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The relationship between liquidity risk and credit risk in banks

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ABSTRACT

This paper investigates the relationship between the two major sources of bank default risk: liquidity risk and credit risk. We use a sample of virtually all US commercial banks during the period 1998–2010 to analyze the relationship between these two risk sources on the bank institutional-level and how this relationship influences banks' probabilities of default (PD). Our results show that both risk categories do not have an economically meaningful reciprocal contemporaneous or time-lagged relationship. However, they do influence banks' probability of default. This effect is twofold: whereas both risks separately increase the PD, the influence of their interaction depends on the overall level of bank risk and can either aggravate or mitigate default risk. These results provide new insights into the understanding of bank risk and serve as an underpinning for recent regulatory efforts aimed at strengthening banks (joint) risk management of liquidity and credit risks.

1. Introduction

What is the relationship between liquidity risk and credit risk in financial institutions? Classic theories of the microeconomics of banking support the view that liquidity risk and credit risk are closely linked. Both industrial organization models of banking, such as the Monti–Klein framework, and the financial intermediation perspective in a Bryant (1980) or Diamond and Dybvig (1983) setting, suggest that a bank's asset and liability structures are closely connected, especially with regard to borrower defaults and fund withdrawals. This does not only hold true for banks' balance sheet business but also for the lending and funding business conducted through off-balance sheet items, as shown by e.g. Holmström and Tirole (1998) or Kashyap et al. (2002). Building on these models, a body of literature has recently evolved focusing on the interaction of liquidity risk and credit risk and the implications for bank stability. Papers such as Goldstein and Pauzner (2005), Wagner (2007), Cai and Thakor (2008), Gatev et al. (2009), Acharya et al. (2010), Acharya and Viswanathan (2011), Gorton and Metrick (2011), He and Xiong (2012a,b), and Acharya and Mora (in press) look into the matter from various angles and derive, mostly from a theoretical perspective, results which show the influence liquidity and credit risk have on each other and also how this interaction influences bank stability.

Anecdotal evidence from bank failures during the recent financial crisis further supports these theoretical and empirical results. Perhaps only indicative in nature, official reports of the FDIC and OCC about the reasons for bank failures (so called "Material Loss Reports"[1]) explicitly state that the majority of commercial bank failures during the recent crisis were partly caused by the joint occurrence of liquidity risks and credit risks. Also, Switzerland-based money center bank UBS addressed the main causes for its substantial losses and subsequent financial distress in the wake of the 2007/2008 financial crisis in a 2008 report to its shareholders[2] as follows: "UBS funding framework and related approach to balance sheet management were significant contributors to the creation of UBS's Subprime exposure" (p. 36). Apparently, the bank did not differentiate between liquid and illiquid assets and the respective term funding and thereby also disregarded the credit risks of the assets. Albeit this evidence is only of anecdotal nature, it might be a sign that the joint occurrence of liquidity and credit risks plays a tremendous role for banks and their stability, and that banks do not account for this joint occurrence in their risk management systems. This assumption

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[1] Material Loss Reports are published by the FDIC and OCC whenever a bank default results in a "material loss" to the FDIC insurance fund. On January 1st 2010, the threshold for a "material loss" to the FDIC fund was raised from 25 million to 200 million US Dollar. The reports contain a detailed analysis of the failed banks' backgrounds and business models and list the failure reasons.

[2] Shareholder Report on UBS's Write-Downs, UBS AG, Zurich, Switzerland, 04-18-2008, available through http://www.ubs.com/global/en/about_ubs/investor_relations/share_information/shareholderreport.html.

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is supported by recent regulatory changes, like the Basel III framework and its Liquidity Coverage Ratio (LCR) and Net Stable Funding (NSF) Ratio, or the Dodd–Frank Act with its proposed liquidity stress-tests. Yet, in spite of this alleged importance and the ample theoretic evidence behind it, no paper has so far analyzed the relation between liquidity risk and credit risk on a broad range and in its different dimensions across the banking sector. As a consequence, many important questions regarding this topic remain unanswered: what is the general relationship between liquidity risks and credit risks in banks? Do liquidity and credit risk jointly influence banks' probability of default (PD)? If so, do banks manage both risks together?

We try to answer these questions by empirically analyzing the relationship between liquidity risk and credit risk in 4046 non-default and 254 default US commercial banks over the period 1998:Q1 to 2010:Q3, using a large variety of different subsamples and tests. We use two main liquidity and credit risk proxy variables.[3] We develop a liquidity risk (LR) proxy variable which measures short-term funding risks of banks, as represented by the relationship of short-term obligations to short-term assets, including off-balance sheet items as for example unused loan commitments. We thereby account for classic "bank run" risks. For credit risk (CR) we develop a proxy variable measuring the unexpected loan default ratio of a bank, as represented by the net loan losses in the current period to the allowances for these loan losses recorded in the previous period. This variable captures the current riskiness of a banks' loan portfolio and the accuracy of a bank's risk management to anticipate near-term loan losses.

In the first step of our analysis we measure the general relationship between liquidity and credit risk in banks. We are specifically interested in whether or not there is a reciprocal relationship between the two factors, i.e. whether or not liquidity risk influences credit risk or vice versa, and if this relationship is positive or negative. Our results show that there is no reliable relationship between liquidity risk and credit risk in banks. We distinguish between the different dimensions of liquidity and credit risk using several proxy variables and control for other possible influence factors in a large number of robustness tests. Furthermore, we incorporate different econometric approaches: a simultaneous equations model controlling for both contemporaneous and lagged influences between liquidity risk and credit risk, and a panel-VAR model together with a correlation analysis to separately control for contemporaneous and lagged relationships. Although the results in some cases show statistical significances, the economic influence is at best marginal.

Given that there is no reliable relationship between the two risk factors across banks, we ask in the second part of our analysis if liquidity risk and credit risk individually and also jointly contribute to bank default risk. For this purpose we include our main proxy variables for liquidity risk and credit risk, as well as the interaction between both risks in a multivariate logistic regression model to determine their contributions to banks' PD. Our results show that both liquidity risk and credit risk individually influence banks' PD. Furthermore, we find that the interaction between the two risk categories has an additional effect on bank PD. Surprisingly, this effect varies for banks with different levels of PD: the joint occurrence of liquidity and credit risks has a PD-aggravating effect for banks with a PD of 10–30%. In contrast, we find that it is mitigating for banks with a high PD of 70–90%. Apparently, the joint effect of simultaneously high liquidity and credit risk has a dampening effect on the otherwise PD-aggravating individual effects of the two risk categories in banks which are close to default. These results might point to a gambling for resurrection behavior. Taken together, our findings suggest that there is an important relation between liquidity risk and credit risk which affects the overall probability of bank default.

Our study contributes to two strands of literature. For liquidity risk, these are the seminal works of Bryant (1980) and Diamond and Dybvig (1983) which have been extended, refined and applied numerous times by e.g. Calomiris and Kahn (1991), Diamond and Rajan (2001), and most recently Berger and Bouwman (2009).[4] The credit risk studies we build on are too numerous to be mentioned in full; the most recent examples include e.g. Illueca et al. (2008), Laeven and Levine (2009), Foos et al. (2010), Houston et al. (2010), and also Rajan and Winton (1995), Boot (2000), and Berger and Udell (2004) (a very in-depth overview of earlier studies is provided by e.g. Altman and Saunders, 1998). The remainder of the paper is structured as follows. Section 2 provides the theoretical background for our analysis. Section 3 describes the data including our proxy variables for liquidity and credit risk and presents descriptive statistics. Section 4 presents the results and Section 5 concludes.

2. Theoretical background

2.1. The reciprocal relationship between liquidity risk and credit risk

Over the past 50–60 years, a tremendous amount of literature has dealt with banks' liquidity and credit risks. Explanations for the way banks work and their major risk and return sources are given by two major research strands regarding the microeconomics of banking: the classic financial intermediation theory, most prominently represented by the Bryant (1980) and Diamond and Dybvig (1983) models and their extensions (such as Qi, 1994, or Diamond, 1997), and also by the industrial organization approach to banking, which features most prominently in the Monti–Klein model of banking organizations and subsequent related research. The models of both strands of literature suggest that, at least in theory, there is a relationship between liquidity and credit risk. The Monti–Klein framework and its extensions (e.g. Prisman et al., 1986) take borrower defaults and sudden fund withdrawals into account, both assumed to be lowering a bank's profit. Because equity, other debt funding and marketable securities are seen as given, banks maximize their profits by maximizing the spread between deposit and loan rates, given an exogenous main refinancing rate as well as stochastic borrower defaults and fund withdrawals. As liquidity risk is seen as a profit-lowering cost, a loan default increases this liquidity risk because of the lowered cash inflow and depreciations it triggers (following e.g. Dermine, 1986). At least in theory, liquidity risk and credit risk should thus be positively correlated. This assumption is supported by the theoretical financial intermediation literature, as modeled by Bryant (1980) as well as Diamond and Dybvig (1983). Extensions of these models show that risky bank assets together with uncertainty about the economy's liquidity needs spark bank runs based on pure panic (Samartín, 2003; Iyer and Puri, 2012). Based on these models, liquidity and credit risk should be positively related and contribute jointly to bank instability.

The idea of a positive relationship between liquidity and credit risk is supported by a very new body of literature which also focuses on the financial crisis of 2007/2008, such as Diamond and Rajan (2005), Acharya and Viswanathan (2011), Gorton and Metrick (2011) and He and Xiong (2012a). Diamond and Rajan's

[3] We investigate two additional risk measures as robustness checks. These are: the BB measure as developed by Berger and Bouwman (2009) for liquidity risk, and the Z-Score as a measure of overall bank stability, following Roy (1952). A detailed discussion of the measures and the results of their analyses are provided in part 4.1.4 of the paper.

