The Review of Financial Studies

How Did Depositors Respond to COVID-19?

Ross Levine
Haas School of Business, University of California, Berkeley

Chen Lin
Faculty of Business and Economics, The University of Hong Kong

Mingzhu Tai
Faculty of Business and Economics, The University of Hong Kong

Wensi Xie†
CUHK Business School, Chinese University of Hong Kong

Why did banks experience massive deposit inflows during the pandemic? We discover that deposit interest rates at bank branches in counties with higher COVID-19 infection rates fell by more than rates at branches—even branches of the same bank—in counties with lower infection rates. Credit drawdowns, national policies, such as the Payment Protection Program, and a flight-to-safety do not account for these cross-branch changes in deposit rates. Evidence suggests that higher local COVID-19 infection rates are associated with households' greater anxiety about future job and income losses, anxiety that induces households to reduce spending and increase deposits. (*JEL* G21, G50, D14)

Received October 28, 2020; editorial decision May 12, 2021 by Editor Itay Goldstein. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

U.S. banks experienced massive deposit inflows during the COVID-19 pandemic. Deposits increased from about \$13 trillion in January 2020 to \$15 trillion in April to \$16 trillion by the end of 2020 (see Figure 1). Personal saving rates and the amount of savings also increased. Each jumped almost threefold from March to April and ended the year about 50% greater than at the start of 2020 (see Figure 2). That deposits and savings rates increased is clear; however, the driving mechanism is unclear.

We thank Itay Goldstein (the editor) and two anonymous reviewers for valuable and constructive comments. We also thank conference participants at the 2021 American Finance Association Conference for helpful remarks and discussions. Lin acknowledges financial support from the Research Grant Council of the Hong Kong SAR, China [project no. T35/710/20R]. Supplementary data can be found on *The Review of Financial Studies* web site.
Send correspondence to Ross Levine, rosslevine@berkeley.edu.

The Review of Financial Studies 34 (2021) 5438–5473

doi:10.1093/rfs/hhab062 Advance Access publication May 21, 2021

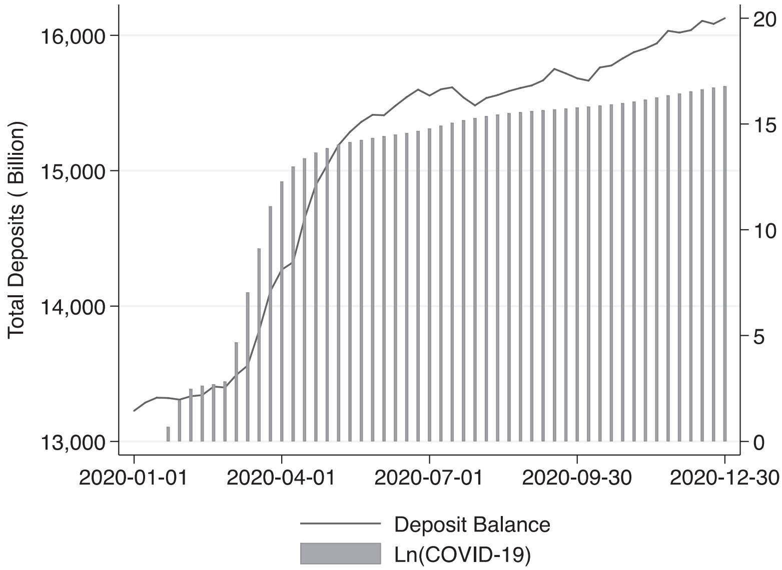

Figure 1
Aggregate trends of deposit during the COVID-19 epidemic
This figure plots the time trend of total deposits in U.S. banks and the log number of total COVID-19 cases from January 2020 through December 2020. The plotted line represents the weekly level of deposits (in billions of dollars), with the scale marked on the left vertical axis. The vertical bars represent the log number of total cumulative COVID-19 cases in the U.S. at the end of each week, with the scale marked on the right vertical axis. *Source*: Federal Reserve Bank of St. Louis.

Existing research offers several distinct, though not mutually exclusive, perspectives on the surge in deposits. First, the precautionary savings view suggests that the pandemic triggered concerns about job and income security that induced households to save more, including in the form of bank deposits (Browning and Lusardi 1996; Carroll and Samwick 1998; Engen and Gruber 2001; Agarwal and Qian 2014; D'Acunto et al. 2020). This view makes testable predictions about the concerns and actions of individuals across U.S. counties given the large cross-county, cross-time variation in COVID-19 infection rates. Specifically, when applied to the 2020 pandemic, the precautionary savings view predicts that local infection rates will be (a) positively related to local concerns about future job losses and incomes, (b) positively associated with increases in local bank deposits, especially retail deposits, as higher infection rates intensify precautionary savings by households, and (c) negatively associated with the interest rates offered on local deposits as the surge in local deposits drives down interest rates, assuming that there is some cross-county segmentation of banking markets.

Second, the flight-to-safety view stresses that the pandemic triggered financial disruptions that induced individuals to reallocate some of their savings into safer investments, such as bank deposits (Kashyap, Rajan, and Stein 2002;

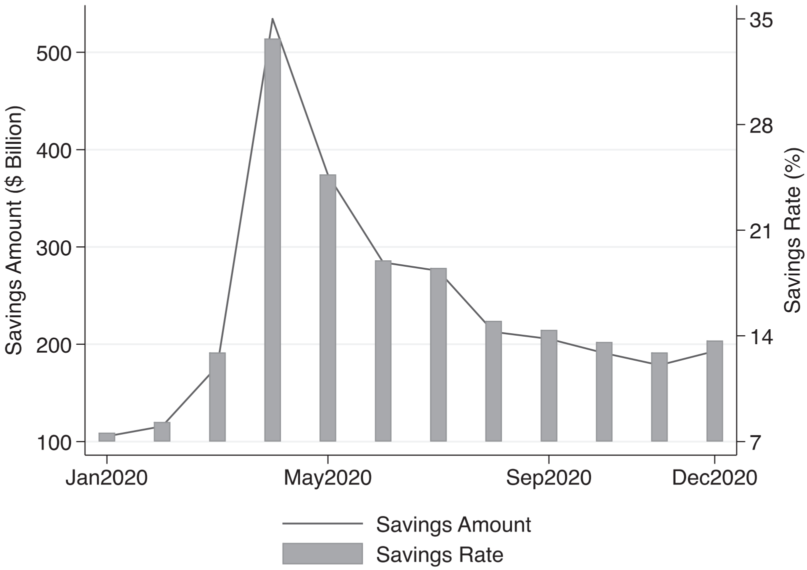

Figure 2
Personal savings and saving rates during the COVID-19 epidemic
This figure plots monthly personal savings and saving rates from January 2020 through December 2020. The bars represent the personal savings rate (measured as the amount of personal savings as a percentage of disposable personal income), with the scale marked on the right vertical axis. The plotted line represents the monthly flow of personal savings (in billions of dollars) (as measured by seasonally adjusted personal disposable income times the seasonally adjusted personal savings rate), with the scale marked on the left vertical axis. *Source*: Federal Reserve Bank of St. Louis.

Gatev and Strahan 2006; Cornett et al. 2011; Lin 2019). To the extent that local COVID-19 infections rates are positively associated with concerns about financial fragility, the following testable predictions follow from the flight-to-safety view. By inducing a flight to safer banks and assets, county-level infection rates will have an especially negative effect on local deposit interest rates among safer banks and an especially positive impact on the insured, relative to uninsured, deposits.

Third, the drawdown-and-deposit view starts by noting that there were large credit line drawdowns in 2020 (e.g., Acharya and Steffen 2020a, 2020b; Li, Strahan, and Zhang 2020; Greenwald, Krainer, and Paul 2020). It then argues that firms may have deposited a large proportion of these funds in banks, triggering the deposit boom. To the extent that firms in counties with higher COVID-19 infection rates were more likely to draw down their credit lines and deposit the proceeds in banks to enhance secure access to liquid resources, this drawdown-and-deposit view offers the following testable implications. There will be (a) a positive relationship between county-level infection rates and increases in local bank deposits, especially the wholesale deposits of firms, (b) a negative relationship between local infection rates and deposit rates for the same reasons noted above, (c) weaker connections between county infection rates and both local deposit and interest rates when conditioning on the degree to which local firms drawdown credit lines, and (d) no connection between local infection rates and deposits in counties in which local firms do not draw down their credit lines or engage in other liquidity management strategies that induce an increase in their holdings of liquid demand deposits.

Fourth, the demand-for-deposits view also starts by noting that during periods of economic duress, such as the COVID-19 crisis and the global financial crisis (GFC), businesses often draw down their lines of credit with banks. However, the demand-for-deposits view stresses that when there is not a correspondingly large infusion of deposits, banks may increase deposit rates to attract sufficient funds to fulfill their role as liquidity providers (Acharya and Mora 2015; Ben-David, Palvia, and Spatt 2017). Indeed, Ivashina and Scharfstein (2010) and Acharya and Mora (2015) collectively show that such a bank liquidity squeeze—large credit line drawdowns without corresponding deposit inflows—induced banks to raise deposit rates and cut new lending in the wake of the GFC. From this perspective, the pandemic-induced surge in deposits might be driven by a shock to the demand for deposits, not a shock to the supply of deposits. The key distinguishing testable implication emerging from the demand-for-deposits view is that local COVID-19 infection rates will be positively, not negatively, related to local deposit rates.

A final view focuses on the policy response to the pandemic. Expansionary macroeconomic policies, such as the aggressive actions of the Federal Reserve and pandemic-motivated U.S. government expenditures of over $3 trillion in 2020, may have boosted deposits. To the extent that more of this funding flowed into counties experiencing higher COVID-19 infection rates, such policies could account for the positive relationship between local infection rates and deposits. This view predicts (a) a weaker connection between local infections and increases in local deposits after controlling for the county-specific receipts of government liquidity support and (b) no connection between local infection rates and deposits before the implementation of the policy response.

In this paper, we use three types of analyses to assess the predictions emerging from these different views regarding why deposits surged during 2020. First, we use weekly branch-level data on deposit interest rates and county-level data on COVID-19 cases. We use weekly data on interest rates on CDs (certificates of deposit) for each bank branch. We use the logarithm of the cumulative number of confirmed COVID-19 cases per ten thousand people per week for each county. Our baseline sample includes 773,732 branch-week observations from January 2019 through December 2020, involving 10,167 branches. We examine deposit interest rates to help distinguish between views stressing supply- or demand-side shocks. The precautionary savings, flight-to-safety, drawdown-and-deposit, and expansionary policy views stress that COVID-19 triggered a surge in the supply of deposits and a corresponding drop in deposit rates. In contrast, the demand-for-deposits view predicts that rates will rise as banks seek to attract funds to satisfy the surge in lending as borrowers draw down credit lines. Second, we examine the relationship between county-level COVID-19 cases and the quantity and composition of bank deposits. By examining the quantity of deposits, we assess whether cross-county differences in COVID-19 infections are associated with corresponding changes in local bank deposits. By examining the composition of deposits—the proportion of retail relative to wholesale deposits and the proportion of insured relative to uninsured deposits, we test conflicting predictions emerging from the different views. Finally, we examine the connection between local infection rates and several measures of the degree to which people become more anxious about their jobs and future incomes and whether these concerns alter their spending behavior. This provides a direct test of the mechanism underlying the precautionary savings view.

