In Search of Liquidity Risk in Bank Stock Returns *

Yasser Boualam† Anna Cororaton‡

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We document that higher measures of liquidity risk on banks balance sheets are associated with lower expected stock returns. We first calculate a measure of liquidity risk, referred to as the *liquidity gap (LG)*, which reflects how much of a bank's volatile liabilities are covered by its stock of liquid assets. We show that the standard factor models – even when augmented with bond risk, market liquidity, and financial-size factors – do not fully explain the cross section of bank stock returns sorted according to this measure. A portfolio that is long in low liquidity risk banks and short in high liquidity risk banks delivers a statistically significant α of 6 percent annually. This effect is not driven by bank characteristics such as size, profitability, or risk measures related to leverage or asset quality, but appears to be partly connected to the degree of complexity of banking organizations and potential valuation errors pre-crisis.

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†Kenan-Flagler Business School - University of North Carolina - Chapel Hill. Contact: boualam@unc.edu

‡The Wharton School - University of Pennsylvania. Contact: annadc@wharton.upenn.edu

1 Introduction

Banking theory has long recognized the role of liquidity shortages in generating episodes of financial stress. As evidenced by the recent crisis, the freeze in interbank markets and the surge in withdrawal from pre-committed credit lines proved to be catalysts to the financial meltdown.[1] Policymakers have since implemented new regulation such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) to mitigate fragility arising from the liquidity risk embedded in bank balance sheets. For example, the LCR requires that banks have a sufficient stock of liquid assets on their balance sheets to withstand sudden withdrawals in funding. In contrast, the NSFR regulates the proportion of long-term assets funded by long-term and stable funding. In order for these measures to be effective however, their role in cushioning liquidity shocks first needs to be firmly established.

We use information contained in bank stock returns to understand balance sheet measures of liquidity risk. More specifically, we use an empirical asset pricing methodology as a market-based assessment of liquidity risk and measure the associated premium commanded by investors. Bank stock returns have traditionally been ignored in the empirical asset pricing literature, but contain a wealth of information on how markets perceive bank risks. It is natural to investigate this data to further our understanding of bank liquidity. By investigating how cross-sectional heterogeneity in liquidity risk affects bank stock returns, we provide insight on the proposed regulatory measures. We follow two steps in our analysis. We first construct a measure of bank liquidity risk, referred to as the *liquidity gap (LG)*, which reflects banks' ability to immediately service sudden outflows due to pre-committed liquidity guarantees on both the liability and asset sides. We measure liquidity risk from granular balance sheet information in the quarterly Y-9C bank holding company reports to the Federal Reserve from 1991-2016 and in COMPUSTAT from 1974-1990.[2] *LG* is defined as

[1] See Gorton and Metrick (2012) and Ivashina and Scharfstein (2010).

[2] Throughout the paper, we refer to bank holding companies and banks interchangeably.

the amount of volatile liabilities less liquid assets and normalized by total liabilities. A type of liability is included in our measure if the volatility of its inflows and outflows is relatively high. A salient feature of LG, relative to other measures proposed in the literature, is that it particularly focuses on non-stable sources of funding, and is thus directly related to the LCR.

We merge LG to bank stock prices and perform a portfolio sorting exercise to calculate expected returns and risk premia. The first main result of our paper is that banks with higher balance sheet measures of liquidity risk have significantly lower expected risk-adjusted returns. In particular, we show that α's are statistically significant after controlling for a number of risk factors, including the Fama-French five factors, factors reflecting exposure to long term bonds and credit risk, and the Pastor-Stambaugh market liquidity factor. Investors in a portfolio that is long in banks with low liquidity risk and short in banks with high liquidity risk earn an annual average of 6 percent in risk-adjusted returns. These findings hold even after controlling for bank characteristics such as size, profitability and risk measures related to leverage, asset quality or default likelihood. They are also robust to a variety of checks and to alternative measures of liquidity risk including the liquidity mismatch measure in Berger and Bouwman (2009).

Our data shows that banks with higher measures of liquidity risk are also less profitable and have more volatile earnings. In addition, they have relatively higher risk-weighted assets, z-scores, and more charge-offs and defaulting loans. We also show that banks with higher measures of liquidity risk are typically larger. Our findings are consistent with the results in Gandhi and Lustig (2015) who show that a size factor specific to the financial industry explains bank stock returns. However, we find statistically significant α's even after controlling for size.

We examine a number of other bank characteristics that could be correlated with LG and could potentially drive our results. These include bank profitability, leverage, net charge-offs, and tail risk. While our results overall hold across the distribution of these characteristics, they are particularly more pronounced for less profitable and highly leveraged banks. This is not necessarily surprising and confirms that liquidity risk (and corresponding anomaly) materializes itself more prominently within more deteriorated balance sheets.

We further explore potential determinants behind the relative underperformance of high-liquidity risk banks. For example, we examine the possibility of endogenous sorting among banks whereby banks that are in fact the most exposed to a systematic liquidity risk endogenous choose to keep their liquidity mismatch low and thus appear as safe. If such theory holds in our setting, we would expect a portfolio that is long in low liquidity risk banks and short in high liquidity risk banks to perform badly during recessions. However, we observe that this portfolio actually performed very well at the onset of the recent financial crisis.

A closer analysis of our results across multiple sample periods, also suggests that while the liquidity risk anomaly is strongly present pre-crisis, it has significantly disappeared post 2010. A possible explanation to this finding has to do with the fact that investor may have underestimated the importance of liquidity risk or mismeasured it. We confirm our interpretation by studying the effect of the degree of complexity of banking organizations on our liquidity anomaly. Controlling for complexity, we show that the α of a long-short portfolio based on liquidity risk declines by about 40%. This suggests that the complexity of banking organization play a key role in assessing the liquidity risk of given institution. As banks become more complex and opaque, investors may be more likely to underestimate the inherent liquidity risk and thus more prone to valuation errors.

There are two ways to interpret our results in the context of assessing the new liquidity regulations. First, we consider a world where in markets are efficient and investors are correctly pricing the relevant risks faced by banks. Our results suggest that investors command premia for risks that are negatively correlated with LG. An important implication of this is that by focusing on the LCR, policymakers might not be fully accounting for all risk sources. Second, consider the case of potential valuation errors, which is possible given the results on bank complexity. This implies that banks might not face the appropriate cost of capital when making financing decisions, and policymakers should be concerned about over- or under-investment of banks depending on its LG measure. Unless investors make the appropriate adjustment to price in liquidity risk going forward, the tightening of bank requirements may be inefficient in curtailing financial fragility.

Literature review. This paper draws from the literature on the measurement of bank liquidity risk, theories on bank financial fragility, and asset pricing. To our knowledge, this is the first paper examining the link between liquidity risk and bank stock returns.

The link between banks' role as liquidity creators and fragility is at the core of banking theory.[3] Seminal papers have focused on liquidity risk mainly stemming from pressures within bank liabilities. Diamond and Dybvig (1983) argued that the mismatch between the long-term nature of assets and short-term demand deposits can generate a self-fulfilling equilibrium in which all bank depositors run on the bank. Holmstrom and Tirole (1998) also investigate the interaction and non-synchronicity between bank assets and liability as a factor driving liquidity risk. Allen and Gale (2000) analyze the systemic nature of liquidity risk in light of a bank contagion model. Goldstein and Pauzner (2005) develop a global games approach to bank runs, whereby there is a natural distinction between bank liquidity and solvency.

More recent papers have looked at liquidity risk taking into account the interplay between the asset and liability sides. Two papers are particularly relevant to our analysis. Kashyap et al. (2002) develop a model where banks combine deposit-taking activities with lending through commitments, and show that banks are not necessarily exposed to high liquidity risk as long as the outflows due to deposits and loan commitment are not synchronous. Acharya et al. (2010) discuss the strategic reasons behind the countercyclicality of bank liquidity. They also show some empirical evidence

[3] See surveys in Allen and Babus (2009) and Allen et al. (2013).

suggesting that bank's choice of liquidity depends on the level of solvency risk and the ability to raise external financing. We contribute to this literature by revisiting some of these empirical predictions but from an asset pricing perspective.

While the theoretical link between bank liquidity and financial fragility has been studied quite extensively, there is little empirical investigation of the theory in the context of asset prices. More generally, very few papers have looked at stock returns of financial firms. A few exceptions include Gandhi and Lustig (2015) who show that bank size is a risk factor and captures a too-big-to-fail subsidy on large banks, and Baker and Wurgler (2013) who show a low-risk anomaly and its implication for banks cost of capital.[4] Our paper is different in that we focus specifically on the role of liquidity risk in explaining the cross-section of bank stock returns.

The paper is also more broadly related to the empirical banking literature investigating the connection between bank liquidity and crises. Gatev and Strahan (2006), Gatev et al. (2009), and Cornett et al. (2011) show that banks are typically hedged against liquidity shocks as credit line drawdowns are usually compensated by deposit inflows in crisis periods, highlighting the fact that the banking system was viewed as safe thanks to government guarantees. Consistent with our findings, they argue that banks that are most exposed to liquidity demand shocks are not necessarily the most fragile because these are also the banks receiving the highest amounts of deposit influx. Acharya and Mora (2015) on the other hand argues that this liquidity hedging mechanism was not at play during the 2007-2009 crisis until the government explicitly stepped in. Our paper therefore attempts to reconcile these views by looking at the market assessment of liquidity as reflected in bank asset prices.

Our paper contributes to the small but growing literature starting with Berger and Bouwman (2009) which measures liquidity mismatch from the entire balance sheet. They show that that there was a

[4] Other papers include Schuermann and Stiroh (2006) and Adrian et al. (2014).

mismatch build-up leading up to the recent financial crisis and a subsequent decline.[5] While most of these papers have analyzed the events surrounding the crisis, they have not yet analyzed the asset pricing implications of liquidity risk.[6] We address this gap in the literature.

Lastly, our paper is related to the literature analyzing the recent banking regulations in Basel III. We contribute to the debate on optimal liquidity policy and the role of the newly implemented liquidity requirements.[7]

The rest of the paper is organized as follows. Section 2 describes the data and the construction of the liquidity risk measure. Section 3 presents the empirical results while Section 4 explores the relationship between liquidity risk and various bank characteristics. Section 5 provides a discussion of potential underlying mechanisms while Section 6 discusses policy implications. Section 7 concludes.

2 Data

Liquidity risk arises due to the mismatch in the availability of safe assets to cover sudden withdrawals, or the inability to roll over liquid liabilities. In order to measure the effect of this risk on stock returns, we first need detailed information on bank balance sheets. We use granular accounting information from the Y-9C reports to the Federal Reserve between 1991-2016 and from COMPUSTAT prior to 1991 to measure liquidity risk at Bank Holding Company level. We define a measure called the *Liquidity Gap (LG)* as the difference between highly volatile liabilities and liquid assets, normalized by total liabilities. This section carefully describes the data construction process.

[5]Other papers include Berger and Bouwman (2013), Berger et al. (2014). Bai et al. (2014) used market based weights to create a more nuanced measure. Also see Brunnermeier et al. (2014) for a theoretical exposition.

[6]Bai et al. (2014) looked at how firms with different liquidity mismatch ratios affect firms in terms of stock returns. They argue that firms with higher liquidity mismatch should perform worse during the recent financial crisis.

[7]See Allen (2014) and Diamond and Kashyap (2015) and surveys in Allen and Babus (2009) and Allen et al. (2013).

2.1 Liquidity Gap

Bank Holding Companies (BHC) provide detailed information on their balance sheets, income statements, and off-balance sheet activities to the Federal Reserve each quarter through the FR Y-9C reports. BHC's with assets consolidated from all legal subsidiaries that exceed $500 million are required to file these reports. Since the Y-9C forms have changed over time, we ensure consistency of the data series by using definitions given by the Fed's data dictionary and by going through the archived forms available on their website.[8] All variables are adjusted for inflation using the Consumer Price Index (CPI). The Appendix provides the mnemonics for the different data series used.

In our final sample, consistent data series based on the Y-9C reports are available starting in Q1-1991. Although different types of financial holding companies are required to report the Y-9C, we restrict our sample to bank holding companies, and exclude savings and loan holding companies and securities holding companies.[9] In the baseline analysis, we exclude the following observations: (1) real estate or C&I loans are less than 0; (2) deposits are less than 0; (3) equity is less than 0; (4) consumer loans are more than 50 percent; and (5) non-typical BHC's.[10]

The various supporting schedules in the Y-9C reports provide enough granularity for us to calculate different measures of liquidity risk. For this study, we are particularly interested in measuring banks' ability to cover sudden withdrawals and to finance day-to-day operations without any distress, inline with the liquidity coverage ratio. This includes the ability to roll over short-term debt to fund asset holdings or purchases and the provision of pre-committed liquidity guarantees. As such, we define

[8] The data dictionary and historical forms are available at the Federal Reserve Board's website.

[9] Savings and loan holding companies and securities holding companies comprise less than 1 percent of the observations in the merged CRSP-Y-9C sample.