[4] Most recent works on liquidity also include Gatev and Strahan (2006), Carletti et al. (2007), Nyborg and Österberg (2010), and Freixas et al. (2011). An overview over the existing bank liquidity literature is provided by Tirole (2011).

paper (2005) builds on the model developed in Diamond and Rajan (2001). It explains that if too many distressed economic projects are funded with loans the bank cannot meet the depositors' demand. If these assets deteriorate in value, more and more depositors will claim back their money. The main result is that higher credit risk accompanies higher liquidity risk through depositor demand. Acharya and Viswanathan's (2011) model is based on the assumption that financial firms raise debt which has to be rolled over constantly and which is used to finance assets. They show that more debt in the banking system yields higher "bank run" risk: in times of crisis when asset prices deteriorate, banks find it more difficult to roll over debt, i.e. they have a liquidity problem. He and Xiong (2012a), in building on Diamond and Dybvig (1983), also focus on debt rollover risk. They state that the debt maturities of lenders (e.g. investment banks) on short-term debt are spread across time and rolled over to avoid bank-run risk if all debt contracts expire at the same time. The authors derive an equilibrium in which each lender will not roll over the debt contract if the fundamental asset value falls below a certain threshold. The result is a "rat race" in which lenders are more likely to run if the asset values decrease. A different perspective on the relationship between liquidity and credit risk is provided by Gorton and Metrick (2011). Their empirical analysis shows how a bank run based on investor panic can happen in modern-day securitized banking,[5] as opposed to bank runs in traditional banking. Their evidence suggests that in the recent financial crisis perceived credit risk in the form of subprime loans caused refinancing rates and funding haircuts in the interbank market to increase substantially. The paper shows how perceived credit risk (as opposed to actual credit risk) can lead to liquidity risk in banks. Based on the assumptions and outcomes of the microeconomic models, their extensions and the latest papers discussed above, our hypotheses for the relationship between liquidity and credit risk are:

H_1. There is an interdependency between liquidity risk and credit risk.

H_2. Liquidity risk and credit risk have a positive relationship, i.e. liquidity and credit risk increase or decrease jointly.

H_1 seems uncontested and straightforward based on the presented literature. However, with regard to H_2, we also acknowledge that a very recent and still developing body of literature suggests the possibility that the relationship between liquidity and credit risk in banks might be negative, given that certain assumptions and economic features are met. This is shown by papers such as Wagner (2007), Cai and Thakor (2008), Gatev et al. (2009), Acharya et al. (2010) and Acharya and Naqvi (2012). However, these papers mostly focus on specific aspects of liquidity (such as e.g. certain assets or deposits), very specific credit risk features (such as e.g. loan commitments) or only focus on very specific economic circumstances. We believe that on a broad basis and in a data set of small and medium-sized retail banks during good economic conditions as well as in crisis, the positive relationship between liquidity and credit risk should be prevalent.

2.2. The influence of liquidity risk and credit risk on bank default probability

From a theoretical perspective, the relationship between liquidity risks and credit risks seems to be clearly established. The logical follow-up question then is: how are banks affected by this relationship in their overall risk structure? To derive a testable hypothesis for this question, we draw on the literature explaining bank defaults. After all, the ultimate risk a bank faces is the risk of going out of business. A thorough understanding of bank risk should therefore focus on bank default reasons. There is a vast body of empirical literature testing the influence a wide variety of accounting-, market- and general economic factors have on banks' PDs. Papers such as Meyer and Pfifer (1970), Martin (1977), Espahbodi (1991), Thomson (1991, 1992), Cole and Fenn (1995), Cole and Gunther (1995), and Kolari et al. (2002) show that banks' default risk is mainly driven by low capitalization, low earnings, over-exposure to certain categories of loans, and excessive loan defaults. Aubuchon and Wheelock (2010), Ng and Roychowdhury (2011), Cole and White (2012), Berger and Bouwman (in press), and DeYoung and Torna (2013) are especially relevant to our work because they focus on bank defaults during the recent financial crisis. Generally, they find that excessive investment banking activities, bad macroeconomic conditions in the banks' immediate vicinity, low equity, and heavy concentrations in commercial real estate loans substantially increased banks' PDs during the recent crisis. Interestingly, all these studies provide clear evidence that credit risk plays a vital part for the overall stability condition of a bank, but largely ignore liquidity risk. Although some studies include proxies for liquidity, they mostly focus on the CAMEL-based asset-side liquidity (i.e. the relationship of short-term to long-term assets) or the general funding liquidity (such as the ratio of short-term to long-term deposits). Maturity transformation risks are largely ignored, just as the relationship between liquidity risks and credit risks.

Deeper insight into the matter is only provided by two papers. An empirical study of Acharya and Mora (in press) explains the role of banks as liquidity providers during financial crises. In doing so, they provide evidence that failed banks during the recent financial crisis suffered from liquidity shortages just before the actual default. Apparently, distressed banks faced severe liquidity issues, especially in comparison to healthy banks. They document this by showing that failed or near-failed banks scramble for (retail) deposits by offering high CD rates in aggressive marketing campaigns. Indirectly, their results point to the fact that the joint occurrence of liquidity and credit risk might push banks into default. A more direct channel of how liquidity and credit risk can jointly cause default is theoretically shown by He and Xiong (2012b). They analyze the relationship between liquidity and credit risk from a company's wholesale funding perspective. The channel they identify which connects liquidity risk to credit risk and ultimately with default risk is debt rollover risk. The results of the paper show that investors demand higher illiquidity premia for corporate bonds due to liquidity risk in the market for corporate bonds. Upon rolling over their companies' debt in illiquid bond markets and in order to avoid default, equity holders of the issuing firms must pay for the difference between the lower liquidity premia in matured bonds and the higher illiquidity premia in newly issued bonds. As a consequence of having to absorb these losses on behalf of the debt holders, equity holders might therefore choose to default earlier. An illiquidity shock in corporate debt markets can therefore lead to higher default rates. Although the presented model encompasses corporate debt in general, they specifically relate their results to financial institutions. The findings of He and Xiong (2012b) are especially relevant in light of recent research showing that companies, especially financial institutions, are prone to very short-term debt structures (Brunnermeier and Oehmke, 2013), which increase the frequency of debt rollovers. Pairing these results with the findings of other bank default studies showing that credit risk posed a serious threat to bank stability during the recent crisis (such as e.g. Cole and White, 2012), leads us to the following hypothesis:

[5] Securitized banking is defined as bank business in which loans are packaged into special "funds" which are then sold to investors in the form of securities. The financing from these transactions does not stem from retail or corporate deposits but from the interbank repo market.

Table 1
Bank defaults in the financial crisis period by default reason.

	August–December 2007	2008	2009	January–September 2010	Total
Loan loss only	1	12	51	42	106
Liquidity loss only	–	–	1	–	1
Loan and liquidity loss	–	5	51	61	117
Fraud	–	1	2	2	5
Other	1	2	19	3	25
Total	2	20	124	108	254

The table shows the number of bank defaults in the US included in our sample since the start of the financial crisis in August 2007, until the third quarter of 2010. The default reasons have been predominantly identified using official data on bank default reasons published by bank supervisory and regulatory authorities (FDIC and OCC) in so called "Material Loss Reports". These reports are published whenever a bank default results in a "material loss" to the FDIC insurance fund. On January 1st 2010, the threshold for a "material loss" to the FDIC fund was raised from 25 million to 200 million US Dollar. The reports contain a detailed analysis of the failed banks' backgrounds and business models and list the failure reasons. For those defaults where information on the failure reasons could not be obtained through official sources, we collected indicative evidence from newspaper articles or press releases of the banks.

H_3. Liquidity risk and credit risk jointly contribute to bank default probability.

On top of the theoretical and empirical evidence presented above, we believe that anecdotal evidence on bank failures during the recent crisis might provide further intuitive support for H_3. Table 1 shows that almost half of all 254 commercial bank failures between August 2007 and September 2010 have been caused by the joint occurrence of illiquidity and loan losses. Although this number is generated using multiple different sources, such as FDIC and OCC Material Loss Reports or newspaper articles, we believe that it might be an indication that the joint occurrence of liquidity risks and credit risks might have played a role in causing bank defaults during the recent financial crisis.

3. Data and descriptive statistics

3.1. Data and sample selection

For all bank balance sheet, profit & loss account, and off-balance sheet items we use official FFIEC Call Report data on a quarterly basis, publicly obtainable through the Federal Reserve Bank of Chicago. Banks in our dataset are solely US-based and -held banks. We deliberately exclude all US-based and -chartered subsidiaries of foreign bank holding companies, as well as all thrifts and money center banks to obtain a more homogeneous bank sample in terms of ownership and governance. All banks are analyzed on the charter bank and not on the bank holding company level.[6] The required information on bank ownership and chartering is taken from the FDIC regulatory database, publicly obtainable through the FDIC website.[7] The balance sheet, profit & loss account, and off-balance sheet items for our subsample of failed banks are also derived from quarterly Call Report data, as provided by the Federal Reserve Bank of Chicago. Additional information, such as the date of failure, was obtained through the FDIC's failed banks list.[8] Note that mergers during our observation period are treated as if banks had already merged by the beginning of our observation period.[9] Further information was collected from three additional datasets. We use the official St. Louis Federal Reserve "FRED" public database for all macroeconomic data, such as GDP, savings quota or interest rates. For a regional analysis based on FDIC regions we use FDIC Quarterly Banking Reports. The reports are published quarterly and contain a large variety of data regarding the performance of all FDIC-insured banks. Table 2 provides brief descriptions of the variables used in our analyses. We also make use of Allen N. Berger's and Christa Bouwman's publicly available data set of liquidity values for US commercial banks over our observation period, downloadable from Christa Bouwman's personal website.[10] We use this data to calculate our secondary liquidity risk proxy, the BB Measure. The composition and calculation of this data set is described in Berger and Bouwman (2009). All explanatory variables are described in detail in Table 2.

3.2. Liquidity risk and credit risk proxy variables

We use two main variables to measure risk: one measure of liquidity risk, and one of credit risk. For the purposes of this paper, we call the liquidity proxy variable liquidity risk (LR); for credit risk we observe the credit risk (CR) variable. Note that in further robustness checks we also include the BB measure and the classical *Z*-score which we discuss in more detail later on. The description of each variable together with its calculation is provided in Table 3.

