# An Analysis of Liquidity Risk and Banking Crisis

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# An Analysis of Liquidity Risk and Banking Crisis

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# Abstract

Lessons learned from the recent financial crisis displayed a different scenario in which liquidity shortage in the interbank lending and wholesale funding became the major cause of extensive banking crisis. The crisis of confidence that started with subprime losses suddenly accelerated after the Lehman bankruptcy. Unlike market risk, credit risk and operational risk, it is usually difficult to find the formal measurement of liquidity risk, which implies why liquidity risk is often called the “known unknowns”. The traditional notion that bank run occurs due to the withdrawal of depositors is not applicable to the recent crisis, while the inherent mechanism of liquidity risk is still not fully studied in the aspect of behavioral pattern of general investors. The goal of this dissertation is to supplement the previous theories and concepts on banking crisis with more detailed investigation of liquidity risk in banking institutions. More specifically, this dissertation studies general investors’ framing effect of decision-making and how this pattern affects the resource allocation and investment strategy of commercial banks. Moreover, since the funding liquidity risk can be evaluated by examining the structure of liabilities as well as off-balance sheet items, the synergy between deposit-taking and lending should be reconsidered.

Chapter 1 presents an introduction of liquidity risk regulation and measurement tools in the banking system. The first section reviews the practice of financial risk regulation. The second section presents the classification of liquidity risk, namely, market liquidity risk and funding liquidity risk and analyzes the intrinsic shortcomings of the measurement methods in each category. The third section discusses the new reform in liquidity risk regulation in Basel III, especially focusing on Liquidity Coverage Ratio and Net Stable Funding Ratio. The fourth section presents the research motivation and analytical framework employed in this dissertation.

Chapter 2 focuses on the dynamic features of banking crisis. The purpose of this chapter is to set the tone in a macroeconomic perspective for exploring latent system-wide nature in the banking sector. Typical systemic risk measurement barely captures the dynamic risk characteristics of the whole banking system. As experience of past financial crises shows, major indicators in financial markets have clustered volatility during the periods of economic downturns, while this chapter is centered on the overall dynamic profile of the commercial banking sector and the Ratio of Adjusted Weighted Estimated Loss as an indicator of banking crisis is introduced to analyze the volatility clustering in a system-wide perspective. The results show that the volatility of the crisis indicator tends to cluster together when distress signals begin to appear in the market. Leverage effect is also presented in the results by applying EGARCH model. The analysis of the effect of cyclic shocks discusses the process of risk transferred from exogenous shocks to endogenous contagion. The results have implications for a better understanding of the relationship between business cycle and banking crisis.

Chapter 3 studies general investors' framing effect of decision-making on bank run equilibrium and how this pattern affects the resource allocation and investment strategy of commercial banks. The theoretical framework discusses the bank run equilibrium with the employment of framing effect in Prospect Theory. Few derived versions based on the classic bank run model have taken into account the framing effect of general lenders. This chapter revisits the issue by developing a model of bank run equilibrium combined with biased risk preference, which is applied to analyze how portfolio allocation and liquidity buffer in commercial banks are affected by liquidation cost and the reference point. Another improvement arises from the incorporation of liquidity buffer into the constraints of the bank run maximization programming. In the setting of this chapter, liquidity buffer is defined to meet the contingent demands from wholesale funding. The results present the condition on which the liquidity buffer of a particular bank should be provided. Liquidation cost is positively correlated with the lower bound of liquidity buffer. The location of the reference point is very important in determining the payoffs received by early withdrawals and late withdrawals. The effect of the reference point on liquidity buffer partially depends on the slope of yield curve term structure. Higher reference point could typically cause a lower portion of long-term investment. The empirical evidence supports the theoretical results to some extent.

Chapter 4 re-evaluates the sources of funding liquidity risk in financial intermediaries and analyzes the relationship between liquidity demands and bank failures. The function of credit intermediation and liquidity provision is the specialness of depository institutions. However, since the funding liquidity risk can be evaluated by examining the structure of liabilities as well as off-balance sheet activities, the advantage of combining deposit-taking and lending to share the cost of holding certain amount of liquid assets needs be reconsidered. The activities from both on-balance sheet and off-balance sheet not only provide liquidity to borrowers and depositors but also reduce the cost of liquidity holding, because the validity of this mechanism depends on the prerequisite that exercises on loan commitments and withdrawals on deposits are not perfectly correlated. However, it matters to reveal the dynamic connections between the two sources of liquidity risk for the purpose of analyzing the real impact on individual banks from a more microscopic perspective. As the evidence shows, by using an inclusive data set from 2001 to 2016, a winner-take-all effect is uncovered and could cause simultaneous claims for cash flow from both deposits and borrowings through loan commitments. Particular banks in critical financial condition will experience this typical double outflow. Similar results are shown in the subsamples of large banks and small banks. The evidence of connection between the double outflow and bank failure is presented by applying Support Vector Machine to predict bank failures based on the outflow variables as input features. It indicates that double outflow should be taken into consideration in addition to the traditional indicators such as financial ratios. The results also provide new insights on liquidity management of commercial banks.

The last chapter presents concluding remarks and policy implications. It summarizes the major conclusion that behavioral patterns underlying liquidity risk play an indispensable part in financial distress of individual institutions as well as liquidity shortage in the whole banking sector. In a system-wide context, dynamic features of banking crisis provide a supplementary understanding to improve the current static measurement of systemic risk. Potential directions of future research, especially on the topic of optimal liquidity buffer in commercial banking sector, are also presented.

# Contents

# Chapter 1 Introduction

## 1.1 Liquidity Risk Management in Banking

During the period of the financial crisis from 2007 to 2009, a sudden and large-scale disruption in funding sources contributed to an emerging form of banking crisis, drew more attention and caused unprecedented consequences since the Great Depression in the 1930s: prices of most assets fell drastically, the cost of bank borrowing rose substantially, and financial market volatility skyrocketed to levels that have rarely been seen (Ivashina and Scharfstein, 2010). The liquidity risk embedded in the crisis is not new to both individual financial institutions and regulatory authorities, however it has not been taken into account in both academics and industries until the Basel III introduced regulatory requirements on liquidity for banking institutions in 2010. The new accord is intended to strengthen bank capital sufficiency by building up bank liquidity and restraining bank leverage (Basel Committee on Banking Supervision, 2011). The original version of Basel III rule required banks to fund themselves with 4.5% of common equity (Basel Committee on Banking Supervision, 2010). Liquidity risk management has become one of the focal points in corporate governance, as well as credit risk, operational risk and market risk. The Bank of International Settlement defines liquidity as the ability of a bank to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses (Bank of International Settlement, 2008). The fundamental role of banks in the maturity transformation of short-term deposits into long-term loans makes banks inherently vulnerable to liquidity risk, and this feature can affect not only the operation of an individual institution but also the liquidity provision mechanism of the whole banking sector.

The financial industry transformed dramatically over the past few decades becomes more sensitive to the runs on short-term funding (IMF, 2010). What has been observed in the recent crisis is the very lesson that should be learned by the whole banking sector. The depositors' incentives of bank runs are basically unchanged due to prevalent psychological features when they are making financial decisions. Without regulation, firms would under-hoard the positions of liquidity in normal situation (Tirole, 2011), increasing the possibility of runs when the macro circumstances worsen. Liquidity risk management as a self-insurance is therefore of great importance to the viability of business operations. The relation between liquidity risk management conducted by specific institutions and rescue facilities from central banks should be complementary rather than substitutable. The former one is an ex ante defensive action while the latter is considered as the ex post remedy.

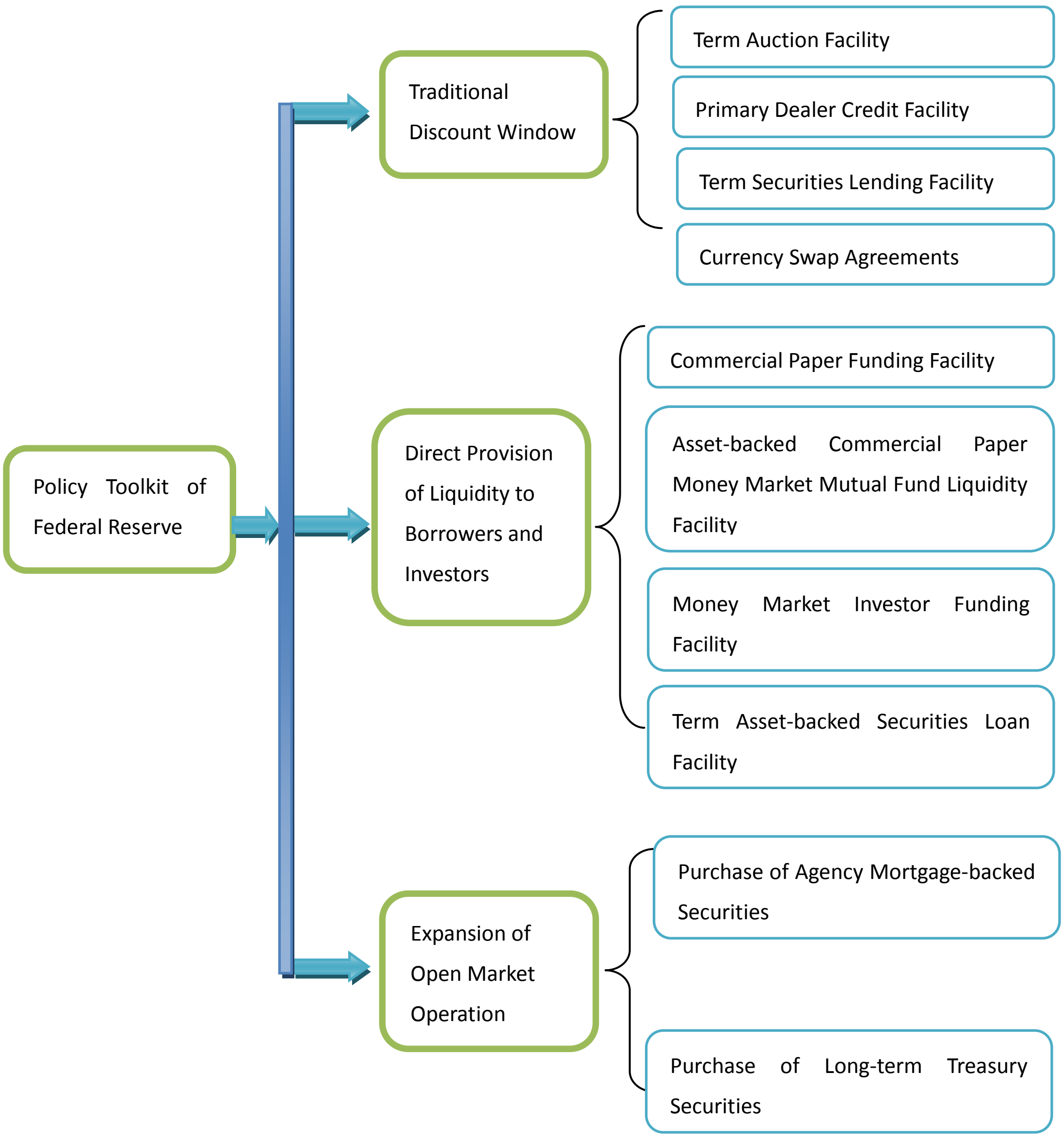
Traditional measures of liquidity regulation are routinely taken in two directions: deposit insurance and discount window access of central banks (Federal Reserve Bank, 2014). The implementation of deposit insurance has led to a comforting result, where there were relatively few liquidity problems in the commercial banking system funded primarily by deposits over several ensuing decades after the establishment of Federal Deposit Insurance Corporation (Benston and Kaufman, 1998). In the time interval of about 20 years before 1993, deposit insurance and taxpayers' funds account for over half of the rescue programs for banking failure (Goodhard and Schoenmaker, 1995). Intuitively, lending of last resort through discount window helps depository institutions to improve their insolvency. When depository institutions are receiving rescues from central banks, preventative hoarding of liquid assets will slow down the declining rate of credit creation. However, if the moral hazard generated by the regulatory procedures is taken into consideration, banks are inclined to maintain a merely sustainable level of liquid assets in their balance sheets in non-crisis periods, while they might not opt for a self-insuring strategy by increasing the liquidity holding when a crisis is looming.

Whether both measures will create moral hazard of bank decision-makers is still an arguable issue, in other words, there is inconsistency between the opposing views. Previous studies conducted by Dewatripont and Tirole(1993), and other related work such as Freixas and Rochet (1997), Boot and Greenbaum (1993) and Matutes and Vives

(1995) propose theoretical frameworks in which the public safety net, functioning as assistance providers for banks in distress and protecting stake holders from losses, increases the motivation of bank decision-makers to take on excessive risk. A different analytical viewpoint such as the model presented by Gropp and Vesala (2004) argues that deposit insurance will not generate more moral hazard if a certain portion of the liabilities are excluded from the safety net, and the non-deposit creditors will hence have the incentive to take an effective monitoring on the bank in a more rigorous effort.

Lending of last resort has been ought to be effective for addressing liquidity shortage for individual institutions. However, the implementation of that policy normally did not follow the Bagehot's rule proposed in *Lombard Street*, suggesting that the lender of last resort should lend without any limits to solvent firms who have high-quality collateral at high interest rates. In reality, authoritative central banks, such as Federal Reserve and European Central Bank, make the lending much easier by providing liquidity at lower rates and doing little quality checking on the collateral. Charging too much collateral may not be effective as expected to reduce the moral hazard. The creditors might have even more incentives to run if the central bank requires excessive collateral that the guarantee on other short-term funding declines.

In addition to traditional discount window, provision of liquidity to market participants is another method in the rescue package (Sarkar, 2009). Moreover, open market operation applied to the direct purchase of illiquid securities under pressure is another available choice. Central banks transforming illiquid toxic assets to liquid securities can actually confuse the general concept that moral hazard will be generated by the employment of liquidity facilities because the effective control of realized losses at least ostensibly signifies the risk-taking of depository institutions is not irrationally excessive. But the truth might be something else. It should be noted that the major objective of central banks is to avoid losses in the systemic scope, which will have extensive impacts on reputational or even political uncertainty. That explains why lending of central banks will mitigate the negative externalities spreading into the real economy from the banking sector. Central banks choose to make the purchase on particular asset categories which have macroeconomic repercussions when the price drops precipitously (Goodfriend, 2011). The assets only embedded with idiosyncratic risk are mostly ignored. It naturally produces a herding effect in which bank managers tend to selectively arrange the portfolios with macro-economically important assets, increasing the market concentration, which will not be helpful to the reduction of the aggregate risk. Figure 1.1 shows the regulatory tools used by the Federal Reserve during the recent financial crisis.




Source: Sarkar, A. (2009). Liquidity Risk, Credit Risk, and the Federal Reserve's Responses to the Crisis. *Financial Markets and Portfolio Management*

Figure 1.1 Regulation Tools of Federal Reserve during the Subprime Crisis

The boundary between illiquidity and insolvency can be very blurry in some critical circumstances, especially in the periods of market liquidity stress of some particular problematic assets (Ericsson and Renault, 2006). Insolvency may result from value depreciation or even default of particular assets. It has been documented that the credit risk embedded in a particular asset is entangled with the market liquidity risk (Imbierowicz and Rauch, 2014). Longstaff, Mithal and Neis (2005) used the data of credit default swaps and conclude that spreads of corporate bonds comprise of default and non-default components, and also found that the non-default component was strongly related to the illiquidity of the specific corporate bond and the overall liquidity condition of the bond's market. As in Ericsson and Renault (2006), both liquidity and credit risk contribute to the yield spreads of corporate bonds. While there are still two questions to be solved: (1) how to explain the interaction between credit risk associated with market liquidity risk and funding liquidity risk if the credit risk of assets can be transferred to the funding liquidity risk within a banking institution and (2) if credit risk and funding liquidity risk are not correlated, what are the determinants of funding liquidity risk as an exogenous variable. Earlier versions of Basel Accord take capital sufficiency as the first priority indicator of the health of a banking institution (Basel Committee on Banking Supervision, 1988, 2004). A number of banks experienced failure or assistance even if they were sufficiently capitalized before the liquidity shock occurred (Gertler and Kiyotaki, 2015). The focus of regulation, at least partially, has been deviated from the requirements on capital sufficiency to the holding of liquidity assets.

Among the literature focusing on the studies of depositors' exogenous behavioral patterns, the seminal classic model developed by Diamond and Dibvig (1983) enhanced our understanding of funding liquidity risk of depository institutions in terms of bank runs. The feature of self-fulfillment is their primary conclusion in which natural fragility of banking institutions accounts for the failure of individual organizations and the banking crisis as a whole (Diamond and Dibvig, 1983). When a bank is faced with unexpected liquidity demands, the reason for the distress could be insolvency as a fait accompli, or it could be the investors' concern about future insolvency of the bank. At this point, the function of liquidity regulation is ensuring the financial competence of the bank as well as conveying a message to reassure the confidence of investors. Another duty of liquidity regulation is to discern whether the liquidity distress is idiosyncratic or systematic, and keeping the necessary information transparent and publicly available.

Effective liquidity risk management helps to ensure the ability of a bank to meet cash flow obligations, which are uncertain as they are typically affected by external shocks and stakeholders' behavioral pattern. Liquidity risk management is of paramount importance because a liquidity shortfall at a single institution can have system-wide repercussions under some unfavorable circumstances. Previous studies mostly emphasize the risk management of credit risk, such as the theoretical framework presented by Froot, Scharfstein and Stein (1993) and empirical results developed by Cebenoyan and Strahan (2004), showing the improvement of active credit risk management in a bank is associated with higher leverage ratio and more risk loans in the portfolio, thus enhancing the credit creation to the real economy. But the conclusions also indicate that active risk management may not be conducive to reducing the aggregate risk due to more aggressive portfolio strategies (Cebenoyan and Strahan, (2004). Liquidity risk can only be partly hedged by better management of asset return risk (Acharya and Schaefer, 2006). Furthermore, modeling risk is another issue to be concerned in the risk management system. False assumptions and defective modeling frameworks that have become "common sense" for bank managers before the recent financial crisis, while this conceptual fallacy leads to misunderstanding of financial risks and inaccuracy of estimating models (Van Deventer, Imai and Mesler, 2013). The development of financial market in the past decade has increased the complexity of liquidity risk and its management. Conflicts of interests can also disrupt the basic functioning and execution process of the risk management practice within a firm.

In the recent financial turmoil, asset markets, especially the markets of mortgage-related securities, were in the boom and funding was readily available at low cost in the early period. Institution-specific liquidity management systems identify the liquidity demand faced by them on the assumption that the access to market funding would never shut down. However, the sudden reverse of trend in market conditions exemplified how quickly the general liquidity can evaporate. Although the responsibility of liquidity risk management intuitively falls on the shoulders of both individual banks and supervisory authorities, the top-down regulation should still take the leading role. The Basel Committee on Banking Supervision published a paper titled *Liquidity Risk: Management and Supervisory Challenges*, in which the difficulties in discussion highlighted that many banks had failed to take account of a number of basic principles of liquidity risk management when the overall liquidity was plentiful (Basel Committee on Banking Supervision, 2008). Many of the heavily-exposed banks did not have an adequate framework that satisfactorily accounted for the liquidity risk posed by individual products and business lines, and therefore incentives at the business level were misaligned with the overall risk tolerance of the bank. Many banks had not considered the amount of liquidity they might need to satisfy contingent obligations. Contingency Funding Plans are not always incorporated in the stress tests among the institutions.

For the purpose of performing a better banking regulation, Basel Committee review the *2000 Sound Practices for Managing Liquidity in Banking Organizations* and make extensive revisions to provide a new guidance for the management and supervision of liquidity risk based on the lessons learned from the financial crisis (Basel Committee on Banking Supervision, 2008). Major revisions are specified as follows:

- Importance of establishing a liquidity risk tolerance
- Maintenance of an adequate level of liquidity, including through a cushion of liquid assets
- Necessity of allocating liquidity costs, benefits and risks to all significant business activities;
- Identification and measurement of the full range of liquidity risks, including contingent liquidity risks

- Design and use of severe stress test scenarios
- Need for a robust and operational contingency funding plan
- Management of intraday liquidity risk and collateral
- Public disclosure in promoting market discipline

In addition, the guidance also emphasizes the importance of supervisors assessing the adequacy of a bank's liquidity risk management framework and its level of liquidity, and suggests steps that supervisors should take if the liquidity positions are deemed inadequate (Basel Committee on Banking Supervision, 2008). The principles also stress the importance of effective cooperation between supervisors and other key stakeholders, such as central banks, especially in times of stress (Basel Committee on Banking Supervision, 2008).

Table 1.1 Principles of Liquidity Management and Supervision

| Layer | Specific Principles |
| --- | --- |
| Fundamental principle for the management and supervision of liquidity risk | Principle 1: A bank is responsible for the sound management of liquidity risk. |
| Governance of liquidity risk management | Principle 2: A bank should clearly articulate a liquidity risk tolerance that is appropriate for its business strategy and its role in the financial system. |
| | Principle 3: Senior management should develop a strategy, policies and practices to manage liquidity risk in accordance with the risk tolerance and to ensure that the bank maintains sufficient liquidity. |
| | Principle 4: A bank should incorporate liquidity costs, benefits and risks in the internal pricing, performance measurement and new product approval process for all significant business activities (both on- and off-balance sheet), thereby aligning the risk-taking incentives of individual business lines with the liquidity risk exposures their activities create for the bank as a whole. |
| Measurement and management of liquidity risk | Principle 5: A bank should have a sound process for identifying, measuring, monitoring and controlling liquidity risk. |
| | Principle 6: A bank should actively monitor and control liquidity risk exposures and funding needs within and across legal entities, business lines and currencies, taking into account legal, regulatory and operational limitations to the transferability of liquidity. |
| | Principle 7: A bank should establish a funding strategy that provides effective diversification in the sources and tenor of funding. |
| | Principle 8: A bank should actively manage its intraday liquidity positions and risks to meet payment and settlement obligations on a timely basis under both normal and stressed conditions and thus contribute to the smooth functioning of payment and settlement systems. |
| | Principle 9: A bank should actively manage its collateral positions, differentiating between encumbered and unencumbered assets. |
| | Principle 10: A bank should conduct stress tests on a regular basis for a variety of short-term and protracted institution-specific and market-wide stress scenarios (individually and in combination) to identify sources of potential liquidity strain and to ensure that current exposures remain in accordance with a bank's established liquidity risk tolerance. |
| | Principle 11: A bank should have a formal contingency funding plan (CFP) that clearly sets out the strategies for addressing liquidity shortfalls in emergency situations. |

| | |
|---|---|
| | Principle 12: A bank should maintain a cushion of unencumbered, high quality liquid assets to be held as insurance against a range of liquidity stress scenarios, including those that involve the loss or impairment of unsecured and typically available secured funding sources. |
| Public disclosure | Principle 13: A bank should publicly disclose information on a regular basis that enables market participants to make an informed judgement about the soundness of its liquidity risk management framework and liquidity position. |
| The role of supervisors | Principle 14: Supervisors should regularly perform a comprehensive assessment of a bank's overall liquidity risk management framework and liquidity position to determine whether they deliver an adequate level of resilience to liquidity stress given the bank's role in the financial system. |
| | Principle 15: Supervisors should supplement their regular assessments of a bank's liquidity risk management framework and liquidity position by monitoring a combination of internal reports, prudential reports and market information. |
| | Principle 16: Supervisors should intervene to require effective and timely remedial action by a bank to address deficiencies in its liquidity risk management processes or liquidity position. |
| | Principle 17: Supervisors should communicate with other supervisors and public authorities, such as central banks, both within and across national borders, to facilitate effective cooperation regarding the supervision and oversight of liquidity risk management. |

Source: Basel Committee on Banking Supervision (2008), "*Principles for sound liquidity risk management and supervision*".

This guidance focuses on the practical operations of liquidity risk management at medium and large banking institutions, however, the sound principles have broad applicability to all types of banks. The implementation of the sound principles by both banks and supervisors should be tailored to the size, nature of business and complexity of a bank's activities. Table 1.1 presents the layers of management and specific implementations. Macroeconomic circumstances and regulation standards vary in different countries, the compatibility of regulatory mandates is thus of great importance as well. As long as maturity transformation functions as the source of profitability of banking institutions, tighter liquidity requirements will impede the growth of the institutions. If the cost of holding excessive liquidity is delivered to the borrowers of financial intermediaries, there will not be socially optimal arrangements of wealth because of the burden added to the real economy. On the other hand, integrated risk management system is often more effective than separate measurements to create incentivized effects (Van Deventer, Imai and Mesler, 2013), therefore, it is advantageous to combine liquidity risk management tools with other risk management measurements. Stress testing will work as a complementary procedure to the Basel Accord in order to enhance the effectiveness of the regulatory measures.

By analyzing the effects of liquidity regulation on the liquidity management practice of individual institutions, Banerjee and Mio(2014) find that stringent regulatory policy affect neither the size of the balance sheet of financial institutions in the sample of UK banks, or the lending to non-financial sectors. Banks replaced claims on other financial institutions with cash, central bank reserves and government bonds and reduced the interconnectedness of the banking sector without affecting lending to the real economy.

Until recently, Basel Committee on Banking Supervision issued two liquidity regulation indicators: Liquidity Coverage Ratio and Net Stable Funding Ratio (Basel Committee on Banking Supervision, 2013, 2014). Both institution-wide self-insurance and system-wide regulation are taken into consideration in the two ratios, because they not only reflect the protective measures within each institution，but also can be used by regulators to make efficient assessment on the financial condition in the whole banking sector. In this new framework of rules (Basel Committee on Banking Supervision, 2013, 2014), regulators have, for the first time, designed global standards for the minimum liquidity requirements held by banking institutions. Prior to this there were a few countries that had quantitative minimum requirements, but the large majority, including the US, relied on subjective regulatory judgment as to when liquidity levels were so low that a bank should be forced to remedy them (Tarullo, 2014). In practice, very little was done to force banks to shore up liquidity. The details of these two ratios will be presented in the third section of this chapter.

## 1.2 The Classification of Liquidity Risk

### 1.2.1 Market Liquidity and Funding Liquidity

As the recent financial crisis shows, liquidity mismatch is the intrinsic source of liquidity risk (Diamond and Dibvig, 1983). The relatively short term of funding source in commercial banks contributes to the natural mismatch of maturity between both sides of the balance sheet. Traditional norms of deal with liquidity risk include keeping liquid assets in the book to meet the unexpected commitments from claim holders.

The primary role of liquidity risk management is to (1) prospectively assess the need for funds to meet obligations and (2) ensure the availability of cash or collateral to fulfill those needs at the appropriate time by coordinating the various sources of funds available to the institution under normal and stressed conditions (Jorion, 2007).

In the sector of commercial banking, market liquidity risk and funding liquidity risk are two components of liquidity risk. The Committee of European Banking Supervisors defines those two types of liquidity risk (Committee of European Banking Supervisors, 2008) as follows:

Market liquidity risk, or asset liquidity risk, is the risk that a position cannot easily be unwound or offset at short notice without significantly influencing the market price, because of inadequate market depth or market disruption. It refers to the unpredictable variation of transaction costs.

Funding liquidity risk is the current or prospective risk arising from an institution's ability to meet its liabilities and obligations as they come due without incurring unacceptable losses (Committee of European Banking Supervisors, 2008).This dissertation focuses primarily on funding liquidity risk.

One of the features of market liquidity risk is that the magnitude of liquidity shock could be immense once it abruptly occurs (Abiad, 2003), indicating a nonlinear regime-switching status. Liquidity spirals proposed by Brunnermeier and Pedersen (2005) present an explanation for the sudden drying-up of the market. On the side of liabilities, margin call is a destabilizing factor to de-lever their positions in times of crisis.

There is a linkage between those two sources of risk. The value of assets which can be taken as collateral to raise funds declines and the ability to raise money will be harmed. Banks make their own borrowings based on their assets as collaterals, and the collateral with high liquidity will receive a low “hair-cut” accordingly. The discount demonstrates how market liquidity determines funding liquidity.

Another feature is the contagion among asset categories transacted in related markets, which means one shock from a specific market can be transferred to another, causing a wide scope of liquidity shortage (Allen and Gale, 2000). The evidence from Acharya and Pedersen (2005) suggested that illiquid securities tended to become more illiquid during market-wide asset and liquidity shocks, which implies individual securities are highly correlated with systemic liquidity in the whole market. Massive mispricing of underlying securities and derivatives during the recent crisis arise from the miscalculation of correlations between different assets.

### 1.2.2 Assessment of Liquidity Risk

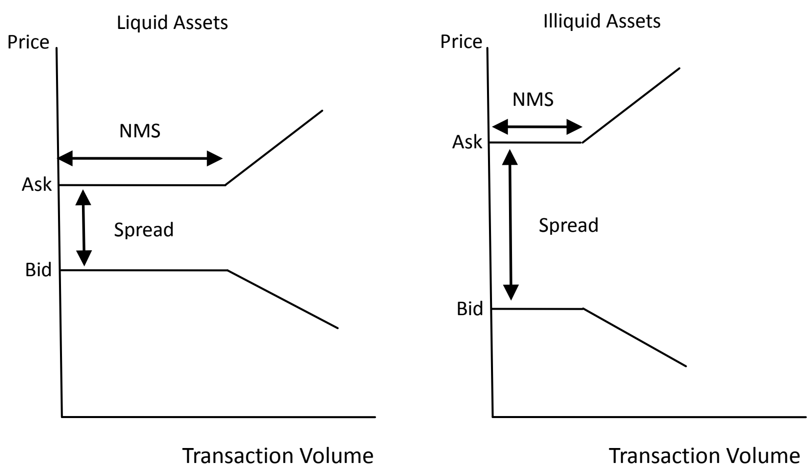
Before stepping into the measurement of liquidity risk, normal market size (*NMS*) is a definition that should be stated first. How to define the Normal Market Size is the prerequisite of liquidity risk measurement. The definition of normal market size is a system that categorizes the size of transactions that are normal for a particular security and forces market makers to deal within these sizes (Jorion, 2007).

Asset type and time horizon are definitely the determining factors of the market liquidity. In addition to those fundamental elements, the liquidity of financial assets is mostly affected by market conditions. The traditional measure of market liquidity is bid-ask spread (Amihud and Mendelson, 1986). It is an indicator of the round-trip transaction cost of a marketable security. The spread takes the form as follows (Jorion, 2007):

$$Spread = \frac{Ask\ Price - Bid\ Price}{Ask\ Price}$$

Where *Ask Price* represents the price quoted by the seller of a security and *Bid Price* represents the price a buyer is willing to pay.

A tight bid-ask spread shows the particular asset has high market liquidity. Market depth is the volume of tradable assets without causing dramatic changes of prices, and is also an indicator of the *NMS*. A more intuitive understanding can be made by comparing the market impact of liquid assets and illiquid assets. Liquid assets with higher *NMS* have a deeper market, while plenty of derivatives' market depth is very thin during the period of crisis. Price-quantity function can be used to describe the market impact. With transaction volume being smaller than the normal market size, the liquidity is exogenous and depends on the market conditions. Beyond the *NMS*, endogenous liquidity comes to affect the price in the transaction dramatically (Jorion, 2007). When selling a bulk of an asset in a liquid market, the price may temporarily drop, but will bounce back in a short time period. The speed of the price recovery defines the resilience of an asset, which is the speed at which the price of an asset will recover from previous drops.




Source: Financial Risk Manager Handbook 6th edition

Figure 1.2 Market Depth of Liquid Assets and Illiquid Assets

Asset fungibility is another factor concerning the liquidity of an asset (Viswanath and Frierman, 1995). Securities traded in centralized exchanges are typically more fungible than privately traded financial products (Miller and Puthenpurackal, 2005). Counterparties in private markets may demand discounts when the market narrows. The determinants of market liquidity risk is summarized in Table 1.3

The measurement of market liquidity risk is not particularly tractable, while it can be evaluated through the calculation of Value-at-Risk by incorporating liquidity into the model. It can be conducted by increasing the horizon or volatility (Berkowitz, 2000). However, a disadvantage in this method ensues: those adjustments are ad hoc or too subjective to assess the liquidity embedded in the assets.

Table 1.3 Factors of Market Liquidity Risk

| Time Horizon | Asset Type | Market Conditions | Fungibility |
|---|---|---|---|
| The urgency to sell the asset will exacerbate the liquidity risk. | Simple assets are more liquid than complex assets Bid-ask spread, Market depth. | Exchanges are typically deep markets. The depth of OTC markets is limited. | If a position can be easily replaced, the substitution costs are low and the liquidity tends to be higher. |

Note: summarized by the author

Funding liquidity risk arises from the liabilities side, for either on-balance-sheet or off-balance-sheet items. The task hence falls into the matter of accurately distinguishing stable funding sources from unstable funding sources. In general, unsecured funding belongs to the unstable sources. Within the unsecured funding category, retail deposits are more stable than capital market instruments. Among off-balance-sheet items, loan commitments, letters of credit and financial guarantees provided by a bank will create a contingent claim on liquidity if the credit lines are drawn (Hassan, Karels and Peterson, 1994).

Measurements of funding liquidity risk are mainly based on institution-wide financial reports which merely reflect stationary cross-sectional status of an institution. The following are some examples of funding liquidity measure.

The loan-to-deposit ratio (*LTD*) is a widely used metric to measure a bank's liquidity by dividing the bank's total loans defined as *Loans* by its total deposits defined as *Deposits* (Van den End, 2016). This number is expressed as a percentage. If the ratio is too high, it means that the bank may not have enough liquidity to cover any unforeseen fund requirements.

$$LTD = \frac{Loans}{Deposits}$$

The long-term funding ratio (*LTFR*) is based only on the cash flow profile arising from on-balance-sheet and off-balance-sheet items of a banking institution (Vento and La Ganga, 2009). It indicates the share of assets with a maturity of *n* years or more, funded through liabilities of the same maturity.

$$LTFR_n = \frac{\sum_i Outflow_{i,n}}{\sum_j Inflow_{j,n}}$$

Where $Outflow_{i,n}$ and $Inflow_{j,n}$ respectively represent the assets with maturity longer than n years and the liabilities with maturity longer than the same threshold.

Cash Capital Position (*CCP*) is another measure for funding liquidity risk (Raffis, 2007). In general, in order to guarantee an appropriate balance sheet structure with respect to liquidity risk, illiquid assets should be funded by stable liabilities, or otherwise total marketable assets (*TLA*) should be funded by total volatile liabilities (*TVL*). The difference between *TLA* and the sum of *TVL* and commitments to lend (*CTL*) is specified as the form of cash capital position (Vento and La Ganga, 2009).

$$CCP = TLA - TVL - CLT$$

Other than preventative measures for funding liquidity risk, it is also necessary to conduct ex-post remedy procedures to limit the potential losses. Contingency Funding

Plan is a conventional way to make this effort (Matz, 2007).

The measure of funding liquidity risk takes account of cash demand faced by banking institutions within a time interval. There has hardly been a common method adopted by most banks so far. Generally, there are two approaches of conducting liquidity risk assessment in banking. The first one is analytical approach such as Value at Risk and the second is cash flow projection (Jorion, 2007).

