Funding Liquidity Creation by Banks*

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Abstract

Relying on theories in which bank loans create deposits—a process we call "funding liquidity creation"—we measure how much funding liquidity the U.S. banking system creates. Private money creation by banks enables lending to not be constrained by the supply of cash deposits. During the 2001–2020 period, 92 percent of bank deposits were due to funding liquidity creation, and during 2011–2020 funding liquidity creation averaged $10.7 trillion per year, or 57 percent of GDP. Using natural disasters data, we provide causal evidence that better-capitalized banks create more funding liquidity and lend more even during times when cash deposit balances are falling or unchanged.

* This paper does not reflect the views of the Federal Reserve Bank of Philadelphia or of the Federal Reserve System. Any errors or omissions are the authors' responsibility.

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I. Introduction

It has long been recognized that a key role of banks in the economy is to create liquidity. A standard view of liquidity creation by banks is that they do so by "transforming" illiquid assets into liquid liabilities (e.g. Bryant (1980), Diamond and Dybvig (1983), and Berger and Bouwman (2009)), a process referred to as "qualitative asset transformation" (e.g. Greenbaum, Thakor and Boot (2019)). This view assigns a central role to bank deposits in the sense that banks are viewed as collecting deposits from savers, keeping a fraction as reserves (the "fractional reserve banking system") and lending out the rest to those who wish to finance illiquid projects. Although the projects are illiquid, bank deposits are liquid claims on the bank in that depositors can withdraw on demand. The supply of deposits is thus the primary determinant of bank lending[1]. There is an alternative view of bank liquidity creation, which holds that rather than being constrained in their lending by the availability of deposits, banks *create* deposits though their lending, e.g., Wicksell (1906), Schumpeter (1912), and Keynes (1930). The mechanism by which this happens is that when a bank makes a loan of say x, it enters the loan as an asset worth x and makes an offsetting deposit entry of x on its balance sheet, thereby creating a deposit even though no one deposited x in cash in the bank. The borrower receives a depository receipt from the bank that it can use to make payments to others that are needed to invest in a project[2]. As Schumpeter (1954) wrote: "It is much more realistic

[1] Consequently, a loose monetary policy elevates bank lending by replenishing bank deposits and a tight policy reduces it by draining deposits, goes the argument, as expounded by Bernanke and Blinder (1988) in explaining "the bank lending channel of monetary policy"; see also Bernanke and Gertler (1995), Kashyap and Stein (1995), Walsh (2003), and Kishan and Opiela (2000). Since the central bank supplies reserves to the banking system via open market operations or discount window lending, given a fixed money multiplier, an increase in reserves leads to higher bank deposits and bank lending, and a decrease leads to a shrinkage in both.

[2] Think of the borrower receiving a check book from the bank that enables use of the checks to make payments.

to say that the banks…*create deposits in their act of lending* than to say that they lend the deposits that have been entrusted to them." On a bank's balance sheet, the assets (loans) and liabilities (deposits) are added with the same amount when the bank lends "money" out and reduced with the same amount when it gets repayments. For more recent discussions of this view, see Disyatat (2011), McLeay, Radia, and Thomas (2014a, 2014b), Gross and Siebenbrunner (2019), and Jakab and Kumhof (2015).

As Donaldson, Piacentino and Thakor (2018) have shown, this view not only explains how modern banks evolved from ancient commodity warehouses, but also provides a theory of banks that create private money, thereby creating *funding liquidity* that enables the economy to invest more in real projects than its entire (fiat money) endowment at the time. Broadly speaking, funding liquidity creation is the amount by which bank lending (or total deposits) exceeds available cash deposits. The bank's private money serves as working capital for borrowers who use it to pay for the labor provided by the workers they hire. Terminal output is high enough—via incentive compatibility constraints on the amount of funding liquidity created by banks—to ensure that workers' deposit claims on the bank can be satisfied. In this view, banks are no longer mere conduits for channeling liquidity from savers who deposit money with the bank to borrowers who take that money and invest it in real projects. Rather, banks create this funding liquidity on their own, and the constraint on lending comes via loan demand and bank-specific factors like capital, not only deposits[3].

[3] Moreover, as Jakab and Kumhof (2015) point out, this also explains why the quantity of central bank reserves do not causally impact bank lending—since central banks target interest rates and stand ready to supply whatever reserves banks demand at that rate, the quantity of reserves is a *consequence* of lending, not its cause. Furthermore, as shown in Xiong and Wang (2022), increasing reserves to capital-constrained banks might even reduce bank lending.

These views of bank liquidity creation complement each other, showing that banks not only create liquidity in the process of providing intertemporal consumption smoothing to savers by financing illiquid projects with demand deposits, but also create funding liquidity that involves financing illiquid projects beyond the economy's initial endowment by the issuance of deposit claims not backed by cash deposits. Nonetheless, these two views make different predictions about the drivers of bank liquidity creation and thus call for different measures of liquidity creation.

In this paper, we empirically explore funding liquidity creation by banks ask the following research questions: (1) How much funding liquidity do U.S. banks create? (2) What are the cross-sectional characteristics of this funding liquidity creation insofar as it relates to bank-specific factors? (3) In terms of distinguishing between the traditional deposit-availability view of bank lending and the funding-liquidity-creation view of banks, is there any causal evidence that banks lend more even when their inflow of cash deposits is not increasing?