The liquidity risk (LR) variable is calculated by subtracting the volume of all assets which the bank can quickly and at low cost turn into cash to cover possible short-term withdrawals from the volume of liabilities which can be withdrawn from the bank on short notice. We also account for off-balance sheet liquidity risk through e.g. unused loan commitments. The LR proxy additionally accounts for a bank's risk exposure to the interbank lending market and derivative markets. The result of these factors is standardized by total assets. All included items are displayed in Table 3. The final value of the LR variable can be either positive or negative. A negative value indicates that a bank has more short-term assets than obligations; the bank can therefore cover possible short-term withdrawals on the liabilities side through liquid assets. The lower the ratio the lower the liquidity risk. By contrast, a positive value indicates that a bank would have to tap sources other than only short-term assets to cover the withdrawals of (all) short-term liabilities. This implies a very high liquidity risk in cases such as a bank run. Thus, we use LR to account for classic "bank run" risk, i.e. the risk of not being able to meet all short-term payment obligations. By observing LR we incorporate the immediate funding risks a bank might face in case of sudden liquidity withdrawals or asset deterioration.

We calculate our credit risk (CR) variable by dividing the average net loan losses (loan charge-offs minus loan recoveries) in the current year by the average loan loss allowance recorded in the previous year. Note that we do not use quarterly but annual data for its derivation as banks in most cases adjust the incorporated variables during the year leading up to the annual balance sheet recording date, a pattern also observable in our data. The measure describes a bank's economic ability to cover near-term future loan

[6] As a robustness check, we repeat all analyses using the BHC-level instead of the institutions-level. The results remain unchanged.
[7] http://www2.fdic.gov/IDASP/main.asp.
[8] http://www.fdic.gov/bank/individual/failed/banklist.html.
[9] We test our results by also excluding all merged banks from our data set. All findings remain unchanged.
[10] http://faculty.weatherhead.case.edu/bouwman/.

Table 2
Description of variables.

Variable name	Unit	Description
Ratio trading assets/total assets	%	Amount of assets held for trading purposes as reported on balance sheet divided by the amount of total assets as recorded on balance sheet
Ratio agricultural/total loans	%	Amount of agricultural loans as reported on balance sheet divided by the amount of total loans as reported on balance sheet
Ratio real estate/total loans	%	Amount of real estate loans as reported on balance sheet divided by the amount of total loans as reported on balance sheet
Total assets	Thd. USD	Total assets as reported on balance sheet
Capital ratio	%	Total (Tier 1 and Tier 2) equity divided by total assets as reported on balance sheet
Ratio short-term/long-term deposits	%	Amount of short-term deposits (transaction and demand deposits) divided by the amount of long-term deposits (savings and time deposits) as reported on balance sheet
Return on assets	%	Net income as reported on P&L divided by total assets as reported on balance sheet
Standard deviation return on assets	%	The standard deviation of a bank's return on assets over the last 8 quarters
Efficiency ratio	%	Operating expenses as reported on P&L divided by total revenues as reported on P&L
Loan growth	%	Quarterly growth of total loan volume
Net off-balance sheet derivative exposure	Thd. USD	Difference of off-balance sheet (OBS) derivatives for which the bank is beneficiary minus OBS derivatives for which bank is guarantor
Other net off-balance sheet exposure	Thd. USD	Total amount of off-balance sheet (OBS) assets minus OBS liabilities other than derivatives
Crisis dummy	0/1 Dummy	Dummy variable which is 1 in the financial crisis period, i.e. from 2007:Q3
Ratio short-term/total deposits	%	Amount of short-term deposits (transaction and demand deposits) as reported on balance sheet divided by total deposits
Leverage in the banking industry	%	Average quarterly leverage of all US commercial banks
GDP	bn. USD	Gross domestic product of the US
Gross private savings	bn. USD	Gross private savings of all US households
Savings ratio	%	Ratio of Gross Private Savings to GDP
Yield spread	%	Spread between 1-month US T-Bills and 10-year US Treasuries
Interest rate	%	Federal funds rate

The table contains descriptions of all observed and analyzed variables and ratios of the paper's analyses.

losses. Considering the numerator, it is the same as in Angbazo (1997) and closely related to Dick (2006) who uses loan write-offs for the calculation. Normalization with the loan loss allowance in the previous year should result in a proxy better suited for our analysis. Our measure does not only represent short-term credit risk, because it can be changed and/or influenced by bank management on a short-term basis, but also proxies for unexpected loan losses: if the ratio is above 1 the bank can be assumed to have unanticipated loan losses. Thus, a higher ratio implies higher credit risk. We choose this variable as our main credit risk proxy because it allows us to capture a bank's loan risk management. We are able to observe the accuracy with which loan losses are anticipated and if a bank faces immediate (asset-) risks due to heavy and unexpected loan losses.[11]

3.3. Descriptive statistics

We analyze a dataset of 4046 non-default US commercial banks over the period from 1998:Q1 until 2010:Q3. We also include 254 default banks in our sample but over the period 2006:Q1 to 2010:Q3. In all analyses which exclude default banks we use the time period 1998:Q1 to 2008:Q4; when we include default banks we use data from 2006:Q1 until 2010:Q3. We have three reasons for this. We exclude the period after 2008:Q4 in our general analyses because government interventions such as the Troubled Asset Relief Program (TARP) were introduced at the end of 2008 and could influence results on the relationship between liquidity risk and credit risk. We only include data after 2008:Q4 to be able to incorporate a sufficient number of bank defaults in our data sample. Only a very few bank defaults are observable prior to 2008. Therefore, we extend the observation period in our analyses acknowledging that government interventions may induce some impact on variables. The reason to start in 2006:Q1 when including default banks is that we only include the last 8 quarters prior to default of these banks in our analyses to observe mainly default-specific patterns. The descriptive results are shown in Table 4.

The table shows the results for non-default banks from 1998:Q1 until 2008:Q4 for the total sample as well as subdivided into small, medium and large banks. This classification uses the 25th and the 75th percentile of total assets of this sample as the threshold in each year.[12] Table 4 also shows the descriptive statistics for default banks from 2006:Q1 until 2010:Q3 and for non-default banks over the same period for comparison. The results for non-default banks from 1998:Q1 until 2008:Q4 show an average LR of about 7.3% and an average CR of about 11.1%. This implies ceteris paribus high liquidity risk but low credit risk. The LR values increase by bank size meaning that larger banks tend to have a more fragile balance sheet structure in terms of liquidity risk. The CR values are comparable across all size subsamples. Non-default banks in our dataset have an average asset size of 1.09 billion US Dollar whereas the

[11] We acknowledge that US bank supervising authorities might use these or similar ratios to measure banks' liquidity risk and credit risk. It can thus be possible that banks in our dataset merely follow the supervisors' orders and keep the ratios at the minimum levels required. A possible relationship might therefore not be caused by bank management but by regulators. As target ratios for risk measures are not disclosed by US supervisors we are unable to control for this. However, we do not believe that this poses a problem for the analyses at hand. First, empirical studies show that US banks tend to "do more" than asked for by the regulators, e.g. in terms of capital (as suggested by e.g. Flannery and Rangan, 2008, or Berger et al., 2008). A bank with a stricter risk management will thus also be safer even if the supervisor demands minimum requirements. Second and most importantly, supervisors do not call for a joint management of liquidity risk and credit risk. If all banks strictly observed the minimum supervisory boundaries for liquidity risk and credit risk separately, we would be able to determine whether or not banks additionally managed both risk sources jointly.

[12] We also apply other size subsamples in our analyses to check the robustness of our results. First, we exclude all banks which have total assets of less than 1bn. US Dollar, i.e. very small banks. Second, we split the sample based on the size of deposits using the same size clustering as in the main analysis, to account for size differences in retail-oriented banks which we mostly focus on. Third, we define the bottom 50 percentile of the banks in terms of asset size as "small" banks and run the analysis separately for this group. Regardless of the size definition the results remain unchanged.

Table 3
Bank liquidity risk and credit risk proxy variables.

Category	Proxy	Calculation	Values	Description
Liquidity risk	Liquidity risk (LR)	*[(Demand Deposits + Transaction Deposits + Brokered Deposits + NOW Accounts + Unused Loan Commitments) – (Cash + Currency & Coin + Trading Assets + Fed Funds Purchased + Commercial Paper + Securities available for Sale) ± Net Inter-Bank Lending Position ± Net Inter-Bank Acceptances ± Net Derivative Position]/ Total Assets*	Values above zero imply that the bank is cet. par. not able to endure a sudden bank run	LR shows to what degree a bank is capable of dealing with sudden and unexpected liquidity demand (e.g. a bank run). The indicator calculates to what degree a bank can cover this demand with liquid (readily available) assets. A high value indicates high liquidity risk. It is standardized by total assets
Liquidity risk	Berger–Bouwman (BB) measure	*Cat Fat/Total Assets*	High values indicate a high level of liquidity creation and in general high liquidity risk	The BB measure (as proposed by Berger and Bouwman, 2009) represents a bank's total liquidity creation. It shows the total US Dollar denominated amount of liquidity a bank creates for the economy. Liquid items held by the bank are therefore labeled illiquid as the bank extracts liquidity from the economy. The idea is that banks provide depositors with availability of their deposits and contemporaneously use deposited money to grant loans. The CatFat measure (also including OBS liquidity creation) is taken from the data publicly provided by the authors. The measure is standardized by total assets
Credit risk	Credit risk (CR)	$\frac{Loan\ Charge-offs_t - Loan\ Recoveries_t}{Loan\ Loss\ Allowance_{t-1}}$	Values above 1 indicate unexpected losses	CR is calculated using annual means of quarterly data. Dividing the net loan charge-offs by the loan loss allowance in the previous year (including the excess allowance on loans and leases) indicates to what degree a bank was expecting the current period's losses in the period before that
Bank stability risk	*Z*-score	$ln\left(\frac{Return\ on\ Assets + Capital\ Ratio}{Standard\ Dev.Return\ on\ Assets}\right)$	A lower value indicates higher riskiness	The *Z*-score (as originally proposed by Roy, 1952) is the sum of the return on assets and the ratio of total equity to total assets divided by the standard deviation of the return on assets. We use the last 8 quarters for the latter's derivation in each quarter. It is a bank risk indicator and measures a bank's distance to insolvency. Accordingly, it is inversely related to the probability of default. It is recommendable to use its natural logarithm because of its high skewness (e.g., Laeven and Levine, 2009)

The table displays descriptions and calculations of the two main proxy variables for bank liquidity risk and credit risk, as well as the additional robustness proxy variable for liquidity risk, the BB measure, and the *Z*-score as an overall indicator of bank risk.

distribution among banks is strongly skewed. Non-default banks in the period 1998:Q1 to 2008:Q4 have a return on assets of 0.724%, a standard deviation of the return on assets of 0.400%, a rather small portion of trading assets (0.04%), slightly fewer private than commercial loans, and about 10% of their total loan portfolio is invested in agricultural and over 60% in real estate loans. The return on assets, the proportion of trading assets to total assets, and the ratio of real estate and also commercial loans to total loans increase by bank size. By contrast, smaller banks grant a larger proportion of agricultural and private loans as a percentage of their total loan portfolio and are also slightly less efficient. We also observe that small- and medium-sized banks do not perform any notable off-balance sheet activities. Comparing non-default banks in 1998:Q1 to 2008:Q4 to the period 2006:Q1 to 2010:Q3 we observe that LR substantially decreased indicating less liquidity risk in the later period. This is to a large extent driven by the substantial increase of trading assets which are included in our LR measure. As trading assets are very liquid and can be disposed of quickly and at low cost, the strong increase in securities holdings results in a lower LR. In contrast, our CR measure indicates an increase of credit risk over time from 11.1% to 16.6%.