Funding liquidity risk is inherent in financial institutions due to the maturity gap between assets and liabilities. This subtype of liquidity risk may put a financial institution into a critical situation even if it is technically solvent. When the liquidity needs come from depositors, the bank has to liquidate a proportion of its assets portfolio to raise enough cash for the funding needs. Liquidation time horizon is hence essential to the liquidity risk. When liquidity shock such as margin calls or deposit outflows occurs, a bank has to either look for other stable sources of funding or sell a portion of its assets to meet the liquidity needs. In this situation, it gives rise to a negative feedback from further drops of asset prices as the theory of liquidity spirals suggests. Using fire sale to liquidate assets is obviously inappropriate to raise funds in a short time period, so decision makers need to consider liquidity buffer as a means for the contingent demand. Whether capital can work as liquidity buffer is still an open question to be discussed, because capital is neither a type of state-contingent liquidity such as lines of credit, nor an unconditional liquidity facility such as treasury securities. More attention should be drawn into real available categories of liquid assets to work as buffer.

However, it is difficult to determine the optimal liquidity buffer for an institution since the market circumstances are ever-changing and strategies should not be either too conservative or too aggressive. The key to solve this issue is a thorough understanding of the exogenous liquidity needs and the behavioral patterns. The risk appetite of the counterparties whom financial institutions borrow from needs to be analyzed. Research by Caballero and Krishnamurthy (2005) shows interesting results. Their premise is that institutions and fund-managers exhibit the usual risk-averse behavior in markets they understand well, but have “ambiguity aversion” towards investments in markets they do not regularly participate in. During the financial crisis, the change of risk aversion led to restricted flows of capital across markets. The stop of rolling over short-term funding in the recent subprime crisis is a good example of the risk appetite and behavioral patterns of investors.

System-wide shocks as well as institution specific shocks are both triggers of liquidity shock. However, this thesis focuses on the idiosyncratic characteristics to study institutional feature prevalently inherent in the management practice of banking institutions.

## 1.3 Liquidity Regulation

During the early phase of liquidity shortage in the financial crisis from 2007 to 2009, a great number of banks – despite adequate capital levels – still experienced difficulties because they did not manage their liquidity in a prudent manner (Dewally and Shao, 2014). The crisis drove home the importance of liquidity to the proper functioning of financial markets and the banking sector. The regulatory principles mentioned in the previous section are the practical actions taken by the regulation authorities on the issue of liquidity risk management. To complement these principles, the Committee has further strengthened its liquidity framework by developing two minimum standards for funding liquidity (Basel Committee on Banking Supervision, 2013 and 2014). These standards have been developed to achieve two separate but complementary objectives. The first objective is to promote short-term resilience of a bank's liquidity risk profile by ensuring that it has sufficient High Quality Liquid Assets (*HQLA*) to survive a significant stress scenario lasting for one month. The Committee developed the Liquidity Coverage Ratio to achieve this objective (Basel Committee on Banking Supervision, 2013). The second objective is to promote resilience over a longer time horizon by creating additional incentives for banks to fund their activities with more stable sources of funding on an ongoing basis (Basel Committee on Banking Supervision, 2013). The Net Stable Funding Ratio (*NSFR*), which supplements the *LCR* and has a time horizon of one year (Basel Committee on Banking Supervision, 2014). It has been developed to provide a sustainable maturity structure of assets and liabilities.

### 1.3.1 Liquidity Coverage Ratio

The objective of the *LCR* is to increase the short-term resilience of a bank's liquidity profile by ensuring that it has sufficient high-quality liquid resources to withstand an acute stress scenario lasting for 30 days. Given the balance sheet and the firm's activities, this stress scenario defines the potential net cash drain. To determine the cash flow drain, every source of liquidity risk has to be carefully analyzed. The *LCR* standard is defined as (Basel Committee on Banking Supervision, 2013):

$$\frac{Stock\ of\ high\ quality\ liquid\ assets}{Total\ net\ cash\ outflows\ over\ the\ next\ 30\ days} \geq 100\%$$

The *LCR* underpins the short-term resilience of a bank's liquidity risk profile. The *LCR* came into effect on 1 January 2015 and is subject to a transitional arrangement before reaching full implementation on 1 January 2019 (Basel Committee on Banking Supervision, 2013). Banks should also notify supervisors immediately if their *LCR* has fallen, or is expected to fall, below 100%.To complement the *LCR* and *NSFR*, in 2012 the Federal Reserve launched the Comprehensive Liquidity Assessment and Review (*CLAR*) for firms in the Large Institution Supervision Coordinating Committee (*LISCC*) portfolio (Tarullo, 2014). Like the Comprehensive Capital Analysis and Review (*CCAR*), *CLAR* is an annual horizontal assessment, with quantitative and qualitative elements, overseen by a multidisciplinary committee of liquidity experts from across the Federal Reserve.

Frequency and scope are two important variables in the calculation of *LCR* (Basel Committee on Banking Supervision, 2013). In the frequency of calculation and reporting, the *LCR* should be used on an ongoing basis to help monitor and control liquidity risk. The *LCR* should be reported to supervisors at least monthly, with the operational capacity to increase the frequency to weekly or even daily in stressed situations at the discretion of the supervisor. The time lag in reporting should be as short as feasible and ideally should not surpass two weeks.

As of the application scope, the *LCR* standard and monitoring tools should be applied to all internationally active banks on a consolidated basis, but may be used for other banks and on any subset of entities of internationally active banks as well to ensure greater consistency and a level playing field between domestic and cross-border banks.

The selection of high quality liquid assets is slightly subjective because some categories of assets may not be as liquid under critical market circumstances. The decision process depends on the discretion of the bank managers.

### 1.3.2 Net Stable Funding Ratio

The objective of the *NSFR* is to promote resilience over a longer-term horizon and to incentivize banks to more closely match the maturity of their funding with the maturity of assets (Basel Committee on Banking Supervision, 2014). In contrast to the *LCR*, the *NSFR* is designed as a medium to long-term measure intended to provide a sustainable maturity structure of assets and liabilities, aiming to limit over-reliance on short-term wholesale funding. The *NSFR* standard is defined as (Basel Committee on Banking Supervision, 2014):

$$\frac{Available\ amount\ of\ stable\ funding}{Required\ amount\ of\ stable\ funding} \geq 100\%$$

While central banks across the world are increasingly adopting the Basel III standards (Basel Committee on Banking Supervision, 2014), putting such standards into operational practice remains a challenge. Data infrastructure and calculation methods are one part of that challenge – and the incorporation of liquidity risk considerations into day-to-day decision making is the second. As well as putting in place the right technology infrastructure, banks need to educate their stakeholders. And appropriate governance must ensure that incentives are both balanced and compatible with creating an organization-wide liquidity risk culture.

While there is thus a need for a longer-term structural standard such as the *NSFR*, the conceptual challenges in crafting it were greater than in designing the *LCR*. Simply extending the *LCR* to one year, that is, requiring firms to hold enough liquidity to survive a one-year funding market freeze--seemed the kind of excessive self-insurance that would lead to undesirably reduced maturity transformation and financial intermediation. So a different set of standards needed to be developed, which themselves occasioned considerable discussion about the effects and incentives they would create. Also, one could argue that the *NSFR* should have aimed for a more complete term structure in order to protect against maturity mismatches within and beyond the one-year mark, and to create stronger incentives for firms to extend the maturity of their funding arrangements.

## 1.4 Motivation and Research Objectives

Weaknesses in liquidity risk management based on quantitative evaluation are highly exposed by the disruption of financial markets in the past decade. The FDIC facilitates a shift from the traditional implementation of asset-based liquidity risk management to liability-based approaches and strategies concerning off-balance sheet activities. The traditional way of managing liquidity risk is to construct a reserve of liquid assets to meet unexpected demands of liquidity. However, it is still difficult to determine whether a bank’s liquidity holding is optimal or the most appropriate under different market conditions and macroeconomic circumstances. New regulatory measurements such as Liquidity Coverage Ratio are relatively subjective and still needs to be tested in future implementation. That’s why we have to go back to the original question: what are the determinants of banks’ liquidity buffer? Among the determinants, how does the behavioral pattern of depositors affect banks’ portfolio allocation? Previous analyses made conclusions based on the assumption that creditors, depositors and other stakeholders who have claims against banks are rational decision-makers, while the real profile of the behavioral pattern would be differently portrayed due to the framing effect existing in the decision-making process of general investors. It would be reasonable to place liquidity buffer in the discussion of bank run equilibrium in order to better our understanding of the inefficiency of asset-based liquidity risk management and it would be helpful to examine whether the bank run equilibrium will be affected when the assumption of economic rationality is altered.

On the other side of the shift, liability-based management as well as off-balance sheet strategies depends on external market conditions which would be an exogenous factor out of the control of the institution itself. The risk management strategy may not function well as market conditions change. For instance, wholesale borrowing that was under pressure during the recent financial crisis implies the necessity that we should take consideration of the dynamics of unexpected funding demands when the strategies of liquidity risk management are drafted. Before the recent crisis, the new form of bank run through not rolling over short-term funding did not appear, implying that the simultaneous liquidity demands from liabilities and off-balance sheet contingent claims did not occur and little attention has been drawn to what actions should be taken to meet the double liquidity demand. During the second phase of the recent crisis, as it is shown in the fourth chapter of this dissertation, double liquidity demand did occur and had noticeable association with bank failures. That motivates me to conduct research on the relationship between deterministic claims from liabilities and contingent claims from off-balance sheet activities.

The two motivations discussed above are combined to form the focal point pertaining to institution level. But the whole liquidity risk profile of a particular banking institution is not only dependent on the idiosyncratic risk features, but also the macroeconomic environment. In other words, institution-specific liquidity risk plus systemic liquidity risk makes up the whole risk profile. While liquidity risk measurement is clearly not a leading indicator of banking crisis, otherwise, it would be efficient for both regulators and the supervised banks to take measures beforehand rather than ex post rescue response. Therefore, it is necessary to straightforwardly study the dynamic characteristics of the banking crisis itself in a systemic scope and how cyclic shocks impact the banking system. The analysis will provide complementary insights to the current systemic risk measurements, which are typically cross-sectional and static, and display macroeconomic status of the whole banking sector in business cycles.

The general objective is to investigate the linkage between liquidity risk and banking crisis and explain why liquidity risk management is ineffective to protect most financial institutions from failure during crisis by analyzing the intrinsic driving factors behind liquidity risk faced by banking institutions. Specifically, this dissertation is organized to address the following three aspects in both systemic and idiosyncratic perspectives.

Firstly, in the analysis of system level, the first objective is to investigate the volatility clustering of banking crisis by using Generalized Autoregressive Conditional Heteroskedasticity model and the second mission is to describe how the exogenous shocks affect the banking system and eventually cause a crisis.

The second task is to reevaluate the conditions of bank run equilibrium by modifying the assumption of economic rationality and examine how bank's liquidity buffer and portfolio allocation would be affected by liquidation cost and risk preference under the impact of framing effect.

The third objective is to investigate the relationship between claims from liabilities and contingent demands from off-balance sheet items and whether liquidity risk based on that relationship would improve bank failure prediction.

# Chapter 2 Banking Crisis and Cyclic Shocks: An Empirical Perspective on System-wide Volatility

## 2.1 Introduction

Business models of the whole banking industry have been undergoing development to an advanced sophistication for decades (Beck, Demirgüç-Kunt and Levine, 2010). However banking failures happened occasionally and more recently subprime securitized products formed to be a major driving force to the financial crisis from the mid-2007 to the early times of 2009 (Financial Crisis Inquiry Commission, 2011), and they also have tremendous impacts on the systemic credit risk and reveal the potential instability which both business and academia did not notice beforehand. Similarly, reflections from regulators were slow and not strong enough to identify and control the risk when financial institutions were still in operation with profits on the eve of a bigger system-wide crisis. Historical experience shows that shocks from several elementary macroeconomic factors can cause a collapse of the financial system, especially the banking sector.

Under typical circumstances, systemic risk results from two major sources: exogenous shocks from the fluctuations of macroeconomic variables and internal interacting process within the system. How credit risk can be transferred through the system and eventually trigger an overall crisis is still an open question. It is difficult to portray a perfectly concrete picture of the fundamental and principal mechanism by countable empirical or ex-ante hypothesized mathematical models with limited available data resources. The macroeconomic factors in the banking system have cyclical properties (Albertazzi and Gambacorta, 2009) and how to measure the cyclic attributes through an adequately persuasive assessment method is at the core of the model specification in this chapter.

Something more striking is that volatility of a particular system, such as the banking sector, tends to cluster together when distress signals begin to appear in the market and consequently accumulates to form a real crisis. The volatility could be very low while the financial system is becoming more vulnerable so that the financial institutions would have the incentive to increase the leverage level and enlarge maturity mismatches (Brunnermeier and Sannikov, 2014). However, traditional methods have some difficulty to completely explain the volatility clustering during crises. The interactions between institutions can cause risk transfer and default contagion through the system, and also could result in contagions from both asset prices and business counterparties (Staum, 2012). Theoretical frameworks of modeling counterparty risk are developed to detect the correlations when a firm's default could lead to another firm's distress (Davis and Lo, 2001; Jarrow and Yu, 2001), but empirical applications are still in an early phase to practical utilization in real business world.

Under certain circumstances, banks tend to respond homogeneously to macroeconomic volatilities (Calmès and Théoret, 2014). Nontraditional businesses of banks are more sensitive to the volatility of macroeconomic variables (Lukas and Stokey, 2011). The exogenous shocks may distort the information transfer and thus force financial institutions to reallocate their portfolios of assets (Bernanke and Gertler, 1989). Evidence shows that system-wide uncertainty will cause dispersion in loan-to-asset ratios among affected institutions (Baum et al, 2009). Moreover, exogenous sources of shocks could be created by monetary policy and banks with less liquid assets will be affected more severely (Kashyap and Stein, 2000).The internal dispersion will further aggregate the damage to the system. Another finding shows that non-systemic feature is the major component of a firm's risk (Campbell et al., 2001).

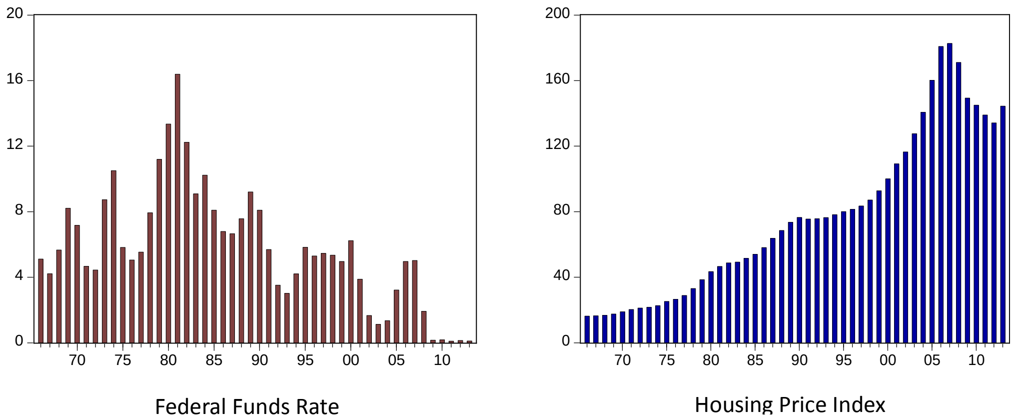
Value at risk (VaR) method is widely applied as a measure for the systemic risk based on hypothesized distributions of the value of losses (Jorion, 1997). One recent extension of VaR is conducted by creating CoVaR to assess the marginal risk of each individual institution (Adrian and Brunnermeier, 2016). Expected shortfall is another frequently used framework in estimating risk and has been developed and derived into various forms such as systemic expected shortfall and marginal expected shortfall (Tarashev et al, 2009; Acharya et al., 2010), and one of its underpinning building blocks is that the probability distribution of losses should be prescribed as a premise. By using the expected shortfall approach, another point of view shows that interconnectedness among banks plays a significant role in systemic risk aggregation (Drehmann and Tarashev, 2013). An exogenous framework through the application of Default Intensity Model (DIM) was employed in the analysis, where the properties of credit risk is formulated as the insurance price against the risk faced by financial institutions (Huang et al., 2009). Another research shows that systemic risk can be measured by defining an event that individual banks fail simultaneously whereas there is no clear boundary when the combined failures of individual banks become a systemic disaster (Lehar, 2011). Systemic risk is also defined as a failure-based measure by calculating the conditional probability of bank failures in a large portion of the whole financial intermediaries (Giesecke and Kim, 2011). Some researchers investigated the early warning system based on different theoretical foundations to predict the financial crisis (Gramlich et al, 2010 and Illing and Liu, 2006).

The clustering effect in terms of systemic volatility occurs occasionally accompanied by different business cycles, especially in the periods of severe financial crisis. Furthermore, excess clustering could not be completely explained by the direct triggering reasons. It is intuitive to form a hypothesis to summarize the mechanism of the occurrence of financial crisis, especially in banking systems. It has the following two stages:

Stage 1: Exogenous shocks cyclically give rise to the volatility of both commodity prices and capital costs including but not limited to interest rate uncertainty and trigger to impact the solvency and asset values among financial institutions and investors. This early phase could be referred to as out-of-system shocks.

Stage2: System-wide crisis will be caused by endogenous contagion within the financial sector and also lead to recession among sectors.

Shocks out of the system of banking could be of a small variety. Interest rate fluctuations and deregulation are typically considered as one of the major determinants to the savings and loans crisis during the 1980s (Curry and Shibut, 2000). The interacting effects would also produce a combined thrust for the crisis to eventuate. As deregulation measures were progressed in the 1990s, securitization which has been one of the most profitable businesses of banking industry started to bring real estate market onto the platform and the two factors involved each other intensively until the burst of housing bubble (Financial Crisis Inquiry Commission. 2011). At the next phase of a canonical banking crisis, the system in a whole did not recover promptly from the downturn trends, but would experience a subsequent and successive in-system contagion process among counterparty institutions and result in recession in other sectors. Figure 2.1 shows the federal funds rate and housing price index from 1966 to 2013.




Source: Federal Reserve and S&P/Case-Shiller Home Price Indices.

Figure 2.1 Federal Funds Rate and U.S. Housing Price Index 1966-2013

Based on this fundamental hypothesis proposed above, this chapter focused on the system-wide dynamics of how systemic risk driven by macroeconomic shocks was created and transferred through the mechanism by exploiting the commercial banking system with the evidence from the United States. The first objective of this chapter is to investigate the volatility clustering of risk in commercial banking system by designing empirical and idiosyncratic determinant proxies for overall systemic risk, and the second objective is to demonstrate how the exogenous sources of triggers have affected the banking system and eventually caused a crisis.

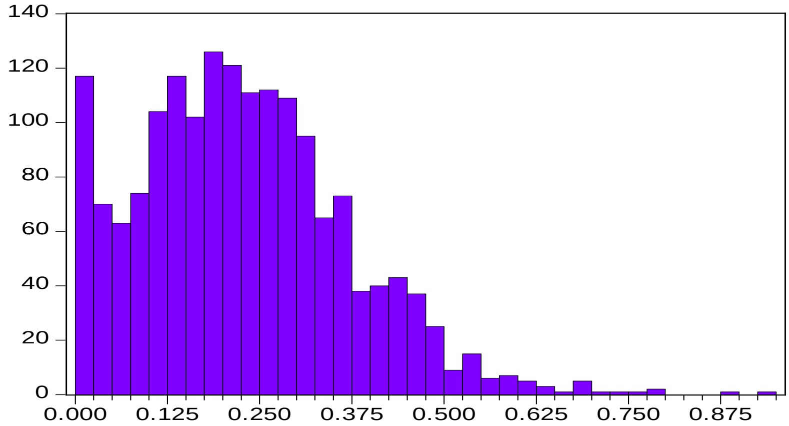
This chapter is structured as follows: section 2.2 discusses empirical design for measurements of systemic risk; section 2.3 reports the results of clustering estimation and robustness tests; section 2.4 presents the empirical results of estimation with cyclic shocks; the last section concludes this work.

## 2.2 Empirical Design

This section is assigned to conduct the model specifications of this study in accordance with the application of the hypothesis in section 2.1. The first empirical framework is the construction of the risk measurement of banking crisis and makes a further description of the volatility feature. The second framework is about the impacts of shocks and contagion effect within the system.

### 2.2.1 Empirical Measurement of Banking Crisis

The first priority in this chapter is to seek an approximate agent for systemic risk. It should be noted that the model is established in the circumstance when the Federal Deposit Insurance Corporation was founded as a protector after the Great Depression. Different from conventional methods of calculating systemic risk in commercial banking by equity asset prices or credit spreads in related corporate bonds or credit derivatives, which are typically available and highly frequent but to some degree represent in an indirect way to institution-level events (Freixas, Parigi and Rochet, 2000), this section employed an empirical measurement based on historical data of banking failures. The distribution of estimated losses of individual commercial banks in Figure 2.2 also shows that traditional methodology may not be efficient to monitor the volatility and potential losses in a systemic approach and miscalculations of traditional monitoring tools could be explained by fat tail effect (Wu and Shieh, 2007). This is the reason why the uniqueness of focusing directly on historical performance is a more applicable path to pursue an understanding of banking crisis.




Source: Federal Deposit Insurance Corporation Historical Statistics on Banking - Failures and Assistance Transactions.

Figure 2.2 Distribution of Failures and Assistance Transactions

In order to reflect the banking industry crisis and credit crunch in the model, an effective measurement need to be specified along with the financial crisis events and at the same time should take account of factors derived from cyclic shocks. The recent experience in banking industry of the United States shows that credit issues such as systemic defaults or insolvency are still rare events and it is difficult to capture the whole picture if an investigation with a short time interval is conducted. After the deposit insurance institution was established, the banking system referring to both commercial banking and investment banking had been functioning with stability for several decades until the savings and loans crisis. The regulations were relatively slow to respond to the variations of out-of-system conditions, and the legitimated deregulation could hardly be justified as a de facto stabilizer. However, the regulatory factor is released from this study because the main objective is to discuss the credit risk transfer mechanism through the banking sector rather than make an assessment of regulations. With this consideration, a new measure framework regarded as Ratio of Adjusted Weighted Estimated-Loss is developed for the analysis of malfunction in the banking system. One of its obvious features is that these measured values are extracted and processed directly from the historical data of banking failures rather than derived from priori conceptions. In other words, this measure itself could be considered as a "proxy-free" variable which indicates the banking crisis as a whole instead of an approximate representative, which means there is less need of efforts to pursue the rationality and justifiability of the measure due to its self-describing characteristics.

The *rawel* measures the level of overall loss for each sampled year instead of each individual financial institution[1]. For this particularly investigation, the assessment is conducted to describe and characterize the commercial banking system in the United States as the example to support the evidence and other types of institutions such as saving and loans associations and credit unions would be ruled out because of the differences of business structures. In this study, the overall loss is treated as a random variable which is one parametric attribute of the banking system. The form of *rawel* is presented by:

$$rawel_t = \frac{safb_t}{tacb_t} \times \left(\sum_{i=1}^{k}(ar_{it} \times \frac{el_{it}}{aib_{it}})\right) \qquad (1)$$

Where $k$ indicates the number of failed banks in one observation year $t$; the term $safb_t$ is the summed assets of failed banks in year $t$ and $tacb_t$ is the total assets of the commercial banking in year $t$; the whole term in the parenthesis represents the ratio of weighted estimated-loss before adjustment for each year and the $el_{it}$ representing the estimated loss is the amount of loss for each commercial bank that went bankrupt in a specific year, and correspondingly, the $aib_{it}$ represents assets of the individual bank $i$ at year $t$. The term $ar_{it}$ represents the weight of bank $i$'s assets in the sum of annually total assets of failed banks at year $t$.

It should be mentioned that this ratio of $rawel_t$ is considered as a general representative of the gross level of losses to convert the periodical variable set into a

[1] The sample may not include all U.S. depository institutions but only present the FDIC-insured commercial banking institutions due to the availability of bankruptcy information and the homogeneity of business operations

cross-sectional variable in order to avoid the heterogeneity among different banks and present a total expression for the system.

During this extraction of real occurrences, a question will be raised that the samples in the stable periods such as 2003 and 2004 will form an inadequate support to the calculation because zero occurrence of banking failure does not mean zero credit risk in the system and therefore the measure would not be unbiased. Due to this consideration, adjustments made to ultimately approximate the implicit actual value are necessary and that is coped with as missing data problems. The specific processing technique will be presented in the next section.

### 2.2.2 Characterization of Volatility Clustering

Volatility is an indicator implying the time-varying feature of financial variables. The clustering of volatility has been explored by researchers from various practical angles in both financial markets and other industrial sectors (Lux and Marchesi, 2000). By considering the compatibility between applicable models and the issue in this study, the series of estimated losses of banking system which is represented by *rawel* could be tested for time-varying volatility clustering under the framework of Generalized Autoregressive Conditional Heteroskedasticity (Bollerslev, 1986). The GARCH model is not only a robust instrument to capture volatility of asset prices with favorable features of high frequency such as market quotes of financial equity claims, but also can be used to analyze annually orchestrated indicators even though the explanatory power might be compromised. One special part of this study is to conduct the analysis on directly extracted indicators of banking crisis. A typical form of GARCH is presented in the following equations:

$$r_t = \varphi x' + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \gamma v + \alpha \varepsilon_t^2 + \beta \sigma_{t-1}^2 \tag{3}$$

Equation (2) presents the mean equation and $\varepsilon_t$ represents the error term. In equation (3), the conditional heteroskedasticity is the function of three components including long-term mean$\upsilon$, square of stochastic error $\varepsilon_t^2$ and lagged-term variance $\sigma_{t-1}^2$, different weights of $\alpha, \beta, \gamma$ have been allocated for each term as coefficients. One important feature of this model is that the coefficients of volatility equation should all be positive and the sum should be less than 1.

The GARCH model is assumed to be a sound method to capture the volatility feature in financial markets, however, the relatively low frequency of data could compromise the robustness and fitness of the model. Due to the limitation of coefficients in the model, requirements should be released to detect the issue in a more comprehensive fashion, therefore the derived Exponential GARCH model (Nelson, 1991) was employed to characterize the volatility in a way where

$$\log(\sigma_t^2) = \beta_0 + \beta_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta_2 \log(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

Other than the release of limitations, another significant feature is that the leverage effect becomes exponential after taking logarithmic volatility into consideration. The coefficient $\gamma$ follows the null hypothesis that the impact of informational shocks will be symmetric if it's equal to zero, otherwise, asymmetric information effect will be detected with positive coefficient indicating more powerful upward information and negative figure indicating the opposite.

As the autocorrelation test shows that only one-term lagged value could present significance under 95% confidence level, I construct the mean equation with one term lagged in the autocorrelation setting, where the model is specified as follows, equation (5) is introduced with only lagged terms, equation (6) includes exogenous variables and balance sheet indicators functioning as state variables to show the reactions of commercial banking system to the shocks of macroeconomic fluctuations.

$$rawel_t^{lag} = \beta_0 + \beta_1 rawel_{t-1} + \varepsilon_t \tag{5}$$

$$rawel_t^{ex} = \beta_0 + \beta_1 ffr_t + \beta_2 niir_t + \beta_3 ncf_t + \beta_4 sglr_t + \beta_5 rawel_{t-1} e^{1+hpr_t} + \varepsilon_t \tag{6}$$

The first mean equation takes into consideration that only one-term lagged variable is selected for ultimate explanatory capability. In the second model incorporating exogenous impacts, variable $ffr_t$ represents the federal funds rate, $sglr_t$ stands for the proportion of gains and losses of securities in the total value of investment securities in commercial banks, and $niir_t$ is the net interest income rate; $ncf_t$ represents logarithmic rate of net charge-offs; the lagged term is adjusted by multiplying the exponential growth rate of housing price to detect the combined impact from the emphasis on the housing market, where $hpr_t$ is the growth rate of a nationwide housing price index and exponential growth rate can narrow the range between different prices to account for the effects with limited overstatement. The variable $ffr_t$ is employed as the exogenous control variable in this initial setting because empirical facts have shown that the variation of benchmark interest rate was a dominant factor to the stability of financial institutions. On the other hand, after the savings and loans crisis stabilized, real estate market has been involved as one of the major causes of financial turbulence since securitization was implemented in major financial intermediaries and the collateralized credit boomed, so it is reasonable to embrace real estate values, which is represented by housing price, into the model. I select housing price index as another control variable as well as federal funds rate, and the effects of the banking crisis measurement will be discussed as a comparison in the robustness test.

This arrangement with two versions of mean equations provides insights about a comparison between two macroeconomic states: one is treating the banking system as entirety and trying to demonstrate the dynamic behavior in an integral angle, and the other is to decompose the process into determinant factors for the purpose of detecting detailed patterns.

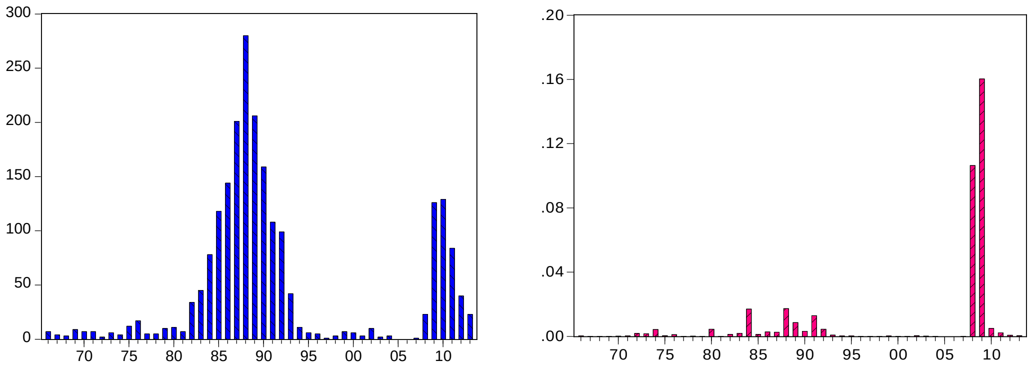
### 2.2.3 Exogenous shocks

Since the credit defaults or bankruptcies of banking are still rare events but both business cycle and credit cycle are all behaving in a longer time span, as a result, the short time interval and inadequacy of available data for *rawel* may not match up with the cyclic variables. In this specification of exogenous shocks I defined a more straightforward expression for systemic uncertainty. The Ratio of Failed Assets is therefore compiled in this description.

The Ratio of Failed Assets (*rfa*) is expressed as follows, similar to *rawel* measurement. This indicator is also created on the perspective of system-level integration and calculated on an annual time series.

$$rfa = \frac{TotalAssetsofFailedBanks}{TotalAssetsoftheBankingSystem} \tag{7}$$

The total assets of failed banks are not the exact representatives of the bankruptcy magnitude of the system but could be considered as the "contaminated" assets which would have the potential to lose their values or need to be bailed out. Since the financial crisis during 2007 and 2009 was the biggest turmoil after the Great Depression during the 1930s, the ratio is extremely higher than any other periods in the sample time span. The ratio of failed assets shows that extreme values indicating great magnitude of systemic losses emerge after a typical stationary period as Figure 2.3 shows, which implies cyclic fluctuations have been experienced by the whole system. Much of the clustered fluctuations could be explained by the counterparty risk which may reflect its characteristics on the prices of related derivative securities. This argument is also corresponding to the evidently existing time lag from the asset bubble bust to systemic crisis.




Note: Data source from FDIC.

Figure 2.3 Number of Failed Banks and Ratio of Failed Assets from 1966 to 2013

Among the exogenous variables influencing commercial banking system, a certain portion of them are fluctuating and have the property of cyclic movement. It is assumed that two exogenous variables should be considered as driving factors of the shocks by taking account of the empirical default data in the sampled period, because it is, to some extent, obviously presented that the massive commercial banking failures occurred during two remarkable periods: the savings and loans crisis and the subprime crisis. According to this assumption, federal funds rate and housing price index are selected as proxy measures to the two assumed exogenous variables. In other words, the model in this section is built to explore the shocks from the fluctuations of interest rate and real estate market.

To detect the relations between out-of-system shocks and system-wide indicators and among in-system variables by contagion, the Vector Autoregression methodology was employed to investigate the effects and it is to some extent a useful examiner of the interacting driving dynamics between variables. The focus of this part is to explore the interconnectedness instead of unidirectional causes. Restricted form of VAR is also applied in the analysis and could provide error correction term to express the long-term relationship.

## 2.3 Clustering Estimation

### 2.3.1 Data Selection and Descriptive Statistics

The failure data of commercial banking stems from the datasets of Federal Deposit Insurance Corporation and I selected two series of indicators of banking failures: one series dates from 1986 when the estimated loss value became available to 2013 and the other ranges from 1966 to 2013. To construct the estimators more accurately, variables in commercial banks are selected and those of savings institutions and other depository institutions are excluded.

In addition, another variable used in the robustness test should be defined beforehand. The deviation between ratios of estimated losses of individual banks in each sampled year is another estimator that can be interpreting the extent of difference among failed commercial banks. The standard deviation of the estimated-loss ratios is introduced to the expression by calculating yearly figures as a cross-section observation. Two forms of measure are employed: one is the standard deviation of regular form; the other form denoted by $dev_t$ takes weights to different square deviations with the same asset weighted ratio in equation (8).

$$dev_t = \sum_{i=1}^{k} ar_{it} \times (el_{it} - \overline{el}_t)^2 \tag{8}$$

These two forms indicate similar tendencies through the sampled period. It is more reasonable to take the latter one into the model because the standard deviation with weights illustrates more information and accuracy contained in the process.

On the other hand, it is clearly shown that the standard deviation will overestimate the systemic importance during some periods with less banking failure events, such as from 1998 to 1999. To construct a variable more approximate to the reality, the weighted standard deviation is multiplied by banking failure count divided by the mean to reflect the systemic importance factor for each observation year. Then the revised weighted standard deviation termed as $devr_t$ is specified as follows:

$$devr_t = \frac{k}{\bar{k}} \sum_{i=1}^{k} ar_{it} \times (el_{it} - \overline{el}_t)^2 \tag{9}$$

Where $\bar{k}$ indicates the mean of the failure counts of the sampled period. This measure gives rise to a general assessment of the dispersion effect implying that the extent of diversification is effective indicator to observe the severity of contagion within the system. For instance, if huge figures of this measurement cluster together, then it means that the banks with insolvency issues could be of a big range from small institutions to major market participants.

Both the ratio of estimated loss and the deviation are regarded as random variables in this model, therefore zero-value observations of them will be considered less reasonable given the fact that they are expressing the implicit properties while treating banking system as a whole. Then those zero-value observations in the dataset are viewed as missing points. In this chapter, stochastic regression imputation is applied in solving the missing observations. Adding the regression average variance to the imputed values to incorporate errors will bring more robustness than simple regression imputation because it provides uncertainty to the missing data. After the imputation, the non-normality of both figures is not impacted. Figure 2.4 shows a comparison between $rawel_t$ and $devr_t$ in the sample period

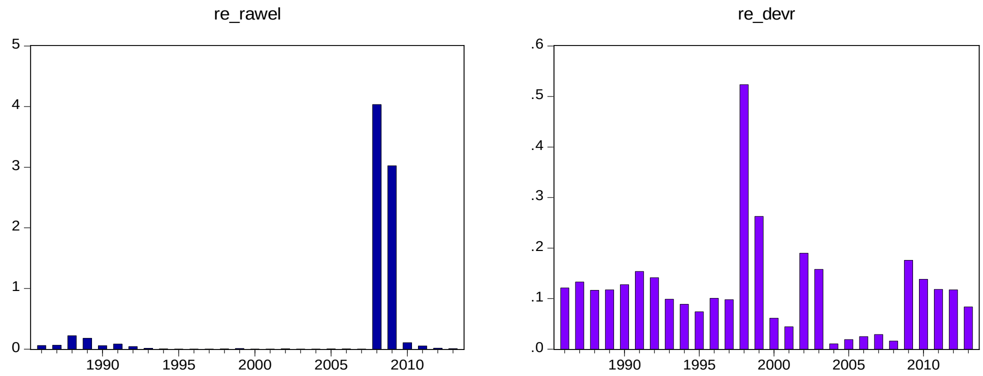



Figure 2.4 Comparison between $rawel_t$ and $devr_t$

after Imputations from 1986 to 2013

The descriptive statistics selected for each defined measurement are provided in the Table 2.1. The revised versions of $rawel_t$ and $devr_t$ are also presented. No variables in the selected samples show positive normality.