Our main results are as follows: First, the amount of aggregate funding liquidity creation by U.S. banks is substantial. For example, during 2001–2010, on average only about 8 percent of total bank deposits were accounted for by cash, with 92 percent due to funding liquidity created by the lending activities of banks. In the past decade (2011–2020), funding liquidity creation has averaged $10.7 trillion, about 57 percent of GDP. As predicted by theory, bank funding liquidity creation as a percentage of deposits declines when there is QE.

Second, at the individual bank level, there is cross-sectional variation in funding liquidity creation, with higher-capital banks creating more liquidity, controlling for bank size. Moreover, larger banks create more funding liquidity. After 2010, banks receiving greater supervisory attention create more liquidity.

Third, we turn to natural disasters as a natural experiment to study what drives banks' private liquidity generation in a causal sense. Natural disasters are useful for isolating the impact of loan demand factors on funding liquidity creation. Natural disasters are exogenous shocks that are not influenced by bank decisions. In addition, natural disasaters create the possibility of diminished deposit inflows occurring at the same time as elevated loan demand. So if the traditional view that deposits create loans holds, we should expect a decline in lending during those times. However, the funding liquidity creation theory predicts the opposite—since loan demand is expected to rise in response to a need for reconstruction funds, banks will create deposits via lending to meet this demand even when cash deposits are declining. Consistent with the latter view, we find that there is a causal link between bank capital and funding liquidity creation during natural disasters. Although cash balances at banks decline or are unchanged, banks with higher capital and with branches closer to the disaster create more funding liquidity. Our tests are careful to check for pretrends –we compare the endogenous variables in the quarter before the natural disaster to make sure that there is no pretrend between the affected and unaffected banks in liquidity creation. Moreover, we also include time-state fixed effects in many of the regressions to help control for time-varying local economic conditions.

Many strands of the banking literature are relevant to our paper. In addition to the earlier-cited papers, our paper is related most closely to the empirical literature on bank liquidity creation, pioneered by the important contribution of Berger and Bouwman (2009).[4] They develop different measures of bank liquidity creation by examining different items on the bank's balance sheet and assigning weights to them. The basic idea their measures rest on is

[4] See also Brunnermeir, Gorton and Krishnamurthy (2013). Their paper develops a liquidity mismatch index to measure the mismatch between the market liquidities of assets and liabilities. Bai, Krishnamurthy and Weymuller (2018) conduct an empirical examination using that measure. These papers are more closely related to Berger and Bouwman (2009) than ours.

that maximum liquidity is created when illiquid assets are transformed into liquid liabilities and maximum liquidity is destroyed when liquid assets are transformed into illiquid liabilities or equity. The weights aim to measure the degree of liquidity of an asset or liquidity item. Our measure of liquidity creation is different in many respects. First, it seeks to measure funding liquidity creation as opposed to the extent to which a bank transforms illiquid assets into liquid liabilities. Second, our measure is tied to the theory of funding liquidity creation and its predictions, whereas their measure speaks more broadly to the issue of the liquidity transformation role of banks.

The vast literature on bank capital and its effect on bank lending as well the consequences of such supply shocks for borrowers is also relevant.[5] The evidence strongly indicates that banks that suffer negative capital shocks lend less (e.g., Peek and Rosengren, 2000) and that banks that have more capital can gain advantage over banks with less capital during financial crisis (e.g., Berger and Bouwman, 2013). Moreover, bank credit supply shocks have large effects on firm investment (e.g., Amiti and Weinstein (2018)).

The rest of the paper is organized as follows: In Section II, we develop our liquidity creation measure and provide data on its intertemporal evolution and its cross-sectional properties. In Section III, we present the results that examine whether funding liquidity creation goes up or down during natural disasters, and also tease out the causal effect of bank capital on funding liquidity creation. Section IV concludes with a discussion of the policy implications.

[5] Thakor (2014) provides a review.

II. An Empirical Measure of Funding Liquidity Creation

A. Measure of Liquidity Creation

We use the public Call Report data to construct our liquidity measure. The Call Report data include detailed information of bank balance sheets that are submitted to bank regulators on a quarterly basis. The unit of observation is bank by quarter in our data between 1973 and 2020. We first measure the funding liquidity creation multiplier as the ratio of deposits to cash. This corresponds to the liquidity multiplier in Donaldson, Piacentino and Thakor (2018). Since total deposits capture the total amount loaned out, this represents the multiple of cash deposits that loans represent.[6] Cash here captures both cash in vault and other cash like assets such as deposits with the Federal Reserve.

$$\text{liquidity multiplier} = \text{deposits} / \text{cash}$$

Alternatively, we can also measure the dollar amount of bank funding liquidity creation as the difference between deposits and cash. This captures the dollar value of funding liquidity creation. Both measures capture the idea that banks can use private money to generate funding liquidity beyond the initial endowment of cash, and in doing so have a deposit balance that exceeds cash deposits.

