can be explained by a possible strong "precautionary motive" of liquidity hoarding during the 2007:Q3 to 2009:Q2 period of time. Considering the situation that prevailed, small banks hoarded liquidity because they hedged themselves against unexpected liquidity needs for credit line drawdowns and depositor fund withdrawals and prevailing counterparty credit risk in the interbank market.

[Insert Table 9 about here]

6. CONCLUSION

Previous empirical research findings regarding the effect of bank liquidity on failure risk are mixed and sometimes, contradicting. As noted above, some papers find that liquidity is negatively and significantly related to bank failure (Ng & Roychowdhury, 2014). In contrast, several studies find that liquidity is positively and significantly related to bank failure (Almanidis & Sickles, 2012; Cleary & Hebb, 2016). Four other studies find liquidity to be insignificant (e.g., Cole & White, 2012; Berger & Bouwman, 2014; De Jonghe, 2010; DeYoung & Torna, 2013). The findings of this research show that the relationship between liquidity and failure risk depends crucially on the bank size. This study provides empirical support for both the moral hazard effect theory that predicts that higher liquidity may lead to lower probability of default and the precautionary motive theory according to which higher liquidity may result in higher probability of default based on the bank size. The preferred "cat fat" liquidity creation measure of Berger & Bouwman (2009) provides evidence that for large banks,

¹⁰ The "TED spread" is the spread between the interest rate on interbank lending (as measured by the LIBOR interest rate on three-month Eurodollar deposits) and the interest rate on three-month U.S. Treasury bills. The TED spread provides an assessment of counterparty risk from one bank lending to another, reflecting both liquidity and credit risk concerns.

liquidity is significantly negatively related to failure risk. For small banks, liquidity is significantly positively related to failure risk. A variety of robustness checks have been applied to verify the findings. The tests show that the main findings of this study with regard to large and small banks are qualitatively unchanged. As for medium banks, the main result and 2SRI estimation show that the relationship between bank liquidity and failure risk is insignificant. However, in the robustness check about alternative bank size, a positive and statistically significant relationship between liquidity and failure risk exists, suggesting that "precautionary motive" effect dominates for these banks. These findings are also aligned with proposed H3, that is, either the moral hazard effect or the precautionary motive may dominate for these banks or these effects may simply offset each other.

The result that the relationship between bank liquidity and failure risk differs based on bank sizes has important implications for policymakers as it provides novel insights for the design of prudential regulation and supervision of banks. Since the recent financial crisis of 2007-2009, liquidity risk management has become one of the top priorities for regulators, and new liquidity requirements, such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) have been proposed under Basel III in December 2010. It is well known that regulators impose and adjust liquidity requirements of banks for safety and soundness reasons. This study sheds new light on how the design features of bank regulators may have to consider banks sizes as part of base criteria for liquidity requirements to enhance regulation efficiency. In this regard, the findings of the study show that higher liquidity makes large banks safer, whilst small banks with higher liquidity buffers are exposed to higher failure risk.

Beyond the scope of this article, other interesting avenues remain open to further research. In particular, how will the Basel III liquidity requirement - liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), affect the relationship between bank liquidity and failure risk? How will a bank's liquidity management affect the relationship between bank liquidity and the probability of default? What is the interaction between idiosyncratic and aggregate liquidity risk? And how will this interaction affect a bank's liquidity management policy?