In our baseline analyses of deposit rates, we regress deposit interest rates at the branch-week level on the county's COVID-19 infection rate in the previous week. The analyses include (1) branch fixed effects to help account for any time-invariant, branch-specific factors, (2) state-by-week fixed effects to control for all time-varying national and state-specific considerations, such as national financial market fluctuations, national policies, as well as state-level economic conditions, policies, and demographics, and (3) bank-by-week fixed effects to control for time-varying bank characteristics (e.g., liquidity shocks) that might be simultaneously correlated with COVID-19 infection and deposit interest rates. This econometric approach evaluates differences in interest rates across a bank's branches in different counties.

We discover that deposit interest rates at bank branches in counties with higher COVID-19 infection rates fall by more than rates at branches—even branches of the same bank—in counties with lower infection rates. The drop in deposit rates following increases in infection rates—in conjunction with a surge in bank deposits—suggests that shocks to the supply of deposits dominate any increases in banks' demand for deposits. Thus, unlike the GFC (Acharya and Mora 2015), we do not find that the 2020 pandemic banks increased deposit rates during the 2020 pandemic to attract deposits to satisfy their roles as liquidity providers.

We also find that the negative relationship between local deposit and infection rates holds when controlling for expansionary macroeconomic policies. We do this in two ways. First, as emphasized above, the analyses include state-week fixed effects (as well as branch and bank-week effects) that control for all time-varying national and state policies. Second, to address the possibility that macroeconomic policies differentially shaped counties by their COVID-19 inflection rates, we also (a) conduct the analyses over the period before the Coronavirus Aid, Relief, and Economic Security (CARES) Act, and (b) condition on local receipts of loans from the Paycheck Protection Program (PPP). All of the results hold. Indeed, when controlling for county-level receipts of PPP loans, we find that the estimated coefficient for COVID-19 infection rates hardly changes, and the PPP loan indicator does not enter significantly. These results suggest that these fiscal policies do not account for the strong, negative relationship between local COVID-19 infection rates and the interest rates offered by local bank branches.

Next, we address a key prediction from the flight-to-safety view: local COVID-19 infection rates trigger a flight to safer banks that induces an especially large drop in local deposit interest rates among such banks. To assess this prediction, we utilize two types of indicators. First, we use measures of the degree to which investors view banks as too-big-to-fail; that is, has the Financial Stability Board categorized them as "systemically important," do the banks hold more than $100 billion of assets, do the banks have geographically diverse or more concentrated branch networks, etc. We then test whether the relationship between local deposit rates and local infection rates differs by bank size. Second, we examine bank-specific indicators of prepandemic financial conditions. In particular, we use the capital-asset ratio, the Tier 1 capital-asset ratio, the ratio of liquid to total assets, the proportion of nonperforming loans, the return-on-assets, and the bank's exposure to unused lines of credit. We then test whether the impact of local COVID-19 infection rates on local deposit rates varies by these differential indicators of bank stability. We find no evidence that the sensitivity of deposit rates to local COVID-19 cases varies across banks by either too-big-to-fail measures of safety or financial indicators of stability.

Next, we use two strategies to evaluate a prediction from the corporate drawdown-and-deposit view. This view predicts that local COVID-19 infection rates induced firms to draw down their lines of credit and deposit those funds with local banks, accounting for the negative relationship between deposit and infection rates. If this drawdown-and-deposit view holds, then we should (a) observe a weaker connection between deposit and infection rates when controlling for the degree to which local firms draw down their lines of credit, and (b) find that the connection holds only among counties in which local firms draw down their lines of credit with banks and/or engage in other liquidity-enhancing practices that induce an increase in local deposits. Thus, our first strategy involves controlling for the amount of credit drawdowns by firms in each county. For the second strategy, we distinguish counties by the degree of liquidity management strategies by local firms. In particular, we consider the degree to which local firms change their cash holdings, revolving credit, and total debt. Implementing these two strategies, we find no evidence that the drawdowns-and-deposit view accounts for our findings. Controlling for credit line drawdowns does not materially alter the estimated relationship between local deposit and infection rates. Moreover, the deposit-COVID-19 nexus holds across counties in which local firms used different liquidity management strategies. These results do not imply that the drawdown of corporate credit lines accounts for none of the aggregate increase in bank deposits. Instead, the findings suggest that the drop of deposit rates in counties more heavily exposed to COVID-19 cases is unlikely to be driven by local firms depositing drawdowns at banks or implementing other liquidity management strategies that boost their deposits at local banks.[1]

Besides examining deposit rates, we also analyze the connections between local COVID-19 infection rates and both the quantity and composition of bank deposits to test the differing views for why deposits surged during the pandemic. In particular, the precautionary savings view stresses that local infection rates intensify concerns about job losses that induce households to increase savings, suggesting an especially large surge in retail deposits. In contrast, the drawdown-to-deposit view focuses on firms depositing the proceeds of their drawdowns in banks, suggesting an especially strong, positive connection between infection rates and wholesale deposits. The flight-to-safety view also makes predictions about the composition of deposits. It stresses that savers flee to safer investments, suggesting an especially big increase in insured deposits in areas with higher infection rates.

Unlike the deposit rate data, which is available at the branch-week level, data on the quantity and composition of deposits are more limited. The FDIC's Summary of Deposits provides annual data on branch deposits as of June 30 each year. We use these data to examine the relationship between local COVID-19 infection rates and changes in local branches' deposits from June 30, 2019, to June 30, 2020. The Call Reports provide quarterly data at the bank level that distinguish between (a) retail and wholesale deposits and (b) insured and uninsured deposits. We use these data to examine the relationship between a bank's exposure to COVID-19 infections across its branches and changes in the composition of deposits.

We discover a strong, positive relationship between local COVID-19 infection rates and the quantity of deposits at local branches and between a bank's exposure to COVID-19 and the proportion of retail deposits. We find no relationship between a bank's exposure to COVID-19 and the proportion of insured deposits; that is, there is no evidence of an especially large flow of funds into insured deposits. While consistent with precautionary savings effects, these findings do not provide much evidence supporting the predictions from the flight-to-safety or drawdown-to-deposit views.

We conclude our analyses by directly testing the critical mechanism underlying the precautionary savings view: local COVID-19 infection rates intensify concerns among residents about their economic futures such that they increase precautionary savings. To assess this premise, we examine measures of residents' anxieties about and perceptions of their job security and future incomes, as well as the realization of actual labor market outcomes. To measure

1 It is also worth noting the surge in deposits was much larger and more enduring than that for credit line drawdowns. As shown by Li, Strahan, and Zhang (2020), credit drawdowns rose most dramatically during the initial weeks of the crisis, when the demand for liquidity spiked, rising by almost $500 billion by April. Deposits, however, surged by almost $900 in March; they rose an additional $800 in April; and the surge deposits totaled almost $3 trillion in 2020. Also, Chodorow-Reich et al. (2020) and Greenwald, Krainer, and Paul (2020) show that large firms almost entirely account for the drawdowns of precommitted lines of credit.

individuals' anxiety about employment and income, we use two data sources. First, we measure the intensity with which individuals search online for information about job losses and savings. We obtain these data from Google Trends, which is available weekly for each Nielsen Designated Market Area. Second, we use weekly, individual-level survey data on the degree to which an individual (a) expects someone in their household to lose a job and (b) reduces spending due to concerns about future income losses. We obtain these data from a new database, the Census Household Pulse Survey, designed to obtain information about the public's response to the pandemic. Third, we examine data on actual employment and unemployment insurance claims per capita at the county-week level.

Consistent with the precautionary savings view, we find the following. There is a strong positive relationship between local COVID-19 infection rates and the intensity of online searches on topics related to unemployment and saving, providing a direct link between local infection rates and residents' anxieties about their economic futures. Furthermore, COVID-19 infection rates are positively associated with (a) individuals' expectations that somebody in their household will lose their job in the next month and (b) individuals' assessments that they have cut spending due to concerns about their future incomes. These findings strengthen the empirical connection between infection rates and local concerns about future jobs and incomes. Finally, we show that local COVID-19 infection rates are also associated with a deterioration in actual local labor market conditions, with employment falling and unemployment insurance claims rising more in areas with higher infection rates.

To summarize the findings, we return to the predictions from the five views discussed above on why deposits surged during the pandemic. First, consistent with the precautionary savings view, local COVID-19 infection rates are associated with (a) an intensification of local individuals' anxieties about future job losses, increased expectations of future income losses, and reductions in current spending due to those expectations, (b) a boom in local bank deposits, especially retail deposits, and (c) declines in the interest rates offered on local deposits. Second, regarding the predictions from the flight-to-safety view, we do not find that local infection rates are associated with (a) a larger reduction in local deposit interest rates among safer banks or (b) a larger increase in insured, relative to uninsured, deposits. Third, the drawdown-and-deposit view does not account for the cross-county relationship between deposits and infection rates. That is, we do not find (a) a weaker connection between county exposure to local COVID-19 and deposit rates after controlling for local firms drawdowns or that the connection holds only in counties in which local firms engage in liquidity management strategies that might boost deposits, and (b) a larger increase in wholesale deposits relative to retail deposits. Fourth, the evidence is inconsistent with the demand-for-deposits view, as COVID-19 infection rates are associated with material declines—not increases—in deposit rates. Finally, the findings that the deposit-COVID-19 nexus holds when (a) controlling for government liquidity support through the PPP and (b) restricting the analysis to a period before the implementation of the CARES Act suggest that the expansionary macroeconomic policy view does not account for the estimated sensitivity of deposit rates to infection rates.

Our work contributes to research on the degree to which banks effectively provide liquidity during periods of economic duress. Pioneering research by Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006) shows that inflows of deposits during periods of market stress have often allowed banks to satisfy credit line drawdowns and provide other forms of liquidity. However, the GFC was different. Deposits did not surge, straining the ability of banks to act as liquidity providers (Ivashina and Scharfstein 2010; Cornett et al. 2011; Acharya and Mora 2015). The pandemic-induced economic crisis is different still, as the unprecedented increase in deposits allowed banks to provide liquidity during 2020 (Li, Strahan, and Zhang 2020).

This raises the question: Why was 2020 different? One key difference between the pandemic-induced crisis and the GFC is that the GFC was at its core a financial crisis that triggered intense concerns about financial stability, while the COVID-19 crisis was at its core a public health emergency that triggered intense anxieties about future income (Bernanke 2020; Reinhart 2020). Furthermore, by 2020, the public had experienced the Federal Reserve's aggressive, far-ranging, and largely indiscriminate support of banks in response to the GFC, potentially making savers less concerned about formal distinctions between insured and uninsured deposits within banks or cross-bank differences in financial performance. From this perspective, it is perhaps unsurprising that individuals more readily funneled additional savings into banks in 2020 as a precaution against potential losses of jobs and income than they did during the GFC.