[10] We also exclude the following institutions: Metlife (RSSD9001 = 2945824) which is primarily an insurance company, Goldman Sachs Group (2380443) and Morgan Stanley (2162966) which became BHC's in 2008, and American Express Company (1275216) and Discover Financial Services (3846375) which are primarily consumer loan banks.

the liquidity gap as follows:

$$LG = \frac{\text{Volatile Liabilities} - \text{Liquid Assets}}{\text{Total Liabilities}},$$

where we identify volatile liabilities and liquid assets from balance sheet data. The difference between these two particular categories captures whether a BHC's liquid assets are sufficient to service its volatile liabilities, and hence reflects liquidity risk. We normalize by total liabilities.[11]

We classify items on the balance sheet as volatile when they are characterized by relatively high volatile inflow and outflow rates using the following methodology. We first calculate the time-series standard deviation of the growth rates over four quarters of each major type of liability for each BHC.[12] We then define flow volatility as the cross-sectional average of these standard deviations across banks. Table 1 ranks the different types of liabilities on a bank's balance sheet and their corresponding volatilities.[13] We include the top four most volatile liabilities in the liquidity measure.[14] This includes trading liabilities, other borrowed money including commercial paper, overnight federal funds purchased and repurchase agreements, and non-interest bearing deposits and balances in foreign offices. Standard deviations of the annual growth rates of these items range from 0.52-0.61. On average, volatile liabilities have a standard deviation of 44 percent, while non-volatile liabilities have a standard deviation of around 11 percent. In the aggregate, this covers around 33 percent of the total liabilities of all bank holding companies. On an equal-weighted basis, volatile liabilities average around 11 percent across banks. Excluding data from 2008 onwards does not change the relative ranking of the different types of liabilities according to volatility.

We define liquid assets as assets that can easily and immediately be converted to cash without loss

[11] Results are robust to alternative normalization variables.

[12] We remove seasonality and smooth growth rates by calculating growth $= \frac{x_t - x_{t-4}}{0.5(x_t + x_{t-4})}$.

[13] An alternative way of calculating volatility is to calculate for each bank the standard deviation of the annual growth rates for each major liability category which measures the degree of inflow and outflow for each category and take an average across banks. This alternative calculation ranks the different types of liabilities according to volatility similarly and in particular, the top volatile liability categories are the same.

[14] While the cutoff for specifying whether a certain type of liability is volatile is arbitrary, we use different cutoffs in the analysis as a robustness measure.

of value. Consistent with the classification proposed in Berger and Bouwman (2009), these assets include cash and balances due from other institutions including reserves at the central bank, all securities, trading assets, federal funds sold and securities purchased under agreements to resell.

Our *LG* measure is closely related to the definition of the Liquidity Coverage Ratio (LCR) defined in Basel III and by the Federal Reserve and builds on the definition of volatile liabilities mentioned in the U.S. Government Accountability Office (GAO) report on large BHC's. Consistent with the LCR, we focus specifically on volatile liabilities rather than all liquid liabilities. This excludes "liquid" but stable liabilities such as insured deposits but still captures major sources of funding for banks.[15] The LCR also measures the amount of high quality liquid assets (HQLA) available to service liquid liabilities that can be withdrawn within the next 30 days. In other words, the regulation specifies weights on each liability category depending on how likely it is to be withdrawn and on each asset category depending on how easily it can be converted to cash taking into account price impact, similar to our measure. We define *LG* since calculating the LCR according to the proposed regulations requires a level of detail not available in the Y-9C reports.

Berger and Bouwman (2009) (BB thereafter) provides an alternative measure referred to as liquidity mismatch, which incorporates all on-balance sheet and off-balance sheet activities of a bank. BB classifies all asset, liability, equity and off-balance sheet items reported in Y-9C as either liquid, semi-liquid or illiquid. Illiquid assets and liquid liabilities worsen liquidity mismatch while liquid assets, illiquid liabilities and equity improve liquidity mismatch. An important distinction between our measure of liquidity risk and BB comes from the interpretation of the weights that are assigned to the different items on the balance sheet. In particular, they assign a positive weight on illiquid assets which is interpreted to mean that the bank has created illiquidity. However, we are more concerned about the servicing of liabilities while taking into account the resale value of assets to do

[15]For example, "stable deposits" enter the calculation of LCR with a weight of 3 percent only. For further details, see the GAO report on bank holding companies dated July 2014 and available at http://www.gao.gov/assets/670/665162.pdf and the liquidity coverage ratio section of the Federal Register dated May 2015 and available at http://www.gpo.gov/fdsys/pkg/FR-2015-05-28/pdf/2015-12850.pdf.

so. Hence, in our definition, we assign a zero resale value to illiquid assets. This does not imply a zero resale value generally, but only for the immediate servicing of volatile liabilities. We think that this is reasonable considering that volatile liabilities have very short duration and selling illiquid assets might not be feasible immediately. Similarly, Bai et al. (2014) derive a model-based measure of liquidity risk called the Liquidity Mismatch Index (LMI). As in the LCR, they calculate the LMI using time-varying weights on each liability item reflecting the likelihood of withdrawal on each asset item reflecting convertibility to cash. In essence, this measure captures the shortage of liquid assets available to service liquid liabilities. However, as in the BB measure, they assign a positive weight to illiquid assets.

2.2 Liquidity Risk Measure Before 1991

Given the limited availability of detailed balance sheet data from the Y-9C reports prior to 1991, we use annual accounting variables from COMPUSTAT to start our analysis in 1974. We first combine COMPUSTAT with the Y-9C reports using a link table constructed by the New York Fed.[16] We then run a regression of LG on COMPUSTAT variables for the sample after 1991 and use the regressions coefficients to predict LG prior to 1991 for BHC's with a three-digit header SIC code corresponding to 602 or 671.[17] Using this method, we extend the sample back to 1974.[18] Variables in this regression are chosen to maximize the sample both before and after 1991 - a large overlap between Y-9C and COMPUSTAT variables after 1991 is crucial to get precise coefficient estimates, but at the same time these variables should be available for many BHC's prior to 1991.[19] The Appendix provides the list of variables in COMPUSTAT used in the regression. Not surprisingly,

[16] The merger between the BHC identifier RSSD9001 from Y-9C to PERMCO from COMPUSTAT is based on the version of the link table dated March 2014.

[17] Note that 97 percent of the merged CRSP and Y-9C data between 1991-2014 has an SIC code of 6020.

[18] Studies which Stock return data for a large number of financial firms are not available prior to 1970's. Papers which use bank s Ghandi and Lustig (2015) use data starting 1972 while Baker and Wurgler (2014) use data starting 1971.

[19] While we use the projection exercise to obtain liquidity gaps ratios prior to 1991, we also calculate predicted ratios for banks after 1991 for which Y-9C data is not available but COMPUSTAT is available.

cash, and debt in current liabilities and long-term debt are some of the key accounting variables that explain the liquidity gap measure.

For the projection exercise, we run both an OLS regression and a panel regression with bank fixed effects. We first run a regression for the sample from 2000-2016 where both Y-9C and COMPUSTAT data are available, use the sample from 1991-1999 as an out of sample test of the regression where both datasets are still available, and impute LG from 1974-1990 where only COMPUSTAT data is available. In particular,

$$LG_{i,t} = \sum_{j=1}^{N} \beta_j x_{j,i,t} \quad \text{if year } > 2000$$

$$\hat{LG}_{i,t} = \sum_{j=1}^{N} \hat{\beta}_j x_{i,j,t} \quad \text{if year } < 2000.$$

Here, $LG_{i,t}$ is the liquidity risk for each bank i at time t, $x_{j,i,t}$ is the j^{th} explanatory variable where $j = 1...N$ and β_j are the coefficients. Table A4 shows results from this projection exercise. COMPUSTAT variables can largely explain movements in LG as seen in the R-squared of the OLS regression at 91 and the R-squared of the panel regression at 88.

We use predicted values from the OLS regression throughout the paper, and use the predicted values from the panel regression as a robustness exercise. To gauge out-of-sample performance, we run a regression of actual liquidity risk on predicted liquidity risk between 1991-1999. Table A4 shows that the coefficient on predicted LG is highly statistically insignificant from 1 and R-squared values are around 85 percent, suggesting that the predictive regressions perform very well. Coefficients from these regressions shed light on which variables affect LG. The types of liquid assets or volatile liabilities available may have changed before and after 1991, however we assume that the response of banks in terms of liquidity management has remained the same.

2.3 Descriptive Statistics for Overall Sample

Table (2) presents summary statistics for balance sheet items, income statement items, liquidity characteristics and bank organization characteristics on an equal-weighted bases using both the Y-9C reports and COMPUSTAT. Definitions of the variables are provided in the Appendix. Over the post-1991 sample period, there were 33,168 BHC-quarter observations, while over the pre-1991 period, there were 4,621 BHC-year observations. Over the entire sample period, there were 1,091 unique BHC's. In the following analysis, we focus mostly on the summary statistics in Panel A from the Y-9C reports. Panel B presents descriptive statistics from COMPUSTAT data.

Total bank assets have averaged around $24.6 billion, however the median has been around $1.77 billion highlighting the skewness of the distribution of banks size. In 2014-Q4, the top 5 percent of BHC's held 78 percent of total assets in the sample. On the liabilities side, 77 percent of funding comes from deposits while on the assets side, 65 percent are held in loans. On average, 25 percent of banks are considered complex by regulators and each BHC has an average of 2-3 banking subsidiaries.

Liquidity gap is -0.19 on average, where the negative sign suggests that banks have held enough liquid assets against liquid liabilities over the entire sample period. There is a substantial amount of heterogeneity across banks and over time as shown in Figure 1. A majority of banks have negative liquidity gap ratios on their balance sheet over the sample period, while over half of the observations in the highest portfolio have positive liquidity gap. Throughout the period 1992-2016, about 10% of banks in our sample experience a positive liquidity mismatch in a given year. This number peaks to 27.5% during the financial crisis, as exhibited in Figure 2. While we would also expect higher measures of liquidity risk during the build-up to the savings and loan crisis in the early 1990's, it is important to note that we only include public financial firms with a three-digit header SIC code corresponding to 602 or 671 (commercial banks) and we exclude savings and loan holding companies from the Y-9C sample.

At the aggregate level, Figure 3 shows that there are periods when the total liquidity gap turns positive, suggesting that the banking system as whole does not hold enough liquid assets to withstand extensive cash outflows related to volatile liabilities. These episodes have occurred during recessions and are most pronounced during the recent financial crisis.

3 Liquidity Mismatch Effect in Bank Stock Returns

This section investigates the (risk-adjusted) returns of portfolios of bank stocks sorted with respect to our liquidity mismatch measure. We first merge monthly data on bank stock returns obtained from CRSP to the combined Y-9C and COMPUSTAT dataset.[20] Following Fama and French (1993), we sort banks according to LG and form our stock portfolios monthly as of December of the previous year. In particular, December accounting information in year $t-1$ is used to sort monthly stock returns from January to December of year t. Portfolio rebalancing occurs on a yearly frequency. LG uses accounting information available six-months prior to when returns are measured to avoid look-ahead bias, so that the release of accounting variables and the sorting of returns ensures that the information has been fully disseminated to the public.[21] We then form 5 quintile portfolios sorted according to LG. As in Campbell et al. (2008), we limit turnover costs by holding the constructed portfolios for a year, and by excluding stocks with price below $1 at the date of formation. The final sample consists of about 155,000 BHC-month observations from January 1974 - December 2016. Over this time period, we observe 1,092 unique BHC's, and an average of around 300 unique BHC's per year.

[20]This merge uses the same link table provided by the New York Fed used to merge the Y-9C and COMPUSTAT datasets.

[21]Information from the Y-9C reports are available on the Chicago Fed's website around 24 hours after the reports are received. We perform a robustness check where stock returns from January-December of year t are sorted based on liquidity gap computed as of June of year $t-1$.

3.1 Main Specification

To see which systematic factors explain the cross section of bank stock returns, we run linear factor regressions $r^e_{p,t+1} = \alpha_p + \beta'_p f_{t+1} + \epsilon_{p,t+1}$, where $r^e_{p,t+1}$ are monthly excess returns for each liquidity-gap-sorted portfolio p, f_{t+1} are the risk factors, and β_p represent the loadings on the factors. We analyze the cross-section of bank stock returns through the lens of the following factor model specifications: (i) raw excess returns, (ii) CAPM, (iii) Fama-French three-factor model, (iv) Fama-French five-factor model augmented with two bond risk factors and Pastor-Stambaugh liquidity factor. The 4$^{\text{th}}$ specification above represents our baseline factor model. It nests model specifications (i), (ii), and (iii) and has the following eight factors:

$$f_t = [market \quad smb \quad hml \quad rmw \quad cma \quad ltg \quad crd \quad ps]$$

The first five factors $[market \quad smb \quad hml \quad rmw \quad cma]$ correspond to the standard five Fama-French factors reflecting the market return, size (small minus big), value (high minus low), profitability (robust minus weak), and investment (conservative minus aggressive), available from Ken French's website and WRDS. Similar to Gandhi and Lustig (2015), we also include two bond risk factors, namely ltg (excess returns on the US 10-year Government Bond Total Return Index obtained from Global Financial Data) and crd (excess returns on an index of investment grade corporate bonds (CRD) generated by Dow Jones). These bond factors capture banks' potential exposure to maturity and credit risks. Lastly, we add the Pastor-Stambaugh traded liquidity factor ps obtained from WRDS, in order to control for banks' exposure to market liquidity.