REFERENCES

- Acharya, Viral, Sergei A. Davydenko, and Ilya A. Strebulaev. 2012. "Cash Holdings and Credit Risk." *The Review of Financial Studies* 25 (12): 3572. <u>http://search.proquest.com/docview/1152167046?accountid=10382</u>.
- Acharya, Viral V, and Tanju Yorulmazer. 2007. "Too Many to Fail—an Analysis of Time-Inconsistency in Bank Closure Policies." *Journal of financial intermediation* 16 (1): 1-31.
- Acharya, Viral V., and Ouarda Merrouche. 2013. "Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis*." *Review of Finance* 17 (1): 107-160. <u>http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=84556168&site=ehost-live</u>.
- Acharya, Viral V., and Nada Mora. 2015. "A Crisis of Banks as Liquidity Providers." *The Journal of Finance* 70 (1): 1-43. doi: 10.1111/jofi.12182.
- Acharya, Viral V., and David Skeie. 2011. "A Model of Liquidity Hoarding and Term Premia in Inter-Bank Markets." *Journal of Monetary Economics* 58 (5): 436-447. doi: <u>http://dx.doi.org/10.1016/j.jmoneco.2011.05.006</u>.
- Afonso, Gara, Anna Kovner, and Antoinette Schoar. 2011. "Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis." *Journal of Finance* 66 (4): 1109-1139. doi: 10.1111/j.1540-6261.2011.01670.x.
- Allen, Franklin, and Elena Carletti. 2008. "The Role of Liquidity in Financial Crises." *Working Papers -- Financial Institutions Center at The Wharton School*: 1-36. <u>http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=35788910&site=ehost-live</u>.
- Allen, Franklin, Elena Carletti, and Douglas Gale. 2009. "Interbank Market Liquidity and Central Bank Intervention." *Journal of Monetary Economics* 56 (5): 639-652. doi: <u>http://dx.doi.org/10.1016/j.jmoneco.2009.04.003</u>.
- Allen, Linda, Stavros Peristiani, and Anthony Saunders. 1989. "Bank Size, Collateral, and Net Purchase Behavior in the Federal Funds Market: Empirical Evidence." *Journal of Business*: 501-515.
- Almanidis, P, and R Sickles. 2012. Banking Crises, Early Warning Models, and Efficiency.
- Ashcraft, Adam B. 2006. "New Evidence on the Lending Channel." *Journal of Money, Credit & Banking (Ohio State University Press)* 38 (3): 751-775. http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=20519691&site=ehost-live.
- Bayazitova, Dinara, and Anil Shivdasani. 2012. "Assessing Tarp." *Review of Financial Studies* 25 (2): 377-407. doi: 10.1093/rfs/hhr121.
- Berger, Allen N., and Christa H. S. Bouwman. 2009. "Bank Liquidity Creation." *The Review of Financial Studies* 22 (9): 3779-3837. doi: http://dx.doi.org/10.1093/rfs/hhn104.
- ———. 2013. "How Does Capital Affect Bank Performance During Financial Crises?" Journal of Financial Economics 109 (1): 146-176. doi: <u>http://dx.doi.org/10.1016/j.jfineco.2013.02.008</u>.
- Berrospide, Jose. 2013. "Bank Liquidity Hoarding and the Financial Crisis: An Empirical Evaluation." Board of Governors of the Federal Reserve System (U.S.).

- Betz, Frank, Silviu Oprică, Tuomas A Peltonen, and Peter Sarlin. 2014. "Predicting Distress in European Banks." *Journal of Banking & Finance* 45: 225-241.
- Black, Lk, and Ln Hazelwood. 2013. "The Effect of Tarp on Bank Risk-Taking." J. Financ. Stab. 9 (4): 790-803. doi: 10.1016/j.jfs.2012.04.001.
- Castiglionesi, Fabio, Fabio Feriozzi, GyÖNgyi LÓRÁNth, and Loriana Pelizzon. 2014. "Liquidity Coinsurance and Bank Capital." *Journal of Money, Credit and Banking* 46 (2-3): 409-443. doi: 10.1111/jmcb.12111.
- Christensen, Jens H. E., Jose A. Lopez, and Glenn D. Rudebusch. 2013. "Do Central Bank Liquidity Facilities Affect Interbank Lending Rates?" *Journal of Business & Economic Statistics* 32 (1): 136-151. doi: 10.1080/07350015.2013.858631.
- Cleary, Sean, and Greg Hebb. 2016. "An Efficient and Functional Model for Predicting Bank Distress: In and out of Sample Evidence." *Journal of Banking & Finance* 64: 101-111. doi: <u>http://dx.doi.org/10.1016/j.jbankfin.2015.12.001</u>.
- Cole, R. A., and L. J. White. 2012. "Deja Vu All over Again: The Causes of U.S. Commercial Bank Failures This Time Around." *J. Financ. Serv. Res.* 42 (1-2): 5-29. doi: 10.1007/s10693-011-0116-9.
- Collier, Charles, Sean Forbush, Daniel Nuxoll, and John O'Keefe. 2003. "The Scor System of Off-Site Monitoring: Its Objectives, Functioning, and Performance." *FDIC Banking Review* 15 (3): 17-32.
- De Jonghe, Olivier. 2010. "Back to the Basics in Banking? A Micro-Analysis of Banking System Stability." *Journal of Financial Intermediation* 19 (3): 387-417. doi: 10.1016/j.jfi.2009.04.001.
- DeYoung, Robert, and Gökhan Torna. 2013. "Nontraditional Banking Activities and Bank Failures During the Financial Crisis." *Journal of Financial Intermediation*. doi: 10.1016/j.jfi.2013.01.001.
- Diamond, Douglas W., and Raghuram G. Rajan. 2005. "Liquidity Shortages and Banking Crises." *Journal of Finance* 60 (2): 615-647. doi: 10.1111/j.1540-6261.2005.00741.x.
- Duchin, Ran, and Denis Sosyura. 2014. "Safer Ratios, Riskier Portfolios: Banks' Response to Government Aid." *Journal of Financial Economics* 113 (1): 1-28.
- Engen, Eric M, Thomas Laubach, and Dave Reifschneider. 2015. "The Macroeconomic Effects of the Federal Reserve's Unconventional Monetary Policies."
- Fawley, Brett W, and Luciana Juvenal. 2012. "Quantitative Easing: Lessons We've Learned." *The Regional Economist* (Jul).
- Fazzari, Steven M, and Bruce C Petersen. 1993. "Working Capital and Fixed Investment: New Evidence on Financing Constraints." *The RAND Journal of Economics*: 328-342.
- Fischer, Markus, Christa Hainz, Jörg Rocholl, and Sascha Steffen. 2014. "Government Guarantees and Bank Risk Taking Incentives."
- Flannery, Mark J. 2010. "What to Do About Tbtf?" Federal Reserve Bank of Atlanta 2010 Financial Markets Conference—Up From the Ashes: The Financial System After the Crisis, Atlanta, May.