Our work also complements research on banks during the pandemic. Acharya and Steffen (2020b) document a "dash for cash" as firms drew down bank credit lines to increase their cash holding. Li, Strahan, and Zhang (2020) show that a large inflow of deposits helped banks satisfy these liquidity demands during the crisis. None of this research studies why deposits surged during the COVID-19 crisis. The focus of our work is different. We examine different views as to why deposits surged during the 2020 pandemic.

Our research on banks connects to the growing exploration of how the COVID-19 pandemic influenced different components of the U.S. financial system. This emerging work studies changes in the financing of bond funds (Falato, Goldstein, and Hortaçsu 2020), equity funds (Pástor and Vorsatz 2020), and money market funds (MMFs) (Eren, Schrimpf, and Sushko 2020; Li et al. 2021), as well as research on the pricing and functioning of stock markets (Alfaro et al. 2020; Baker et al. 2020; Gormsen and Koijen 2020) and bond markets (Haddad, Moreira, and Muir 2021; Kargar et al. 2021; O'Hara and Zhou Forthcoming). For example, Falato, Goldstein, and Hortaçsu (2020) discover outflows from corporate bond funds, especially funds holding less liquid bonds and bonds more vulnerable to fire-sale spillovers. Eren, Schrimpf, and Sushko (2020) document a reallocation of funds from unsecured funding markets and into secured funding markets and government MMFs. These findings on the flow of funds out of risky funds and into safer funds are consistent with the "flight-to-safety" view. Our research complements this work by abstracting from aggregate flows at the national level and exploiting cross-county variation in COVID-19 infections and bank deposits to study the factors shaping the surge in deposits. These county and branch-level analyses do not provide much support for the view that a flight-to-safety accounts for the bulk of cross-county differences in bank deposits or interest rates; rather, the cross-county evidence is consistent with the predictions from the precautionary savings view.

1. Data

1.1 COVID-19

The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) provides daily data on the number of confirmed COVID-19 cases for each U.S. county, starting on January 22, 2020. To measure county-specific exposure to the pandemic, we compute *ln(Cases per capita)* as the logarithm of one plus the cumulative number of confirmed cases per 10,000 people in a county each day. The Census provides county-level population data. To generate weekly COVID-19 exposure data from daily observations, we use the value of *ln(Cases per capita)* on Friday. As shown in Table 1, the average number of cases per 10,000 people equals 180 across county-weeks, where the number of *Cases per capita* is greater than zero from January through December 2020.

1.2 Deposit rate data

To evaluate the impact of COVID-19-exposure on deposit rates, we obtain data from RateWatch, which provides weekly interest rate data at the branch level for each type of deposit product. We use deposit rates on retail accounts. Our analyses focus on the most commonly tracked retail deposit product among U.S. branches, 12-month certificates of deposits (CDs) with an account size of \$10,000. The key results hold when using CDs with different features, such as 24- and 36-month CDs with an account size of \$10,000 and 12-month CDs with an account size of \$100,000. Our primary sample includes 231,681 branch-week observations over the period from January 2019 through December 2020, involving 10,167 branches. We use the data in 2019 as a prepandemic benchmark.

1.3 Deposit flow data

To measure changes in deposit flows in response to local COVID-19-exposure, we obtain data from two complementary data sources: (a) the FDIC's Summary

Table 1
Summary statistics

	N	Mean	SD	p25	p50	p75
Branch-week level:						
Deposit rate (%)	774,956	0.77	0.61	0.27	0.60	1.16
County-week level:						
ln(Cases per capita)	227,337	1.470	2.235	0.000	0.000	3.097
ln(Cases per capita) (>0)	81,719	4.089	1.785	2.695	4.359	5.610
Cases per capita (>0)	81,719	180.39	233.37	13.81	77.20	272.02
Employment	32,005	−0.079	0.100	−0.137	−0.062	0.001
Unemployment insurance claims	56,678	0.878	1.277	0.217	0.442	1.000
Branch level:						
Deposit growth	83,724	0.168	0.496	0.072	0.145	0.227
Bank-quarter level:						
%Retail deposits	35,916	0.797	0.150	0.738	0.832	0.900
%Insured deposits	35,916	0.659	0.149	0.579	0.679	0.760
Size ($billion)	35,921	1.278	4.601	0.112	0.244	0.592
Equity-asset ratio	35,921	0.121	0.041	0.098	0.112	0.132
ROA	35,921	0.006	0.005	0.003	0.005	0.008
Liquidity ratio	35,921	0.300	0.163	0.181	0.264	0.387
Tier1	30,493	18.22	11.98	12.62	15.11	19.55
NPL	35,685	0.010	0.012	0.002	0.006	0.012
Unused commitments	35,685	0.042	0.041	0.012	0.031	0.060
Nielsen DMA-week level:						
Search vol: Unemployment	21,840	21	24	3	6	35
Search vol: Lose job	7,488	8	20	0	0	0
Search vol: Layoff	12,896	10	16	0	4	13
Search vol: Save money	21,736	55	20	42	57	70
Search vol: Rainy day fund	21,528	30	19	17	30	42
Individual level:						
Expect job loss	1,848,909	0.251				
Spending change due to concerns about the economy/layoff	772,966	0.347				

This table reports the summary statistics for the key variables used in the analysis.

of Deposits (SOD) and (b) the Call Reports. SOD provides annual data on branch deposits as of June 30 in each year for all FDIC-insured banking institutions, which allows us to measure changes in branch deposits from June 30, 2019, to June 30, 2020, and relate these changes to a branch's exposure to local COVID-19 infection rates. In particular, *Deposit growth* is the log difference of deposits held at a bank's branches between June 30, 2019, and June 30, 2020. Thus, SOD provides data on branch deposits at an annual frequency.

The Call Reports provide quarterly data at the bank level that distinguish between (a) retail and wholesale deposits and (b) insured and uninsured deposits. While the deposit rate data and the SOD data on deposits are available at the branch level, the disaggregated data on retail, wholesale, insured, and uninsured deposits are available only at the bank level. Using data from the Call Reports, we compute (a) *%Retail Deposits*, which equals the amount of retail deposits as a proportion of total deposits for each bank in a quarter, where retail deposits include demand, savings, and time deposits of less than $100,000, and wholesale deposits include time deposits of larger than $100,000 and brokered deposits; and (b) *%Insured deposits*, which equals the amount of insured deposits as a proportion of total deposits for each bank in a quarter, where insured deposits refer to deposit accounts of $250,000 or less. We then evaluate the association between bank-specific exposure to COVID-19 through branch networks and the composition of deposits in each bank.

1.4 Paycheck protection program

To capture the extent to which local businesses in a county received paychecks from the U.S. government, we compute the amount of Paycheck Protection Program (PPP) loans received by small businesses in each county and each week. We obtain data on PPP loans from the U.S. Department of the Treasury, which provides loan-level information on size, origination date, geographic location, borrower characteristics, etc.[2] Accordingly, we compute *ln(PPP)* as the log cumulative amount of PPP loans originated in a county up to the Friday of the previous week.

1.5 Corporate liquidity management

1.5.1 Credit drawdowns. To distinguish increases in deposits associated with corporations drawing down their credit lines and depositing those funds in banks from increases in deposits from other sources, we obtain information on daily firm-level credit drawdowns during the pandemic from the S&P Leveraged Commentary & Data (LCD) database following Acharya and Steffen (2020b). LCD provides information on revolving credit drawdowns by U.S. firms from the beginning of March 2020 through September 2020 at the individual-loan level. We observe the drawdown amount, credit line limit, the date of drawdown, and the borrowing company for each loan. Based on these data, we construct a measure of credit drawdowns for each county-week observation. For county c in week t, *ln(Drawdown)* equals the log cumulative amount of credit drawdowns by firms headquartered in county c as of Friday of week t-1, normalized by the sum of total assets of firms headquartered in the same county.

1.5.2 Cash holding and debt usage. In addition to drawing down precommitted credit lines from their local banks, local firms may engage in other liquidity management strategies during the COVID-19 crisis that could affect changes in corporate deposits. To measure changes in firms' balance sheets resulting from their liquidity management strategies, we examine changes in firms' cash holdings, revolving credit, and total debt.

We obtain quarterly financial items from Capital IQ Financial Fundamental and detailed debt components from Capital IQ Debt Capital Structure. Capital IQ Capital Structure provides quarterly information on a firm's revolving credit, term loans, commercial paper, bonds, notes, etc. We construct three measures that reflect the consequence of corporate liquidity management. For firm i in

[2] The Treasury does not provide data on the exact loan size for loans larger than $150,000. They provide a size range only. Our analysis uses the midpoint of each size category as a proxy for the loan size.

quarter t, $\Delta Cash_i$ equals the change in cash holdings for the firm from quarter t-1 to t. $\Delta RevolvCredit_i$ equals the change in the outstanding balance of used revolving credit for the firm from quarter t-1 to t. $\Delta TotalDebt_i$ equals the change in total debt (including all components in debt structure) for the firm from quarter t-1 to t. To the extent that some firms draw down credit lines and deposit those funds with the banks, we should observe an increase in cash holdings and revolving credit. We then compute the aggregate changes in cash holdings among firms headquartered in a given county. For county c in quarter t, $\Delta Cash_c = \sum_{i=1}^{N}(\Delta Cash_i)$, where there are N firms headquartered in the county. The other two county-specific measures, $\Delta RevolvCredit_c$ and $\Delta TotalDebt_c$, are constructed similarly.[3] As information on firms' headquarters is available only for publicly listed companies, these measures capture publicly listed firms' changes in cash, revolving credit, and total debt.

1.6 Bank characteristics

We examine the relationship between local COVID-19 infection rates and local deposit rates, while differentiating by bank and county characteristics. On bank size, we consider four indicator variables: whether a bank's total assets fall, respectively, between the bottom tercile and the top tercile of the sample (*Medium banks*), above the top tercile of the sample (*Large banks*), above \$100 billion (*Mega banks*), and whether or not the Financial Stability Board designates the bank as systematically important (*Systematically important banks*). On the extent to which the bank is a multistate bank, we use the number of states in which a bank has branches (*#States*). On the lack of geographic dispersion of a bank's deposits across counties, that is, the geographic concentration of deposits, we use the Herfindahl-Hirschman index of deposit market shares across counties (*Concentration*). We also consider several basic financial ratios, such as the ratio of the book value of bank equity to total assets (*Equity-asset ratio*), the return on assets (*ROA*), the ratio of liquid assets to total assets (*Liquidity ratio*), the Tier 1 capital ratio (*Tier1*), nonperforming loans as a share of total loans (*NPL*), and the value of unused loan commitments as a share of total loans plus unused loan commitments (*Unused commitments*).