B. Time Series Behavior of Aggregate Funding Liquidity Creation

Panel (a) of *Figure* 1 plots the aggregate liquidity multiplier between 1976 and 2020. The aggregate liquidity multiplier is the ratio of total deposits across all banks to the total amount

[6] Funding liquidity creation in theory is the amount by which the total deposits of the bank exceed its fiat money or cash deposits. This is because any deposits not represented by cash deposits must be created as private money by the bank in the process of lending.

of cash (and cash equivalents, including federal fund reserves) in the Call Report data. The ratio was around 5 in the 1980s. A ratio of 5 suggests that about four-fifths of the total amount of deposits arose from the lending activities of banks. The liquidity multiplier started increasing steadily between 1980 and 2008. Lower reserve requirements, better cash management techniques to minimize cash holdings, the increasing opportunity costs of holding reserves and higher loan demand in mortgages all likely contributed to the increase in the liquidity multiplier. The ratio increased to above 16 before it decreased dramatically during the financial crisis in 2008, reflecting a cratering of loan demand. The large and sudden drop post-crisis was mostly driven by QE programs by the Federal Reserve, which increased cash holdings largely in the form of reserves on banks' balance sheets. The ratio has slowly recovered after the end of the QEs in late 2014, but decreased significantly again after the Federal Reserve implemented more QE purchases during the COVID-19 pandemic. Panel (b) of *Figure* 1 shows that bank loans exhibit a pattern very similar to the liquidity multiplier.

Another way to look at the data is to compute the percentage of deposits in the banking system represented by cash (and cash equivalents) and thus the percentage represented by funding liquidity creation. This information is provided in Panel (c) of *Figure* 1, which plots the percentage of deposits accounted for by liquidity creation over time. The first two rows of *Table* 1 Panel (a) provide the data at the aggregate level for both the percentage accounted for by cash and its complement, the percentage accounted for by bank funding liquidity creation. The third and fourth rows of Panel (a) of *Table* 1 provide data on the dollar volume of aggregate funding liquidity created over time and expressed as a percentage of GDP.

Two points are worth discussing. First, as Panel (a) of *Table* 1 shows, a very high percentage of deposits in the U.S. banking system is accounted for by private money creation by banks. This percentage was as high as 92 percent during 2001–2010. This implies that the availability of cash deposits is not a big constraint on bank lending. Second, as Panel (a) *Table* 1 shows, banks create a massive amount of funding liquidity. For example, in the past decade, the average standing amount of funding liquidity created by banks is on average $10.7 trillion, and this was about 57 percent of GDP. Panel (d) of *Figure* 1 shows the sharp increase in the standing amount of funding liquidity as a percentage of GDP after 2000.

C. Cross-Sectional Behavior: Bank-Level Liquidity Creation

We can construct the liquidity measure at the bank level. Panel (b) of *Table* 1 shows the average liquidity multiplier across banks over different time periods. We can see that the liquidity measures follow a similar pattern over the different time periods as the aggregate time-series plot. The average liquidity multiplier increased from the 1970s to mid-2000s before falling.

Panel (b) of *Table* 2 also shows the average liquidity multiplier by different cross-sections. The multiplier is winsorized at 1 percent level within each year to remove outliers. We sort banks by their equity ratio, asset size, and whether the bank is a top five bank in a Federal Reserve district. Banks that are better capitalized have higher average liquidity multipliers between 1980 and 2000. The relationship is less clear in the other periods. Larger banks, as measured by total assets, have higher liquidity multipliers than smaller banks. This suggests that larger banks use more private money creation to create funding liquidity on average. Finally, the top five banks in a Federal Reserve district also have a lower liquidity multiplier before 2000, but the relationship is reversed after 2010. The reason for identifying the top banks in a Federal Reserve district is motivated by the evidence provided by Hirtle, Kovner and Plosser (2020) that the top-ranked banks in a Federal Reserve district receive more supervisory attention than other banks. We want to see how this affects funding liquidity creation. Our results suggest that, after 2010, greater supervisory attention led to a stronger encouragement to lend and create funding liquidity.

Panel (b) of *Table* 2 reports average liquidity multipliers by different cross sections. *Table 2* shows the average liquidity multipliers by size and equity ratio, while controlling for each other. These results are obtained by regressing bank level liquidity multipliers on indicators of equity ratio tertiles and asset tertiles. The regressions are run for different sample periods. The results show that conditioning on asset size, banks with higher equity ratios have on average higher liquidity multipliers and this relationship is stronger in later time periods. Similarly, conditional on equity tertiles, larger banks tend to have higher liquidity multipliers. This indicates that on average larger and better-capitalized banks create more private money that generates higher levels of funding liquidity, especially after the 1980s.

III. Funding Liquidity During Natural Disasters and the Causal Impact of Bank Capital on Liquidity Creation

To study what drives banks' private liquidity generation in a causal sense, we turn to natural disasters as a natural experiment. Natural disasters are useful for isolating the impact of loan demand factors on funding liquidity creation. First, natural disasters are exogenous shocks that are not influenced by bank decisions, which ameliorates endogeneity concerns. Second, damage caused by natural disasters increase the demand for investment, loans and cash withdrawal, so they create the possibility of diminished deposit inflows occurring at the same time as elevated loan demand. Thus, in contrast to most settings in which higher deposit inflows occur when loan demand is also higher, natural disasters provide an avenue for us to see how an increase in investment opportunity for borrowers increases funding liquidity generation by banks, as measured by the liquidity multiplier.

