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Funding liquidity creation by banks☆

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ABSTRACT

Relying on theories in which bank create private money by making loans that 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. Large banks as well as the top banks in Federal Reserve districts create more liquidity.

1. 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; Berger and Bouwman 2009), and Luck and Schempp (2023), 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.[2]

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 through their lending, e.g., Wicksell (1906); Schumpeter (1912); 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.[3] As Schumpeter (1954) wrote: "It is much more realistic 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 et al., (2014a, 2014b); Jakab and Kumhof (2015), and Gross and Siebenbrunner (2019).

As Donaldson et al., (2018) have shown, this view not only explains how modern banks evolved from ancient commodity warehouses, but also provides a contemporary theory of banks that create private money,

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[2] 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.

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

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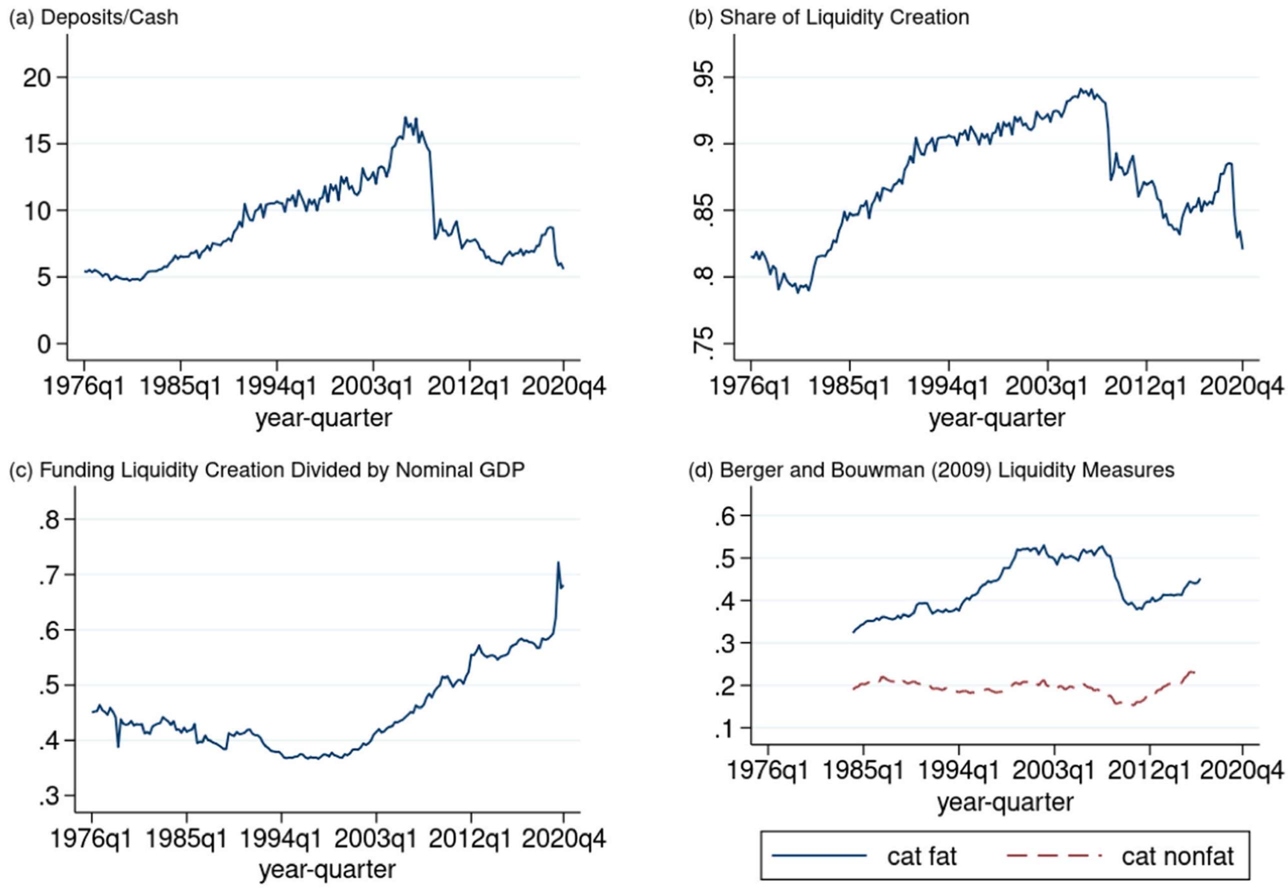

Fig. 1. Evolution of Aggregate Funding Liquidity Creation. Note: Panels (a) to (c) in this figure plot the aggregate liquidity over time between 1976 and 2020. Banks data is from the public Call Report. Panel (a) plots the ratio of total deposits to total cash and cash like assets across all banks; Panel (b) plots the 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 (c) 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. Panel (d) plots the liquidity measures from Berger and Bouwman (2009). The series plotted are "catfat" and "cat nonfat" in their paper. We aggregated the bank level measures to the country level and then normalized using their measure of GTA. GTA is defined as the total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve. Their data is available for 1984–2016.