2. Empirical Strategy

We begin our evaluation of the relation between COVID-19 and deposit rates using the following baseline regression model:

$$\begin{aligned} Deposit\,Rate_{br,c,t} = {} & \alpha_0 + \beta Ln(Cases\,per\,Capita)_{c,t-1} \\ & + \alpha_{br} + \alpha_{s,t} + \alpha_{b,t} + \alpha_{day} + \varepsilon_{br,c,t}, \end{aligned} \tag{1}$$

[3] Acharya and Steffen (2020b) show that the data on drawdowns in Capital IQ are very similar to the cumulative drawdowns from the daily data in LCD.

where br, c, and t index branch, county, and week, respectively. The dependent variable, $Deposit\ Rate_{br,c,t}$, represents the deposit rate on 12-month CDs offered by branch br located in county c during week t. $ln(Cases\ per\ capita)_{c,t-1}$ denotes the logarithm of one plus the cumulative number of confirmed cases per capita in county c on Friday of week t-1. We estimate the model using ordinary least squares (OLS) and report standard errors two-way clustered at the county and week levels. As noted, we estimate the model from January 2019 through the end of 2020 to include a prepandemic period in the analyses.

As an initial strategy for isolating the relation between COVID-19 and deposit rates, we include an array of fixed effects. First, we include branch (α_{br}) fixed effects to account for time-invariant influences at the branch level. These fixed effects condition out branch and local community traits shaping the cross-sectional distribution of deposit rates. For example, to the extent that market structure does not change much over these weeks, these fixed effects account for differences in the market power of branches (Berger and Hannan 1989, 1991). Second, we control for state-by-week fixed effects ($\alpha_{s,t}$) to account for all time-varying factors at the state level. Therefore, these state-week fixed effects control for differences in state responses to the pandemic that may reflect differences in policies, demographics, economic conditions, etc. Thus, including state-week fixed effects helps isolate the relationship between $ln(Cases\ per\ capita)_{c,t-1}$ and local deposit rates. Third, time-varying bank characteristics might be simultaneously correlated with COVID-19 infection rates and deposit rates across the bank's branches. For example, the pandemic and the policy response to the crisis could differentially shape the evolution of bank actions and bank risk, potentially altering deposits and the rates offered on those deposits. To address this concern, we control for bank-by-week fixed effects ($\alpha_{b,t}$). In this way, we focus on the differential response of local bank branches within the same bank to differential exposures to local COVID-19 cases. Finally, we include survey day fixed effects because all branches are not surveyed on the same day of the week about their deposit rates. To address the concern that common shocks on particular survey days affect deposit rates across all branches, we include survey date fixed effects (α_{day}).[4]

In conducting the baseline analyses, we also consider the possibility that expansionary monetary and fiscal policies account for the surge in bank deposits, which we call the national policy view. Our empirical strategy of combining branch-level data on interest rates, county-level data on COVID-19 cases, and weekly observations directly addresses the possibility that national monetary and fiscal policies—and even state-level policies—account for our examination of the relationship between deposit rates and COVID-19 cases. Specifically, including state-time, and even bank-time fixed effects, in the

[4] Thus, for each branch-week observation, the vector of fixed effects, α_{day}, includes five dummy variables, one for each day of the week. The actual survey day dummy variable equals one, and the other day dummy variables equal zero.

regressions makes it unlikely that aggregate policies account for the time-varying relation between branch interest rates and county-level COVID-19 exposure. We also go further in assessing the national policy view. We test whether the relationship between branch deposit rates and local COVID-19 cases changes (a) when restricting the analyses to periods before government liquidity support (primarily through the PPP) and (b) when conditioning on measures of county-specific exposure to PPP.

3. Deposit Rate and COVID-19

3.1 Baseline results

Results in Table 2 show that deposit rates drop more in counties with higher COVID-19 infection rates. As shown in the baseline analyses reported in columns 1 and 2, *ln(Cases per capita)* enters negatively and significantly. In terms of the economic magnitude of the estimated relationship, the coefficients in column 1 indicate that a one-standard-deviation increase in *ln(Cases per capita)* among exposed counties (1.8) is associated with a 5.2-basis-point (=1.8*0.029) decline in deposit rates, which is equivalent to 8.5% of the standard deviation of *Deposit Rate*. As shown in column 2, the results are robust to including bank-time fixed effects. Including these effects focuses the analyses on the degree to which deposit rates across branches of the same bank vary across counties with different COVID-19 infection rates. When limiting the analysis to such within-bank variations, the estimated coefficient for *ln(Cases per capita)* falls (in absolute value terms). In particular, the coefficients in column 2 indicate that a one-standard-deviation increase in *ln(Cases per capita)* among exposed county-weeks is associated with a 2.1-basis-point decline in *Deposit Rate*, which is 3.4% of the standard deviation of *Deposit rate*.

We also examine whether the relationship between local bank deposits and local COVID-19 infection rates is transient or whether it holds throughout 2020. We repeat the analyses in Table 2, while separately examining the first and second half of 2020. As shown in Internet Appendix 3, the negative association between local deposit interest rates and local COVID-19 infection rates is similar when examining the first half or the second half of 2020. These results indicate that the sensitivity of local deposits to local infection rates did not change much during 2020.

Figure 3 plots the relation between branch-level deposit rates and local COVID-19 cases. The vertical axis represents the residual deposit rate after conditioning out branch, state-week, and survey date fixed effects (*Deposit rate*). The horizontal axis equals the residual values of *ln(Cases per capita)*, where the residuals are computed after conditioning out state-week fixed effects. We divide residual *ln(Cases per capita)* into 100 bins. Each dot represents the average deposit rate across branches located in counties with residual *ln(Cases per capita)* falling into the corresponding percentile. As

Table 2
Deposit rates and COVID-19

	(1)	(2)	(3)	(4)	(5)	(6)
	Deposit rate					
	Baseline		Before CARES		Control for PPP	
ln(Cases per capita)	−0.0294***	−0.0118**	−0.0875***	−0.0235**	−0.0289***	−0.0113**
	(0.0076)	(0.0048)	(0.0151)	(0.0102)	(0.0076)	(0.0047)
ln(PPP)					−0.0033	−0.0046
					(0.0032)	(0.0036)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
State-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-week FE	No	Yes	No	Yes	No	Yes
Survey date FE	Yes	Yes	Yes	Yes	Yes	Yes
N	773,732	231,681	490,908	154,055	773,732	231,681
R^2	.8005	.9512	.9181	.9731	.8005	.9512

This table reports regression results relating deposit rates to local COVID-19 cases. The dependent variable, *Deposit rate*, is the interest rate on the 12-month certificate of deposit at each branch in each week. The main explanatory variable is *ln(Cases per capita)*, which equals the log number of COVID-19 cases divided by population (in 10,000) in a county as of Friday of the previous week. Columns 1 and 2 report the baseline regression results using a sample period from January 2019 through December 2020. Columns 3 and 4 repeat the regressions in columns 1 and 2, while restricting the analyses to the period until March 27, 2020, when the CARES Act was passed. Columns 5 and 6 control for the amount of PPP loans received by small businesses in each county and week. *ln(PPP)* is the log cumulative amount of PPP loans divided by population (in 10,000) that are originated in a county, up to the Friday of the previous week. *Survey date* is the calendar date when the branch is surveyed about its deposit rate in a week. Heteroscedasticity-robust standard errors clustered by county and week are reported in the parentheses. **p* <.1; ***p* <.05; ****p* <.01.

shown, there is a strong negative relation between deposit rates and COVID-19 exposure.

Next, we turn to the national policy view. This view stresses that expansionary monetary and fiscal policies in response to the pandemic account for the surge in deposits and the drop in deposit interest rates. Regarding monetary policy, we note that the regressions include a full array of time and state-by-time fixed effects to account for the impact of national Federal Reserve policies on local deposit rates. Regarding fiscal policy, there might be concerns that counties with more COVID-19 cases receive more support from the government. For example, the U.S. Government passed the CARES (Coronavirus Aid, Relief, and Economic Security) Act on March 27th, and the U.S. Treasury mailed coronavirus economic assistance checks on April 29th. Our empirical design reduces the possibility that national or state policies account for the findings because the analyses condition on branch, bank-time, and state-time fixed effects.

We go further to mitigate concerns that U.S. government policies drive the results. We repeat the analyses in columns 1 and 2 of Table 2, while (a) restricting the analyses to the period ending on March 27, 2020, which is when the U.S. Congress passed the CARES ACT and (b) controlling for the amount of Paycheck Protection Program (PPP) loans received by small businesses in each county and each week. In this way, we omit the impact of the CARES Act and control for payments associated with the PPP. As shown in Table 2, all of the results hold over this shorter period associated with the pre-CARES-Act

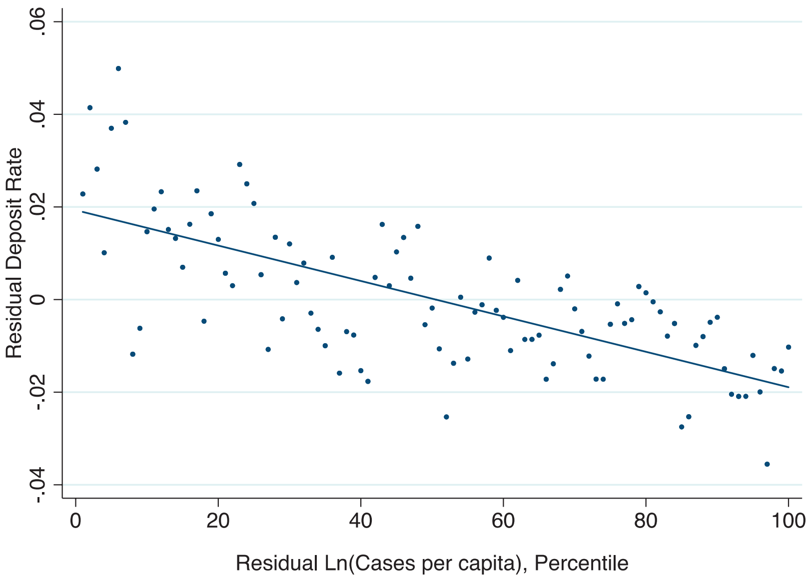

Figure 3
Deposit rates and COVID-19 exposure
This figure plots the relationship between deposit rates and each branch's county-level exposure to COVID-19. *Deposit rate* is the residual deposit rate in each branch in each week from January 2019 through December 2020, after conditioning out branch, state-week, and survey date fixed effects. *ln(Cases per capita)* is measured at the county level and equals the residual log number of cases per 10,000 people, after conditioning out county and state-week fixed effects. We divide *ln(Cases per capita)* into 100 bins, so that each dot represents the average *Deposit rate* across branches located in counties with residual *ln(Cases per capita)* falling into the corresponding percentile. The fitted line relates bank deposit rates to exposure to COVID-19. *Source*: RateWatch and John Hopkins University.

period (columns 3 and 4) and when conditioning on the amount of PPP loans received by local small businesses in each county-week (columns 5 and 6). These findings suggest that the rate-reducing effects of local infection rates are not a simple manifestation of government liquidity injections.[5]

3.2 Heterogeneity by bank characteristics

Next, we investigate whether the negative association between local deposit interest rates and local COVID-19 infection rates varies across banks with distinct characteristics. In particular, we examine two views concerning the

