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HIGH LIQUIDITY CREATION AND SYSTEMIC RISK IN THE U.S. BANKING SECTOR

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ABSTRACT

This study focuses on bank liquidity creation as a comprehensive measure of all bank's on and off balance sheet activities, and it specially formulates and tests the hypothesis which address the issue as to whether high total bank liquidity creation has a positive effect on systemic risk. Using a sample of large US commercial banks from 2000 to 2014, this study finds that there is a positive association between liquidity creation and systemic risk. After the Berger and Bouwman's (2009) preferred liquidity creation is decomposed into its two main components, the results suggest that on balance sheet liquidity creation has no significant effect on the level of systemic risk, while off balance sheet liquidity creation strongly positively contributes to systemic risk. These results demonstrate that off balance sheet liquidity creation is the main component for explaining the cross-sectional variation in the level of systemic risk. The empirical findings also indicate that liquidity creation, especially its off balance component, has a stronger positive effect on systemic risk during the financial crisis in 2008.

KEYWORDS: Liquidity creation, systemic risk, financial crisis, bank risk-taking.

1. INTRODUCTION

The recent financial crisis has been the most adverse crisis since the great depression in 1930s, and many banks all around the world have been involved in intriguing the turmoil. The recent crisis showed how a negative shock to a financial institution can propagate from one country to another, and trigger financial instability. It also emphasized that the aggregate risk in the financial market is more important than firm stand-alone risk (Anginer, Demirguc-Kunt & Zhu. 2014).

In the aftermath of global financial crisis, the concept of systemic risk gained important place in economic policy debates as well as among academia. The concern about systemic risk has led to the foundation of important organizations in the United State and Europe. In 2010, Financial Stability Oversight Council and European Systemic Risk Board were founded to identify and monitor systemic risk as well as providing financial stability and constraining the buildup of excessive risk in the system.

It is important for bank regulators and supervisors to analyze the determinants of bank's attributes contributing to systemic risk. Such understandings can help not only to develop available systemic risk measure, but it can also help to improve early warning indicators. In addition, this information can help regulators to develop an optimal taxation policy where the tax is levied according to bank's contribution to systemic risk.

In the past few years, many researchers have been trying to find a new way of measuring systemic risk, however, there are few literatures focusing on bank specific characteristics affecting systemic risk. The investigation on bank specific attributes influencing the level of systemic risk is the main motivation of this study. In this regard, the relationship between systemic risk and liquidity creation as one of the main characteristics of commercial and depository banks is investigated. This study aims to extend the growing body of previous literature by examining whether liquidity creation as a good way of measuring bank output affects the level of systemic risk. Therefore, this study aims to fill the gap between these two strands of literature by testing and formulating this hypothesis.

Perhaps the most closely related paper to this study is the recent work by Berger and Bouwman (2010) who demonstrate that high liquidity creation is a good indicator for predicting a future financial crisis. After detrending, deseasonalizing the liquidity creation and controlling for different macroeconomic factors, Berger and Bouwman (2010) show that aggregate liquidity creation has been abnormally high before banking crises (credit crisis of 1990–1992 and subprime mortgage crisis in 2007). Using logit regressions, they find that when on and off balance sheet liquidity creation (total liquidity creation) is relatively high, there is a high tendency for a financial crisis occurrence. Their evidence especially stresses on the important role of off balance sheet liquidity creation for predicting a future financial crisis. However, this study examines high liquidity creation in the context of systemic risk.

Another related study is Mayordomo, Rodriguez-Moreno, and Peña (2014) who investigate bank's holding of derivatives on systemic risk. They use different off balance sheet items, in particular derivatives, and find that bank's aggregate holding derivatives do not have any significant effect on systemic risk. Although they examine some parts of bank's off balance sheet activities such as derivatives (not guarantees), they did not account for the total off balance sheet activities. Therefore, accounting for the total bank's off balance activities distinguishes this work from Mayordomo's et al. (2014).

Consistent with the studies by Adrian and Brunnermeier (2011) and Pais, and Stork (2013) who argue that large banks contribute the most to systemic risk, this study focuses on the large US commercial banks to investigate the relationship between liquidity creation and systemic risk. More importantly, large US financial institutions are labeled as "Too-Big-to-Fail" which poses a systemic thread to the financial market. Financial Crisis Inquiry Commission (2011: 298–386) argues that after the recent financial meltdown the financial system has become more intertwined than before, and it emphasizes the important role of large financial institutions in the stability of financial system. Another reason for choosing large US banks is that large commercial banks create most of liquidity in the banking sector (81%), however, they constitute a negligible fraction (2%) of total banks in the US (Berger & Bouwman 2009).

The main findings of this study are as follows. First total liquidity creation is positively associated with systemic risk. Second, additional sets of panel regressions are run according to on and off balance sheet liquidity creation to further examine whether the main finding is driven by on balance sheet liquidity, off balance sheet liquidity creation or both. The analyses suggest that the effect of off balance sheet liquidity creation is positively associated with systemic risk, while on balance sheet liquidity creation has no significant effect on the level of systemic risk. The latter finding indicates that off balance sheet liquidity creation is the main component for explaining the cross-sectional variation in the level of systemic risk. Said differently, the significant effect of total liquidity creation which supports the hypothesis is driven primarily by off balance sheet component of liquidity creation. Finally, the empirical findings also suggest that there is a positive strong association between systemic risk and total liquidity creation as well as on and off balance sheet liquidity creation during the 2008 financial crisis.

1.1. Purpose of the study

The main purpose of this study is to empirically examine if liquidity creation as a measure of bank core activity influences the level of systemic risk. The reason for choosing liquidity creation is that it is not only the main function of commercial and depository banks, but it is also important for economic growth (Berger & Sedunov 2015; Fidrmuc, Fungacova, & Weill 2015).

This study conjectures that high total liquidity creation positively contributes to systemic risk for several reasons. First, the trigger of the financial crisis was due to an increase in subprime mortgages. Berger and Bouwman (2008) argue that high liquidity creation in the banking sector was followed by 2007 subprime crisis mainly resulted from loose lending standards. These relaxed lending standards before the crisis allowed banks to extend credits and especially their off balance sheet activities.

Second, not only does high liquidity creation encourage bank risk taking, but it also leads to an increase in the probability of bank failure (see Acharya & Naqvi 2012; Fungacova, Turk & Weill 2015). Furthermore, Diamond and Dybving (1983) document that liquidity creation causes banks to be fragile to bank run, and this bank run can lead to a financial crisis through bank contagion. In addition to Diamond and Dybving's (1983) study, Berger and Bouwman (2009) also highlight the importance of high liquidity creation as a predictor of a financial crisis.

Third, Berger and Bouwman (2008) argue that high off balance sheet activities such as loan commitments can "sow the seed of crisis", and they argue that high liquidity created by banks leads to the financial instability. Last but not least, Foos , Norden , and Weber (2010) find that a growth in bank loan increases the riskiness of banks which can be used by supervisors as an early warning indicator. One can also argue that as the major activity of banks (liquidity creation) increases, banks put not only themselves at risk but the whole financial system, because they make themselves more illiquid by creating liquidity for the public.

Motivated by the evidence found in the aforementioned papers, the linkage between liquidity creation and systemic risk is investigated in this study. In this regard, systemic risk measure (SRISK) proposed by Brownless and Engle (2011) is employed as the systemic risk measure. Also, the amount of liquidity created by commercial banks is calculated using Berger and Bouwman's (2009) approach. This study uses Berger and Bouwman's (2009) preferred liquidity creation measure which accounts for both on and off balance sheet bank activities. They call their favorable measure 'catfat', and this measure classifies the loan according to the information merely on product category. Also, in order to investigate whether the significant effect of liquidity creation is caused by its off balance liquidity creation, on balance liquidity creation or both, catfat measure is decomposed into its two components.

1.2. Research hypothesis and contribution

This thesis formulates and tests the hypothesis postulating that high total liquidity creation has a positive contribution to systemic risk. In line with this hypothesis, Berger and Bouwman (2008) find that prior to the banking crises the aggregate liquidity creation has been abnormally high, and they argue that banking crises occur following an "abnormal" positive liquidity creation. The importance of off balance sheet liquidity creation has been highlighted in several studies (see for example Berger & Bouwman 2009, 2010; Thakor 2005), thus this thesis accounts for on and off balance sheet creation of liquidity.

This study aims to fill the gap between two strands of literature, namely, liquidity creation and systemic risk, by empirically examining whether high liquidity creation can explain the cross-sectional variation in the level of systemic risk. Although the recent study by Acharya and Thakor (2015) stresses that high leverage as an instrument of liquidity creation increases bank risk taking, there is not any previous study examining the relationship between liquidity creation and systemic risk. To my knowledge, this is the first attempt to empirically examine this linkage. As a result, this study contributes to the growing body of literature on factors that affect systemic risk. This research also sheds light on the understanding of determinants of a bank's contribution to the systemic risk. The main hypothesis of this study is of the following form:

H_1 = High total liquidity creation contributes positively to systemic risk.

1.3. Structure of the study

The study is structured as follows. Section 2 discusses previous related studies. Section 3 presents the definition of systemic risk, and section 4 provides two types of systemic risk failure. Sections 5 and 6 discuss how SRISK is calculated. Section 7 presents the construction of liquidity creation measure. Section 8 describes data and methodology. Section 9 reports the empirical results. Section 10 provides the empirical results for the two components of total liquidity creation. Section 11 investigates the robustness of the main finding that supports the hypothesis. Section 12 concludes the study.

2. PREVIOUS RELATED STUDIES

This study is closely related to two strands of literature, namely, systemic risk and liquidity creation. Although there are various ways to measure systemic risk, there are few studies on bank specific characteristics influencing systemic risk. According to the previous studies, size of financial institutions, non-interest income, financial derivatives, banks competition, the amount of leverage, good corporate governance, and non-performing loans are some of the factors affecting systemic risk.

Brunnermeier, Dong, and Palia (2012) use the non-interest income to interest income ratio as a proxy for shadow banking system. They find a positive association between non-traditional banking activities and systemic risk. Non-interest income ties to non-traditional banking such as income from securitization, while interest income accounts for traditional banking activities such as deposit taking and lending. Although previous study by Brunnermeier et al. (2012) differentiates between two different banking activities, namely, interest and non-interest incomes, they only employ a limited information on bank output using income statement of commercial banks.

In addition, Mayordomo et al. (2014) use off balance sheet items, in particular derivatives, and they find that among various types of derivatives, foreign exchange and credit derivatives have a positive association with systemic risk, while interest rate derivatives have a negative association. They also demonstrate that non-performing loans and leverage ratio have even larger effects on the level of systemic risk than derivatives.

The previous findings also emphasize on the role of leverage as a double-edged sword. While high leverage increases market discipline, it can also cause market fragility. At individual bank level and micro-prudential level, Diamond and Rajan (1999), through a theoretical framework, show that leverage increases market discipline and liquidity creation through improving loan quality. They argue that leverage allows the bank manager to enhance the liquidity creation by choosing better asset classes. In contrast, the recent financial crisis highlighted that an increase in leverage led to the fragility of financial institutions. The reason is that high leverage involves financial institutions in risky assets (illiquid loans) choice and widespread security activities which cause collective and aggregate fragility of banks.

Previous studies by Adrian and Shin (2010), Goel, Song and Thakor (2014), and Shleifer and Vishny (2010a) document the role of high leverage in the recent financial crisis. Adrian and Shin (2010) find that leverage is procycilcal and positively related to the size of balance sheet. They argue that bank leverage is high during market boom and relatively low during market distress. This feature of leverage can clearly be seen when the balance sheet is actively updated to the recent change in market price. Furthermore, Shleifer and Vishny (2010a) propose a stylized model which shows how leverage leads to financial instability.

In addition to the aforementioned studies, Acharya and Thakor (2015) develop a theoretical framework which shows a positive association between leverage-based liquidity creation and systemic risk. Unlike Diamond and Rajan's (1999) study which only allows leverage to discipline the bank manager for generating liquidity, Acharya et al. (2015) use equity and leverage to discipline the bank manager for liquidity creation. This model enables them to link between micro-prudential and macro-prudential objectives. In their model, there is a difference between using leverage and equity in generating liquidity. While leverage increases the liquidity creation, the equity has a reduction role. The reason is that the bank manager needs to make a payment from ex-post cash flow to financiers if they use equity as a way of financing, whereas leverage does not need any cash flow to be foregone. Acharya et al. (2015) also show that while each levered financial institution increases discipline in the market, it can also enhance the aggregate systemic risk. They argue that a negative aspect of leverage as an instrument of liquidity creation is that it contributes positively to the systemic risk, indicating that high leverage increases the exposure to systemic risk.

Good corporate governance is another factor influencing systemic risk. The recent study by Iqbal, Strobl and Vähämaa (2015) shows that there is a positive relationship between strong corporate governance mechanism and the level of systemic risk especially during the financial crisis. They demonstrate that those financial institutions which protect shareholders right and have good corporate governance practices contribute positively to systemic risk. The reason is that these financial institutions similar to any other firms aim to maximize shareholder value. In order to satisfy their shareholders before the financial crisis, these firms might increase their profitability by taking excess risk. They also argue that good corporate mechanism is not always beneficial for institutions, since good corporate practices can encourage the financial institutions to take risk excessively.