We use the ASU SHELDUS database for natural disaster data in the U.S.[7] The ASU SHELDUS database collects hazard data for the U.S. and covers natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods and heavy rainfall. The database contains information on the date of an event, affected location and the direct losses caused by the event (property and crop losses, injuries, and fatalities) since 1960. We focus on large disasters with a Presidential Disaster Declaration (PDD) and use quarterly natural disaster damage for properties and crops at the county level. Damages are measured in 2019 U.S. dollars.

A bank is affected by a natural disaster if it has a branch located in the county where damage occurred. Information about the location of bank branches is obtained from the Summary of Deposits data. Hence, a bank is defined to be in a treatment group if the bank has at least one branch located in the county with damage in a particular quarter. And the control group is defined as the banks whose headquarters are in the same state of the affected banks, but do not have any branches in areas affected by the natural disaster. Using banks located in the same state as a control helps mitigate the endogeneity problems of common local economy shocks.

[7] CEMHS, 2022. Spatial Hazard Events and Losses Database for the United States, Version 19.0. [Online Database]. Phoenix, AZ: Center for Emergency Management and Homeland Security, Arizona State University

We then merge the natural disaster damage data with the Call Report data by banks' headquarter county. We restrict the sample to banks with $1 billion in assets or less (in 2019 dollars). The largest banks usually have multiple locations across different states. By restricting the sample to small banks, we attempt to ensure that banks in our sample and hence their customers are more likely to be directly impacted by the natural disasters. There is evidence that small banks focus their lending mostly within their home state or local geographic area (e.g., Berger, Rosen and Udell (2007)).

The identification strategy also helps to isolate the demand effects of natural disasters on banks. Natural disasters are usually local and hence aggregate credit conditions and the supply of funds to banks are not likely affecting bank decisions. We examine the contemporaneous effects of the natural disasters in the results below, which helps rule out the concerns of insurance payments as a result of the natural disasters. Insurance payouts and aid may take months to reach households. In addition, by focusing on the smaller banks, intra-bank transfers of liquidity are also limited. Thus, the immediate impact of natural disaster on banks is likely to be through the demand channel of cash withdrawal on the liability side of the bank's balance sheet and loan demand on the asset side.

Table 3 reports summary statistics of the key variables of interest in the quarter prior to a natural disaster event. The banks are sorted by whether it is affected by a natural disaster in the following quarter condition on there isn't any natural disaster in the current quarter in the same state. A bank is affected if it has any branches located in counties affected by natural disasters in the following quarter. The idea of this table is to see whether the variables of interest show any differences between the to-be-affected and the not-to-be-affected banks in the quarter prior to the natural disaster. The table shows that there is no different trends in the liquidity ratio between the to-be-affected and the not-to-be-affected banks.

Table 4 reports the regression results using the natural disaster damage as natural experiment shocks at the bank-quarter level. The dependent variables are bank balance sheet variables and the liquidity creation measure as defined previously. The independent variable is an indicator variable that takes the value of 1 if a bank has any branches located in counties affected by natural disasters. And the indicator variable takes the value of zero if a bank has no affected branches but is located in the same states as those affected banks. All regressions control for banks' size. Bank and year-quarter fixed effects are also included to absorb time-invariant bank level variables and aggregate all time-series patterns.

Column (1) reports the impact of natural disaster damage on loan growth. Banks with branches affected by natural disasters have a 0.6 percent higher loan growth in a quarter, or 2.4 percent at an annual rate. The positive effect of natural disasters to loan growth is consistent with what the literature has found, although the literature emphasizes the loan demand channel (Koetter, Noth and Rehbein (2020), Blickle, Hamerling and Morgan (2021)). Column (2) shows that the impact of natural disasters on bank deposits is also positive at 0.3 percent a quarter, or 1.2 percent annually, while Column (3) shows that cash withdrawal is negative, but statistically insignificant. However, funding liquidity creation increases when banks are affected by natural disasters. Column (4) shows that banks with branches in affected areas have a 0.3 percent (or 1.2 percent annually) higher funding liquidity creation. This suggests that banks increase private money creation despite cash withdrawal by depositors. Natural disasters increase funding liquidity creation by inducing banks to create more private money. Columns (5) to (8) repeat the analysis to control for year-quarter-state fixed effects to control for time-varying local economic conditions. Even with this stricter set of fixed effects, Column (8) shows that banks with branches in affected areas have faster funding liquidity creation.

Table 5 provides evidence on the effect of bank capital on funding liquidity creation by examining pre-disaster capital levels of banks. Banks are sorted into quintiles by their lagged Tier-1 Capital Ratio. As predicted by the theory, a higher level of pre-disaster capital leads to more funding liquidity creation. Columns (1)-(4) report regressions with interacted terms between the treatment indicator as in *Table* 4 and the quintile indicators of lagged bank capital ratio. The middle quintile is served as the benchmark case. The results show that banks with branches in natural disaster areas and in the highest capital ratio quintile have the fastest growth in loans, deposits, and funding liquidity creation.