[5] We were concerned that pandemic-induced declines in bank lending, rather increases in the supply of deposits, drive the reduction in deposit rates. Such a lending-deposit channel would be consistent with the findings in Ben-David, Palvia, and Spatt (2017) that lending drives the demand for deposits and hence the interest rates that banks offer on those deposits. Therefore, we examine the relationship between COVID-19 infection rates and bank lending. Internet Appendix 1 shows this lending-deposit channel did not drive developments in the U.S. banking system during the 2020 pandemic. Indeed, we find that lending (and lending that excludes credit drawdowns) increased more among banks with branches in counties with higher COVID-19 infection rates. Furthermore, we examine whether the sensitivity of lending to COVID-19 exposure varies across banks of different sizes. We find that lending increases more among small- and medium-sized banks. This finding is consistent with the view that smaller banks tend to increase lending more in response to surges in local deposits.

cross-bank heterogeneity of the relationship between interest rates and exposure to the pandemic. First, the flight-to-safety view suggests that COVID-triggered financial panic would induce an especially larger surge in deposits, and a correspondingly larger reduction in deposit rates, among banks that depositors view as safer. To assess this prediction, we measure the safety of banks using (a) indicators of bank size and systemic importance, as larger and more systematically important banks might be considered too-big-to-fail (*Medium Banks*, *Large Banks*, *Mega Banks*, and *Systematically Important Banks*) and (b) indicators of the financial condition of banks (*Equity-Asset Ratio*, *ROA*, *Liquidity Ratio*, *Tier1*, *NPL*, and *Unused Commitments*), where Section 1 and Table A.1 define these size and financial indicators. Second, banks with more geographically extensive branch networks might use their internal capital markets to smooth the impact of surges in local deposits on local deposit interest rates. To assess this prediction, we use two measures of banks' branch networks: (a) *#States* equals the number of states in which a bank has branches, and (b) *Concentration* equals the Herfindahl-Hirschman index of deposit across counties, which is negatively associated with the geographic expansiveness of a bank's network.

To test whether the negative association between deposit rates and COVID-19 cases varies across banks in these ways, we repeated the baseline analyses while differentiating banks by indicators of safety and the geographical distribution of their branch networks. In these analyses, we focus on testing cross-bank heterogeneity within counties. Thus, we now also include county-week fixed effects, in addition to branch, bank-week, and survey date fixed effects. As a result, the regression no longer includes *ln(Cases per capita)* as a separate explanatory variable (because it is subsumed in the county-week fixed effects), and we focus only on the differential relationship between *ln(Cases per capita)* and *Deposit Rate* by bank characteristics.

Two key findings emerge from the results reported in Table 3. First, the sensitivity of deposit rates to local COVID-19 cases does not vary across banks by size, whether they are systemically important, or by their financial condition. In particular, none of the interaction terms between *ln(Cases per capita)* and *Medium banks*, *Large banks*, *Mega banks*, *Systematically important banks, Equity-asset ratio*, *ROA*, *Liquidity ratio*, *Tier1*, *NPL*, and *Unused commitments* enters significantly. Thus, there is no evidence that the sensitivity of local deposit rates to local COVID-19 infection rates depends on banks' safety. Second, the sensitivity of deposit rates to COVID-19 cases does not vary by the extensiveness of a bank's branch network. As shown in Table 3, the interaction terms between *ln(Cases per capita)* and both *#States* and *Concentration* enter insignificantly. These two findings suggest that (a) local COVID-19 shocks reduce local branch deposit interest rates and (b) the deposit-rate-reducing effects of local COVID-19 cases do not vary significantly across banks by their size, whether they are defined as systemically important, their financial condition, or the geographic extensiveness of their branch networks. Overall,

Table 3
Deposit rates and COVID-19, heterogeneity by bank characteristics

	(1)	(2)	(3)
		Deposit rate	
*Medium banks*ln(Cases per capita)*	0.0364	0.0103	0.0136
	(0.0470)	(0.0430)	(0.0423)
*Large banks*ln(Cases per capita)*	0.0152	−0.0252	−0.0257
	(0.0411)	(0.0396)	(0.0396)
*Mega banks*ln(Cases per capita)*	0.0189	0.0106	−0.0155
	(0.0155)	(0.0206)	(0.0302)
*Systematically important banks*ln(Cases per capita)*	0.0037	−0.0011	0.0275
	(0.0149)	(0.0182)	(0.0220)
*#States*ln(Cases per capita)*		0.0001	−0.0005
		(0.0008)	(0.0011)
*Concentration*ln(Cases per capita)*		−0.0685	−0.0625
		(0.0464)	(0.0545)
*Equity-asset ratio*ln(Cases per capita)*			0.1099
			(0.3423)
*ROA*ln(Cases per capita)*			1.3488
			(1.5358)
*Liquidity ratio*ln(Cases per capita)*			−0.1474
			(0.1159)
*Tier1*ln(Cases per capita)*			−0.0028
			(0.0041)
*NPL*ln(Cases per capita)*			1.3720
			(1.1389)
*Unused commitments*ln(Cases per capita)*			0.2864
			(0.1731)
Branch FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
Survey date FE	Yes	Yes	Yes
N	159,077	159,077	151,568
R^2	.9687	.9687	.9691

This table reports regression results relating deposit rates to local COVID-19 cases while differentiating by bank characteristics and covers the period from January 2019 through December 2020. The dependent variable, *Deposit rate*, is the interest rate on the 12-month certificate of deposit at each branch in each week. The main explanatory variable is *ln(Cases per capita)*, which equals the log number of COVID-19 cases divided by population (in 10,000) in a county as of Friday of the previous week. The regressions also include the interaction between *ln(Cases per capita)* and several bank characteristics. Specifically, we examine a bank's size (*Medium banks*, *Large banks*, *Mega banks*, *Systematically important banks*), the number of states in which a bank has branches (*#States*), the degree to which a bank's deposits are concentrated in one or a few counties (*Concentration*), as well as basic bank financial ratios, such as the ratio of the book value of bank equity to total assets, the return on assets, the ratio of liquid assets to total assets, the Tier 1 capital ratio, nonperforming loans as a share of total loans, and the value of unused loan commitments as a share of total loans plus unused loan commitments (*Equity-asset ratio*, *ROA*, *Liquidity ratio*, *Tier1*, *NPL*, and *Unused commitments*), which are measured at the beginning of each quarter or the most recent available quarter. Table A.1 defines the variables in detail. *Survey date* is the calendar date when the branch is surveyed about its deposit rate in a week. Heteroscedasticity-robust standard errors clustered by county and week are reported in the parentheses. *p <.1; **p <.05; ***p <.01.

the results in Table 3 indicate that the perceived safety and financial condition of banks do not account for the flow of deposits across banks in response to local COVID-19 cases. These findings suggest that the flight-to-safety view alone cannot account for the relationship between deposits and local COVID-19 cases.[6]

[6] We also examine a cross-county implication of the precautionary savings view, which stresses that increases in local COVID-19 infection rates intensify concerns among residents about their economic futures. Suppose the

4. Corporate Deposits and COVID-19

In this section, we examine the extent to which the negative association between local deposit interest rates and local COVID-19 infection rates is accounted for by corporations drawing down their lines of credit with local banks and depositing those funds in local banks, rather than being accounted for by retail depositors increasing bank deposits. To conduct this examination, we implement two strategies. First, we control for the amount of credit drawdowns by firms in each county. As described in Section 1, we use data from the LCD to compute the amount of credit drawdowns for each county-week, *ln(Drawdown)*. Because of limitations to the availability of credit drawdown data, using the LCD data materially reduces the sample. Consequently, we first present the results in Table 4 without including *ln(Drawdown)* (columns 1 and 4). We then condition on (a) *ln(Drawdown)* in columns 2 and 5 and (b) both *ln(Drawdown)* and the flow of government support into each county through the Payment Protection Program (*ln*(*PPP*)) in columns 3 and 6. Furthermore, we conduct these analyses using two samples. The smaller sample (columns 1–3) restricts the analyses to counties where at least one company in the Capital IQ database has its headquarters (i.e., CIQ counties). The larger sample (columns 4–6) includes all counties. For this larger sample, we assume that credit drawdowns are zero in non-CIQ counties.[7]

---

precautionary savings view is contributing to the surge in deposits. In that case, we should observe that deposit rates fall by more in response to COVID-19 cases in counties in which increases in infection rates are likely to trigger greater anxieties about economic fragility. To gauge the extent to which COVID-19 cases trigger economic fears among people in a county, we consider two indicators. First, we examine political affiliation. Research suggests that people aligned with the Democrat Party responded with greater concern to the COVID-19 pandemic and its economic consequence than those aligned with the Republican Party. To measure party affiliation, we use county-level data on the percentage of the votes won by Donald Trump in the 2016 presidential election. As a second measure of the likely sensitivity of economic anxiety in a county to increases in infection rates, we use measures of social capital, that is, the degree of community cohesion and engagement (as measured by community engagement in sports teams and clubs, as well as religious, civic, business, labor, and political groups). The assumption underlying this measure is that local COVID-19 cases are likely to induce less fear in communities with stronger social connections because stronger social capital provides greater support and insurance during times of duress. The empirical findings reported in Internet Appendix 2 support these implications of the precautionary savings view.

7 In Internet Appendix 4, we repeat the analyses in Table 4, while including additional measures of credit drawdowns. These extra measures exploit the size heterogeneity of firms, as drawdowns by larger and smaller firms might have different implications for local deposits. We divide firms into large and small firms based on whether total assets fall above or below the sample median. We consider nine additional types of credit drawdown measures. First, we separately control for *ln(Drawdown by large firms)* and *ln(Drawdown by small firms)*. Second, the *Avg. drawdown ratio* equals the equally weighted average ratio of a firm's cumulative amount of credit drawdowns divided by the firm's total assets across firms headquartered in the county. Third, we compute *Avg. drawdown ratio* separately for large versus small firms. Fourth, the *Wgt-avg. drawdown ratio* equals the value-weighted average ratio of a firm's credit drawdowns divided by the firm's total assets across firms headquartered in the county. The weight for each firm in a county is its total assets. Fifth, the *Wgt-avg. drawdown ratio by large firms* (or *Wgt-avg. drawdown ratio by small firms*) equals the value-weighted average ratio of a firm's cumulative amount of drawdowns divided by the firm's total assets across large (or small) firms headquartered in the county, where the weight for each firm in a county is its total assets. The next four measures are constructed in a similar manner to the second through the fifth measures, except that we compute each firm's drawdown ratio by dividing the firm's credit drawdowns by the sum of outstanding debt and undrawn credit. As shown in Internet Appendix 4, *ln(Cases per capita)*, the variable of interest, enters negatively and significantly in all specifications.