We report our results on a value-weighted basis using market capitalization in Table 3 and on a equal-weighted basis in Table 4. These results cover our four factor model specifications with returns expressed in annualized percentage points, Newey-West standard errors corrected with 6 lags, and t-statistics shown in parentheses. The first five columns show results for each of the quintile portfolios. The last column shows the long-short portfolio that goes long the stocks with the lowest liquidity gap and short the stocks with the highest liquidity gap.

Given that the results are overall similar across both weighting schemes, we focus below on describing the patterns obtained on a value-weighted basis. Panel A first reports unconditional excess returns which are declining almost monotonically with the level of LG. The average excess return for the low LG portfolio is 9.6 percent, while the average excess return for the high LG portfolio is 6.3 percent. The long-short portfolio yields an average an annual return of 3.3 percent. We also show α's obtained from CAPM and the three-factor Fama-French model. These specifications all show an even more striking alpha pattern as the relative performance of high-liquidity gap stocks actually worsens as we control for the risk factors. The long-short portfolio reflects an average excess return of 5.5 percent (with a t-stat of 2.8) for the CAPM and 7.3 percent (with a t-stat of 3.7) for the three-factor Fama-French model. Lastly, we show the α's for our baseline specification which includes eight factors, described above. Results show that the α on the long short portfolio is 6.0 percent and is still statistically significant (with a t-stat of 2.9).

The widening of these differences is better understood in light of the factor loadings. Panels B and C reports the associated coefficients for the CAPM and three-factor Fama-French specifications, respectively, while Panel D reports the factor loadings for our eight-factor baseline model. Overall, our results show that the loadings on the market are (almost) monotonically increasing with the liquidity gap measure, ranging from 0.88 to 1.29 in our main specification. The fact that high liquidity gap banks are more exposed to aggregate market risk can be partly attributed to the fact that these banks tend to be more levered. The factor loadings on hml are also similarly increasing in liquidity gap, going from 0.62 for the first portfolio to 1.26 for the fifth one. The loading patterns on smb however exhibit a hump shape, first increasing between the first (0.16) and second portfolio (0.26), before continuously declining until the last portfolio (-0.07). The factor loadings (and their differences across portfolios) on profitability rmw and investment cma appear to be quite marginal.

This suggests that such factors have little power in explaining common variations in financial stock returns (as opposed to non-financials), and could technically be omitted without much impacting our results.

With the exception of portfolio 3, we also observe overall increasing patterns for *ltg* suggesting that that banks with highest liquidity gap tend to be more exposed to long-term bonds. This is not surprising given that the liquidity mismatch on banks balance sheets tend to be positively correlated with their maturity gap. Conversely , we observe a decreasing pattern in *crd* (with the exception of portfolio 3) suggesting that high liquidity-gap banks are less exposed to credit market relative to low liquidity-gap banks. This however seems at odd with the results in Table 2 which show that banks with the highest liquidity mismatch tend to have higher charge-offs and risk-weighted assets. Finally, the loadings on the liquidity factor *ps* also exhibit a clear pattern showing that banks with the largest liquidity mismatch tend to be much more negatively exposed to market liquidity compared to banks with the lowest mismatch.[22]

3.2 Long-Short Portfolio Cumulative Returns

The results reported above hold unconditionally. A natural question to ask is whether the abnormal returns we uncover are concentrated in a particular period of time or exhibit a different pattern depending on good vs. bad times.Figure 4 shows the cumulative returns for $1 invested in the long-short portfolio in the beginning of the sample period in 1974 with net proceeds at the end of the period reinvested in each subsequent period, for both the raw returns and the risk-adjusted returns. $1 invested in the risk-adjusted portfolio increases about 10-fold over the entire sample period, while raw returns increase by 2.5-fold.

[22] Results for portfolio deciles provide similar results and are reported in Table 5 for our main specification.

4 Liquidity Mismatch and Bank Characteristics

Table 2 reported the average characteristics associated with LG-sorted portfolios, calculated on an equally-weighted basis.[23] Examining these summary statistics is useful in narrowing down the potential mechanisms underlying the observed empirical relationships and testing the robustness of our findings. There are substantial differences in bank characteristics across portfolios. In the data, BHC's with higher LG tend to be larger, rely less on deposits and core-deposits as a source of funding, and are more levered according to both equity and Tier-1 capital. In addition, these BHC's hold more loans as assets on their balance sheets relative to liquid and cash-equivalent assets, and have higher risk-weighted assets. Idiosyncratic risk, as measured by the average 8-quarter rolling standard deviations of either net income as a fraction of total assets (ROA) or equity (ROE) is also monotonically higher for banks with higher liquidity mismatch. Z-score and credit risk - measured as the amount of charge-offs less recoveries as a fraction of previous allowances - are also higher for banks with higher LG. Lastly, these banks are more complex according to a subjective complexity index reported by the Federal Reserve, and have relatively more banking subsidiaries.

These differences in characteristics could potentially drive the relative underperformance of high LG banks, thus limiting any liquidity risk effect. In this section, we focus on the following characteristics exhibiting higher levels of heterogeneity across portfolios: (i) size, (ii) profitability, (iii) leverage, (iv) charge-offs, and (v) tail risk.[24]

We attempt to test the robustness of our original results by controlling for such differences in bank characteristics in two different ways: (i) double sort portfolio exercises and (ii) cross-sectional regressions in the spirit of Fama-Macbeth (1973).

[23] Panel B of Table (2) presents the descriptive statistics prior to 1991 using COMPUSTAT data. Since the variables presented in this table are used to create the liquidity profile measure, the monotonic pattern of each variable with the liquidity gap is to be expected and shows results consistent with the projection results.

[24] While we focus here on bank characteristics, the analysis could be extended to account for characteristics at the stock level, pertaining for example, to trading volume, number of analyst coverage, or institutional holdings share.

4.1 Size

Gandhi and Lustig (2015) show that size is a key factor for bank stock returns. They argue that larger banks have an implicit too-big-to-fail guarantee which makes them appear safer to shareholders, eventually leading to commanding relatively small risk premia. It is thus critical to control for any potential size effect in our results, especially given that such characteristic is monotonically increasing in our liquidity risk measure as shown in Table 2. We test the robustness of our findings to bank size considerations through two different approaches. First, we include a financial-specific size factor, as advocated by Gandhi and Lustig (2015). Second, we run a double sorting exercise. Note that size is also a control in our Fama-Macbeth regressions later on.

First, we augment our 8-factor baseline specification with a financial-sector-specific size factor, constructed along the lines of Gandhi and Lustig (2015) methodology. Results are reported in Tables 6 and 7 for both value-weighted and equal-weighted returns. In particular we show that while controlling for a financial-sector-specific size factor does reduce our alphas by about 1 to 1.5%. These remain relatively high and statistically significant, with 4.5% α (t-statistic of 2.3) for value-weighted returns, and 5% (t-statistic of 4.1). The loadings on the financial-size specific factors exhibit an overall declining pattern, suggesting the prevalence of small banks among the least liquidity-distressed portfolios. This helps attenuate the extent of the alpha difference between low and high liquidity gap portfolios. Also, the large negative loadings associated with the fourth and fifth portfolio is consistent with the interpretation of Gandhi and Lustig (2015) that market participants perceive large banks as more likely to receive government subsidies in periods of financial distress.

As an additional robustness check, we also perform the following double sorting exercise. We first rank BHC's according to size (measured by total assets) then rank them by LG within each size portfolio. Panel A of Table 8 shows that the α's (computed based on value-weighted returns and our baseline factor model), for the long-short portfolio by liquidity risk are still statistically significant across all bank sizes. Put together, these results confirm that there is an additional risk factor captured by the liquidity risk measure above and beyond bank size.

4.2 Profitability

We also consider bank profitability which we proxy by Return-on-Assets (ROA), defined as income (or loss) before extraordinary items and other adjustments divided by lagged assets. Indeed, it is possible that investors may particularly favor banks with low liquidity risk measures since they have higher ROAs (and ROEs) and thus push their stocks rices disproportionately higher. Similarly, we perform a double sort exercise by first sorting banks on their ROA, then on our liquidity mismatch measure. Results are shown in Panel C of Table 8. Although, the LS portfolio alphas are statistically significant across all profitability buckets, they appear to be clearly more pronounced for low to medium ROA banks.

4.3 Bank Risk Characteristics

Another critical concern has to do with banks potentially substituting liquidity risk with other forms of risk. Although bank may appear as safe from a liquidity risk perspective, they may still simultaneously engage in other risky behaviors which can ultimately generate higher financial fragility and command larger risk premia. This may for example encompass risks at the balance-sheet level through higher leverage, or at the asset side level through making riskier investments. Even though, the risk characteristics patterns reported in Table 2 do not suggest the prevalence of this risk substitution, since banks with low liquidity mismatch also typically have lower levels of leverage, lower charge-offs, and higher z-scores, we run double sorts in order to test whether the abnormal returns are particularly concentrated in a particular set of portfolios.

Leverage/Capital ratio. While financial fragility is associated with both excessive leverage and higher liquidity mismatch, a bank that facing liquidity shocks might not necessarily be insolvent. Indeed, large liquidity mismatches on a bank's balance sheets may a priori be particulary damaging when associated with deteriorating bank fundamentals. Furthermore, capital ratio is also a key explanatory variable for bank stock returns, as shown in Bouwman et al. (2017). Summary statistics show that banks with higher liquidity risk measures also tend to have higher leverage, higher risk-weighted assets, and lower Tier 1 capital ratios. These characteristics are monotonically increasing in the LG and thus may drive our results. Panel B of Table 8 presents results from a double-sorting analysis on bank leverage, which is defined here as the ratio of total asset to equity. Our results show that the risk-adjusted LS portfolio α's are particularly important and statistically significant for high leverage banks. Unlike size however, the results are strongest for the BHC's with high leverage. This is not surprising as we expect liquidity mismatch to be particularly for banks with relatively weaker balance sheets.

Asset quality. We explore the importance of asset quality in driving our results, by analyzing the effect of net charge-offs on bank excess returns. Our double sort results show that the alpha differential pattern are statistically significant for low and medium charge-off levels.

Tail risk. We also investigate the importance of bank risk management, which we proxy with tail risk. We define tail risk as the negative of the average return on a bank's stock for the bottom 5% return days per year, following Ellul and Yerramilli (2013). While the alpha patterns subsist across the distribution, they appear to be slightly more pronounced for higher tail-risk banks, again highlighting the strength of the liquidity effect for relatively weaker banks.

4.4 Characteristics Regressions a la Fama-Macbeth (1973)

Let us now turn to cross-sectional regressions in order to determine the importance of the liquidity gap measure in explaining the cross-section of bank stock returns. We follow the Fama-Macbeth (1973) methodology and proceed in two stages. We first construct time series associated with the factor loadings on the Fama-French three factors $f = [market \quad smb \quad hml]$ for each individual bank stock, based on 60-month rolling windows:[25]

$$r^e_{t+1} = \beta_i' f_{t+1} + \epsilon_{i,t+1}$$

Second, we run monthly cross-sectional regressions of excess returns on the liquidity gap measure, the constructed factor loadings $[\beta_i^{market}, \beta_i^{smb}, \beta_i^{hml}]_t$, and other individual bank characteristics, including (i) size, (ii) equity/asset ratio, (iii) net charge-offs, (iv) non-interest income share, (v) tail risk, (vi) ROA, (vii) z-score, and (viii) book-to-market. We then average out all the estimated coefficients over the whole sample period. Because we are interested in testing the effect on liquidity gap on excess returns while controlling for the bank characteristics listed above, we restrict our sample period to January 1993 to December 2016 (288 months) to make sure that all our independent variables are available. The results of our tests are reported in Table 10, with column (5) representing the full specification accounting for all variables and nesting those reported in columns 1 to 4. Across all models, the liquidity gap enters with a negative sign, as already shown by the portfolio sort results, confirming that banks with high liquidity gap measure earn negative premia, all else equal. The associated regression coefficient is relatively stable and varies from -0.063 in model (3) to -0.094 in model (5). It is statistically significant at the 5% or 10% level across all specifications with the exception of model (3). Thus, according to specification in column (5), a one standard deviation increase in liquidity gap (i.e., +0.16) is accompanied with a 110 bps decline in

[25] For simplicity, we omit here both *cma* and *rmw* factors given that they are marginally important as our results show above.

annual returns, holding all other variables fixed. Note also that our full specification can explain up to 21.30% of the annual variation in bank stock returns, with the liquidity gap measure accounting for about 0.50% of such variation.

5 Discussion: What Drives the Liquidity Risk Anomaly?

What are the determinants behind the relative underperfomance of high-liquidity risk banks? We attempt to explore potential explanations throughout this section.

5.1 Sources of Liquidity Risk

Our measure of liquidity mismatch bundles together two sources of risks that may both generate distress on a bank's balance sheet, namely a fire sale risk on the asset side and a run risk on the liability side. In an attempt to isolate the source of the liquidity effect we uncover, we disentangle our liquidity risk measure into two components: volatile liabilities on the one hand and liquid assets on the other. Indeed, the summary statistics reflect similar patterns, in that that banks with higher liquidity gaps have both higher holdings of volatile liabilities and less liquid assets as a ratio to total assets.