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.[4]

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 may lend more in some circumstances 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 Quantitative Easing (QE) by the Federal Reserve. As a response to the Great Financial Crisis, the Federal Reserve conducted the QE program by purchasing large amounts of government bonds or other financial assets in order to

[4] 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.

increase money supply and stimulate economic activity, when short-term nominal interest rates hit the zero lower bound. The QE program leads to large increases in reserves and cash held by banks, which makes the funding liquidity ratio lower as shown in the Panel (a) of Fig. 1.

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. We explain later how these results are either predicted by the theory or can be explained through reasonable extrapolations of the theory. These findings are potentially useful for regulators wo may have an interest in ways to stimulate more funding liquidity creation, with its attendant (positive) consequences for the real economy.[5]

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 disasters create the possibility of diminished deposit inflows occurring at the same time as elevated loan demand.[6] 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.[7] Our tests are careful to check for pre-trends – we compare the endogenous variables in the quarter before the natural disaster to make sure that there is no pre-trend 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.

As an additional exercise connected with natural disasters, we use the Covid-19 shock and examine its effects. We use county-level differences in stay-home orders as shocks to banks. We find that banks with branches affected by these stay-home orders displayed an increase in the funding liquidity creation ratio.

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).[8] 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 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. Nevertheless, we compare our measure of funding liquidity creation to their measure. Although the magnitudes are, not surprisingly, different, we see similar overall patterns in liquidity creation in the U.S. when we use the measures from Berger and Bouwman (2009).

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.[9] 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 an advantage over banks with less capital during financial crises (e.g., Berger and Bouwman, 2013). These papers are consistent with the theory of funding liquidity creation—as well as the evidence presented in this paper—that bank capital is an important determinant of bank liquidity creation. Moreover, bank credit supply shocks have large effects on firm investment (e.g., Amiti and Weinstein 2018). Also relevant are papers that examine the effects of QE on market outcomes (e.g., Tobe and Uno 2024), and the impact of liquidity shocks on banking outcomes (e.g., Bergman et al., 2020).

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 tease out the causal effect of bank capital on funding liquidity creation. Section IV concludes with a discussion of the policy implications.

2. An empirical measure of funding liquidity creation

2.1. Measure of funding liquidity creation

In this section, we discuss how we construct our funding liquidity creation measure. To do this, we revisit the Donaldson, Piacentino, and Thakor (DPT, 2018) model and build our empirical proxies for funding liquidity creation based on their model. The following notation is useful to see how we map the DPT theory into our empirical measures. Let

L = total loans;

A_C = liquid marketable securities that are cash-equivalent;

D_L = deposits created by the bank in its lending process ("fake deposits" in the terminology of DPT);

D_C = cash deposits in the bank;

E = bank equity;

D_T = total deposits in the bank, which is equal to $D_L + D_C$.

In the basic DPT model, the economy's entire (cash) endowment is directly invested in real projects by entrepreneurs.[10] That is, in contrast

[5] These consequences for the real economy can have significant welfare implications, as pointed out by Lo and Thakor (2023), who discuss how banks can help close the funding gap that impedes biomedical innovation and the development of life-saving therapeutics.

[6] Most liquidity shocks lead simultaneously to an increase in loan demand contemporaneously with an increase in cash deposits, e.g., fracking-related liquidity shocks; see Thakor (2023). In this sense, natural disasters offer a somewhat unique opportunity to examine a setting in which there is a stark contrast between the predictions of the two theories of liquidity creation. For another recent paper that uses natural disaster data, see Rauf (2023) who uses the data to establish a causal link between bank capital and the prices customers pay for the loan commitments they purchase from banks. The paper shows that customers pay higher prices for commitments (which are essentially funding liquidity guarantees) for commitments purchased from higher-capital banks.

[7] Our findings are also consistent with the view that loanable cash deposits do not necessarily constrain bank lending. Recently, Calomiris, Mason and Wheelock (2023) have provided evidence that disproves the Friedman and Schwartz (1963) assertion that the doubling of bank reserve requirements in 1936–37 caused the 1937–38 recession. Rather, they find that the new reserve requirements had an insignificant impact on bank credit supply

[8] See also Brunnermeir et al., (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.

[9] Thakor (2014) provides a review.