Pais, and Stork (2013) analyze the effect of size of financial institutions on individual bank risk as well as systemic risk. Pais, and Stork (2013) find that larger banks have a greater effect on the aggregate level of systemic risk. However, the impact of bank size on stand-alone bank risk is not huge. After the recent global financial crisis, policymakers and regulators realized the prominent role of large financial institutions in financial contagion. That is why the recent reforms adopted in banking regulation paid more attention to large and highly interconnected financial institutions.

In addition, Anginer et al. (2014) investigate the linkage between bank competition and systemic risk. They find that bank competition and systemic risk are negatively corrected to one another, suggesting that high competition in the banking sector can lead to more stable financial system. They also demonstrate that the baking system is instable either in countries in which they have more state-owned banks, or in countries in which they have policies constraining competition amidst banks. In order to tackle instability problem in the banking sector, they argue that stronger institutional environment should be established in these countries. Anginer et al. (2014) also argue that higher competition among banks not only leads to larger innovation and better quality of financial products in the banking sector, but it also leads to financial stability. Furthermore, they believe that as the competition increases in the banking sector, banks are encouraged to diversify their risk, and thus they are more stable to negative externalities.

In addition to the literature focusing on factors affecting systemic risk, this study is also closely related to the literature on liquidity creation. Financial intermediation theory considers liquidity creation as one of the most crucial roles of banks. Bhattacharya and Thakor (1993) discuss the reasons why financial intermediaries exist. They also discuss bank liquidity transformation and maturity transformation as one of the key issues in the banking theory. Furthermore, they show how banks improve capital and credit allocations in the economy. Even a long time ago, Adam Smith (1776) emphasizes the important role of banks in generating liquidity. Smith (1776: II.2.41) discusses this role of banks and he states "*That the trade and industry of Scotland, however, have increased very considerably during this period, and that the banks have contributed a good deal to this increase, cannot be doubted.*".

Liquidity created by banks has also an important role in economic growth (see e.g. Bencivenga & Smith 1991; Berger & Sedunov 2015; Fidrmuc, Fungacova, & Weill 2015). For example, Berger and Sedunov (2015) show that there is a positive relationship between liquidity creation and GDP, and they document that liquidity creation has larger effects on economic growth than any other bank services.

Liquidity created by banks can also improve welfare in society and has an important implication in macro-economy (e.g, Bernanke 1983; Dell'Ariccia, Detragiache, & Rajan 2008). For instance, Dell'Ariccia, Detragiache, and Rajan, (2008) demonstrate that the banking sector distress has an exogenous negative effect on economic activities, suggesting that during a financial distress real economy suffers the most when it heavily depends on the banking sector. Their finding suggests that a banking crisis causes economic distress and not vice versa, because distressed banks can decrease bank lending to the real economy. In other words, a banking crisis has severe and devastating effects on the economic activities.

Acharya, Shin, and Yorulmazer, (2009) also highlight the crucial role of liquidity creation during the crisis. They show that bank's choice of liquidity or their portfolio is countercyclical, suggesting that banks tend to hold liquid assets during a financial distress and risky or illiquid assets during a market boom. The reason is that if banks have enough high liquid resources during a market distress, they benefit from potential fire sale gains.

According to liquidity creation theory, banks create liquidity for both depositors and borrowers on and off balance sheet. On the one hand, depositors withdraw funds on demand because they are uncertain about the time of consumption. Therefore, banks are obliged to provide liquidity for them if depositors demand. On the other hand, banks originate illiquid loans for borrowers as well. Therefore, liquidity creation enhances the allocation of credit and capital in the economy.

Traditionally liquidity can be created on the balance sheet of banks by financing illiquid assets (illiquid loans) with liquid liabilities (deposits) (Bryant 1980; Diamond & Dybvig 1983). According to liquidity creation theory, banks create liquidity for the public when they transform an illiquid claim such as a long term loan to a liquid claim such as a demand deposit. Diamond and Dybvig's (1983) model focuses on the liability side of balance sheet. They argue that withdrawal risk or a bank run is one of the risks that banks face as a liquidity creator when they are financed with liquid deposits, and banks can eliminate this risk through federal deposit insurance. In addition, they propose a model showing that if banks are able to keep liquid deposit claims, this would improve welfare in society. The recent study by Donaldson, Piacentino and Thakor (2016) highlights the role of banks as on and off balance sheet liquidity creators. Through their model they show that as the assets become more illiquid, the amount of liquidity created by banks increases. In other words, when banks focus more on the asset side of balance sheet, they give out more loans which in return increase the investment in the economy.

Banks can also create liquidity off their balance sheet for depositors and customers via loan commitments or other kinds of claims such as standby letters of credit (see e.g. Boot, Greenbaum, & Thakor 1993; Holmstrom & Tirole 1998; Kashyap, Rajan, & Stein 2002; Thakor 2005). Kashyap et al. (2002) illustrate how banks are able to create liquidity off their balance sheet. They argue that, on the one hand, banks consider loan commitments as illiquid assets, due to the fact that the bank needs to provide funding to their customers in the future if demanded. On the other hand, customers consider loan commitments similar to demand deposits because loan commitments enable them to withdraw funds at any time during the life of the contract. As a result, according to liquidity creation theory, banks create liquidity off their balance sheet by keeping illiquid claims and provide liquid claims for the public. Kashyap et al. (2002) also argue that provided that there is an imperfect negative correlation between commitment lending and deposit withdrawals, these two bank activities can work well together, and thus, banks take advantage of involving in these two functions as a liquidity creator.

In parallel, Thakor (2005) proposes a theoretical model in which loan commitments are considered as an instruments of off balance sheet liquidity creation as well as an instrument against future credit rationing by banks. He shows how loan commitments change bank lending behaviors during the market distress and market boom. He finds that during the market boom and when the interest rate is low, the supply of credit increases inefficiently which results in over-lending by banks.

In addition, Allen and Gale (2004) develop a theoretical framework arguing that incomplete contracts offered by banks such as demand deposits increase bank default. Consequently, one can argue that liquidity can be seen as a channel through which contagion can propagate. In parallel, previous study by Fungacova et al. (2015) shows that high liquidity creation leads to an increase in the probability of bank failure. They argue that those banks with high liquidity creation are more likely to fail than other banks, and thus banks whose liquidity creation proliferates are more fragile.

It has been also shown that bank liquidity creation tied with an increase in the risk exposure. Acharya and Naqvi (2012) develop a stylized model showing that excess bank liquidity encourages the bank manager to take excess risk by underpricing downside risk. They explain how bank lending behaviors cause the recent financial crisis when the bank liquidity was high. In their model, deposits collected from savers and investors are the main determinants of bank liquidity. After collecting the deposits, a fraction of them are set aside as reserves and the rest of the collected deposits are given out as loans. On the one hand, in banks, when the loan officers' compensations are tied to higher volume of loans, they try to give out loans excessively to increase their compensations. This volume-based compensation in banks leads to underpriced downside risk. On the other hand, when there is a high tendency for macroeconomic risk, investors search for safe securities, and eventually, they deposit their money in the bank which increases the bank liquidity. As the bank is flooded with liquidity, managers are easing lending standards and mispricing the downside risk. This aggressive behavior leads to an increase in bank risk-taking, as well as an asset price bubble. They also argue that their model has a "leaning against liquidity approach" and the central banks should tighten the monetary policy when bank liquidity is excessively high.

One can also argue that low interest rates can increase bank liquidity creation, and then this rise in liquidity creation can result in an increase in bank risk taking by selling abundant illiquid long term loans. The 2008 financial crisis provided ample evidence for this arguments. In 2003, the Fed decreased the interest rate unprecedentedly to 1% which was the lowest amount since 1958. This expansionary monetary policy allowed bank to become involved in over-lending as well as increased liquidity creation. As discussed before, high liquidity creation could encourage bank managers to increase their actual risk positions by mispricing the downside risk of investment projects before the recent financial crisis.

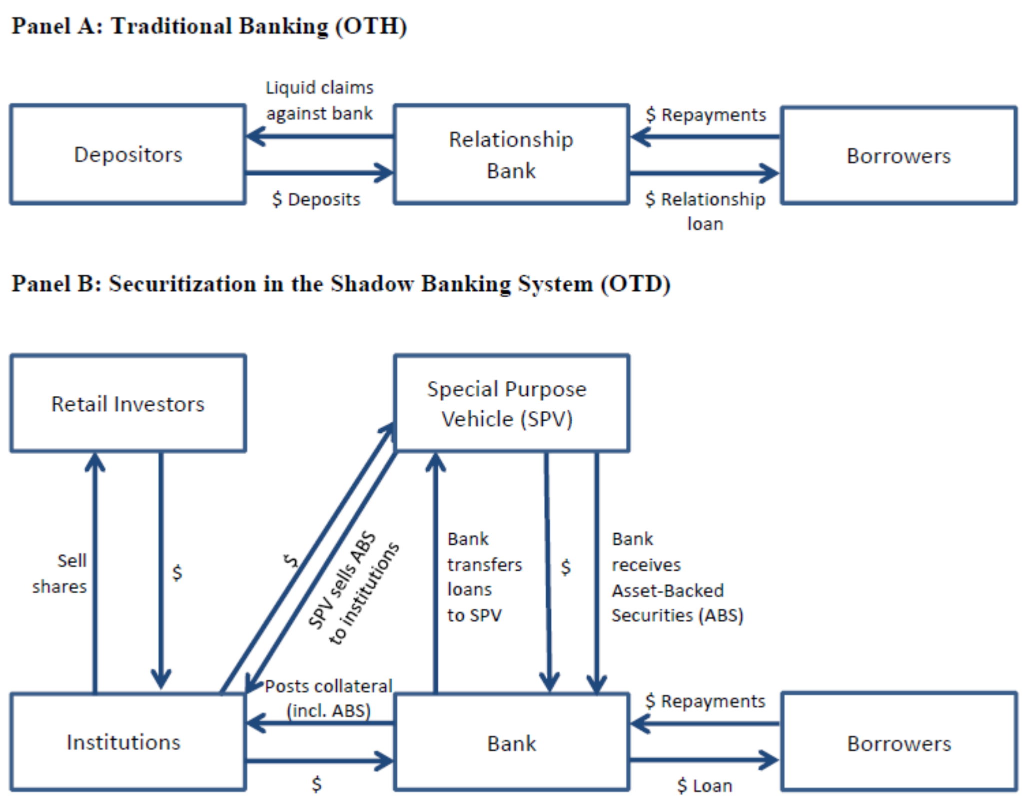
Consistent with the aforementioned argument, Altunbas, Gambacorta, and Marques-Ibanez (2010) analyze the linkage between the low interest rates as a way of implementing expansionary monetary policy and bank risk-taking. They find that over a long period of time a low interest rate leads to an increase in bank risk-taking. In parallel, a previous study by Berger and Bouwman (2010) shows that a loose monitory policy affects liquidity created by medium and small size banks, while this effect is ambiguous for large banks in normal times. They also report that a loose monitory policy has a weaker influence on banks of any size during the financial crisis, meaning that it is less effective during the financial distress. This discussion on liquidity creation and bank risk-taking would justify that main hypothesis of this study.

The recent global financial crisis also stressed the importance of off-balance sheet bank activities which mostly occurred through securitization process in the shadow banking system. These activities deviated banks from traditional banking system and emphasized the importance of off-balance sheet liquidity created by banks. Hence, in the past few years, on and off balance sheet activities have been indispensable. Berger and Bouwman (2008) argue that the recent financial crisis was followed by a high liquidity creation in the banking sector and they stress the role of off balance sheet liquidity creation in intriguing the turmoil.

The rise in bank's off balance sheet activities are closely related to moving banks from traditional banking (originate to hold model) towards non-traditional banking (originate to distribute model). Thus, originate to hold (OTH) and originate to distribute (OTD) models are the main two models in the banking sector. The OTH model focuses on relationship lending. According to the definition proposed by Boot (2000), the relationship banking is *"the provision of financial services by a financial intermediary that: invests in obtaining customer-specific information, often proprietary in nature, and evaluates the profitability of these investments through multiple interactions with the same customer over time and/or across products"*. In this model, banks hold illiquid loans they make on their balance sheet until they mature. Upfront screening and regular monitoring are the advantages of the OTH model which reduces the bank moral hazard.

In the OTD model, banks can also create liquidity by making loans that are eventually securitized or sold. The OTD model enables banks to remove the loans from their balance sheet. Through selling loans or, in particular, securitization, banks no longer need to keep the loans on their balance sheet until maturity, instead they can free up capital by selling the loans to SPV and use the extra capital to generate new loans. While some papers highlight the advantage of securitization as one of the components of OTD model, others stress the downside of it. Among these studies, Aghion, Bolton, and Tirole (2004) illustrate that securitization reduces upfront screening by banks because the loans can proceed to other banks. In addition, Thakor (2005) and Dell'Ariccia and Marquez (2006) report that during the economic boom, this problem worsens, and banks decrease their lending standards which lead to an increase in financial instability. Consequently, as bank lending standards aggravate, banks are able to originate more loans and make themselves illiquid while creating liquidity for borrowers and customers. Figure 1 compares securitization in the shadow banking and traditional banking.

Figure 1. Originate-to-Hold (OTH) versus Originate-to-Distribute (OTD) Model.