Table 2.1 Descriptive Statistics of Selected Variables

| | $rawel_t$ | $re\_rawel_t$ | $devr_t$ | $re\_devr_t$ | $rfa_t$ |
|---|---|---|---|---|---|
| Mean | 0.286 | 0.286 | 0.113 | 0.119 | 0.008 |
| Maximum | 4.035 | 4.035 | 0.523 | 0.523 | 0.160 |
| Minimum | 0.000 | 0.000 | 0.000 | 0.010 | 0.000 |
| S.D. | 0.928 | 0.928 | 0.103 | 0.098 | 0.0274 |
| Kurtosis | 13.146 | 13.147 | 10.017 | 11.454 | 24.755 |
| Jarque-Bera | 175.118 | 175.142 | 80.355 | 113.569 | 1125.89 |

### 2.3.2 Volatility Clustering

The volatility is implicitly contained in the stochastic process of systemic risk even though the robustness is to some extent weakened due to the relatively lower frequency of data calculated at each year end. As previously stated, if it is hypothetically accepted that each individual bank is considered identical and can independently generate random variables through invariant distribution, the time series of individual bank's estimated loss also present volatility clustering in certain time intervals and tends to be conforming to the case in yearly calculation.

The best fitted characterization comes from GARCH (1, 1) as Table 2.2 presents. The ratio series after revision shows more robustness and goodness of fit in both GARCH and EGARCH test. It implies that the empirical result is in accordance with the hypothesis in which missing data points will cause biased consequences, and justifies that the imputation is reasonable for the empirical design. By comparing general conditional variance with exponential conditional variance, explanatory power is not presented explicitly with the limited hypothesis of GARCH model despite the significance of the coefficients, of which the sum should be less than one on the condition that each coefficient should be positive. Therefore, the results imply that the GARCH model is not convergent. In contrast, EGARCH model provides a better interpretation of the behavior of volatility with released limitations of coefficients. The EGARCH results are essentially unchanged and no asymmetric information effect has been expressed by this setting. It conveys information that positive shocks and negative shocks are not behaving in an unbalanced fashion which means that one source of volatility cannot dominate the other.

Table 2.2 Estimated parameters of the GARCH Models

| | $rawel_t^{lag}$ | | $rawel_t^{ex}$ | | $re\_rawel_t^{lag}$ | | $re\_rawel_t^{ex}$ | |
|---|---|---|---|---|---|---|---|---|
| | (a) | (b) | (a) | (b) | (a) | (b) | (a) | (b) |
| *Constant* | 0.0519 | 0.0011 | 4.810*** | 1.919*** | 0.034 | -0.001 | 4.796*** | 1.361*** |
| | (1.6652) | (0.1571) | (3.552) | (4.413) | (0.557) | (-0.015) | (6.696) | (3.706) |
| $ffr_t$ | — | — | -0.366*** | -0.138*** | — | — | -0.363*** | -0.101*** |
| | — | — | (-3.712) | (-4.153) | — | — | (-6.802) | (-3.734) |
| $niir_t$ | — | — | -5.301*** | -2.196*** | — | — | -5.356*** | -1.548*** |
| | — | — | (-3.116) | (-4.541) | — | — | (-6.047) | (-3.696) |
| $ncf_t$ | — | — | 0.550*** | 0.126 | — | — | 0.528*** | 0.114** |
| | — | — | (4.870) | (1.514) | — | — | (5.351) | (2.386) |
| $sglr_t$ | — | — | -119.260*** | -42.995*** | — | — | -107.775*** | -29.496*** |
| | — | — | (-7.612) | (-3.675) | — | — | (-5.711) | (-3.603) |
| *Rewel_lag/ exp*rawel_ lag* | 0.601*** | 0.591*** | 0.087 | 0.047 | 0.606*** | 0.651*** | 0.061 | 0.040* |
| | (6.179) | (6.987) | (1.290) | (1.204) | (5.224) | (4.318) | (1.314) | (1.896) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | GARCH Test | | | | |
| *V* | -0.002 | — | 0.009 | — | -0.003** | — | 0.003 | — |
| | (-1.506) | — | (0.747) | — | (-2.343) | — | (0.549) | — |
| *ARCH* | -0.118*** | — | 1.661** | — | -0.153*** | — | 2.344** | — |
| | (-5.358) | — | (2.222) | — | (-4.578) | — | (2.196) | — |
| *GARCH* | 1.390*** | — | -0.016 | — | 1.474*** | — | -0.010 | — |
| | (12.792) | — | (-0.103) | — | (11.659) | — | (-0.411) | — |
| | | | | EGARCH Test | | | | |
| $\beta_0$ | — | 0.678*** | — | -5.692*** | — | 0.452*** | — | -6.296*** |
| | — | (4.565) | — | (-3.878) | — | (3.506) | — | (-6.401) |
| $\beta_1$ | — | -0.996*** | — | 3.390*** | — | -0.620*** | — | 3.547*** |
| | — | (-5.330) | — | (4.402) | — | (-5.253) | — | (6.348) |
| $\beta_2$ | — | 1.027*** | — | 0.393 | — | 1.023*** | — | 0.392* |
| | — | (26.196) | — | (0.948) | — | (34.240) | — | (1.646) |

Note:

(i) The figures in the parenthesis are *z*-statistics and figures with *, ** and *** are significant at 90%, 95% and 99% confidence level, respectively.

(ii) The denotation *rawel_lag* applies to lag equations and the denotation *exp*rawel_ lag* meaning the exponential growth of *hpi* multiplied by one term lagged *rawel* applies to the exogenous equations.

The conditional standard deviations of each measure are shown in the following figures. Variables after revision generally approximate to the original variables. The exponential counterparties reflect the implied volatility of *rawel* value. With exogenous variables, the raw value series express a magnitude effect within certain time intervals, for instance from 2000 to 2004 when actually failure numbers and volumes are both minor. This result conveys another insight that the *rawel* variable in the setting with exogenous control factors are following the cyclic trend due to the unique equation structure while on the other side the *rawel* variable in auto regression setting seems monotonically rising until the crisis occurred in mid-2007. It shows different scenarios between the two settings and actually the risk has been accumulated until the final burst. Hence there is a gap in between when the banking industry was experiencing a stable period and it is too vague to observe the risk accumulation. Through this comparison, this disparity could be highlighted even if not be positioned precisely.

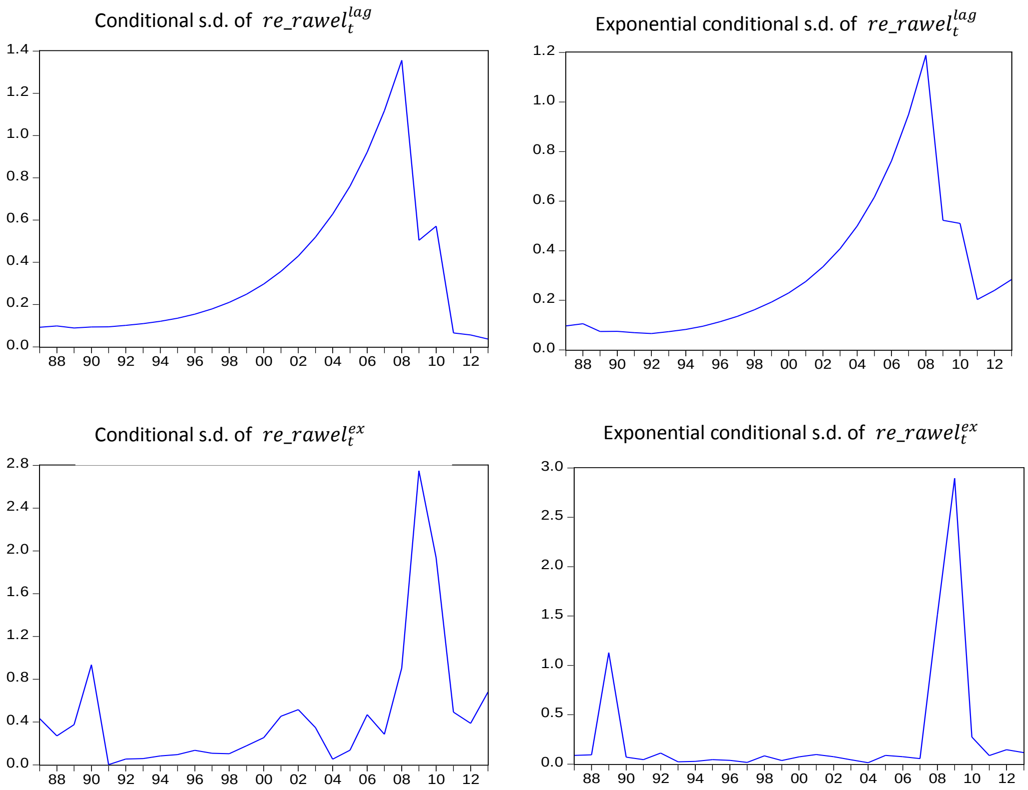



Figure 2.5 Conditional Standard Deviation

### 2.3.3 Robustness Test

To test the robustness of the model, a reconsideration of correlations between variables has been conducted on a hypothesized basis that shocks from interest rate and real estate market constitute the major reason for the volatility clustering of banking failures. The federal funds rate $ffr_t$, therefore, is put into the model as the same role as exponential growth rate of housing price index, and the latter one is considered as an independent factor. By switching different control variables, the fit of goodness and compatibility is specified in the following table.

Table 2.3 Robustness Test 1

| | $rawel_t^{ex}$ | | $re\_rawel_t^{ex}$ | |
|---|---|---|---|---|
| | (a) | (b) | (a) | (b) |
| *Constant* | 2.354*** | 2.327*** | 2.330** | 2.019*** |
| | (3.146) | (15.478) | (2.133) | (4.628) |
| $exp\_hpi_t$ | -1.076*** | -0.973*** | -1.079*** | -0.791*** |
| | (-3.961) | (-15.041) | (-2.751) | (-4.732) |
| $niir_t$ | 1.641*** | 0.913*** | 1.722*** | 0.527** |
| | (3.479) | (6.698) | (4.243) | (2.222) |
| $ncf_t$ | 0.471*** | 0.250*** | 0.589*** | 0.193*** |
| | (4.618) | (7.148) | (5.804) | (3.436) |
| $sglr_t$ | -61.864*** | -16.964*** | -72.503*** | -18.804*** |
| | (-2.875) | (-3.769) | (-3.333) | (-3.202) |
| *Rewel_lag** | 0.070 | 0.072* | 0.048 | 0.014 |
| *ffr_ lag* | (0.837) | (1.662) | (0.353) | (0.343) |
| | | GARCH test | | |
| *V* | 0.019 | — | 0.034 | — |
| | (0.914) | — | (0.777) | — |
| *ARCH* | 1.987 | — | 1.323 | — |
| | (1.617) | — | (1.333) | — |
| *GARCH* | -0.320 | — | -0.427 | — |
| | (-1.002) | — | (-0.668) | — |
| EGARCH test | | | | |
| $\beta_0$ | — | -5.921*** | — | -4.686*** |
| | — | (-4.673) | — | (-3.241) |
| $\beta_1$ | — | 3.771* | — | 4.482*** |
| | — | (4.563) | — | (3.916) |
| $\beta_2$ | — | 0.310 | — | 0.828** |
| | — | (1.382) | — | (2.428) |
| $\gamma$ | — | — | — | — |
| | — | — | — | — |

Note:

(i) This test only contains exogenous equations.

(ii) Coefficient $\gamma$ representing the effect of asymmetric information is zero in this model so it is not presented in this table.

(ii) The figures in the parenthesis are *z*-statistics and figures with *, ** and *** are significant at 90%, 95% and 99% confidence level, respectively.

The result is basically unchanged and the exponential GARCH test is much better performing than the original GARCH. Similar to the result of *rawel* previously discussed, the revised version of variable has shown a marginally more power of explanation but not a dominant one. The uncertainty of housing price will bring negative effect to the banking system as well as the federal funds rate. But the effect magnitude of housing price is greater than $ffr_t$ and forms to be a more straightforward facilitator to the crisis.

The second robustness test showed in Table 2.4 is conducted by replacing the independent variable *rawel* for *devr*. The result implies that exponential GARCH model could also capture the volatility clustering of the revised weighted standard deviation *devr* to the approximate degree. On the other hand, the lag equation shows less explanatory capacity in both GARCH test and EGARCH test. In the setting of exponential equation, all coefficients are significant at least at the confidence level of 90%. It provides the evidence that exponential GARCH framework is a well-structured model for the specification of volatility.

Table 2.4 Robustness Test 2

| | $devr_t^{lag}$ | | $devr_t^{ex}$ | | |
|---|---|---|---|---|---|
| | (a) | (b) | (a) | (b) | (c) |
| *Constant* | 1.201 | -0.000 | 0.066 | 0.189*** | -0.120*** |
| | (0.268) | (-0.000) | (0.449) | (4.298) | (-6.461) |
| $ffr_t/dhpi_t$ | — | — | -0.009 | -0.013*** | -0.003*** |
| | — | — | (-0.824) | (-4.381) | (-7.236) |
| $niir_t$ | — | — | -0.056 | -0.244*** | 0.224*** |
| | — | — | (-0.316) | (-4.416) | (7.590) |
| $ncf_t$ | — | — | 0.137*** | 0.023*** | 0.021* |
| | — | — | (3.619) | (5.194) | (1.774) |
| $sglr_t$ | — | — | 1.509 | 0.357 | 5.487*** |
| | — | — | (0.616) | (0.914) | (6.518) |
| *devr_lag/* | 0.752** | 0.777*** | 0.278*** | 0.277*** | 0.101*** |
| *multi* | (2.235) | (16.140) | (7.596) | (82.858) | (57.289) |
| GARCH test | | | | | |
| *V* | 15.115 | — | 0.001 | — | — |
| | (0.374) | — | (1.313) | — | — |
| *ARCH* | -0.084*** | — | 0.552** | — | — |
| | (-5.803) | — | (2.165) | — | — |
| *GARCH* | 0.580 | — | -0.031 | — | — |
| | (0.560) | — | (-0.239) | — | — |
| EGARCH test | | | | | |
| $\beta_0$ | — | -0.123 | — | -5.788*** | -5.695*** |
| | — | (-0.373) | — | (-4.776) | (-4.270) |

| | | | | | |
|---|---|---|---|---|---|
| $\beta_1$ | — | -0.846*** | — | 6.565*** | 5.378*** |
| | — | (-6.516) | — | (5.387) | (5.164) |
| $\beta_2$ | — | 0.887*** | — | 0.842*** | 0.766** |
| | — | (21.764) | — | (3.238) | (2.329) |
| $\gamma$ | — | — | — | — | -1.714* |
| | — | — | — | — | (-1.904) |

Note:

(i) This test contains exogenous equations and one additional test for asymmetric information effect presented in column (c).

(ii) The figures in the parenthesis are *z*-statistics and figures with *, ** and *** are significant at 90%, 95% and 99% confidence level, respectively.

(iii) The denotation *ffr* applies to column (a) and (b) in the exogenous equations; the term *dhpi* regarded as the difference of *hpi* applies to column (c); The denotation *devr_lag* applies to the two lag equations and the *multi* term indicates *exp_hpi*devr_lag* for columns (a) and (b) and *ffr_lag*devr_ lag* for the column (c) correspondingly.

More evidently, asymmetric impacts of information are detected in (c) column where

$$\beta_1 + \gamma = 3.664 \text{ when } \varepsilon > 0$$
$$\beta_1 - \gamma = 7.092 \text{ when } \varepsilon < 0$$ [2]

It implies that the volatility is more sensitive to negative information, and the magnitude of the negative information effect is about twice of the positive information effect. This effect is detected only in the model of standard deviation because the dispersion is a more balanced and unbiased proxy than *rawel* which can be regarded as a generalized mean of each selected subsample. The relation is not blatantly evidenced when applying the generalized mean as a proxy for the measurement, while the dispersion proxy practically improves the analysis.

[2] When the information shock is negative, the sign of $\gamma$ becomes negative and the combination of coefficients should be $\beta_1 - \gamma$, which makes the result of 7.092.

## 2.4. Tests with Cyclic Shocks

### 2.4.1 Impacts from Exogenous Fluctuations

Long-term correlations between different variables can be investigated by the co-integration test. The three chosen financial ratios, *ncfr*, *niir* and *sglr* are modeled as in-system variables in the VAR analysis with *ffr* and *hpi* as shock variables out of system. By testing the unit root in Table 2.5 of each variable under Augmented Dickey-Fuller criteria, the result illustrates variables *rfa*, *ncfr*, *sglr*, *ffr* and *hpi* are stationary under at least 95% confidence level. The only variable not stationary is *niir* but it turns to be stationary as the cycle series *niirc* is selected as the proxy after being processed by Hodrick-Prescott filter (Hodrick and Prescott, 1997).

Table 2.5 Unit Root Test.

| | $rfa_t$ | $ncfr_t$ | $niirc_t$ | $sglr_t$ | $ffr_t$ | $hpi_t$ |
|---|---|---|---|---|---|---|
| t-statistic | -4.717 | -5.516 | -7.276 | -3.996 | -3.915 | -4.112 |
| Prob | 0.000 | 0.000 | 0.000 | 0.003 | 0.019 | 0.012 |

For co-integration relationship, Johansen methodology is employed in this test showed in Table 2.6 for multiple variables. Here presents the results of the co-integration test. As it is specified in Table 2.6, I have conducted co-integration test for every group of paired variables in the hypothesized contagion systems. Both the Trace statistic and Max-Eigen statistic indicate at least one co-integration equation exist in each pair of variables. The same implication applies to the corresponding pairs with one term lagged *rfa*. Exceptions are shown in the correlation with *ncfr* in the hypothesis of none co-integration equations, where trace and max-eigen statistics present different results.

Table 2.6 Co-integration Test

| $rfa$ | No. of CE(s) | Trace (Max-Eigen) | Prob.** | $rfa_{t-1}$ | No. of CE(s) | Trace (Max-Eigen) | Prob.** |
|---|---|---|---|---|---|---|---|
| $ncfr$ | None | 21.983 (12.728) | 0.005 (0.086) | $ncfr$ | None | 16.369 (10.407) | 0.037 (0.187) |
| | At most 1 | 9.256 (9.256) | 0.002 (0.002) | | At most 1 | 5.961 (5.961) | 0.015 (0.015) |
| $sglr$ | None | 25.600 (16.555) | 0.001 (0.021) | $sglr$ | None | 36.164 (21.770) | 0.000 (0.003) |
| | At most 1 | 9.045 (9.045) | 0.003 (0.003) | | At most 1 | 14.394 (14.394) | 0.000 (0.000) |
| $niirc$ | None | 43.311 (33.582) | 0.000 (0.000) | $niirc$ | None | 47.099 (37.116) | 0.000 (0.000) |
| | At most 1 | 9.728 (9.728) | 0.002 (0.002) | | At most 1 | 9.983 (9.983) | 0.002 (0.002) |

By identifying the long-term relationship with co-integration test, a restricted Vector Autoregression model, that is, Vector Error Correction Model (termed as VECM) could be applicable to the analysis. However, it is more reasonable to make a comparison with the unrestricted VAR model so that it is conducted in the exemplified contagion process. Before conducting VAR and VECM analysis, the optimal lag number should be determined. Five major lag selection criteria in Table 2.7 have shown that the optimal lags of the model should be two with the only exception that the AIC value implies four.

Table 2.7 Lag Selection Critieria

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 433.432 | NA | 0.000 | -19.292 | -18.927 | -19.157 |
| 1 | 515.138 | 141.130 | 0.000 | -22.597 | -21.867 | -22.327 |
| 2 | 532.376 | 27.424* | 0.000 | -22.972 | -21.877* | -22.566* |
| 3 | 539.699 | 10.651 | 0.000 | -22.895 | -21.436 | -22.354 |
| 4 | 550.420 | 14.133 | 0.000 | -22.974* | -21.149 | -22.297 |

The risk therefore can be divided by out-of-system shocks and in-system contagion, namely OSS-ISC process. The OSS process abstracted as a VAR system as follows:

$$\begin{bmatrix} Y \\ X \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} + \boldsymbol{A_1} \begin{bmatrix} Y_{t-1} \\ ffr_{t-1} \end{bmatrix} + \boldsymbol{A_2} \begin{bmatrix} Y_{t-2} \\ ffr_{t-2} \end{bmatrix} + \boldsymbol{A_3} \begin{bmatrix} Y_{t-3} \\ ffr_{t-3} \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

Where $Y = [ncfr \quad sglr \quad niirc]^{\mathrm{T}}$ and $X = [ffr \quad hpi]^{\mathrm{T}}$; $A_j$ represents the matrix of parameters with j=1,2,3; The term $u_i$ is the stochastic error.

The VAR results in Table 2.8 exhibit the explanatory performance of the coefficients against in-system variables. In terms of the ratio of net charge-offs, housing price produces more explicit impact to the measure. It could be related to traditional exposure to real estate market and the write-downs of assets proportionally came from fluctuations of housing price. Shocks from interest rate are less significant.

The ratio of securities gains and losses reacts evidently to the federal funds rate in recent period rather than in further lagged periods. The response to the housing market appears to be slow and cannot indicate a direct co-movement in between.

Table 2.8 Results of Vector Autoregression Test

| | $ncfr$ | $ncfr_{t-1}$ | $sglr$ | $sglr_{t-1}$ | $niirc$ | $niirc_{t-1}$ |
|---|---|---|---|---|---|---|
| $constant1$ | 0.002 | 0.002 | 0.001 | 0.002** | 0.006 | 0.006 |
| | (1.094) | (1.099) | (0.625) | (2.302) | (0.566) | (0.661) |
| $ffr_{t-1}$ | -0.000 | -0.000** | -0.000* | -0.000** | -0.001 | -0.012*** |
| | (-0.272) | (-2.083) | (-1.977) | (-2.028) | (-0.362) | (-5.170) |
| $ffr_{t-2}$ | 0.000 | 0.000 | 0.000 | — | 0.006 | 0.016*** |
| | (0.937) | (1.494) | (1.037) | — | (1.036) | (3.788) |
| $ffr_{t-3}$ | -0.000 | -0.000 | 0.000 | — | -0.006 | -0.005 |
| | (-1.106) | (-0.376) | (0.388) | — | (-1.495) | (-1.453) |
| $constant2$ | 0.000* | 0.000* | 0.001 | 0.000 | 0.006 | 0.007 |
| | (1.958) | (1.982) | (0.800) | (0.509) | (0.621) | (0.753) |
| $hpi_{t-1}$ | -0.000*** | -0.000*** | 0.000 | 0.000 | -0.001 | -0.001 |
| | (-3.043) | (-4.449) | (0.304) | (1.015) | (-0.764) | (-0.900) |
| $hpi_{t-2}$ | 0.001** | 0.000*** | -0.000 | -0.000 | 0.001 | -0.001 |
| | (2.452) | (2.919) | (-1.021) | (-1.456) | (0.700) | (0.820) |
| $hpi_{t-3}$ | -0.000 | -0.000 | 0.000 | 0.000* | — | — |
| | (-0.038) | (-1.058) | (1.601) | (1.696) | — | — |
| $hpi_{t-4}$ | -0.000 | — | — | — | — | — |
| | (-1.589) | — | — | — | — | — |

Note:

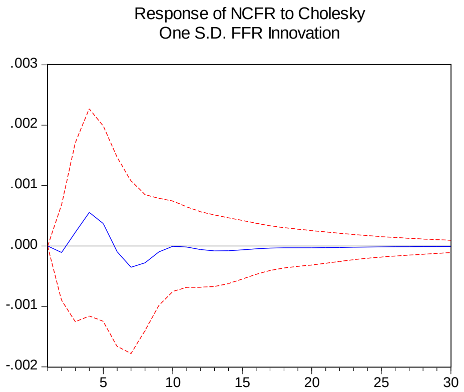
(i) The figures in the parenthesis are *z*-statistics and figures with *, ** and *** are significant at 90%, 95% and 99% confidence level, respectively.

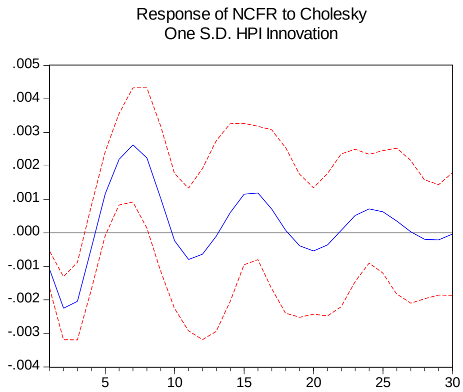
(ii) Each pair under estimation complies with optimal lags criterion.

The impulse responses are presented as follows. Cholesky decomposition method is introduced as the transformation matrix to structure irrelevant error terms.

Given an exogenous shock to the system, responses of *ncfr* to *ffr* is approximately positive and then turns to be negative after a short simulated initial period. The second variable *sglr* responds to *ffr* negatively from the starting point and turns to be positive after about 4 periods. The net interest income measure *niirc* responding to the shocks in a more volatile way shows that the cycle term of *niir* reacts and absorbs the shocks in a longer horizon. In a word, all the three responses tend to be stable after several fluctuations when they are observed through longer time span, and the only distinction is the different timing towards stability. To some extent, it signifies that the ratio of securities gains and losses will bring heavier impact to the ratio of net charge-offs in a more direct way.

Correspondingly, the respond of *ncfr* to the housing market fluctuates around zero more frequently positively to the ratio of net charge-offs whereas responds negatively to the ratio of securities gains and losses.



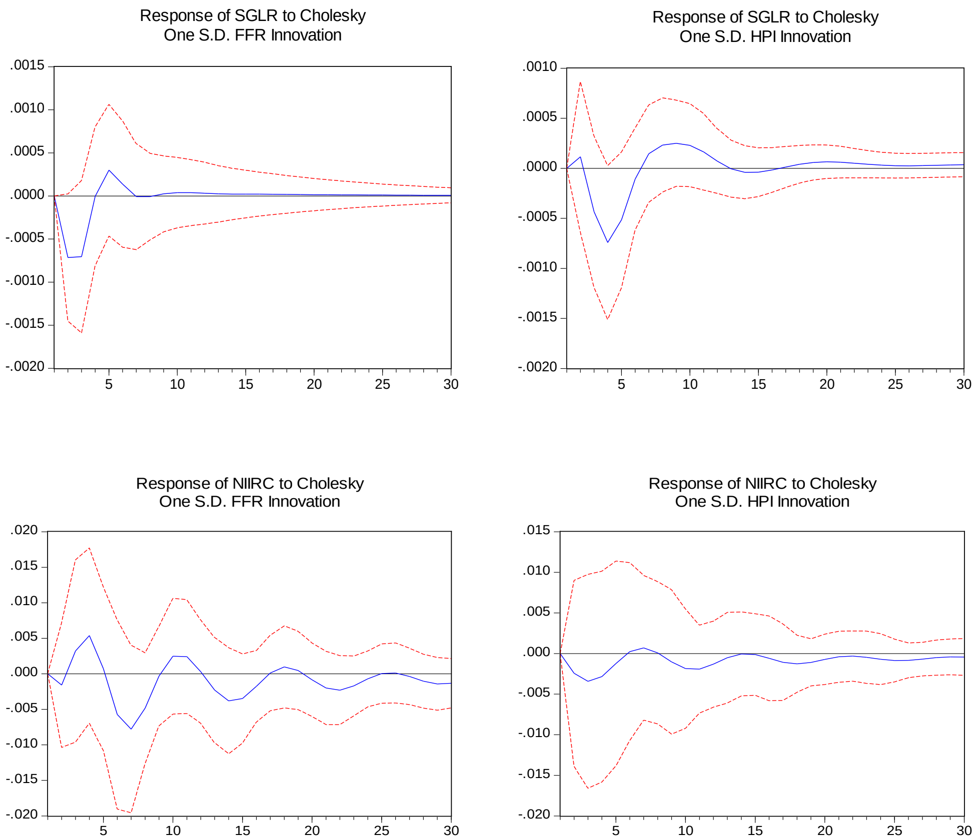



Figure 2.6 Results of Impulse Response

In summary, the diagrams of impulse response presented in Figure 2.6 exhibit that all responses tend to be stationary after the denoted 30 years forward, which indicates that the exogenous shocks are not permanent to the system but will cause a much longer period of turbulence. The speed from back-and-forth pacing to stabilizing is diversified among different pairs of relations where the net charge-offs represent the most volatile response to *hpi* and the indicator which shows less sensitivity is the ratio of securities gains and losses in response to *ffr*.

### 2.4.2 Internal Contagion Process

For a clear description of the contagion process and a capture of this effect in a different angle, the error correction term is introduced in the system to conduct the comparison with unrestricted VAR. The VAR system indicates more stability than the

VECM system by testing the inverse roots of AR characteristic polynomial. The graphs in Figure 2.7 show no roots locate outside the unit circle and imply that the unrestricted VAR model satisfies the stability condition in each system. On the other hand, the VECM structure typically contains unit root(s).

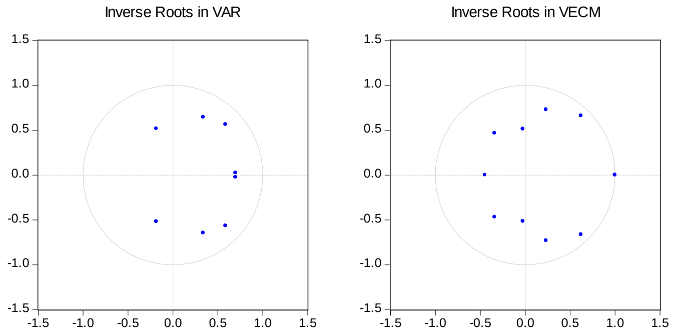



Figure 2.7 Inverse Roots of AR Characteristic Polynomial

As Table 2.9 shows, co-integration equation term is significant in two scenarios of the VECM test: contemporaneous setting and two-term lagged setting. It represents the speed of adjustment toward equilibrium. The positive coefficients in both columns of VECM show that there is no long-term causality. One term lagged model implies more significance than the normal contemporaneous setting. Then after the Wald tests of coefficients of each independent variable, results indicate that short-term impact exists from each pair of relation at least under confidence level of 95% except the impact from d(*niirc*) to $\mathrm{d}(rfa_{t-1})$. Based on the results, the shocks from three independent variables to rfa will be stabilized finally because of the short-term causality relation. The only marginally distinguishable exception of ncfr term which denotes the ratio of net charge-offs just coincides with its own impulse response previously discussed, meaning the fluctuations could not be pacified in a short time horizon.

Table 2.9 VAR and VECM Test

| | Unrestricted VAR | | VECM | |
|---|---|---|---|---|
| | $rfa$ | $rfa_{t-1}$ | $d(rfa)$ | $d(rfa_{t-1})$ |
| Co-integration eq. | — | — | 0.316* | 0.426*** |

| | | | | |
|---|---|---|---|---|
| | — | — | (1.979) | (2.799) |
| $constant$ | 0.011 | 0.009 | 0.004 | 0.002 |
| | (1.051) | (1.122) | (1.311) | (0.765) |
| $ncfr_{t-1}$ | 0.809 | — | -0.344 | — |
| | (0.251) | — | (-0.117) | — |
| $ncfr_{t-2}$ | -5.098 | -1.959 | -4.140 | 2.049 |
| | (-1.138) | (-0.729) | (-1.341) | (0.731) |
| $ncfr_{t-3}$ | 2.844 | 1.065 | -4.026 | -6.063*** |
| | (1.358) | (0.600) | (-1.594) | (-2.658) |
| $sglr_{t-1}$ | -2.696 | — | -4.734*** | — |
| | (-1.423) | — | (-2.741) | — |
| $sglr_{t-2}$ | 7.287*** | -2.942 | 2.532 | -5.586*** |
| | (3.681) | (-1.638) | (1.264) | (-3.287) |
| $sglr_{t-3}$ | -1.475 | 5.529*** | 0.289 | 2.655 |
| | (-0.736) | (3.419) | (0.158) | (1.496) |
| $niirc_{t-1}$ | -0.103 | — | 0.305* | — |
| | (-0.894) | — | (1.976) | — |
| $niirc_{t-2}$ | -0.231 | -0.093 | 0.069 | 0.286** |
| | (-1.479) | (-1.147) | (0.446) | (2.322) |
| $niirc_{t-3}$ | -0.029 | -0.267*** | -0.075 | 0.007 |
| | (-0.224) | (-2.894) | (-0.564) | (0.054) |

Note:

(i) The figures in the parenthesis are z-statistics and the bold results means significant at 90% confidence level; bold figures with one star and two stars are significant at 95% and 99% confidence level respectively.

(ii) Each pair under estimation complies with optimal lags criterion.

(iii) In the VECM system, each independent variable (*ncfr, sglr* and *niir*) in the left column represents the difference of its own time series but not the raw number itself.

Table 2.10 Wald Test for Coefficients in VECM

| | *d(ncfr)* | *d(sglr)* | *d(niirc)* |
|---|---|---|---|
| $d(rfa)$ | 10.117 | 15.818 | 8.778 |
| | (0.018) | (0.001) | (0.032) |
| $\mathrm{d}(rfa_{t-1})$ | 8.142 | 22.970 | 5.891 |
| | (0.017) | (0.000) | (0.053) |

Note: (i) The statistic is chi-square; figure in parenthesis indicates probability.

The differences of variables *ncfr* and *sglr* are showing a pattern of consistency in affecting the independent variable *rfa* while this effect does not exist in unrestricted VAR system. It indicates that a longer impact will be created to the ratio of failed assets and these two indicators will not digest the shocks instantly or in a short period. Through this process, the volatility from shocks out of the system will be transferred through the mechanism to give rise to a potential of financial crisis, which might be, in the context of this study, credit defaults or liquidity squeeze.

### 2.5 Conclusions

The goal of this study is to propose a measure of banking crisis to capture dynamic features of systemic risk. Generalized Autoregressive Conditional Heteroskedasticity is employed to portray the volatility clustering of the banking crisis measure with the data of bank failures selected from Federal Deposit Insurance Corporation. The Ratio of Adjusted Weighted Estimated Loss is calculated as the indicator of banking crisis, providing a straightforward and proxy-free perspective on the risk factor of systemic risk. The results show that the Exponential GARCH model shows the existence of volatility clustering, which indicates that there is a possibility that in general large losses in the banking sector would be followed by large losses. On the other hand, the GARCH model has weaker explanatory capacity in capturing and characterizing the behavior of volatility. Asymmetric information effect of dispersion degree indicates that the banking system will respond more drastically to negative information than positive information. The banking system is more sensitive to weak market confidence than positive information signals.