We perform the same sorting exercise for the period 1992 - 2016 and compare the results to those obtained with liquidity gap sorting. While similar risk-adjusted return patterns appear for both parts of the ratio, the results are slightly more pronounced on the liability side. That said, these remain relatively weaker compared to the full measure. One interpretation of this result is that liquidity risk management at the bank level is based on a more holistic approach jointly considering the liquidity characteristics of both the asset and liability sides. Thus, only considering one side of the balance sheet is not enough to capture liquidity risk.

5.2 Liquidity Risk Anomaly Across Time

The recent financial crisis resulted in various changes to the financial sector. One worry is that extremely negative valuations especially for large banks can force value-weighted expected returns downward and mislead the interpretation of our results, especially since large banks typically have high liquidity risk on their balance sheets. Tables 12 and 13 show our results for both value-weighted and equal-weighted returns across multiple sample periods: (i) 1974 - 1991 (Panel A), (ii) 1992 - 2007 (Panel B), (iii) 2008 - 2009 (Panel C), and (iv) 2010 - 2016 (Panel D). The unconditional pattern we uncover is of the same magnitude and is statistically significant at the 1% level for the periods 1974 - 1991 (8.6%, with a t-stat of 2.70 for the baseline specification) and 1992 - 2007 (6.8%, with a t-stat of 2.76). During the financial crisis, the low-liquidity gap banks appear to severely outperform the high-liquidity gap, even though the pattern seems to be somewhat reversed for our baseline eight-factor specification. Finally, the risk-adjusted returns of the long-short portfolio appear to vanish quite significantly over the period 2010 - 2016 (note that our statistical tests are weak given the short sample period and the alpha patterns are not monotonic as in our previous results). One interpretation of this result is that investors have now a better understanding of the implications of funding liquidity risk on a bank's balance sheet, and appropriately price in this risk onto stock returns, hinting to potential underestimation and mis-pricing of the risk due to liquidity mismatch in the period prior to the financial crisis.

5.3 Liquidity Risk Factor and Aggregate Market Conditions

Next we examine how the liquidity factor defined as the return on the long-short portfolio co-moves with aggregate variables. We compute correlations between monthly portfolio value-weighted returns and a number of systematic factors starting from 1992 until 2016.[26] Figure 4 shows the cumulative returns of our long-short portfolio, against the VIX index and the TED spread over

[26] Results are similar when considering equal-weighted returns.

the period 1992 - 2016. We note that these returns correlate positively with the implied volatility on the S&P500 and are statistically significant at the 1% level, both in terms of levels (0.21) and monthly innovations (0.28). Similarly, we can show that our liquidity factor is positively correlated with the TED rate (0.19), which is calculated as the spread between 3-Month LIBOR based on US dollars and the 3-Month Treasury Bill and obtained from FRED, the Pastor-Stambaugh traded liquidity factor (0.07), and the non-financial sector credit spread of Gilchrist-Zakrajsek (0.09).

All in all, these results are consistent with a flight-to-quality story where investors sell bank stocks with high liquidity risk and hold low liquidity risk bank stocks or even other types of safe assets when uncertainty is high. Times when either market liquidity, aggregate bank funding conditions, or asset credit quality deteriorate are also the times when the liquidity risk factor is high. Indeed, as equity holders load up on low liquidity risk bank stocks and shy away from high liquidity risk ones during stressful times, our liquidity factor tends to widen.

5.4 Other Potential Explanations

The liquidity risk anomaly that we find in U.S. bank stock returns is reminiscent of the distress anomaly observed for non-financial firm. We examine here some of the explanations that have been proposed in this context.

First, a potential rationale for our results may hinge on the fact that our measure of liquidity risk might be correlated with valuation errors of BHC's, in which case investors may not have sufficiently discounted the price of high-liquidity gap banks in order to account for their potential financial fragility. This is a plausible explanation especially in light of the recent financial crisis when multiple banks experienced severe liquidity shortage and distress despite seemingly fulfilling their capital requirements. Investors and regulators may have been more focused on solvency as opposed to liquidity issues, therefore under-pricing liquidity risk. Simply put, it is possible that market participants may have completely neglected or underestimated the extent of liquidity shock spillovers and ensuing systemic within the banking system, or simply relied on inaccurate measures of liquidity. If valuation errors are linked to the difficulty of assessing the soundness of a bank holding company, then controlling for the degree of complexity of a given bank can be informative. Indeed, we should observe that more complex banks exhibit larger risk-adjusted alpha differentials when sorted with respect to the liquidity gap measure. This is to some extent verified through a double sort exercise performed with respect to a complexity indicator that is assigned by the Federal Reserve to BHC's and reported in the Y-9C data. Reasons for being classified as complex include material credit-extending activity, issuing a large amount of debt to the public, engaging in high-risk non-bank financial activities and having complex management practices. The summary statistics in Table 2 show that banks with high LG are more complex. Results are provided in Table 9. Controlling for complexity, we show that the α of a long-short portfolio based on liquidity risk are 2.5% higher relative to non-complex banking organizations, even though they remain statistically significant. This suggests that bank complexity may play an interesting role in conjunction with liquidity risk by exacerbating potential valuation errors.

One particular argument that was put forward in the distress literature (see George and Hwang (2010)), and which is also plausible in our setting has to do with endogenous sorting. Indeed, it is possible that banks that are most exposed to aggregate liquidity risk may endogenously choose low levels of liquidity gap on their balance sheet in order to mitigate their exposure and limit potential distress following adverse liquidity shocks. This story would thus imply that banks with low LG measures should have been more adversely affected in the recent financial crisis relative to banks with low LG. However, this was not experienced during the recent financial crisis as evidenced by Figure 5. Indeed, the portfolio which is long in low risk banks and short in high risk stocks rose dramatically over the period 2008-2010, due to a dramatic decline in the returns of the short leg of the portfolio.

These results call for a deeper explanation related to the endogenous nature of bank liquidity management. Further exploration of mechanisms described in the theoretical banking literature is necessary. For example, Kashyap et al. (2002) emphasize the dynamic aspect behind liquidity management and argues that banks that may appear to be highly exposed to liquidity shocks are also the ones anticipating higher deposit inflows in periods of distress. One related channel that is also left for future research has to do with the ease and cost at which banks can raise inside (equity issuances) or outside liquidity (asset sales) in periods of turmoil. This ability depends on a number of factors including the likelihood of government support and access to the Lender of Last Resort, or ownership structure (Acharya et al. (2013) argue that banks' ability to diversify across investors is particularly important in periods of stress). It also reflects the degree of information asymmetry due to bank opacity and complexity (e.g., a potential lack of information can deter uninsured depositors and investors in periods of market confusion and uncertainty (Gorton (2008)), as well as bank interconnectedness and ability to access trading markets fast enough to avoid large fire sale discounts.

6 Policy Implications

Our results have important policy implications pertaining to the newly implemented bank liquidity requirements. First, under the assumptions that (i) markets are efficient, (ii) investors are correctly pricing the relevant risks faced by banks and that (iii) our liquidity measure is inline with the regulators', our counterintuitive results (i.e., investors command premia for risks that are negatively correlated with LG) seem to suggest that market participants do not consider the liquidity gap on banks balance sheets (or the net stability funding ratio for that matter) as a good proxy for liquidity risk. Indeed these measures are based on static accounting variables that may not fully reflect a banks' ability to generate liquidity (either inside liquidity through equity issuances, or outside liquidity through asset sales) in periods of stress.

An important implication of this is that by focusing only on this form of liquidity measures, regulators may not fully curtail liquidity risk and ensuing financial fragility of certain banks and may simultaneously impose stringent and costly balance sheet requirements on banks with low liquidity risk exposure. Along these lines, the presence of the liquidity risk anomaly we uncover hints at potential adverse effects on the costs of equity/capital of banks as they raise their balance sheet liquidity in order to comply with the new policy requirements.

7 Conclusion

This paper investigates the asset pricing implications of liquidity risk. We show that stocks of banks facing high liquidity risk are associated with lower expected stock returns. We sort banks according to a measure of liquidity risk, referred to as the *Liquidity Gap (LG)* and show that the standard factor models, even when augmented with bond risk, market liquidity, and financial-size factors, cannot fully explain cross section of bank stock returns. A portfolio that is long in low liquidity risk banks and short in high liquidity risk banks delivers a statistically significant α of 6 percent annually. We analyze a number of bank characteristics and find that these anomalous returns are not driven by size, profitability, or leverage. They, however, appear to be linked to bank complexity and potential valuation errors. Our results call for a deeper explanation related to the endogenous nature of bank liquidity management. Further exploration of theoretical mechanisms underlying this liquidity risk anomaly is left for future research.

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Appendix

A Additional Robustness Tests

A.1 Bank consolidation and defaults

Mergers and acquisitions are widespread in the banking industry and might affect our results if such activity systematically increases or decreases LG across banks. As a result, we might attribute differences in liquidity risk and consequently differences in expected returns to changes in M&A activity. In our data, beginning in 2003, BHC's are required to report the total assets of an acquired institution if the acquiree's assets are more than \$10 billion or more than 5 percent of the acquiring parent company, whichever is smaller. We observe 199 such events in the data and the change in LG for the parent holding company before and after the acquisition range from -0.19 to 0.17, with an average statistically insignificant from 0. This reassures that our results are not driven by M&A activity. From CRSP, we observe 266 delistings, 93 percent of which cite mergers as the reason for delisting and none of which overlap with the observed consolidations in the Y-9C reports. All of the stocks that report performance-related changes as the reason for delisting have available returns. As in Campbell et al. (2008), we use the returns of delisted stocks when they are available. Otherwise, delisted stocks are assumed to be sold in the month prior to the delisting and proceeds are reinvested in the portfolio.

B Figures & Tables

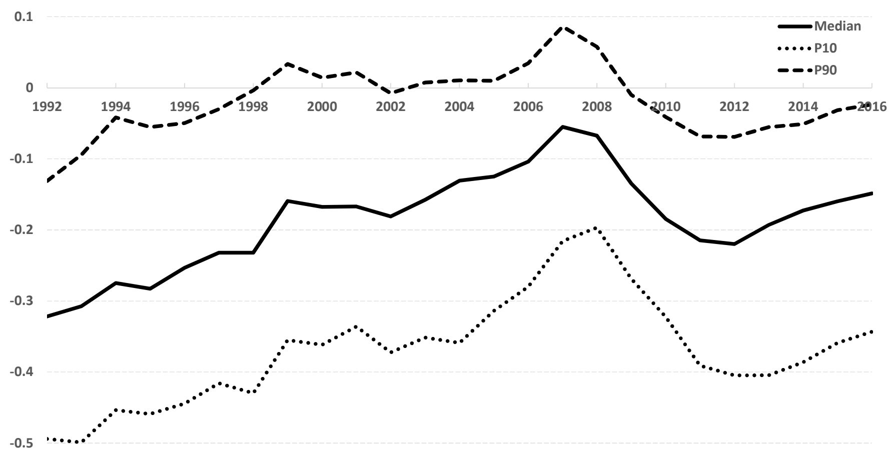


Figure 1.
This figure plots the liquidity gap ratio over the period 1992-2016. The solid black line represents the median of our sample, while the dashed lines represent the 10th and 90th percentiles respectively. Source: authors's calculations based on Federal Reserve Y-9C filings data.

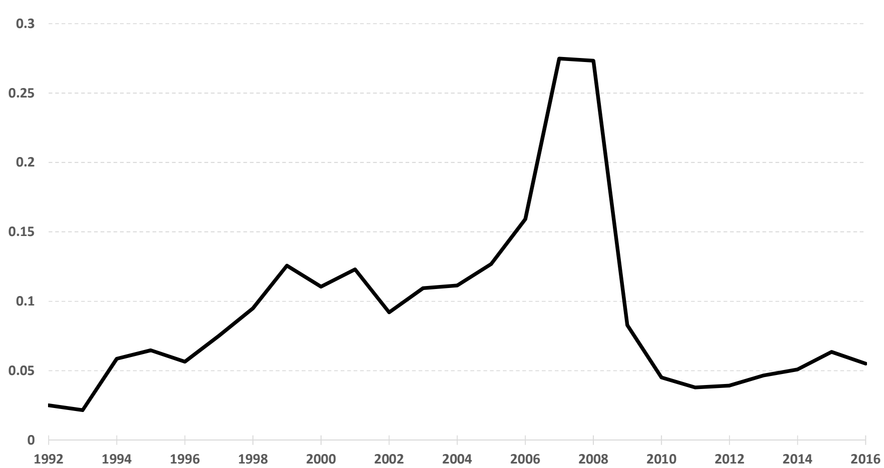


Figure 2.
This figure plots the share of banks with positive liquidity gap over the period 1992-2016. Source: authors's calculations based on Federal Reserve Y-9C filings data.