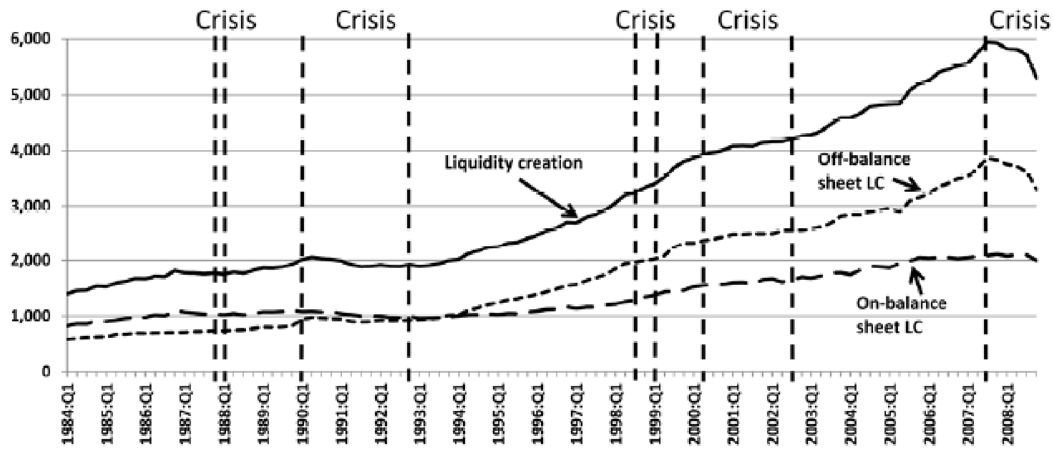


Note: Source: Liquidity: How Banks Create It and How It Should Be Regulated. Bouwman (2013:47) Forthcoming in the oxford handbook of banking.

Banks began adopting the OTD model in their business model by either selling their loans or syndicating loans. Recently, banks have engaged in distributing their loans by creating collateralized loan obligations (CLOs). As a result, the OTH model is gradually replaced with the OTD model, due to a substantial growth in syndicating loans and CLOs. A previous study by Bord and Santos (2012) shows that lead banks have gradually changed their business model from the OTH to the OTD in corporate lending in the past 25 years. Bord and Santos (2012) report that the amount of loans trading in the secondary market soared from $8 billion in 1991 to more than $176 billion by 2005. In addition, they also document that the amount of loans in the syndicated market had a significant growth from $339 billion in 1988 to $2.2 trillion in 2007, indicating a quintuple increase.

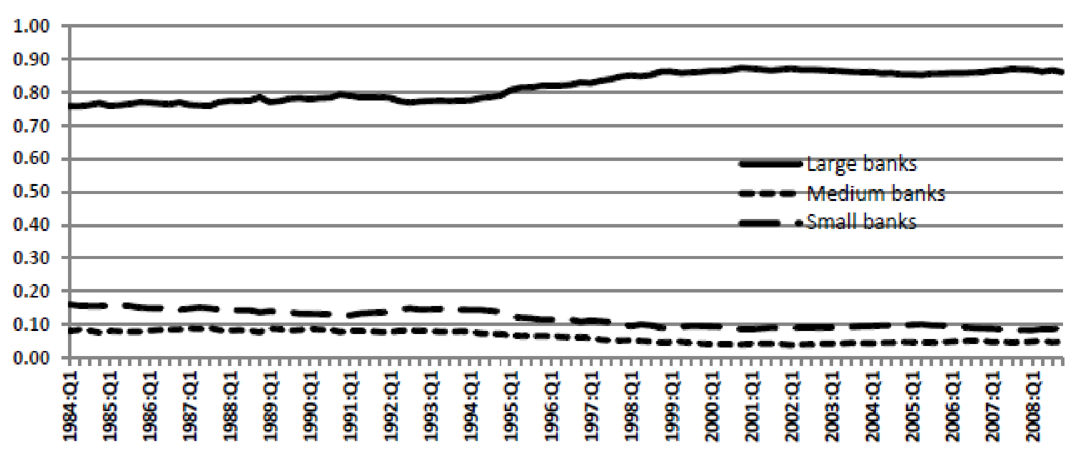
One can argue that changing the business model from the OTH to the OTD can be one reason for a fast increase in liquidity creation in recent years. Consistent with this issue, Berger and Bouwman (2010) document that the liquidity creation has increased over time between 1984 and 2008. However, off balance sheet liquidity creation exceeded on balance sheet liquidity creation in mid-1990s when shadow banking started to rise, and since then it increased faster than ever before. Figure 2 shows the amount of liquidity created by commercial and credit card banks in the US between 1984 and 2008. This figure also splits the liquidity creation into its on and off balance sheet components. As can be seen, liquidity creation has soared from $1.4 trillion in 1984 to $5.3 trillion in 2008, indicating a quadruple increase. Besides, the off balance sheet liquidity created by banks has played a crucial role in total liquidity created by banks. In addition, they show that large banks create a substantial amount of liquidity in the banking sector (figure 3). As can be seen from figure 3, the amount of liquidity created by large banks has risen from 76% in 1984 to over 86% in 2008, while it has negligibly decreased for medium and small size banks in this period.

Figure 2. Liquidity created by US banks from 1984 to 2008.



Note: Source: Bank Liquidity Creation, Monetary Policy, and Financial Crisis. Berger and Bouwman (2010: 37).

Figure 3. Liquidity created by large, medium and small banks in the US.



Note: Source: Bank Liquidity Creation, Monetary Policy, and Financial Crisis. Berger and Bouwman (2010: 37).

3. SYSTEMIC RISK

This section first presents the definition of systemic risk according to the Global Financial Stability Report of the IMF. Then the problem of "too-big-too-fail" (TBTF) moral hazard and systemic risk as well as the definition of a TBTF firm are presented. Finally, the second subsection is concluded by the definition of systematically important financial institutions (SIFIs).

3.1. The definition of systemic risk

The importance of interconnectivity among financial institutions in either creating systemic risk or triggering financial instability was deeply realized after the occurrence of financial crisis in 2008 (see e.g. Plosser 2009; Financial Crisis Inquiry Commission 2011). Financial Crisis Inquiry Commission (2011: 298–386) discusses how over-the-counter (OTC) derivative markets trigger the risk of contagion and interconnectivity in the financial system. They also argue that the intertwined structure of financial system is more concentrated especially after the occurrence of the financial crisis due to broad mergers and accusations during the financial distress. As a result, large and important financial institutions now play even more significant role in the stability of financial system. This market concentration raises special attention to regulators and policymakers for regulating the SIFIs.

After the recent global financial meltdown, the concept of systemic risk gained important place among researchers and regulators all over the world, as it showed how a negative shock to a financial institution can propagate the risk from one country to another, and trigger financial instability. In 2009, the Global Financial Stability Report of the IMF presented a well-defined and useful definition of systemic risk:

"a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and that has the potential to cause serious negative consequences for the real economy"

There is a schizophrenic view about the role of intertwined financial system. While some researchers believe that the tight interconnectivity among financial institutions strengthens the efficiency of financial system, some argue that it also increases the financial instability by increasing the risk of spill-over to the rest of economy. Among the proponent of intertwined financial system, Allen and Gale (2000) argue that more interconnected financial system has the ability to absorb losses, since the losses can be absorbed by more counterparties in the network. In contrast, Vivier-Lirimont (2006) argues that more interconnected financial network leads to financial instability due to the fact that as the number of counterparties which are connected to the distressed bank increases, they can spread the contagion faster into the financial system. In a more complete view, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) demonstrate that interconnectivity amidst financial institutions can lead to financial stability if a small negative shock affects a financial institution. In other words, small negative shocks can be absorbed in an interconnected financial system, and thus interconnectivity leads to the efficiency of financial system. Nonetheless, large negative shocks beyond a certain limit lead to financial fragility, and the interconnectivity among financial institutions acts as a mechanism to spread the financial contagion.

Kaufman (1994: 126) analyzes the financial contagion and he identifies important stylized facts about the financial contagion in the banking sector which can be obviously seen from the definition of systemic risk presented by IMF. One of the stylized facts that Kaufman (1994) identifies is that financial contagion spreads faster and causes serious damage to the real economy. The reason is that the real economy heavily depends upon financial services, and if the financial system collapses, the real economy cannot survive. As a result, when the whole function of financial sector is curtailed, the whole economy is subjected to a halt.

3.2. Too-Big-to-Fail (TBTF) moral hazard and systemic risk

Systemic risk is closely tied to the size of financial institutions. As discussed in previous literature section, Pais, and Stork (2011) find that larger banks have a larger effect on the aggregate level of systemic risk. The reason comes from the moral hazard generated by the TBTF problem, and it has been one of the main drivers of the recent financial crisis (e.g. Bernanke 2010; Acharya & Richardson 2009; Stern & Feldman 2004; Financial Stability Board (FSB) 2010). For example, Financial Stability Board (2010) discusses potential measures to address TBTF problems concerning large and SIFIs to reduce the likelihood of bailouts by the government. In addition, Acharya and Richardson (2009: 32–35) propose a solution for addressing a moral hazard of TBTF problem in creating systemic risk. They argue that each financial institution's contribution to systemic risk should be priced and then an optimal taxation should be levied. Bernanke (2010), the chairman of Federal Reserve, defines the TBTF firm as follows:

"A too-big-to-fail firm is one whose size, complexity, interconnectedness, and critical functions are such that, should the firm go unexpectedly into liquidation, the rest of the financial system and the economy would face severe adverse consequences."

Stern and Feldman (2004: 43–59) argue that financial firms are treated differently by the government than other firms due to the fact that they are more likely to trigger financial instability if they fail. Stern and Feldman (2004: 17–19) also discuss that when financial firms know that they are privileged by the government in consequence of their failure, they are reluctant to invest resources to monitor their risk-taking behaviors, and thus, the firms change their risk-taking behavior because of the TBTF protection. They also believe that the cost of protecting TBTF firms outweighs its benefits, and it increases the probability of a financial crisis. In parallel, Acharya and Richardson (2009: 27–28) also argue that TBTF pushes financial institutions into innovated ways to take advantage of unregulated risk-taking. For instance, banks use the structured investment vehicle (SIV), which is unregulated, to take excess risk and keep their assets off-balance sheet. In this way, the bank is not only exempt from the capital requirement regulation, but they are also developed easily in the financial sector.

As policymakers and regulators realized the importance of contribution of large financial institutions to systemic risk, new requirements were introduced by Basel Committee for SIFIs to reduce the moral hazard caused by the TBTF problem (Basel Committee on Banking Supervision 2011; Basel Committee on Banking Supervision 2013). This requirement has been taken place in order to prevent the probability of financial contagion and improve the ability of banks in absorbing losses. According to Federal Reserve Governor Daniel Tarullo (2009), a systematically important financial institution is defined as:

"Financial institutions are systemically important if the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy.".

According to this definition, a failure of a SIFI not only causes severe damage to the financial system, but it also causes adverse effects on the real economy. Therefore, a collapse of a SIFI is one of the key drivers of systemic risk. The role of SIFIs in the financial contagion makes regulators to monitor them closely in respect to their risk-taking behavior. The reason is that if such financial institutions fail to meet their obligations, the government has to step in and rescue them with taxpayers' money. In the aftermath of the global financial crisis, many governments all over the world faced the question of whether or not they have to rescue these firms. This is the question that no government officials would like to face in the future. That is why they attempt to build a regulatory environment where financial institutions are unable to take excess risk.

The rescue of a bank by government causes the costs on society, and in particular on taxpayers. The reason is that the taxpayers are the ones who provide resources for implicit government guarantees for bank's debt if the bank fails. In 2012, a joint letter was written by 12 leaders to president Van Rompuy and president Barroso claiming that *"Implicit guarantees to always rescue banks, which distort the single market, should be reduced. Banks, not taxpayers, should be responsible for bearing the costs of the risks they take."*. That is why after the recent financial crisis, it has been tried to build a regulatory environment in order to make it less likely for government to rescue financial firms with taxpayers' money.

Acharya, Pedersen, Philippon, and Richardson (2010: 13–16) propose an optimal taxation policy according to marginal expected shortfall (MES) in order that the firm internalizes their systemic risk to the rest of economy. In this taxation system, a tax is levied based on the firm's contribution to systemic risk as well as the losses in debt guaranteed by government. These guarantees can be too-big-to-fail (an implicit guarantee) or deposit insurance (an explicit guarantee) which are not properly priced.

4. THE COMPLEX NATURE OF SYSTEMIC RISK

This section presents two types of systemic failure, namely, contagion and a common shock, identified by Financial Crisis Inquiry Commission (2011: 431–433). In the first subsection domino effect is discussed and in the second subsection fire section is presented in brief.

4.1. Domino effect or Contagion

Financial Crisis Inquiry Commission (2011: 431–432) describes contagion as a "flue" where it can contaminate other financial institutions and spread the sickness through a direct connection via counterparties. For instance, if there is a direct connection between two financial firms, and one of them fails, there is a high tendency that the other one is also fails. Previous work by Markwat, Kole, and Dijk (2009) shows that contagion acts as a domino effect in a financial market. In particular, they demonstrate that the risk of contagion spreads from local to reginal and then global if a stock market crashes. Also, the severity of the contagion propagates from one market to another.

4.2. Fire sale or a common shock

Financial Crisis Inquiry Commission (2011: 432–433) describes a common factor as a "food poisoning" where unconnected small, mid-size and large financial institutions are influenced by it in the same way and at nearly the same time. In this regard, a failure of a financial institution can be considered as an early indicator or a warning flag, and it does not necessarily lead to the failure of other financial institutions in the financial system. However, an analysis of the recent global financial crisis by Shleifer and Vishny (2010b) shows that the fire sale has played a crucial role in the recent financial meltdown through depleting the balance sheet of financial institutions and triggering the risk of contagion. In other words, the fire sale of assets acted as a common factor when losses on the housing securities and other types of assets started at roughly the same time and affected small, mid-size and large unconnected firms as well. They also link fire sales to macroeconomic factors and show that how the weakened balance sheet of financial institutions decreases the financial output and investment. In the fire sale of an asset, a troubled firm has to sell its assets with a significant reduction in value, this sharp reduction in the price forces the prices of similar assets which are held by other firms to go down. As a result, a severe decline in the price starts a financial distress.