[10] In DPT, there is no fiat money or cash per se, but the grain in their model is the analog of fiat money or cash.

to the majority of financial intermediary existence theories (for example, Diamond 1984, Ramakrishnan and Thakor 1984, Millon and Thakor (1985), Holmstrom and Tirole (1997), Coval and Thakor 2005, and Merton and Thakor 2019), savers are not delegating to the bank the task of investing their funds in real projects. Entrepreneurs borrow from banks to pay labor and the bank makes loans using "fake receipts" – private money – not backed by any tangible deposits. Nonetheless, every $1 of such a loan has an offsetting deposit entry that now becomes a liability of the bank. The bank may also provide equity on its balance sheet, but this is a real cash deposit in the bank that is reserved to meet future cash deposit withdrawal and the bank's residual claim on it is as an equity holder. Thus, if one considers only the variables in DPT, we would have:

$$L + A_C = D_L + E,$$

where $E = A_C$. If W is the economy's initial wealth endowment, then aggregate investment in the economy is $W + L$, so the dollar amount of funding liquidty creation is aggregate investment – initial investment $= W + L - W = L$. The funding liquidity creation ratio is:

$$\frac{W+L}{W} = \frac{L}{W} + 1 > 1$$

In the real world, while there is some direct equity investment in projects by entrepreneurs, most investments in real projects through the banking system are made by using cash deposits and deposits created by banks in the lending process ("fake receipts" using the DPT terminology, which is basically private money created by banks). Thus, we modify Eq. (1) as follows:

$$L + A_C = D_L + D_C + E,$$

where $A_C = E$. So one can interpret D_C as being a close analogy of the economy's initial (cash) endowment in the DPT model. Now, we can make two assumptions:

Assumption 1. All investment by savers in the real projects of entrepreneurs is done through delegated investment wherein savers deposit their cash in banks. There is no direct equity investment by (penniless) entrepreneurs. In this case,

$$L = D_L + D_C = D_T$$

and aggregate investment in real projects is L, or the dollar amount of funding liquidity creation is aggregate investment minus initial endowment, which is,

$$L - D_C = D_L$$

The liquidity creation ratio of aggregate investment to initial endowment is

$$\frac{L}{D_C} = \frac{D_L}{D_C} + 1$$

As an alternative to Assumption 1, we could use:

Assumption 2. Entrepreneurs invest their own cash endowments as equity directly in their projects and then borrow additionally from banks to invest in their projects. Non-entrepreneurial investors still avail of delegated investment through banks by depositing their endowments in banks.

All of the equations remain the same as before, except that aggregate investment in real projects now is:

$$L + e$$

where e is the direct equity investment of entrepreneurs in their own projects. The dollar amount of funding liquidity creation is

$$L + e - [D_C + e]$$

where $[D_C + e]$ is the aggregate initial endowment of the economy. Thus, the dollar amount of funding liquidity creation is equal to $L - D_c = D_L$, the same as before. The liquidity creation ratio is

$$\frac{L+e}{D_C+e} = \frac{D_L + D_C + e}{D_C + e} = \frac{D_L}{D_C + e} + 1$$

Typically, e is small relative to D_C. For example, if one uses angel investment as a proxy for direct equity investments by entrepreneurs, then in 2020, for the U.S., e was about $25 billion.[11] By comparison, total deposits in U.S. banks totaled $16 trillion at the end of 2020. Thus, $\frac{D_L}{D_C} + 1$ is a good approximation for $\frac{D_L}{D_C+e}$.

Summary: Regardless of which assumption we use, we have:

- Dollar volume of funding liquidity creation $= D_L = D_T - D_C$
- Liquidity creation ratio $= \frac{D_T}{D_C}$

where $\frac{D_T}{D_C}$ is the exact ratio under Assumption 1 and the approximate ratio under Assumption 2.

We use the public Call Report data to empirically 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. Based on the discussion above, we first measure the funding liquidity creation multiplier as the ratio of total deposits to cash deposits. Cash here captures both cash in vault and other cash-like assets such as deposits with the Federal Reserve, i.e., it basically consists of cash deposits with the bank.

liquidity multiplier = deposits / cash

Alternatively, as explained above, we can also measure the dollar amount of bank funding liquidity creation as the difference between total 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 of fiat money, and in doing so have a deposit balance that exceeds cash deposits.

2.2. *Time series behavior of aggregate funding liquidity creation*

Panel (a) of Fig. 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 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.

Another way to look at the data is to compute the percentage of deposits in the banking system represented by funding liquidity creation. This information is also provided in Panel (b) of Fig. 1, which plots the percentage of deposits accounted for by liquidity creation over time.