The comparison between default and non-default banks in the 2006:Q1 to 2010:Q3 period shows striking differences. Both LR and CR are considerably higher for default banks, indicating a higher overall liquidity risk and credit risk. This is to be expected and in line with the discussed literature and our anecdotal findings in Table 1. The remaining variables are also in line with general expectations. Default banks have a lower capital ratio, a negative return on assets with a substantially higher standard deviation, are less efficient, and have a negative loan growth. Furthermore, default banks are smaller and have smaller portions of private, commercial and agricultural but a much larger portion of real estate loans compared with non-default banks. Note that no default bank performs off-balance sheet activities.

4. Results

4.1. The Relationship between liquidity risk and credit risk

In this subsection we investigate the direct relationship between liquidity risk and credit risk in banks using our risk proxy variables. First, we briefly explain the methodology used in our analyses. This is followed by an analysis of the general relationship between liquidity risk and credit risk. Finally, we examine the relationship subdividing banks in terms of risk.

4.1.1. Methodology

We first observe the relationship between liquidity and credit risk using our proxy variables LR and CR. This analysis addresses the problem that the direction of influence is not clear ex ante. To account for possible reciprocal or lagged relationships between

Table 4
Descriptive statistics.

	Small banks	Medium banks	Large banks	Total	Non-default banks 2006:Q1–2010:Q3	Default banks 2006:Q1–2010:Q3
					Total	Total
Number of observations	44,506	89,012	44,506	178,024	76,874	2032
Number of banks	1011	2024	1011	4046	4046	254
Liquidity risk (LR)	5.6737%	6.0584%	11.3501%	7.285%	−0.622%	4.426%
	(0.206)	(0.199)	(1.402)	(0.723)	(0.514)	(0.289)
Credit risk (CR)	10.163%	11.184%	11.893%	11.106%	16.594%	92.698%
	(0.825)	(0.241)	(0.264)	(0.465)	(0.324)	(1.037)
BB liquidity measure	71.678%	41.523%	38.712%	48.364%	50.700%	42.014%
	(5.833)	(3.457)	(1.060)	(3.845)	(4.251)	(0.403)
Z-score	3.548	3.414	3.359	3.434	3.431	2.234
	(0.536)	(0.442)	(0.409)	(0.465)	(0.584)	(1.390)
Adjusted *Z*-score	3.826	3.717	3.673	3.733	3.742	2.961
	(0.396)	(0.322)	(0.409)	(0.342)	(0.407)	(0.629)
Total assets	28,691	104,341	4,113,788	1,087,790	1,842,543	884,120
	(11,324)	(49,187)	(45,800,000)	(22,900,000)	(37,700,000)	(2,261,911)
Capital ratio	12.020%	10.702%	9.844%	10.817%	10.965%	7.142%
	(0.041)	(0.033)	(0.029)	(0.035)	(0.035)	(0.041)
Return on assets	0.668%	0.741%	0.745%	0.724%	0.553%	−1.780%
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.032)
Standard deviation return on assets	0.402%	0.403%	0.391%	0.400%	0.423%	1.187%
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.012)
Efficiency ratio	41.492%	40.424%	40.552%	40.723%	41.897%	60.680%
	(0.062)	(0.054)	(0.058)	(0.057)	(0.072)	(0.200)
Loan growth	1.385%	1.793%	2.444%	1.854%	1.253%	−0.733%
	(0.072)	(0.054)	(0.060)	(0.060)	(0.061)	(0.089)
Ratio trading assets/total assets	0.005%	0.014%	0.138%	0.043%	7.423%	5.019%
	(0.003)	(0.004)	(0.014)	(0.008)	(0.132)	(0.074)
Ratio private/total loans	14.290%	12.125%	9.716%	12.064%	8.965%	2.172%
	(0.108)	(0.102)	(0.117)	(0.109)	(0.095)	(0.029)
Ratio commercial/total loans	14.118%	14.712%	15.531%	14.768%	13.862%	12.859%
	(0.090)	(0.099)	(0.115)	(0.101)	(0.095)	(0.108)
Ratio agricultural/total loans	20.447%	9.038%	2.389%	10.225%	9.194%	1.658%
	(0.184)	(0.127)	(0.055)	(0.147)	(0.137)	(0.068)
Ratio real estate/total loans	49.651%	62.605%	69.726%	61.149%	66.114%	82.263%
	(0.193)	(0.181)	(0.190)	(0.200)	(0.196)	(0.141)
Ratio short-term/long-term deposits	72.179%	79.772%	58.406%	72.532%	55.152%	15.494%
	(5.727)	(16.061)	(16.934)	(14.456)	(7.173)	(0.164)
Net off-balance sheet derivative exposure	0	0	−137,038	−34,260	−71,081	0
	(0)	(46)	(7,714,435)	(3,857,642)	(5,599,300)	(0)
Other net off-balance sheet exposure	−26	−159	−51,621	−12,991	−34,380	−468
	(420)	(1441)	(1,803,737)	(902,138)	(1,762,250)	(4103)

The table provides a descriptive overview of the data. We report the results for the liquidity risk and credit risk indicators explained in Table 3 as well as further variables, described in Table 2 and used in subsequent analyses. The "adjusted *Z*-score" is calculated by adding a ten to the ratio before logarithmizing it. All variables are shown for the non-default sample in total and split by size ("Small", "Medium" and "Large") employing the 25th and 75th percentile of total assets as threshold in each year. Additionally, the descriptive statistics for the sample of defaulted banks are provided. The standard deviation is shown in parentheses below each variable. For non-default banks we report values for the period 1998:Q1 to 2008:Q4, split by bank size and for the total period. We show the data for default banks in the last 8 quarters prior to default in the time period from 2006:Q1 until 2010:Q3 together with the results for non-default banks over the same period for comparison.

the variables, we employ a structural equations approach where a system of equations is estimated via generalized least squares:

$$\begin{aligned} CR_{i,t} &= \sum_{\tau=0}^{\max,3} LR_{i,t-\tau} + \sum_{\tau=1}^{4} CR_{i,t-\tau} + Control\ Variables_{i,t} \\ LR_{i,t} &= \sum_{\tau=0}^{\max,3} CR_{i,t-\tau} + \sum_{\tau=1}^{4} LR_{i,t-\tau} + Control\ Variables_{i,t} \end{aligned} \quad (1)$$

The equations are estimated simultaneously controlling for the possible endogeneity of the respective independent risk variable in a three stage least squares approach. This allows us to account for both a contemporaneous and a possible time-lagged effect of the independent variable to comprehensively observe its influence on the dependent variable. Furthermore, we are able to address a possible autocorrelation of the dependent variable and also include lagged values of the latter. The appropriateness of a maximum lag length of 4 quarters is confirmed employing the Schwert (1989) and the Ng and Perron (2000) criteria. The test for a unit root of the relevant dependent variable is rejected in a Dickey Fuller GLS test as proposed by Elliott et al. (1996). In addition, control variables accounting for the bank's general health, structure, and interest rate environment are included. These are the log of total assets, the capital ratio, the return on assets, the standard deviation of the return on assets, the efficiency ratio, bank loan growth, the ratio of short-term to long-term deposits, the ratio of trading assets to total assets, the net derivatives exposure, other off-balance sheet items, real estate to total loans, agricultural to total loans, commercial to total loans, individual to total loans, the log of GDP in bn. USD, the savings ratio, the federal funds rate, the yield spread, the quarterly average leverage in the banking industry as well as a time trend and annual time fixed effects.[13] Jointly, these variables have been well established by the body of literature on bank risk and bank stability, such as e.g. Cole and Gunther (1995), Acharya and Viswanathan (2011), Beltratti and Stulz (2012), Cole and White (2012), He and Xiong (2012b), and Berger and Bouwman (in press) for the

[13] Note that all control variables are included with their contemporaneous values. We also test the model using lagged values of the control variables. However, doing so only decreases their significance.

accounting-based variables, and Thomson (1992) and Aubuchon and Wheelock (2010) for the regional macroeconomic variables. In including the interest rate variables and yield curve spreads we follow Bernanke and Gertler (1995) and Bernanke et al. (1999). While the included time trend captures a possible long-term adjustment of a variable due to, for example, a change in the banking business environment or risk management practices, the time fixed effects account for features distinct to specific years.

To calculate the total effect of the independent risk variable on the respective dependent risk variable we sum up the coefficients of the former and divide this by the within-firm standard deviation of the dependent variable. We are thereby able to investigate the average change in the number of standard deviations of the dependent variable when the independent variable changes by one percentage point. Note that it is important to employ the within-firm standard deviation as values could vary substantially across banks while changing much less within one bank. In addition to our simultaneous equations approach we include another robustness check in terms of methodology: we distinguish between possible contemporaneous and lagged relationships. As the direction of influence is not clear we also include correlation analyses for the contemporaneous relationship between liquidity risk and credit risk within a bank. With regard to a possible lagged relationship we analyze both risks in a panel vector autoregressive (panel VAR) model which also controls for a possible autocorrelation of variables using the algorithm provided by Love and Zicchino (2006). Here, we incorporate the same control variables as in our simultaneous equations approach accounting again for the bank's general health, structure, and interest rate environment. Note that for reasons of brevity we only briefly discuss but do not present the panel VAR results in the following.