5. SYSTEMIC RISK MEASUREMENT

This section discusses the theoretical parts of the systemic risk measure which is employed in this study. First, SRISK proposed by Brownlees and Engle (2011) and stress test are compared as they have the same goal. Next, a simple and widely used measure of systemic risk, namely, expected shortfall, (ES) is reviewed. Then, since SRISK is built upon Acharya, Pedersen, Philippon and Richardson's (2010) work, the pivotal components of Acharya's et al. (2010) theoretical analysis framework is presented and SRISK is finally presented.

5.1. Stress test versus systemic risk (SRISK)

One of the tools which has been used by supervisory officials for a long time is stress testing. In the stress test a question can be raised as to if the economy weakens in a particular way, how much capital would a firm requires. Stress tests determine the amount of capital a financial institution needs during a financial crisis by looking at the balance sheets and functioning of the financial institutions. However, the depth and severity of the recent financial crisis showed that there are many weaknesses in the stress testing practices, since these tests were not able to detect undercapitalized financial institutions before the financial crisis (Basel committee on banking supervision 2009). However, Brownlees and Engle (2011) propose a market-based approach which has the same goal as stress tests. They use publically available information which are accessible for everyone. This systemic risk measure estimates the capital shortfall in a crisis, and therefore, it is a good substitute for the stress test which literally measures the amount of capital a financial institution needs during a financial crisis. According to their work, if the stress is designed to reflect a future financial crisis, then the goal is to measure the equation 1.

(1) $$E_{t-1}(Capital\ Shortfall_i|Crisis) = SRISK_{it}$$

Although stress tests and systemic risk measure proposed by Brownlees and Engle (2011) have the same goal, different approaches are used in them. The conditional expectation that is being calculated in the stress test is typically "bottom up" measures where resilience and viability of the financial firm is being assessed. However, the "top-down" stress test has been boosted after the recent global financial crisis. This approach has the same goal while it focuses on macro-prudential perspective (ECB 2013). Brownlees and Engle (2011) use this approach for their new measure of systemic risk. In this regard, they use equity value as a way of measuring the value of the firm's assets.

SRISK proposed by Brownlees and Engle (2011) measures the capital shortfall of a financial institution if a future crisis occurs. In other words, it estimates how much capital a financial firm needs to raise if there is a future financial crisis. SRISK is built upon the theoretical analysis of Acharya et al. (2010). It is estimated using dynamic MES, firm's equity, and its leverage where MES is an equity loss that investors would experience if there is a substantial decline in the market.

Having estimated SRISK indicates that the company which needs a huge amount of capital is not only the weakest company, but also the biggest contributor to the financial crisis. As a result, the main concern is regarding those financial institutions which might fail exactly at the worst possible time when the rest of economy is weak. SRISK labels a financial institution as systematically risky, if they are highly undercapitalized when the financial system as a whole is in a downturn. The first reason is that when systematically important firms are highly levered and they are about to collapse, their equity value declines. Thereby, the firms are no longer able to meet their obligations. This reduction in equity value is one of the main indicators of systemic distress. The second reason is that financial institutions are not able to function properly if their outstanding liabilities are far above their equity values. Such financial institutions are able to raise capital or being taken over in good times. However, during a financial distress, undercapitalized firms cause serious damage to both the financial system and real economy.

Acharya, Engle, and Richardson (2012) argue that SRISK is a good systemic risk measure, due to the fact that it is able to capture reverse causality. In other words, SRISK is able to answer the following questions as to whether the weak firm causes the financial crisis or whether a financial crisis causes a firm to be weak. They believe that SRISK is able to measure both ways which makes it plausible to be employed. In addition, previous research by Billio, Getmansky, W. Lo, and Loriana Pelizzon (2010) discuss this question of causality by using econometrics tool for a systemic risk measure.

5.2. Expected Shortfall (ES)

In order to present dynamic MES proposed by Brownless and Engle (2011), first expected shortfall (ES) is briefly reviewed. ES is a useful and coherent measure of risk which is proposed by Artzner, Delbaen, Eber, and Heath (1999) to address the problem raised in vale-at-risk (VaR). It is a complement of VaR and measures the average value that the loss exceeds the certain level or VaR α-quantile. ES measures the firm's stand-alone risk, and it is a loss that a firm will incur if an extreme event occurs. Thus, ES can be defined as follows:

(2) $$ES_t = \sum_{t=1}^{N} E_{t-1}\left(-R_{i,t} \,\middle|\, R_{m,t} < C\right)$$

where $R_{i,t}$ is the equity return of firm i, and $R_{m,t}$ is the return on the market portfolio. Said differently, ES is an expected loss that is expected to happen if the portfolio has a negative return worse than a threshold, C. ES can be decomposed into smaller components if the firm return $R_{i,t}$ is considered as a summation of each group's return, $R_{i,t} = \sum_i w_i r_{i,t}$.

(3) $$ES_t = \sum_{t=1}^{N} w_i \; E_{t-1}\left(-r_{i,t} \,\middle|\, R_{m,t} < C\right)$$

where w_i is a weight. Therefore, ES is a weighted average of the expected loss of one asset group given the market declines. However, as can be seen in equation 4, MES can be interpreted as each firm's contribution to systemic losses, and can be defined as an expected equity loss of firm i given a broad market index falls more than C. This threshold can be 2% or 40%. The firm's daily equity loss if the market return drops by 2% is a short term MES and the firm's daily equity loss if the market return drops by 40% is long-term MES (Brownless & Engle, 2011). It is important to note that Brownless and Engle (2011) propose a dynamic MES (equation 10) which will be discussed in section 6.

(4) $$MES_t = E_{t-1}\left(-R_{i,t} \,\middle|\, R_{m,t} < C\right)$$

5.3. Systemic risk (SRISK)

In this subsection, first Acharya's et al. (2010) economic model is discussed. The reason is that Acharya's et al. (2010) economic model is the basis of dynamic MES and SRISK theoretical analysis. Then, SRISK developed by Brownlees and Engle (2011) is presented in brief.

Acharya et al. (2010) propose a simple economic model showing that how a financial institution contributes to systemic risk. They show that financial firms are undercapitalized when the market itself suffers capital shortage, and this scenario causes serious damage to the real economy. In order to present the model, they consider a stylized two-period model. In the first period, a financial institution i invests in N assets with uncertain returns based on the capital it has been able to raise in this period. The capital can be raised through risky debt, initial wealth and guaranteed deposit.

(5) $$W + bF + G = X_1 + X_2 + \ldots + X_N$$

Where W is an initial wealth, G is guaranteed demand deposits, F is a long term debt raised for a risky investment, b is discount price of debt, and X is the investment in asset i including rolling debt, and it can be negative for shorts. In the second period, the net value of wealth, W_2, depends on returns, net of debt repayment and net of bankruptcy costs.

(6) $$W_2 = \sum_{i=1}^{N} X_i\, R_i - F - G - Y(\sum_{i=1}^{N} X_i\, R_i - F - G)$$

where R_i is the total returns of asset i, Y is bankruptcy costs when the wealth of the firm is negative or zero, for instance when the equity value is negative. If W_2 is negative, the firm is insolvent and probably cannot raise capital. In this case, if the firm liquidates all of the assets, bondholders are taking a loss. However, if it is positive but low, then the firm may be illiquid and able to raise capital.

A key problem that a firm faces in the first period is to decide about the optimal leverage which is based on a utility function on the value of wealth in the second period. One of the important feature in this equation is the bankruptcy cost. If the firm chooses to raise a huge amount of debt and invest in risky projects, then the probability of bankruptcy is higher. Furthermore, volatility has an important role to play in how much leverage the financial institutions takes on. If the volatility of return is low, the firm takes on more leverage. The reason is that the risk of facing a serious problem is relatively smaller. In other words, when the volatility of financial market is low, there is a high tendency for financial institutions to take on more leverage. Today, as the volatility is slightly lower in comparison to several years ago, more attentions should be paid to insure that firms are not building up leverage which might lead to a future financial crisis.

According to the assumption made by Acharya et al. (2010), when a firm is illiquid or bankrupt, indicating it is undercapitalized, there are not only costs to debtholders, but there are also external costs to real economy. In the severe case when the market as a whole is undercapitalized, the negative externalities from these institutions cause adverse damage to both real and financial sector. Acharya et al. (2010) argue that financial institutions are more likely to take on more risk when the external cost to society is not internalized. As a result, there should be a regulation to force financial institutions to internalize such negative externalities.

Acharya et al. (2010) also argue that during a financial distress, if a financial institution goes bankrupt, this bankruptcy cost cannot be absorbed by other financial firms connected to the bankrupted firm. Consequently, supply of credit for business activities comes to standstill if the financial sector is undercapitalized. The main reason is that firms are not able to raise capital during a financial downturn. The capital shortfall causes not only a cost to debtholders, but it causes also a cost to the economy in particular when the financial sector suffers from capital shortage. That is why measuring capital shortfall for each firm during a crisis is the main motivation in Brownless and Engle's (2011) paper.

If the ratio of asset to equity value that a financial institution should keep in the first period as capital buffer is k, then the capital buffer requirement for the firm at the end of first period is calculated in equation 7.

$$\text{k}(b_1F_{i1} + G_{i1} + W_{i1}) - W_{i1} \tag{7}$$

According to equation 7, the firm faces capital shortfall if the calculated value in equation 7 is positive. Therefore capital shortfall, SRISK , is calculated under an assumption that book value of debt is unchanged in the next six months. The prudential capital requirement, k, is set to be 8%. Having leverage and equity losses in the next six months, and long run marginal expected shortfall (LRMES), SRISK is computed as follows:

$$SRISK_{i,t} = E\left((k(D+E) - E) \,\middle|\, Crisis\right) = kD_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right) \times E_{i,t} \tag{8}$$

Where LRMES $is\ 1 - exp\left(-18 \times MES_{i,t}(2\%)\right)$, D is firm's i book value of debt, E is the market value of equity or market capitalization of firm i and k is set to be 8%. However, V-Lab has recently changed the estimation method of LRMES. In the new method, LRMES is estimated through 1-exp (log(1-C)×β), where C is 40% which is a default value for the six-month crisis, and β is the firm's CAPM beta. It is also important to note that SRISK as a percentage value is defined as of equation 9.

(9) $$SRISK\%_i = \frac{SRISK_i}{\sum_i SRISK_i}$$

SRISK has several key features. One of the main features of SRISK is that it accounts for the size of financial institution. In other words, it rises as the size of the firm increases if the leverage keeps constant. In addition, there is a positive relationship between debt of the firm and systemic risk, suggesting that if the debt of the firm increases, it has a positive effect on systemic risk. A negative externality to the financial firm has also a positive effect on systemic risk.

In brief, SRISK can be computed in three steps. First, MES is estimated dynamically. Brownlees and Engle (2011) present a simple and flexible time series approach to estimate MES dynamically which will be discussed in the next section. In order to estimate MES, time-varying volatility and correlation are modeled via GJR-GARCH and dynamic conditional correlation (DCC) models. Second, LRMES is estimated by extrapolation to a full financial crisis. LRMES is a firm equity loss if market return declines by 40% in the next 6 months. LRMES can be estimated through simulations. Finally, the capital shortfall (SRISK) is calculated.

6. ECONOMETRIC APPROACHES FOR CALCULATING MES

In order to estimate MES dynamically, Brownless and Engle (2011) use a bivariate and flexible time series approach to modeling time-varying volatilities, correlations and tail dependence. In this regard, first the equity return of a firm, $R_{i,t}$, and the market as a whole are modeled. As can be seen from equation 10, return on the broad market, $R_{m,t}$, is the product of volatility process, $\sigma_{m,t}$, and an innovation factor, $\varepsilon_{m,t}$. The return of an individual firm can be estimated similar to the broad market index with the exception that the innovation factor has time varying correlation with the innovation in market return. $\xi_{i,t}$ is firm specific innovation.