- Forssbaeck, Jens, and Caren Xinxia Nielsen. 2015. "Tarp and Market Discipline: Evidence on the Moral Hazardeffects of Bank Recapitalizations." Knut Wicksell Centre for Financial Studies, Lund University.
- Gai, Prasanna, and Sujit Kapadia. 2010. "Liquidity Hoarding, Network Externalities, and Interbank Market Collapse" *Proc. R. Soc. A.*
- Gale, Douglas, and Tanju Yorulmazer. 2013. "Liquidity Hoarding." *Theoretical Economics* 8 (2): 291-324. doi: 10.3982/TE1064.
- Gârleanu, Nicolae, and Lasse Heje Pedersen. 2007. "Liquidity and Risk Management." *American Economic Review* 97 (2): 193-197. <u>http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=25020727&site=ehost-live</u>.
- Goldsmith-Pinkham, Paul, and Tanju Yorulmazer. 2010. "Liquidity, Bank Runs, and Bailouts: Spillover Effects During the Northern Rock Episode." *Journal of Financial Services Research* 37 (2/3): 83-98. doi: 10.1007/s10693-009-0079-2.
- Goodhart, Cae, and Hz Huang. 2005. "The Lender of Last Resort." *J. Bank Financ.* 29 (5): 1059-1082. doi: 10.1016/j.jbankfin.2003.11.003.
- Heider, Florian, Marie Hoerova, and Cornelia Holthausen. 2009. "Liquidity Hoarding and Interbank Market Spreads: The Role of Counterparty Risk."
- Hesse, Heiko, and Nathaniel Frank. 2009. *The Effectiveness of Central Bank Interventions During the First Phase of the Subprime Crisis*: International Monetary Fund.
- Hesse, Heiko, Nathaniel Frank, and Brenda González-Hermosillo. 2008. "Transmission of Liquidity Shocks: Evidence from the 2007 Subprime Crisis." *IMF Working Papers*: 1-21.
- Kim, Chang-Soo, David C. Mauer, and Ann E. Sherman. 1998. "The Determinants of Corporate Liquidity: Theory and Evidence." J. Financ. Quant. Anal. 33 (3): 335-359. doi: 10.2307/2331099.
- Kim, Yunjeen. 2013. "Bank Bailouts and Moral Hazard? Evidence from Banks' Investment and Financing Decisions." *Evidence from Banks' Investment and Financing Decisions (November 2013)*.
- Kolari, James, Dennis Glennon, Hwan Shin, and Michele Caputo. 2002. "Predicting Large Us Commercial Bank Failures." *Journal of Economics and Business* 54 (4): 361-387.
- Labonte, Marc. 2013. "Federal Reserve: Unconventional Monetary Policy Options." *Congressional Research Service*: 7-7500.
- Li, L. 2013. "Tarp Funds Distribution and Bank Loan Supply." *J. Bank Financ.* 37 (12): 4777-4792. doi: 10.1016/j.jbankfin.2013.08.009.
- Mailath, George J, and Loretta J Mester. 1994. "A Positive Analysis of Bank Closure." *Journal of Financial Intermediation* 3 (3): 272-299.
- McAndrews, James, Asani Sarkar, and Zhenyu Wang. 2008. "The Effect of the Term Auction Facility on the London Inter-Bank Offered Rate." *FRB of New York Staff Report* (335).
- Michaud, François-Louis, and Christian Upper. 2008. "What Drives Interbank Rates? Evidence from the Libor Panel." *BIS Quarterly Review, March.*