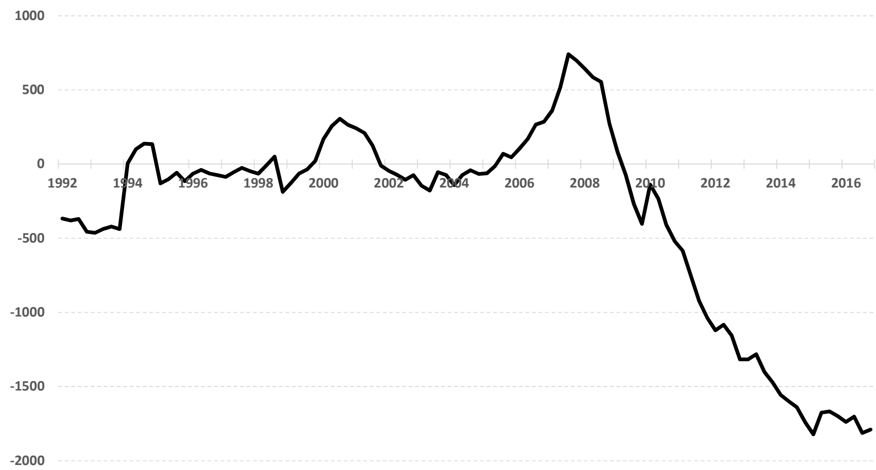
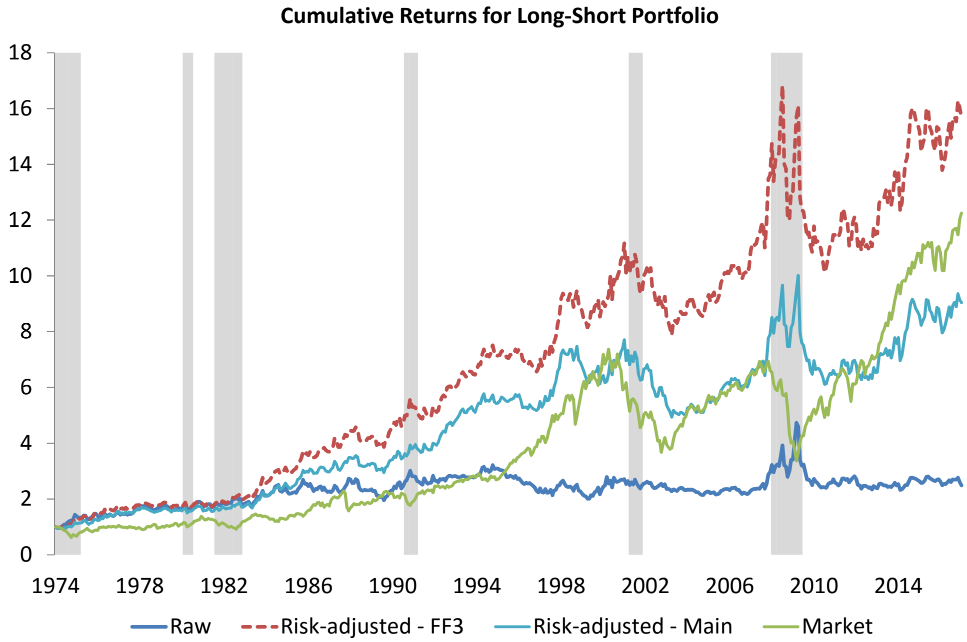


Figure 3.

This figure plots the aggregate dollar amount of volatile liabilities less liquid assets over the period 1992-2016, using data from the Federal Reserve Y-9C. Volatile liabilities include trading liabilities, non-interest bearing balances in domestic non-commercial bank subsidiaries, other borrowed money including commercial paper, overnight federal funds purchased and repurchase agreements, and non-interest bearing deposits and balances in foreign offices. Liquid assets include cash and balances due from other institutions, all securities, trading assets, federal funds sold and securities purchased under agreements to resell.

Panel A. Value-weighted returns



Panel B. Equal-weighted returns

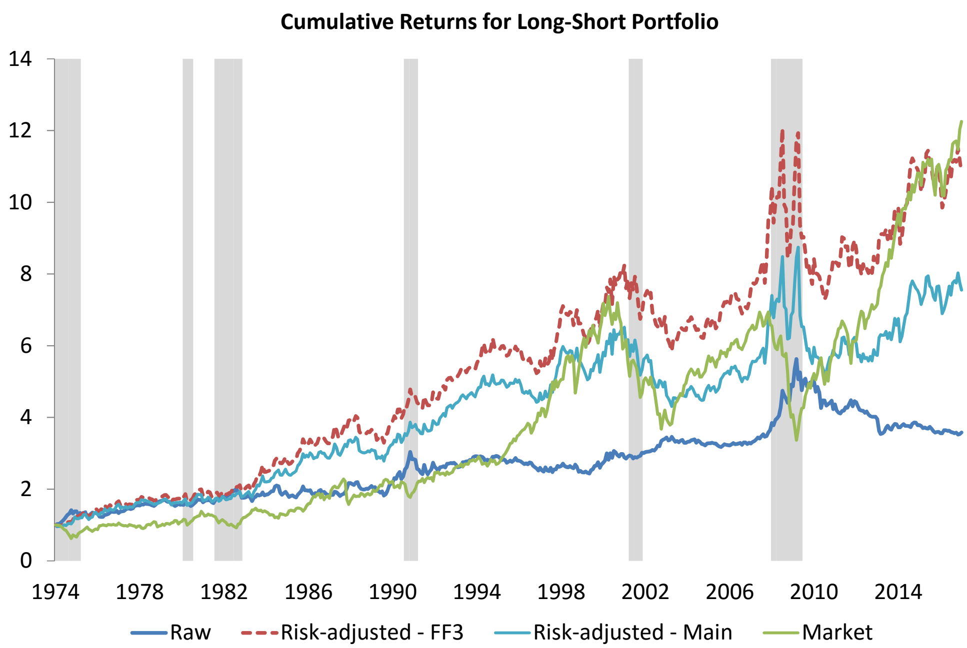


Figure 4.
This figure plots the cumulative returns for $1 invested in the long-short portfolio of banks sorted by LG in the beginning of the sample period in 1974 with net proceeds at the end of the period reinvested in each subsequent period. The figure plots both the raw returns and the risk-adjusted returns which are the residuals from the regression of the raw returns on the excess market return, SMB, HML, and a financial sector specific size factor. The excess market return is also plotted for reference.

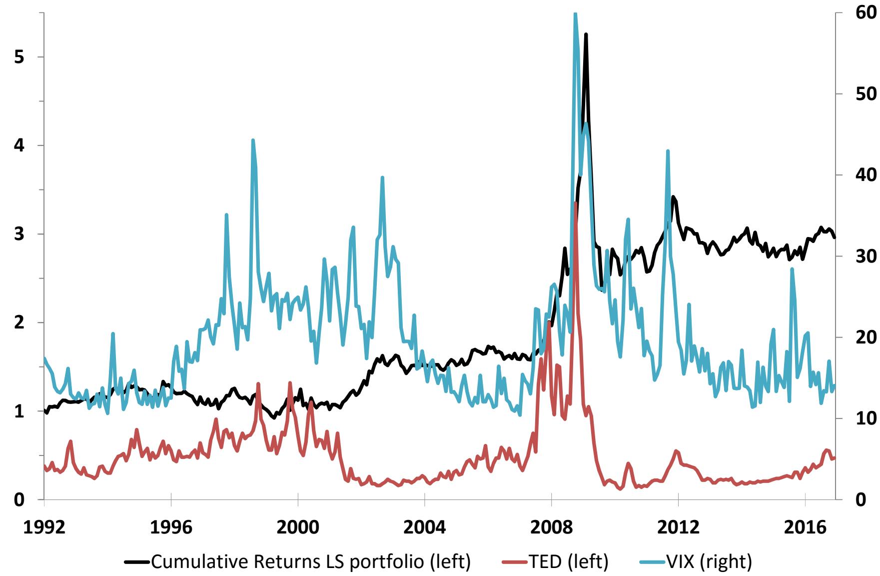


Figure 5.
This figure plots the cumulative returns for \$1 invested in the long-short portfolio of banks sorted by *LG* in the beginning of the sample period in 1992 with net proceeds at the end of the period reinvested in each subsequent period. The figure also plots the VIX index and the TED rate (right axis). The sample period is from 1992 to 2016.

Table 1. Volatility of Liability Types

This table presents the volatility of major liability categories (deposit categories are broken down into foreign vs domestic offices and commercial vs non-commercial subsidiaries) in the Y-9C Federal Reserve quarterly reports from 1991-2016. (1) is the average of the standard deviation of the cross-section 4-quarter growth rates; (2) is the average 4-quarter growth rates; (3) is the share of each liability category to total capital (liabilities plus equity) in the aggregate; (4) is the average share of each liability category to total capital (liabilities plus equity) across banks. Source: Federal Reserve Y-9C reports.

Item	Std Dev	Mean	VW Share	EW Share
Trading Liabilities	0.616	0.126	0.044	0.016
Other Borrowed Money	0.556	0.101	0.119	0.074
Deposits, Foreign	0.537	0.100	0.111	0.067
Federal Funds Purchased and Repos	0.516	0.074	0.084	0.048
Volatile Liabilities	0.439	0.106	0.327	0.120
Other Liabilities	0.414	0.083	0.054	0.014
Subordinated Notes and Debentures	0.256	0.052	0.024	0.018
Non-interest Bearing Deposits, Domestic	0.204	0.095	0.125	0.125
Equity	0.150	0.080	0.103	0.095
Interest Bearing Deposits, Domestic	0.127	0.071	0.369	0.642
Non-volatile Liabilities and Equity	0.112	0.076	0.673	0.880
Deposits in non-commercial banks	0.338	0.049	0.026	0.250
Deposits in commercial banks	0.120	0.077	0.488	0.759
Off-Balance Sheet	0.740	-0.068	0.033	0.037

Table 2. Summary Statistics

Panel A presents summary statistics for balance sheet and income statement variables for portfolios for the sample between 1991 and 2016 (based on 33,168 BHC-quarter observations). We sort bank holding companies into quintiles according to the *LG* in Q4 of year date *t*. Averages are calculated on an equally-weighted basis. Panel B presents summary statistics for balance sheet and income statement variables for portfolios for the sample between 1974 and 1990 (4,621 BHC-year observations). We sort bank holding companies into quintiles according to the predicted *LG* measure in Q4 of year date *t*. Source: Federal Reserve Y-9C reports and Compustat.

Portfolio	1	2	3	4	5	Mean	Std Dev
Panel A. 1991-2016 (Y-9C Data)							
Balance Sheet Items							
Assets, Bil. $	4.16	8.15	14.04	23.11	73.51	24.60	149.98
log(Assets)	21.16	21.22	21.53	21.81	22.62	21.66	1.61
Market Cap, Bil. $	0.60	1.10	1.75	2.80	8.35	2.92	16.31
Book-to-Market	97.20	97.71	97.47	97.37	97.57	97.46	5.07
Deposits/Assets, %	81.74	80.07	78.71	76.41	69.5	77.28	9.41
Core Deposits/Assets, %	70.45	68.06	66.24	63.23	54.37	64.47	13.28
Equity/Assets, %	9.72	9.63	9.38	9.27	9.00	9.40	2.41
Loans/Assets, %	54.80	63.80	67.52	70.13	70.84	65.45	11.86
Real Estate Loans/Assets, %	38.04	44.83	47.64	49.71	48.5	44.86	15.10
C&I Loans/Assets, %	9.81	10.90	11.34	11.79	11.55	11.08	7.38
Consumer Loans/Assets, %	4.75	5.73	5.97	6.15	6.16	5.75	6.18
Income Statement Items							
Net Interest Margin/TA, %	3.75	3.84	3.77	3.81	3.54	3.74	1.18
Non-Int. Income/Income, %	58.46	56.87	58.2	59.46	72.23	61.04	61.06
Return on Assets, %	3.44	3.00	2.60	2.60	2.40	2.80	7.60
Return on Equity, %	8.66	6.95	6.10	6.56	5.91	6.83	26.51
Charge-offs/TA, %	0.33	0.47	0.55	0.58	0.68	0.52	0.96
Risk Characteristics							
Tier-1 Capital/Assets, %	9.23	9.09	8.79	8.68	8.37	8.83	2.21
Risk-weighted Assets/Total Assets, %	64.41	70.74	73.46	75.36	77.58	72.33	11.59
Std Dev of ROA	1.56	1.84	2.08	2.12	2.32	2.00	4.12
Std Dev of ROE	4.69	5.51	6.33	6.83	7.24	6.12	1.03
Tail Risk	5.00	5.30	5.35	5.18	5.22	5.21	3.29
Z-score	3.47	3.35	3.29	3.27	3.19	3.31	1.46
Liquidity Characteristics							
Liquidity Gap Measure	-0.37	-0.25	-0.19	-0.13	-0.02	-0.19	0.16
Volatile Liabilities/Liabilities	0.083	0.099	0.115	0.141	0.228	0.13	0.12
Liquid Assets/Liabilities	0.448	0.342	0.299	0.268	0.249	0.32	0.13
Percent with Mismatch > 0	0.00	0.01	0.02	0.06	0.39	0.10	0.30
Bank Organization Characteristics							
No. of Banking Subsidiaries	2.02	2.20	2.49	2.94	3.09	2.55	4.97
Complexity	0.12	0.14	0.23	0.3	0.45	0.25	0.49
Panel B. 1974-1990 (Compustat)							
Assets, Bil. $	2.42	4.07	5.18	13.79	23.13	9.73	20.84
Market Cap, Bil. $	0.16	0.23	0.30	0.53	0.87	0.42	0.73
Equity/Assets, %	6.77	6.20	5.84	5.51	5.10	5.88	1.6
Debt in Current Liabilities/Assets, %	5.98	8.99	10.74	12.72	16.56	11.01	6.51
Long-Term Debt/Assets, %	1.27	1.42	1.71	1.98	3.12	1.90	1.64
Investment and Advances/Assets, %	26.30	21.11	18.27	15.44	12.85	18.76	7.30
Return on Assets, %	0.77	0.76	0.58	0.57	0.50	0.64	0.97
Liquidity Risk Measure	-0.36	-0.26	-0.20	-0.13	-0.02	-0.19	0.13
Cash/Assets	9.08	9.35	9.50	9.75	8.66	9.27	3.79

Table 3. Returns on Liquidity Gap-Sorted Stock Portfolios - Value-Weighted

Panel A presents raw excess returns (i) and risk-adjusted returns (α) of liquidity-gap-sorted portfolios for CAPM (ii), 3-factor Fama-French(iii), and 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (iv). Panels B-D present the factor loadings on these models. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis. Portfolio returns are annualized and value-weighted based on market capitalization.