(10)

$$R_{m,t} = \sigma_{m,t}\varepsilon_{m,t}$$

$$R_{i,t} = \sigma_{i,t}\left(\rho_{i,m,t}\varepsilon_t + \sqrt{1-\rho_{i,m,t}^2}\xi_{i,t}\right)$$

$$\left(\varepsilon_{m,t}, \xi_{i,t}\right) \sim F$$

F is a non-parametric copula to estimate a tail dependence. Disturbances $(\varepsilon_{m,t}, \xi_{i,t})$ are serially independent with mean zero, variance one, and covariance zero. They $(\varepsilon_{m,t}, \xi_{i,t})$ are uncorrelated but they are not necessarily independent random variables. This is a case where uncorrelatedness is different from independence. The reason is that there might be a tail dependence between the two shocks if the market shock is a large negative number. Also, the disturbance distribution does not follow a specific distributional assumption and it is based on a flexible method for inferential statistics allowing tail dependence. This specification allows disturbance to have a non-linear dependence. If equation 10 is substituted in equation 4, a one-period-ahead expression for MES can be presented as the form of equation 11 which is a function of the tail dependence, asymmetric volatility and time-varying correlation:

(11) $$MES_{i,t} = E_{t-1}(-R_{i,t} \,|\, R_{m,t} < C) =$$

$$\sigma_{i,t}\rho_t E_{t-1}\left(\varepsilon_{m,t} \,|\, \varepsilon_{m,t} < {}^{C}/_{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_t^2}\, E_{t-1}\left(\xi_{i,t} \,|\, \varepsilon_{m,t} < {}^{C}/_{\sigma_{m,t}}\right)$$

The first part of equation is a product of three components, namely, the volatility of the firm, the correlation of the firm return with the market return, and expected shortfall for the market. While the individual firm risk only depends on $\sigma_{i,t}$, systemic risk depends on whether this risk occurs at the same time as the economy is weak. As a result, from the systemic point of view, it is the product of the volatility and the correlation. The third term in the first part of equation is the expected shortfall for the market, but that is actually the same for all firms. It changes over time but it is constant in any cross section. Therefore, correlations and volatilities are changing for each firm. The second part of equation shows the expected value of orthogonal innovation for the firm if the market innovation is in its tail. If the two disturbances are independent, then the whole second part of equation 11 will be zero. However, if there is a tail dependence, a second part of equation 11 appears. Firms are risky if they have high volatility and they are systematically risky if they also have high correlations.

6.1. Tail dependence

According to the equation 11, $E_{t-1}(\xi_{i,t} \,|\, \varepsilon_{m,t} < K)$ and $E_{t-1}(\varepsilon_{m,t} \,|\, \varepsilon_{m,t} < K)$ terms need to be estimated through the non-parametric kernel estimation approach. The tail dependence can be simply estimated by calculating how often the firm's return is in the negative tail when the market return is also in the negative tail. Equation 12 can be used to estimate the tail expectations non-parametrically.

(12) $$\hat{E}_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < K\right) = \frac{\sum_t \xi_{i,t}\, I\,(\varepsilon_{m,t}<K)}{\sum_t I\,(\varepsilon_{m,t}<K)}$$

$$\hat{E}_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < K\right) = \frac{\sum_t \varepsilon_{m,t}\, I\,(\varepsilon_{m,t}<K)}{\sum_t I\,(\varepsilon_{m,t}<K)}$$

where $\hat{E}_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < K\right)$ and $\hat{E}_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < K\right)$ are the average of the market and firm residuals when the market returns are less than a constant, K. This estimation can be smooth by using kernel in equation 13.

(13) $$\hat{E}_{t-1}\left(\xi_{i,t} \mid \varepsilon_{m,t} < K\right) = \frac{\sum_t \xi_{i,t}\;\; G_h\,(K-\varepsilon_m)}{\sum_t\; G_h\,(K-\varepsilon_m)}$$

$$\hat{E}_{t-1}\left(\varepsilon_{m,t} \mid \varepsilon_{m,t} < K\right) = \frac{\sum_t \varepsilon_{m,t}\, G_h\,(K-\varepsilon_m)}{\sum_t\; G_h\,(K-\varepsilon_m)}$$

Where $G_h(t) = \int_{-h}^{h} k(u)\,du$, and $k(u)$ is a kernel function. Scaillet (2005) discusses the properties of such tail expectations in his paper.

6.2. Volatility

In the equation 11, the volatilities are asymmetric GARCH model. In the Brownless and Engle's (2011) paper, the volatility process for estimating $\sigma_{i,t}$ and $\sigma_{m,t}$, is modeled based on asymmetric GARCH proposed by Glosten, Jagannathan and Runkle (1993). The reason for using an asymmetric GARCH model is that although GARCH model is able to capture volatility clustering, it is unable to capture the asymmetric effects in the volatility process and it treats the negative and positive returns alike. In this model an extra parameter is added which captures the leverage effects.

(14) $$\sigma_{m,t}^2 = \omega_{mG} + \alpha_{mG} r_{m,t-1}^2 + \gamma_{mG} r_{m,t-1}^2 I_{m,t-1}^- + \beta_{mG} \sigma_{m,t-1}^2$$

$$\sigma_{i,t}^2 = \omega_{iG} + \alpha_{iG} r_{i,t-1}^2 + \gamma_{iG} r_{i,t-1}^2 I_{i,t-1}^- + \beta_{iG} \sigma_{i,t-1}^2$$

where $I_{i,t}^- = r_{i,t} < 0$ and $I_{i,m}^- = r_{i,m} < 0$. The model is able to capture the leverage effect, indicating a stronger volatility tendency during the market downturn than market boom. The response of the volatility of return is different with negative and positive returns. The parameters of GJR-GARCH process can be estimated using quasi-maximum likelihood (QLM).

6.3. DCC Model

In order to calculate the time varying correlation in equation 11, Brownless and Engle (2011) use DCC model. The reason is that the assumption of the constant conditional correlation proposed by Bollerslev (1990) is not plausible, since the correlation among assets is changing over time. That is why the DCC approach proposed by Engle (2002), and Engle and Sheppard (2001) is applied for estimating time-varying correction. This approach is computed easily in two steps. In the first step, the conditional variance is estimated using GARCH models. In the second step, the conditional correlation is computed based on the given parameters in the first step and after standardizing the residuals by their standard deviations. In the DCC model, the variance covariance matrix ($VARCOVAR_t$) is a positive definite matrix over time and the process is stationary. Brownless and Engle (2011) present the following framework to estimate DCC model.

(15) $$VARCOVAR_t = D_t H_t D_t$$

$$D_t = \begin{bmatrix} \sqrt{\sigma_{it}^2} & 0 \\ 0 & \sqrt{\sigma_{mt}^2} \end{bmatrix}$$

$$H_t = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}$$

where D_t is a diagonal matrix with standard deviation on the diagonal, and zero off the diagonal, $D_t^{ii} = \sqrt{\sigma_{it}^2}$ and if $i \neq j\ then\ D_t^{ij} = 0$. Time-varying standard deviations are estimated using GARCH models. Furthermore, H_t is a conditional correlation matrix which contains correlations between the firm and the market.

The DCC framework does not model the dynamic correlation matrix directly. Instead, a pseudo-correlation matrix, Q_t, is introduced in order to capture the dynamics in the correlation. Therefore, a positive definite matrix, Q_t, is used to estimate the dynamic conditional correlation matrix, H_t. Furthermore, in order to have a positive definite matrix, Q_t , same restrictions as the GARCH model are imposed on Q_t, such as $\alpha > 0, \beta > 0, a + \beta < 1$.

(16) $$H_t = diag\ (Q_t)^{-1/2}\ Q_t\ diag\ (Q_t)^{-1/2}$$

where diag(Q_t) has the same elements of the Q_t matrix on its diagonal and zero off its diagonal, indicating that diag$(Q_t)_{ij} = (Q_t)_{ij}\ 1_{i=j}$. Q_t is the dynamic correlation structure which is defined as of the following form:

(17) $$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta Q_{t-1}$$

In equation 17, $\bar{Q}$ is the unconditional covariance with an average of standardized residuals, and ε_{t-1} has the rescaled standardized residuals. $\bar{Q}$ also indicates the Bollerslev's Constant Conditional Correlation (CCC) Estimator (Bollerslev 1990) which can be calculated as $\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_t \varepsilon_t'$. The equation 17 is similar to GARCH process after "variance targeting" of Engle and Mezrich (1995) is adopted. If variance targeting is not applied, the DCC model estimation would be more complicated. Variance targeting reduces the parameter estimations to two, otherwise $2 + n\frac{n+1}{2}$ parameters are needed to be estimated. This volatility targeting helps DCC model to be more parsimonious.

The DCC model is able to capture stylized facts about correlation, namely correlation clustering and mean reversion. Therefore, if the correlation at time t-1 is high, there is a high tendency that the correlation at time t is also high. Also, a shock at time t-1 influences the correlation in the next period. In addition, if $\alpha+\beta < 1$, the correlation is jumping around the mean, $\bar{Q}$, which is unconditional correlation. The DCC model is mean reverting to unconditional correlation, and the correlation temporarily deviates by going above or below the average. The parameters α and β describe how long the deviation lasts. It is important to note that the estimation of parameters in DCC model can be done by using QLM.

7. BANK LIQUIDITY CREATION MEASURE

In order to construct the liquidity creation measure, Berger and Bouwman's (2009) approach is followed in this study. This measure is a comprehensive measure of bank output, since it measures all bank's on and off balance sheet activities. This approach is easily calculated in three steps. According to Berger and Bouwman (2009), first bank's on and off balance sheet activities are categorized according to information on either maturity or product category except for the loans which are classified based only on category or only on maturity. They argue that the ability of loan sale or securitization is more important than the maturity of loans, indicating the importance of off balance sheet liquidity creation. Thus, Berger and Bouwman develop four different liquidity creation measures which alternatively classify loans based on maturity or category as well as excluding or including off balance sheet items for bank activities.

This study uses Berger and Bouwman's (2009) preferred liquidity creation measure which accounts for both on and off balance sheet liquidity creation. The reason for choosing this measure is that off balance sheet liquidity creation constructs more than half of the liquidity created by the US banks, suggesting the importance of off balance sheet liquidity creation (Berger and Bouwman 2009). Their favorable measure categorizes loans entirely by product category and includes off balance sheet activities as well. Moreover, this study also decomposes their preferred measure, catfat, into its two components, namely, on and off balance sheet liquidity creation for the further investigation.

Bereger and Bouwman's (2009) liquidity creation measure is calculated in three steps. In the first step, they classify all bank's on and off balance sheet activities (e.g. assets, liabilities, equity, derivatives and guarantees) as illiquid, semi-liquid and liquid. The classification of assets and liabilities is based on ease, cost and the time for the bank to provide liquidity for customers when requested. They also use the same approach for classifying bank's off balance sheet activities. Table 1 represents the classification of assets, liabilities and equity as well as derivatives and guarantees. The information on Call Reports is used for this classification. All on and off balance sheet items presented in the table are analogous to the Berger and Bouwman (2009) paper.

Table 1. Construction of liquidity creation measure.

Category measure		
Assets		
Illiquid assets (+1/2)	Semiliquid assets (0)	Liquid assets (-1/2)
Commercial real estate loans Loans to finance agricultural production Commercial and industrial loans Other loans and lease financing receivables Other real estate owned Customers' liability on bankers' acceptances Investment in unconsolidated subsidiaries Intangible assets Premises Other assets	Residential real estate loans Consumer loans Loans to depository institutions Loans to state and local governments Loans to foreign governments	Cash and due from other institutions All securities (regardless of maturity) Trading assets Federal fund sold
Liabilities and equity		
Liquid liabilities (+1/2)	Semiliquid liabilities (0)	Illiquid liabilities and equity (-1/2)
Transaction deposits Saving deposits Overnight federal funds purchased Trading liabilities	Time deposits Other borrowed money	Bank's liabilities on banker's acceptances Subordinated debt Other liabilities Equity
Off-balance sheet guarantees		
Illiquid guarantees (+1/2)	Semiliquid guarantees (0)	Liquid guarantees (-1/2)
Unused commitments Net standby letters of credit Commercial and similar letters of credit All other off-balance sheet liabilities	Net credit derivatives Net securities lent	Net participations acquired
Off-balance sheet derivatives		
		Liquid derivatives (-1/2)
		Interest rate derivatives Foreign exchange derivatives Equity and commodity derivatives

Note: Source: Bank Liquidity Creation. Berger and Bouwman (2009:3791–3792)

Call Reports divide the bank loan portfolio into different categories. It distinguishes between residential and customer loans, or industrial and business loans. For example, Berger and Bouwman (2009) classify commercial loans as illiquid assets, while residential loans are classified as semi-liquid assets. The reason for this classification is that residential loans can be easily securitized with low costs, and they can be easily traded in the market. However, commercial loans are harder to be securitized.

On the liability side of the balance sheet, saving deposits, Fed funds purchased and transaction deposits are considered as liquid. The reason is that customers can easily withdraw funds on demand without any cost. Time deposits are categorized as semi-liquid, since customers withdraw funds with difficulties relative to saving and transaction deposits. Also, equity capital is considered as illiquid liabilities, since investors can obtain funds by trading the equity of banks in the market. As a result, it is the market which can create the liquidity for the investors and not the banks.

Off balance sheet items are classified similar to on balance sheet activities. For example, loan commitments are classified as illiquid because they are similar to illiquid loans and from the bank's point of view they are illiquid. Also, the bank cannot trade them easily. Furthermore, interest rate derivatives, foreign exchange derivatives and equity and commodity derivatives are all categorized as liquid, because they can be easily traded in the market. It is important to note that the gross value of all the aforementioned derivatives are employed in order to calculate off-balance sheet liquidity creation, because the gross values consist of positive and negative values which show the amount of liquidity the bank is creating or absorbing.