- Mora, Nada. 2010. "Can Banks Provide Liquidity in a Financial Crisis?" *Economic Review-Federal Reserve Bank of Kansas City*: 31.
- Morkoetter, S., M. Schaller, and S. Westerfeld. 2014. "The Liquidity Dynamics of Bank Defaults." *Eur. Financ. Manag.* 20 (2): 291-320. doi: 10.1111/j.1468-036X.2011.00637.x.
- Ng, Jeffrey, and Sugata Roychowdhury. 2014. "Do Loan Loss Reserves Behave Like Capital? Evidence from Recent Bank Failures." *Review of Accounting Studies* 19 (3): 1234-1279. doi: 10.1007/s11142-014-9281-z.
- Opler, Tim, Lee Pinkowitz, René Stulz, and Rohan Williamson. 1999. "The Determinants and Implications of Corporate Cash Holdings." *Journal of financial economics* 52 (1): 3-46.
- Sengupta, Rajdeep, and Yu Man Tam. 2008. "The Libor-Ois Spread as a Summary Indicator." *Economic Synopses* 2008 (2008-10-15).
- Terza, Joseph V., Anirban Basu, and Paul J. Rathouz. 2008. "Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling." *Journal of Health Economics* 27 (3): 531-543. doi: 10.1016/j.jhealeco.2007.09.009.
- Thornton, Daniel L. 2009. "What the Libor-Ois Spread Says." Economic Synopses 2009 (2009-05-11).
- Wheelock, David C., and Paul W. Wilson. 2000. "Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions." *Review of Economics and Statistics* 82 (1): 127-138. doi: <u>http://dx.doi.org/10.1162/003465300558560</u>.
- Whited, Toni M. 1992. "Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data." *The Journal of Finance* 47 (4): 1425-1460. doi: 10.2307/2328946.
- Wu, Deming, and Han Hong. 2012. "Liquidity Risk, Market Valuation, and Bank Failures." SSRN Working Paper Series. doi: 10.2139/ssrn.2177583.

Variable	Definition
Panel A: Liquidi	ty ratio
catfat_gta	Berger & Bouwman's (2009) preferred liquidity creation measure normalized by Gross Total Assets
	(GTA)
Panel B: Bank-s	pecific variables
ca	The common equity to total risk-weighted assets
aq	The non-performing assets to total assets
тс	The cost-to-income ratio
earn	The ratio of net income to total assets
ltdrt	The loans-to-deposits ratio
ucrt	The ratio of unused loan commitments to total loans
noniirt	The ratio of non-interest income to total income
banksize	The natural logarithm of total assets
bhc	A dummy variable that takes 1 if bank holding company (BHC) status applies and zero if otherwise.
Panel C: Macroe	economic variables
sloos	Net percentage of domestic banks reporting stronger demand for commercial and industrial loans
fedfunds	The federal funds rate

Appendix 1 Variable definitions

	(1)	(2)	(2)	(4)	(5)
VADIADIES	(1) N	(2) Meen	(3) Sa	(4) Min	(3) May
Panel As Small banks	19	wicali	Su	IVIIII	WIAX
Fallel A: Siliali Daliks	206 010	0.202	0.102	0 000	9 521
caijai_gia	200,040	0.303	0.192	-0.888	0.021
ca	200,040	0.010	0.022	0.001	0.087
uq	200,040	0.024	0.031	0.000	1.640
	200,014	0.789	0.170	0.490	0.450
eurn It dut	200,040	0.005	0.010	-0.333	1 221
llari	200,040	0.705	0.198	0.243	0.521
ucri noniirt	280,848	0.133	0.100	0.000	11 108
honun	280,711	0.820	0.876	-4.971	12 202
bha	200,040	0.821	0.870	9.773	13.808
sloos	280,848	0.851	25 340	60.400	1.000
sioos fadfunda	200,040	1 612	23.349	-00.400	43.300
jeajunas	200,040	1.015	1.870	0.070	5.200
Panel B• Medium banks					
catfat gta	15 602	0.426	0 199	-0 644	3 999
caller_sta	15,602	0.009	0.021	0.000	0.410
aa	15,602	0.026	0.035	0.000	0.518
mc	15,598	0.020	0.055	0.155	19 183
earn	15,602	0.005	0.012	-0.435	0 181
ltdrt	15,602	0.854	0.194	0.155	1 627
ucrt	15,602	0.259	0.321	0.000	9 4 1 4
noniirt	15,598	1.120	2.047	-5.829	13.658
hanksize	15,602	14 157	0.318	13 529	14 908
bhc	15,602	0.958	0.201	0.000	1.000
sloos	15,602	0.206	25.132	-60.400	45.500
fedfunds	15.602	1.471	1.848	0.070	5.260
	- ,				
Panel C: Large banks					
catfat_gta	9,531	0.535	1.257	-0.426	35.567
са	9,531	0.007	0.024	0.000	0.475
aq	9,531	0.022	0.026	0.000	0.441
тс	9,527	0.702	0.314	-21.353	8.970
earn	9,531	0.005	0.011	-0.197	0.069
ltdrt	9,531	0.895	0.244	0.447	1.491
ucrt	9,531	0.633	1.299	0.011	9.430
noniirt	9,531	1.391	2.409	-7.636	15.435
banksize	9,531	16.209	1.323	14.684	21.453
bhc	9,531	0.974	0.160	0.000	1.000
sloos	9,531	0.705	25.169	-60.400	45.500
fedfunds	9,531	1.542	1.866	0.070	5.260