The Vector Autoregression shows that cyclic shocks diffuse into the system and result in contagion in a time-delaying manner. This risk transmission process leads to fluctuations of the system-wide financial indicator represented by ratio of failed assets. The limitation of this research is that the relatively low frequency of time series may compromise the explanatory power of GARCH model, however, if the yearly observations are transformed into quarterly or monthly observations, missing data points will be increased and the results could be biased. Future research based on this study could be conducted in the direction of integrating the dynamic features of banking crisis, in particular, volatility clustering and leverage effect, into the measurement of systemic risk and the findings in this chapter are also conducive to develop leading indicators for banking crisis rather than time lagged assessments.

# Chapter 3 Biased Decision-making and Liquidity Buffer in Commercial Banking

## 3.1 Introduction

Financial innovation has changed the traditional definition of liquidity provision and also altered the risk structure of the banking system amid the boom since 1990s and the burst in the recent financial crisis. Liquidity risk within a financial institution has been inherent for several years even if new business model constantly emerges. However, liquidity shock from liabilities side is relatively unpredictable. Aside from traditional bank run, stop rolling over in the wholesale funding takes a form of "silent run" during the recent credit crunch. The recent crisis shows how quickly the liquidity of an asset can evaporate even if a few signals indicate the crisis coming prior to the crisis. New regulation standards have been established along with the Basel Ⅲ which was enacted in 2010. One of the important reforms is the Liquidity Coverage Ratio which is introduced to monitor liquidity risk and ameliorate the short-term resilience to liquidity shocks of banking institutions. The core of concern is to make sure the banks have liquidity buffer to meet the liquidity needs within a specified time span.

How the framing effect in the decision-making of lenders affect portfolio allocation and liquidity buffer have not been fully studied despite of the progressive development of the epic Prospect Theory (Kahneman and Tversky, 1979). The obscure risk characteristics embedded in particular asset categories such as mortgage-related securities that played a significant role in the financial crisis have critical effects on the stability of both individual banks and the whole banking system.

In both academia and industry, the focus has been partially changed from credit risk to liquidity risk, but the importance of liquidity risk is still underemphasized. Based on the classic model of Diamond and Dybvig (1983), this study applies the concept of reference point in the Prospect Theory to make a further understanding of portfolio allocation and liquidity buffer in commercial banking, which helps to uncover of the natural vulnerability and present policy implications.

The remainder of this chapter is organized as follows. Section 3.2 presents the literature review. Section 3.3 specifies the theoretical model and the conditions of bank run equilibrium. Section 3.4 presents the empirical evidence and section 5 concludes this study.

## 3.2 Literature Review

Along the main storyline of early literature on bank run equilibrium, Diamond and Dybvig (1983) proposed a model that a self-fulfilling bank run is an equilibrium in the classic model. This model is future developed by several researchers. Cooper and Ross (1998) incorporated deposit insurance into the model and analyzed the strategy of holding excess reserves to deal with the allocation. Ennis and Keister (2009a) discussed the intervention policy efficiency in the face of system-wide bank runs and the incentives of depositors. In another framework, Ennis and Keister (2010) argued that banks will be overly optimistic about the needs of depositors and do not have sufficient resources to deal with the needs. While Allen and Gale (1998) disagreed with the view that banking crisis is a version of self-fulfilling prophecy and argued that bank runs are affected by fundamental economic fluctuations in business cycles. With the constraint of sequential service, depositors have the concern that others withdrawing before them will be served better and paid more, thus they have the incentive to participate in a bank run. Green and Lin (2003) used a finite-trader framework to show that ex ante efficient allocation can be implemented even if there are sequential service constraints, which implies that an efficient arrangement of allocation can be made without any bank runs under the mechanism they specified. However, Ennis and Keister (2009b) responded to this argument that the possibility of self-fulfilling bank run cannot be ruled out by changing only one assumption. Goldstein and Pauzner (2005) proposed a model in which the probability of bank runs could be measured and constructed a deposit contract that can make a balance between the benefits of liquidity provision and the cost of bank runs. In the recent crisis, liquidity risk stems from exposure to undrawn loan commitments, withdrawals of funds of wholesale deposits and losses of other short-term financing, rather than the claim of demand deposits, the difference of wholesale funding risk from traditional detail funding risk characterized in later studies. Uhlig (2010) provided a model in which bank runs are typically driven by institutional withdrawals instead of general depositors and discussed the motives of outside investors who will be potential buyers of the securities the distressed banks need to sell. In most of the existing frameworks, relative risk-aversion utility is usually employed, however they did not pay much attention to the psychological framing effect, especially the risk preference features proposed in the Prospect Theory (Kahneman and Tversky, 1979), in which people make decisions depending on how it is presented and what effect it will bring to the bank run equilibrium.

Holmström and Tirole (1997) discussed the moral hazard issue in financial intermediaries and documented that banks will have little incentive to monitor the lending if the net assets decline. Morris and Shin (2004) presented that liquidity black hole of a risky asset will emerge when short-sighted investors trade homogeneously. Diamond and Rajan (2000) argued that equity capital can act as a buffer to protect depositors. Likewise, there are some implications drawn from non-traditional banking businesses. Berger and Bouwman (2009) concluded that commercial banks create over half of their liquidity through off-balance sheet activities. Kashyap et al (2002) argued that synergy exists between deposits and loan commitments and both services require banks to hold balances of liquid assets to provide liquidity on demand. It is also shown that banks which have more illiquid assets tend to reduce lending and negatively affect the overall credit supply (Cornett, McNutt, Strahan, &Tehranian, 2011).Loutskina (2010) discussed the role of securitization in bank liquidity and the effect on funding management, and argued that the banks are holding less liquid assets than before because of the development of securitization.

Insufficient information about the exposure positions the banks held against subprime assets lead to weakening confidence of investors and a large-scale withdrawal occurred despite some of the banks were far from insolvency. Brunnermeier and Pedersen (2009) argued that liquidity in financial system can be classified into two categories: finding liquidity and market liquidity. Brunnermeier (2009) also discussed equity funding and debt with longer maturities and concluded that leveraged investors will be forced to unwind their positions when funding liquidity problems occurred. Deposit funding pressure was widespread and particularly exacerbated in the first phase of the crisis from the asset-backed commercial paper market (Acharya, Schnabl and Suarez, 2013). A concept concluded by Acharya and Moya (2015) emphasizes that the recent crisis is mainly caused by the collapse of liquidity provider mechanism of banks. However, few researches analyze the impact on internal liquidity of banks on the perspective of mortgage-related securities and the corresponding decision-making when they are under severe liquidity pressure.

## 3.3 Theoretical Framework

The purpose of this chapter is to revisit the classic bank-run equilibrium by employing the reference point which is one important anchoring effect from psychological feature of the Prospect Theory. In the theoretical setting, I follow the classic framework of bank run equilibrium originally developed by Diamond and Dibvig (1983) and further studied in several following literature. The original theory analyzes banks' traditional business model with maturity mismatch and suggests that banks are subject to a natural vulnerability and the equilibrium of a self-fulfilling bank-run exists. Retail and wholesale funding are also included in the setting.

### 3.3.1 The Environment

Suppose there are three periods 0, 1 and 2. At period 0, a depository institution has the total endowment of $D$ units as deposits from both retail and wholesale depositors.

Suppose there are $n_r$ retail depositors and $n_w$ wholesale depositors who are holding $D_r$ units and $D_w$ units of deposits respectively. The depository institution has two ways to allocate the endowment, which are storage and investment as the same terminology in the classic model setting. If 1 unit of cash is allocated into storage, the depository institution will receive r in period 1, and if the whole unit of cash is reallocated again in period 1, the yield in period 2 is also 1. If the unit of cash is allocated into investment, it will receive $R$>1 in period 2 and 1-$\tau$ when it is withdrawn prematurely in period 1. The depository institution will decide to put a fraction of endowment into investment, which is denoted by $i$, therefore, the fraction (1-$i$) is allocated in the storage technology. The storage and investment can be considered as liquid assets and illiquid assets respectively, and $\tau \in [0, 1]$ is the liquidation cost.

Depositors as agents who have deposited their funds in the depository institution have intertemporal choices to make use of their accounts. They can choose to withdraw the funds in their accounts in period 1 or period 2. Correspondingly, the depository institution will provide the depositors with $C_E$ in period 1 and $C_L$ in period 2. Assume that the proportion of depositors who will choose to withdraw in period 1 is deterministic, and these depositors are considered as "impatient depositors". On the contrary, depositors who will wait to withdraw till period 2 are "patient depositors". The proportion is denoted by $\pi \in [0, 1]$.

Depositors as homogenous agents have a utility function based on the goods they will consume at each period. The consumption depends upon the cash the depository institution is able to provide. The utility function will take the form of $U(c)$, where c is the consumption or can be simply considered as the cash provided. For the purpose of mathematical tractability, the utility function with an explicit form is specified in this setting. The major feature different from previous literature is that the utility function is strictly concave and increasing only if the independent variable consumption is over certain threshold. If the consumption is less than the threshold, the utility will be negative. It is more realistic in the model of bank run. Assume that the depository institution promised that it would provide 1 unit of cash for every depositor who had 1 unit of deposits and would like to withdraw in period 1. When this promise comes to be invalid, which means the depositor will receive nothing, the utility of the depositor then will be negative instead of zero because this unit of cash is his or her legitimate claim. For that reasoning, when *c* is zero, the utility should not be zero anymore. So the utility will turn into zero from being negative values when consumption reaches some threshold, and this threshold is at most the legitimate claim of the depositor. Every single unit of consumption beyond the threshold will create positive utility for the depositor because it is the real return he or she gains.

$$U(c) = \frac{(\alpha+\beta c)^{1-\gamma}}{1-\gamma} \tag{1}$$

Where $\alpha < 0$ and $\beta > 0$, which implies that the original curve makes a rightward shift along the c axis and the distance it moves is $(-\alpha/\beta)$. The distance is the threshold and $(\alpha/\beta) \in [-1, 0)$ is here defined as threshold coefficient.

$\gamma \in (0, 1)$ is a positive coefficient related to risk preference of depositors. Absolute risk aversion and relative risk aversion are derived from the measure of Arrow (1965) and Pratt (1964), and both of them are decreasing so that it is consistent with intuition and reality. Decreasing risk aversions imply that the agent will increase the risky asset investment if his or her wealth is increased.

The following figure indicates typical utility curves under the setting above. With different coefficient $\gamma$ and threshold coefficient = -1, the curves are concave and in the mean time form an approximation to the fundamental principle of prospect theory created by Kahneman and Tversky in 1979 and further developed in 1992, who argue that the "pain" in losses is bigger than the "joy" in the same amount of gains. The threshold in the utility function can be considered as the reference point.

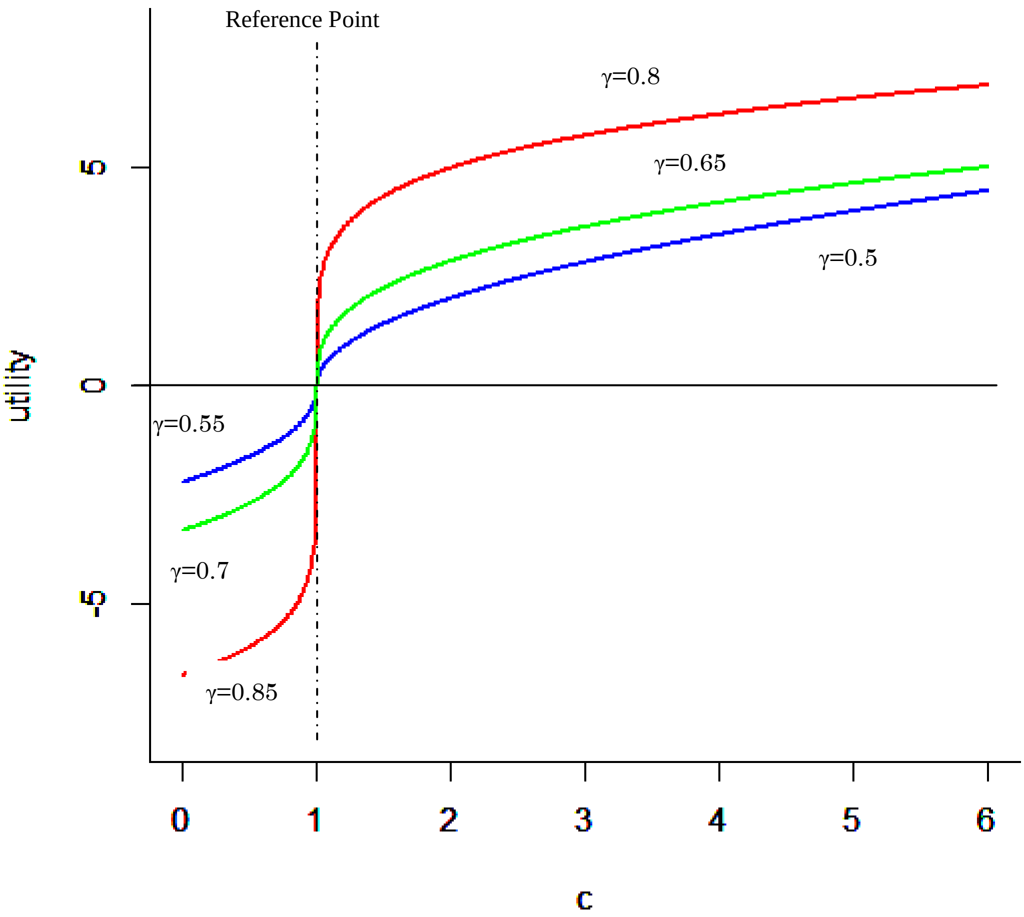



Figure 3.1 Utility Function with Reference Point

### 3.3.2 The Bank Run Equilibrium

The strategy is to find optimal equilibrium solutions to the intertemporal decision-making. The decision maker will have the following maximization problem:

Max

$$\pi U(C_E) + (1-\pi)U(C_L)$$

s. t.

$$\pi C_E = 1 - i$$

$$(1-\pi)C_L = iR$$

$$0 < i < 1, 0 < \pi < 1, R > 1$$

The first-best allocation can be obtained by solving this nonlinear programming:

$$C_E^* = \frac{\frac{\alpha}{\beta}(1-\pi)\left[R^{-1} - R^{\frac{1-\gamma}{\gamma}}\right] + 1}{\pi + (1-\pi)R^{\frac{1-\gamma}{\gamma}}} \tag{2}$$

And

$$C_L^* = \frac{R^{\frac{1}{\gamma}} + \frac{\alpha}{\beta}\pi(R^{\frac{1}{\gamma}} - 1)}{\pi + (1-\pi)R^{\frac{1-\gamma}{\gamma}}} \tag{3}$$

Similarly, the fraction is allocated into investment can be derived based on the results above as well. The equilibrium solutions of $C_E^*$ and $C_L^*$ are to some extent more intricate than the general results through applying utility function with constant relative risk aversion. It is intuitive to see that the payment $C_E^*$ in period 1 is greater than the payment under the assumption of constant relative risk aversion, and the payment $C_L^*$ is just in the opposite situation. This variation of equilibrium will compromise the condition in which a bank run occurs.

When $C_E < 1 - \tau i$, the bank run will not happen in period 1 because the payment $C_E$ is covered by both claims from storage and liquidated investment. In addition, another condition has to be satisfied that the payment for an individual depositor who chooses to withdraw in period 2 should be greater than the payment for period 1 because of the time value of funds. It implies that the unit payment in longer time intervals should be more than the unit payment in shorter time intervals. Here the second condition is formed to be:

$$\frac{C_E^*}{1-i} < \frac{C_L^*}{i} \tag{4}$$

Therefore, the two conditions are equivalently specified as follows:

$$R^{-1} + \frac{1}{\frac{\alpha}{\beta}(1-\tau\pi)} > \left[1 + \frac{1-\tau}{\frac{\alpha}{\beta}(1-\tau\pi)}\right] R^{\frac{1-\gamma}{\gamma}} \tag{5}$$

And

$$\frac{1-i}{i} > \frac{1}{R}\left[\frac{1+\frac{\alpha}{\beta}(1-\pi)(R^{-1}-R^{\frac{1-\gamma}{\gamma}})}{R^{-1}-(1+\frac{\alpha}{\beta}\pi)(R^{-1}-R^{\frac{1-\gamma}{\gamma}})}\right] \tag{6}$$

When

$$\frac{\alpha}{\beta} > -\frac{1}{\pi(1-R^{-\frac{1}{\gamma}})} \tag{7}$$

Liquidation cost may play a major role in this inequality. As argued by Ennis and Keister (2009), if liquidation cost is large enough, bank run will not occur no matter how the other variables are changing. However, in the setting of a utility function with threshold, the conclusive remarks can be reversed easily. In the first condition, it indicates that the possibility of a bank run is not solely dependent on the liquidation cost, which shows, the proportion of "impatient depositors" and the risk preference are also indispensible factors.

When liquidation cost is negligibly little or completely zero, based on the pre-specified infimum boundary of $(\alpha/\beta)$, the condition will not be satisfied because of

$R$>1 and both sides of the inequality are negative. Before the recent financial crisis, assets such as mortgage-related securities with investment-grade ratings were once sufficiently liquid. It did not have to cost too much for commercial banks and investment banks to liquidate the assets. However, as the model implies, there is a potential possibility of a bank run despite of lower liquidation cost. That is the fragile point of banking system in nature, which means a bank run or a funding withdrawal at least in limited magnitude could be triggered by certain exogenous economic shocks. This is consistent with the real economy where one or some of the sources of uncertainty such as investors losing confidence, interest rate increase or credit quality deterioration, could eventually cause a bank run to some extent, even though there is little evident sign prior to the event.

As liquidation cost increases, the right-hand side will turn to be positive so that the condition will always hold no matter how $R$ and $\gamma$ change. It can be specified as in the following. As assumed above, it is definitive that:

$$0 \geq \frac{\alpha}{\beta} \geq -1 \geq \frac{1}{(1-\tau\pi)} \tag{8}$$

Then the following inequality can be satisfied:

$$1 + \frac{1}{\frac{\alpha}{\beta}(1-\tau\pi)} < 0 \tag{9}$$

It indicates that condition (5) will be satisfied only if the term in the square parenthesis is positive, which implies:

$$0 \geq \frac{\alpha}{\beta} > -\frac{1-\tau}{1-\tau\pi} \geq -1 \tag{10}$$

This inequality completely holds when liquidation cost is zero as mentioned. But a higher liquidation cost $\tau$ does not necessarily indicate a satisfaction to the condition.

The real correlation between $\tau$ and $\pi$ is very crucial to this problem. Empirical test about that relationship is beyond the scope of this chapter, but hypothesis according to historical experience can shed some light on this particular issue. High liquidation cost in reality implies poor credit quality or high risk of an asset. Investors (or general depositors) tend to make decisions only based on their own concerns about their funds, in other words, they almost merely care about their banking accounts rather than what kind of intervention strategy the bank will implement or what kind of decisions other peer investors will make. Hence, withdrawal of their funds would be the best choice for them to keep the money safe, and because the investors are homogenous, the others will follow suit to do the same. Therefore, the proportion of early withdrawal will grow dramatically. It is intuitive to speculate that liquidation cost and proportion of “impatient depositors” are positively correlated. Then the condition could be broken if the threshold coefficient is somewhere between -1 and 0, especially during the periods of market-wise credit defaults.

Condition (6) presents the fraction of endowment allocated into investment has connections with other variables. If the utility function is simplified to the original form where $\alpha = 0$ and $\beta = 1$, it is interesting to find that condition (6) becomes much more explicit:

$$\frac{i}{1-i} > R^{\frac{1}{\gamma}} \tag{11}$$

Condition (11) indicates the minimum ratio between $i$ and (1-$i$) is $R^{\frac{1}{\gamma}}$. While putting the threshold coefficient back into the inequality, and suppose that the threshold coefficient is -1, condition (6) will be transformed to the following profile:

$$\frac{i}{1-i} > R \tag{12}$$

Which implies a small fraction of endowment will be allocated into investment because of the fact that $R < R^{\frac{1}{\gamma}}$. This argument furthers our understanding that bank run equilibrium will still be achieved even if condition (5) is satisfied whatsoever.

Proposition 1: if the fundamental interest rate is increasing and a proportion of fixed-income assets have negative convexity, liquidity buffer will be insufficient and the bank run equilibrium exists.

In the balance sheet of a depository institution, rate-sensitive assets (*RSA*) and rate-sensitive liabilities (*RSL*) are both vulnerable to interest changes and vary in different directions. If a bank holds less *RSA* than *RSL*, interest rate increase will cause decline of net interest margin (*NIM*) and deteriorate the balance sheet. A typical banking business model is to "borrow short and lend long" to make profits from the margin, so most of depository institutions are vulnerable to the upside track of interest rate.

Liquidity shock sometimes occurs in a haphazard way, as analyzed in the previous section. The shock will evolve to be a big challenge to the depository institution's capability of preventing itself from a real bank run. The general cases are two scenarios: seeking more funding sources or downsizing the assets positions. When credit crunch exacerbates in the market-wide scope, funding can be seriously scarce so that seeking more funding in the liabilities side will be desperately difficult. The interest rate will thus grow even faster and it will in turn push the lending cost to fly in a skyrocketing mode.

Cutting back certain positions of assets might be a feasible cure to the issue before regulatory agencies and the central bank make a move to intervene, but the resist will not be effective for long in the foreseeable future. Liquid assets, for instance, treasury securities, short-term government bonds, cash and federal funds can be easily liquidated due to lower liquidation cost and relatively higher credit quality. Real estate-related loans and mortgage-related securities account for a major part of the total assets, and the former is typically categorized as illiquid assets. Mortgage-related securities, on the other hand, consist of agency securities and private-label securities. The private-label mortgage-backed securities (or non-agency MBS) have suffered a huge downturn during the recent crisis. The dissimilar destiny of agency MBS is mostly backed by the purchase programs of Federal Reserve. The mortgage-related securities along with some callable bonds may have negative convexity which will slow down the price rise and accelerate the price fall, then the book value will be decreasing even faster than other interest rate sensitive assets. Mildly downsizing the exposures of securities can both provide liquidity for the funding shortage and maintain healthy operations within the institution. Drastically cutting down the positions of assets including long-term loans and corporate bonds is never desirable for depository institutions.

Increasing interest rate affects the equilibrium condition (5) and (6) in different manners. For condition (5), both liquidation cost $\tau$ and the proportion of early withdrawals $\pi$ will increase accordingly. If condition (10) is satisfied, the bank run will be more possible because the return of long-term investment *R* is also growing as fast as fundamental interest rate.

The bank run equilibrium could be even more definitive in terms of condition (10). With the same simplification as presented above, threshold coefficient is set to be -1 right at the lower boundary, condition (12) will be obtained, which implies the ratio between investment and storage should be greater than the increasing *R*. However, it is very counterintuitive in the real economy because the investors would like to hold more liquid and short-term assets instead of illiquid and long-term assets during the credit crunch period. Then the left-side of inequality (12) will become smaller so that the condition will not be satisfied.

Proposition 2: if both absolute and relative risk aversions are decreasing, reference point and risk preference coefficient distorted by credit defaults will challenge condition (5) and (6) and eventually realize the bank run equilibrium.

Defaults of credit derivatives occurred frequently during the recent financial crisis. They coincidentally co-moved with interest rate increase with implicit correlations with each other. But for the purpose of theoretical analysis, I will single out the individual effects of credit defaults on the condition of bank run equilibrium. Suppose the defaults happen in the time when interest rate is low enough, credit risk will create unexpected changes on the threshold coefficient and risk preference coefficient $\gamma$.

As measured by Arrow (1965) and Pratt (1964), absolute risk aversion *A(c)* and relative risk aversion *R(c)* under the utility function specified in this chapter are as follows respectively:

$$A(c) = \frac{\beta\gamma}{\alpha + \beta c} \tag{13}$$

$$R(c) = \frac{\alpha\beta\gamma}{(\alpha + \beta c)^2} \tag{14}$$

Both *A(c)* and *R(c)* are decreasing. This is consistent with several academic works following Friend and Blume (1975) about risk preference. Credit defaults will make a strike to the investors' confidence and distort their decision-making behaviors. In the setting of theoretical model, the coefficient $\gamma$ is going to increase to approach its upper bound 1, which is explicitly reasonable because worse credit quality of assets will drive investors more risk averse, meanwhile, the threshold coefficient is approaching zero. The reason for the latter one is intuitive: when some of the exposures of an investor defaulted, it is possible to calculate Loss Given Default (*LGD*) and Recovery Rate (*RR*) after liquidation. The expectation for legitimate claim will be lowered dramatically. The zero-utility threshold will then move leftward since claiming a small fraction is still better than claiming nothing. As a result, the threshold coefficient will be infinitely close to zero. The extreme scenario of condition (5) is as follows:

$$\lim_{\frac{\alpha}{\beta}\to 0, \gamma\to 1} \left[1 + \frac{1}{\frac{\alpha}{\beta}(1-\tau\pi)}\right] = \lim_{\frac{\alpha}{\beta}\to 0, \gamma\to 1} \left[1 + \frac{1-\tau}{\frac{\alpha}{\beta}(1-\tau\pi)}\right] R^{\frac{1-\gamma}{\gamma}} = \infty \tag{15}$$

With the approximations of both threshold coefficient and risk preference coefficient $\gamma$, condition (6) turns into condition (12). In the single situation of credit defaults, $R$ is presumed to be unchanged; while the left-side of the inequality is decreasing as the fraction of short-term allocation (1-*i*) is growing against long-term investment. Therefore, the bank run equilibrium will be the optimal strategy for depositors.

### 3.4 Extensive Discussion: Liquidity Buffer and Wholesale Funding

Suppose there are three periods 0, 1 and 2. At period 0, a depository institution has the total endowment of *D* units as deposits from both retail and wholesale depositors. Suppose there are $n_r$ retail depositors and $n_w$ wholesale depositors who are holding $D_r$ units and $D_w$ units of deposits respectively. The depository institution has two ways to allocate the endowment, which are storage and investment as the same terminology in the classic model setting. If 1 unit of cash is allocated into storage, the depository institution will have the payoff of r in period 1 and $r^2$ in period 2 if compounded. If the unit of cash is allocated into investment, it will receive *R* in period 2 and $R(1\text{-}\tau)$ when it is withdrawn prematurely in period 1, where $\tau \in [0,1]$ is the liquidation cost.. The depository institution will make a decision on what proportion of endowment will be allocated into investment, which is denoted by i and the fraction (1-*i*) is allocated into storage. The storage and investment can be regarded as liquid assets and illiquid assets respectively.

Both retail and wholesale depositors have inter-temporal choices to make use of their accounts. Retail depositors can choose to withdraw the funds in their accounts in either period 1 or period 2. Correspondingly, the depository institution will provide the depositors with $C_E$ in period 1 and $C_L$ in period 2. Assume that the proportion of depositors who will choose to withdraw in period 1 is deterministic, and these depositors are “impatient depositors” as opposed to “patient depositors” who will wait to withdraw till period 2. The proportion of early withdrawal is denoted by $\pi \in [0,1]$. On the other hand, wholesale lenders take a different form of withdrawal by not rolling over their funding en masse into the next term. The proportion of the wholesale funding which is not rolled over is denoted by$\omega$. There is another assumption that the probability of not rolling over is $\eta$.

Retail depositors as homogenous agents have a utility function based on the goods they will consume at each period. The consumption depends upon the cash the depository institution is able to provide. The utility function will take the same form as it is specified in the previous section.

### 3.4.1 The Bank Run Equilibrium

The strategy for the depository institution is to find the optimal equilibrium in the face of the inter-temporal demands. The maximization problem follows the classic setting that a bank will have the following maximization problem:

There are several conditions to which the maximization will be subject. The first intuition is that the bank should provide patient and impatient depositors with available funds according to respective demand. In the setting of this study, liquidity buffer is introduced to be provided for the contingent demand from wholesale funding. $LB$ and $LB^{\epsilon}$ represent the liquidity buffer held by the institution at time t=1 and t=2 and they can be cash reserves or liquid assets. $LB^{\epsilon}$ is he expected liquidity buffer that is the residual liquid assets remaining in the balance sheet after the bank meets the contingent demands of wholesale lenders. The contingent demands could be characterized by the expected wholesale funding withdrawal $W_1$ at t=1, which is specified by

$$E(W_1) = \eta\omega D_w + (1-\eta) \cdot 0 \tag{16}$$

As it is specified in the previous section, $\eta$ is the probability of the event that lenders stop rolling over the funds to the bank. There will be no cash outflow if lenders keep rolling over the funds. The expected amount of wholesale withdrawal at t=2 can be calculated through the following table. If the wholesale lenders stop rolling over their funds, the amount of $\omega D_w$ will be paid at t=1 and the claim at t=2 will be $(1-\omega)D_w$. Otherwise, if the wholesale lenders keep rolling over the funds to the second period, the bank will hold the funds till t=2 and the whole amount $D_w$ will be repaid at the end of the second period.

Table 3.1 Matrix of Wholesale Funding Demand

| | not rolling over | rolling over |
|---|---|---|
| Probability | $\eta$ | $1-\eta$ |
| Wholesale Claim at t=2 | $(1-\omega)D_w$ | $D_w$ |

Therefore, the expected amount of wholesale withdrawal at t=2 will be

$$E(W_2) = \eta(1-\omega)D_w + (1-\eta)D_w \quad (17)$$

Then the expected liquidity buffer $LB^{\epsilon}$ will be the difference between the expectation of $LB$ and $E(W_2)$. Theoretically, $LB^{\epsilon} = |E(LB) - E(W_2)| = |(\eta(LB - \omega D_w)r + (1-\eta)LBr) - (\eta(1-\omega)D_w + (1-\eta)D_w)|$. Optimally, the liquidity buffer $LB$ at the first period should be designed to perfectly hedge the contingent funding claim from wholesale lenders, hence there will be the equation $LB - \omega D_w = 0$ and the expected liquidity buffer $LB^{\epsilon}$ should be $(1-\eta)LBr - (1-\eta\omega)D_w$.

The amount provided to impatient depositors should be the fraction allocated into storage subtracting liquidity buffer, which is $(1-i)D - LB$. Since π is the proportion of early withdrawal, then the amount provided for impatient depositors, which is $\pi n_r C_E$, should be equal to $(1-i)D - LB$. For patient depositors, the amount should be equal to the fraction of investment plus the expected liquidity buffer $LB^{\epsilon}$ in period 2. The wholesale lenders make this special withdrawal by not rolling over their funding in period 2. The funding amount of not rolling over is $\omega D_w$

Max

$$\pi U(C_E) + (1-\pi)U(C_L)$$

s. t.

$$\pi n_r C_E = (1-i)D - LB$$
$$(1-\pi)n_r C_L = iDR + LB^{\epsilon}$$
$$LB^{\epsilon} = (1-\eta)LBr - (1-\eta\omega)D_w$$

$$\eta\omega D_w \leq LB, R > 1, r > 1, C_E > -\frac{\alpha}{\beta}, C_L > -\frac{\alpha}{\beta}$$

$$0 < i < 1, 0 < \pi < 1,0 < \eta < 1,0 < \omega < 1$$

The first-best allocation can be obtained by solving this nonlinear maximization. By taking partial derivatives of $C_E$ and $C_L$ respectively, the closed-form solutions can be made as follows:

$$C_E^* = \frac{\frac{\alpha}{\beta}(1-\pi)\left[1-(\frac{R}{r})^{\frac{1}{\gamma}}\right]+(Rd+lb^{\epsilon})-\frac{R}{r}lb}{\pi\frac{R}{r}+(1-\pi)(\frac{R}{r})^{\frac{1}{\gamma}}} \tag{18}$$

And

$$C_L^* = \frac{\frac{\alpha}{\beta}\pi\left[1-(\frac{r}{R})^{\frac{1}{\gamma}}\right]+(rd-lb)+\frac{r}{R}lb^{\epsilon}}{(1-\pi)\frac{r}{R}+\pi(\frac{r}{R})^{\frac{1}{\gamma}}} \tag{19}$$

Where

$$lb = \frac{LB}{n_r}, lb^{\epsilon} = \frac{LB^{\epsilon}}{n_r}, d = \frac{D}{n_r}$$

The fraction *i* allocated into investment can be derived based on the results above as well. The equilibrium solutions of $C_E^*$ and $C_L^*$ are to some extent more intricate than the general results through applying utility function with constant relative risk aversion. It is intuitive to see that the payments $C_E^*$ and $C_L^*$ are different from the payments under the assumption of constant relative risk aversion, and this variation of equilibrium will compromise the condition in which a bank run occurs.

### 3.4.2 Liquidation Cost and Risk Preference

When $n_r C_E \leq (1-i)D + iDR(1-\tau) + LB$, the bank run will not happen in period 1 because the cash flow from both storage and liquidated investment is sufficient to cover the payment $C_E$. Then the condition takes the form as follows:

$$C_E^* \leq (1-i)d + idR(1-\tau) + lb$$

In addition, another condition has to be satisfied that the payment for an individual depositor who chooses to withdraw in period 2 should be greater than the payment for period 1 because of the time value of funds. Here the second condition is formed to be:

$$C_E^* < C_L^*$$

By applying the closed-form solutions in the equilibrium, the condition (2) is equivalently specified as follows:

$$i \leq \frac{\Lambda_1 lb - lb^{\epsilon} + \Lambda_2}{\Lambda_3(1-R+R\tau)} \ when \ \tau > \frac{R-1}{R}$$

Where

$$\Lambda_1 = \frac{R}{r}\left[1 + (1-\pi)\left(\frac{R}{r}\right)^{\frac{1-\gamma}{\gamma}} + \pi\right] > 0$$

$$\Lambda_2 = d\left[(1-\pi)\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} + \left(\frac{R}{r}\right)\pi\right] - Rd - \frac{\alpha}{\beta}(1-\pi)\left[1 - \left(\frac{R}{r}\right)^{\frac{1}{\gamma}}\right]$$

$$\Lambda_3 = d\left[(1-\pi)\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} + \left(\frac{R}{r}\right)\pi\right] > 0$$

As the reference point is employed in the model, it indicates that the possibility of a bank run is not solely dependent on the liquidation cost and the risk preference is another indispensible factor. As $\Lambda_3$ is always positive, the upper bound of investment ratio will get lower as the liquidation cost grows.

The risk preference of depositors is typically represented by the reference point (*RP* in the figure below). When all other variables are considered constant, a rightward move of the reference point would cause the investment ratio *i* to decline. However, as the utility becomes negative when the consumption is smaller than the reference point, the concavity will be altered.

Numerical instances are more intuitive as it is depicted below. Scenario A shows the classic equilibrium in which a bank run condition would not be triggered. As the reference point moves rightwards, both $C_E^*$ and $C_L^*$ will decrease and the latter will drop even faster due to a bigger rate of descent. When the reference point goes up by 1 unit, the change of $C_E^*$ will be less than 1 unit and $C_L^*$ will directly decrease.