Table 4
Deposit rates and COVID-19, controlling for corporate credit drawdown

	(1)	(2)	(3)	(4)	(5)	(6)
	Deposit rate					
	CIQ counties			Overall		
ln(Cases per capita)	−0.0075**	−0.0075**	−0.0075**	−0.0035**	−0.0034**	−0.0035**
	(0.0030)	(0.0030)	(0.0030)	(0.0015)	(0.0015)	(0.0015)
ln(Drawdown)		0.0008	0.0008		0.0011*	0.0011*
		(0.0007)	(0.0007)		(0.0006)	(0.0006)
ln(PPP)			−0.0002			0.0004
			(0.0003)			(0.0004)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
State-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey date FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,410	30,410	30,410	58,643	58,643	58,643
R^2	.9546	.9546	.9546	.9529	.9530	.9530

This table reports regression results relating deposit rates to local COVID-19 cases while controlling for the amount of corporate credit drawdowns in each county during the pandemic. The dependent variable, *Deposit rate*, is the interest rate on the 12-month certificate of deposit at each branch in each week. The main explanatory variable is *ln(Cases per capita)*, which equals the log number of COVID-19 cases divided by population (in 10,000) in a county as of Friday of the previous week. The sample period covers March 2020 through September 2020 based on the availability of credit drawdown data from S&P LCD. Columns 1–3 include those counties in which at least one company in the Capital IQ database (i.e., CIQ counties) has its headquarters, while columns 4–6 include all counties assuming that those non-CIQ counties have a zero amount of credit drawdown. *ln(Drawdown)* equals the log cumulative amount of credit drawdowns by publicly listed firms headquartered in a county (normalized by the sum of total assets of publicly listed firms headquartered in the same county), measured as of Friday of the previous week. Other variables have been defined in previous tables. Heteroscedasticity-robust standard errors clustered by county and week are reported in the parentheses. *p <.1; **p <.05; ***p <.01.

The findings in Table 4 suggest that the negative association between deposit rates and COVID-19 cases is not driven by firms drawing down their lines of credit and depositing the funds in local banks. In particular, *ln(Cases per capita)* continues to enter negatively and significantly after conditioning on *ln(Drawdown)*. Moreover, the coefficient estimate for *ln(Cases per capita)* hardly changes across the different specifications that condition, or do not condition, on *ln(Drawdown)* and *ln(PPP)*. Furthermore, the results hold when using the smaller (columns 1–3) or larger (columns 4–6) sample of counties. These results do not imply that the drawdown of corporate credit lines and the deposit of some of those funds at banks account for none of the aggregate increase in deposits at banks. Instead, the findings suggest that the drop of deposit rates in counties more heavily exposed to COVID-19 cases is not driven by local firms' redepositing their drawdowns of precommitted credit lines.

Our second strategy for assessing the roles of corporate credit drawdown—and other corporate liquidity management actions more generally—in accounting for the drop in deposit interest rates focuses on changes in corporate cash holdings, revolving credit, and total debt during the pandemic. This strategy builds on the following observation: If the negative relationship between local deposit rates and local COVID-19 cases is driven by corporate borrowers drawing down precommitted credit lines or engaging in other liquidity management actions, the negative relationship between deposit rates and COVID-19 cases should hold only in counties where local firms engage in such liquidity management strategies.

We begin with quarterly data on firms' changes in cash holdings, revolving credit, and total debt to examine this hypothesis. We then construct six indicator variables for each county-week. Specifically, $\Delta Cash < 0$ ($\Delta Cash \geq 0$) is an indicator that equals one if the change in cash holding is less than zero (greater than or equal to zero) for the companies headquartered in a county during a quarter. We use analogous definitions for the indicator variables $\Delta RevolvCredit{<}0$ ($\Delta RevolvCredit \geq 0$) and $\Delta TotalDebt < 0$ ($\Delta TotalDebt \geq 0$). Finally, given these data, we repeat the baseline regressions while differentiating counties by whether or not local firms' experienced an increase in cash holdings, revolving credit, or total debt during the pandemic. We separately examine each of these potential components of liquidity management. Furthermore, as with the earlier analyses on credit drawdowns, we conduct the analyses on a smaller sample of counties where at least one company in the Capital IQ database has its headquarters (i.e., CIQ counties) and a larger sample that includes all counties.

As reported in Table 5, these findings indicate that the negative association between local deposit rates and COVID-19 cases is not driven by local firms drawing down credit lines and depositing those funds in local banks or by other forms of liquidity management. To see this, consider the examination of changes in cash holding. As shown, both *ln(Cases per capita)* * ($\Delta Cash{<}0$) and *ln(Cases per capita)* * ($\Delta Cash \geq 0$) enter negatively and significantly and with about the same estimated coefficient. This finding suggests that the reduction in deposit rates in counties with higher COVID-19 infection rates holds in counties both with and without local firms boosting their cash holding. Similar results hold when differentiating counties by aggregate changes in revolving credit or total debt. The results hold when restricting the analyses to CIQ counties or when examining all counties.

5. The Quantity and Composition of Deposits

This section examines the connections between COVID-19 infection rates and both the quantity and composition of bank deposits.

5.1 The quantity of deposits at branches

A key feature of the precautionary savings view is that more funds flow into deposits, which drives down deposit rates. As emphasized above, we do not focus on examining the flow of funds into bank branches because (1) we aim to distinguish the supply-side from the demand-side effects of the pandemic by examining prices and (2) branch-level deposit data are publicly available only on June 30th of each year. While recognizing these limitations, we examine the response of branch deposits to local COVID-19 cases using data on changes in branch deposits between June 30, 2019, and June 30, 2020.

Table 5
Deposit rates and COVID-19, differentiating counties by corporate liquidity management

	(1)	(2)	(3)	(4)	(5)	(6)
	Deposit rate					
	CIQ counties			Overall		
(Δ*Cash<0)*	−0.0243***			−0.0159***		
**ln(Cases per capita)*	(0.0068)			(0.0053)		
(Δ*Cash* $\geq$ *0)*	−0.0254***			−0.0121**		
**ln(Cases per capita)*	(0.0066)			(0.0049)		
(Δ*RevolvCredit<0)*		−0.0255***			−0.0159***	
**ln(Cases per capita)*		(0.0067)			(0.0052)	
(Δ*RevolvCredit* $\geq$ *0)*		−0.0247***			−0.0095*	
**ln(Cases per capita)*		(0.0064)			(0.0048)	
(Δ*TotalDebt<0)*			−0.0224***			−0.0146***
**ln(Cases per capita)*			(0.0065)			(0.0050)
(Δ*TotalDebt* $\geq$ *0)*			−0.0277***			−0.0117**
**ln(Cases per capita)*			(0.0068)			(0.0050)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
State-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey date FE	Yes	Yes	Yes	Yes	Yes	Yes
N	107,002	107,002	107,002	206,085	206,085	206,085
R^2	.9563	.9563	.9564	.9563	.9564	.9563

This table reports regression results relating deposit rates to local COVID-19 cases while differentiating counties by changes in local firms' liquidity management. The dependent variable, *Deposit Rate*, is the interest rate on the 12-month certificate of deposit at each branch in each week. The main explanatory variable is *ln(Cases per capita)*, which equals the log number of COVID-19 cases divided by population (in 10,000) in a county as of Friday of the previous week. The sample period covers January 2019 through September 2020 based on the availability of data on corporate credit conditions in Capital IQ. Columns 1–3 include those counties in which at least one company in the Capital IQ database (i.e., CIQ counties) has its headquarters, while columns 4–6 include all counties and assumes that those non-CIQ counties have a zero change in cash holdings, revolving credit, or total credit by publicly listed companies. Δ*Cash<0* (Δ*Cash* $\geq$ *0*) is an indicator that equals one if the change in cash holdings of companies headquartered in a county over a quarter is less than zero (greater than or equal to zero). Δ*RevolvCredit<0* (Δ*RevolvCredit* $\geq$ *0)* is an indicator that equals one if the change in revolving credit of companies headquartered in a county over a quarter is less than zero (greater than or equal to zero). Δ*TotalDebt* $\leq$ *0* (Δ*TotalDebt>0)* is an indicator that equals one if the change in total debt of companies headquartered in a county over a quarter is less than zero (greater than or equal to zero). Other variables have been defined in previous tables. Heteroscedasticity-robust standard errors clustered by county and week are reported in the parentheses. **p* <.1; ***p* <.05; ****p* <.01.

We use the following regression specification:

$$Deposit\,Growth_{br} = \alpha_0 + \beta Ln(Cases\,per\,Capita)_c + \alpha_b + \alpha_s + \varepsilon_{br}, \qquad (2)$$

where there is one observation per branch, data permitting. *Deposit growth*$_{br}$ is the growth in deposits held at branch, *br*, owned by bank *b* in county *c* and is computed over the period from June 30, 2019, to June 30, 2020. *ln(Cases per capita)*$_c$ is the county exposure to COVID-19 cases, that is, the logarithm of one plus the cumulative number of confirmed cases per capita in county *c* as of June 2020. The regression also controls for an array of fixed effects: α_b denotes bank fixed effects, and α_s represents state fixed effects and equals one in the state in which the branch *br* is located and zero otherwise. We estimate the model using OLS and report standard errors clustered at the county level. In some specifications, we also include *Lagged deposit growth*, which equals the growth in deposits held at branch *br* from June 2018 through June 2019.

Table 6
Deposit growth and COVID-19 exposure, cross-branch analyses

	(1)	(2)	(3)	(4)
	Deposit growth			
ln(Cases per capita)	0.0124***	0.0179***	0.0085***	0.0132***
	(0.0023)	(0.0025)	(0.0021)	(0.0024)
Lagged deposit growth			−0.0141	−0.0141
			(0.0180)	(0.0180)
Bank FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
N	82,653	82,653	81,442	81,442
R^2	.0971	.0983	.0954	.0965

This table reports regression results relating deposit growth to local COVID-19 cases at the branch level using data from the FDIC's Summary of Deposit. The dependent variable is the deposit growth between June 2019 and June 2020 in each bank-county. *ln(Cases per capita)* is the log number of COVID-19 cases divided by population (in 10,000) in a county as of June 30, 2020. *Lagged deposit growth* is the log change of deposit amount between 2018 and 2019. Heteroscedasticity-robust standard errors clustered by county (in columns 1 and 2) or bootstrapped standard errors (in columns 3 and 4) are reported in the parentheses. **p* <.1; ***p* <.05; ****p* <.01.

We include lagged growth in deposits to control for potential trends in deposit growth.

As shown in Table 6, the results from estimating Equation (2) indicate a larger increase in deposits among branches in counties more exposed to COVID-19. Furthermore, the results hold when conditioning on (a) bank and state fixed effects and (b) the potential trends in deposit growth. That is, β enters Equation (2) positively and significantly in all specifications.

5.2 Deposit composition: Retail and wholesale deposits

The precautionary savings view holds that the pandemic caused households to become more uncertain and anxious about their economic futures. Households responded by boosting deposits as a precaution against future job and income losses. This view focuses on households in general and not on large, wholesale deposits by firms, wealthy individuals, and brokered deposits. In our empirical assessment of this view, therefore, we distinguish between retail and wholesale deposits, which are available at the bank-quarter level.