Table 1 Summary statistics of main variables

Table 2 Correlation matrix

Panel A: Small banks

	catfat_gta	ca	aq	mc	earn	ltdrt	ucrt	noniirt	bhc	banksize	fedfunds	sloos
catfat_gta	1.00											
ca	-0.06***	1.00										
aq	0.07***	-0.01***	1.00									
mc	-0.06***	0.20***	0.08***	1.00								
earn	0.01***	-0.15***	-0.38***	-0.32***	1.00							
ltdrt	0.06***	0.00	0.00	-0.00	0.01***	1.00						
ucrt	0.04***	0.00	-0.01***	0.00	0.06***	0.00	1.00					
noniirt	0.01***	-0.00	0.00	-0.00	0.00	0.00	0.00	1.00				
bhc	0.10***	-0.14***	-0.00	-0.08***	0.11***	0.01***	-0.01***	0.00	1.00			
banksize	0.30***	-0.06***	0.06***	-0.08***	0.05***	0.01***	0.01***	0.01**	0.16***	1.00		
fedfunds	0.05***	0.01***	-0.22***	0.00	0.11***	0.01***	0.01***	-0.00	-0.00	-0.08***	1.00	
sloos	0.02***	-0.00*	-0.09***	-0.04***	0.09***	-0.00	0.00	0.00	0.00	0.01***	0.13***	1.00

* p<0.05 ** p<0.01 *** p<0.001

Panel B: Medium banks

	catfat_gta	ca	aq	mc	earn	ltdrt	ucrt	noniirt	bhc	banksize	fedfunds	sloos
catfat_gta	1.00											
ca	-0.01	1.00										
aq	-0.06***	0.08***	1.00									
mc	-0.11***	0.06***	0.30***	1.00								
earn	0.06***	-0.03***	-0.37***	-0.56***	1.00							
ltdrt	0.26***	0.07***	-0.01	-0.05***	0.03**	1.00						
ucrt	0.65***	-0.01	-0.13***	-0.07***	0.09***	0.35***	1.00					
noniirt	0.01	-0.00	0.00	-0.01	0.00	-0.00	-0.00	1.00				
bhc	0.13***	-0.21***	-0.06***	-0.02*	-0.02**	0.01	0.02**	0.00	1.00			
banksize	0.09***	-0.01	0.04***	-0.03***	-0.01	0.02*	0.05***	0.00	0.03***	1.00		
fedfunds	0.11***	-0.05***	-0.28***	-0.04***	0.14***	0.04***	0.12***	-0.00	0.00	-0.09***	1.00	
sloos	0.01	0.03***	-0.16***	-0.11***	0.13***	0.02**	0.03***	-0.00	-0.01	0.02*	0.10***	1.00
* p<0.05 **	* p<0.01 *** p	0<0.001										

Panel C: Large banks

	catfat_gta	ca	aq	mc	earn	ltdrt	ucrt	noniirt	bhc	banksize	fedfunds	sloos
catfat_gta	1.00											
ca	-0.04***	1.00										
aq	0.02*	-0.02	1.00									
mc	-0.04***	0.01	0.02	1.00								
earn	0.12***	0.01	-0.38***	-0.32***	1.00							
ltdrt	-0.01	0.02	-0.01	-0.03**	0.02	1.00						
ucrt	0.55***	0.02	-0.05***	-0.07***	0.15***	0.01	1.00					
noniirt	0.00	-0.01	0.01	0.01	0.01	-0.01	0.00	1.00				
bhc	-0.03***	-0.02	0.05***	0.01	-0.04***	0.01	-0.07***	0.01	1.00			
banksize	0.02*	-0.04***	-0.03**	-0.04***	0.03**	0.02*	0.24***	0.01	0.07***	1.00		
fedfunds	0.04***	-0.01	-0.31***	0.03**	0.17***	0.03**	0.05***	-0.01	0.02*	-0.04***	1.00	
sloos	0.02	-0.01	-0.20***	-0.07***	0.18***	-0.04***	-0.01	-0.01	-0.02	0.01	0.11***	1.00
	0.01.111	0.001										