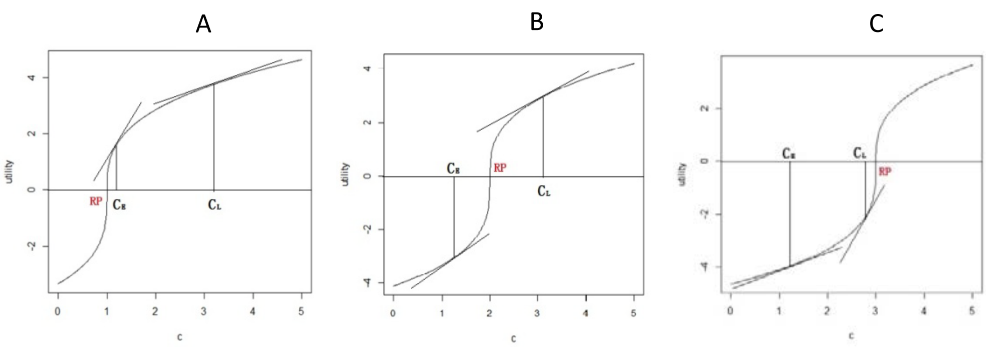



Figure 3.2 Reference Point and the Equilibrium Solutions

Scenario B and C are also possible status in which both the "impatient" and "patient" depositors will suffer from a negative utility. The condition (2) will not be satisfied eventually if the reference point keeps increasing. It implies that there will be a bank-run equilibrium even if the first condition sustains. In general, the investment ratio i should be negatively correlated with the reference point.

$$\frac{\partial C_E^*}{\partial\left(-\frac{\alpha}{\beta}\right)} = \frac{(1-\pi)\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} - (1-\pi)}{(1-\pi)\left(\frac{R}{r}\right)^{\frac{1}{\varphi}} + \pi\frac{R}{r}} < 1$$

And

$$\frac{\partial C_L^*}{\partial(-\frac{\alpha}{\beta})} = \frac{\pi\left[(\frac{r}{R})^{\frac{1}{\gamma}} - 1\right]}{(1-\pi)\frac{r}{R} + \pi(\frac{r}{R})^{\frac{1}{\gamma}}} < 0$$

### 3.4.3 Liquidity Buffer

Liquid assets held by financial institutions as a buffer could function as the "first resort" against contingent liquidity shortage. The transformation of condition (1) and (2) in terms of liquidity buffer is specified as follows:

$$lb + \frac{r}{R} lb^{\epsilon} > dr + \frac{\alpha}{\beta}\left[(1-\pi)\frac{r}{R} + \pi\right]$$

$$\Lambda_1 lb - lb^{\epsilon} \geq \Lambda_3(1 - R + R\tau)i - \Lambda_2$$

Through the combination of the two conditions above, the condition turns to be:

$$\left(\frac{R}{r} + \Lambda_1\right) lb > \frac{\alpha}{\beta}\left\{2 - \left(\frac{R}{r}\right)^{\frac{1}{\gamma}} + \pi\left[\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} + \left(\frac{R}{r}\right) - 2\right]\right\} +$$
$$i\Lambda_3(1 - R + R\tau) + d\left[2R - (1-\pi)\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} - \left(\frac{R}{r}\right)\pi\right]$$

First, it is clear that this particular lower bound of liquidity buffer will be raised with a higher liquidation cost$\tau$, which means the ideal position of liquidity buffer should be positively correlated with the liquidation cost. Before the recent financial crisis, assets such as mortgage-related securities with investment-grade ratings were once sufficiently liquid. It did not have to cost too much for investors to liquidate the assets. However, as the model implies, if the liquidation cost suddenly moves upwards due to liquidity shocks, the liquidity buffer should be increased accordingly. The shortage of buffer will lead to liquidity stress.

The reference point affects the liquidity buffer in a more subtle way. To some extent, it depends on the relationship between the proportion of "impatient depositors" and the term structure of the market interest rate. If the following condition is satisfied:

$$\pi < \frac{\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} - 2}{\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} + \left(\frac{R}{r}\right) - 2}$$

When

$$\left(\frac{R}{r}\right)^{\frac{1}{\gamma}} > 2$$

Then the correlation between the reference point and the liquidity buffer will be positive. The ratio of long-term rate R to short-term rate r can be obtained by taking the term structure as a proxy, while the coefficient $\gamma$ is difficult to be observed in the real world. In the recent years, prevailing low interest rates flatten the slope of the term structure, making the ratio of $R$ to $r$ drop to an extent that condition (8) is reversed. In that situation, the lower bound of the liquidity buffer declines when the reference point moves rightwards regardless of any change of other variables.

## 3.5 Empirical Evidence

### 3.5.1 Methodology and Data

The analysis in the previous section could shed some light on how the portfolio structure and liquidity buffer would be affected by the liquidation cost and the reference point. In this section, empirical tests are conducted to find support for the theoretical work. The empirical framework is described in the following linear panel model:

$$IR_{i,t}^{k} = B_{0,i}^{k} + \beta_1^{k} TAU_{i,t-1} + \beta_5^{k} GAP_{i,t-1} + \sum \beta_5^{k}\, Controls_{i,t} + \mu_{i,t} \qquad (20)$$

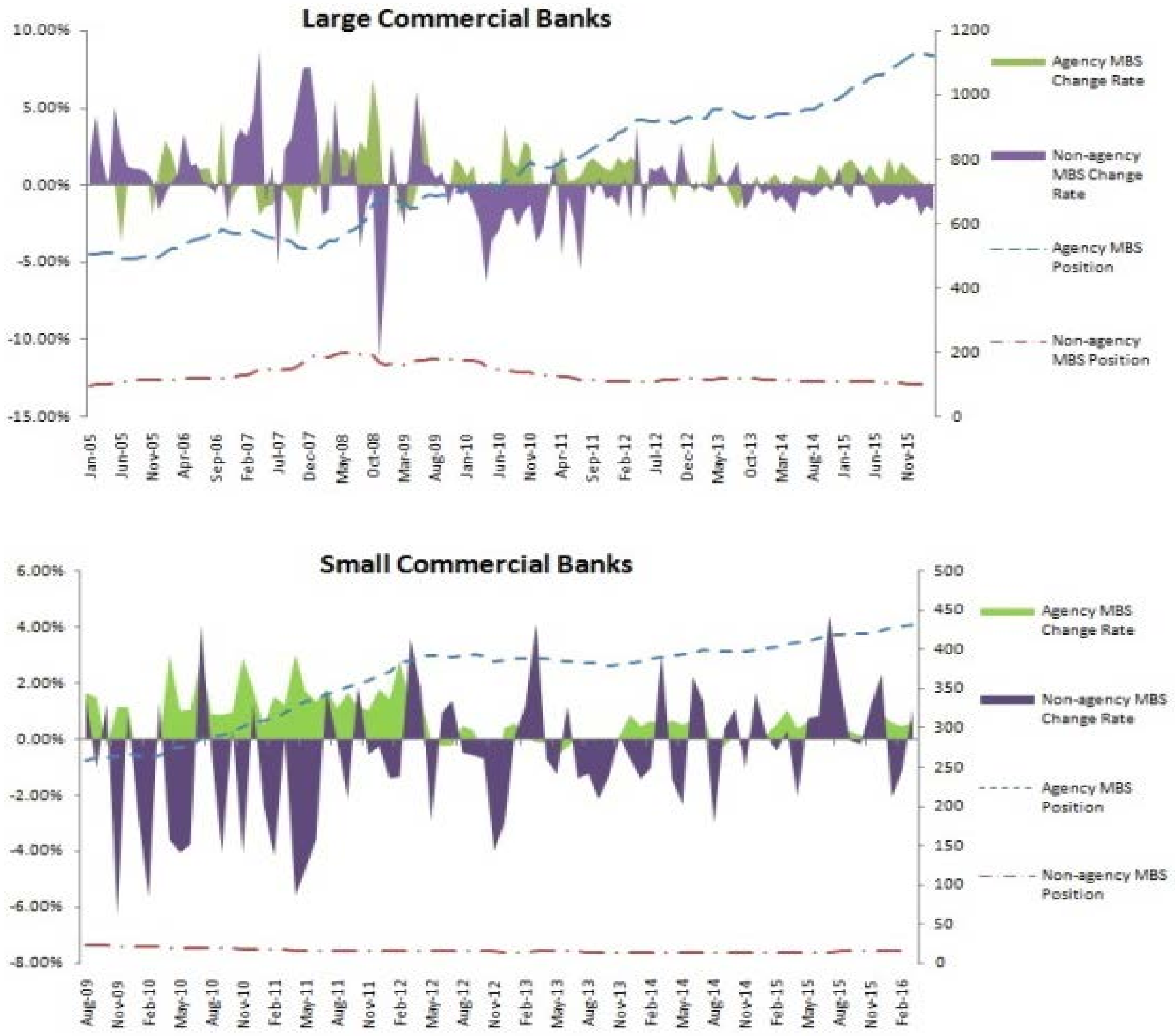
Where IR means the investment ratio $i$ specified in the theoretical setting, and $TAU$ represents the liquidation cost of a particular asset. Controls are a series of control variables. A perfect proxy variable for the reference point is hard to be acquired straightforwardly. However, a circuitous method can be applied to find an observable indicator, which is denoted by $GAP$ and takes the following form:

$$GAP = \frac{interestrate_L - interestrate_S}{fundamentalrate} \quad (21)$$

In this definition, $\text{interest rate}_\text{L}$ and $\text{interest rate}_\text{S}$ indicate the long-term and short-term deposit rate respectively, and $\text{fundamental rate}$ represents a basic risk-free interest rate in the corresponding quarter. In this study, the average 3-month Treasury bill rate is selected as the basic rate. In theory, the bigger the variable $GAP$ is, the harder for the reference point to get close to $C_L^*$. With the introduction of $GAP$, the negative correlation between the reference point and $IR$ is converted into an expected positive correlation.

The data in this study is selected from the FFIEC Call Reports. The range is from the first quarter of 2001 to the last quarter of 2016. The whole sample is also divided into three periods: pre-crisis (2001Q1-2007Q2), crisis (2007Q3-2009Q1) and post-crisis (2009Q2-2016Q4).

The interest rate spread between the yield of Mortgage-backed Securities (MBS) and U.S. Treasury securities and U.S. Government agency obligations is calculated for the explanatory variable IR. There are two reasons for choosing MBS in the model portfolio: first, securities are typically the option for liquidation when liquidity shocks occur, and MBS is an important part in this category; second, it also helps to understand the feature of banking liquidity risk for the fact that MBS was involved deeply in the recent financial crisis. Within this asset category of MBS, non-agency MBS market is shrinking to a record and agency MBS nearly dominates the aggregate market after the recent crisis. Agency and non-agency MBS positions in both large and small domestic banks diverged since the onset of the crisis. The empirical analysis is only conducted in the level of aggregate exposure.




Source: Federal Reserve Assets and Liabilities of Commercial Banks in the United States-H8.

Figure 3.3 Agency[3] and Non-agency MBS Exposures in Large and Small Banks

In the calculation of $GAP$, the interest rate spread of Savings Deposits, Time Deposits and Time Deposits to Transactions Deposits are selected into the dataset.

Note: MBS issued by U.S. government agencies or by U.S. government-sponsored enterprises such as the GNMA, FNMA and FHLMC. Pass-through securities not guaranteed by the U.S. government and other MBS issued by non-U.S. government issuers and those collateralized by MBS issued or guaranteed by FNMA, FHLMC, or GNMA. The variable TA is the logarithm of the raw data.

Control variables consist of profitability (ROA), capital sufficiency (Tier Ⅰ Risk-based Capital Ratio), liquidity sufficiency (Liquidity Ratio) and potentiality of non-performing loans (Provisions for Loan and Lease Losses standardized by Total Assets) and bank size (Total Assets).

Table 3.2 Descriptive Statistics of Selected Variables

| Variables | Description | Mean | Median | s.d. |
|---|---|---|---|---|
| *IR* | Investment Ratio | 0.45 | 0.45 | 0.37 |
| *TAU* | Liquidation Cost | 0.05 | 0.00 | 7.50 |
| *GAP1* | Interest Rate Spread of Deposits Accounts (standardized by T-bill rate) | 0.02 | 0.01 | 1.58 |
| *GAP2* | | 0.08 | 0.02 | 1.60 |
| *GAP3* | | 0.09 | 0.02 | 2.32 |
| *LIQRAT* | Liquidity Ratio | 0.09 | 0.07 | 0.08 |
| *CAPRAT* | Capital Ratio | 0.18 | 0.15 | 0.21 |
| *ROA* | Returns on Assets | 0.01 | 0.01 | 0.01 |
| *PTLL* | Provisions for Loans and Leases | 0.01 | 0.00 | 0.63 |
| *TA* | Total Assets | 12.03 | 11.87 | 1.35 |

Source: Calculated with the raw data from FFIEC Call Reports.

### 3.5.2 Empirical Results

According to the theoretical model, the relationship between the investment ratio and the liquidation cost is negative. The empirical results indicate that a significant linkage does exist in the group of small commercial banks, and the sign of the coefficient TAU is also consistent in large commercial banks in spite of insignificance. This finding is consistent with previous literature even if the model construction is changed with the introduction of liquidity buffer as a variable.

The coefficient of Liquidity Ratio is more significant in large banks than that in small banks. Banks with higher Capital Ratio tend to have a higher investment ratio i, especially in the subsample of small banks, but institutions with better ROA typically have a lower proportion of mortgage-backed securities. Size effect represented by total assets shows banks with bigger size will make more investment into MBS, although the size effect is already controlled by separating large banks from small banks.

Table 3.3 Panel Regression of Portfolio Allocation

| | Large Banks | | | Small Banks | | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| *TAU* | -0.012 | -0.012 | -0.011 | -0.083*** | -0.083*** | -0.083*** |
| | (-1.260) | (-1.265) | (-1.263) | (-4.652) | (-4.642) | (-4.643) |
| *GAP1* | -0.549 | | | 0.042*** | | |
| | (-0.290) | | | (3.859) | | |
| *GAP2* | | 2.083** | | | 0.098 | |
| | | (2.167) | | | (1.585) | |
| *GAP3* | | | -0.026*** | | | 0.095 |
| | | | (-3.331) | | | (1.604) |
| *LIQRAT* | -0.221** | -0.247** | -0.265*** | -0.010 | -0.012 | -0.012 |
| | (-2.431) | (-2.566) | (-3.186) | (-0.427) | (-0.506) | (-0.483) |
| *CAPRAT* | 0.315* | 0.286* | 0.278 | 0.029*** | 0.029*** | 0.029*** |
| | (1.946) | (1.691) | (1.636) | (3.740) | (3.649) | (3.696) |
| *ROA* | -0.936*** | -0.717** | -0.724** | -1.399*** | -1.429*** | -1.439*** |
| | (-2.905) | (-2.090) | (-2.154) | (-9.767) | (-9.937) | (-10.012) |
| *PTLL* | 0.284 | 0.625* | 0.649** | 0.000*** | 0.000*** | 0.000*** |
| | (1.085) | (1.780) | (1.983) | (6.230) | (6.420) | (6.486) |
| *TA* | 0.075*** | 0.077*** | 0.078*** | 0.125*** | 0.124*** | 0.124*** |
| | (5.846) | (6.062) | (6.172) | (23.844) | (23.614) | (23.599) |
| Bank Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 28687 | 28534 | 28474 | 272757 | 272868 | 272932 |
| R-squared | 0.032 | 0.036 | 0.034 | 0.042 | 0.041 | 0.041 |

Note: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

The coefficient of $GAP1$ is significant and consistent with the theory in small banks. On the other hand, the interest rate spread between time deposits and transactions deposits, represented by $GAP2$ and $GAP3$, is more evident in large banks. However, the negative coefficient of $GAP3$ is not coherent with the theory.

The result on liquidity buffer is more interesting. Just as the theoretical model suggests, the coefficient of the liquidation cost is positive in both large and small banks after the financial crisis, albeit significance only exists in the latter one. Reverse situation occurs in pre-crisis period and during the crisis, which implies that commercial banks did not raise the position of liquidity buffer in accordance with the increase of $TAU$. That could exacerbate the liquidity shortage amid the credit crunch. Small commercial banks have similar results despite massive wholesale funding withdrawals mostly occurred in core money center banks. In post-crisis period, the coefficient of liquidation cost is significantly positive.

In the post-crisis era, the general interest rate has been low, and the positive coefficient of $GAP3$ in large banks is consistent with the theoretical specification, especially in small banks. The significant coefficient also exists in large banks during the crisis suggests that the unobservable $\gamma$ might be a neutralizer even though the term structure is steep during the crisis.

Table 3.4 Panel Regression of Liquidity Buffer

| | Large Banks | | | Small Banks | | |
|---|---|---|---|---|---|---|
| | Pre-crisis | Crisis | Post-Crisis | Pre-crisis | Crisis | Post-Crisis |
| *TAU* | -0.000 | -0.007*** | 0.003 | 0.002 | -0.000 | 0.004** |
| | (-1.048) | (-7.120) | (0.99) | (1.332) | (-1.162) | (2.255) |
| *GAP3* | 0.138 | 2.591*** | 0.005*** | 1.420 | 0.242 | -0.000 |
| | (1.565) | (8.350) | (7.266) | (1.135) | (1.486) | (-0.005) |
| *LIQRAT* | 0.228*** | 0.181** | 0.592*** | 0.153*** | 0.105*** | 0.516*** |
| | (3.736) | (2.387) | (23.191) | (24.808) | (10.028) | (54.409) |
| *CAPRAT* | 0.049 | 0.064 | -0.014 | -0.027*** | -0.016** | 0.004*** |
| | (1.267) | (0.857) | (-0.660) | (-5.892) | (-2.092) | (2.945) |
| *ROA* | -0.071 | 0.133 | 0.100 | 0.109*** | 0.020 | 0.444*** |
| | (-1.192) | (1.317) | (1.551) | (5.821) | (0.272) | (10.693) |
| *PTLL* | -0.131 | 1.251*** | 0.197*** | 0.000*** | 0.552*** | 0.198*** |
| | (-1.513) | (4.980) | (3.318) | (-16.903) | (7.682) | (5.239) |
| *TA* | -0.008*** | 0.005 | -0.007*** | -0.013*** | 0.017*** | -0.003** |
| | (-5.210) | (0.776) | (-3.379) | (-18.82) | (4.122) | (-2.178) |
| Bank Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 9758 | 3066 | 15660 | 124043 | 31383 | 117615 |
| R-squared | 0.198 | 0.210 | 0.384 | 0.115 | 0.051 | 0.298 |

Note: ***, **, and * indicate 1%, 5%, and 10% significance respectively.

## 3.6 Conclusions

This study focuses on the portfolio allocation and liquidity buffer and how they are affected by the liquidation cost and risk preference. The biggest difference of this chapter from previous literature is the employment of framing effect in the classic bank run model and the analysis of determinants of liquidity buffer that a bank should hold in the face of funding liquidity shock. Wholesale funding, which plays a key role in the recent financial crisis, is also incorporated in analysis of bank run conditions. This chapter builds the connection between liquidity buffer and wholesale funding, and proposes a new perspective that the holding of liquidity buffer should be determined in line with wholesale liquidity needs. In the theoretical environment, I changed the typically assumed anticipation of depositors that late withdrawals will be paid less that early withdrawals.

The liquidation cost is negatively correlated with the investment ratio $i$, which is consistent with most previous literature. As the reference point moves rightwards, the investment ratio $i$ will decrease, which implies that a more significant framing effect represented by a higher reference point negatively correlates with the portion of endowment allocated into long-term project. The relatively high proportion of illiquid assets shows the real decision-maker formulates an investment strategy without considering the stylized risk preference of lenders. In other words, the theoretical model of bank run with reference point indicates that the proportion of long-term assets should be restrained as a result of the increase of liquidation cost or the rightward move of the reference point. Empirical results are evident except *GAP*3 in large banks. The lower bound of liquidity buffer will be raised as the liquidation cost increases. This indicates that the ideal liquidity buffer positively correlates with the difficulty of market clearing of the long-term investment. The empirical results show that large commercial banks should have raised their holding of liquidity buffer in keeping with the upward trend of liquidation cost before the crisis. Since the banks failed to augment the position of liquid assets, the coefficient consequently displays negative significance during the crisis period. The negative coefficient of liquidation cost in the second regression implies that liquidity buffer in large banks is insufficient during the crisis period. The relationship between liquidity buffer and the reference point maintains negative regardless of how steep the term structure will be. The results are conducive to deepen the understanding of the natural fragility in the liquidity management of commercial banks.

One practical implication based on the results of this chapter is the exploration and discussion of optimal liquidity buffer. It is clear that liquidity buffer could not be a constant variable which represents the absolutely optimal value of liquidity holding in commercial banks, while the liquidity buffer should be dynamic and adjustable under different economic circumstances. On the other hand, it is also necessary to study the framing effect of general depositors, especially institutional wholesale lenders, and incorporate the effect into the modeling of bank run and more extensive banking crisis. The reference point helps to explain the unobservable factors overlooked by the traditional analytical framework.

# Chapter 4 Liquidity Risk and Winner-take-all Effect

## 4.1 Introduction

The liquidity shock in the 2007-2009 financial crisis has been studied more intensively in recent literature. Unlike traditional scenarios, the specific form of liquidity shock has evolved from deposit outflow to the draw-downs of unused lines of credit and interbank financial arrangements. External factors such as the behavioral patterns of borrowers and depositors are no longer perfectly exogenous to the liquidity run dynamics. The bank strategy in liquidity management is also involved and has real impact on the bank run process. These include undrawn loan commitments, obligations to repurchase securitized assets, margin calls in the derivatives markets, and withdrawal of funds from wholesale short-term financing arrangements. Liquidity risk is typically entangled with credit risk in the later stage of the recent crisis. Among those factors, the sources of liquidity risk come from both balance sheets and off-balance sheets and the shock of shortage from these two sources have a severely negative impact on the entire banking system and the real economy.

The classic model shows the existence of a bank-run equilibrium indicating that the transformation of illiquid assets into liquid liabilities such as demand deposits exposes banks to liquidity risk (Diamond and Dibvig, 1983). This natural fragility exposes banks with unexpected runs from depositors when the market liquidity is tightening. Demand depositors have the incentive to monitor the banks due to liquidity mismatch and make an incentive-compatible environment (Calomiris and Kahn, 1991). After causing a series of banking crisis, policy makers and academics start to look for a more stringent regulatory mechanism which aims to bring forward narrow banking to avoid the liquidity mismatch, while this arrangement could eliminate the liquidity provision function of banks and squeeze the access to funding (Diamond and Rajan, 2001). In consideration of both sides of the balance sheets of banks, a prevailing theory argues that banks typically have synergy effects between lending and deposits, which is established on the basis of no perfect correlations between the two activities, and the synergy could be an effective mechanism to lower the opportunity costs of holding liquid assets (Kashyap et al, 2002). By and large, lending through financial intermediaries is directed under the contracts of commitments, which serves as an influential form of relationship lending. Borrowers in the relationship lending could draw their lines of credit at needs and the lender would be then under pressure if the amount of the draw-down is not fully anticipated. Commercial banks are regarded as the institutions with a special feature that they can hedge the liquidity risk in association with the borrowers demand as the market liquidity dries up. A complementary discussion argues that one aspect of the uniqueness of commercial banks is to provide insurance against systematic liquidity shocks (Gatev and Strahan, 2006). While a later paper provides results showing that the liquidity of bank stock return increases along with more unused loan commitments conditioned on insufficient transactions deposits (Gatev, Schuermann and Strahan, 2009).The ability to combine lending with deposit-taking is the reason why commercial banks have advantage to lower general market lending cost. With the synergy between both sides of the balance sheet, commercial banks, compared with shadow banking institutions, are investing more patiently in illiquid assets with relatively lower fundamental risk (Hanson et al, 2015).

Funding liquidity in the liabilities side of a financial intermediation is closely interwoven with the market liquidity of its portfolio of assets, and they are combined to form a spiral of liquidity risk in the critical times of financial crisis (Brunnermeier and Pedersen, 2009).On the other hand, off balance sheet activities also have significant impact on new lending as draw-downs accelerated in the period of liquidity shortage (Cornett, McNutt, Strahan and Tehranian, 2011), hence worse availability of deposits and heavier burden of credit lines together restrain banks' ability to increase lending (Ivashina and Scharfstein, 2010). One example for explaining the important role of the off balance sheet loan commitments is that more than a half of the liquidity creation was conducted through this particular channel during 1993 and 2003 (Berger and Bouwman, 2009).

However, the correlation between the two sources of liquidity risk may not be consistent in response to different market conditions, especially in the scenario during the recent financial crisis, which means that the loan commitments and deposits can be more correlated than theoretically expected in an unfavorable timing. Evidence also shows that the synergy could not hold before the operation of the federal deposit insurance system (Pennacchi G, 2006).

The observation in this chapter is consistent with the findings of previous research. In most of the context of discourses, the synergy is assumed to be a fundamental rule to construct further discussions. While lines of credit extended to firms by a bank are a group of flexible debt instruments, which fluctuate more drastically than other financing channels due to the bank’s discretionary power. The correlation coefficients calculated between the two variables, just as the literature shows, are generally weakly positive and also slightly negative in some special circumstances. However, little attention has been focused on the dynamic relationship between deposits and lending from the perspective of external stakeholders. It is important to parse the difference between static and dynamic features because depositors and borrowers could make their decisions on a basis far from the standpoint of banks.

What is crucial in the issue is that determining the proper amount of liquid assets possessed by banks would be very challenging if the behavioral patterns of liquidity needs could not be uncovered thoroughly. The reason to reconsider the synergy effect between the two activities is based on one observed key fact: although the synergy does exist in terms of the banking sector as a whole, the dynamic correlation could be highly positive to a particular individual bank, which will in turn jeopardizes the benefits brought by the synergy effect and amplifies liquidity risk. More specifically, if deposits flow out of a bank that experiences draw-downs on loan commitments at the same time, the pressure of liquidity needs could be extremely high and thus the liquidity of the bank drains eventually. In other word, the flight-to-quality phenomenon during critical time of scarce liquidity may not occur to some institutions even though their portfolios of assets are still in good shape. The empirical evidence in the following sections shows that positive correlations exist when both the outflows and draw-downs are controlled, which indicates that a bigger deposits outflow are typically accompanied by a greater loan commitments draw-down in some specific banks. This winner-take-all effect could threaten financial health of certain banks and even drive some institutions to fail even if the whole banking system is abundant with liquidity.

The major motivation of this chapter is to sort the idiosyncrasy out from the overall profile and to highlight the significance hidden under the peaceful surface in a micro perspective. The dynamic features of deposits and lending are taken into the issue as exogenous variables on the grounds that depositors and borrowers are relatively independent decision-makers to the banking system. The contributions of this study are threefold:

The rest of this chapter is focused on the synergy effects and the effects they have on the liquid assets holding strategies of commercial banking institutions. The rest of this chapter is organized as follows: section 4.2 presents an overview of loan commitments and deposits in commercial banks; section 4.3 shows the empirical analysis of the dynamics of synergy effect; section 4.4 presents an extension of analysis and section 4.5 concludes this chapter.

## 4.2 A Revisit to the Synergy between Loan Commitments and Deposits

### 4.2.1 A Glance at Loan Commitments in U.S. Commercial Banks

Loan commitments have been the major way of extending credit to businesses particularly in recent decades. Under a loan commitment, the borrower has the right to use the line of credit to fund his or her investment project and the bank has the obligation to guarantee the liquidity according to the covenants specified in the commitment contract.

Commercial and industrial loans (C&I loans) are typically short-term and the customers who are businesses rather than individuals utilize the loans to fund working capital or capital expenditures. To issue a C&I loan, collaterals may be requested by the bank in usual circumstances and a commitment fee as well as an interest rate based on the predominating benchmark interest rate will be charged. In the early stage, original commitments are only made to finance commercial and industrial businesses (Summers, 1975). It still appears to be a dominant way of issuing C&I loans: the majority of C&I loans are made under the commitments offered by commercial banking institutions, and the proportion has been continuously over 70% since the beginning of this century. A loan commitment can be viewed as a put option with which the customer has the right to execute the contract at a specific interest rate.

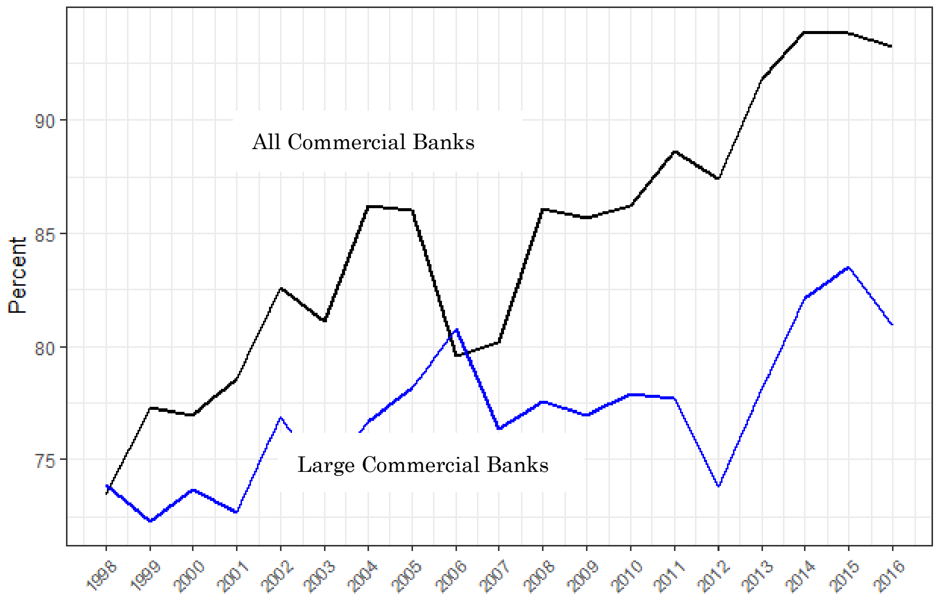
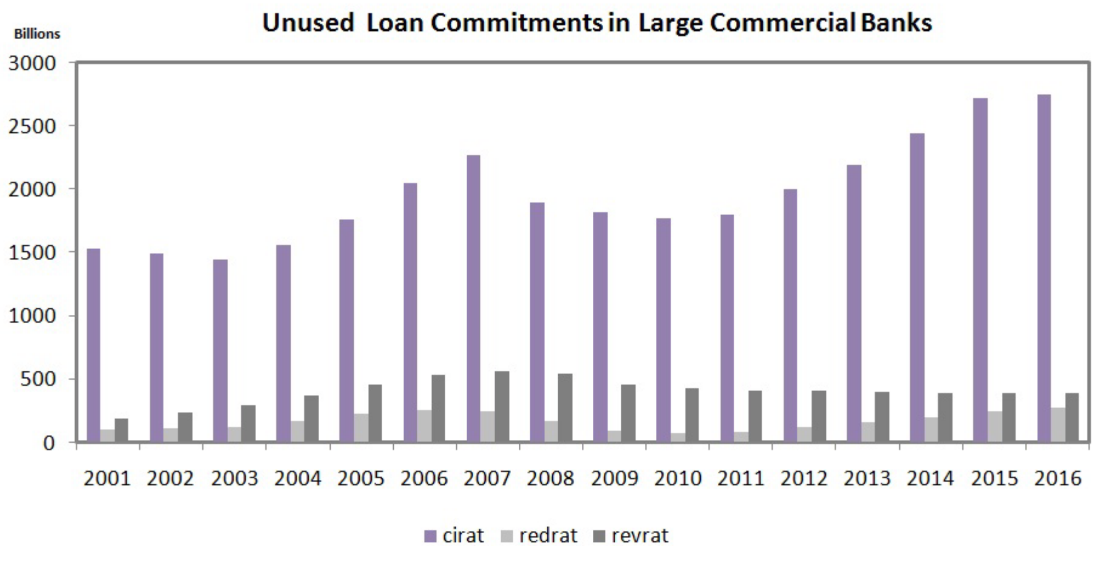



Figure 4.1 Percent of Amount of Loans Made Under Commitment for All Commercial and Industry Loans

Source: Commitment Status of Economic Data in Federal Reserve Bank of St. Louis.

Commercial banks are exposed to liquidity risk because of the guarantee they provide for the potential borrowers, albeit the banks have the comparatively sufficient capacity of credit rationing. The impact from the real economy may be amplified when a large number of customers rush to the bank to draw down the commitments within a short period of time, leading to credit tension in the banking system. In this chapter I select three types of loan commitments of U.S commercial banks: revolving open-end lines secured by 1-4 family residential properties (home equity loans), commitments to fund commercial real estate, construction, and land development loans secured by real estate and other unused commitments[4]. In the balance sheets of U.S. banks, unused commitments for commercial and industrial loans account for the major part of total commitments in both large and small banks. The two variables have experienced conspicuously huge decline during the financial crisis from 2007 to 2009. However, as the financial system is getting more stable in the period of aftermath, the paths of recovery from the crisis diverge significantly in terms of bank size. The commitments for C&I loans in large banks have reached a higher level than the previous climax before the onset of credit crunch in the nearly unchanging environment of low interest rate. It may have connections with the rescue facilities from the Federal Reserve. Since the revolving credit lines sunk into depression after the liquidity shock, any sign of an upward trend is still obscure regardless of bank size.




[4] This item reports the unused portion of all other commitments not reportable above. Include commitments to extend credit through overdraft facilities or commercial lines of credit and retail check credit and related plans.

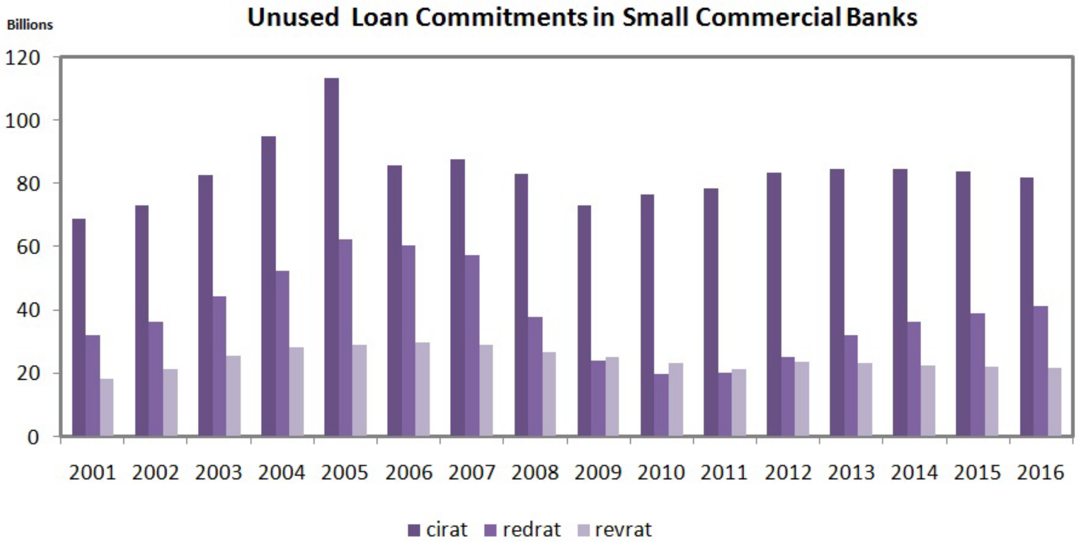



Figure 4.2 Total Unused Loan Commitments in Large and Small Banks

Data source: calculated with raw data from FFIEC Call Reports.