We first construct a measure of each bank's exposure to COVID-19 cases through its branch networks. In particular, for bank b in quarter t,

$$BankExposure_{b,t} = \sum_j Ln(Cases\,per\,Capita)_{j,t} * Deposit_{b,j} \Big/ Total\,deposit_b, \tag{3}$$

where j indexes the counties so that $ln(Cases\ per\ capita)_{j,t}$ equals the log one plus the number of cumulative confirmed cases per 10,000 people in county j as of quarter t. $Deposit_{b,j}$ equals the amount of deposits held in bank b in county j as of June 2019. $Total\ deposit_b$ equals the total amount of deposits held in bank b as of June 2019.

Table 7
Deposit composition and bank exposure to COVID-19, bank-by-quarter analyses

	(1)	(2)	(3)	(4)
	%Retail deposits		*%Insured deposits*	
Bank exposure	0.0013***	0.0014***	0.0002	0.0000
	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Bank char.	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	35,819	32,083	35,819	32,083
R^2	.9655	.9698	.9673	.9700

This table reports regression results relating the composition of deposits in a bank to the bank's exposure to COVID-19 cases through its branch network. The unit of analysis is at the bank-quarter level. The dependent variable is the proportion of retail deposits (as a share of total deposits) at the end of each quarter from 2019 Q1 to 2020 Q3 of each bank (in columns 1 and 2), and the proportion of insured deposits (in columns 3 and 4). *Bank Exposure* equals the weighted average of *ln(Cases per capita)* across counties where a bank operates, where the weights are the share of the bank's total deposits in 2019 collected from each respective county. *Bank Char.* represents a vector of time-varying bank characteristics that includes *Size*, *Equity-asset ratio*, *ROA*, *Liquidity ratio*, *Tier1*, *NPL*, and *Unused commitments*, measured at the beginning of each quarter. Table A.1 defines the variables in details. Heteroscedasticity-robust standard errors clustered at the bank level are reported in the parentheses. *p <.1; **p <.05; ***p <.01.

We then use the following regression specification to assess the impact of a bank's exposure to COVID-19 on the proportion of retail deposits from 2019 Q1 to 2020 Q3:

$$\%Retail\,Deposits_{b,t} = \alpha_0 + \beta\,Bank\,Exposure_{b,t} + X_{b,t-1} + \alpha_b + \alpha_t + \varepsilon_{b,t}, \quad (4)$$

where there is one observation per bank-quarter. *%Retail Deposits*$_{b,t}$ is the amount of retail deposits as a proportion of total deposits in bank b in quarter t. *Bank Exposure*$_{b,t}$ is the bank's exposure to COVID-19 cases as defined above. $X_{b,t-1}$ is a vector of bank characteristics including *Size*, *Equity-asset ratio*, *ROA*, *Liquidity ratio*, *Tier1*, *NPL*, and *Unused commitments*, measured at the beginning of quarter t. The regressions also condition on bank (α_b) and quarter fixed effects (α_t).

The estimation results reported in Table 7, columns 1 and 2, show a disproportionately large increase in retail deposits among banks more exposed to COVID-19 through their branch networks. The results are robust to including or excluding an array of bank traits, namely, *Size*, *Equity-asset ratio*, *ROA*, *Liquidity ratio*, *Tier1*, *NPL*, and *Unused commitments*. These results are consistent with the view that precautionary savings play a dominant role in the surge in bank deposits.

5.3 Deposit composition: Insured and uninsured deposits

We also distinguish between insured and uninsured deposits. Studies of depositor behavior find that uninsured depositors are more sensitive to bank performance than insured depositors, such that the ratio of insured to uninsured deposits increased following negative shocks to bank performance (e.g., Acharya and Mora 2015; Martin, Puri, and Ufier 2018; Chen et al. 2020). We examine the proportion of insured and uninsured deposits during the COVID-19 crisis. If the surge in bank deposits from the pandemic is due to a flight to safety, we should observe an increase in insured relative to uninsured deposits as COVID-19 cases rise in a county. To examine this view, we use a specification similar to Equation (4), except that the dependent variable is now *%Insured* $deposits_{b,t}$, which equals the proportion of insured to total deposits in bank b in quarter t.

As shown in Table 7, we find no evidence that the proportion of insured deposits rises more in banks that are more exposed to the pandemic. In contrast to the 2008 financial crisis, the surge in bank deposits associated with the COVID-19 crisis is not driven by a disproportionately large inflow of insured deposits. These results are consistent with the view that deposits increased because of concerns about the "real" economy and hence uncertainty about future income, not concerns about the safety of banks.

6. Economic Futures and COVID-19

A key premise underlying the precautionary savings view is that local COVID-19 infection rates intensify concerns among local residents about their economic futures such that they increase precautionary savings. This section directly examines the connection between local COVID-19 cases and (a) residents' anxieties and assessments of their future incomes and (b) the actual labor market conditions in the locales. Specifically, we examine whether residents of regions with larger COVID-19 infection rates (a) search online more intensively about issues related to unemployment and saving, (b) indicate a higher expected probability that they will lose their jobs and therefore change their spending behavior, and (c) suffer from worse labor market conditions.

6.1 Google Searches related to employment uncertainty and saving

To measure residents' anxiety about their economic futures, we begin by using internet search data from Google Trends on the intensity with which people in a particular region search for information about issues related to employment uncertainty and saving. Specifically, we use the Google Search volume index for unemployment-related terms (e.g., unemployment, lose job, layoff) to measure employment uncertainty. To measure individuals' concerns about saving, we use the Google Search volume index for saving-related terms (e.g., save money, rainy day fund). The search index is available for each Nielsen Designated Market Area (DMA) level at a weekly frequency. We interpret a higher value of the search index as reflecting greater concern about that particular topic in a DMA. We then evaluate how the search volume index in a DMA-week reacts to local COVID-19 cases in the same DMA, measured on the Friday of the previous week.

The results presented in Table 8 indicate a strong positive relationship between COVID-19 infection rates in a DMA and the intensity of online searches on topics related to unemployment and saving. As shown, *ln(Cases per capita)* enters positively and significantly in all specifications where the

Table 8
Google Search trends and COVID-19 exposure

	(1)	(2)	(3)	(4)	(5)
	Search vol: Unemployment	*Search vol: Lose job*	*Search vol: Layoff*	*Search vol: Save money*	*Search vol: Rainy day fund*
ln(Cases per capita)	4.2473***	2.5702***	0.8667**	1.1573***	1.4566***
	(0.7608)	(0.6809)	(0.4225)	(0.3720)	(0.3486)
DMA FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
N	21,840	7,488	12,896	21,736	21,528
R^2	.8871	.1249	.5687	.5413	.3584

This table reports regression results relating Google Search volume on the listed keywords to local COVID-19 cases. The dependent variable is the search volume for unemployment (column 1), lose job (column 2), layoff (column 3), save money (column 4), and rainy-day fund (column 5). *ln(Cases per capita)* is the log number of COVID-19 cases divided by population (in 10,000) at the Nielsen Designated Market Areas (DMA) level as of the Friday of the previous week. Standard errors clustered by DMA and week are reported in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

dependent variable is the Google Search volume index for keywords related to unemployment (column 1), lose job (column 2), layoff (column 3), save money (column 4), and rainy day fund (column 5). These findings offer a direct link between local COVID-19 cases and residents' anxieties about their economic futures.

6.2 Individual expectations about the economy

Next, we investigate the connection between COVID-19 infection rates and residents' expectations about their future economic conditions and spending patterns. To do this, we collect data from a new database, the Census Household Pulse Survey, which is designed to collect information on how the coronavirus pandemic has affected people's lives. The survey is conducted at a weekly frequency. It covers almost 2 million respondents for which we observe the state in which each respondent resides, allowing us to exploit variations across individuals residing in different states.

We examine two questions in the survey: one focuses on expectations of job loss, and the second focuses on changes in spending due to concerns about the economy. The first question is the following: "Do you expect that you or anyone in your household will experience a loss of employment income in the next 4 weeks because of the coronavirus pandemic?" Based on the responses to this question, we construct the indicator variable, *Expect job loss*, that equals one if a respondent chooses yes to this question and zero otherwise. The second question focuses on whether concerns about future economic conditions have altered spending patterns. The survey asks: "In the last 7 days, for which of the following reasons have you or your household changed spending?" We construct an indicator variable, *Spending changes due to concerns about the economy/layoff*, that equals one if the respondent or a household member changed spending due to concerns about being laid off or having hours reduced and/or concerns about the economy, and zero otherwise. The responses to

Table 9
Census COVID-19 household pulse survey

A. Expected job loss

	(1)	(2)	(3)	(4)
	Expect job loss			
	Overall		No job loss yet	
ln(Cases per capita)	0.0090***	0.0067***	0.0031**	0.0033**
	(0.0024)	(0.0019)	(0.0012)	(0.0014)
Individual char.	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	1,848,909	1,540,622	1,121,279	938,208
R^2	.0162	.3525	.0058	.0240

B. Spending changes due to concerns about the economy/layoff

	(1)	(2)	(3)	(4)
	Spending changes due to concerns about the economy/layoff			
	Overall		No expense difficulty yet	
ln(Cases per capita)	0.0289***	0.0255***	0.0320***	0.0327***
	(0.0049)	(0.0050)	(0.0052)	(0.0057)
Individual char.	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	772,966	601,937	402,133	329,985
R^2	.0032	.0635	.0032	.0219

This table reports regression results relating information on individuals' expectations of changes in their future income and spending to local COVID-19 cases using individual survey data from the Census COVID-19 Impulse Survey. The dependent variable is an indicator that equals one if respondents expect that they or someone in their household will experience a loss of employment income in the next four weeks because of the coronavirus pandemic (panel A), and an indicator that equals one if the respondent or the respondent's household changed spending due to concerns about being laid off or having hours reduced due to the pandemic (panel B). *ln(Cases per capita)* is the log number of COVID-19 cases divided by population (in 10,000) in a state as of the day before each survey wave begins. Columns 1 and 2 include all respondents in the survey (panels A and B); columns 3 and 4 of panel A restrict the sample to those respondents who have not yet experienced a loss of employment income; and columns 3 and 4 of panel B restrict the sample to those respondents who have no difficulty in paying for usual household expenses, including, but not limited to, food, rent or mortgage, car payments, medical expenses, student loans, etc. *Individual char.* represents a vector of individual responder characteristics that include *Female*, *Hispanic*, *White*, *Education*, *#HHMember*, *#Kids*, *Employed*, *HH job loss*, *Income*, and *Health*. Standard errors clustered by state are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

these questions allow us to shed additional light on the precautionary savings mechanism by examining the relationship between COVID-19 cases and residents' anxiety about losing a job in the next month and whether residents are changing spending due to concerns about their economic futures.