4.1.2. The general relationship between liquidity and credit risk

We first investigate our sample of non-default banks in the period 1998:Q1 to 2008:Q4. We split this time period into the pre-financial crisis period 1998:Q1 to 2007:Q2 and the financial crisis period 2007:Q3 to 2008:Q4. This allows us to account for a possible substantial and nonlinear shock. We also subdivide banks by size.[14] In this first part of our analysis we test the first two hypotheses, as postulated in part 2 of the paper.

The results are reported in Table 5. For the pre-financial crisis period, the results show some statistically significant reciprocal relationships between LR and CR. However, even though the estimation model produces statistically significant coefficients for most of the coefficients of the variables, two things are of special interest here: first, we do not detect any kind of striking or prevailing pattern in the direction or strength of the reciprocal influence the variables have on each other. From a statistical point of view, there are no singular variables or combinations thereof which might reveal any kind of clear-cut relationship between the two variables, neither within a certain subsample nor across all banks. Second, we see that the actual economic impact of the relationship is negligible. The largest overall change in the number of standard deviations of the dependent variable induced by a one percentage point change in the independent variable is 0.0471 in absolute value (found in the total pre-financial crisis sample employing only the contemporaneous variable of LR). The values for the subsamples and model specifications for which we find the statistically most meaningful relationship between the variables, such as e.g. the model employing all four lags of the independent variable (CR) in the small and large bank subsamples, are even smaller with 0.0016 and 0.0049 in absolute values. These values are too small to indicate an economically meaningful relationship between LR and CR. Furthermore, even the sign of the effect alternates. These findings are supported when we observe the results for the financial crisis period. Although some coefficients are statistically significant, the economic relevance is negligible. Also, none of the coefficients in the model specifications testing the influence CR (as an independent variable) has on LR (as the dependent variable) are statistically meaningful. On the right hand side of Table 5 we also show the results for the correlation analysis. The correlation coefficients indicate a negative relationship in the crisis period which, however, is economically not meaningful. Overall, the results on the general relationship between liquidity risk and credit risk do not indicate any considerable co-movement. This means that the first part of our empirical analysis cannot confirm any of our postulated hypotheses.

4.1.3. The relationship between liquidity risk and credit risk by degree of bank risk

In this section we divide the sample according to a bank's riskiness relative to all banks in our sample. Why might banks of different riskiness behave differently in terms of risk? A bank with a high loan charge-off rate has a higher credit risk than another bank with few charge-offs. Risk officers might be aware of the higher credit risk and thus keep liquidity risk low, i.e. liquid assets high, so that the total level of bank default risk does not increase too much. In contrast, risk officers in banks with low credit risk do not necessarily have to manage both factors jointly because overall risk is limited. A higher level of liquidity risk might even be desired by bank management to generate higher profits as the risk of bankruptcy would still be within reason. The relationship between both risks in low (liquidity or credit) risk banks should be either significantly positive or insignificant. We again subdivide banks by their size and additionally group banks in subsamples by their (liquidity or credit) risk using the 25th and the 75th percentile in the respective risk category. We furthermore divide the analysis of these subsamples by economically different risk periods. Here, we use the pre-financial crisis period 1998:Q1 to 2007:Q2 and the financial crisis period 2007:Q3 to 2008:Q4. In addition, we incorporate our sample of default banks in the period 2006:Q1 to 2010:Q3 and again use data in the last 8 quarters prior to their default. To investigate the relationship between liquidity risk and credit risk we use our structural estimation approach incorporating only the contemporaneous independent risk variable, for brevity, together with the same control variables as in the previous section. In addition to the coefficient of the contemporaneous other risk variable, we again report the change in the number of standard deviations of the dependent variable when the independent risk variable changes by 1 percentage point. We also show the respective value for LR and CR for each subsample in parentheses. Table 6 presents the results.

Panel A in Table 6 shows the results for our bank subsamples in the pre-financial crisis period 1998:Q1 to 2007:Q2. The comparison of the values for our measures of CR and LR shows that banks with higher credit risk also have marginally higher liquidity risk (6.65% versus 10.42% LR across all banks). In contrast, different levels of liquidity risk do not seem to induce substantial differences in credit risk (10.62% versus of 10.71% CR across all banks). These descriptive results are supported in our simultaneous equations regression models. Some coefficients reveal statistical significances but their economic relevance is negligible, just as our results in Table 5. The results are similar in our correlation and panel VAR analyses not shown here for brevity. Panel B in Table 6 shows the results for banks subdivided by their relative riskiness in the financial crisis period 2007:Q3 to 2008:Q4. Comparing Panels A and B, we observe that credit risk is at the same level for low credit risk banks (−3.21% versus −2.77%) while being substantially higher

[14] As already mentioned before, we repeat all analyses using further different definitions of bank size. All results remain unchanged regardless of size clustering.

Table 5
The relationship between liquidity risk and credit risk.

	Regression analysis – simultaneous equations											Correlation	
	Pre-Financial Crisis				Financial Crisis		Pre-Financial Crisis				Financial Crisis	Pre-Fin. Crisis	Financial Crisis
CR – ALL BANKS						LR – ALL BANKS							
LR (t)	0.0062***	0.0090	−0.0194	0.0321	0.0080***	CR (t)	−0.0026**	−0.0009	0.1605	−1.8227*	0.0006	0.0061	−0.0306***
LR (t − 1)		−0.0028	0.0154	−0.0292		CR (t − 1)		−0.0014	−0.1404	1.5214*			
LR (t − 2)			0.0095**	0.0170***		CR (t − 2)			0.0047***	−0.0336*		Δ St. Dev.s of CR	
LR (t − 3)				−0.0128***		CR (t − 3)				0.0266**		0.0005	−0.0036
Total Effect	0.0062	0.0062	0.0055	0.0071	0.0080	Total Effect	−0.0026	−0.0023	0.0249	−0.3083	0.0006	Δ St. Dev.s of LR	
Change in # of within-firm St. Dev.s of CR	0.0471	0.0005	0.0004	0.0005	0.0009	Change in # of within-firm St. Dev.s of LR	−0.0003	−0.0003	0.0030	−0.0366	0.0001	0.0007	−0.0075
CR – SMALL BANKS						LR – SMALL BANKS							
LR (t)	0.0120**	−0.2263***	−0.2475**	−0.3123	0.0066	CR (t)	−0.0022***	−0.0292*	−0.0339**	−0.1032***	−0.0002	0.0124	0.0008
LR (t − 1)		0.2307***	0.2445***	0.2915**		CR (t − 1)		0.0247*	0.0281*	0.0879***			
LR (t − 2)			0.0069	0.0098		CR (t − 2)			0.0009	−0.0042***		Δ St. Dev.s of CR	
LR (t − 3)				0.0134		CR (t − 3)				0.0069***		0.0007	0.0001
Total Effect	0.0120	0.0044	0.0039	0.0024	0.0066	Total Effect	−0.0022	−0.0045	−0.0049	−0.0126	−0.0002	Δ St. Dev.s of LR	
Change in # of within-firm St. Dev.s of CR	0.0007	0.0002	0.0002	0.0001	0.0007	Change in # of within-firm St. Dev.s of LR	−0.0003	−0.0006	−0.0006	−0.0016	0.0000	0.0016	0.0002
CR – MEDIUM BANKS						LR – MEDIUM BANKS							
LR (t)	0.0116***	0.0736	0.0420	−0.0806	0.0142**	CR (t)	−0.0030***	0.0210***	0.0187**	0.0105	−0.0007	0.0143*	−0.0246*
LR (t − 1)		−0.0603	−0.0365	0.0591		CR (t − 1)		−0.0193***	−0.0168**	−0.0099			
LR (t − 2)			0.0071	0.0162		CR (t − 2)			−0.0008	0.0001		Δ St. Dev.s of CR	
LR (t − 3)				0.0154		CR (t − 3)				−0.0020		0.0011	−0.0031
Total Effect	0.0116	0.0133	0.0126	0.0101	0.0142	Total Effect	−0.0030	0.0017	0.0011	−0.0013	−0.0007	Δ St. Dev.s of LR	
Change in # of within-firm St. Dev.s of CR	0.0009	0.0011	0.0010	0.0008	0.0018	Change in # of within-firm St. Dev.s of LR	−0.0004	0.0002	0.0001	−0.0002	−0.0002	0.0018	−0.0064
CR – LARGE BANKS						LR – LARGE BANKS							
LR (t)	−0.0011*	0.0142	−0.0153	0.0337	−0.0063**	CR (t)	0.0004	−0.0112	0.0453	0.1251***	−0.0029	−0.0159	−0.0726***
LR (t − 1)		−0.0149	0.0010	−0.0424*		CR (t − 1)		0.0083	−0.0644**	−0.1212***			
LR (t − 2)			0.0126***	0.0222***		CR (t − 2)			0.0384***	0.0022		Δ St. Dev.s of CR	
LR (t − 3)				−0.0136***		CR (t − 3)				0.0444***		−0.0017	−0.0076
Total Effect	−0.0011	−0.0007	−0.0017	−0.0001	−0.0063	Total Effect	0.0004	−0.0029	0.0193	0.0505	−0.0029	Δ St. Dev.s of LR	
Change in # of within-firm St. Dev.s of CR	−0.0001	−0.0001	−0.0002	0.0000	−0.0007	Change in # of within-firm St. Dev.s of LR	0.0000	−0.0003	0.0019	0.0049	−0.0007	−0.0015	−0.0180

The table shows results of quarterly data from 1998:Q1 to 2008:Q4, subdivided into a pre-financial crisis period and the financial crisis period starting in 2007:Q3. We report the results of a regression analysis which estimates a system of structural equations (simultaneous equations) via three-stage least squares, separated into the pre-financial crisis and the financial crisis period. Further control variables are (not shown in the table): the first four lags of the dependent variable, the log of total assets, the capital ratio, the return on assets, the standard deviation of the return on assets, the efficiency ratio, bank loan growth, the ratio of short-term to long-term deposits, the ratio of trading assets to total assets, the net derivatives exposure, other off-balance sheet items, real estate to total loans, agricultural to total loans, commercial to total loans, individual to total loans, the log of GDP in bn. USD, the savings ratio, the federal funds rate, the yield spread, the quarterly average leverage in the banking industry, and a time trend. All regressions control for annual time fixed effects. On the right hand side of the table we report the mean of within-firm correlations of variables with significances determined via a Wilcoxon signed rank test. The change in the number of standard deviations is calculated using the total effect on the variable divided by its within-firm standard deviation in percent.