Interestingly, the relationship between funding liquidity creation and the bank's equity capital ratio is not monotonic. Banks in the lowest capital ratio quintile also have slightly higher growth loans and funding liquidity, relative to the middle quintile banks. As shown in *Figure 2*, the relationship is more like J-shaped. While the highest liquidity creation by the highest-capital banks is consistent with the theory, the non-monotonicity may be explained by the possibility that banks in the lowest quintile of capital lend more aggressively to gamble their way out of their low capital situation.

IV. Conclusion

We have proposed a new empirical measure of funding liquidity creation by banks and argued that bank lending and the funding liquidity banks create are not constrained by deposit availability. This measure complements the measure of bank liquidity creation developed by Berger and Bouwman (2009). We have also provided evidence of higher lending and funding liquidity creation by banks when their cash deposits are falling. Rather than deposits, it is the bank's capital ratio that influences how much funding liquidity it can create. Given this, attempts by the central bank to stimulate economic growth by flooding the economy with liquidity that then shows up as higher deposit balances in banks will not necessarily be effective in increasing bank lending. This was recently evident during the period immediately following the official recognition of the COVID-19 pandemic in March 2020 in the U.S. Deposits at U.S. banks grew by an unprecedented $2 trillion between March and July 2020 as a variety of liquidity provision programs infused huge amounts of cash into the economy, but bank lending did not increase commensurately. Our paper sheds light on why—the important drivers of banks' liquidity creation are bank capital and loan demand, suggests our analysis.

V. References

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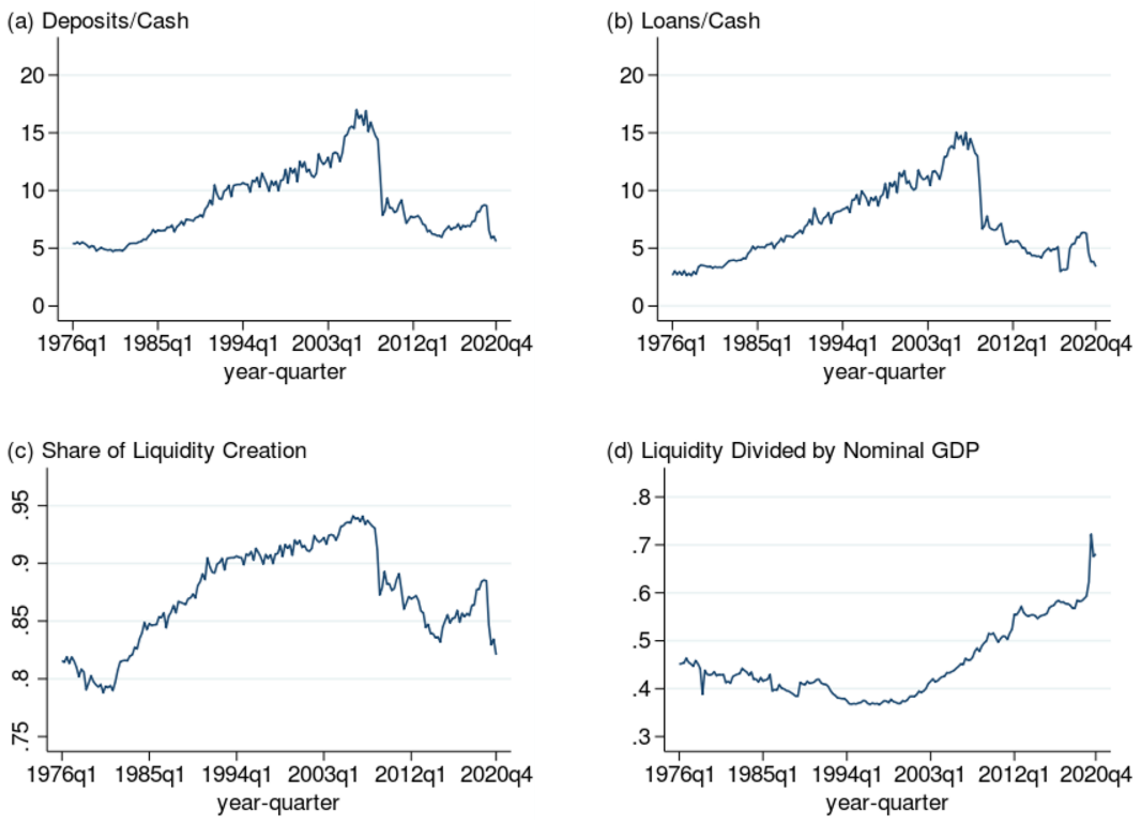
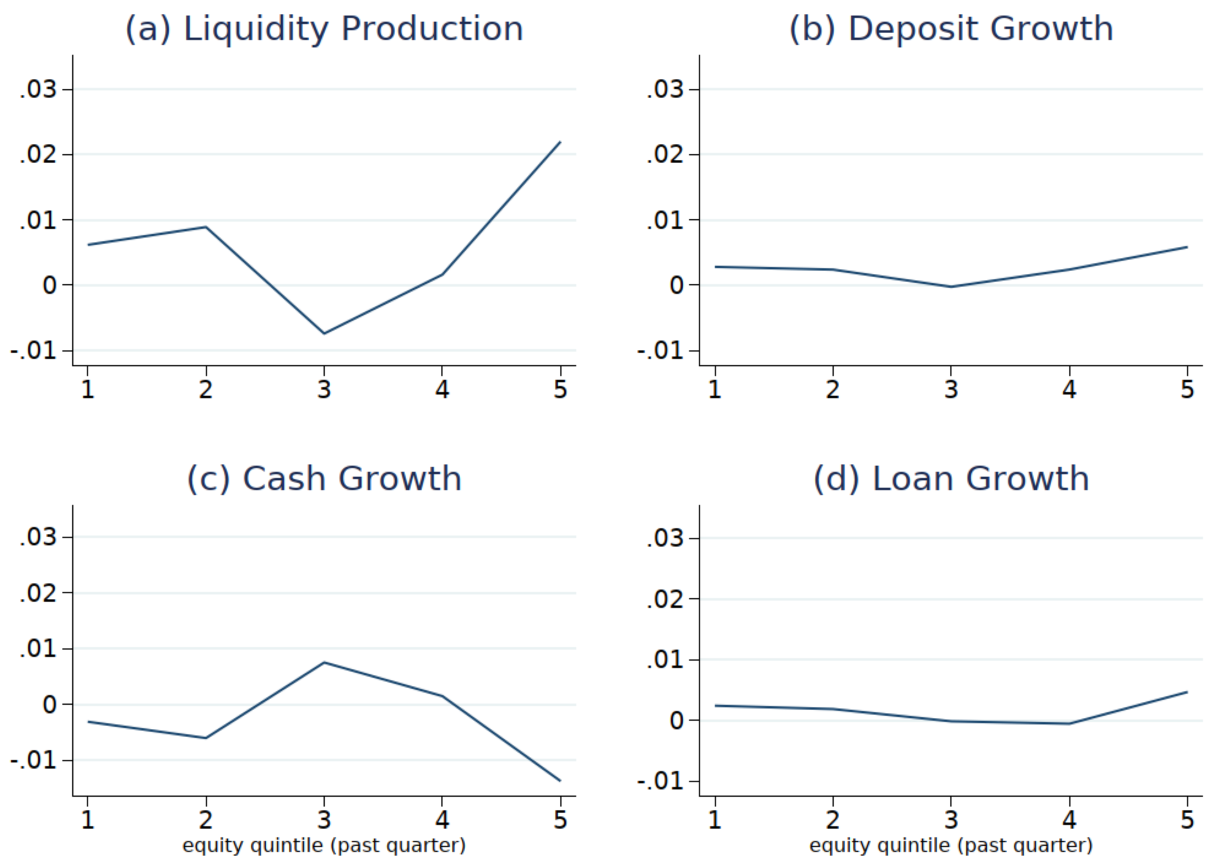
VI. Figures and Tables