In the second step, positive (+1/2), negative (-1/2) and neutral (0) weights are assigned to each on and off balance sheet item classified in the first step. The assigned weights are in parallel with financial intermediation theory arguing that liquidity is created on the balance sheet when illiquid assets are transformed to liquid liabilities. In other words, banks create liquidity by removing illiquid item (e.g. long term illiquid assets) from the public and in return provide liquid items for the public (e.g. short-term deposits). A positive (+1/2) weight is given to liquid liabilities and illiquid assets, and a negative (-1/2) weight is given to illiquid liabilities and equity capital and liquid assets. A neutral (0) weight is assigned to semi-liquid items. In this regard, banks can create maximum liquidity if illiquid assets are financed by liquid liabilities. In addition, banks can destroy liquidity if liquid assets are financed by illiquid liabilities. Table 1 also presents the positive, zero and negative weights assigned to each items. In the third step, all bank activities classified in the first step and all weights assigned in the second step are combined and Berger and Bouwman's (2009) favorable liquidity creation measure is constructed:

$$(18) \quad Liquidity\ Creation = \Big[\big[\big({}^{1}/_{2} \times illiquid\ assets\big) + (0 \times semi - liquid\ assets) + (-{}^{1}/_{2} \times liquid\ assets)\big] + \big[\big({}^{1}/_{2} \times liquid\ liabilities\big) + (0 \times semi - liquid\ liabilities) + (-{}^{1}/_{2}\ illiquid\ liabilities)\big] + \big({}^{1}/_{2}\ equity\ capital\big) + \big[\big({}^{1}/_{2} \times illiquid\ quarantees\big) + (0 \times semi - liquid\ guarantees) + \big(-{}^{1}/_{2} \times liquid\ guarantees\big) + (-{}^{1}/_{2} \times liquid\ derivatives\big]\Big]$$

8. DATA AND METHODOLOGY

This study analyzes a sample of 26 large US commercial and depository banks with the period spanning 2001–2014. Although the dataset used in this study seems small, it covers on average almost 42% of all commercial banks regarding bank's total assets value over the sample period. Also, the dataset employed in this study composes of either SIFIs or non-SIFIs.

In order to collect the data, first all the US commercial banks are identified for which the systemic risk measure, SRISK, is available on the NYU Stern's V-Lab website. Then, from the preliminary sample, the commercial banks are eliminated for which the Call Reports are not available on the Federal Financial Institutions Examination Council (FFIEC) website. Thus, the dataset used in this study is an intersection of available data from Federal Financial Institutions Examination Council (FFIEC) website and V-Lab website. This criterion leaves 26 US banks with an unbalanced panel of 360 firm-year observations. The dataset consists of 8 SIFIs, and 18 non-SIFIs. Table 2 reports the US commercial banks which are considered as systematically important banks, according to the Financial Stability Board, as of November 2015. Moreover, Table 3 represents other banks used in this study which are considered as non-SIFIs. It is important to note that the data on Goldman Sachs and Morgan Stanley are collected from 2008 onwards when they changed their business strategy towards commercial banks.

Table 2. Systematically important financial institutions.

Name	Ticker
Bank of America	BAC
Bank of New York Mellon	BK
Citibank	C
Goldman Sachs	GS
JP Morgan Chase	JPM
Morgan Stanley	MS
State Street	STT
Wells Fargo	WFC

Table 3. Non-systematically important financial institutions.

Name	Ticker
Branch Banking & Trust	BBT
Capital One	COF
Comerica Bank	CMA
Compass Bank	CBSS
Commerce Bank	CBSH
Fifth Third Bank	FITB
Huntington National Bank	HBAN
Keybank	KEY
Manufacturers and Traders Bank	MTB
M&I Marshel and Ilsley Bank	MI
National City Bank	NCC
Northern Trust	NTRS
PNC Bank	PNC
Regions Bank	RF
Sovereign Bank	SOV
Suntrust Bank	STI
Synovus Bank	SNV
Zions	ZION

In order to calculate the liquidity creation measure, first Call Reports which contain detailed financial information are collected from the Federal Financial Institutions Examination Council (FFIEC) website. The bank liquidity creation for each bank in dollar value -not the aggregate- is calculated for all 360 panel observations consistent with Berger and Bouwman (2009) liquidity creation measure which was discussed before. The data on liquidity creation for virtually all banks in the US is also publically available at Bouwman website. After calculating the liquidity creation measure, all figures were compared with the available data to ensure the validity of the data.

After calculating the liquidity creation measure, this measure is also broken down into its two main components, namely, on balance sheet liquidity creation (LC.onBS) and off balance sheet liquidity creation (LC.offBS) for the further investigation. The reason for the liquidity creation breakout is to investigate which component is the main variable for explaining the cross-sectional variation in the level of systemic risk.

In this study, several variables are included in the regression as control variables which are assumed to have an effect on the level of systemic risk. According to previous studies discussed before, there are various determinants of bank's contribution to systemic risk. Different bank specific characteristics such as size, profitability, and loan growth are controlled for. Non-performing loans as a balance sheet quality factor are also used as a control variable. The data on control variables are collected from Bureau van Dijk Bankscope.

Size is one of the factors influencing systemic risk as documented by Pais and Stork (2011). However, unlike other studies which use logarithm of total assets (logTA) as a proxy for size, this study controls for size by including dummy variables for bank average total assets. In order to account for bank size, banks are grouped into three size classes (small, medium and large) according to their average total assets over the sample period, then dummy variables are assigned to each bank based on this size criterion. The reason for including dummy variables instead of logTA is that logTA is strongly positively correlated with liquidity creation measure causing potential multicollinearity. Another reason for employing this modified firm-specific effects is that while commercial banks considerably differ in total assets in each cross section, the total assets appear to display only little variation over time implying that banks being in the upper tercile at time t are likely to be in the same tercile at time t+1 and so on.

In addition to bank size, return on asset (ROA) is a proxy for bank profitability, and it is computed as net income to total assets. Also, in this analysis, the percentage change in outstanding loans is a proxy for bank's growth. Non-interest income is another factor influencing systemic risk as documented by Brunnermeier et al. (2012). Thus, the ratio of non-interest income to total income (NON-INTI) which is a proxy for non-traditional banking activities is also included in the regression as a control variable. In addition, consistent with the recent study by Mayordomo et al. (2014), deposits to assets (DtA) is included in the regression as a proxy for traditional banking activities. In this regard, Mayordomo et al. (2014) discuss that since deposit taking is a traditional banking activity, DtA ratio can negatively contribute to systemic risk, because it provides a cushion to absorb losses. The ratio of non-performing loans to total assets (NON-PRFML) is also controlled for in the panel regression, because the recent study by Mayordomo et al. (2014) documents that non-performing loans to total loans has a significant positive effect on systemic risk.

It is important to note that similar to studies by Iqbal et al. (2015), Brunnermeier et al. (2012) and Mayordomo et al. (2014), this study controlled for capital ratio (leverage ratio) in the panel regression at the beginning of the study, however, later this variable was excluded from the regression due to two reasons. First, this variable did not have any significant effect as the coefficient on this variable was insignificant in all model specifications. Second, including capital ratio not only had any significant effect, but including this variable reduced the explanatory power of the model by reducing the adjusted R^2.

The detailed accounting information, definitions, sources and calculations of each variable used in this study are listed in table 4. As shown in table 4, all the financial statements and balance sheet variables are extracted from Bureau van Dijk Bankscope. Also, Call Reports are extracted in order to calculate the liquidity creation measure.

Table 4. Variable Definitions.
The table reports the definitions of variables employed in this study as well as sources of the accounting ratios, systemic risk and the liquidity creation measure. The table also reports calculation methods used in this study

Variable	Name	Calculation	Source
SRISK	Systemic risk measure (in $ billion)	-	NYU Stern's V-Lab
LC.catfat	Total liquidity creation (in $ billion)	Calculated from equation 18	Call Reports from FFIEC website
LC.onBS	On balance sheet liquidity creation (in $ billion)	Decomposition of LC.catfat	-
LC.offBS	Off balance sheet liquidity creation (in $ billion)	Decomposition of LC.catfat	-
DtA	Deposits to total assets	$\frac{Deposits}{Total\ assets}$	Bankscope
ROA	Return on asset	$\frac{Net\ income}{Total\ assets}$	Bankscope
LG	Loan growth	%change in loans	Bankscope
NON-INTI	Non-interest income	$\frac{Non-interest\ income}{Total\ assets}$	Bankscope
NON-PRFML	Non-performing loan	$\frac{Non-performing\ loans}{Gross\ loans}$	Bankscope

In order to empirically investigate the relationship between liquidity creation and systemic risk, this study applies several alternative panel regressions with fixed-effects as presented below:

$$(19)\ \text{SRISK}_{\boldsymbol{it}} = \alpha + \beta_1 LC_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3\ LG_{i,t-1} + \beta_4 DtA_{i,t-1} + \beta_5 NON-INTI_{i,t-1} + \beta_6 NON-PRFML_{i,t-1} + \sum_{i=1}^{n-1} \delta_i State_i + \sum_{t=2001}^{2014} \gamma_t YEAR_t + \varepsilon_{i,t}$$

$$(20)\ \text{SRISK}_{\boldsymbol{it}} = \alpha + \beta_1 LC_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3\ LG_{i,t-1} + \beta_4 DtA_{i,t-1} + \beta_5 NON-INTI_{i,t-1} + \beta_6 NON-PRFML_{i,t-1} + \sum_{i=1}^{n-1} \delta_i BankSize_i + \sum_{t=2001}^{2014} \gamma_t YEAR_t + \varepsilon_{i,t}$$

where $SRISK_{it}$ is the systemic risk measure for firm i at time t. LC is alternatively defined as total liquidity creation, LC.catfat, which measures on and off balance sheet liquidity creation for each bank in dollar amount or one of its components, namely, on balance sheet liquidity creation (LC.onBS) or off balance sheet liquidity creation (LC.offBS), for each bank in dollar value. The definitions on control variables can be found in table 4. One lagged period is used for all explanatory variables to reduce the endogeneity problem.

It is important to note that in the first panel specification (equation 19), state fixed-effects, $\sum_{i=1}^{n-1} \delta_i State_i$ are included in the regression by adding state dummy variables which control for both observable and unobservable time-invariant variables across states and they deal with potential omitted variable bias. Furthermore, in the second panel regression modification (equation 20), bank size fixed-effects are included in the regression by adding three binary variables where the first dummy indicates the 33% of the banks that exhibit the highest average in total assets over the sample period, and the third dummy indicates the banks exhibiting the lowest 33% of average total assets over the sample period. In addition to state and bank fixed-effects, time fixed effects $\sum_{t=2001}^{2014} \gamma_t YEAR_t$, are also included in the regression by adding fiscal dummy variables.

In order to examine the effect of liquidity creation on systemic risk during the 2008 financial crisis, equation 19 and 20 are modified in such a way that an interaction term, $LC \times CrisisDummy$, is included in the regression. The CrisisDummy is a dummy variable which takes the value 1 if the year is 2008, and zero otherwise. In this analysis, 2008 is considered to be an exogenous shock as Lehman Brothers collapsed in September 2008.

One can argue that why firm fixed-effect is not used in this study. There are several reasons why this study uses state and bank size fixed-effects instead of firm fixed-effects. First, as discussed before, due to potential multicollinearity problem this analysis uses a modified firm fixed-effects by sorting all banks with respect to the average total assets over the sample period into three deciles in order to account for bank size. Therefore, bank size fixed-effects and firm fixed-effects cannot be applied at the same time in the regression model. Second, including firm fixed-effects in the panel regressions makes the coefficient on the liquidity creation measure insignificant. The reason might be due to the fact that a large fraction of SRISK is explained by firm fixed-effects, and that is why the coefficient on the liquidity creation measure appears to be no longer significant. The recent study by Iqbal et al. (2015) also excludes firm fixed-effects from their panel regression specifications due to the same problem. Third, relatively small sample size would affect degree of freedom, and including dummy variables for each firm leads to estimation of more parameters in the panel resulting in a lack of power in t statistics. Said differently, since the sample is relatively small, using the modified firm-specific effects may also increase the power of the test statistics because it ensures more degrees of freedom for estimating the point estimators in the panel than simple firm-specific effects.

9. EMPIRICAL ANALYSIS

In this section, first descriptive statistics for each variable employed in this study is reported. Next, pairwise correlations for the variables used in this analysis is presented. Then, the variance inflation factor (VIF) test is conducted to ensure the explanatory variables do not suffer from multicollinearity problem. Finally, regression results for different model specifications are discussed.

9.1. Descriptive statistics

Table 5 presents the descriptive statistics for the variables employed in the empirical analysis. It can be clearly seen from the table that the sample of commercial banks used in this study is heterogeneous with regard to the liquidity creation variable, as the value of LC.catfat measure lies between -50.26 and 808.68. The positive and negative values of liquidity creation indicate that large banks not only create liquidity for the public, but they also destroy it in some cases. In addition, the sample of large US commercial banks is heterogamous regarding SRISK, as it varies from -53 to a maximum of 142.97. The heterogeneity can also be seen with regard to control variables, reflecting the fact that the dataset used in this study is diverse and it is an appropriate sample of the entire population.