* p<0.05 ** p<0.01 *** p<0.001

		Bank failure risk								
	(1)	(2)	(3)							
VARIABLES	Small banks	Medium banks	Large banks							
catfat_gta	2.764***	0.257	-2.879***							
	(0.35)	(0.94)	(1.05)							
ca	-1.180**	-0.015*	-0.035*							
	(0.59)	(0.01)	(0.02)							
aq	0.021***	0.030***	0.031***							
	(0.00)	(0.00)	(0.00)							
mc	0.023**	0.128	0.271							
	(0.01)	(0.12)	(0.32)							
earn	-0.045***	-0.041***	-0.023***							
	(0.00)	(0.01)	(0.01)							
ltdrt	-1.706***	-0.083	-0.043							
	(0.29)	(0.33)	(0.11)							
ucrt	-4.765***	0.459	0.309							
	(0.62)	(0.69)	(0.43)							
noniirt	-0.000	-0.001	-0.035**							
	(0.00)	(0.00)	(0.02)							
bhc	-0.008	7.517***	_11							
	(0.09)	(1.11)								
banksize	0.308***	-0.451	-0.716***							
	(0.04)	(0.33)	(0.24)							
fedfunds	-0.638	0.000	-10.806							
	(0.50)	(0.00)	(15.19)							
sloos	-0.050***	0.028	-0.018							
	(0.01)	(0.02)	(0.04)							
Constant	-11.423***	-9.943**	4.807							
	(0.69)	(4.88)	(4.34)							
Time dummies for report date	Yes	Yes	Yes							
Observations	286,710	10,709	6,875							
Pseudo R-squared	0.535	0.563	0.563							

Table 3 The effect of bank liquidity on failure risk

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

¹¹ The coefficient on *bhc* is zero and standard error is omitted because of perfect prediction. In other words, "*bhc*" predicts failure perfectly in this case.

Bank failure risk							
	(1)	(2)	(3)				
VARIABLES	Small banks	Medium banks	Large banks				
catfat_gta	2.990***	0.876	-3.593**				
	(0.38)	(1.21)	(1.49)				
resid	-1.279**	-1.814*	2.661				
	(0.54)	(1.08)	(2.52)				
ca	-1.162**	-0.016	-0.037*				
	(0.58)	(0.01)	(0.02)				
aq	0.021***	0.030***	0.031***				
	(0.00)	(0.00)	(0.00)				
mc	0.042**	0.168	0.219				
	(0.02)	(0.33)	(0.27)				
earn	-0.045***	-0.041***	-0.022***				
	(0.00)	(0.01)	(0.01)				
ltdrt	-1.686***	-0.096	-0.001				
	(0.28)	(0.52)	(0.10)				
ucrt	-4.831***	0.335	0.528				
	(0.73)	(0.76)	(0.52)				
noniirt	-0.000	-0.001	-0.039***				
	(0.00)	(0.01)	(0.01)				
bhc	-0.013	7.506***	_12				
	(0.09)	(1.76)					
banksize	0.286***	-0.492	-0.768***				
	(0.05)	(0.39)	(0.27)				
fedfunds	-0.667*	-0.000	-0.361				
	(0.40)	(0.01)	(0.36)				
sloos	-0.048***	0.028	-0.044***				
	(0.01)	(0.03)	(0.01)				
Constant	-11.265***	-9.580*	6.030				
	(0.76)	(5.76)	(4.36)				
Time dummies for report date	Yes	Yes	Yes				
Observations	286,707	10,708	7,091				
Pseudo R-squared	0.536	0.565	0.515				

Table 4 Two-stage residual inclusion (2SRI) model

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

¹² The coefficient on *bhc* is zero and standard error is omitted because of perfect prediction. In other words, "*bhc*" predicts failure perfectly in this case.