Figure 1. Evolution of Aggregate Liquidity



Note: This figure plots the aggregate liquidity over time between 1976 and 2020. Banks data is from the public Call Report. Panel (a) plots the ratio of total deposits to total cash and cash like assets across all banks; Panel (b) plots the ratio of total bank loans to total cash and cash like assets across all banks; Panel (c) plots the share of aggregate deposits across all banks in the Call Report data accounted for by liquidity creation. The amount of liquidity creation is computed as the difference between deposits and cash (and cash equivalents); Panel (d) plots the amount of funding liquidity creation as a share of nominal GDP over time. The amount of liquidity creation is computed as the difference between deposits and cash and cash equivalents.

Figure 2. Funding Liquidity Creation and Equity Ratio



Note: This figure shows the amount of funding liquidity creation and other bank level variables in response to natural disaster shocks by the banks' past quarter tier-1 capital ratio quintile. It plots the coefficient estimates in Table 3 by tier-1 capital ratio quintile. The vertical axis measures the growth rate of corresponding variables if a bank has a branch located in the affected area of a natural disaster relative to banks located in the same state but not affected by the natural disaster. The regression coefficient estimates are obtained using the public Call Report data between 1994 and 2019. The sample is restricted to banks with $1 billion in assets or less in 2019 dollars.

Table 1. Summary Statistics of Funding Liquidity Creation

(a) By Time Periods

Aggregate Liquidity	(1)	(2)	(3)	(4)	(5)
Average by Periods	1976-1980	1981-1990	1991-2000	2001-2010	2011-2020
Share of Liquidity Creation	0.80	0.85	0.91	0.92	0.86
Share of Cash	0.20	0.15	0.09	0.08	0.14
Funding Liquidity ($trillion)	1.0	1.8	3.0	5.9	10.7
Funding Liquidity/GDP	0.44	0.41	0.38	0.45	0.57