	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Alphas			
Excess Returns	0.096***	0.089***	0.086***	0.081**	0.063	0.033
	(3.29)	(2.99)	(2.61)	(2.46)	(1.60)	(1.61)
CAPM alpha	0.037*	0.033	0.021	0.013	-0.017	0.055***
	(1.86)	(1.46)	(0.95)	(0.50)	(-0.67)	(2.84)
3-factor alpha	0.004	-0.004	-0.024	-0.028	-0.069***	0.073***
	(0.25)	(-0.21)	(-1.33)	(-1.22)	(-3.54)	(3.73)
8-factor alpha	0.017	-0.001	-0.009	-0.018	-0.043**	0.060***
	(0.91)	(-0.04)	(-0.42)	(-0.77)	(-2.17)	(2.93)
			Panel B. CAPM			
β^{M}	0.827***	0.792***	0.902***	0.953***	1.132***	-0.305***
	(18.17)	(18.51)	(16.22)	(13.81)	(14.30)	(-4.46)
			Panel C. 3-Factor Fama-French (regression coefficients)			
β^{M}	0.892***	0.871***	1.025***	1.116***	1.321***	-0.430***
	(18.61)	(20.94)	(23.12)	(16.76)	(20.01)	(-6.41)
β^{smb}	0.179***	0.172***	0.091*	-0.158	-0.124*	0.303***
	(3.17)	(2.68)	(1.93)	(-1.42)	(-1.73)	(4.71)
β^{hml}	0.536***	0.612***	0.788***	0.785***	0.971***	-0.435***
	(7.81)	(9.59)	(11.60)	(7.92)	(8.88)	(-3.61)
			Panel D. 5-Factor Fama-French + ltg + crd + ps (regression coefficients)			
β^{M}	0.880***	0.873***	0.992***	1.122***	1.286***	-0.406***
	(18.88)	(24.26)	(24.52)	(17.06)	(20.25)	(-7.06)
β^{smb}	0.164**	0.264***	0.129**	-0.036	-0.069	0.233***
	(2.53)	(4.94)	(2.25)	(-0.36)	(-0.87)	(3.12)
β^{hml}	0.619***	0.744***	0.958***	0.974***	1.261***	-0.642***
	(7.29)	(9.61)	(9.99)	(7.84)	(9.05)	(-4.21)
β^{rmw}	-0.001	0.002***	0.000	0.002**	-0.000	-0.001
	(-0.85)	(2.66)	(0.43)	(2.39)	(-0.02)	(-0.64)
β^{cma}	-0.002	-0.003***	-0.004***	-0.004**	-0.006***	0.004**
	(-1.26)	(-2.60)	(-2.71)	(-2.19)	(-3.42)	(2.23)
β^{ltg}	0.011	0.145	0.075	0.200	0.250*	-0.238
	(0.09)	(1.31)	(0.79)	(1.31)	(1.75)	(-1.50)
β^{crd}	-0.070	-0.134	-0.017	-0.210	-0.228	0.158
	(-0.41)	(-0.76)	(-0.09)	(-0.88)	(-0.95)	(0.69)
β^{ps}	-0.054	-0.118**	-0.177***	-0.233***	-0.210**	0.156**
	(-1.23)	(-2.29)	(-2.61)	(-2.78)	(-2.49)	(2.00)
N	516	516	516	516	516	516

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4. Returns on Liquidity Gap-Sorted Stock Portfolios - Equally-Weighted

Panel A presents raw excess returns (i) and risk-adjusted returns (α) of liquidity-gap-sorted portfolios for CAPM (ii), 3-factor Fama-French(iii), and 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (iv). Panels B-D present the factor loadings on these models. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis. Portfolio returns are annualized and computed on an equally-weighted basis.

	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Alphas			
Excess Returns	0.126***	0.112***	0.116***	0.096***	0.091**	0.035**
	(4.74)	(3.72)	(3.59)	(2.92)	(2.47)	(2.32)
CAPM alpha	0.083***	0.065***	0.064**	0.039	0.025	0.058***
	(3.79)	(2.62)	(2.42)	(1.44)	(0.90)	(4.57)
3-factor alpha	0.046***	0.024	0.019	-0.008	-0.021	0.067***
	(2.74)	(1.24)	(0.91)	(-0.40)	(-0.94)	(5.40)
8-factor alpha	0.037**	0.015	0.015	-0.012	-0.021	0.058***
	(2.38)	(0.83)	(0.80)	(-0.64)	(-1.07)	(4.44)
			Panel B. CAPM			
β^M	0.605***	0.660***	0.739***	0.808***	0.926***	-0.321***
	(13.97)	(13.51)	(13.27)	(14.24)	(15.01)	(-9.57)
			Panel C. 3-Factor Fama-French (regression coefficients)			
β^M	0.641***	0.710***	0.801***	0.889***	1.029***	-0.389***
	(17.10)	(16.63)	(18.25)	(17.14)	(18.01)	(-11.79)
β^{smb}	0.359***	0.361***	0.366***	0.302***	0.181**	0.179***
	(6.06)	(5.89)	(6.15)	(3.85)	(2.32)	(4.67)
β^{hml}	0.534***	0.619***	0.691***	0.746***	0.758***	-0.224***
	(8.84)	(10.67)	(10.17)	(10.20)	(11.07)	(-5.80)
			Panel D. 5-Factor Fama-French + ltg + crd + ps (regression coefficients)			
β^M	0.632***	0.691***	0.765***	0.881***	1.003***	-0.371***
	(19.68)	(18.57)	(18.23)	(18.47)	(19.62)	(-11.38)
β^{smb}	0.449***	0.460***	0.451***	0.426***	0.292***	0.157***
	(8.96)	(9.21)	(7.74)	(6.39)	(4.01)	(3.45)
β^{hml}	0.570***	0.671***	0.770***	0.849***	0.907***	-0.337***
	(9.29)	(10.27)	(10.05)	(9.50)	(11.60)	(-5.93)
β^{rmw}	0.002***	0.003***	0.002**	0.003***	0.002**	0.000
	(3.77)	(3.72)	(2.48)	(3.35)	(2.36)	(0.54)
β^{cma}	-0.001	-0.002	-0.002*	-0.002*	-0.003**	0.002**
	(-1.30)	(-1.61)	(-1.80)	(-1.78)	(-2.49)	(2.48)
β^{ltg}	0.019	0.001	0.016	0.130	0.188*	-0.169***
	(0.29)	(0.01)	(0.18)	(1.34)	(1.89)	(-2.61)
β^{crd}	0.110	0.168	0.205	0.026	0.012	0.098
	(1.02)	(1.36)	(1.28)	(0.15)	(0.07)	(0.90)
β^{ps}	-0.067*	-0.091**	-0.137***	-0.176***	-0.142**	0.075**
	(-1.89)	(-2.24)	(-2.86)	(-3.02)	(-2.46)	(2.12)
N	516	516	516	516	516	516

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5. Returns on Liquidity Gap-Sorted Stock Portfolios - Deciles

This table presents risk-adjusted returns (α) and regression coefficients of liquidity-gap-sorted portfolios for the 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (specification iv), and including a financial size factor. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. Portfolio returns are annualized and computed as value-weighted based on market capitalization (Panel A), and equal-weighted (Panel B).

Panel A: value-weighted

	Low	2	3	4	5	6	7	8	9	High	Low-High
alpha	0.022	0.006	-0.002	-0.005	-0.011	-0.008	-0.019	-0.026	-0.062***	-0.036	0.058**
β^{M}	0.790***	0.918***	0.819***	0.912***	0.924***	0.994***	1.076***	1.140***	1.200***	1.320***	-0.530***
β^{smb}	0.238***	0.213***	0.316***	0.277***	0.164*	0.184***	0.150	-0.030	-0.068	-0.044	0.281***
β^{hml}	0.556***	0.733***	0.747***	0.764***	0.735***	0.996***	1.034***	0.976***	1.080***	1.291***	-0.735***
β^{rmw}	-0.000	0.000	0.003***	0.002*	0.002	0.000	0.003***	0.003**	0.001	-0.000	-0.000
β^{cma}	-0.001	-0.002	-0.002	-0.003**	-0.002	-0.004**	-0.004**	-0.003**	-0.003**	-0.007***	0.006***
eβ^{ltg}	0.028	0.038	0.146	0.150	0.073	0.056	0.309*	0.199	0.184	0.276	-0.249
β^{crd}	-0.074	-0.106	-0.044	-0.173	0.061	0.002	-0.316	-0.210	-0.132	-0.255	0.181
β^{ps}	-0.006	-0.134**	-0.095	-0.132**	-0.059	-0.213**	-0.200**	-0.213***	-0.171**	-0.205**	0.200**

Panel B: equal-weighted

	Low	2	3	4	5	6	7	8	9	High	Low-High
alpha	0.044***	0.029*	0.017	0.012	0.010	0.019	-0.009	-0.015	-0.009	-0.033	0.078***
β^{M}	0.581***	0.679***	0.662***	0.719***	0.748***	0.780***	0.869***	0.891***	0.967***	1.039***	-0.458***
β^{smb}	0.433***	0.468***	0.442***	0.477***	0.435***	0.467***	0.450***	0.400***	0.297***	0.287***	0.146**
β^{hml}	0.510***	0.630***	0.662***	0.681***	0.739***	0.801***	0.805***	0.887***	0.889***	0.925***	-0.414***
β^{rmw}	0.002***	0.003***	0.003***	0.003***	0.002***	0.002**	0.003***	0.003***	0.002**	0.002*	0.000
β^{cma}	-0.001	-0.001	-0.001	-0.002	-0.002*	-0.002	-0.002	-0.003**	-0.004***	-0.003**	0.002*
β^{ltg}	0.009	0.025	0.025	-0.020	0.016	0.012	0.174*	0.085	0.213**	0.160	-0.151*
β^{crd}	0.119	0.118	0.180	0.152	0.188	0.227	-0.040	0.093	-0.042	0.068	0.051
β^{ps}	-0.037	-0.099**	-0.095**	-0.083	-0.116**	-0.160***	-0.166***	-0.183***	-0.121**	-0.164**	0.127**
N	516	516	516	516	516	516	516	516	516	516	516

* p<0.10, ** p<0.05, *** p<0.01

Table 6. Returns on Liquidity Gap-Sorted Stock Portfolios - Financial Size Factor - Value-Weighted

This table presents risk-adjusted returns (α) and regression coefficients of liquidity-gap-sorted portfolios for the 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (specification iv), and including a financial size factor. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis. Portfolio returns are annualized and are value-weighted based on market capitalization.

	(1)	(2)	(3)	(4)	(5)	(6)
alpha	0.028	0.008	0.008	0.007	-0.018	0.045**
	(1.44)	(0.40)	(0.41)	(0.33)	(-0.90)	(2.28)
β^{M}	0.701***	0.728***	0.716***	0.702***	0.868***	-0.167***
	(15.87)	(14.06)	(13.98)	(10.15)	(14.19)	(-3.01)
β^{smb}	0.311***	0.383***	0.355***	0.308***	0.274***	0.038
	(4.64)	(6.21)	(6.05)	(3.58)	(3.70)	(0.52)
β^{hml}	0.516***	0.661***	0.801***	0.733***	1.022***	-0.506***
	(5.62)	(9.21)	(11.37)	(7.55)	(10.79)	(-3.97)
β^{rmw}	-0.000	0.002***	0.001*	0.004***	0.001	-0.001
	(-0.06)	(3.33)	(1.65)	(3.57)	(1.41)	(-1.44)
β^{cma}	-0.001	-0.002**	-0.002**	-0.001	-0.004**	0.003
	(-0.56)	(-1.99)	(-2.11)	(-1.04)	(-2.39)	(1.51)
β^{ltg}	-0.040	0.103	-0.005	0.079	0.129	-0.170
	(-0.35)	(1.00)	(-0.06)	(0.65)	(1.10)	(-1.06)
β^{crd}	0.035	-0.049	0.144	0.036	0.016	0.018
	(0.21)	(-0.30)	(0.90)	(0.19)	(0.09)	(0.09)
β^{ps}	-0.036	-0.104**	-0.149***	-0.191***	-0.169***	0.132**
	(-0.92)	(-2.30)	(-2.70)	(-3.19)	(-2.72)	(1.99)
$\beta^{smb^{fin}}$	-0.262***	-0.212***	-0.403***	-0.614***	-0.611***	0.348***
	(-4.28)	(-3.77)	(-7.64)	(-7.74)	(-9.78)	(4.76)
N	516	516	516	516	516	516

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 7. Returns on Liquidity Gap-Sorted Stock Portfolios - Financial Size Factor - Equal-Weighted

This table presents risk-adjusted returns (α) and regression coefficients of liquidity-gap-sorted portfolios for the 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (specification iv), and including a financial size factor. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis. Portfolio returns are annualized and computed on an equally-weighted basis.