Bank failure risk							
	(1)	(2)	(3)				
VARIABLES	Two-year	Three-year	Five-year				
antfat ata	2 209***	0 <i>C</i> 79***	2 107***				
cattat_gta	(0.10)	(0.14)	(0.10)				
	(0.19)	(0.14)	(0.10)				
ca	-0.320	0.163**	0.284				
	(0.40)	(0.08)	(0.05)				
aq	0.024***	0.025***	0.023***				
	(0.00)	(0.00)	(0.00)				
mc	0.044***	0.041***	0.038***				
	(0.02)	(0.01)	(0.01)				
earn	-0.041***	-0.039***	-0.039***				
	(0.00)	(0.00)	(0.00)				
ltdrt	0.001	-0.001	0.003**				
	(0.03)	(0.01)	(0.00)				
ucrt	-2.145***	-0.753***	-0.785***				
	(0.35)	(0.10)	(0.05)				
noniirt	-0.000	-0.000	-0.000*				
	(0.00)	(0.00)	(0.00)				
bhc	-0.084	-0.180***	-0.343***				
	(0.06)	(0.05)	(0.04)				
banksize	0.375***	0.412***	0.410***				
	(0.03)	(0.02)	(0.02)				
fedfunds	0.479***	1.040***	0.707***				
	(0.11)	(0.06)	(0.02)				
sloos	-0.049***	-0.032***	0.019***				
	(0.01)	(0.01)	(0.00)				
Constant	-14.882***	-15.816***	-12.673***				
	(0.51)	(0.39)	(0.22)				
Time dummies for report date	Yes	Yes	Yes				
Observations	286,710	286,710	286,710				
Pseudo R-squared	0.478	0.413	0.302				

Table 5 Alternative measures of bank failure risk-small banks

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

Bank failure risk							
	(1)	(2)	(3)				
VARIABLES	Two-year	Three-year	Five-year				
	0 407***	2 007***	2 242***				
cattat_gta	2.48/****	3.000****	5.545****				
	(0.58)	(0.45)	(0.35)				
ca	-0.019***	-0.023***	-0.020***				
	(0.01)	(0.01)	(0.00)				
aq	0.038***	0.03/***	0.034***				
	(0.00)	(0.00)	(0.00)				
mc	-0.236*	-0.354***	-0.421***				
	(0.14)	(0.11)	(0.11)				
earn	-0.022***	-0.017***	-0.015***				
	(0.00)	(0.00)	(0.00)				
ltdrt	-0.007	-0.007	-0.005				
	(0.01)	(0.01)	(0.00)				
ucrt	-0.279	-0.776*	-1.377***				
	(0.56)	(0.46)	(0.28)				
noniirt	-0.001	-0.001	-0.001				
	(0.00)	(0.00)	(0.00)				
bhc	3.329***	1.974***	0.844***				
	(0.83)	(0.51)	(0.32)				
banksize	-0.940***	-0.936***	-0.738***				
	(0.22)	(0.18)	(0.14)				
fedfunds	-0.001	-0.000	-0.001				
	(0.01)	(0.00)	(0.00)				
sloos	0.012	0.010	0.010				
	(0.02)	(0.02)	(0.01)				
Constant	0.709	2.187	1.154				
	(3.33)	(2.59)	(2.09)				
Time dummies for report date	Yes	Yes	Yes				
Observations	11,999	12,913	15,013				
Pseudo R-squared	0.484	0.412	0.334				

Table 6 Alternative measures of bank failure risk-medium banks

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

	Bank failure risk							
	(1)	(2)	(3)					
VARIABLES	Two-year	Three-year	Five-year					
catfat_gta	-2.639***	-1.880***	-0.864*					
	(0.71)	(0.56)	(0.45)					
ca	-0.052***	-0.047***	-0.032***					
	(0.02)	(0.01)	(0.01)					
aq	0.040***	0.041***	0.037***					
	(0.00)	(0.00)	(0.00)					
mc	-0.369	-0.270	-0.269					
	(0.40)	(0.37)	(0.35)					
earn	-0.024***	-0.022***	-0.019***					
	(0.01)	(0.01)	(0.01)					
ltdrt	-0.098	-0.094	-0.071					
	(0.09)	(0.07)	(0.06)					
ucrt	0.279	-0.172	-1.115**					
	(0.40)	(0.43)	(0.48)					
noniirt	-0.023*	-0.022**	-0.021**					
	(0.01)	(0.01)	(0.01)					
bhc ¹³	-	-	-					
banksize	-0.719***	-0.672***	-0.607***					
	(0.16)	(0.12)	(0.09)					
fedfunds	-5.636	-3.530	1.586***					
	(9.85)	(6.65)	(0.26)					
sloos	-0.011	-0.001	0.007					
	(0.03)	(0.02)	(0.01)					
Constant	4.729	3.826*	2.259					
	(2.94)	(2.24)	(1.53)					
Time dummies for report	Yes	Yes	Yes					
Observations	7 166	8 260	0.276					
Deservations	/,400	8,20U 0,455	9,270					
Pseudo K-squared	0.528	0.455	0.340					

Table 7 Alternative measures of bank failure risk-large banks

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

¹³ The coefficient on *bhc* is zero and standard error is omitted because of perfect prediction. In other words, "*bhc*" predicts failure perfectly in this case.