(b) By Cross-sections

Liquidity Multiplier: Deposits / Cash	(1)	(2)	(3)	(4)	(5)
	1976-1980	1981-1990	1991-2000	2001-2010	2011-2020
Overall	12.8	14.9	21.9	25.1	17.0
Equity ratio (1st tertile)	13.4	14.1	21.4	26.2	17.0
Equity ratio (2nd tertile)	13.1	15.4	22.1	25.7	18.2
Equity ratio (3rd tertile)	11.8	15.3	22.2	23.2	15.9
Total assets (1st tertile)	12.3	14.3	19.4	20.7	12.9
Total assets (2nd tertile)	12.6	15.6	22.6	25.9	17.0
Total assets (3rd tertile)	13.4	14.9	23.7	28.6	21.2
Top Banks in District	6.05	6.76	12.9	23.4	22.4
Non-top banks in district	12.8	15.0	22.0	25.1	17.0

Note: Panel (a) shows different measures of aggregate liquidity using the Call Report data by different time periods. The measures include the share of total deposits accounted for by liquidity creation, the share of total deposits accounted for by cash, the total dollar value of funding liquidity generated through liquidity creation, and the funding liquidity amount normalized by quarterly GDP. Funding liquidity creation is computed as the difference between deposits and cash. The measures are computed at the quarterly frequency and then are averaged over different time periods (6-10 years). The data covers the period between 1976 and 2020. Panel (b) shows average liquidity multiplier across banks by different cross-sections for different time periods. Liquidity multiplier is computed as the ratio of deposits to cash or cash equivalents. The multiplier is winsorized at 1 percent level within each year. The ratio is computed at the bank level before being averaged over the different cross-sectional groups and time periods. The banks are sorted into different cross-sectional groups by equity ratio (equity divided by assets) and by total asset size, and whether a bank is a top five largest bank in assets in a Federal Reserve district every quarter. The data source is public Call Report and the data covers the period between 1976 and 2020.

Table 2. Regression of Liquidity Multiplier on Bank Size and Equity Ratio Tertile

	(1) 1973-1980	(2) 1981-1990	(3) 1991-2000	(4) 2001-2010	(5) 2011-2020
Base case (1st equity tertile and 1st asset tertile)	13.4	13.9	18.7	22.0	13.3
	(0.060)	(0.046)	(0.069)	(0.12)	(0.096)
Relative to the base case					
1st equity tertile and 2nd asset tertile	-0.87	0.53	2.96	3.74	3.50
	(0.075)	(0.060)	(0.091)	(0.15)	(0.13)
1st equity tertile and 3rd asset tertile	0.60	0.012	4.01	6.90	7.28
	(0.071)	(0.056)	(0.086)	(0.14)	(0.13)
2nd equity tertile and 1st asset tertile	0.17	1.25	1.18	-0.40	0.63
	(0.077)	(0.060)	(0.091)	(0.15)	(0.14)
2nd equity tertile and 2nd asset tertile	-0.33	1.86	4.02	4.05	4.54
	(0.074)	(0.058)	(0.089)	(0.15)	(0.13)
2nd equity tertile and 3rd asset tertile	-0.58	1.37	4.73	6.81	8.45
	(0.075)	(0.059)	(0.090)	(0.15)	(0.13)
3rd equity tertile and 1st asset tertile	-2.22	0.093	0.72	-2.49	-1.38
	(0.070)	(0.055)	(0.086)	(0.14)	(0.13)
3rd equity tertile and 2nd asset tertile	-1.25	2.44	4.62	3.92	3.04
	(0.076)	(0.059)	(0.091)	(0.15)	(0.14)
3rd equity tertile and 3rd asset tertile	-0.46	2.97	7.02	5.99	7.87
	(0.087)	(0.069)	(0.099)	(0.17)	(0.14)
N	294146	565292	423828	319866	247842

Note: This table shows regression results of bank level liquidity multiplier on bank size and equity ratio tertile indicators. Liquidity multiplier is computed as the ratio of deposits to cash or cash equivalents. The multiplier is winsorized at 1 percent level within each year. The banks are sorted into different cross-sectional groups by equity ratio (equity divided by assets) and by total asset size, and the dependent variables are indicators of whether the bank falls into a particular group. The unit of observation for each regression is bank by quarter-year. Regressions are run using samples in different periods. The data source is public Call Report and the data covers the period between 1976 and 2020. Standard errors are reported in parentheses.

Table 3. Comparison of Treated and Control Groups before Disaster Events

	affected		not affected			
	mean	sd	mean	sd	diff	t-stat
Chang in log(loans)	0.026	0.155	0.025	0.144	-0.001	(-1.735)
Change in log(deposits)	0.026	0.139	0.021	0.132	-0.005***	(-6.862)
Change in log(cash)	0.019	0.425	0.015	0.430	-0.003	(-1.518)
Change in log(deposits/cash)	0.007	0.416	0.006	0.416	-0.001	(-0.502)
Observations	48532		159296		207828	

Note: This table shows summary statistics of variables the quarter before a natural disaster event for affected and not affected banks. These variables are obtained from the public Call Report data between 1994 and 2019. The sample is restricted to banks with $1 billion in assets or less in 2019 dollars. A bank is "affected" if a bank has at least one branch located in disaster affected counties. Averages and standard deviations are taken for observations in the quarter before a natural disaster event which is not a disaster quarter itself. The last two columns test the difference of the means of the two groups. One, two, and three asterisks indicate 10, 5, and 1 percent statistical significance, respectively.