* The statistical significance of results is indicated at the 10%-level.
** The statistical significance of results is indicated at the 5%-level.
*** The statistical significance of results is indicated at the 1%-level.

Table 6
The relationship between liquidity risk and credit risk by bank risk.

		Bank Size			
		Small	Medium	Large	Total
Panel A: Risky banks in the pre-crisis period (1998:Q1–2007:Q2)					
Lower credit risk	Effect on LR	0.021***	0.043***	−0.057	0.001
	St. Dev.s Change of LR	0.0026	0.0050	−0.0040	0.0002
	(CR; LR)	(−3.87; 4.51)	(−3.07; 4.79)	(−2.24; 15.88)	(−3.21; 6.65)
Higher credit risk	Effect on LR	−0.003***	−0.002*	0.027**	0.001
	St. Dev.s change of LR	−0.0003	−0.0003	0.0025	0.0001
	(CR; LR)	(41.94; 7.01)	(33.66; 5.6)	(30.81; 23.03)	(34.80; 10.42)
Lower liquidity risk	Effect on CR	0.046***	0.009	0.023	0.020**
	St. Dev.s change of CR	0.0030	0.0005	0.0019	0.0013
	(CR; LR)	(11.97; −20.23)	(10.38; −18.73)	(9.59; −19.22)	(10.62; −19.25)
Higher liquidity risk	Effect on CR	−0.062**	0.028**	−0.002***	0.003***
	St. Dev.s change of CR	−0.0036	0.0022	−0.0002	0.0002
	(CR; LR)	(9.96; 29.06)	(10.37; 29.31)	(12.43; 58.41)	(10.71; 35.75)
Panel B: Risky banks in the financial crisis period (2007:Q3–2008:Q4)					
Lower credit risk	Effect on LR	−0.007	−0.004	−0.079	−0.006
	St. Dev.s Change of LR	−0.0013	−0.0008	−0.0171	−0.0013
	(CR; LR)	(−3.80; 5.61)	(−2.42; 5.26)	(−0.86; 2.27)	(−2.77; 5.01)
Higher credit risk	Effect on LR	0.000	−0.005	−0.003	−0.001
	St. Dev.s Change of LR	−0.0001	−0.0013	−0.0006	−0.0002
	(CR; LR)	(50.70; 7.47)	(41.94; 8.93)	(48.47; 19.85)	(45.60; 12.23)
Lower liquidity risk	Effect on CR	0.104**	0.041*	−0.040	0.020
	St. Dev.s Change of CR	0.0123	0.0054	−08.0048	0.0025
	(CR; LR)	(10.33; −18.34)	(11.73; −17.52)	(17.44; −17.05)	(12.88; −17.61)
Higher liquidity risk	Effect on CR	0.002	−0.052**	−0.002	0.010***
	St. Dev.s Change of CR	0.0002	−0.0064	−0.0002	0.0011
	(CR; LR)	(9.65; 29.51)	(14.14; 29.36)	(22.67; 53.22)	(14.4; 33.79)
Panel C: Defaulted banks 2 years prior to default (2006:Q1–2010:Q3)					
No default	Effect on LR	0.004**	0.004***	−0.009**	−0.002*
	St. Dev.s change of LR	0.0003	0.0003	−0.0005	−0.0002
	(CR; LR)	(11.04; 1.2)	(14.73; 1.81)	(20.05; 3.92)	(15.05; 2.16)
Default	Effect on LR	−0.003	0.005	−0.030***	−0.008
	St. Dev.s change of LR	−0.0002	0.0003	−0.0020	−0.0007
	(CR; LR)	(115.11; 6.61)	(89.93; 5.71)	(90.87; 3.01)	(92.7; 4.49)
No default	Effect on CR	0.023***	0.019***	0.022***	0.022***
	St. Dev.s change of CR	0.0014	0.0012	0.0012	0.0013
	(CR; LR)	(11.04; 1.2)	(14.73; 1.81)	(20.05; 3.92)	(15.05; 2.16)
Default	Effect on CR	2.098	0.135	0.038	0.016
	St. Dev.s change of CR	0.0277	0.0024	0.0007	0.0003
	(CR; LR)	(115.11; 6.61)	(89.93; 5.71)	(90.87; 3.01)	(92.7; 4.49)

The table shows results of quarterly data employing the variables defined in Tables 2 and 3 with LR and CR as the proxy for liquidity risk and credit risk, respectively. It shows the regression results estimating a system of structural equations (simultaneous equations) via three-stage least squares including further control variables not shown in the table. The "Effect on variable X" shows the regression coefficient of the other relevant contemporaneous variable on variable X in the simultaneous equations regression. All regressions include only one contemporaneous independent variable. The change in the number of standard deviations is calculated using the respective effect on the variable divided by the variable's within-firm standard deviation in percent. Furthermore, we report the respective values of CR and LR in % in parentheses. Banks are assigned a high (low) level of credit risk if they are in the upper 75th (lower 25th) percentile of CR and a high (low) level of liquidity risk if they are in the upper 75th (lower 25th) percentile of LR, subdivided by the pre-crisis (Panel A) and the crisis (Panel B) period. The bank size is determined using the 25th and the 75th percentile of total assets of all non-default banks in each year. Panel A includes the time period 1998:Q1 to 2007:Q2, Panel B the period from 2007:Q3 to 2008:Q4, and Panel C contains data from 2006:Q1 to 2010:Q3. Panel C incorporates 254 bank defaults where we use quarterly data of the two years prior to default for default banks. The control variables in the regressions not shown in the table are the first four lags of the dependent variable, the log of total assets, the capital ratio, the return on assets, the standard deviation of the return on assets, the efficiency ratio, bank loan growth, the ratio of short-term to long-term deposits, the ratio of trading assets to total assets, the net derivatives exposure, other off-balance sheet items, real estate to total loans, agricultural to total loans, commercial to total loans, individual to total loans, the log of GDP in bn. USD, the savings ratio, the federal funds rate, the yield spread, the quarterly average leverage in the banking industry, and a time trend. All regressions control for annual time fixed effects.
* The statistical significance of coefficients is indicated at the 10%-level.
** The statistical significance of coefficients is indicated at the 5%-level.
*** The statistical significance of coefficients is indicated at the 1%-level.

for high credit risk banks (34.80% versus 45.60%). We do not find any considerable differences in liquidity risk between both time periods and liquidity risk categories. In some instances liquidity risk even decreased in the financial crisis period. However, the coefficients of LR and CR in our simultaneous equations models in Panel B reveal even fewer statistical significances compared to the pre-financial crisis period. Again, the values are economically negligible. Panel C in Table 6 shows the results for non-default and for default banks in the time period 2006:Q1 to 2010:Q3. A comparison of the values for LR and CR reveals substantial differences in each bank size subsample. In all cases, credit risk is much larger for default banks, and liquidity risk is slightly larger for small and medium sized banks. The coefficients of LR and CR in our simultaneous equations model show some statistical significances for non-default banks and almost no statistically significant relationship for our sample of default banks. The only exception is large default banks for which we find statistically significant coefficients which suggest a negative influence of CR on LR. However, the economic impact is only marginal, which is why we do not interpret this result as an indication for any kind of meaningful relationship between the variables. Again, all results are supported in the unreported correlation and panel VAR analyses.

Overall, the results in this subsection indicate that regardless of the granularity of risk category, time period and bank size, liquidity risk and credit risk have no economically meaningful relation. This means that neither our original hypotheses H_1 and H_2, nor our alternative explanation for the relationship of liquidity and credit risk in banks with different degrees of riskiness are confirmed by our empirical findings.

4.1.4. The relationship between liquidity risk and credit risk – robustness tests

In addition to our analyses by bank size, time period, and different levels of bank risk we investigate the result of no meaningful relationship between liquidity risk and credit risk in further robustness tests not displayed for brevity. First, we replace our original main variables CR and LR with two proxy variables for liquidity risk and overall bank stability: the so called "BB measure" and the classic *Z*-score, explained in Table 3. The BB measure was developed by Berger and Bouwman (2009) to represent the absolute amount of liquidity a bank creates for the economy on both its balance sheet and through off-balance sheet business. We use the calculated liquidity values in US Dollar (called "CatFat" in Berger and Bouwman, 2009) normalized by a bank's total assets as our secondary liquidity measure. The notion behind this ratio is built on the seminal research of Bryant (1980) and Diamond and Dybvig (1983), modeling banks as pools of liquidity which provide long-term availability of cash to borrowers and short-term availability of cash to depositors. A higher amount of this maturity transformation is associated with a higher liquidity risk for the bank.

The *Z*-score is used as a measure of overall bank risk. Following the literature, we calculate the *Z*-score as the ratio of the sum of the return on assets (RoA) and the capital ratio, divided by the standard deviation of the return on assets. For the derivation of the standard deviation of the RoA we use the previous eight quarters of a bank's RoA. The capital ratio is calculated as the ratio of total equity to total assets. The *Z*-score measures the number of standard deviations a bank's return on assets has to decrease from its expected value before the bank is insolvent because equity is depleted (Roy, 1952). Accordingly, a high *Z*-score indicates low bank risk. As the regular score is highly skewed we apply the natural logarithm to the *Z*-score following Laeven and Levine (2009) and Houston et al. (2010). Furthermore, in some analyses which incorporate defaulted banks we use an adjusted *Z*-score, adding a constant of 10 to the ratio before logarithmizing it. The reason is that otherwise negative values for banks prior to default could not be analyzed, reducing the information set only due to technicalities.[15] We use these two measures in a robustness test for our results generated through the simultaneous equations regression. We re-run the original estimation procedure as discussed in part 4.1.1 and presented in Table 5, only replacing the main risk proxy variables CR and LR with the BB measure and the *Z*-score. The results are not reported for reasons of brevity. We see our original results as presented in Table 5 supported. We detect no clear patterns of reciprocal relationships between variables which are statistically or economically meaningful. Our original results are therefore supported.