	(1)	(2)	(3)	(4)	(5)	(6)
alpha	0.036**	0.011	0.014	-0.008	-0.014	0.050***
	(2.34)	(0.66)	(0.76)	(-0.43)	(-0.69)	(4.05)
β^M	0.649***	0.749***	0.782***	0.820***	0.884***	-0.235***
	(16.41)	(15.49)	(15.63)	(15.16)	(15.19)	(-6.14)
β^{smb}	0.435***	0.412***	0.437***	0.476***	0.390***	0.045
	(7.62)	(7.20)	(6.74)	(6.96)	(4.66)	(0.89)
β^{hml}	0.581***	0.705***	0.780***	0.814***	0.839***	-0.259***
	(9.02)	(10.01)	(9.53)	(8.86)	(11.03)	(-5.37)
β^{rmw}	0.002***	0.003***	0.002**	0.003***	0.003***	-0.000
	(3.66)	(3.43)	(2.40)	(3.50)	(2.66)	(-0.32)
β^{cma}	-0.001	-0.002*	-0.002*	-0.002	-0.003**	0.001*
	(-1.38)	(-1.88)	(-1.81)	(-1.47)	(-1.99)	(1.75)
β^{ltg}	0.024	0.018	0.021	0.112	0.154	-0.129**
	(0.36)	(0.25)	(0.23)	(1.17)	(1.57)	(-2.11)
β^{crd}	0.100	0.134	0.195	0.061	0.082	0.018
	(0.89)	(1.02)	(1.19)	(0.38)	(0.46)	(0.18)
β^{ps}	-0.069*	-0.097**	-0.139***	-0.170***	-0.131**	0.062**
	(-1.93)	(-2.30)	(-2.87)	(-3.07)	(-2.39)	(2.03)
$\beta^{smb^{fin}}$	0.026	0.085	0.025	-0.088	-0.173**	0.199***
	(0.61)	(1.55)	(0.41)	(-1.25)	(-2.45)	(4.20)
N	516	516	516	516	516	516

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 8. Factor Regressions - Double Sorts

This table presents risk-adjusted returns (α) of portfolios double-sorted first by bank characteristic then by LG for the the baseline 8-factor model. Sample period: 1974 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis.

Portfolio	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Size (total assets)			
Small	0.025	0.001	-0.001	-0.009	-0.015	0.040**
	(1.19)	(0.03)	(-0.04)	(-0.43)	(-0.64)	(2.55)
Medium	0.011	-0.014	0.006	-0.019	-0.036*	0.047***
	(0.61)	(-0.68)	(0.31)	(-0.92)	(-1.72)	(2.92)
Big	0.004	-0.021	-0.021	-0.051**	-0.038*	0.042*
	(0.20)	(-0.92)	(-0.87)	(-2.38)	(-1.76)	(1.85)
			Panel B. Leverage (total asset/common equity)			
Low	0.008	-0.010	-0.037*	-0.018	-0.024	0.032
	(0.38)	(-0.50)	(-1.72)	(-1.00)	(-1.10)	(1.31)
Medium	0.022	0.013	-0.010	-0.022	0.007	0.015
	(0.97)	(0.56)	(-0.40)	(-0.93)	(0.33)	(0.66)
High	0.016	-0.009	-0.014	-0.054**	-0.043	0.059*
	(0.71)	(-0.37)	(-0.49)	(-2.05)	(-1.61)	(1.76)
			Panel C. Profitability (return-on-assets)			
Low	0.046*	-0.016	-0.053*	0.003	-0.024	0.071**
	(1.84)	(-0.65)	(-1.77)	(0.13)	(-0.74)	(1.98)
Medium	0.010	-0.001	0.003	-0.018	-0.066***	0.076***
	(0.50)	(-0.07)	(0.11)	(-0.72)	(-2.80)	(3.10)
High	0.014	-0.011	-0.012	-0.018	-0.029	0.043*
	(0.72)	(-0.46)	(-0.64)	(-0.79)	(-1.36)	(1.78)
			Panel D. Tail risk			
Low	0.040*	-0.007	0.009	-0.014	-0.020	0.060**
	(1.93)	(-0.35)	(0.47)	(-0.58)	(-0.97)	(2.55)
Medium	-0.009	-0.009	-0.017	-0.036	-0.038	0.028
	(-0.45)	(-0.40)	(-0.81)	(-1.40)	(-1.45)	(0.94)
High	0.003	-0.025	0.017	-0.039	-0.067**	0.069**
	(0.10)	(-0.95)	(0.55)	(-1.20)	(-2.56)	(2.14)
			Panel E. Charge-offs (net charge-offs over total assets)			
Low	0.026	-0.014	-0.002	-0.034	-0.035	0.061**
	(1.08)	(-0.56)	(-0.09)	(-1.29)	(-1.56)	(2.38)
Medium	0.014	-0.006	-0.012	-0.059**	-0.072***	0.085***
	(0.69)	(-0.28)	(-0.57)	(-2.48)	(-2.74)	(2.71)
High	0.023	-0.008	0.009	-0.010	0.000	0.023
	(1.09)	(-0.36)	(0.40)	(-0.45)	(0.00)	(0.95)
N	516	516	516	516	516	516

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 9. Factor Regressions - Double Sorts - Complexity

This table presents risk-adjusted returns (α) of portfolios double-sorted first by bank characteristic then by LG for the baseline 8-factor model. Complexity is 0/1 index is provided by the Federal Reserve, and refers to bank holding companies with complex include material credit-extending activity, issuing a large amount of debt to the public, engaging in high-risk non-bank financial activities and having complex management practices. Sample period: 1993 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis.

Portfolio	Low	(2)	(3)	(4)	High	Low-High
Not Complex	0.068***	0.069**	0.042	0.065***	0.028	0.040**
	(3.40)	(2.57)	(1.54)	(2.60)	(1.00)	(2.32)
Complex	0.043	0.052*	0.017	0.019	-0.021	0.064**
	(1.50)	(1.82)	(0.53)	(0.64)	(-0.78)	(2.20)
N	288	288	288	288	288	288

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 10. Fama-Macbeth (1973) Cross-Sectional Regressions

This table presents the results for the Fama-Macbeth monthly cross-sectional regressions for bank stock excess returns. The independant variables include the liquidity gap measure, constructed factor loadings $[\beta_i^{market}, \beta_i^{smb}, \beta_i^{hml}]_t$, based on a 60-month rolling windows, and other individual bank characteristics, including (i) size (total assets), (ii) equity/asset ratio, (iii) net charge-offs, (iv) non-interest income share, (v) tail risk, (vi) ROA, (vii) z-score, and (viii) book-to-market. The sample period is January 1993 to December 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Liquidity Gap	-0.094*	-0.067*	-0.063	-0.076*	-0.068**
	(-1.89)	(-1.75)	(-1.61)	(-1.95)	(-2.06)
β^M		0.015	0.016	0.013	0.019
		(0.32)	(0.34)	(0.29)	(0.44)
β^{smb}		0.032	0.032	0.033	0.041*
		(1.46)	(1.36)	(1.45)	(1.88)
β^{hml}		-0.009	-0.009	-0.009	-0.001
		(-0.31)	(-0.29)	(-0.32)	(-0.04)
Size			0.0478	0.0382	-0.0125
			(0.51)	(0.42)	(-0.15)
Equity/Assets				-0.684**	-0.953
				(-2.49)	(-1.03)
Net Charge-offs					-3.604**
					(-2.48)
Non-interest Income Share					0.000
					(1.22)
Tail Risk					-1.274***
					(-2.61)
ROA					-0.006
					(-0.62)
Z-score					0.015***
					(2.67)
B/M					0.240
					(0.32)
Constant	0.115***	0.102***	0.101***	0.162***	-0.081
	(2.75)	(3.33)	(3.22)	(3.73)	(-0.11)
R^2	1.14	13.61	14.40	15.41	21.30
Number of observations	70722	70722	69242	69242	64143
Number of periods	288	288	288	288	288

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 11. Returns on Sorted Stock Portfolios - by Liquidity Gap Component - Value-Weighted

This table presents raw excess returns (i) and risk-adjusted returns (α) of liquidity-gap-sorted portfolios for CAPM (ii), 3-factor Fama-French(iii), and 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (iv). Portfolio returns are annualized and are value-weighted based on market capitalization. The results are presented for the period 1992 - 2016, for (i) Liquidity Gap, (ii) Ratio of volatile liabilities to total liabilities, (iii) ratio of liquid assets to total liabilities. Note that the sorting for (iii) is in reverse order so that portfolio 1 (5) reflects lower (higher) liquidity risk. Standard errors are Newey-West corrected with 6 lags. *t*-statistics are in parenthesis.

	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Alphas - Liquidity Gap			
Excess Returns	0.129***	0.113***	0.102**	0.108***	0.072	0.058
	(4.10)	(3.02)	(2.54)	(2.68)	(1.38)	(1.64)
CAPM alpha	0.077**	0.053	0.040	0.041	-0.020	0.097***
	(2.51)	(1.54)	(1.19)	(1.12)	(-0.51)	(3.32)
3-factor alpha	0.040*	0.006	-0.008	-0.011	-0.073***	0.113***
	(1.78)	(0.27)	(-0.32)	(-0.43)	(-2.95)	(4.26)
8-factor alpha	0.047**	0.026	0.029	0.038	-0.015	0.062**
	(1.98)	(1.04)	(0.98)	(1.25)	(-0.60)	(2.53)
			Panel B. Alphas - Volatile Liabilities / Total Liabilities			
Excess Returns	0.121***	0.123***	0.105***	0.087*	0.085*	0.036
	(3.38)	(3.18)	(2.74)	(1.94)	(1.82)	(1.23)
CAPM alpha	0.068*	0.069*	0.048	0.019	-0.002	0.069***
	(1.95)	(1.77)	(1.38)	(0.48)	(-0.05)	(3.07)
3-factor alpha	0.023	0.018	0.003	-0.038	-0.050**	0.073***
	(1.02)	(0.68)	(0.12)	(-1.52)	(-2.38)	(3.74)
8-factor alpha	0.035	0.031	0.021	-0.005	0.011	0.024
	(1.54)	(1.07)	(0.85)	(-0.19)	(0.41)	(1.04)
			Panel C. Alphas - Liquid Assets / Total Liabilities (reverse order)			
Excess Returns	0.078	0.087*	0.093**	0.120***	0.057	0.022
	(1.57)	(1.69)	(2.18)	(3.01)	(1.09)	(0.60)
CAPM alpha	-0.018	0.02	0.023	0.054	-0.011	-0.007
	(-0.57)	(-0.43)	(-0.67)	(-1.43)	(-0.25)	(-0.19)
3-factor alpha	-0.058**	-0.022	-0.029	0.000	-0.064*	0.005
	(-2.37)	(-0.66)	(-1.11)	(-0.01)	(-1.93)	(0.16)
8-factor alpha	0.022	-0.021	0.005	0.036	-0.035	0.057
	(-0.69)	(-0.55)	(0.18)	(-1.07)	(-1.17)	(1.38)
N	300	300	300	300	300	300

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 12. Returns on Liquidity Gap-Sorted Stock Portfolios - by Periods - Value-Weighted
This table presents raw excess returns (i) and risk-adjusted returns (α) of liquidity-gap-sorted portfolios for CAPM (ii), 3-factor Fama-French(iii), and 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (iv). Portfolio returns are annualized and are value-weighted based on market capitalization. The results are presented for the following sample periods: A. 1974 - 1991, B. 1992 - 2007, C. 2008 - 2009, D. 2010 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis.