[11] See Edwards (2021).

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.

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 (c) of Fig. 1 shows the sharp increase in the standing amount of funding liquidity as a percentage of GDP after 2000.

Panel (d) of Fig. 1 plots the liquidity creation measures in Berger and Bouwman (2009). The data were downloaded from the authors' website and aggregated to the U.S. level at the quarterly frequency. The "cat fat" measure is their preferred measure while the "cat nonfat" measure excludes off-balance sheet items. The plot shows that the "cat fat" measure shows similar patterns to that of the liquidity ratio in Panel (a), while the "cat nonfat" measure missed the increase in liquidity creation in the 1990s till before the Great Financial Crisis, reflecting the importance of inclusion of off-balance items in liquidity measure. This shows the liquidity ratio as defined in our paper, while simple and easy to calculate, captures the overall pattern of liquidity creation well, despite not explicitly using bank off-balance variables.

2.3. 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 1 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. This finding is consistent with prediction in Donaldson et al., (2018). 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. This is not directly predicted by the theory but may reflect more aggressive lending behavior by large banks. Alternatively, closer to the Donaldson et al., (2018) theory, large banks may have lower safeguarding costs—perhaps due to scale economies –than small banks. 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 et al. (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.

3. Funding liquidity during natural disasters and the causal impact of bank capital on liquidity creation

A key feature of the theory of funding liquidity creation is that banks do not need additional cash (fiat money) deposits to make additional loans. Thus, a good causal test of the prediction of the theory that loans create deposits is to see if during times when a bank's fiat money deposits are either stagnant or declining, total deposits—which also

Table 2
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.

include the bank's private money creation through its lending process –go up as the bank lends more (using private money creation to enable the lending) in response to higher loan demand. Situations in which loan demand is going up but fiat money (cash) deposits at banks are declining are not common. Natural disasters provide exactly this setting. Thus, to study what drives banks' private liquidity generation in a causal sense, we turn to natural disasters as a natural experiment, since they 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 increases 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.[12] 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 disaster events 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. Between1994 and 2019, about 3400 PDD events occurred in the U.S. These disasters cover all event types recoded by the SHELDUS database, and 32,723 county-quarters in all 50 states were affected. 3077 counties were affected by at least one event during this time period.[13] Flooding is the most frequent hazard type, affecting almost 9000 county-quarters, following by wind, hurricane, thunderstorm and winter weather.[14] Conditional on having a disaster event, the average damage amount in a county-quarter is about 28 million dollars or about 487 dollars per capita, both in 2019 U.S. dollars. During the sample period, about 50,000 bank-quarter report disaster damage, about 6.7 percent of the sample observations.

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 as that 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. In addition to the indicator treatment variable, we also use the per capita damage amount in 2019 dollars to capture the severity of the damages.

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 et al., 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 2 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 are no differences in trends in the liquidity ratio between the to-be-affected and the not-to-be-affected banks,[15] i.e., the parallel trends assumption is satisfied:

$$\boldsymbol{y_{it}} = \beta_1 \boldsymbol{treated_{it}} + \beta_2 \boldsymbol{y_{it-1}} + \beta_3 \boldsymbol{X_{it}} + \boldsymbol{\alpha_i} + \boldsymbol{\alpha_t} + \boldsymbol{\epsilon_{it}} \quad (1)$$

Eq. (1) shows our main regression specification using the natural

[12] 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

[13] A county is affected if it reports a positive amount of damage in the data set.

[14] Other less frequent disaster types include avalanche, drought, earthquake, hail, heat, landslide, lightning, tornado, tsunami, volcano and wildfire.

[15] The affected banks have slightly slower growth in deposits than the non-affected banks. This is potentially due to the on average smaller size of the affected banks. Bank size is controlled for in the regression analysis.

Table 3
Regressions of Natural Disaster Damage.

Panel (a)