In an additional robustness check we account for the geographical differences in the US banking landscape by making use of the regional zoning of the Federal Deposits Insurance Corporation (FDIC). We divide our sample by the FDIC region the bank is located in to additionally control for bank location. For all regions, we construct subsamples by bank asset size and (financial crisis) time period. We find the results of our previous analyses confirmed: although some coefficients for LR and CR are statistically significant in the simultaneous equations models, they are too small for an economically meaningful relationship between liquidity risk and credit risk. We furthermore control for two important factors which could influence bank risk management: interest rate volatility and a varying level of bank profits. In times of heightened interest rate volatility, banks might suffer from market-induced interest rate shocks distorting their "regular" risk management of liquidity risk and credit risk. To account for this, we exclude volatile interest rate environments from our observation period. We use the period from 2003:Q3 to 2004:Q2 for low and stable interest rates and the period 2006:Q3 to 2007:Q2 for a period of high and stable interest rates.[16] Furthermore, we account for varying levels of bank profits. The reason is that banks with different levels of available funds over time might manage risks differently. We therefore examine only banks with stable earnings as we expect these to have a more consistent risk management. For this, we exclude all banks with a standard deviation of the return on assets above the 25th percentile range of each bank size group and the total sample in each of our stable interest rate periods. All tests support our results of no economically meaningful relationship between LR and CR.

4.2. The impact of liquidity risk and credit risk on bank defaults

To examine the importance of liquidity and credit risk for banks we ask whether and, if so, how both risks predict default rates. Moreover, do both risks jointly have an impact on banks' default probability? The lack of an economically meaningful relationship between the two risk types we find in our prior analyses might be an indication of a lack of joint management of these risks in banks. If this were true, we should find that a joint (unmanaged) increase in liquidity risk and credit risk contributes strongly to banks' default probability, as stated in our hypothesis H_3. Next to the results regarding the co-movement of both variables presented above, we believe there are two main theoretical reasons supporting this assumption. First, the body of literature on liquidity risk as well as the body of literature on credit risk as presented in part 2 of the paper have both established that each risk category separately has strong implications for banks' PD. Second, the currently evolving body of literature analyzing the relationship between liquidity risks and credit risks in financial institutions, also presented in part 2, strongly suggests that the reciprocal relationship between the two risk categories has strong implications for overall bank stability, too. An additional supportive factor might be the anecdotal evidence presented in Table 1. It suggests that the joint occurrence of liquidity problems and too high credit risks was among the main default reasons for banks during the recent financial crisis. From a hypothetical perspective, we therefore have strong reasons to test whether or not liquidity and credit risks separately but also jointly have a strong influence on banks' PD.

To test this in an empirical setting we run a multivariate logistic regression model using a sample of default and non-default banks in the period 2006:Q1 to 2010:Q3. Each regression uses an indicator variable as dependent variable which is 1 in the default quarter and zero otherwise. In the regressions, all independent variables are lagged by one quarter to enable us to test our hypothesis H_3 that liquidity risk and credit risk jointly contribute to bank PD. We control for bank characteristics and include the log of total assets, the capital ratio, the return on assets, the standard deviation of the return on assets, the efficiency ratio, bank loan growth, the ratio of trading assets to total assets, the ratio of short-term to long-term deposits, real estate to total loans, agricultural to total loans, commercial to total loans and individual to total loans. We furthermore control for macroeconomic influences using the log of GDP and the savings ratio, and for monetary policy incorporating

[15] We also repeat all analyses which include the adjusted Z-score with the unadjusted, regular, Z-score. All findings remain robust.

[16] The federal funds rate was at 1% from 2003:Q3 to 2004:Q2. In 2006:Q3 and 2006:Q4 it was at 5.2%, and at 5.3% in 2007:Q1 and 2007:Q2.

[17] We use the GDP and savings ratio of the state in which the bank is located in, weighted by the bank's deposits in each state if it operates in multiple states. As a robustness check, we also use country-level GDP and savings ratios. The results remain unchanged.

Table 7
The impact of liquidity risk and credit risk on bank default probability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CR	2.1158***		2.1490***	1.2017***		0.6024***	0.6554***	0.6801***	0.7577***	0.6554***
LR		1.5100***	2.1626**		4.1499***	2.7657***	2.6925***	2.4843***	2.4149***	2.6925**
CR * LR			−0.0672***				−0.0723***	−0.0697***	−0.0730***	−0.0723***
log(Assets)				0.1735	0.0967	0.1050	0.0995	0.1228		0.0995
Capital ratio				−74.0580***	−141.7423***	−91.8352***	−91.6822***	−90.1090***	−124.0115***	−91.6822***
Return on assets (RoA)				−17.1258*	−66.8141***	−42.9991***	−40.5738***	−39.1823***	−38.7935***	−40.5738**
Standard deviation RoA				32.2035*	46.7184***	33.9768**	33.2391**	31.8779**	30.6376*	33.2391***
Efficiency ratio				−0.0012	−0.0022	−0.0015	−0.0013	−0.0012		−0.0013
Loan growth				−5.7484**	−12.3225***	−9.0978***	−8.2982***	−8.1877***	−6.3278***	−8.2982***
Trading assets/total assets				−3.2839**	3.5154*	1.8865	2.1145			2.1145
Short-term/long-term deposits				−0.0192***	−0.1193***	−0.0814***	−0.0837***	−0.0770***	−0.0749***	−0.0837***
Fraction real estate loans				5.3963	9.9493**	6.4597	6.3940	6.2189		6.3940*
Fraction agricultural loans				0.3100	6.8923	3.3762	3.2587	3.0966		3.2587
Fraction commercial loans				2.6685	7.9441*	4.4907	4.6170	4.4068		4.6170
Fraction individual loans				−6.1024	−71.1602***	−48.2160***	−49.8591***	−45.5226***	−50.6224***	−49.8591**
log(GDP in bn. USD)				−1.5484	−8.8776	−5.3738	−7.2389	−6.7385		−7.2389
Savings ratio				93.7508***	200.4552***	141.7323***	137.5782***	133.4052***	130.7370***	137.5782***
Interest rate				−6.0950***	−15.2433***	−10.0139***	−12.0115***	−11.2182***	−10.6048***	−12.0115***
Yield curve				−0.6394**	−1.5931***	−1.0854**	−1.1996**	−1.1475**	−1.0025***	−1.1996**
Leverage in the banking industry				158.2597**	285.8776***	212.1700***	203.8396***	199.1852***	209.3999***	203.8396**
Constant	3.7828***	−5.7091***	3.9352***	−136.5803	−196.2858	−154.2701	−127.6505	−127.9436	−193.2442***	−127.6505
Defaults	205	205	205	205	205	205	205	205	205	205
Obs.	75,582	75,989	75,582	75,582	75,639	75,582	75,582	75,582	75,582	75,582
R-squared	48.78%	26.02%	59.12%	67.68%	69.83%	70.74%	70.98%	70.91%	70.35%	70.98%

The table reports results from logit regressions of bankruptcy indicators on predictor variables. The data are constructed so that the predictor variables are observable prior to the quarter when default occurs. The regressions include data from 2006:Q1 to 2010:Q3. The variables are defined as in Tables 2 and 3. The "adjusted *Z*-score" is calculated by adding a ten to the ratio before logarithmizing it. Standard errors in models (1) to (9) are clustered at the bank level, following e.g. DeYoung and Torna (2013). Model (10) shows significances derived from bootstrapped standard errors using 100 replications.

* The statistical significance of results is indicated at the 10%-level.

** The statistical significance of results is indicated at the 5%-level.

*** The statistical significance of results is indicated at the 1%-level.

the interest rate and the yield curve spread.[17] To control for the overall risk in the banking sector we include the total average leverage in the banking industry. The compilation of these control variables is based on prior literature analyzing determinants of bank default- and stability risk. The accounting-based control variables are based on e.g. Cole and Gunther (1995), Cole and White (2012), Beltratti and Stulz (2012), He and Xiong (2012b), and Berger and Bouwman (in press). The macroeconomic variables are based on Aubuchon and Wheelock (2010) and Thomson (1992), the bank industry-wide risk predictor stems from Acharya and Viswanathan (2011), including the interest rates and yield curve spreads is based on Bernanke and Gertler (1995) and Bernanke et al. (1999). Jointly, these variables control for bank default determinants other than credit and liquidity risk. As can be seen in Table 7, we run the model in 10 different settings, using both full and parsimonious specifications as well as a resampling method. We run the regression by only including the singular risk proxy variables (models 1 and 2), and their interaction term (model 3), as well as the combination of the variables with the full set of control variables (models 4–7). Additionally, we exclude the variable trading assets from the regression to rule out collinearity as it is also included in LR (Model 8) and furthermore only use the statistically significant control variables (model 9). Model 10 is the same as our main model 7 but reports significances derived from bootstrapped standard errors using 100 replications. We perform regression models 9 and 10 because of the rather small number of event outcomes per predictor variable in our full model. Following, e.g., Peduzzi et al. (1996) and Vittinghoff and McCulloch (2006), we use a parsimonious specification with more event outcomes per predictor variable and resampling via bootstrapping to verify the results from our main model. Table 7 shows the results.