	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Alphas - 1974 - 1991			
Excess Returns	0.090*	0.072	0.070	0.027	0.025	0.064**
	(1.89)	(1.42)	(1.33)	(0.48)	(0.39)	(2.19)
CAPM alpha	0.038	0.018	0.008	-0.041	-0.051	0.089***
	(1.38)	(0.60)	(0.28)	(-1.27)	(-1.45)	(3.52)
3-factor alpha	0.009	-0.017	-0.032	-0.060*	-0.091***	0.101***
	(0.36)	(-0.63)	(-1.16)	(-1.89)	(-2.92)	(3.82)
8-factor alpha	0.010	-0.020	-0.009	-0.046	-0.076**	0.086***
	(0.35)	(-1.09)	(-0.33)	(-1.13)	(-2.25)	(2.70)
N	216	216	216	216	216	216
			Panel B. Alphas - 1992 - 2007			
Excess Returns	0.145***	0.121***	0.085*	0.123***	0.092**	0.053*
	(4.00)	(3.04)	(1.96)	(3.31)	(2.11)	(1.83)
CAPM alpha	0.108***	0.083**	0.042	0.078**	0.026	0.082***
	(2.95)	(2.11)	(1.03)	(2.12)	(0.68)	(2.87)
3-factor alpha	0.056*	0.017	-0.023	0.021	-0.036	0.093***
	(1.84)	(0.69)	(-0.76)	(0.71)	(-1.27)	(3.43)
8-factor alpha	0.039	0.011	-0.018	0.017	-0.029	0.068***
	(1.45)	(0.45)	(-0.65)	(0.60)	(-1.07)	(2.76)
N	192	192	192	192	192	192
			Panel C. Alphas - 2008 - 2009			
Excess Returns	-0.003	-0.042	0.053	-0.179	-0.255	0.252
	(-0.02)	(-0.20)	(0.23)	(-0.64)	(-0.58)	(0.73)
CAPM alpha	0.054	0.041	0.137	-0.090	-0.102	0.156
	(0.43)	(0.35)	(1.16)	(-0.49)	(-0.54)	(0.89)
3-factor alpha	0.016	0.055	0.139	-0.133	-0.062	0.078
	(0.19)	(0.69)	(1.16)	(-1.53)	(-0.35)	(0.37)
8-factor alpha	-0.021	-0.028	0.263*	-0.167	0.021	-0.041
	(-0.15)	(-0.29)	(1.78)	(-0.97)	(0.16)	(-0.27)
N	24	24	24	24	24	24
			Panel D. Alphas - 2010 - 2016			
Excess Returns	0.130**	0.139*	0.154*	0.156**	0.119	0.012
	(2.15)	(1.91)	(1.93)	(2.15)	(1.49)	(0.35)
CAPM alpha	-0.017	-0.026	-0.004	-0.016	-0.057	0.039
	(-0.43)	(-0.47)	(-0.08)	(-0.32)	(-1.02)	(1.25)
3-factor alpha	0.001	-0.015	0.010	-0.006	-0.047	0.048
	(0.03)	(-0.34)	(0.23)	(-0.17)	(-1.18)	(1.57)
8-factor alpha	0.047	0.051	0.085**	0.067*	0.017	0.029
	(1.58)	(1.18)	(2.17)	(1.78)	(0.48)	(1.03)
N	84	84	84	84	84	84

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 13. Returns on Liquidity Gap-Sorted Stock Portfolios - by Periods - Equal-Weighted

This table presents raw excess returns (i) and risk-adjusted returns (α) of liquidity-gap-sorted portfolios for CAPM (ii), 3-factor Fama-French(iii), and 5-factor Fama-French model augmented with bond factors (ltg, crd) and liquidity factor ps (iv). Portfolio returns are annualized and are equal-weighted basis. The results are presented for the following sample periods: A. 1974 - 1991, B. 1992 - 2007, C. 2008 - 2009, D. 2010 - 2016. Standard errors are Newey-West corrected with 6 lags. t-statistics are in parenthesis.

	Low	(2)	(3)	(4)	High	Low-High
			Panel A. Alphas - 1974 - 1991			
Excess Returns	0.106**	0.076	0.076	0.054	0.047	0.060**
	(2.45)	(1.60)	(1.49)	(1.00)	(0.73)	(2.16)
CAPM alpha	0.063**	0.025	0.020	-0.009	-0.024	0.087***
	(2.27)	(0.88)	(0.63)	(-0.27)	(-0.68)	(4.29)
3-factor alpha	0.027	-0.016	-0.024	-0.050*	-0.073**	0.100***
	(1.14)	(-0.70)	(-0.96)	(-1.97)	(-2.49)	(5.00)
8-factor alpha	0.022	-0.017	-0.012	-0.045*	-0.060**	0.082***
	(1.00)	(-0.97)	(-0.66)	(-1.70)	(-2.19)	(3.55)
N	216	216	216	216	216	216
			Panel B. Alphas - 1992 - 2007			
Excess Returns	0.157***	0.146***	0.146***	0.153***	0.136***	0.021
	(4.16)	(3.53)	(3.24)	(3.46)	(2.88)	(1.11)
CAPM alpha	0.132***	0.122***	0.119**	0.122***	0.096*	0.036*
	(3.43)	(2.83)	(2.57)	(2.69)	(1.94)	(1.79)
3-factor alpha	0.076***	0.064*	0.052	0.050	0.015	0.062***
	(2.64)	(1.83)	(1.58)	(1.59)	(0.44)	(3.89)
8-factor alpha	0.067***	0.056*	0.045	0.041	0.011	0.056***
	(2.60)	(1.85)	(1.58)	(1.59)	(0.39)	(3.42)
N	192	192	192	192	192	192
			Panel C. Alphas - 2008 - 2009			
Excess Returns	-0.033	-0.269*	-0.315*	-0.286	-0.389*	0.356***
	(-0.24)	(-1.79)	(-2.00)	(-1.64)	(-1.99)	(4.33)
CAPM alpha	0.023	-0.197	-0.246**	-0.214*	-0.301**	0.324***
	(0.30)	(-1.68)	(-2.22)	(-1.90)	(-2.28)	(3.90)
3-factor alpha	-0.026	-0.247*	-0.301***	-0.267**	-0.331**	0.304***
	(-0.35)	(-1.92)	(-2.96)	(-2.16)	(-2.22)	(3.27)
8-factor alpha	-0.032	-0.107	-0.193	-0.123	-0.242	0.209*
	(-0.26)	(-0.67)	(-1.36)	(-1.15)	(-1.44)	(2.08)
N	24	24	24	24	24	24
			Panel D. Alphas - 2010 - 2016			
Excess Returns	0.179***	0.217***	0.212***	0.211***	0.187***	-0.008
	(3.23)	(2.89)	(3.18)	(2.89)	(2.80)	(-0.31)
CAPM alpha	0.064	0.097	0.076	0.082	0.058	0.006
	(1.53)	(1.57)	(1.32)	(1.29)	(1.00)	(0.22)
3-factor alpha	0.084***	0.114***	0.097**	0.100**	0.074*	0.009
	(3.09)	(2.71)	(2.38)	(2.38)	(1.81)	(0.33)
8-factor alpha	0.108***	0.141***	0.115***	0.121***	0.091**	0.017
	(3.95)	(3.20)	(2.84)	(2.80)	(2.25)	(0.61)
N	84	84	84	84	84	84

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table A1. Data Series

Item	Start	End	Mnemonic
Liabilities			
Deposits in domestic commercial subsidiaries (DC)			
Noninterest bearing balances, DC	1981-Q2	Present	BHCB2210
Interest bearing balances, DC	1986-Q2	Present	BHCB3187
Money market deposits and other savings accounts, DC	1981-Q2	Present	BHCB2389
Time deposits $<$ 100k, DC	1986-Q2	Present	BHCB6648
Time deposits $>$ 100k, DC	1986-Q2	Present	BHCB2604
Domestic non-commercial subsidiaries (NDC)			
Noninterest bearing balances, NDC	1986-Q2	Present	BHOD3189
Interest bearing balances, NDC	1986-Q2	Present	BHOD3187
Money market deposits and other savings accounts, NDC	1986-Q2	Present	BHOD2389
Time deposits $<$ 100k, NDC	1986-Q2	Present	BHOD6648
Time deposits $>$ 100k, NDC	1986-Q2	Present	BHOD2604
Deposits in foreign offices	1986-Q2	Present	BHFN6631 + BHFN6636
Overnight federal funds purchased and securities sold under agreements to resell	1988-Q2	1996-Q4	BHCK 0278 + BHCK 0279
	1997-Q1	2001-Q4	BHCK2800
	2002-Q1	Present	BHDMB993 + BHCKB995
Trading Liabilities	1989-Q3	1993-Q4	BHCT3548
	1994-Q1	Present	BHCK3548
Other borrowerd money (including commercial paper)	1981-Q2	2000-Q4	BHCK2309 + BHCK2332 + BHCK2333
	2001-Q1	Present	BHCK3190
Subordinated debt (notes and debentures)	1981-Q2	Present	BHCK4062
	2005-Q1	Present	BHCKC699
Other liabilities	1981-Q2	Present	BHCK2750
Equity	1986-Q2	Present	BHCK3210 + BHCK3000
Liquid Assets			
Cash and balances due from depository institutions			
Non interest bearing balances, currency, coin	1981-Q2 -	Present	BHCK0081
Interest-bearing balances in US offices	1981-Q2	Present	BHCK0395
Interest-bearing balances in foreign offices, etc	1981-Q2	Present	BHCK0397
All securities (investment securities, held to maturity and available for sale)	1981-Q2	1993-Q4	BHCK0390
	1994-Q1	Present	BHCK1754 + BHCK1773
Trading assets	1976-Q4	1994-Q4	BHCK2146
	1995-Q1	Present	BHCK3545
Overnight federal funds sold and securities purchased under agreements to resell	1988-Q2	1996-Q4	BHCK0276 + BHCK0277
	1997-Q1	2001-Q4	BHCK1350
	2002-Q1	Present	BHDMB987 + BHCKB989

Table A2. Data Series

Variable	Definition
Assets	BHCK2170
Market Cap	SHROUT*abs(PRC)
Book-to-Market	Assets divided by (Size plus Total Liabilities)
Deposits	Non-interest bearing deposits (BHDM6631 + BHFN6631) plus Total interest-bearing deposits (BHDM6636 + BHFN6636)
Core Deposits	Total Demand deposits (BHCB2210) plus NOW, ATS and other transaction accounts (BHCB3187+BHOD3187) plus Non-transaction savings deposits (BHCB2389+BHOD2389) plus Total time deposits less than \$100k (BHCB6648 + BHOD6648) plus Non-interest bearing balances in domestic offices of other depository institutions (BHOD3189) less Brokered deposits issued in denominations of less than \$100k (BHDMA243 + BHDMA164)
Leverage (Equity/Assets)	Total equity capital (BHCK3210) plus Minority interest in consolidated subsidiaries and similar items (BHCK3000), divided by Assets
Loans	BHCK2122
Real Estate Loans	BHCK1410
C&I Loans	BHDM1766
Consumer Loans	BHDM1975
Net Interest Margin	BHCK4074
Nonint. Income/Income	Total non-interest income (BHCK4079) divided by Total interest and non-interest income (BHCK4107 + BHCK4079)
Return on Assets	Income (Loss) before extraordinary items and other adjustments (BHCK4300), divided by lagged Assets
Return on Equity	Income (Loss) before extraordinary items and other adjustments (BHCK4300), divided by lagged Equity
Bad Loans	Total loans, leasing financing receivables and debt securities and other assets, past due 90 days or more and still accruing (BHCK5525) and non accrual (BHCK5526) divided by lagged Assets
Charge-offs/TA	Charge-offs on allowance for loan and lease losses (BHCK4635), divided by lagged TA
Tier-1 Capital	BHCK8274
Risk-weighted Assets	BHCKA223
Credit Risk	Charge-offs on allowance for loan and lease losses (BHCK4635) less Recoveries on allowance for loan and lease losses BHCK4605, divided by Allowance for loan and lease losses (BHCK3123)
Tail Risk	the negative of the average return on a bank's stock for the bottom 5% return days per year, following Ellul and Yerramilli (2013)
Z-score	log(Return on Assets plus Tier-1 Capital divided by Standard deviation of return on assets)
No. of Banking Subsidiaries	RSSD9146
Complexity	RSSD9057

Table A3. Projection of liquidity gap measure on Compustat variables

This table presents results from regression of liquidity gap on Compustat variables normalized by total assets (TA). (1) is an OLS regressions and (2) is a panel regression with bank level fixed effects. Source: Federal Reserve Y-9C reports and Compustat.

	(1) mismatch	(2) mismatch
CEQTA	0.0723	0.0981
	(2.99)	(3.92)
CHTA	-0.596	-0.370
	(-19.21)	(-11.99)
DLCTA	1.332	1.252
	(118.46)	(104.33)
DLTTTA	1.160	1.070
	(102.66)	(82.06)
IVAOTA	-0.744	-0.518
	(-71.37)	(-42.29)
RECTTA	0.314	0.551
	(32.27)	(47.73)
SALETA	0.195	0.0260
	(5.04)	(0.68)
Constant	-0.367	-0.559
	(-38.71)	(-54.58)
N	5478	5478
R^2	0.909	0.876

t statistics in parentheses

CEQ= Common Ordinary Equity - Total; CH= Cash; DLC= Debt in Current Liabilities - Total; DLTT= Long-Term Debt - Total; IVAO =Investment and Advances - Other; RECT=Receivables - Total; SALE= Sales Turnover (Net).

Table A4. Performance of Out-of-Sample Projection

This table presents the out-of-sample performance of the projection exercise to extend the sample back from 1991 to 1974. First, we run regressions of liquidity mismatch calculated from Y-9C on accounting variables from Compustat from 2000-2014. We use the estimated coefficients to calculate predicted values from 1991-1999 for which both Compustat and Y-9C data are still available. (1) shows the correlation between the actual and predicted values of the liquidity profile ratio from an OLS regression while (2) shows the correlation between actual and predicted values of the liquidity profile ratio using a panel regression with fixed effects. t statistics in parentheses.

	(1)	(2)
	Actual	Actual
Predicted, OLS	1.018***	
	(129.29)	
Predicted, with FE		1.055***
		(121.88)
Constant	-0.00505**	0.00508**
	(-2.27)	(2.10)
N	2730	2730
R^2	0.860	0.845

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$