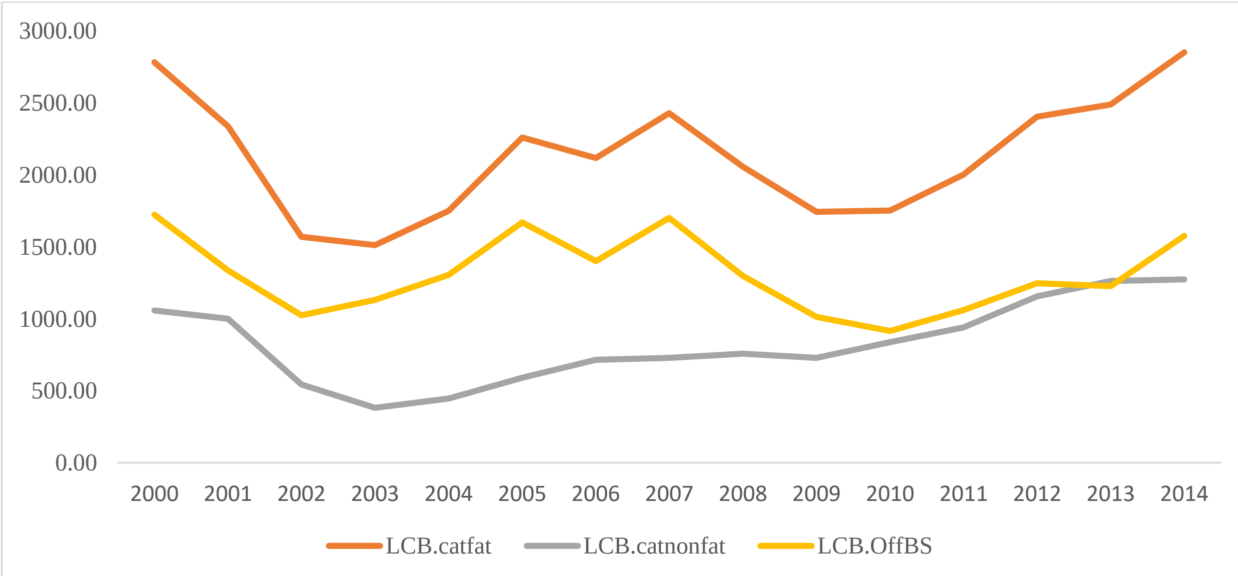
Table 5. Descriptive statistics.

The table represents the descriptive statistics (mean, median, standard deviation, minimum, maximum, first and third quartile, and the number of observations) for the sample. The descriptive statistics obtained using information of the 26 large US banks reported in tables 2 and 3 from 2000 to 2014.

Variable	Mean	Median	St.dev	Min	Max	P25	P75	No.of obs
SRISK($ billions)	6.795	-0.125	27.68	-53.01	142.97	-2.429	3.797	346
LC.catfat($ billions)	90.326	35.191	145.89	-50.26	808.68	11.521	79.631	360
CR	10.34	9.54	3.547	5.543	31.795	8.086	11.716	359
ROA	0.001	0.011	0.01	-0.061	0.045	0.007	0.013	359
LG	14.825	6.49	40.036	-42.22	382.27	0.77	14.35	357
DtA	0.803	0.807	0.06	0.411	0.917	0.775	0.84	358
NON-INTI	43.78	39.69	20.375	-18.56	175.04	30.44	50.84	358
NON-PRFML	1.713	0.9	2.624	0	36.57	0.45	2.32	355

Figure 4 shows how the dollar amount of total liquidity created by the large US banks and its on and off balance sheet components changes over the sample period from 2000 to 2014. As can be seen from the figure, there are two downward slops over the sample period representing the recent financial crisis and dot.com bubble crisis. Before the recent global financial meltdown, total and off balance sheet liquidity creation increased significantly, while on balance sheet liquidity creation almost remained unchanged. However, after the recent financial crisis, on balance sheet liquidity created by large banks has started to increase. The figure also indicates that most of liquidity created by the large banks are coming from their off balance sheet activities.

Figure 4. Liquidity creation (in $ billion) by large US banks over the sample period.



9.2. Correlation matrix

Table 6 reports the correlations among variables. The correlation matrix shows that LC.catfat is strongly positively correlated with SRISK (48%), suggesting that high liquidity creation is associated positively with systemic risk. Furthermore, the correlation matrix indicates that NON-PRFML is strongly positively correlated with systemic risk, while DtA has a negative association with systemic risk which are consistent with a recent study by Mayordomo et al. (2014). In parallel with the study by Brunnermeier et al. (2012) who document that banks which are more involved in non-interest income activities positively contributes to systemic risk, the ratio of non-interest income to total assets is also positively associated with systemic risk.

Table 6. Correlation matrix.
The table reports pairwise correlations for the variables used in this study, namely, systemic risk (SRISK), total liquidity creation measure (LC.catfat), return on assets (ROA), non-performing loans (NON-PRFML), non-interest income (NON-INTI), deposit to total assets (DtA), and loan growth (LG). The correlation matrix obtained using information of the 26 large US banks reported in tables 2 and 3 from 2000 to 2014.

	LC.catfat	ROA	NON-INTI	NON-PRFML	LG	DtA
SRISK	0.482	-0.207	0.040	0.442	-0.065	-0.094
LC.catfat	1.000	-0.030	-0.074	0.262	-0.032	-0.148
ROA		1.000	0.243	-0.379	-0.127	-0.199
NON-INTI			1.000	-0.084	-0.108	-0.205
NON-PRFML				1.000	-0.045	-0.076
LG					1.000	0.010
DtA						1.000

9.3. Variance inflation factor test

It is important to note that variance inflation factor (VIF) test is performed to ensure that the results are not influenced by multicollinearity problem between explanatory variables. Table 7 reports the VIF test for all explanatory variables. As can be seen, the VIF test suggests that the regression models do not suffer from multicollinearity as almost all VIF values are around 1.

Table 7. Variance inflation factor (VIF) test.
The table reports the VIF test for the explanatory variables used in the empirical analysis: total liquidity creation measure (LC.catfat), return on assets (ROA), non-performing loans (NON-PRFML), non-interest income (NON-INTI), deposit to total assets (DtA), and loan growth (LG).

Variable	Centered VIF
LC.catfat	1.183
DtA	2.352
ROA	1.626
LG	1.398
NON-INTI	1.73
NON-PRFML	1.106

9.4. Regression results

As discussed before, several alternative panel regressions are performed for examining the linkage between liquidity creation and systemic risk. Table 8 shows the estimates of 6 alternatives for the main regressions (equation 19 and 20). Models 1–3 account for state fixed-effects, while models 4–6 include bank size fixed-effects. Furthermore, year fixed-effects are excluded from the regression when DummyCrisis is included in the regression. The table also reports that the explanatory power of the models, adjusted R^2, varies from 34% to 44%, suggesting that independent variables are able to explain a substantial amount of variation in SRISK. In is also important to note that the liquidity creation measure can solely explain almost 35% of the variation in systemic risk measure. Not surprisingly, the F statistics are statically significant at 1% level for all the models, indicating a joint significance of explanatory variables.

Table 8. Regression results of 6 model specifications.

The table reports the results of the panel regression model which is applied to a sample of 26 large US banks that spans from 2000 to 2014 for six panel specifications. Columns 1–6 report the results based on state fixed-effects and bank size fixed-effects. Columns 1 and 4 contain the results of solely including liquidity creation measure. Columns 2 and 5 contain the results of the main panel regression models. Columns 3 and 6 consider the effect of liquidity creation on systemic risk by including an interaction term. The results correspond to the estimated coefficient and the t-statistics (in parentheses) that are based on robust standard errors, which are adjusted for heteroscedasticity. ***, **, and * indicate statistical significance level of 1%, 5% and 10% respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Liquidity creation variable:						
LC.catfat	0.116***	0.109***	0.091***	0.091***	0.086***	0.071***
	(5.80)	(5.21)	(4.86)	(3.70)	(3.33)	(3.03)
LC.catfat × $\text{DummyCrisis}^{2008}$			0.161***			0.165***
			(7.45)			(7.20)
DummyCrisis			2.373			3.030
			(1.23)			(1.50)
Control variables:						
DtA		-82.19**	-72.51**		-49.418*	-31.418
		(2.46)	(-2.02)		(-1.70)	(-1.27)
ROA		-108.818	-219.935		-308.578	-369.96*
		(-0.54)	(-1.13)		(-1.25)	(-1.66)
LG		-0.016	-0.013		-0.035	-0.028
		(-0.67)	(-0.49)		(-1.19)	(-0.94)
NON-INTI		0.099*	0.107*		0.180***	0.195***
		(1.86)	(1.89)		(3.53)	(3.51)
NON-PRFML		2.843***	4.663***		2.539**	4.324***
		(2.66)	(5.42)		(2.15)	(4.81)
Constant	-8.031**	50.523*	41.468		29.343	11.979
	(-2.28)	(1.82)	(1.39)		(1.19)	(0.57)
State fixed-effect	Yes	Yes	Yes			
Year fixed-effect	Yes	Yes	No			
				Yes	Yes	Yes
Bank size fixed-effect				Yes	Yes	No
Year Fixed-effect						
No. of obs	320	313	313	320	313	313
Adjusted R-square	0.354	0.400	0.442	0.338	0.381	0.424
F-stats	7.47***	7.45***	12.78***	11.17***	10.16***	24.00***

As shown in columns 1–6 of table 8, there is a significant positive relationship between liquidity creation of an individual bank at time t-1 and its contribution to systemic risk at time t, since all the coefficients on LC.catfat in different model specifications are positive and statistically highly significant. This finding supports the hypothesis postulating that high liquidity creation positively contributes to systemic risk.

To ensure that the empirical results are not driven by spurious correlation between independent variables, first only the main variable of analysis, namely, LC.catfat, is included in models 1 and 4. Second, models 2 and 5 include other control variables to further ensure that the results would hold in the presence of other potential control variables. After including other control variables, the coefficient estimates on LC.catfat in models 2 and 5 are still positive and highly statistically significant. The results are the same when either state fixed-effects or bank size fixed-effects are included in the regression, indicating that after including bank size fixed-effects or removing potential omitted variable biased, LC can still explain the cross sectional variation in the level of systemic risk. For example, the coefficient on LC.catfat in model 2 implies that $1 increase in liquidity creation increases SRISK on average by $0.11. This finding suggests that if liquidity created by a commercial bank increases by $100, the bank would need to raise $11 capital in a future crisis. Given that the average total liquidity creation for the sample used in this study is almost $90 billion; $1 billion increase in liquidity creation would increase SRISK by $110 million which can be considered as economically significant.

It is also important to note that columns 3 and 6 of table 8 include the interaction term, $LC.catfat \times CrisisDummy$, to examine the effect of liquidity creation in the 2008 financial crisis. As shown, the coefficients on the interaction terms are positive and highly statistically significant in both models, indicating that liquidity creation has a stronger positive effect on the level of systemic risk during the financial crisis. For example, the coefficient in model 3 implies that $1 increase in liquidity creation would be associated with $0.25 increase in SRISK in 2008 which suggests that a bank would need to raise more capital during the financial crisis. The crisis effect can be found by adding the coefficients on the interaction term and the coefficient on LC.catfat.

The significant effects of each explanatory variable can be explained in agreement with previous studies. First, the positive and significant effect of liquidity creation on systemic risk is consistent with the recent study by Berger and Bouwman (2010) documenting that high total liquidity creation is an indicator of a future financial crisis. Second, the positive and significant effect of NON-PRFML is consistent with the previous study by Mayordomo et al. (2014) who find that non-performing loans have a strong positive impact on systemic risk. Third, in regard to the negative and significant effect of DtA which is a proxy for traditional banking activities; previous studies by Brunnermeier et al. (2012) and Mayordomo et al. (2014) also find similar results, suggesting a negative relationship between traditional banking activities and systemic risk. Finally, the positive and significant effect of NON-INTI is in parallel with the study by Brunnermeier et al. (2012) documenting that banks with higher non-interest income positively contributes to systemic risk.

10. DECOMPOSING TOTAL LIQUIDITY CREATION

The dollar amount of liquidity creation calculated using Berger and Bouwman's (2009) preferred measure is decomposed into its two components in order to investigate whether the main finding is driven by on balance sheet liquidity creation, off balance sheet liquidity creation, or both. Table 9 shows 8 different models which alternatively account for on balance sheet liquidity creation (LC.onBS) or off balance sheet liquidity creation (LC.offBS). While models 1–4 include state fixed-effects, models 5–8 account for bank size fixed-effects. The results for either state fixed-effects or bank size fixed-effects reported in table 9 are roughly similar. Furthermore, models 3–4 and models 7–8 add an interaction term to the regression to examine the effect of these two components on systemic risk during the financial crisis.

It is important to note that the coefficients on LC.onBS in models 1 and 5 are not significantly different from zero at any significance level, indicating that an increase in on balance sheet liquidity creation of an individual commercial bank at time t-1 does not impose any significant effect on its contribution to the level of systemic risk. However, there is a significant relationship between off balance sheet liquidity creation of an individual bank at time t-1 and its contribution to systemic risk at time t, since the coefficients on LC.offBS in models 2 and 6 are positive and statistically highly significant.

It is important to note that the coefficient in model 2, for example, implies that $1 increase in off balance sheet liquidity creation is positively associated with roughly $0.20 increase in systemic risk, indicating a greater effect of off balance sheet liquidity on systemic risk compared to the coefficient on LC.catfat in table 8. Given that the average off balance sheet liquidity creation for the sample used in this study is almost $56 billion; $1 billion increase in off liquidity creation would increase SRISK by roughly $200 million which can be considered as economically significant. This result is consistent with the previous literature by Berger and Bouwman (2010) finding that high off balance sheet liquidity creation is the main driver of their analysis on the prediction of an impending financial crisis.

Models 3–4 and 7–8 include an interaction term, $LC \times CrisisDummy$, which is the product between one of the decomposed liquidity creation measures and crisisDummy. CrisisDummy takes a value 1 if the year is 2008 and zero otherwise. The positive and significant effects of the interaction terms in models 3–4 and 7–8 suggest that both on and off balance sheet liquidity creation have a stronger and positive effect on the level of systemic risk during the financial crisis. However, the effect of on balance sheet liquidity creation is weaker than the effect of off balance sheet liquidity creation during the crisis. For example, the coefficients in models 3 and 4 imply that $1 increase in on or off balance sheet liquidity creation would be associated with approximately $0.12 and $0.32 increase in SRISK in 2008 respectively. Not surprisingly, CrisisDummy in models 3–4 and 7–8 is highly statistically significant, indicating that banks were systematically risky during the 2008 financial crisis. Furthermore, the positive significant effects of NON-PRFML and NON-INTI on systemic risk are in parallel with previous literature as discussed before.