According to Table 7, all specifications show that higher liquidity risk as well as higher credit risk increases a bank's PD. This finding is to be expected and in line with the findings of prior literature. However, next to the separate effects the two risk categories have on bank PD, we are especially interested in the joint impact of both LR and CR on bank PD. Table 7 shows that the interaction term between LR and CR is highly significant and negative at the 1% level across all specifications. This finding would suggest that there is a joint and negative influence of the interaction between liquidity risk and credit risk on bank stability. However, one pivotal thing must be taken into consideration in the interpretation of the coefficient: the body of literature on the interpretation of interaction terms' coefficients in logit (i.e. non-linear) regression estimations tells us that the statistical significance of the coefficient as well as its sign cannot be interpreted in the same way as a coefficient of a linear regression. Instead, the direction of influence as well as the significance of the interaction term might vary across differing observations, which is why the coefficient of the interaction term cannot necessarily be interpreted as statistically significant and negative. We therefore follow Norton et al. (2004) in calculating the cross derivative of the expected value of the dependent variable to compute the direction and magnitude of the interaction effect. Also, to correctly estimate the statistical significance of the interaction term, our significance test is based on the estimated cross-partial derivative instead of the coefficient of the interaction term itself. The results of this analysis reveal two interesting findings about the influence a joint occurrence of liquidity risks and credit risks has on banks' PDs. First, the interaction effect of both risk categories has a statistically significant influence on bank PD only for certain levels of bank PD. Second, the direction of influence the interaction effect has on bank PD changes across different levels of bank PD. We find that the joint occurrence of both risk categories has statistically significant PD-aggravating effects for all banks with an overall PD between about 10% and 30%. If the PD increases beyond this level, the effect is reverting but statistically insignificant. If the PD levels reach 70–90%, the effect becomes statistically significant again, but has now a PD-mitigating influence. How can these results be interpreted? First, it is interesting to note that banks with varying overall levels of stability risk show different reactions to the occurrence of liquidity and credit risk. Apparently, banks' proneness to fail is influenced by different factors across varying risk levels.

Looking at the first group of banks with PDs between 10% and 30%, we believe the PD-increasing effects are straightforward: it shows that next to the separate risk categories, which also show up positive in the regression specifications including the interaction term, the interaction between the two categories additionally amplifies banks' default risk. The separate and joint effects of the risks can therefore almost be seen as additive. The second effect for the group of banks with high PDs between 70% and 90% might not be as straightforward. Why would the joint occurrence of liquidity risks and credit risks actually have a mitigating effect on the PD when the PD is high? We believe that these results might capture a "gambling for resurrection"-behavior of banks. The existing body of literature on bank distress has long established that banks facing immediate distress behave differently than banks in regular economic conditions, especially in terms of risk-taking. Based on Merton (1977), it can be shown that banks supported by explicit (deposit insurance) or implicit (e.g. too-big-too-fail) state guarantees considerably increase their risk-taking when facing distress. The basic idea is straightforward. A bank facing the danger of going out of business has two options: first, to continue running the failed business model until the point of default is reached or second, to engage in high-risk business which carries great reward but also great risks. The risks are negligible because without the high-risk business activity the bank would very likely face elimination anyway. The only thing saving the bank from failure is an improbable but potentially very high payoff from the risky business. In simple terms: There is (almost) only upside for shareholders and management of banks close to default when engaging in very risky strategies. This behavior is well-documented in the prior literature, such as Keeley (1990), Corbett and Mitchell (2000), Gropp and Vesala (2001), and Freixas et al. (2003). Our results suggest that banks increase their liquidity risks and credit risks jointly in a last effort to avoid default. In some instances, this gamble is successful and therefore mitigates the risk of failure. This reasoning is supported by our results: a successful gambling for resurrection through a joint increase in liquidity risks and credit risks which mitigates a financially distressed bank's PD. We believe that it is actually rather unsurprising that we find this effect for our sample banks during the recent financial crisis. A large body of literature shows that many failing thrifts engaged in gambling for resurrection behavior during the savings & loan crisis in the US (Barth et al., 1991; NCFIRRE Report, 1993; Akerlof and Romer, 1993; Pontell, 2005). Pairing these empirical findings with the theoretic explanations for the reasoning behind gambling for resurrection should lead us to believe that distressed banks might also have engaged in this behavior during the recent financial crisis.

Taken together, our results therefore have one major implication: liquidity risks and credit risks have a strong influence on banks' default risk. Separately, both risk categories are able to strongly increase a bank's PD. Jointly, the effect varies for banks with different levels of PD. Whereas banks with modest PDs face an additional increase in default risk through the interaction of liquidity and credit risks, banks with high PD levels are able to benefit from this interaction effect in terms of mitigated default risk. Hence, to fully understand and evaluate what drives banks' PDs it is not sufficient to analyze liquidity risk and credit risk separately. These results therefore confirm our hypothesis H_3 that liquidity risk and credit risk jointly contribute to bank default risk.

4.3. The Impact of liquidity risk and credit risk on bank defaults – robustness test

To verify our results of Section 4.2 we use a robustness test, as presented in Appendix A of this paper. Again, we use the two additional risk measures, the BB measure and the (adjusted) *Z*-score, already introduced in Section 4.1.4 of the paper. We re-run the same logit regression model using the corrected calculations of the interaction term following Norton et al. (2004), replacing the LR and CR variables with the BB measure and the *Z*-score. We acknowledge that the *Z*-score measures the distance to default and is used here as an explanatory variable for the probability of default, implying that both are conceptually close.[18] In line with general expectations, we find a negative and statistically highly significant coefficient of the *Z*-score in all models. This means that a bank has a higher PD the closer it is to the default barrier. For the BB measure we find significant and positive coefficients. Accordingly, banks with higher liquidity creation also have a higher default probability. This result is intuitively correct, supports our findings from prior analyses and validates our estimation procedure. The results of the singular variables therefore support the results of our main analysis. For the interaction term, we again calculate the cross-partial derivative and *z*-statistics across different PDs. We find that the results are as expected: a mirror image of our main analysis' results using the LR and CR variables due to the inverted relationship of the (adjusted) *Z*-score and risk.

5. Conclusion

Liquidity risk and credit risk are the two most important factors for bank survival. This study investigates the relationship between these factors in virtually all commercial banks in the US over the period 1998:Q1 to 2010:Q3. We show that each risk category has a significant impact on bank default probability. We also document that the interaction of both risk categories significantly determines banks' PDs, albeit in different fashions. Whereas the interaction between liquidity risk and credit risk aggravates the PD of banks with PDs between 10% and 30%, it mitigates the PD-risk of high-risk banks with PDs of 70–90%. This calls for a joint management of liquidity risk and credit risk in banks. Using various combinations of subsets of our sample, proxy variables for liquidity risk and credit risk, possible macroeconomic and microeconomic shocks, and econometric techniques, we do not find a reliable direct relationship between liquidity risk and credit risk in banks.

Our results have several interesting implications. The existing bodies of literature considering the impact of either liquidity risk or credit risk on bank stability are both very large; however, surprisingly few studies consider the relationship between both risks. To our knowledge, we are the first to empirically shed some light on the relationship between liquidity risk and credit risk in banks from various perspectives and angles. Our results provide several recommendations for bank (risk) management and bank supervisors. The years 2007/2008 have shown that distrust between banks, to most extents driven by large credit risks in their portfolios, can cause a freeze of the market for liquidity. Regulators and central banks had to intervene to prevent the financial system from collapsing. However, our results suggest that a joint management of liquidity risk and credit risk in a bank could sub-

[18] As the Z-score is calculated using the return on assets, its standard deviation, and the capital ratio, we exclude these variables in regressions including the Z-score.

Table A1
The impact of liquidity risk and credit risk on bank default probability using alternative measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adjusted *Z*-score	−9.6847***		−9.8424***	−12.1030***		−11.5609***	−11.8256***	−11.8151***	−11.8256***
BB		0.0127***	0.2673***		0.0273**	0.0528***	0.4554***	0.3445***	0.4554***
Adj. *Z*-score * BB			−0.0785***				−0.1371***	−0.1030***	−0.1371***
log(Assets)				0.1282	0.2807**	0.1404	0.1620		0.1620*
Capital ratio					−143.2822***				
Return on assets (RoA)					19.5095**				
Standard deviation RoA					97.5318***				
Efficiency ratio				−0.0078	−0.0006	−0.0034	−0.0027		−0.0027
Loan growth				−4.4003	−8.7705***	−4.3493*	−4.3751*	−4.4218**	−4.3751***
Trading assets/total assets				−4.1531*	−8.3511***	−4.1553*	−4.1139*	−3.6593*	−4.1139**
Short-term/long-term deposits				−0.0381***	−0.0722***	−0.0350***	−0.0397***	−0.0051**	−0.0397***
Fraction real estate loans				7.2644	4.0512	6.9943	7.2662		7.2662
Fraction agricultural loans				7.9536	1.5804	6.7799	8.4301		8.4301
Fraction commercial loans				6.3047	5.6009	6.1629	6.3660		6.3660
Fraction individual loans				−16.2283	−13.3631	−14.3651	−17.1755		−17.1755**
log(GDP in bn. USD)				−52.4053***	−117.0016***	−48.2372***	−50.4192***	−35.0935***	−50.4192***
Savings ratio				135.0988***	63.5287***	123.5489***	130.6438***	139.8474***	130.6438***
Interest rate				−0.8245	−5.1283***	−3.2304*	−1.0531		−1.0531
Yield curve				−0.8267**	−0.7177*	−0.8386**	−0.7537*	−0.3686	−0.7537
Leverage in the banking industry				244.9915***	0.4992	233.7004***	232.8967***	283.8955***	232.8967***
Constant	21.6850***	−5.7171***	21.9547***	296.0293*	1,107.494***	266.7895*	286.5092*	102.7969	286.5092
Defaults	205	205	205	205	205	205	205	205	205
Obs.	77,081	76,688	76,664	75,639	75,243	75,243	75,243	75,243	75,243
R-squared	68.80%	21.20%	78.99%	87.06%	88.40%	87.12%	87.23%	86.04%	87.23%

The table reports results from logit regressions of bankruptcy indicators on predictor variables. The data are constructed so that the predictor variables are observable prior to the quarter when default occurs. The regressions include data from 2006:Q1 to 2010:Q3. The variables are defined as in Tables 2 and 3. The "adjusted *Z*-score" is calculated by adding a ten to the ratio before logarithmizing it. Standard errors in models (1) to (8) are clustered at the bank level, following e.g. DeYoung and Torna (2013). Model (9) shows significances derived from bootstrapped standard errors using 100 replications.

* The statistical significance of results is indicated at the 10%-level.

** The statistical significance of results is indicated at the 5%-level.

*** The statistical significance of results is indicated at the 1%-level.

stantially increase bank stability. Our results therefore support and underpin recent regulatory efforts like the Basel III framework and the Dodd–Frank Act which put stronger emphasis on the importance of liquidity risk management in conjunction with the asset quality and credit risk of a bank.

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Appendix A

See Table A1.

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