Note: *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments.

On the other hand, the dynamic characteristics revealed in Figure 3 and Figure 4 present the three types of major loan commitments: commercial and industrial loan commitments (represented by other loan commitments), unused loan commitments for real estate development (secured) and revolving lines of credit. I calculate the average quarterly changes of each type commitments in large commercial banks through the period from the beginning of 2001 to the end of 2016, the changes are standardized by total assets of each institution. It can be clearly observed that a sharp decline occurred during the recent financial crisis, which indicates that widespread draw-downs have been made in the emergent time of credit crunch. The type of commitments that has been drawn down the most is for financing commercial and industrial loans. The claim, to some extent, caused liquidity outflow from the banking system and brought pressure to the balance sheets of the banks that have depended heavily on the form of commitments to issue loans, even though evidence shows that loan commitments are typically associated with strong financial capacity of a financial institution (Greenbaum and

Thakor, 1993).

The specialty owned by the financial intermediaries is employed to solve the problem of asymmetric information about borrowers. In consequence, banks used to extend lines of credit through commitments to the customers who have healthy operations on their businesses. This could be an explanation for the slightly better quality and fewer problems of loans under commitments (Avery and Berger, 1991). In spite of that rationale, what have occurred during the period of liquidity shortage may not be associated with the loan quality, instead, broad draw-downs of loan commitments could be driven by idiosyncratic behavioral reactions of the borrowers to the market liquidity shock in overall scope. The firms that have commitment contracts with the financial intermediaries will take precautionary measures to cope with fluctuating indicators such as interest rates and the contract of a loan commitment automatically becomes an effective instrument to make discretionary strategies. Banks, on the contrary, have far less bargaining chips to prevent cash outflow except for the terms and restrictive covenants in the contracts. Cash, treasury securities and other liquid assets are combined together to form a liquidity buffer to take care of the contingency of liquidity needs.

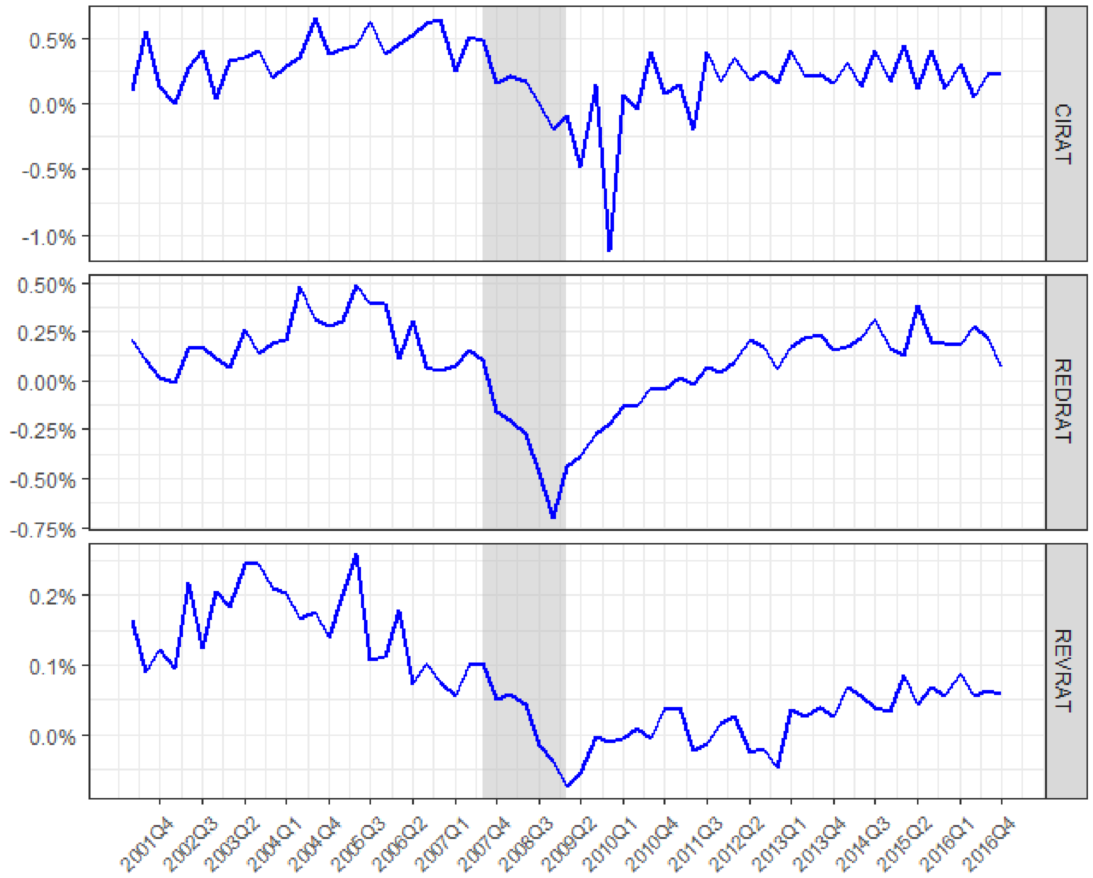



Figure 4.3 Average Quarterly Changes of Unused Commitments in Large Commercial Banks

Data source: Calculated with the data from FFIEC Call Report.

Note: *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments.

Similar scenarios could not be observed in small commercial banks. Only the unused commitments for secured real estate development experienced a severe decline during the crisis. The commitments for commercial and industrial loans in small commercial banks show seasonal fluctuations especially after the crisis. The commitments for real estate development is more pro-cyclical and basically follows the housing bubble and the subsequent burst. In general, the liquidity risk contributing to the whole banking sector from the loan commitments draw-downs in small commercial banks has a much less significance than large commercial banks.

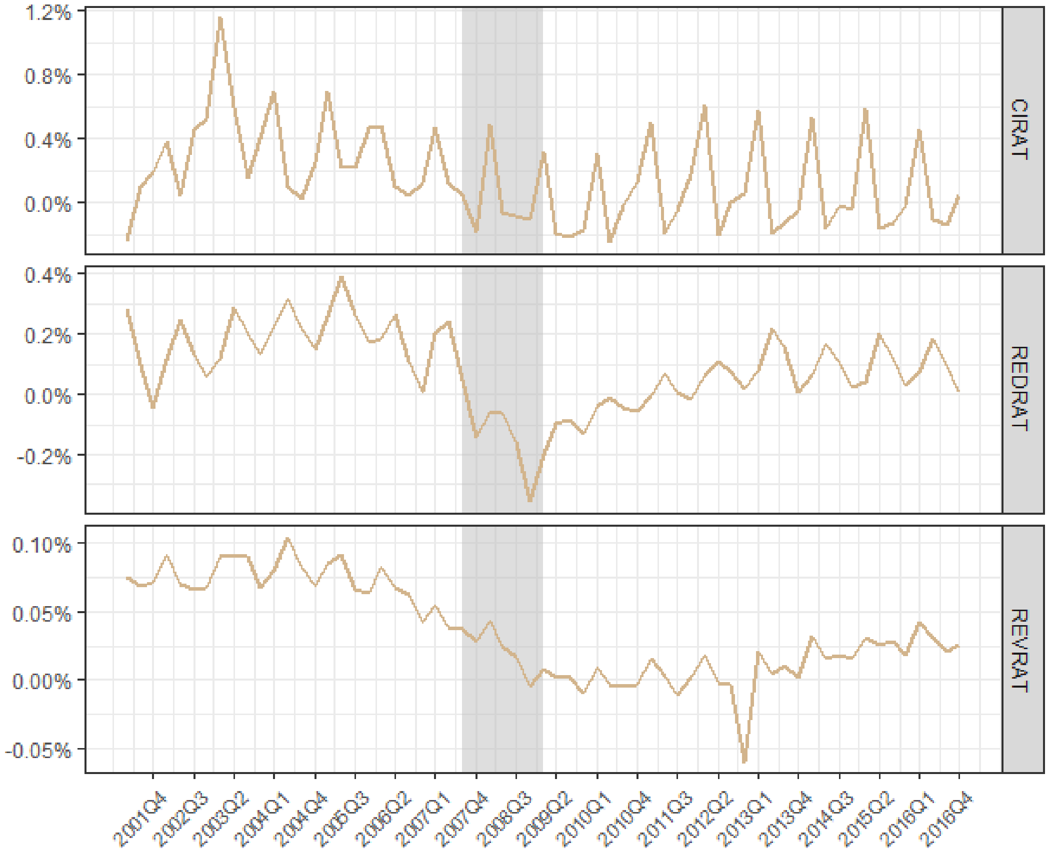



Figure 4.4 Average Quarterly Changes of Unused Commitments in Small Commercial Banks

Data source: Calculated with the data from FFIEC Call Report.

Note: *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments

However, by taking a closer perspective, a different story might be revealed. The gap between the biggest inflow and the biggest outflow (noted by *IOGap*) of loan commitments in large commercial banks shows a clear differentiation within the banking system. I calculate the quarterly changes of each of the unused commitments items of the off-balance sheet statements and pick up the maximum increase and decrease to draw the figure below, winsorizing the top 1% and the bottom 1% of to eliminate the outliers. The result heuristically implies that the draw-downs and new offers of commitments frequently occur at the same time, which means some banks experience harsh claims for liquidity under the contracts of commitments while some others have the ability to enlarge the volume of its unused loan commitments even during the period of liquidity shortage. In other words, the gap belt of each loan commitment is aggressively changing over time. This phenomenon may imply a consistent pattern hidden under the common surface where the overall profile of the banking sector could not reveal microscopic behaviors in institution-level. In the following section, the empirical tests will give explanations to this phenomenon. The gaps are getting narrower shortly after the crisis in both *Redrat* and *Revrat*, but the rebound trend is also on the track.

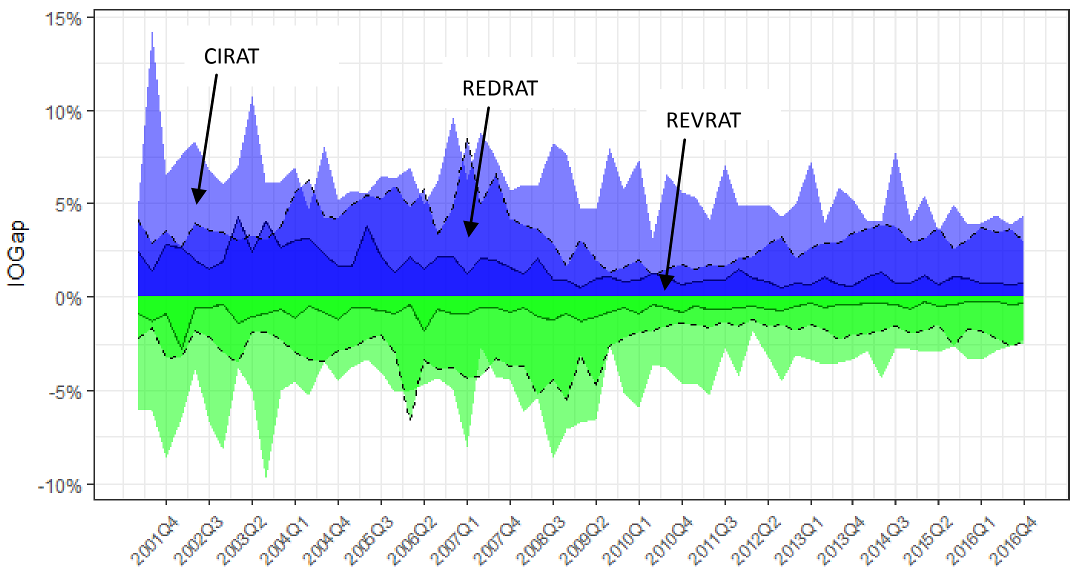



Figure 4.5 Range Belts of Loan Commitments in Large Commercial Banks

Data source: Calculated with the data from FFIEC Call Report.

Note: *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments

Since the federal deposit insurance system was established, traditional bank run incurred by withdrawals of uninsured depositors scarcely occurs in recent years. In the 2007-2009 financial crisis, a variant of bank run stepped on the stage and caused a series of takeovers and failures. Short-term lenders suddenly ceased to roll over the funding to commercial banks and interbank lending also froze up, leads to tightened liquidity in the banking sector and shrinking credit creation to the real economy. The motivation of this chapter is to propose a new perspective of liquidity risk management in commercial banks based on the understanding of the new form of bank run. The tricky part of the issue is whether there is a possibility to detect the hidden pattern before the occurrence of crisis. In the long run, the turmoil like the recent crisis is typically a rare event, indicating that it is difficult to obtain adequately comprehensive insights simply by delving into the extreme cases. Through the analysis of the dynamic features of the traditional synergy effect between lending and deposit-taking, a consistent but undiscovered pattern could be detected and identified.

As of the side of liabilities in the balance sheet, the average quarterly changes of transactions deposits and non-transactions deposits[5] standardized by total liabilities are shown as follows. Unlike loan commitments, neither transactions deposits nor non-transactions deposits have experienced a sharp decline during the crisis period (shown in grey shadow). To some degree, the reason for the difference may come from the government interventions. The rescue facilities from the Federal Reserve Bank to save large financial institutions were very helpful to withstand the storm of credit crisis, and the deposit insurance limit was temporarily raised from \$100,000 to \$250,000 and eventually the new limit became permanent in 2010, which also helped to recover the confidence of average depositors. Turmoil in other financial markets facilitated the flight-to-quality effect so that cash looking for safe heaven flows into the banking system.

[5] The selected deposits accounts are deposits of Individuals, partnerships, and corporations. Total demand deposits are included in the transactions accounts and money market deposit accounts (MMDAs) are included in the non-transactions accounts.

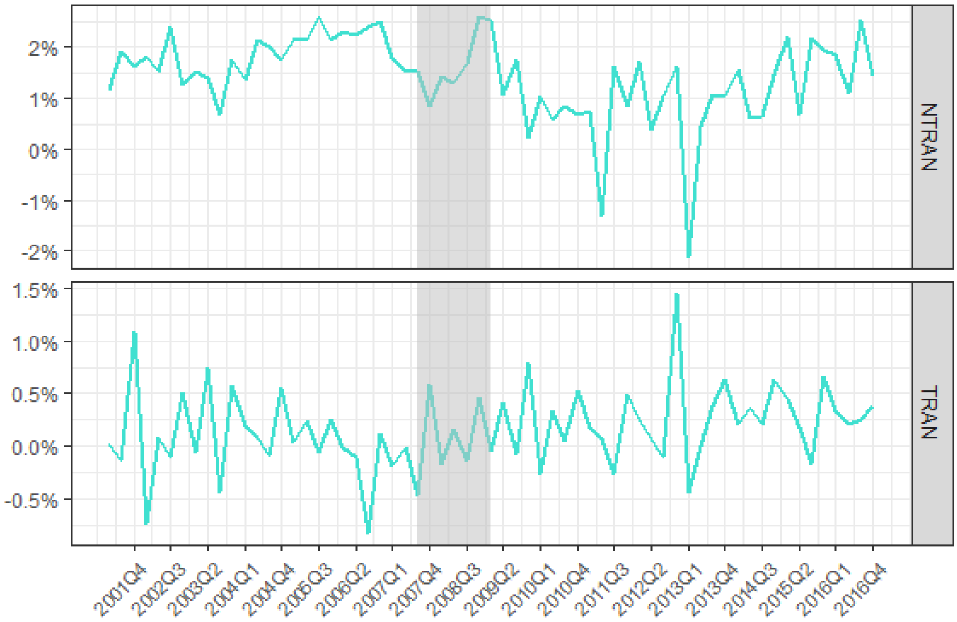



Figure 4.6 Average Quarterly Changes of Deposits in Large Commercial Banks

Data source: Calculated with the data from FFIEC Call Report.

Note: *Nontran* and *Tran* represent nontransactions deposits and transactions deposits respectively.

However, the range between the funding inflow at top 1% and outflow at bottom 1% conveys message similar to the loan commitments. The *IOGap* fluctuates as giant inflows and outflows occur simultaneously. This pattern seems to be consistent in the selected sample period and it signifies that banks will encounter severe liquidity shortage if large outflows of deposits and considerable draw-downs of loan commitments unexpectedly coincide with each other. A winner-take-all effect is to be investigated, which implies that the liquidity in banking could flow into the banks in healthy operation from the banks with poor quality of assets in some macroeconomic circumstances. The *IOGap* only shows one aspect of the whole profile, thus the comprehensive behavior including discretionary decision-making, interim irrational reactions and conventional governance policy and strategies of each individual commercial bank has to be analyzed empirically in more details.

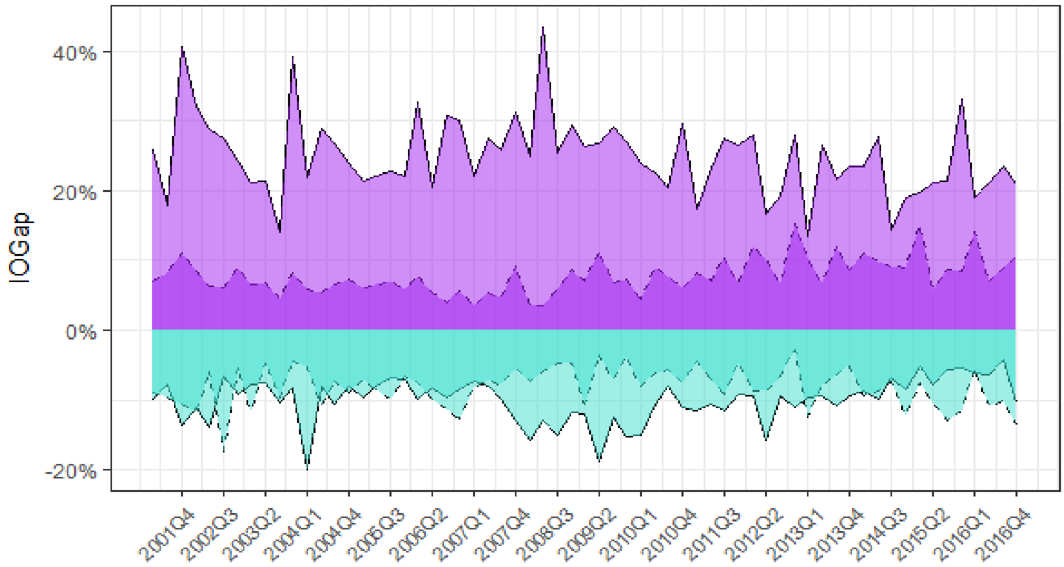



Figure 4.7 Range Belts of Deposits in Large Commercial Banks

Data source: Calculated with the data from FFIEC Call Report.

### 4.2.2Data and Model Specification

The data sets are drawn from the FFIEC Call Reports and the time interval selected is from the first quarter of 2001 to the last quarter of 2016. The sample contains nearly the whole period in this century and the financial crisis period is also included. The tests will be conducted in terms of the whole sample, large banks group and small banks group. The criterion to classify large commercial banks and small commercial banks is whether the total assets of the specific bank is greater than 1 billion U.S. dollars. The data is collected at the level of consolidated balance sheet.

The baseline empirical model is to describe the relationship between unused loan commitments and transactions deposits to analyze the synergy effect, which is specified as follows:

$$COMM_{i,t}^{k} = B_{0,i}^{k} + \beta_1^{k} DEPO_{i,t} + Controls + \mu_{i,t}$$

Where *COMM* is the ratio of one specific item of unused loan commitments to total assets and *DEPO* is the ratio of transactions deposits to the total liabilities in an individual bank. The superscript *k* represents *Revrat*, *Redrat* and *Cirat* respectively. Fixed effect and time effect are also controlled. The hypothesis in the baseline model is that the coefficients of transactions deposits are expected to be slightly positive if the synergy does exist between the two variables. Nevertheless, in this chapter, the baseline model is not at the centerpiece empirically, and the focus of this chapter is to disclose whether or not this relationship between the two variables can be perfectly positive as the market funding condition evolves.

On top of the baseline model, the practical model to be tested is about the exploitation of a dynamic mechanism, capturing whether the actual liquidity withdrawals from both deposits in the balance sheets and commitments in the off-balance sheets have a co-movement during the liquidity squeeze period. Two dummy variables are modeled into the equation to control the relations in concern. The specific form is as follows:

$$DEPORAT_{i,t}^{k} = T_{0,i}^{k} + B_{0,i}^{k} + \beta_1^k COMMRAT_{i,t-1} + \beta_2^k D_1 + \beta_3^k D_1 + \beta_4^k COMMRAT_{i,t-1} \times D_1 + \beta_5^k COMMRAT_{i,t-1} \times D_2 + Controls_{i,t} + \mu_{i,t}$$

Where *DEPORAT* stands for the ratio of quarterly change of deposits accounts to total liabilities and *COMMRAT* is the ratio of quarterly change of loan commitments to total assets, they represent relative liquidity pressure on both liabilities side and off-balance sheet activities is the dummy variable indicating 1 if both changes of deposits and commitments are positive and indicates 1 if they are both negative. Bank fixed effect and time fixed effect will be included in the model. Controls represent control variables for size, profitability, capital sufficiency, liquidity degree of assets and potentiality of non-performing loans. One issue in this model is that long-term relationship could not be detected after the transformation into the difference model. Fortunately, the purpose of this research is to investigate the short-term interaction which is much more essential in the analysis of liquidity shock and conducive to uncover the hidden pattern behind the long-term synergy.

Table 4.1 Two Sample t-test

| Panel A Transactions Deposits | | | | | | |
|---|---|---|---|---|---|---|
| | mean | | | median (in difference) | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅰ) | (Ⅱ) | (Ⅲ) |
| *Lnta* | 12.345*** | 12.212*** | 12.034*** | 0.058*** | 0.050*** | 0.128*** |
| *Caprat* | 0.165*** | 0.169*** | 0.175*** | -0.001*** | 8.42E-04*** | -0.002*** |
| *Liqrat* | 0.088*** | 0.098*** | 0.103*** | 0.003*** | 0.008*** | 0.009*** |
| *ROA* | 0.005*** | 0.005*** | 0.005*** | 6.82E-04*** | 0.001*** | 3.19E-04*** |
| *PTLL* | (0.003)*** | (0.003)*** | (0.003)*** | 4.96e-07 | 3.176e-05*** | 3.40e-05*** |

| Panel B Non-transactions Deposits | | | | | | |
|---|---|---|---|---|---|---|
| | mean | | | median (in difference) | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅰ) | (Ⅱ) | (Ⅲ) |
| *Lnta* | 12.401*** | 12.257*** | 12.080*** | 0.123*** | 0.114*** | 0.166*** |
| *Caprat* | (0.163)*** | (0.168) | (0.173)*** | -0.005*** | -0.004*** | -0.006*** |
| *Liqrat* | (0.086)*** | 0.095*** | 0.101*** | -0.002*** | 0.002*** | 0.004*** |
| *ROA* | 0.005*** | 0.005*** | 0.005*** | 4.16E-04*** | 2.37E-04*** | -1.02E-04*** |
| *PTLL* | (0.002)*** | (0.002)*** | (0.002)* | -1.80E-04*** | -1.23E-04*** | -4.29e-05*** |

***, **, *are significant at the 1%, 5%, and 10% level respectively.

The two sample t-test in Table 4.1 shows the difference of means of control variables in the occurrence of double inflow and double outflow. As it implies, cash flow tends to rush into the banks with larger total assets. The indicator of overall bank performance represented by *ROA* reflects the same effect. The difference of capital ratio, on the other hand, is significantly positive in Panel A but negative in Panel B. Banks having experienced double outflow typically have more provisions for loans and leases.

## 4.3 Empirical Tests for the Synergy

### 4.3.1 The Winner-take-all Effect

The theoretical hypothesis is straightforward and intuitive. By calculating cross-sectional correlations between the ratios of deposits change and loan commitments and making scatter plot for the pair of correlation and fundamental funding cost, a pattern is looming. In expectation, the fitted curve for the scatter plot should be in a bell or inverse-U shape. When the funding cost is low, businesses will have the motivation to sign contracts of loan commitments with commercial banks to ensure the low financing cost. On the other hand, depositors will have the incentive to withdraw their cash from banks to pursue higher returns at other capital markets. As a result, the correlations tend to be negative or slightly positive. When the funding cost is high, the relationship should be negative as well for the opposite reason. The correlations will be increasing as the funding cost grows because business customers will keep the pace of obtaining loan commitments due to their expectation of upswing interest rate and at the same time depositors are willing to gradually transfer cash to commercial banks for improved returns. Similar explanation can be made when the interest rate is on the downside track. However, the real results are not consistent with the scenario hypothesized by theory. As I select three types of loan commitments and two classifications of deposits, it is easy to calculate the correlation coefficients in pairs between the two variables. By plotting the correlation with the basic funding cost, the phenomenon characterized in the hypothesis can be observed. In the plots, I select the federal funds rate as the benchmark for market funding cost.

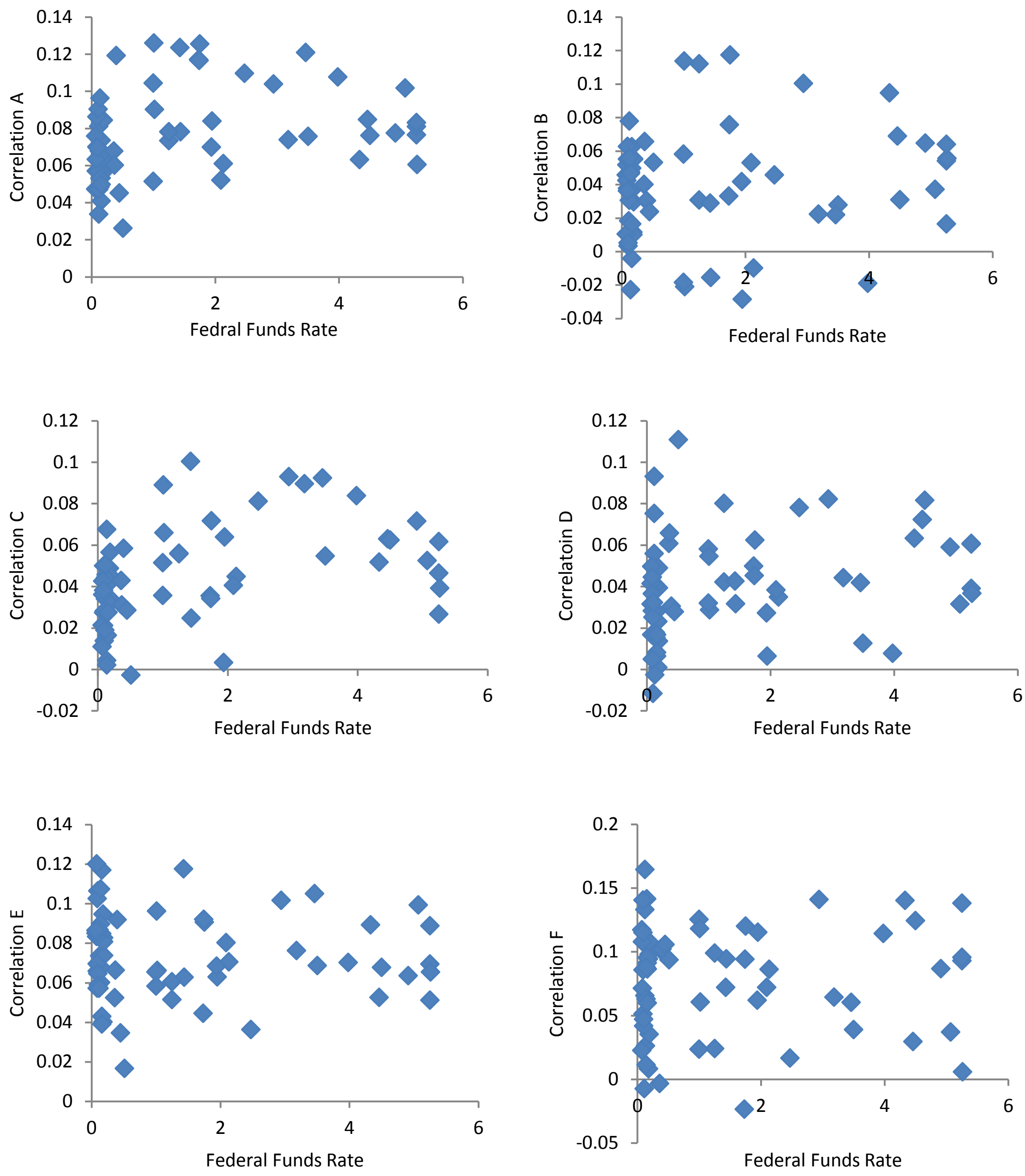



Figure 4.8 Correlation – FFR Scatter Plot

Data source: Calculated with the data from FFIEC Call Report.

It is obviously shown in Figure 4.8 that only two pairs of correlation (Correlation A and Correlation C) out of the whole six pairs have significant inverse-U shape, which can be tested by regressing quadratic equations. The insignificance arises majorly from the existence of two classes of outliers: strong correlations when the funding cost is extremely low and high and weak correlations when the funding cost is in the average range. The latter type of outliers should not be paid much attention to because they are supportive of the argument of previous literature which concludes the synergy effect based on the fact that lending and deposit-taking not perfectly correlated. The former kind of outliers in the high and low end of the funding cost spectrum is the one needed to be interpreted.

Some explanations about the outliers situated in the undesirable region could be found, at least partially, by highlighting the winner-take-all effect. The existence of winner-take-all effect implies that banks with better performance in their asset portfolios will receive cash flow into the deposits, while other banks with poor corporate governance and lower asset quality will experience deposit outflow during the time of liquidity shortage. In the off balance sheet activities, the unused portion of loan commitments will be drawn in general for the same reason of low liquidity. 6But customers will have more incentive to draw funds from the banks that, in the anticipation of the customers, have the possibility of financial distress or failure. It will lead to the phenomenon that banks with poor financial status could experience a double outflow of funds, including both deposit outflow and loan commitment draw-downs, on the contrary, banks in good health will face the opposite situation. The double outflow can be observed more clearly by comparing the failed banks with the non-failed banks through the selected sample period.

Table 4.2 Double Outflow in Failed Banks and Non-failed Banks

| Panel A | Number of Bank Failure* | Mean Estimated Loss | Average Number of Double Outflow in Failed Banks | Average Number of Double Outflow in Non-failedBanks |
|---|---|---|---|---|
| 2001 | 1 | - | - | 0.075 |
| 2002 | 10 | 19,158 | 0.125 | 0.076 |
| 2003 | 3 | 30,984 | - | 0.086 |
| 2004 | 3 | 2,998 | - | 0.090 |
| 2005 | 0 | - | - | 0.085 |

[6] The draw-down of loan commitments will increase the realized loans in the assets and also increase deposits in the liabilities. The double outflow of funds occurs only when the increased deposits from draw-down of loan commitments and the existing deposits simultaneously experience withdrawals, and the financial institution will face more pressure on available liquidity.

| | | | | |
|---|---|---|---|---|
| 2006 | 0 | - | - | 0.090 |
| 2007 | 2 | - | - | 0.121 |
| 2008 | 24 | 280,866 | 0.152 | 0.141 |
| 2009 | 126 | 152,923 | 0.282 | 0.151 |
| 2010 | 139 | 109,759 | 0.426 | 0.175 |
| 2011 | 86 | 67,923 | 0.509 | 0.188 |
| 2012 | 48 | 49,419 | 0.452 | 0.183 |
| 2013 | 24 | 52,214 | 0.313 | 0.189 |
| 2014 | 18 | 21,722 | 0.559 | 0.171 |
| 2015 | 8 | 113,363 | 0.281 | 0.146 |
| 2016 | 5 | 9,473 | 0.400 | 0.129 |

Panel B

| | Last Quarter | 2 Quarters | 3 Quarters | 1 Year |
|---|---|---|---|---|
| Before Crisis | 14.28 | - | 14.28 | - |
| During Crisis | 27.54 | 27.54 | 15.94 | 5.80 |
| After Crisis | 46.50 | 45.75 | 37.50 | 38.50 |

Note: * indicates efficient number of double outflow.

The phenomenon of double outflow in failed banks shows a different picture from that in healthy banks which are still in operation till the date of data selection. In Panel A, the quarterly average number of times of double outflow is much higher in the group of failed banks, despite the incompleteness of data due to the scarcity of bank failures. Panel B shows the proportion of double outflow occurrence in 3, 6, 9 and 12 months before the announcement date of bank failure. The double outflow could happen as early as one year before the failure.

The empirical specifications in this chapter are designed as a similar framework of the setting in the paper of Kashyap et al, 2002. The part distinguishable is to divide the loan commitments into different items to analyze the effects from each elementary off-balance sheet activity. I choose three types of unused commitments as the independent variables to be tested in the model. They are commitments to commercial real estate construction and land development, commitments to revolving, open-end lines secured by 1-4 family residential properties and commitments for commercial and industrial loans.[7] Transactions deposits and non-transactions deposits are included as

[7] The majority of this item is the category of commitments to commercial and industrial loans

dependent variables.

From the results in Table 1, it is indicated that the synergy effect of winner-take-all exists in nearly every pair of relationships in the sample of all commercial banks. The coefficients of the interaction terms are positive with statistical significance and the value subtracted by the base coefficients of the corresponding independent variable is still positive, which means deposits and loan commitments tend to move in the same direction when there is a double outflow or double inflow. In particular, the coefficients of double inflow appear to be smaller than that of double outflow. Double outflow from deposits and loan commitments would cause liquidity shortage or even disaster to the banks with poor performance of operation and diminishing confidence of both depositors and loan commitments users.

The variable which controls the bank size is irrelevant with change of transactions and non-transactions deposits. However, the relationship with capital ratio represented by the particular item of Total Risk-based Capital Ratio is significantly negative through all models. This effect is not notably significant in the group of large commercial banks, while small commercial banks as the majority of the whole sample accounts for the reason. Liquidity ratio is positively correlated with the growth of deposits, which supports the logic that banks with better financial status will have more deposits inflow and the liquidity sufficiency is further enhanced. The relationship becomes slightly weaker in the models of non-transactions deposits. The coefficients of provisions to loans and leases can also provide to some extent consistent evidence that banks with higher provisions will experience lower inflow of deposits, albeit this indicator does not represent realized losses in the asset portfolios.