	(1) Chang in log (loans)	(2) Change in log (deposits)	(3) Change in log (cash)	(4) Change in log (deposits/cash)	(5) Change in cat fat measure	(6) Change in NFSR	(7) Change in log (deposits/cash)
I(bank with affected branches)	0.0029***	0.0027***	-0.0025	0.0067***	0.0035***	-0.00084***	
	(0.00046)	(0.00049)	(0.0020)	(0.0019)	(0.0013)	(0.00024)	
Weighted amount damage (log)							0.00058***
							(0.00012)
Lagged bank assets (log)	-0.055***	-0.046***	-0.051***	-0.016***	-0.038***	0.0021***	-0.017***
	(0.00061)	(0.00068)	(0.0026)	(0.0025)	(0.0022)	(0.00033)	(0.0014)
Lagged ROA	-0.079***	0.42***	0.080	-0.35***	-0.89***	-0.042***	-0.37***
	(0.016)	(0.018)	(0.066)	(0.066)	(0.12)	(0.0085)	(0.036)
Lagged efficiency ratio	0.0053***	0.022***	0.013***	0.0016	0.065***	-0.00050***	0.0016***
	(0.00025)	(0.00053)	(0.0011)	(0.0010)	(0.0029)	(0.00013)	(0.00028)
Lagged diversification ratio	-0.0064***	-0.035***	-0.017***	-0.0020	-0.11***	-0.0025***	-0.0044***
	(0.0011)	(0.0014)	(0.0048)	(0.0046)	(0.0060)	(0.00059)	(0.0016)
Lagged nonperforming ratio	-0.30***	-0.41***	0.053	-0.56***	-1.01***	0.041***	-0.47***
	(0.011)	(0.011)	(0.045)	(0.044)	(0.035)	(0.0056)	(0.025)
N	233742	226887	233743	233677	173810	220600	741438
r2	0.22	0.24	0.19	0.19	0.14	0.12	0.16
Other controls							
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel (b)

	(1) Chang in log (loans)	(2) Change in log (deposits)	(3) Change in log (cash)	(4) Change in log (deposits/cash)	(5) Change in cat fat measure	(6) Change in NFSR	(7) Change in log (deposits/cash)
I(bank with affected branches)	0.0033***	0.0017***	0.00095	0.0037*	0.0017	-0.00063**	
	(0.00052)	(0.00055)	(0.0022)	(0.0021)	(0.0015)	(0.00027)	
Weighted amount damage (log)							0.00021
							(0.00015)
Lagged bank assets (log)	-0.055***	-0.047***	-0.051***	-0.016***	-0.037***	0.0016***	-0.018***
	(0.00063)	(0.00069)	(0.0027)	(0.0026)	(0.0022)	(0.00034)	(0.0014)
Lagged ROA	-0.11***	0.40***	0.10	-0.42***	-0.87***	-0.032***	-0.39***
	(0.016)	(0.019)	(0.067)	(0.067)	(0.12)	(0.0087)	(0.036)
Lagged efficiency ratio	0.0052***	0.022***	0.012***	0.0017	0.067***	-0.00047***	0.0016***
	(0.00025)	(0.00053)	(0.0011)	(0.0010)	(0.0030)	(0.00013)	(0.00028)
Lagged diversification ratio	-0.0066***	-0.035***	-0.016***	-0.0029	-0.12***	-0.0024***	-0.0045***
	(0.0011)	(0.0014)	(0.0048)	(0.0046)	(0.0060)	(0.00059)	(0.0015)
Lagged nonperforming ratio	-0.25***	-0.35***	-0.024	-0.40***	-0.95***	0.028***	-0.38***
	(0.011)	(0.012)	(0.046)	(0.045)	(0.036)	(0.0058)	(0.026)
N	233436	226588	233437	233371	173564	220306	741201
r2	0.23	0.26	0.21	0.21	0.15	0.13	0.18
Other controls							
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter-state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dependent variable	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, funding liquidity creation, the "cat fat" liquidity measure from Berger and Bouwman (2009), the net stable funding ratio (NSFR). The first four variables are obtained from the public Call Report data between 1994 and 2019, while the "cat fat" measure in Column (5) is between 1994 and 2016. 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. Column (6) reports a regression of the change in liquidity ratio on the branch weighted amount of damages in log from natural disaster events. Regressions in Panel (a) include time and bank fixed effects, while those in Panel (b) include bank and time by state fixed effects to control for time-varying local economic conditions. All regressions control for lagged bank characteristics and lagged dependent variable. The bank characteristics include size, return on assets, efficiency ratio, diversification ratio, and nonperforming loan ratio. Standard errors are reported in parentheses. One, two, and three asterisks indicate 10, 5, and 1 percent statistical significance, respectively.

disaster damage as natural experiment shocks at the bank-quarter level, where y_{it} is the variable of interest, such as a measure of liquidity creation, $treated_{it}$ is the treatment variable indicating whether a bank is affected by natural disasters in a quarter, X_{it} is the bank characteristic controls. α_i and α_t are bank and time fixed effects, respectively. Panel (a) of Table 3 reports the regression results. The dependent variables are bank balance sheet variables and the liquidity creation measure as defined previously. For columns (1) to (6), 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, return on assets, efficiency ratio, diversification ratio,