Table 4. Regressions of Natural Disaster Damage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Chang in log(loans)	Change in log(deposits)	Change in log(cash)	Change in log(deposits/cash)	Chang in log(loans)	Change in log(deposits)	Change in log(cash)	Change in log(deposits/cash)
I(bank with affected branches)	0.0029***	0.0027***	-0.0026	0.0064***	0.0033***	0.0018***	0.00049	0.0039*
	(0.00048)	(0.00047)	(0.0020)	(0.0019)	(0.00053)	(0.00052)	(0.0022)	(0.0021)
Lagged bank assets (log)	-0.043***	-0.043***	-0.045***	-0.0060**	-0.043***	-0.043***	-0.046***	-0.0051*
	(0.00064)	(0.00065)	(0.0026)	(0.0026)	(0.00066)	(0.00066)	(0.0027)	(0.0026)
N	232688	224907	234019	232584	232367	224610	233701	232266
r2	0.18	0.18	0.19	0.19	0.19	0.21	0.21	0.21
Other controls								
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Year-quarter-state FE	No	No	No	No	Yes	Yes	Yes	Yes
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows regression results of different bank level measures on whether a bank has natural disaster exposures. The disaster exposure data is from the ASU SHELDUS database. The dependent variables are changes in log loan amount, log deposit amount, log cash amount, and funding liquidity creation. These measures are obtained from the public Call Report data between 1994 and 2019. The sample is restricted to banks with $1 billion in assets or less in 2019 dollars. The indicator variable of "affected" takes the value 1 if a bank has at least one branch located in disaster affected counties. Columns 1-4 include time and bank fixed effects, while columns 5-8 include band and time by state fixed effects to control for time-varying local economic conditions. All regressions control for lagged banks size and lagged dependent variable. Standard errors are reported in parentheses. One, two, and three asterisks indicate 10, 5, and 1 percent statistical significance, respectively.

Table 5. Regressions of Natural Disaster Damage by Capital

	(1)	(2)	(3)	(4)
	Chang in log(loans)	Change in log(deposits)	Change in log(cash)	Change in log(deposits/cash)
I(bank with affected branches)	-0.0065	-0.0016	0.0052	0.0011
	(0.0071)	(0.0017)	(0.0074)	(0.0015)
I(equity ratio lowest quintile)	-0.021***	-0.0035**	0.017**	-0.0095***
	(0.0065)	(0.0016)	(0.0067)	(0.0014)
I(equity ratio 2nd quintile)	-0.017***	-0.0019	0.014**	-0.0043***
	(0.0057)	(0.0014)	(0.0059)	(0.0012)
I(equity ratio 4th quintile)	0.0091	0.0019	-0.0064	0.0071***
	(0.0058)	(0.0014)	(0.0060)	(0.0013)
I(equity ratio 5th quintile)	0.022***	0.016***	-0.0027	0.027***
	(0.0073)	(0.0017)	(0.0075)	(0.0016)
I(bank with affected branches)* I(equity ratio lowest quintile)	0.017*	0.0035	-0.013	0.0031
	(0.0099)	(0.0024)	(0.010)	(0.0021)
I(bank with affected branches)* I(equity ratio 2nd quintile)	0.015	0.0030	-0.012	0.0017
	(0.0099)	(0.0024)	(0.010)	(0.0021)
I(bank with affected branches)* I(equity ratio 4th quintile)	0.0093	0.0029	-0.0060	-0.00058
	(0.010)	(0.0024)	(0.010)	(0.0022)
I(bank with affected branches)* I(equity ratio 5th quintile)	0.030***	0.0062**	-0.021**	0.0042*
	(0.010)	(0.0025)	(0.011)	(0.0023)
Lagged bank assets (log)	-0.0051	-0.048***	-0.051***	-0.042***
	(0.0051)	(0.0012)	(0.0053)	(0.0011)
N	84057	84082	84700	82247
r2	0.22	0.22	0.22	0.22
Other controls				
Bank FE	Yes	Yes	Yes	Yes
Year-quarter-state FE	Yes	Yes	Yes	Yes
Lagged dependent variable	Yes	Yes	Yes	Yes

Note: This table shows regression results of regressing different bank level measures on whether a bank has natural disaster exposures interacted with lagged tier-1 capital ratio quintile indicators. The disaster exposure data is from the ASU SHELDUS database. The dependent variables are changes in log loan amount, log deposit amount, log cash amount, and funding liquidity creation. These measures are obtained from the public Call Report data between 1994 and 2019. The sample is restricted to banks with $1 billion in assets or less in 2019 dollars. The indicator variable of "affected" takes the value 1 if a bank has at least one branch located in disaster affected counties. The middle quintile is served as the reference group. All regressions control for lagged banks size and lagged dependent variable. Bank and year-quarter-state fixed effects are also included to absorb time-invariant bank level variables and aggregate all time-series patterns. Standard errors are reported in parentheses. One, two, and three asterisks indicate 10, 5, and 1 percent statistical significance, respectively.