Table 4.3 Synergy Tests for All Commercial Banks

| | Transactions Deposits | | | Non-transactions Deposits | | |
|---|---|---|---|---|---|---|
| | ( I ) | ( II ) | ( III ) | ( I ) | ( II ) | ( III ) |
| *D1* | 0.015*** | 0.012*** | 0.013*** | 0.022*** | 0.016*** | -0.002*** |
| | (54.676) | (39.369) | (50.381) | (31.807) | (12.800) | (-2.990) |
| *D2* | -0.012*** | -0.017*** | -0.018*** | -0.004 | 0.011 | 3.0E-04 |
| | (-3.710) | (-13.156) | (-36.606) | (-0.243) | (0.401) | (0.218) |
| *Revrat* | -1.025*** | | | -1.661*** | | |
| | (-8.322) | | | (-8.368) | | |
| *Redrat* | | -0.627*** | | | -1.053*** | |
| | | (-30.347) | | | (-27.939) | |
| *Cirat* | | | -0.066 | | | 0.009 |
| | | | (-1.076) | | | (0.852) |
| Control Variables | | | | | | |
| *Lnta* | -0.001 | -0.001 | 0.033 | 0.012 | 0.013 | 0.170 |
| | (-0.353) | (-0.243) | (1.487) | (0.741) | (0.799) | (1.395) |
| *Caprat* | -0.109*** | -0.109*** | -0.138*** | -0.127*** | -0.127*** | -0.162*** |
| | (-15.401) | (-15.406) | (-15.743) | (-20.157) | (-20.242) | (-17.650) |
| *Liqrat* | 0.136*** | 0.130*** | 0.091** | 0.144*** | 0.126** | -0.148 |
| | (8.426) | (7.956) | (2.034) | (2.769) | (2.329) | (-0.612) |
| *ROA* | 0.084 | 0.083 | -0.036 | -0.445** | -0.425** | 0.217 |
| | (0.294) | (0.291) | (-0.376) | (-2.264) | (-2.195) | (0.597) |
| *PTLL* | -1.6E-04 | -1.7E-04 | -0.412*** | -0.001** | -0.001** | -0.685*** |
| | (-1.088) | (-1.178) | (-4.511) | (-2.455) | (-2.518) | (-4.103) |
| *Revrat*D1* | 1.908*** | | | 3.966*** | | |
| | (11.769) | | | (10.581) | | |
| *Revrat*D2* | 4.163** | | | 16.899 | | |
| | (2.120) | | | (1.483) | | |
| *Redrat*D1* | | 0.964*** | | | 1.928*** | |
| | | (26.989) | | | (15.335) | |
| *Redrat*D2* | | 1.212*** | | | 7.979* | |
| | | (7.758) | | | (1.949) | |
| *Cirat*D1* | | | 0.313*** | | | 0.463*** |
| | | | (4.488) | | | (4.848) |
| *Cirat*D2* | | | 0.484*** | | | 0.646 |
| | | | (3.572) | | | (1.154) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 463,123 | 463,123 | 178,637 | 463,123 | 463,123 | 178,637 |
| R-square | 0.18 | 0.19 | 0.22 | 0.02 | 0.02 | 0.02 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) The sample of *Cirat* is from the first quarter of 2010 to the fourth quarter of 2016.

3) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments[8].

The empirical regressions for large commercial banks with a threshold of total assets greater than $1 billion show an even stronger effect in the consideration of double liquidity inflow and outflow. Both deposits and unused loan commitments of large commercial banks account for the larger part of the whole banking sector, and some of them are regarded as TBTF institutions which have received a series of generous rescue facilities from the Federal Reserve Bank. Even a tiny disturbance in funding liquidity of large banks would give rise to an overall turmoil of much bigger magnitude. The winner-take-all effect itself could cause severe liquidity shortage within a specific group of banks, let alone the deterioration of asset quality in some major banks during the crisis period. As it is shown in the Table 2, the winner-take-all effect is slightly stronger than that of the whole sample. However, there is an exception in regressing non-transactions deposits against the commitments for commercial and industrial loans. During the recent financial crisis, borrowers rushed to draw down their existing lines of credit, much of which were financing commercial and industrial loans. The momentum of commitment draw-downs caused a transitory increase of loan origination. The change of non-transactions deposits is negatively correlated with the change of commitments for commercial and industrial loans, which implies that less draw-down on commitments corresponds to larger outflow of deposits.

The bank size control variable is positively correlated with the quarterly changes of transactions deposits, which is different from the results of whole sample in Table 1. It reveals a fact that funding is chasing the banks with bigger size. The information about financial status and operation for large banks, especially the money center banks, is more

[8]This item of unused commitments is divided into three categories since the first quarter of 2010, which are commitments for commercial and industrial loans, commitments for loans to financial institutions and all other unused commitments

available and accessible for the general public and investors. The depositors will make their withdrawal decisions based on the judgment that the bank will suffer from a financial distress in the near future, while the judgment can be subjective and arbitrary. The inflow into the banks with larger size is more significant in transactions deposits. Non-transactions deposits, to some degree, have a different strategic behavior.

Unlike the results of all commercial banks, there is no homogeneous effect of the capital ratio on the flow of deposits in the group of large banks. The coefficients of ROA also suggest a different pathway cash flow from small commercial banks. Large banks with stronger financial performance will receive inflow of non-transactions deposits. The sample period of unused commitments for commercial and industrial loans is relatively shorter than the former two categories, while this does not affect the consistency in the coefficients of liquidity ratio. The capital ratio in this subsample is approximately irrelevant with the change of deposits. In model (Ⅱ) of transactions and non-transactions deposits, the bank fixed effect is not significant, indicating that the large banks are homogenous in the relationships with REDRAT.

Table 4.4 Synergy Tests for Large Commercial Banks

| | Transactions Deposits | | | Non-transactions Deposits | | |
|---|---|---|---|---|---|---|
| | (Ⅰ) | (Ⅱ) | (III) | (Ⅰ) | (Ⅱ) | (III) |
| *D1* | 0.014*** | 0.011*** | 0.013*** | 0.023*** | 0.021*** | -0.001 |
| | (24.824) | (25.728) | (17.338) | (9.434) | (16.972) | (-0.619) |
| *D2* | -0.012*** | -0.013*** | -0.012*** | -0.037*** | -0.030*** | 0.004 |
| | (-14.660) | (-23.654) | (-13.660) | (-9.270) | (-18.450) | (1.305) |
| *Revrat* | -0.312*** | | | -0.751** | | |
| | (-2.570) | | | (-2.019) | | |
| *Redrat* | | -0.595*** | | | -1.114*** | |
| | | (-11.941) | | | (-11.439) | |
| *Cirat* | | | -0.640*** | | | 0.364*** |
| | | | (-6.594) | | | (3.512) |
| Control Variables | | | | | | |
| *Lnta* | 0.005** | 0.005** | 0.016** | 0.026* | 0.026* | 0.124 |
| | (2.341) | (2.371) | (2.400) | (1.808) | (1.746) | (1.501) |
| *Caprat* | -0.004 | -0.004 | -0.005* | -0.039 | -0.038 | -0.035 |
| | (-1.340) | (-1.384) | (-1.921) | (-1.239) | (-1.191) | (-1.219) |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Liqrat* | 0.031*** | 0.031*** | 0.075*** | 0.063*** | 0.060*** | 0.198*** |
| | (3.646) | (3.662) | (4.007) | (3.489) | (3.324) | (2.924) |
| *ROA* | -0.021 | -0.011 | -0.056 | 0.237** | 0.216* | 0.416** |
| | (-0.752) | (-0.365) | (-0.651) | (2.044) | (1.896) | (2.138) |
| *PTLL* | 0.002*** | 0.002*** | -0.093*** | -0.004 | -0.004 | -0.531*** |
| | (3.951) | (4.409) | (-3.763) | (-0.444) | (-0.445) | (-8.151) |
| *Revrat*D1* | 1.023*** | | | 4.697*** | | |
| | (5.910) | | | (4.259) | | |
| *Revrat*D2* | 0.468** | | | 0.765* | | |
| | (2.167) | | | (1.888) | | |
| *Redrat*D1* | | 0.768*** | | | 2.340*** | |
| | | (10.629) | | | (11.933) | |
| *Redrat*D2* | | 0.640*** | | | 1.535*** | |
| | | (8.958) | | | (12.489) | |
| *Cirat*D1* | | | 0.833*** | | | 0.700** |
| | | | (5.972) | | | (2.423) |
| *Cirat*D2* | | | 0.845*** | | | -0.533*** |
| | | | (5.159) | | | (-3.352) |
| Bank Fixed Effects | Yes | No | Yes | Yes | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 35,807 | 35807 | 17,490 | 35,807 | 35,807 | 17,490 |
| R-square | 0.09 | 0.10 | 0.08 | 0.07 | 0.06 | 0.04 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) The sample of *Cirat* is from the first quarter of 2010 to the fourth quarter of 2016.

3) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments.

In the empirical tests for the subsample of small commercial banks, the effects of double inflow and outflow are not as significant as results in the whole sample and the subsample of large banks show, and the double outflow interaction terms are not strictly different from the main effects in the models with non-transactions deposits. One of the reasons is that drastic decline of deposits and draw-downs of loan commitments in small commercial banks do not occur regularly and simultaneously since the beginning of this century. Loan commitment contracts signed with small commercial banks only account for a limited portion of the total amount of unused commitments. Wholesale funding is not the primary tool to finance their lending for small institutions, especially regional organizations like community banks. On the side of the transactions deposits, double outflow and double inflow are much more evident.

The capital ratio is negatively correlated with the change of both categories of deposits, which is quite different from that in the group of large banks. It indicates that the higher capital ratio a small commercial bank has, the lower inflow of funds into the deposits there would be. With higher capital ratio, banks will not have as much cash as the ones with lower capital ratio, thus less opportunity of investment into the assets of higher returns, therefore, the capacity of pursuing profits will be weakened. The coefficients of provisions to loans and leases also provide evidence that poor financial status is generally connected with less deposit inflow. The normally opposite indicator, liquidity ratio, conveys a similar message that the abundance of cash and treasury securities gives banks more resistance to withstand contingent liquidity shock. The confidence of depositors plays a key role in those two situations. As described above, the source of deposits in small commercial banks mostly comes from retail banking, which gives the banks less room to make discretionary choice to adjust the structure of asset portfolios.

Table 4.5 Synergy Tests for Small Commercial Banks

| | Transaction Deposits | | | Nontransaction Deposits | | |
|---|---|---|---|---|---|---|
| | ( I ) | ( II ) | (III) | ( I ) | ( II ) | (III) |
| *D1* | 0.016*** | 0.013*** | 0.013*** | 0.022*** | 0.015*** | -0.002** |
| | (51.993) | (38.428) | (47.958) | (26.125) | (10.993) | (-2.231) |
| *D2* | -0.012*** | -0.017*** | -0.018*** | 0.002 | 0.013 | -4.2E-04 |
| | (-3.055) | (-12.332) | (-34.595) | (0.089) | (0.464) | (-0.257) |
| *Revrat* | -1.151*** | | | -1.761*** | | |
| | (-7.957) | | | (-8.403) | | |
| *Redrat* | | -0.627*** | | | -1.050*** | |
| | | (-29.243) | | | (-26.974) | |
| *Cirat* | | | -0.060 | | | 0.008 |
| | | | (-1.063) | | | (0.862) |
| Control Variables | | | | | | |
| *Lnta* | -0.001 | -0.001 | 0.045 | 0.014 | 0.015 | 0.210 |
| | (-0.319) | (-0.181) | (1.518) | (0.651) | (0.732) | (1.285) |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Caprat* | -0.111*** | -0.111*** | -0.141*** | -0.128*** | -0.128*** | -0.166*** |
| | (-19.695) | (-19.668) | (-23.004) | (-22.813) | (-22.809) | (-16.693) |
| *Liqrat* | 0.140*** | 0.133*** | 0.069 | 0.146*** | 0.129** | -0.211 |
| | (8.304) | (7.825) | (1.395) | (2.648) | (2.261) | (-0.769) |
| *ROA* | 0.088 | 0.086 | -0.058 | -0.489** | -0.456** | 0.181 |
| | (0.288) | (0.281) | (-0.584) | (-2.240) | (-2.147) | (0.509) |
| *PTLL* | -1.8E-04 | -1.9E-04 | -0.489*** | -0.001** | -0.001*** | -0.776*** |
| | (-1.100) | (-1.190) | (-7.701) | (-2.552) | (-2.639) | (-3.540) |
| *Revrat*D1* | 2.034*** | | | 3.888*** | | 0.344** |
| | (10.856) | | | (8.972) | | (2.532) |
| *Revrat*D2* | 4.770** | | | 20.201 | | 0.704 |
| | (2.104) | | | (1.444) | | (1.165) |
| *Redrat*D1* | | 0.971*** | | | 1.920*** | |
| | | (25.761) | | | (14.528) | |
| *Redrat*D2* | | 1.236*** | | | 8.219* | |
| | | (7.492) | | | (1.936) | |
| *Cirat*D1* | | | 0.331*** | | | 0.344*** |
| | | | (4.883) | | | (2.530) |
| *Cirat*D2* | | | 0.484*** | | | 0.704 |
| | | | (3.432) | | | (1.161) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 427,316 | 427,316 | 161,147 | 427,316 | 427,316 | 161,147 |
| R-square | 0.19 | 0.19 | 0.23 | 0.02 | 0.02 | 0.02 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) The sample of *Cirat* is from the first quarter of 2010 to the fourth quarter of 2016.

3) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate; *Cirat* is the ratio of quarterly change of other unused commitments.

The interpretation of the results could lead to the explanation of why the liquidity shock has brought disastrous consequences to the banking system. When market condition is deteriorating and liquidity in general is shrinking, loan commitment customers who have typically signed the contracts before the occurrence of the first event of disturbance will draw down the lines of credit because of the fear of uncertain financing cost in the future.

In the meanwhile, depositors, especially wholesale depositors would have the incentive to withdraw their money from the bank in which they consider their accounts are too risky to hold as cash or deposit, and transfer the amount into other banks which they consider as safe heaven.

The problem is these two contingent liquidity demands could coincide with one another at some particular banks. The safer banks are the winners who will take all, on the other hand, risky banks are going to lose all, and this effect will deepen the differentiation between the banks that benefit and the banks that suffer. The liquidity shock effect will be doubled up and eventually exacerbate the stress faced by the banks with poor financial capability. Since wholesale funding is relatively more capricious than retail funding, this particular behavioral pattern forms the prelude of the new form bank run.

### 4.4 An Extended Test in the Dimension of Deposit Maturity

For delving deeper into the nature of the winner-take-all effect, an extended test will be conducted in this section. The previous models only divide the deposits into transactions account and non-transactions account, while the classification will be based on the dimension of deposit maturity. According to the maturity and repricing data in the Call Reports for time deposits of less than $100,000, I select the item of time deposits with a remaining maturity or next repricing date of: a) three months or less, b) over three months through 12 months, c) over one year through three years and d) over three years. In the table below, model (Ⅰ) through (Ⅳ) are the four classifications of maturity respectively. The whole sample is separated by bank size into large bank group and small bank group. The variable of commitments for commercial and industrial loans is not included in this setting. The dummy variables *D1* and *E1* indicate double inflow, on the contrary, *D2* and *E2* indicate double outflow.

The results show that the change of time deposits with different maturity does not make significant distinctions in the scenario of double inflow. By regressing the four types of time deposits against the variable *Revrat* which represents the change of home equity loan commitments, the coefficients in the interaction terms are not as significant and robust as the scenario of double inflow in the group of large banks. In the subsample of small banks, the relationship is more evident as the maturity of deposits becomes shorter, which supports the intuition that deposits with shorter term may be more sensitive to external shocks.

In the subsample of large banks, the relationship with capital ratio is significant only if the maturity is more than three years. On the contrary, small banks have this significant relationship when the maturity of time deposits is generally less than one year. Liquid assets are more connected with the change of deposits in small commercial banks.

In every model of both large and small commercial banks, the variation of time deposits is irrelevant with the indicator of profitability represented by *ROA* and potentiality for non-performing loans represented by *PTLL*, indicating that time depositors make their decision of withdrawal on liquidity without considering the actual financial status of the particular bank.

## 4.5 Liquidity Feature and Bank Failure Prediction

### 4.5.1 Feature Construction based on Funding Liquidity Risk

Feature construction is very important to the accuracy of prediction in statistical learning models. This section focuses on extracting features based on domain knowledge. As it is discussed in the previous sections, liquidity shock from both deposit withdrawals and loan commitment draw-dawns are the source of liquidity risk, and this fact forms my motivation in this section to construct average cash flow change of these two variables as features in the prediction model. The prediction horizon ranges from one quarter to eight quarters prior to the failure of each selected commercial banking institution. The control variables selected in the previous sections of this chapter is also taken as prediction inputs for the purpose of comparison. Quarterly change of nontransactions deposits and quarterly change of revolving lines of credit are selected as the liquidity risk factors in the prediction. The control variables are total assets, capital ratio, liquidity ratio, returns on assets and provisions for loans and leases.

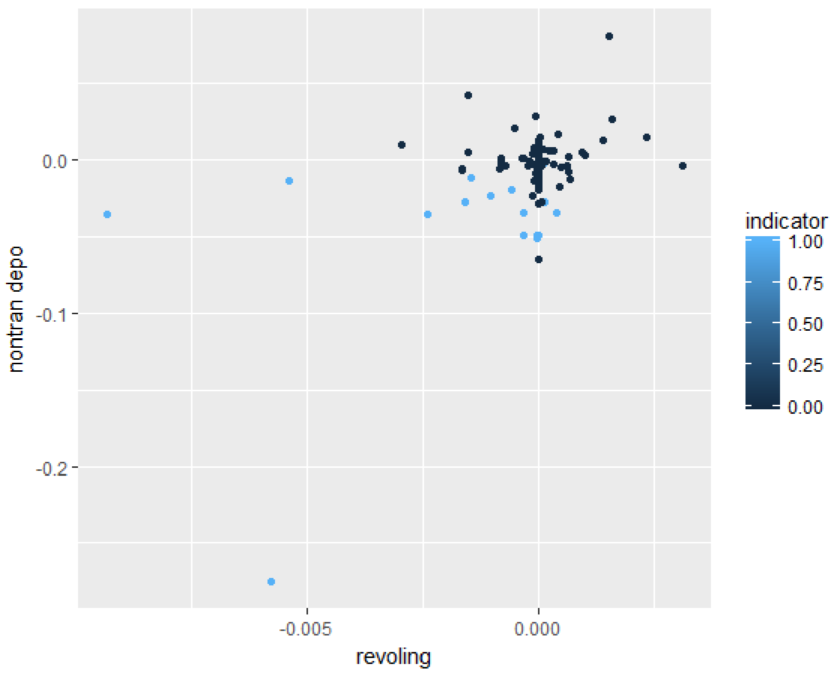
The prediction model used in this section is Support Vector Machine which is initially developed in the 1990s (Vapnik, 1995; Vapknik, 1998a and Vapnik, 1998b). Statistical theory in general has limits with small sample. Likewise, the failures of banks are rare events compared with the majority of solvent banks. That is why support vector machine is more applicable to classify banks with different risk levels and identify the occurrence of bank failure. The detailed description of Support Vector Machine is presented in the appendix.

The objective of the prediction is to examine whether the features construction based on liquidity risk factors can improve the performance of prediction through combining the selected features with traditional predictive features such as financial indicators.

### 4.5.2 Prediction Results with Support Vector Machine

The sample data set has 934 banks, in which there are 467 failed banks and 467 non-failed banks. To make contemporaneous comparison between failed banks and non-failed banks, the group of non-failed banks is constructed in the same periods as the failed banks. Then the data dates back to 8 quarters before the bank failure to collect liquidity risk factors and financial indicators in every quarter. This methodology has more explanatory power than selecting data from different periods as one cross section.

The sample is constructed in the period ranging from 2008 to 2016. The testing set comprises of 96 failed banks and 96 non-failed banks in the period from 2012 to 2016 and the training set comprises of 373 banks for each category in the period from 2008 to 2012. By selecting a cross section of 2014 as an example, Figure 4.9 plots the relationship between the quarterly change of non-transactions deposits and revolving lines of credit of failed and non-failed banks. Both variables are calculated into the average of four quarters. It shows that failed banks are more likely to have a double outflow.



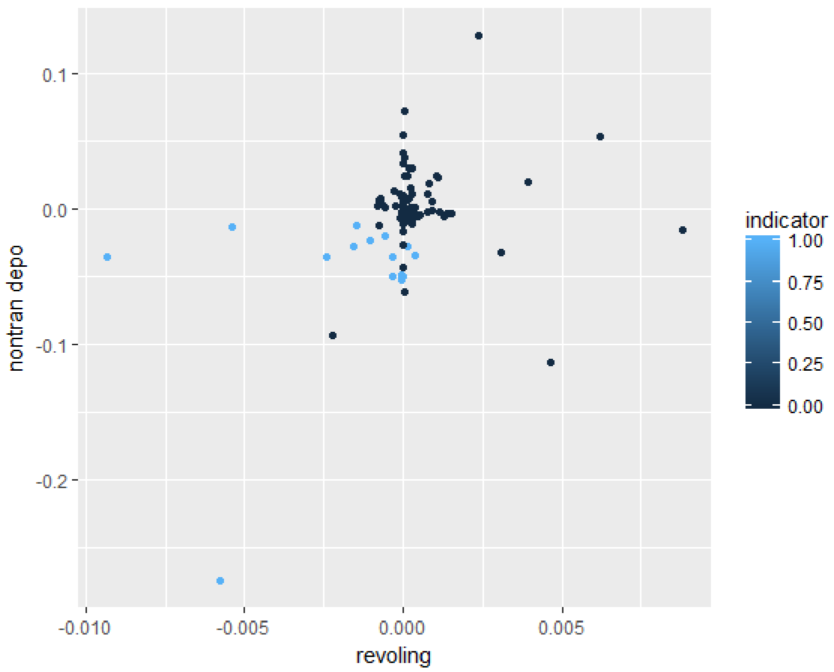




Figure 4.9 Scatter Plot of Quarterly Change of Deposits and Loan Commitments

Note: nontran depo represents the average of quarterly changes of nontransactions deposits and revolving indicates the average of quarterly changes of revolving lines of credit. Blue color indicates the sample of failed banks and black color indicates non-failed banks.

The prediction results are presented as follows. Table 4.6 and 4.7 are the results from linear kernel. It shows high accuracy to identify failed banks with traditional financial indicators. Prediction with liquidity risk factors presents lower accuracy in each group of sample, while the dimension of factors is reduced to only two and the calculation is simplified and more efficient. It implies the connection between double outflow and bank failures is substantial.

Table 4.6 Prediction Results with Linear Kernel in the Training Sample

| Panel A | Prediction shorter than 1 Year | | | | |
|---|---|---|---|---|---|
| | | 1 Quarter | 2 Quarters | 3 Quarters | 4 Quarters |
| *TRAD* | Failed Banks | 0.949 | 0.900 | 0.849 | 0.795 |
| | Non-failed Banks | 0.943 | 0.938 | 0.927 | 0.911 |
| | Sum | 0.946 | 0.919 | 0.888 | 0.853 |
| *DOF* | Failed Banks | 0.571 | 0.555 | 0.488 | 0.477 |
| | Non-failed Banks | 0.881 | 0.809 | 0.809 | 0.732 |
| | Sum | 0.726 | 0.682 | 0.648 | 0.605 |
| *Combined* | Failed Banks | 0.946 | 0.908 | 0.849 | 0.787 |
| | Non-failed Banks | 0.943 | 0.938 | 0.930 | 0.911 |
| | Sum | 0.945 | 0.923 | 0.889 | 0.849 |
| Panel B | Prediction longer than 1 year | | | | |
| | | 5 Quarter | 6 Quarters | 7 Quarters | 8 Quarters |
| *TRAD* | Failed Banks | 0.747 | 0.741 | 0.701 | 0.690 |
| | Non-failed Banks | 0.897 | 0.827 | 0.762 | 0.737 |
| | Sum | 0.822 | 0.784 | 0.731 | 0.714 |
| *DOF* | Failed Banks | 0.294 | 0.197 | 0.722 | 0.132 |
| | Non-failed Banks | 0.854 | 0.938 | 0.287 | 0.970 |
| | Sum | 0.574 | 0.567 | 0.505 | 0.550 |
| *Combined* | Failed Banks | 0.765 | 0.773 | 0.704 | 0.698 |
| | Non-failed Banks | 0.895 | 0.786 | 0.770 | 0.748 |
| | Sum | 0.831 | 0.780 | 0.736 | 0.723 |

Note: *TRAD* represents the model with traditional financial indicators and *DOF* indicates the model with liquidity risk factors. *Combined* represents the model combining all variables together.

The results in Table 4.6 shows that the prediction accuracy declines as the time dates back further, and similar results can be found in testing set. In other words, the results fit the intuition that recent variables have more forecasting capability than the outdated variables. The prediction performance is better in the testing sample than in the training sample.

Combining traditional financial indicators with liquidity risk features could make the accuracy higher than traditional method. The declining speed of prediction accuracy slows down as the liquidity risk factors are added as inputs. It may imply that features construction based on liquidity risk factors mostly outperforms traditional silo feature selection methods.

Table 4.7 Prediction Results with Linear Kernel in the Testing Sample

| | | | | | |
|---|---|---|---|---|---|
| Panel A | Prediction shorter than 1 Year | | | | |
| | | 1 Quarter | 2 Quarters | 3 Quarters | 4 Quarters |
| *TRAD* | Failed Banks | 0.990 | 0.979 | 0.969 | 0.938 |
| | Non-failed Banks | 0.969 | 0.969 | 0.935 | 0.946 |
| | Sum | 0.979 | 0.974 | 0.952 | 0.942 |
| *DOF* | Failed Banks | 0.625 | 0.625 | 0.656 | 0.531 |
| | Non-failed Banks | 0.823 | 0.875 | 0.806 | 0.795 |
| | Sum | 0.724 | 0.750 | 0.730 | 0.661 |
| *Combined* | Failed Banks | 0.990 | 0.979 | 0.958 | 0.938 |
| | Non-failed Banks | 0.969 | 0.969 | 0.946 | 0.946 |
| | Sum | 0.979 | 0.974 | 0.952 | 0.942 |
| Panel B | Prediction longer than 1 year | | | | |
| | | 5 Quarter | 6 Quarters | 7 Quarters | 8 Quarters |
| *TRAD* | Failed Banks | 0.937 | 0.884 | 0.884 | 0.895 |
| | Non-failed Banks | 0.946 | 0.945 | 0.934 | 0.901 |
| | Sum | 0.941 | 0.914 | 0.909 | 0.898 |
| *DOF* | Failed Banks | 0.558 | 0.600 | 0.526 | 0.526 |
| | Non-failed Banks | 0.728 | 0.758 | 0.813 | 0.593 |
| | Sum | 0.642 | 0.677 | 0.667 | 0.559 |
| *Combined* | Failed Banks | 0.958 | 0.916 | 0.895 | 0.905 |
| | Non-failed Banks | 0.946 | 0.923 | 0.923 | 0.901 |
| | Sum | 0.952 | 0.919 | 0.909 | 0.903 |

Note: *TRAD* represents the model with traditional financial indicators and *DOF* indicates the model with liquidity risk factors. *Combined* represents the model combining all variables together.

As it is shown in Table 4.8 and Table 4.9, the results with radial kernel indicate that the features of liquidity risk factors can also slightly improve the prediction accuracy. The effect is more obvious when the prediction horizon is longer. The results are visualized in Figure 4.10 and Figure 4.11.

Table 4.8 Prediction Results with Radial Kernel in the Training Sample

| Panel A | Prediction shorter than 1 Year | | | | |
|---|---|---|---|---|---|
| | | 1 Quarter | 2 Quarters | 3 Quarters | 4 Quarters |
| *TRAD* | Failed Banks | 0.954 | 0.906 | 0.895 | 0.833 |
| | Non-failed Banks | 0.951 | 0.943 | 0.925 | 0.900 |
| | Sum | 0.953 | 0.925 | 0.910 | 0.866 |
| *DOF* | Failed Banks | 0.617 | 0.577 | 0.569 | 0.585 |
| | Non-failed Banks | 0.849 | 0.825 | 0.741 | 0.762 |
| | Sum | 0.733 | 0.701 | 0.655 | 0.673 |
| *Combined* | Failed Banks | 0.962 | 0.935 | 0.889 | 0.863 |
| | Non-failed Banks | 0.943 | 0.949 | 0.925 | 0.881 |
| | Sum | 0.953 | 0.942 | 0.907 | 0.872 |
| Panel B | Prediction longer than 1 year | | | | |
| | | 5 Quarter | 6 Quarters | 7 Quarters | 8 Quarters |
| *TRAD* | Failed Banks | 0.779 | 0.776 | 0.768 | 0.779 |
| | Non-failed Banks | 0.878 | 0.822 | 0.772 | 0.696 |
| | Sum | 0.829 | 0.799 | 0.770 | 0.738 |
| *DOF* | Failed Banks | 0.490 | 0.472 | 0.175 | 0.464 |
| | Non-failed Banks | 0.773 | 0.816 | 0.924 | 0.810 |
| | Sum | 0.632 | 0.644 | 0.549 | 0.636 |
| *Combined* | Failed Banks | 0.811 | 0.806 | 0.760 | 0.717 |
| | Non-failed Banks | 0.870 | 0.816 | 0.764 | 0.786 |
| | Sum | 0.841 | 0.811 | 0.762 | 0.751 |

Note: *TRAD* represents the model with traditional financial indicators and *DOF* indicates the model with liquidity risk factors. *Combined* represents the model combining all variables together.

Table 4.9 Prediction Results with Radial Kernel in the Testing Sample

| Panel A | Prediction shorter than 1 Year | | | | |
|---|---|---|---|---|---|
| | | 1 Quarter | 2 Quarters | 3 Quarters | 4 Quarters |
| *TRAD* | Failed Banks | 0.990 | 0.969 | 0.969 | 0.948 |
| | Non-failed Banks | 0.969 | 0.948 | 0.935 | 0.946 |
| | Sum | 0.979 | 0.958 | 0.952 | 0.947 |
| *DOF* | Failed Banks | 0.625 | 0.615 | 0.646 | 0.531 |
| | Non-failed Banks | 0.823 | 0.885 | 0.849 | 0.785 |
| | Sum | 0.724 | 0.750 | 0.746 | 0.656 |
| *Combined* | Failed Banks | 0.990 | 0.979 | 0.958 | 0.938 |
| | Non-failed Banks | 0.969 | 0.958 | 0.946 | 0.946 |
| | Sum | 0.979 | 0.969 | 0.952 | 0.942 |
| Panel B | Prediction longer than 1 year | | | | |
| | | 5 Quarter | 6 Quarters | 7 Quarters | 8 Quarters |

| | | | | | |
|---|---|---|---|---|---|
| *TRAD* | Failed Banks | 0.947 | 0.958 | 0.926 | 0.916 |
| | Non-failed Banks | 0.935 | 0.890 | 0.890 | 0.890 |
| | Sum | 0.941 | 0.925 | 0.909 | 0.903 |
| *DOF* | Failed Banks | 0.611 | 0.579 | 0.516 | 0.653 |
| | Non-failed Banks | 0.707 | 0.769 | 0.857 | 0.571 |
| | Sum | 0.658 | 0.672 | 0.683 | 0.613 |
| *Combined* | Failed Banks | 0.968 | 0.979 | 0.905 | 0.947 |
| | Non-failed Banks | 0.946 | 0.923 | 0.901 | 0.879 |
| | Sum | 0.957 | 0.952 | 0.903 | 0.914 |

Note: *TRAD* represents the model with traditional financial indicators and *DOF* indicates the model with liquidity risk factors. *Combined* represents the model combining all variables together.

The learning model based on radial kernel shows similar results. Comparing failed banks with non-failed banks, the misclassification in the group of failed banks is higher, especially in the longer time horizon, while the group of non-failed banks is hardly affected by both time horizon and the selection of different kernels. It implies that an appropriate feature construction based on domain knowledge can improve the efficiency of prediction.

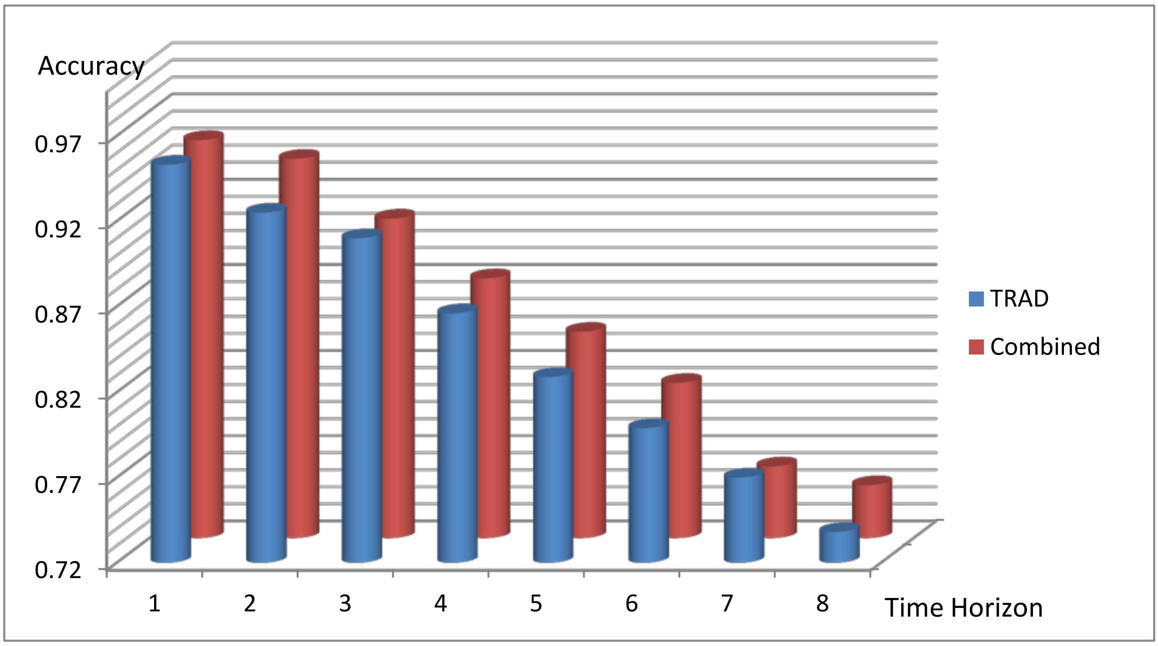



Figure 4.10 Comparison of Prediction Performance with Radial Kernel in Training Sample

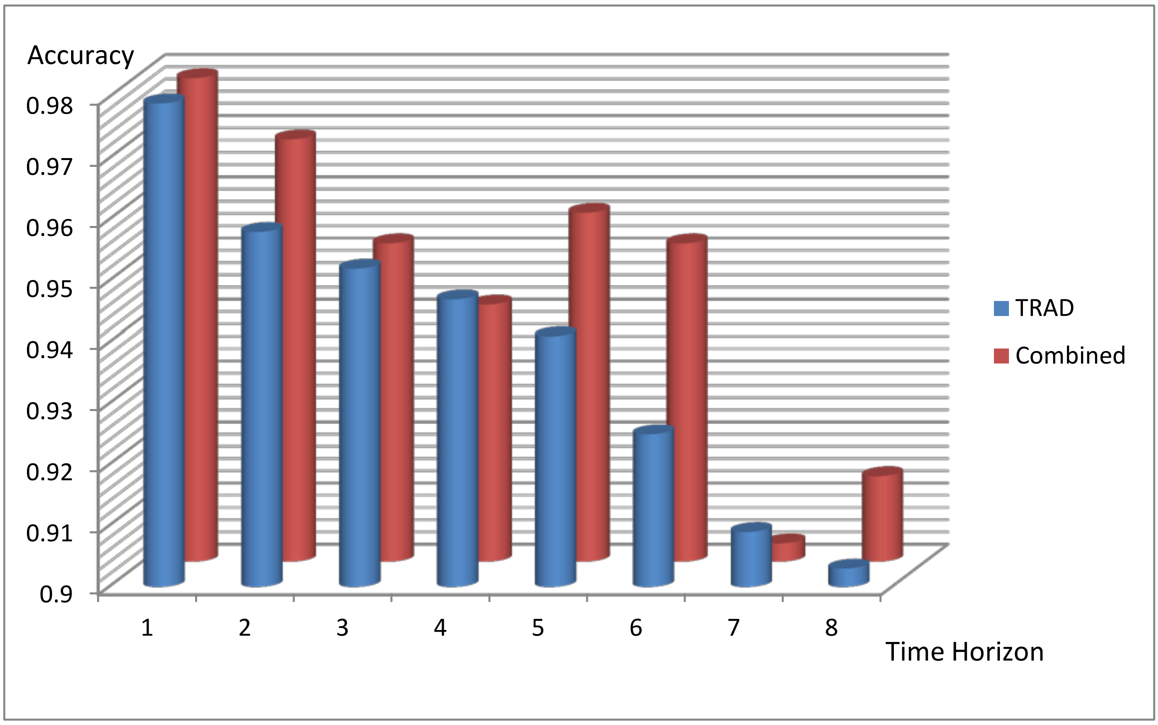



Figure 4.11 Comparison of Prediction Performance with Radial Kernel in Testing Sample

## 4.6 Conclusions

Liquidity risk is at the core of financial risk, along with the other two risks: market risk and credit risk. In the perspective of one particular banking institution, the key to identify liquidity risk is to capture the real behavioral pattern from each claim underneath the existing operating framework. The synergy between lending and deposit-taking is one of the advantages of banks to maintain their specialness as financial intermediaries, while the unique characteristic depends on the fact that they two activities are not perfectly correlated. As it is shown in the cross-sectional correlation coefficients, the overall relationship between loan commitments and deposits is slightly positive or sometimes negative. In the hypothesis of this study, the curve between the correlation and the corresponding fundamental funding cost should be in the shape of inverse-U. However, a hidden pattern, winner-take-all effect, has long been undiscovered behind the synergy appearance. In consequence, there are outliers in the curves and thus the shape of inverse-U does not fit all the curves of every chosen pair of variables.