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Table 9. Regression results of liquidity creation decomposition.

The table reports the results based on two components of liquidity creation after decomposition. The panel regression model is applied to a sample of 26 large US banks that spans from 2000 to 2014 for eight panel specifications. Columns 1–8 report the results based on state fixed-effects and bank size fixed-effects. Columns 1 and 5 contain the results of the main panel regressions for on-balance sheet liquidity creation. Columns 2 and 6 contain the results of the main panel regression models for off-balance sheet liquidity creation. Columns 3 and 7 consider the effect of on-balance sheet liquidity creation on systemic risk by including an interaction term. Columns 4 and 8 consider the effect of off-balance sheet liquidity creation on systemic risk by including an interaction term The results correspond to the estimated coefficient and the t-statistics (in parentheses) that are based on robust standard errors, which are adjusted for heteroscedasticity. ***, **, and * indicate statistical significance level of 1%, 5% and 10% respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
<u>Liquidity creation variable</u>:								
LC.catnonfat	-0.18		-0.016		0.006		0.002	
	(-1.13)		(1.03)		(0.31)		(0.13)	
LC.catnonfat × $DummyCrisis^{2008}$			0.134***				0.142***	
			(4.44)				(6.39)	
Dummy2008			17.517***				17.257***	
			(6.88)				(7.09)	
LC.OffBS		0.196***		0.169***		0.165***		0.141***
		(6.34)		(5.18)		(4.15)		(3.63)
LC.OffBS × $DummyCrisis^{2008}$				0.147***				0.162***
				(4.62)				(4.67)
Dummy2008				7.599***				7.182***
				(4.36)				(4.18)
<u>Control variables:</u>								
DtA	-50.898	-26.838	-53.607	-20.296	-48.996	-22.674	-43.570	-3.052
	(-1.15)	(-1.12)	(-1.11)	(-0.65)	(-1.45)	(-0.98)	(-1.43)	(-0.14)
ROA	-147.528	-2.006	-271.112	-142.796	-130.446	-173.538	-260.584	-259.525
	(-0.52)	(-0.01)	(-1.02)	(-0.82)	(-0.51)	(-0.90)	(-1.01)	(-1.33)

LG	-0.018	-0.007	-0.020	-0.009	-0.035	-0.022	-0.036	-0.021
	(-0.58)	(-0.45)	(-0.64)	(-0.48)	(-1.24)	(-0.99)	(-1.22)	(-0.90)
NON-INTI	0.192**	0.131**	0.192**	0.145**	0.075	0.172***	0.099*	0.186***
	(2.42)	(2.27)	(2.47)	(2.41)	(1.49)	(3.37)	(1.83)	(3.23)
NON-PRFML	4.709***	2.238**	5.798***	4.310***	4.568***	2.062*	5.592***	4.110***
	(5.70)	(1.96)	(7.65)	(6.61)	(5.28)	(1.89)	(8.95)	(4.42)
Constant	50.029	12.605	48.934	3.379	44.341	3.348	36.749	-15.116
	(1.40)	(0.53)	(1.23)	(0.13)	(1.54)	(0.16)	(1.37)	(-0.81)
State fixed-effect	Yes	Yes	Yes	Yes				
Year fixed-effect	Yes	Yes	No	No				
Bank size fixed-effect					Yes	Yes	Yes	Yes
Year fixed-effect					Yes	Yes	No	No
No. of obs	313	313	313	313	313	313	313	313
Ajusted R-square	0.252	0.531	0.248	0.541	0.255	0.486	0.349	0.514
F-stats	4.29***	12.05***	5.89***	18.53***	6.07***	15.07***	11.36***	32.72***

11. ROBUSTNESS TESTS

In this section, alternative model specifications, and other additional robustness checks are performed to ensure the robustness of the main empirical finding. It is important to note that table 10 only reports bank size fixed-effects for the robustness check in order to account for bank size in the panel regressions, however the results are also similar if state fixed-effects are included in the regressions.

First, in order to ensure that the results are not driven by extreme values and outliers, SRISK is winsorized at the 5^{th} and 95^{th} percentiles, and then the regression is re-estimated using this winsorized variable. As can be seen from the column 1 of table 10, the estimation result is consistent with the main empirical finding, suggesting that the result is not driven by outliers.

Second, in order to make sure that the finding is not driven by distressed banks in the sample, a dummy variable is added to the regression (Failedbank) where it takes the value 1 for either failed banks or the banks which have been taken over during the sample period and zero otherwise. Equation 21 is employed to examine whether the main finding is caused by failed banks. Again, the estimate of this regression is similar to the main empirical finding as shown in the column 2 of table 10.

$$(21)\quad \text{SRISK}_{\boldsymbol{it}} = \alpha + \beta_1 LC_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3\, LG_{i,t-1} + \beta_4 DtA_{i,t-1} + \beta_5 NON-INTI_{i,t-1} + \beta_6 NON-PRFML_{i,t-1} + \delta_0\, Failedbanks + \sum_{t=2001}^{2014} \gamma_t YEAR_t + \varepsilon_{i,t}$$

In the third and fourth robustness tests, longer time lags are included in the main regression (equation 20) to examine whether the main result is sensitive to the number of lags chosen. The column 3 of table 10 shows the model with second lags while model 4 shows the result for estimating the regression with third lags. This robustness check is important because it shows that liquidity creation can be employed as an early warning indictor. The estimations of the regressions with the longer time lags are similar to the main finding.

In the fifth robustness check, an alternative regression specification is modeled to further examine the robustness of the main result. As can be seen from the column 5 of table 10, the estimation of this model specification (equation 22) is once again consistent with the main fining, suggesting that high liquidity creation has a positive contribution to systemic risk. The alternative regression is modeled as of the following form:

$$(22)\ \Delta SRISK_{it} = \Delta LC_{it} + \beta_2 ROA_{i,t-1} + \beta_3\ LG_{it} + \beta_4 DtA_{i,t-1} + \beta_5 NON - INTI_{i,t-1} + \beta_6 NON - PRFML_{i,t-1} + \sum_{i=1}^{n-1} \delta_i BankSize_i + \sum_{t=2001}^{2014} \gamma_t YEAR_t + \varepsilon_{i,t}$$

where Δ is the difference in the variable between time t-1 and t. This model specification tests whether the changes in SRISK from year t-1 to t is influenced by the changes in liquidity creation measure. The reason why SRISK, LC and LG are considered at current time (at time t) instead of one period lagged values is that employing delta automatically considers the difference between t-1 and t. In other words, there is no need to use first lagged values of SRISK, LC and LG, because t-1 is embedded in the delta operator. However, one lagged values of other variables are used in this alternative model specification because these variables are just a ratio.

Table 10. Robustness check.

The table reports the robustness check results of the panel regression model which is applied to a sample of 26 large US banks that spans from 2000 to 2014. Column 1 contains the result based on winsorized systemic risk measure. Column 2 contains the result when failed banks taken into consideration. Column 3 and 4 contain the results based on longer time lags. Column 5 reports the estimation of an alternative regression specification. The results correspond to the estimated coefficient and the t-statistics (in parentheses) that are based on robust standard errors, which are adjusted for heteroscedasticity. ***, **, and * indicate statistical significance level of 1%, 5% and 10% respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Liquidity creation variable:					
LC.catfat	0.073***	0.084***	0.105***	0.131***	0.104**
	(4.60)	(3.56)	(3.77)	(3.53)	(2.41)
Control variables:					
DtA	-29.111	-30.882	-35.767	-31.476	-21.91**
	(1.42)	(-1.31)	(-1.47)	(-1.53)	(-2.18)
ROA	-219.472	-203.131	-239.502	-293.913	-109.60*
	(-1.17)	(-1.07)	(-0.98)	(-1.54)	(-1.74)
LG	-0.015	-0.033	-0.036	-0.025	-0.022
	(-0.76)	(-1.33)	(-1.57)	(-1.06)	(-1.36)
NON-INTI	0.198***	0.191***	0.192***	0.184***	0.039
	(4.26)	(3.91)	(4.88)	(4.53)	(1.44)
NON-PRFML	2.405***	2.851***	2.021	2.462	-0.117
	(2.83)	(2.78)	(1.49)	(0.85)	(-0.49)
Constant	11.575	13.254	16.984	13.511	17.701*
	(0.70)	(0.63)	(0.80)	(0.75)	(1.73)
Bank size fixed-effect	Yes	No	Yes	Yes	Yes
Year fixed-effect	Yes	Yes	Yes	Yes	Yes
No. of obs	313	313	288	263	314
Ajusted R-square	0.456	0.382	0.402	0.486	0.252
F-stats	13.45***	10.65***	10.63***	12.11***	6.02***

12. CONCLUSION

The recent global financial crisis showed how oversized balance sheet in the banking sector, probably caused by lax lending standards, not only causes severe damage to the system, but it also triggers financial instability. In addition, the recent financial meltdown highlighted the importance of bank's off-balance sheet activities which mostly occurred through securitization process in shadow banking system. These activities deviate banks from traditional banking system and emphasize the importance of off-balance sheet liquidity created by banks.

This study focuses on bank liquidity creation as one of the core activities of commercial banks which has enormously increased in the past few years. According to liquidity creation theory, banks indeed not only create liquidity on their balance sheet, but they also create it off their balance sheet. Thereby, bank's on and off balance sheet activities are indispensable components. This study focuses on liquidity creation because it is also an important factor for macro-economy. However, too much creation of liquidity is not always beneficial for the economy, and sometimes it may cause financial fragility. Therefore, the aim of this study is to examine whether high total liquidity creation has a positive contribution to the level of systemic risk.

Using one of the prominent measures of systemic risk proposed by Bownless and Engle (2011), and a comprehensive measure of liquidity creation developed by Berger and Bouwman (2009), this study finds that high liquidity provision contributes positively to systemic risk. The results also show that the effect of liquidity creation during the financial crisis is stronger. Furthermore, after liquidity creation breakout, the empirical analysis further finds that although the impact of on balance sheet liquidity creation is smaller than the effect of off balance sheet liquidity creation on systemic risk during the 2008 financial crisis, systemic risk is not generally influenced by on balance sheet liquidity creation. This result acknowledges that the main finding is primarily driven by off balance sheet liquidity creation.

The findings in this study offer several important implications. First, high liquidity creation not only increases bank risk-taking and probability of bank failure as documented in previous studies, but it also contributes positively to systemic risk. Second, since high liquidity provision creates negative externalities for both financial system and real economy, regulators and supervisors should pay more attention to high liquidity creators as they can positively contribute to systemic risk. The results also demonstrate that when banks create high liquidity, they actually make themselves illiquid which may raise the probability of bank failure and cause a cost not only to the real economy, but cause also a cost to taxpayers. The results further demonstrate that high liquidity creators take on more risk when the external cost is not internalized. By even incorporating liquidity creation in taxation policy, high liquidity creators can not only internalize their systemic risk to the rest of economy, but they can minimize taxpayer losses.

Finally, the findings also convey a clear signal to regulators and supervisors about bank lending behavior and bank degree of leverage. This information also helps regulators to constrain the buildup of excessive risk in commercial banks before it is too late. In addition, a linkage between liquidity creation and systemic risk can be seen as an early warning indicator for commercial banks. If banks, on the one hand, rely on lending excessively, and on the other hand if their loan portfolio grows faster than their liabilities (financing illiquid asset with liquid liabilities grows), that would lead to higher bank illiquidity and more risk. This issue was seen clearly before the crisis when there was no regulation and supervisory about bank liquidity.

Although this study has several implications, it also has a limitation. The sample used in this analysis is relatively small and it only accounts for 26 large US commercial banks which can constrain the generalizability of the results. Hence, future research can focus on extending the dataset to a larger sample size for more concise analysis. In this regard, small, other large US commercial banks as well as international banks can also be included in the analysis.

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APPENDIX 1. Correlation between bank size and liquidity creation

This study uses a modified firm fixed-effects due to potential multicollinearity problem. Instead of using logarithm of total assets (logTA) as a proxy for size, this study sorts all banks with respect to the average total assets over the sample period into three deciles as discussed throughout the study. In this section, the correlation matrix is reported to show the correlation between size variable (logTA) and liquidity creation measure (LC.catfat). As can be seen from correlation matrix, logTA is strongly positively correlated (75%) with the variable of interest, namely, LC.catfat. Since this study accounts for large US banks, a strong correlation between LC.catfat and the size variable could be due to the fact that liquidity creation is mostly generated by large banks as documented by Beregr and Bouwman (2010).

	LC.catfat	LogTA	ROA	NON_INTI	NON_PRFML	LG	DtA
SRISK	0.48	0.45	-0.21	0.04	0.44	-0.07	-0.09
LC.catfat	1.00	**0.75**	-0.03	-0.07	0.26	-0.03	-0.15
LogTA		1.00	-0.19	0.10	0.31	-0.09	-0.25
ROA			1.00	0.24	-0.38	-0.13	-0.20
NON_INTI				1.00	-0.08	-0.11	-0.20
NON_PRFML					1.00	-0.05	-0.08
LG						1.00	0.01
DtA							1.00