Table 4
Regressions of Natural Disaster Damage by Capital.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chang in log (loans)	Change in log (deposits)	Change in log (cash)	Change in log (deposits/cash)	Change in cat fat measure (Berger and Bouwman, 2009)	Change in NFSR
I(bank with affected branches)	-0.00081	-0.00053	0.0081	-0.0089	-0.00056	0.00079
	(0.0015)	(0.0016)	(0.0074)	(0.0072)	(0.0045)	(0.00087)
I(equity ratio lowest quintile)	-0.0038***	-0.010***	0.013**	-0.020***	-0.030***	0.0020***
	(0.0013)	(0.0014)	(0.0066)	(0.0064)	(0.0041)	(0.00077)
I(equity ratio 2nd quintile)	-0.0022*	-0.0051***	0.013**	-0.017***	-0.017***	0.0017**
	(0.0012)	(0.0012)	(0.0058)	(0.0056)	(0.0036)	(0.00068)
I(equity ratio 4th quintile)	0.0019	0.0074***	-0.0039	0.0086	0.028***	-0.00068
	(0.0012)	(0.0013)	(0.0059)	(0.0057)	(0.0038)	(0.00069)
I(equity ratio 5th quintile)	0.016***	0.028***	0.0029	0.022***	0.091***	-0.0045***
	(0.0015)	(0.0016)	(0.0074)	(0.0072)	(0.0052)	(0.00087)
I(bank with affected branches)* I	0.0026	0.0018	-0.011	0.013	-0.0010	-0.000098
(equity ratio lowest quintile)	(0.0020)	(0.0021)	(0.010)	(0.0098)	(0.0061)	(0.0012)
I(bank with affected branches)* I	0.0027	0.0020	-0.013	0.016*	0.0023	-0.0011
(equity ratio 2nd quintile)	(0.0020)	(0.0021)	(0.010)	(0.0097)	(0.0061)	(0.0012)
I(bank with affected branches)* I	0.0027	-0.00047	-0.0073	0.010	-0.0012	-0.0018
(equity ratio 4th quintile)	(0.0021)	(0.0022)	(0.010)	(0.0099)	(0.0064)	(0.0012)
I(bank with affected branches)* I	0.0060***	0.0042*	-0.022**	0.028***	0.0084	-0.0015
(equity ratio 5th quintile)	(0.0022)	(0.0023)	(0.011)	(0.010)	(0.0075)	(0.0013)
N	83459	82028	83459	83446	63058	82041
r2	0.23	0.25	0.24	0.24	0.20	0.16
Other controls						
Bank characteristic controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dependent variable	Yes	Yes	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, funding liquidity creation, the "cat fat" liquidity measure from Berger and Bouwman (2009), and the net stable funding ratio. The first four variables are obtained from the public Call Report data between 1994 and 2019, while the "cat fat" measure in Column (5) is between 1994 and 2016. 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 serves as the reference group. All regressions control for lagged bank characteristics and lagged dependent variable. The bank characteristics include size, return on assets, efficiency ratio, diversification ratio, and nonperforming loan ratio. 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.

and nonperforming loan ratio.[16] Bank and year-quarter fixed effects are also included to absorb time-invariant bank level variables and aggregate all time-series patterns.

Column (1) in Panel (a) reports the impact of natural disaster damage on loan growth. Banks with branches affected by natural disasters have a 0.3 percent higher loan growth in a quarter, or 1.2 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 et al.,2020; Blickle et al., 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 0.7 percent (or 12.8 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.

Column (5) repeats the exercise using the "cat fat" measure of liquidity from Berger and Bouwman (2009) and the result is similar. Similarly, Column (6) repeats the exercise with the growth of the net stable funding ratio (NSFR) as the dependent variable and the results are similar.[17] Column (7) uses the branch weighted damage amount as treatment variable. This variable captures not only whether a bank is affected by natural disasters, but potentially the magnitude of the effects of those natural disasters. The result is consistent with Column (4). Panel (b) of Table 3 repeats 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 (4) shows that banks with branches in affected areas have faster funding liquidity creation.

$$y_{it} = \gamma_1 \textbf{\textit{treated}}_{it} + \gamma_2 \textbf{\textit{Capital Quintile}}_{it-1} + \gamma_3 \textbf{\textit{treated}}_{it} \times \textbf{\textit{Capital Quintile}}_{it-1} + \gamma_4 y_{it-1} + \gamma_5 \boldsymbol{X}_{it} + \alpha_i + \alpha_{st} + \epsilon_{it} \tag{2}$$

Table 4 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.[18] As shown in Eq. (2), we then interacted the treated variables with these quintiles in the regressions. 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 3 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,

[16] Bank size is measured by total assets. Return on assets captures profitability of a bank, which is computed as net income divided by total assets. Efficiency ratio is calculated as the ratio of non-interest expense to bank revenue. Diversification is the ratio of non-interest income to total operating income. And nonperforming loan ratio is the share of 90+ days overdue or nonaccrual loans as the total loan portfolio of a bank.