The empirical results are supportive to the effect. Through the analysis of the dynamic relationship between loan commitments and deposits, the winner-take-all effect is uncovered evidently. Banks which experience a large amount of draw-downs on the loan commitments will also face the outflow of deposits. Furthermore, different dynamic features are unfolded by separating the whole sample into subsamples of large banks and small banks. This phenomenon is concealed under the calm surface of aggregate banking system in the world without large-scale turbulence, but will cause severe liquidity shortage for one particular institution during the period of contingent shock. The results in this study can be extended to conduct future research on the dynamic interaction between a generalized line of credit and wholesale borrowings. Prediction of bank failure by applying Support Vector Machine provides evidence that liquidity risk factors are substantially connected to the bank failures.

# Conclusions

Liquidity risk in banking has not been paid enough attention until the onset of the recent financial crisis during 2007 to 2009. Rapid withdrawals by participants in money markets are the major contributor to the spread of financial distress and liquidity shortages, and the scale is well beyond what the positions of subprime structured products would have caused. The regulatory capital requirements are not formulated to prepare for such extreme events. The general objective is to investigate the relationship between liquidity risk and banking crisis and explain why liquidity risk management is ineffective to protect most financial institutions from failure during crisis by analyzing the inherent driving factors underlying liquidity risk faced by banking institutions. Briefly, the analysis is conducted to address the following questions: (1) what are the dynamic features of banking crisis in a macroeconomic perspective; (2) what are the conditions of bank run equilibrium when depositors' stylized risk preference is taken into consideration and how bank's liquidity buffer and portfolio allocation would be affected by liquidation cost and risk preference; (3) what is the relationship between claims from liabilities and contingent demands from off-balance sheet activities and whether liquidity risk factors based on that relationship would improve bank failure prediction.

The major contribution of this dissertation is the display of a linkage between liquidity risk and banking crisis by showing the natural fragility generated by liquidity risk in banking. Two focal points that determine liquidity risk include inherent driving factors behind liquidity risk, such as the effect of stylized risk preference on the equilibrium of self-fulfilling bank run and portfolio allocation; and the operational fallacies in liquidity risk management such as the insufficiency of liquidity buffer to meet the demands from both liabilities and off-balance sheet contingent claims.

More specifically, the contributions of each chapter are presented in the following.

## Summary of Contributions

In the analysis of macroeconomic dynamic features of banking crisis, the Ratio of Adjusted Weighted Estimated Loss is designed and calculated as the indicator of banking crisis, providing a straightforward and proxy-free perspective to signify banking crisis. As the experience of past financial crises shows, the indicator of banking crisis tends to have clustered volatility in the sample period from 1986 to 2014. The results show that the Exponential GARCH model outperforms GARCH model in characterizing the existence of volatility clustering, which indicates that there is a tendency that in general large losses in the banking sector would be followed by large losses. The leverage effect, namely, the asymmetric information effect, indicates that the banking system will fluctuate more intensely when it is shocked by negative information. In other words, the banking system is more sensitive to negative signals from weak market confidence than positive information signals. By testing the effect of cyclic shocks on banking system, the Vector Autoregression shows that cyclic shocks diffuse into the system and result in contagion in a time-delaying manner. This risk transmission process leads to fluctuations of the system-wide financial indicator represented by ratio of failed assets.

Chapter 3 studies general investors' framing effect of decision-making and how this pattern affects the portfolio allocation and liquidity buffer of commercial banks. The theoretical framework presents a bank run model with two variants: the first model is combining the classic Diamond-Dibvig model with the framing effect and a reference point, and the second model introduces liquidity buffer into the first one, which builds up a connection between liquidity buffer and wholesale funding, and proposes a new perspective that the holding of liquidity buffer should be determined in line with wholesale liquidity needs. The results indicate the condition on which the liquidity buffer of a particular bank should provide. Liquidation cost is positively correlated with the lower bound of liquidity buffer. The effect of the reference point on liquidity buffer partially depends on the slope of yield curve term structure. Higher reference point could typically cause a lower portion of long-term investment. Consistent with most previous research, the liquidation cost is negatively correlated with the investment ratio, which means commercial banks have less incentive to make nominal high-return investments when the market liquidity is under pressure. As the reference point moves rightwards, the investment ratio will decrease, which implies that a more significant framing effect represented by a higher reference point negatively correlates with the portion of endowment allocated into long-term project. The relatively high proportion of illiquid assets shows the real decision-maker formulates an investment strategy without considering the stylized risk preference of lenders. The empirical evidence shows that large commercial banks should have increased their liquid assets due to the upward trend of fundamental interest rates before the recent crisis. The negative coefficient of liquidation cost in the second regression also implies that liquidity buffer in large banks is insufficient during the crisis period. The relationship between liquidity buffer and the reference point maintains negative regardless of what shape the term structure will take. The results are conducive to deepen the understanding of the natural fragility in the liquidity management of commercial banks.

Chapter 4 re-evaluates the relations between deposit-taking and lending. The two activities from both balance sheet and off-balance sheet could share the cost of holding liquid assets and provide liquidity to both sides of the balance sheets. The existence of that advantage is only based on a prerequisite that the draw-downs on loan commitments and the withdrawals on deposits are not perfectly correlated. As the evidence shows, with quarterly change of deposits and loan commitments as variables, banks which experience a large amount of draw-downs on the loan commitments will also face the outflow of deposits through the whole sample period. In the opposite direction, the inflow of deposits and the increase of loan commitments also occur simultaneously. This phenomenon is significant in all subsamples including the group of large banks, the group of small banks and the whole sample, and it is termed as a winner-take-all effect which is hidden but inherent and could cause double outflow of liquidity from particular banks. The effect of double outflow on bank failure is evidenced by using the two variables as features to predict bank failures. Support Vector Machine is applied as the method of forecasting. The results indicate that models with financial indicators as traditional features have better prediction performance, while models using the only two double outflow indicators also have a predictive power to some extent. Furthermore, combining double outflow indicators with traditional features improves the prediction accuracy and the improvement generally becomes more significant as the forecasting horizon gets longer. It provides new insights on the feature construction of bank failure prediction and implies that liquidity risk factors should be regarded as important features in the identification of banks in distress.

## Policy Implications

### About Supervision

The initiatives of liquidity risk regulation and the enrichment of assessment frameworks are not the solutions to liquidity crisis, but just a start of the long-term practice. Regulatory ratios are typically too subjective because they are established on the basis of scenario simulations, estimations and projections, which will be affected by experts' domain knowledge, past experience and mathematical hypotheses. In general, empiricism prevails over other ideology and almost dominates the research of financial risk management, including liquidity risk management. However, there is a question that is not frequently mentioned: is the past experience always enough to explain the future? If the answer is yes, then it is difficult to give explanations for why the recent liquidity crisis of such magnitude has not been paid much attention and failed to be effectively prevented by the "conceptually" most knowledgeable and experienced regulatory authorities in the United States. Liquidity risk regulation should not merely depend on indicator monitoring, stress tests and practical implementations such as on-site examination, it is more appropriate to conduct a framework of comprehensive management of liquidity risk by employing both empirical evaluations and behavioral pattern recognition for stakeholders. Horizontal expansion could be a better option than vertical exploitation.

### About Prediction

Bank failure prediction should consider both solvency factors and liquidity risk factors. In the prediction of a specialized field, feature construction is generally more important than the selection of predictive models. Conventional predictions focus on financial data which are time lagged variables and poor leading indicators. Data in the financial markets can reflect timely information but they are bad proxies for the financial condition within an institution. Domain knowledge, therefore, plays a significant role in the effective construction of features. One of the findings in this dissertation shows that natural fragility of a banking institution not only arises from the maturity mismatch mechanism of financial intermediation, but also exogenous determinants dependent on the decision-making of the bank’s customers and creditors. As the evidence in the prediction tests implies, liquidity risk factors are valuable to improve the accuracy in a longer forecasting horizon. Traditional models supplemented by liquidity risk factors should be the direction of future research.

### About Rescue

The rescue plan is never fair. There are still some untouchable and unsolvable problems in banking crisis for the time being. In the system level, volatility clustering of banking crisis implies that crisis in the banking sector is not a one-time event isolated from each other, but a sequence of highly interconnected events. It is partially due to the business lines of financial institutions are intertwined with each other and financial distress of an institution will be transferred to its counterparty through the channel of business lines. The contagion among counterparties makes the clustering possible. But regulatory authorities are unable to constraint business relationships among financial institutions because it would definitely impair the function of intermediation and lead to inefficiency in the productivity of the real economy. The rescue facilities from the

Federal Reserve during the crisis make a tradeoff to prioritize too-big-to-fail banks over other small institutions. That measure is to some degree unfair but necessary. When it is hard to save the whole picture, it is wise to save the most valuable part of it. The collapse of a money center bank will cause catastrophic consequences and the cost would be inestimable. So the discussion is not about whether large banks behoove to be labeled as a high priority, it is about what ramifications should be considered. In a word, regulators need to provide sufficient resources to safeguard giant institutions. That is the optimal rescue strategy to address the systemic financial distress despite of certain inevitable sacrifices.

# Appendix A

MBS Difference Model for All Commercial Banks

| Panel A | | | | |
|---|---|---|---|---|
| | Large Commercial Banks | | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | -0.109** | -0.100** | -0.073*** | -0.022** |
| | (-2.310) | (-2.297) | (-2.601) | (-2.295) |
| Redrat | -0.340*** | -0.400*** | -0.175*** | -0.079*** |
| | (-10.538) | (-12.664) | (-7.442) | (-5.286) |
| D1 | 0.004*** | 0.004*** | 0.003*** | 0.001*** |
| | (12.605) | (10.584) | (10.696) | (4.582) |
| D2 | -0.005*** | -0.006*** | -0.003*** | -0.001*** |
| | (-15.467) | (-7.396) | (-10.919) | (-7.519) |
| E1 | 0.004*** | 0.005*** | 0.003*** | 0.001*** |
| | (13.211) | (10.497) | (11.469) | (6.266) |
| E2 | -0.007*** | -0.007*** | -0.004*** | -0.002*** |
| | (-17.999) | (-14.619) | (-12.943) | (-8.987) |
| Lnta | 0.001 | 0.002 | 0.000 | 1.5E-04 |
| | (1.417) | (0.754) | (0.295) | (0.418) |
| Caprat | -0.003 | -0.003 | -0.013 | -4.2E-04** |
| | (-1.171) | (-0.526) | (-1.288) | (-2.264) |
| Liqrat | 0.003 | 0.003 | -0.002 | -1.9E-05 |
| | (1.584) | (1.266) | (-0.487) | (-0.019) |
| ROA | 0.018 | 0.034 | 0.006 | 0.006 |
| | (1.013) | (1.315) | (0.235) | (0.59) |
| PTLL | -1.1E-04 | -8.7E-06 | -5.1E-04 | -2.0E-04 |
| | (-0.372) | (-0.033) | (-1.020) | (-0.656) |
| Revrat*D1 | 0.294*** | 0.590*** | 0.348*** | 0.084*** |
| | (4.573) | (5.571) | (6.225) | (4.426) |
| Revrat*D2 | 0.116** | 0.101 | 0.055* | 0.023 |
| | (2.095) | (1.159) | (1.716) | (1.539) |
| Redrat*E1 | 0.453*** | 0.623*** | 0.239*** | 0.090*** |
| | (11.23) | (12.441) | (7.741) | (6.225) |
| Redrat*E2 | 0.522*** | 0.646*** | 0.266*** | 0.088*** |
| | (10.275) | (12.804) | (7.579) | (3.725) |
| Bank Fixed Effects | No | No | Yes | No |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 35,807 | 35,807 | 35,807 | 35,807 |
| R-square | 0.21 | 0.13 | 0.15 | 0.06 |

Panel B

| | Small Commercial Banks | | | |
|---|---|---|---|---|
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.403*** | -0.447*** | -0.224*** | -0.065*** |
| | (-6.258) | (-5.030) | (-3.295) | (-9.240) |
| Redrat | -0.376*** | -0.471*** | -0.191*** | -0.043*** |
| | (-23.319) | (-22.988) | (-16.259) | (-19.174) |
| D1 | 0.008*** | 0.009*** | 0.005*** | 0.002*** |
| | (36.979) | (26.478) | (26.836) | (33.952) |
| D2 | -0.007*** | -0.006*** | -0.004*** | -0.001*** |
| | (-13.255) | (-5.834) | (-3.984) | (-4.646) |
| E1 | 0.009*** | 0.010*** | 0.005*** | 0.002*** |
| | (51.31) | (25.513) | (16.583) | (36.734) |
| E2 | -0.005 | -4.7E-04 | 0.002 | -0.002*** |
| | (-1.261) | (-0.076) | (0.262) | (-5.029) |
| Lnta | 0.003 | 0.009 | 0.005 | 2.8E-05 |
| | (1.398) | (1.204) | (1.330) | (0.154) |
| Caprat | -0.008*** | -0.004*** | 0.000 | -9.7E-06 |
| | (-24.554) | (-9.156) | (-0.687) | (-0.410) |
| Liqrat | 0.010* | 0.011** | 0.001 | 0.001*** |
| | (1.932) | (2.301) | (0.250) | (2.883) |
| ROA | -0.034 | -0.061 | -0.034 | -0.008 |
| | (-1.219) | (-1.350) | (-1.127) | (-1.195) |
| PTLL | 0.000 | -9.4E-05 | -3.6E-05 | 3.0E-07 |
| | (-1.102) | (-1.383) | (-0.584) | (0.074) |
| Revrat*D1 | 0.525*** | 0.681*** | 0.350*** | 0.106*** |
| | (6.966) | (5.853) | (4.109) | (6.170) |
| Revrat*D2 | 0.998*** | 1.435** | 0.767 | 0.274* |
| | (2.742) | (2.011) | (1.231) | (1.672) |
| Redrat*E1 | 0.415*** | 0.644*** | 0.249*** | 0.056*** |
| | (25.408) | (22.71) | (11.626) | (11.270) |
| Redrat*E2 | 1.475*** | 2.305** | 1.390 | 0.109** |
| | (2.601) | (2.368) | (1.415) | (2.075) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 427,316 | 427,316 | 427,316 | 427,316 |
| R-square | 0.07 | 0.04 | 0.03 | 0.07 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate;

MBS Difference Model for Large Commercial Banks

| | | | | |
|---|---|---|---|---|
| Panel A | | | | |
| | | Before the crisis | | |
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.011 | 0.038 | -0.101 | 0.070* |
| | (-0.764) | (1.241) | (-0.984) | (1.658) |
| Redrat | -0.016** | -0.010 | -0.002 | 0.010 |
| | (-2.153) | (-0.511) | (-0.117) | (1.096) |
| Trarat | 0.002 | 0.018* | 0.025*** | 0.016** |
| | (0.252) | (1.810) | (2.717) | (2.551) |
| Ntrarat | 0.013*** | 0.025*** | 0.024*** | 0.011** |
| | (2.624) | (3.583) | (3.905) | (1.994) |
| lnta | 0.001* | -0.001 | -3.8E-04 | -0.002 |
| | (1.756) | (-0.444) | (-0.404) | (-1.326) |
| caprat | 0.003 | 0.010* | 0.013* | 0.005 |
| | (1.286) | (1.928) | (1.851) | (0.922) |
| liqrat | -0.006** | -0.021*** | -0.012** | -0.002 |
| | (-2.042) | (-2.703) | (-2.057) | (-0.876) |
| roa | 0.006 | -0.024 | 0.051** | -0.021 |
| | (0.572) | (-0.976) | (2.067) | (-1.115) |
| ptll | -2.7E-06 | -0.001 | -0.002 | 2.7E-05 |
| | (-0.007) | (-1.309) | (-0.654) | (0.134) |
| Bank Fixed Effects | Yes | No | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 11,331 | 11,331 | 11,331 | 11,331 |
| R-square | 0.02 | 0.03 | 0.03 | 0.01 |
| Panel B | | | | |
| | | During the crisis | | |
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.043 | -0.044 | -0.025 | 0.099 |
| | (-1.274) | (-0.377) | (-0.384) | (1.243) |
| Redrat | -0.008 | 0.003 | -0.005 | 0.001 |
| | (-0.898) | (0.139) | (-0.558) | (0.105) |
| Trarat | 0.018** | 0.022* | 0.020* | -0.014 |
| | (2.248) | (1.714) | (1.794) | (-0.704) |
| Ntrarat | 2.2E-04 | 0.006 | 0.004 | -0.006 |
| | (0.103) | (0.925) | (0.942) | (-0.503) |
| lnta | 0.001 | 0.012*** | 0.011** | 0.018 |
| | (0.525) | (4.618) | (2.250) | (1.410) |
| caprat | -0.005 | 0.012 | 0.044*** | 0.036 |
| | (-0.709) | (1.011) | (2.684) | (1.167) |
| liqrat | -0.014 | -0.028** | -0.014** | -0.011 |

| | | | | |
|---|---|---|---|---|
| | (-1.578) | (-2.093) | (-2.184) | (-1.129) |
| roa | -0.008 | -0.013 | -0.035 | -0.022 |
| | (-0.642) | (-0.841) | (-1.640) | (-0.530) |
| ptll | -0.014 | 0.015 | -0.006 | 0.020 |
| | (-0.763) | (0.681) | (-0.335) | (1.023) |
| Bank Fixed Effects | No | Yes | Yes | No |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 3,775 | 3,775 | 3,775 | 3,775 |
| R-square | 0.02 | 0.05 | 0.06 | 0.10 |

Panel C

| | After the crisis | | | |
|---|---|---|---|---|
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | 0.003 | 0.087 | 0.058 | 0.007 |
| | (0.320) | (1.546) | (0.978) | (0.887) |
| Redrat | 0.015** | 0.025 | 0.029* | -0.002 |
| | (2.135) | (1.100) | (1.753) | (-0.404) |
| Trarat | 0.001 | 3.1E-04 | 0.005 | 3.2E-04 |
| | (0.243) | (0.058) | (1.032) | (0.424) |
| Ntrarat | 2.0E-04 | 0.002 | 0.002 | -1.2E-04 |
| | (0.863) | (0.856) | (0.906) | (-0.811) |
| lnta | 2.0E-04 | 0.001 | -2.9E-04 | 0.001** |
| | (0.595) | (1.008) | (-0.432) | (2.154) |
| caprat | 2.1E-04** | 0.001* | 6.1E-05 | 4.4E-06 |
| | (2.189) | (1.943) | (0.343) | (0.077) |
| liqrat | -0.005** | -0.011** | 0.005 | -2.1E-04 |
| | (-2.364) | (-2.408) | (1.609) | (-0.215) |
| roa | -0.005 | -0.162*** | 0.014 | 0.022 |
| | (-0.742) | (-2.953) | (1.091) | (1.365) |
| ptll | 0.003 | -0.191** | 0.002 | 0.001 |
| | (0.983) | (-2.351) | (0.867) | (0.306) |
| Bank Fixed Effects | No | No | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 19,313 | 19,313 | 19,313 | 19,313 |
| R-square | 0.01 | 0.10 | 0.03 | 0.01 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate;

MBS Difference Model for Small Commercial Banks

| | | | | |
|---|---|---|---|---|
| Panel A | | | | |
| | Before the crisis | | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | 0.011* | 0.041* | 0.011 | -0.004 |
| | (1.829) | (1.665) | (1.479) | (-1.629) |
| Redrat | 0.002 | 0.001 | 1.2E-04 | 1.3E-04 |
| | (1.175) | (0.271) | (0.056) | (0.148) |
| Trarat | 0.007** | 0.017** | 0.002 | 1.2E-04 |
| | (2.214) | (2.296) | (0.730) | (0.402) |
| Ntrarat | 2.0E-04 | 0.001 | 1.6E-04 | 7.6E-05 |
| | (1.180) | (1.244) | (0.716) | (1.184) |
| lnta | -3.1E-05* | 0.001*** | 5.8E-05 | 6.8E-05*** |
| | (-1.652) | (2.928) | (0.238) | (4.587) |
| caprat | 4.1E-04** | 0.006*** | 0.002** | 1.5E-04** |
| | (2.310) | (3.235) | (2.485) | (2.392) |
| liqrat | -0.001*** | -0.008*** | -0.004*** | -2.7E-05 |
| | (-2.801) | (-4.500) | (-5.266) | (-0.154) |
| roa | -0.003 | -0.041*** | 0.001 | -0.005 |
| | (-0.675) | (-3.714) | (0.137) | (-1.278) |
| ptll | 3.7E-06 | 1.2E-05 | 3.6E-06 | 2.6E-06 |
| | (1.063) | (1.314) | (1.344) | (0.923) |
| Bank Fixed Effects | No | Yes | Yes | No |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 182,204 | 182,204 | 182,204 | 182,204 |
| R-square | 0.012 | 0.014 | 0.007 | 0.001 |
| Panel B | | | | |
| | During the crisis | | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | -0.012* | 0.044 | -0.012 | 0.015** |
| | (-1.852) | (0.800) | (-1.292) | (2.192) |
| Redrat | -0.008** | 0.006 | 0.006 | -0.008** |
| | (-2.326) | (0.587) | (1.151) | (-2.097) |
| Trarat | 0.001 | 0.014 | 0.006 | 0.001 |
| | (0.553) | (1.474) | (1.111) | (0.711) |
| Ntrarat | 0.004*** | 0.016*** | 0.007** | 0.003* |
| | (3.960) | (2.945) | (1.995) | (1.845) |
| lnta | 1.5E-04*** | 0.005* | 0.004*** | 0.002* |
| | (3.482) | (1.813) | (3.136) | (1.813) |
| caprat | 0.001 | 0.021** | 0.005* | 0.001 |
| | (1.501) | (2.162) | (1.832) | (1.179) |
| liqrat | -0.002*** | -0.021*** | -0.008* | -0.004 |

| | | | | |
|---|---|---|---|---|
| | (-2.804) | (-3.759) | (-1.809) | (-1.510) |
| roa | -0.020*** | -0.064*** | 0.035 | 0.034* |
| | (-4.136) | (-3.178) | (1.041) | (1.803) |
| ptll | -0.007* | -0.012 | 0.027 | 0.010 |
| | (-1.671) | (-0.847) | (1.420) | (0.873) |
| Bank Fixed Effects | No | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 48,819 | 48,819 | 48,819 | 48,819 |
| R-square | 0.007 | 0.060 | 0.141 | 0.119 |

Panel C

| | After the crisis | | | |
|---|---|---|---|---|
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.005 | 0.005 | 0.023* | -0.003 |
| | (-0.623) | (0.448) | (1.735) | (-0.741) |
| Redrat | -0.006* | 0.018*** | 0.005 | 3.3E-04 |
| | (-1.868) | (2.663) | (1.341) | (0.315) |
| Trarat | 9.1E-05 | 0.002 | 3.7E-04 | 1.3E-04 |
| | (0.680) | (1.140) | (0.847) | (0.572) |
| Ntrarat | 4.8E-04*** | 0.005*** | 0.005*** | 0.004*** |
| | (5.401) | (12.408) | (29.932) | (51.130) |
| lnta | 6.0E-06 | 1.1E-04 | 3.7E-04* | 2.4E-05 |
| | (0.278) | (0.312) | (1.854) | (0.453) |
| caprat | 9.7E-05* | 2.7E-04 | 2.3E-04** | -5.9E-06 |
| | (1.759) | (1.281) | (1.992) | (-0.355) |
| liqrat | -0.001*** | -0.006*** | -0.003*** | -0.001*** |
| | (-3.003) | (-4.688) | (-3.121) | (-2.740) |
| roa | 5.7E-05 | -0.011 | -0.002 | 0.001 |
| | (0.125) | (-1.351) | (-0.777) | (1.216) |
| ptll | 0.002 | -0.003 | -0.001 | -1.3E-04 |
| | (1.188) | (-0.983) | (-0.707) | (-0.405) |
| Bank Fixed Effects | No | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 187,658 | 187,658 | 187,658 | 187,658 |
| R-square | 0.004 | 0.017 | 0.027 | 0.122 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate;

Difference Model of Treasury Securities for Large Commercial Banks

| Panel A | | | | |
|---|---|---|---|---|
| | Non-crisis Period | | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | 0.054 | -0.002 | -0.053* | 0.046*** |
| | (0.827) | (-0.150) | (-1.689) | (3.439) |
| Redrat | 0.029 | 0.019 | 0.002 | 0.003 |
| | (1.054) | (1.287) | (0.076) | (0.375) |
| Trarat | 0.014 | 0.005 | 0.042*** | 0.017*** |
| | (1.524) | (0.832) | (3.141) | (3.320) |
| Ntrarat | 4.6E-04 | 0.002 | 0.041*** | 0.008*** |
| | (0.479) | (0.529) | (5.565) | (2.682) |
| lnta | 3.7E-04*** | -6.8E-05* | -1.3E-04* | 8.7E-05 |
| | (4.070) | (-1.725) | (-1.736) | (0.470) |
| caprat | 0.013 | 0.003 | 0.006 | 1.2E-04 |
| | (1.537) | (0.659) | (1.234) | (0.601) |
| liqrat | -0.009** | -0.003 | -0.004 | -0.004** |
| | (-2.108) | (-1.080) | (-1.419) | (-2.264) |
| roa | -0.044 | -0.016 | 0.083 | 0.019** |
| | (-1.278) | (-1.575) | (1.455) | (2.541) |
| ptll | -0.012** | -0.005 | 0.081 | 0.001 |
| | (-2.026) | (-0.316) | (1.079) | (0.671) |
| Bank Fixed Effects | No | No | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 12,767 | 9,589 | 23,008 | 22,835 |
| R-square | 0.020 | 0.010 | 0.048 | 0.029 |

| Panel B | | | | |
|---|---|---|---|---|
| | Crisis Period | | | |
| | (Ⅰ) | (Ⅱ) | (Ⅲ) | (Ⅳ) |
| Revrat | -0.081 | 0.010 | 0.170 | 0.054 |
| | (-1.047) | (0.185) | (0.690) | (1.148) |
| Redrat | 0.040 | -0.012 | 0.033 | -0.001 |
| | (0.618) | (-0.653) | (0.904) | (-0.065) |
| Trarat | 0.023 | 0.002 | 0.017 | 0.003 |
| | (1.499) | (0.207) | (0.636) | (0.632) |
| Ntrarat | 0.027** | -0.001 | 0.046** | 0.005 |
| | (2.042) | (-0.134) | (2.520) | (1.466) |
| lnta | 0.002 | 8.3E-05 | 0.008** | 0.005** |
| | (0.661) | (0.543) | (2.002) | (2.371) |
| caprat | 0.069* | 0.001 | -0.046 | 0.021** |
| | (1.898) | (0.055) | (-1.445) | (2.333) |
| liqrat | -0.011 | 0.001 | -0.048** | -0.008** |

| | | | | |
|---|---|---|---|---|
| | (-0.792) | (0.128) | (-2.216) | (-2.235) |
| roa | -0.024 | 0.027 | 0.008 | 0.055 |
| | (-0.483) | (1.372) | (0.169) | (1.057) |
| ptll | 0.065* | -0.043 | 0.235 | 0.017 |
| | (1.788) | (-0.589) | (1.123) | (0.538) |
| Bank Fixed Effects | Yes | No | Yes | Yes |
| Time Fixed Effects | No | No | Yes | Yes |
| Observations | 1,362 | 830 | 2,969 | 2,796 |
| R-square | 0.027 | 0.009 | 0.070 | 0.077 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate;

Difference Model of Treasury Securities for Small Commercial Banks

| Panel A | | | | |
|---|---|---|---|---|
| | | Non-crisis Period | | |
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.169 | -0.017 | 0.042 | 0.006 |
| | (-1.296) | (-0.336) | (0.716) | (0.529) |
| Redrat | -0.017 | -0.012 | 0.090* | -0.004 |
| | (-1.192) | (-0.553) | (1.871) | (-0.476) |
| Trarat | 0.019*** | -0.006 | -0.041 | 0.002 |
| | (3.348) | (-0.706) | (-1.138) | (0.631) |
| Ntrarat | 0.012*** | 0.007* | 0.024*** | 0.034*** |
| | (2.628) | (1.654) | (3.287) | (5.964) |
| lnta | -1.4E-04 | -4.0E-04** | 2.0E-04*** | 0.001*** |
| | (-1.057) | (-2.039) | (2.567) | (2.946) |
| caprat | -6.2E-05 | 2.6E-04 | 0.009*** | -5.0E-05 |
| | (-0.048) | (1.301) | (3.880) | (-0.198) |
| liqrat | -0.007*** | -0.007*** | -0.008*** | -0.013*** |
| | (-3.407) | (-3.417) | (-5.644) | (-9.059) |
| roa | 0.118 | -0.016 | -0.081*** | 0.027*** |
| | (1.481) | (-0.771) | (-5.611) | (3.645) |
| ptll | 0.059* | 0.007 | -1.2E-04 | 7.1E-05*** |
| | (1.867) | (0.779) | (-1.005) | (15.104) |
| Bank Fixed Effects | No | No | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 64,528 | 55,510 | 280,324 | 230,517 |
| R-square | 0.024 | 0.005 | 0.050 | 0.038 |

| Panel B | | | | |
|---|---|---|---|---|
| | | Crisis Period | | |
| | ( I ) | ( II ) | (III) | (IV) |
| Revrat | -0.413 | -0.155 | 0.020 | -0.012 |
| | (-1.019) | (-0.687) | (0.302) | (-0.934) |
| Redrat | -0.107* | 0.029 | -0.027 | 0.007 |
| | (-1.868) | (0.395) | (-1.414) | (1.136) |
| Trarat | -0.041 | -0.036 | 0.075*** | -0.004 |
| | (-0.686) | (-0.782) | (4.594) | (-0.259) |
| Ntrarat | 0.062 | -0.009 | 0.059*** | 0.013*** |
| | (1.113) | (-0.367) | (4.714) | (2.687) |
| lnta | 0.025* | 0.002* | 7.5E-06 | 0.006*** |
| | (1.747) | (1.720) | (0.034) | (3.305) |
| caprat | 0.012** | 0.013 | 0.012** | -0.001 |
| | (1.974) | (0.984) | (2.513) | (-0.084) |

| | | | | |
|---|---|---|---|---|
| liqrat | -0.035* | 0.015 | -0.024*** | -0.021** |
| | (-1.809) | (0.917) | (-5.803) | (-2.170) |
| roa | 0.305 | -0.040 | -0.048 | 0.124 |
| | (0.989) | (-0.467) | (-1.542) | (1.301) |
| ptll | 0.145 | 0.057 | -0.016 | 0.113 |
| | (1.332) | (0.627) | (-0.911) | (1.191) |
| Bank Fixed Effects | Yes | No | No | Yes |
| Time Fixed Effects | Yes | No | Yes | Yes |
| Observations | 5,147 | 4,511 | 38,457 | 28,928 |
| R-square | 0.104 | 0.007 | 0.035 | 0.019 |

Note: 1) ***, **, *are significant at the 1%, 5%, and 10% level respectively.

2) *Revrat* is the ratio of quarterly change of revolving, open-end lines secured by 1-4 family residential properties; *Redrat* is the ratio of quarterly change of commitments to fund commercial real estate, construction, and land development loans secured by real estate;

# Appendix B

The objective is to find g(x) as an approximate function to the unknown hypothesis f(x) functional margin:

$$\hat{\gamma} = yf(x) = y(\omega^T x + b) = y(< w, x > +b)$$

The distance from sample points to the classification hyperplane：

$$\gamma = \frac{f(x)}{\|\omega\|}$$

Geometrical Margin:

$$\tilde{\gamma} = y\gamma = \frac{\hat{\gamma}}{\|\omega\|}$$

Let $\hat{\gamma} = 1$, then the maximization turns to be maximization of geometrical interval to achieve the largest confidence. According to Vapnik (1998), Hastie et al. (2001) and Schoo¨lkopf and Smola (2002) aseparating hyperplane satisfies for a non-linear and separable case

max $$\frac{1}{\|\omega\|}$$

s. t. $$y_i(\omega^T x_i + b) > 0 \quad for\ i = 1,2, \dots \dots . n$$

Maximizing$\frac{1}{\|\omega\|}$ equals minimizing $\frac{1}{2}\|\omega\|^2$, then it becomes a problem of convex programming. One general solution is QP (quadratic programming).

But QP is not the most efficient method, which is the reason why it should be transformed to dual form.

ω should be a linear combination of support vectors, at the same time, the label y is also embedded as input.

$$\omega = \alpha_1 y_1 x_1 + \alpha_2 y_2 x_2 + \alpha_3 y_3 x_3 + \cdots + \alpha_n y_n x_n$$
$$= \sum_{i=1}^{n} \alpha_i y_i x_i$$

So the original form of f(x) is transformed to be:

$$\mathrm{f}(x) = < w, x > +b = < \sum_{i=1}^{n} \alpha_i y_i x_i \, , x > +b = \sum_{i=1}^{n} \alpha_i y_i < x_i, x > + b$$

However, not every dataset can be linearly separated. Kernel function is thus introduced into the model to map the features in lower dimensions to higher dimensions.

After being mapped by a specific kernel function, $< w, x >$ is transformed to be $< \mathrm{w}', \mathrm{x}' >$

$$\mathrm{f(x)} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \alpha_{\mathrm{i}} \mathrm{y}_{\mathrm{i}} \mathrm{K}(\mathrm{x}_{\mathrm{i}}, \mathrm{x}) + \mathrm{b}$$

Traditional kernel functions are linear, sigmoid, polynomial and Gaussian.

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