(1) (2) (3) VARIABLES Small banks Medium banks Large banks catfat_gta 7.030*** 2.686*** -1.054** (1.01) (0.43) (0.47) ca -1.228 -1.177* -0.015** (1.22) (0.72) (0.01)	
VARIABLES Small banks Medium banks Large banks catfat_gta 7.030*** 2.686*** -1.054** (1.01) (0.43) (0.47) ca -1.228 -1.177* -0.015** (1.22) (0.72) (0.01)	
catfat_gta 7.030^{***} 2.686^{***} -1.054^{**} (1.01)(0.43)(0.47)ca -1.228 -1.177^* -0.015^{**} (1.22)(0.72)(0.01)	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	
ca -1.228 -1.177* -0.015** (1.22) (0.72) (0.01)	
(1.22) (0.72) (0.01)	
aq 0.020*** 0.021*** 0.025***	
(0.00) (0.00) (0.00)	
mc 0.043 -0.026 0.026	
(0.03) (0.02) (0.02)	
earn -0.042*** -0.049*** -0.037***	
(0.00) (0.00) (0.00)	
ltdrt -4.935*** -0.970*** -0.196	
(0.83) (0.35) (0.24)	
ucrt -9.111*** -4.766*** -0.400	
(1.73) (0.79) (0.29)	
noniirt -0.000 -0.002 -0.001	
(0.00) (0.00) (0.00)	
bhc -0.891*** 0.059 1.715***	
(0.20) (0.11) (0.35)	
banksize 0.762** 0.250*** 0.060	
(0.33) (0.09) (0.06)	
fedfunds 0.733 -1.733 0.001***	
(2.14) (3.34) (0.00)	
sloos 0.018 -0.041 0.008	
(0.06) (0.07) (0.01)	
Constant -12.284*** -10.187*** -9.542***	
(3.69) (2.09) (0.90)	
Time dummies for report date Yes Yes Yes Yes	
Observations 38,216 142,462 41,945	
Pseudo R-squared 0.474 0.533 0.500	

Table 8 An alternative measure of bank size

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

Bank failure risk								
	(1)	(2)	(3)					
VARIABLES	Small banks	Medium banks	Large banks					
catfat_gta	1.870***	0.415	-1.925					
	(0.62)	(1.24)	(1.36)					
ca	-1.064	0.012	-0.031					
	(1.38)	(0.01)	(0.03)					
aq	0.024***	0.042***	0.023***					
	(0.00)	(0.00)	(0.00)					
mc	-0.108	-0.135	-1.015*					
	(0.07)	(0.61)	(0.56)					
earn	-0.043***	-0.026**	-0.042***					
	(0.00)	(0.01)	(0.01)					
ltdrt	-1.650***	-0.094	-0.071					
	(0.47)	(0.34)	(0.13)					
ucrt	-1.757**	1.054	-0.036					
	(0.89)	(0.81)	(0.60)					
noniirt	-0.000	-0.021**	-0.034*					
	(0.00)	(0.01)	(0.02)					
bhc	-0.182	13.034***	_14					
	(0.16)	(1.71)						
banksize	0.412***	0.231	-0.490*					
	(0.07)	(0.47)	(0.26)					
fedfunds	2.219***	0.045*	-10.536					
	(0.78)	(0.03)	(24.85)					
sloos	-0.014***	-0.007	-0.005					
	(0.00)	(0.01)	(0.01)					
Constant	-10.869***	-31.134***	6.769					
	(0.94)	(8.67)	(6.27)					
Time dummies for report date	Yes	Yes	Yes					
Observations	49,364	2,751	996					
Pseudo R-squared	0.456	0.533	0.340					

Table 9 Additional check: the recent financial crisis of 2007-2009

* Statistically significance at the 0.1 level.

** Statistically significance at the 0.05 level.

¹⁴ The coefficient on *bhc* is zero and standard error is omitted because of perfect prediction. In other words, "*bhc*" predicts failure perfectly in this case.