[17] We follow Vazquez and Federico (2015) to construct the NSFR measure.

[18] The equity ratios are sorted within a year and a state to minimize the cross-state and cross-time trends.

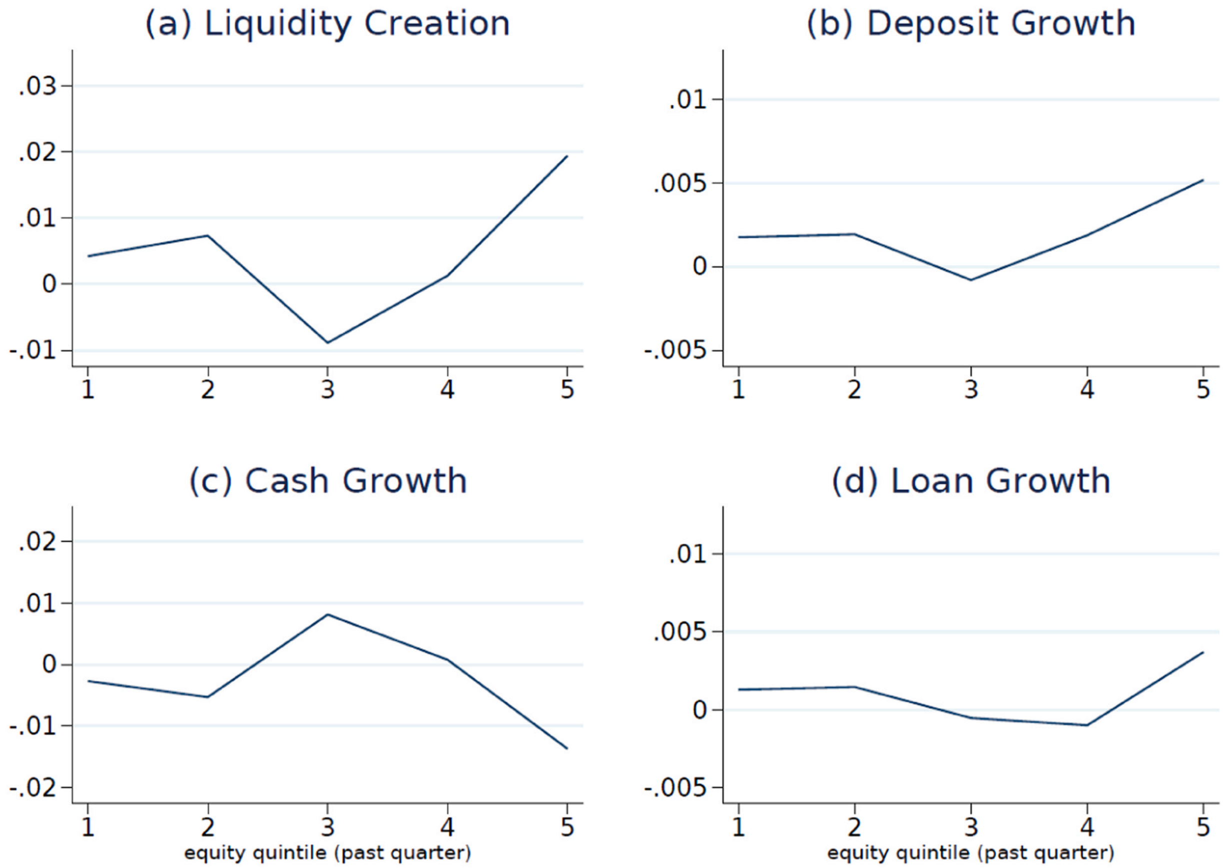

Fig. 2. Funding Liquidity Creation and Equity Ratio. Note: This figure shows the amount of funding liquidity creation and other bank level variables in response to natural disaster shocks by the banks' past quarter tier-1 capital ratio quintile. It plots the coefficient estimates in Table 3 by tier-1 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.

and funding liquidity creation. Column (5) report results using the "cat fat" measure from Berger and Bouwman (2009), while Column (6) report results using the NSFR measure. The coefficient estimates of interest in the regressions with these alternative measures are marginally statistically insignificant.

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 Fig. 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.

We wish to note an important point here. Ideally, we would like to exclude insurance payouts made in the quarter of the natural disaster. Unfortunately, we do not have access to local level insurance claim data to be able to do this. However, we do not believe this a major issue for us—typically it takes longer than a quarter to settle insurance claims, which validates our identification. For example, United Policyholders publishes many post-natural-disaster surveys. In their survey related to the 2020 California wildfires, 58 % of survey respondents had not settled their dwelling insurance claims after 12 months. For the North Bay fires in 2017, even six months after the natural disaster, 80 % of survey respondents had not settled the dwelling portion of their claims, and 60 % of survey respondents had not settled the contents portion of their claims. From these surveys, we also see that while the speed of insurance payouts varies, even when there were insurance payouts, a very large share of respondents reported insufficient insurance coverage and the need for additional funds for repairs and rebuilds. Thus, we expect loan demand to increase after natural disasters even when there are timely insurance payouts.

As an additional exercise, we use county-level differences in COVID-19 stay-home order as shocks to banks. Table 5 is similar to Table 3 in the paper except that we use the COVID shock instead of the natural disaster shock. The data sample is between 2018 and 2022. Columns (1) to (4) of Table 5 show that banks with branches affected by COVID stay-home orders in a quarter have an increase in the liquidity creation ratio, but the increase in liquidity comes from reduction in cash and not an increase in loans. The estimated coefficients become statistically significant when state by time fixed effects are included in Columns (5) to (8). This indicates that the results in Columns (1) to (4) are mainly driven by time-varying local conditions at the state level.

During the COVID-19 pandemic, besides the stay-home orders, many government measures both at the federal and state were implemented at the same time. These measures include many transfer programs, drastic monetary policy and financial easing programs targeting banks. These factors make the statistical identification and interpretation of the COVID-19 shock results difficult.

4. 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

Table 5
Regressions of COVID-19 Stay Home Order Shocks.

	(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 branches in counties with Covid stay home order)	-0.00084	0.00062	-0.019***	0.017***	0.00036	0.0023	0.025	-0.021
	(0.0011)	(0.0010)	(0.0065)	(0.0062)	(0.0036)	(0.0034)	(0.022)	(0.021)
Lagged bank assets (log)	-0.14***	-0.076***	-0.28***	0.17***	-0.14***	-0.078***	-0.28***	0.17***
	(0.0022)	(0.0021)	(0.013)	(0.013)	(0.0022)	(0.0022)	(0.014)	(0.013)
Lagged ROA	0.020	-0.010	-0.10	0.18**	0.021	-0.010	-0.11	0.19**
	(0.013)	(0.012)	(0.078)	(0.075)	(0.013)	(0.012)	(0.077)	(0.074)
Lagged efficiency ratio	0.0081***	0.013***	-0.0085***	0.024***	0.0079***	0.013***	-0.0091***	0.025***
	(0.00051)	(0.00061)	(0.0026)	(0.0029)	(0.00051)	(0.00061)	(0.0027)	(0.0029)
Lagged diversification ratio	-0.010***	-0.017***	0.0078	-0.026***	-0.0100***	-0.017***	0.0082	-0.026***
	(0.00092)	(0.0010)	(0.0052)	(0.0053)	(0.00091)	(0.00099)	(0.0053)	(0.0053)
Lagged nonperforming ratio	-0.28***	-0.020	-0.61***	0.019	-0.24***	-0.0042	-0.56***	-0.0053
	(0.031)	(0.029)	(0.18)	(0.18)	(0.030)	(0.029)	(0.18)	(0.18)
N	77641	77622	77633	77628	77602	77582	77594	77589
r2	0.25	0.25	0.16	0.14	0.29	0.29	0.19	0.17
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 branches in counties affected by COVID-19 stay home orders. The COVID-19 stay home order data is from the Center of Disease Control website. The dependent variables are changes in log loan amount, log deposit amount, log cash amount, and funding liquidity creation. Data are obtained from the public Call Report data between 2018 and 2022. The sample is restricted to banks with $1 billion in assets or less. The indicator variable of "affected" takes the value 1 if a bank has at least one branch located in a county with a stay home order or recommendation in a quarter. Columns (1)-(4) include time and bank fixed effects, while Columns (5)-(8) include bank and time by state fixed effects to control for time-varying local economic conditions. All regressions control for lagged bank characteristics and lagged dependent variable. The bank characteristics include size, return on assets, efficiency ratio, diversification ratio, and nonperforming loan ratio. Standard errors are reported in parentheses. One, two, and three asterisks indicate 10, 5, and 1 percent statistical significance, respectively.

by Berger and Bouwman (2009), but the policy implications of funding liquidity creation are significantly different. 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. Our paper sheds light on why—the important drivers of banks' liquidity creation are bank capital and loan demand, suggests our analysis.

CRediT authorship contribution statement

Edison G.Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anjan Thakor:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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