As reported in Table 9, COVID-19 infection rates are positively associated with (a) individuals' expectations that they will lose their jobs in the next month (panel A) and (b) individuals' assessments that they have cut spending due to concerns about the economy or that they will lose their jobs (panel B). The coefficient estimates on the state-specific *ln(Cases per capita)* are positive and statistically significant in all specifications. The results hold when (a) including or excluding an array of individual characteristics, namely, *Female*, *Hispanic*, *White*, *Education*, *#HHMember*, *#Kids*, *Employed*, *HH job loss*, *Income*, and *Health* and (b) restricting the analyses to all respondents or those respondents who have not experienced any economic difficulties at the time of

Table 10
Employment and COVID-19 exposure

	(1)	(2)	(3)	(4)
	Employment		Unemployment insurance claims	
ln(Cases per capita)	−0.0206***	−0.0083***	0.1441***	0.0671***
	(0.0028)	(0.0024)	(0.0252)	(0.0157)
County FE	Yes	Yes	Yes	Yes
Week FE	Yes	No	Yes	No
State-week FE	No	Yes	No	Yes
N	31,224	31,144	54,413	54,369
R^2	.7885	.8290	.5763	.7581

This table reports regression results relating information on employment and unemployment insurance claims to local COVID-19 cases using data from the Economic Tracker (Chetty et al. 2020). The dependent variable is the percentage change in employment relative to January 2020 of each county in a week (columns 1 and 2) and the number of initial unemployment insurance claims per 100 people in the 2019 labor force (columns 3 and 4). *ln(Cases per capita)* is the log number of COVID-19 cases divided by population (in 10,000) in a county as of the Friday of the previous week. Standard errors clustered by county and week are reported in parentheses. *p <.1; **p <.05; ***p <.01.

the survey (columns 3 and 4). The results are consistent with the view that a higher COVID-19 infection rate triggers greater concerns and anxieties about individuals' economic futures and that they respond by reducing spending as these concerns mount.

6.3 Labor market conditions

Finally, we turn from examining the connection between local COVID-19 infection rates and residents' concerns about their economic futures to focusing on the connections between local infection rates and actual labor market conditions in those locales. We obtain weekly data on employment and unemployment insurance claims from the Economic Tracker, where those data are compiled by Chetty et al. (2020) and the Opportunity Insights Team. Based on firm paycheck and individual earnings data from four complementary data sources (Paychex, Intuit, Earnin, and Kronos), the Economic Tracker constructs *Employment*, which equals employment at the county-week level relative to employment in January 2020. In addition, based on data from the Department of Labor and state government agencies, Economic Tracker also constructs *Unemployment insurance claims*, which equals the total number of initial claims divided by the 2019 labor force (in 100 people). We then examine the relationship between *ln(Cases per capita)* and *Employment* and *Unemployment insurance claims*.

As shown in Table 10, the intensity of local COVID-19 infection rates is negatively associated with local labor market conditions. In particular, when the dependent variable is *Employment* (columns 1 and 2), the coefficient estimates on *ln(Cases per capita)* are negative and statistically significant. When the dependent variable is *Unemployment insurance claims* (columns 3 and 4), *ln(Cases per capita)* enters with a positive and statistically significant coefficient. These results are consistent with the view that local COVID-19 infection rates are associated with greater deterioration in local job market conditions.

Taken together, the results presented in Tables 8–10 indicate that local COVID-19 infection rates are associated with (a) an intensification of concerns among residents about their economic futures, (b) a greater reported tendency by residents to reduce their spending due to concerns about future income, and (c) an actual deterioration of local labor market conditions. These results are fully consistent with the precautionary savings explanation for why deposits surged by more and deposit interest rates fell by more in locales more heavily affected by COVID-19 cases.

7. Conclusion

Why did banks experience massive deposit inflows during the pandemic? Using branch-week data on deposit interest rates, information on the quantity and composition of deposits, and measures of individuals' anxieties about job and income losses, we assess predictions emerging from different theories of why deposits surged during 2020.

We discover the following. First, local COVID-19 infection rates are associated with (a) increases in concerns about future job losses, increased expectations of future income losses, and reductions in current spending due to those expectations, (b) increases in local bank deposits, especially retail deposits, and (c) decreases in local deposit interest rates. These findings are fully consistent with the precautionary savings view of why deposits increased in 2020.

Second, local COVID-19 infection rates are not associated with (a) larger decreases in local deposit interest rates among safer banks, that is, banks with stronger prepandemic financial ratios or that are considered too-big-to-fail, or (b) larger increases in insured, relative to uninsured, deposits. These findings raise concerns that a simple flight-to-safety view can account for much of the cross-county relationship between deposits and COVID-19 infection rates.

Third, we discover that (a) the relationship between local deposit and infection rates is insensitive to controlling for the degree to which local firms draw down their lines of credit or differentiating counties by the degree to which local firms engage in liquidity management strategies to boost corporate deposits, and (b) there is an increase in the proportion of retail relative to wholesale deposits in response to COVID-19 infection rates. These findings suggest that although credit line drawdowns were a major feature of the pandemic, they do not account for the cross-county pattern of the increases in bank deposits across the United States.

Finally, it is important to stress that the negative relationship between deposit interest rates at the branch-week level and COVID-19 infection rates at the county-week level hold when conditioning on the bank-week, state-week, and branch fixed effects, as well as when controlling for (or not controlling for) government liquidity support through the PPP and when conducting the analyses throughout 2020 or when restricting the analysis to pre-CARES. These findings suggest that national and state policies do not account for the findings and that the findings emerge even when comparing two branches of the same bank.

Table A.1
Variable definitions

Variable	Definition	Source
Key variables		
Deposit rate	Weekly interest rates (in %) at the branch level for the most commonly tracked deposit product among U.S. branches, that is, 12-month certificates of deposits (CDs) with an account size of $10,000	RateWatch
ln(Cases per capita)	Log of one plus the cumulative number of confirmed cases per 10,000 people in a county on each day	Johns Hopkins University (JHU); Census
Bank exposure	Weighted average of *ln(Cases per capita)* across counties where a bank operates, weighted by the bank's deposit market share in 2019 in each county	JHU; Census; Summary of Deposits (SoD)
Deposit quantity and composition		
Deposit growth	The log difference of deposits held at a branch between June 30, 2019, and June 30, 2020	Summary of Deposits
%Retail deposits	For each bank in a quarter, the amount of retail deposits (deposits excluding time deposits of larger than $100,000 and brokered deposits, RCON2200-RCONJ473-RCONJ474-RCON2365) as a proportion of total deposits	Call Report
%Insured deposits	For each bank in a quarter, the amount of insured deposits (RCONF049+RCONF045) as a proportion of the total amount of deposits	Call Report
PPP and corporate liquidity management		
ln(PPP)	Log cumulative amount of PPP (Paycheck Protection Program) loans originated in a county divided by population (in 10,000), measured as of the Friday of the previous week	U.S. Department of the Treasury
ln(Drawdown)	Log cumulative amount of credit drawdowns by publicly listed firms headquartered in a county divided by total assets of publicly listed firms headquartered in the same county, measured as of the Friday of the previous week	S&P Leveraged Commentary & Data (LCD)
ΔCash<0	An indicator that equals one if the change in cash holdings among companies headquartered in a county over a quarter is less than zero	Capital IQ Financial Fundamental
ΔCash $\geq$ 0	An indicator that equals one if the change in cash holdings among companies headquartered in a county over a quarter is greater than or equal to zero	Capital IQ Financial Fundamental

(*Continued*)

Table A.1
Continued

Variable	Definition	Source
ΔRevolvCredit<0	An indicator that equals one if the change in the amount of revolving credit among companies headquartered in a county over a quarter is less than zero	Capital IQ Capital Structure
ΔRevolvCredit ≥ 0	An indicator that equals one if the change in the amount of revolving credit among companies headquartered in a county over a quarter is greater than or equal to zero	Capital IQ Capital Structure
ΔTotalDebt<0	An indicator that equals one if the change in total debt among companies headquartered in a county over a quarter is less than zero	Capital IQ Capital Structure
ΔTotalDebt ≥ 0	An indicator that equals one if the change in total debt among companies headquartered in a county over a quarter is greater than or equal to zero	Capital IQ Capital Structure
Bank characteristics		
Medium banks	An indicator that equals one if a bank's total assets fall between the bottom tercile and the top tercile of the sample	Call Report
Large banks	An indicator that equals one if a bank's total assets fall above the top tercile of the sample	Call Report
Mega banks	An indicator that equals one if a bank's total assets of over $100 billion	Call Report
Systematically important banks	An indicator that equals one if a bank is a systematically important bank	Call Report; The Financial Stability Board
#States	The number of states in which a bank operates	Summary of Deposits
concentration	Herfindahl–Hirschman index (HHI) of banks' deposit market share across counties	Summary of Deposits
Size	Book value of total assets (in $billion)	Call Report
Equity-asset ratio	Book value of total equity divided by book value of total assets	Call Report
ROA	Operating income divided by total assets	Call Report
Liquidity ratio	Total liquid assets divided by total assets, where liquid assets include cash, federal funds sold and reverse repos, and marketable securities	Call Report
Tier1	Tier 1 capital divided by risk-weighted assets	Call Report
NPL	Nonperforming loans (loans past-due by over 90 days) divided by total loans	Call Report
Unused commitments	Unused commitments for C&I loans divided by the sum of undrawn C&I loans and total outstanding loans	Call Report

(*Continued*)

Table A.1
Continued

Variable	Definition	Source
Economic uncertainty and household expectation		
Search vol: Unemployment	A search volume index for keywords "unemployment" in each Nielsen Designated Market Areas (DMA) in a week. Searching volumes are reported on a scale from 0 to 100 during the specified time frame from January 2018 through December 2020, where higher values indicate more popularity as a fraction of total searches in a location	Google Trends
Search vol: Lose job	A search volume index for keywords "lose job", "losing job", or "job loss" in each DMA in a week. Searching volumes are reported on a scale from 0 to 100 from January 2018 through December 2020, where higher values indicate more popularity as a fraction of total searches in a location	Google Trends
Search vol: Layoff	A search volume index for keywords "lay off", "layoff", or "laid off" in each DMA in a week. Searching volumes are reported on a scale from 0 to 100 from January 2018 through December 2020, where higher values indicate more popularity as a fraction of total searches in a location	Google Trends
Search vol: Save money	A search volume index for keywords "save money", or "saving money" in each DMA in a week. Searching volumes are reported on a scale from 0 to 100 from January 2018 through December 2020, where higher values indicate more popularity as a fraction of total searches in a location	Google Trends
Search vol: Rainy day fund	A search volume index for keywords "rainy day savings" or "rainy day fund" in each DMA in a week. Searching volumes are reported on a scale from 0 to 100 from January 2018 through December 2020, where higher values indicate more popularity as a fraction of total searches in a location	Google Trends
Employment	The percentage change in the employment level relative to January 2020 of each county in a week	Economic Tracker

(*Continued*)

Table A.1
Continued

Variable	Definition	Source
Unemployment insurance Claims	The number of initial unemployment insurance claims per 100 people in the 2019 labor force	Economic Tracker
Expect job loss	An indicator that equals one if a respondent chooses yes to “Do you expect that you or anyone in your household will experience a loss of employment income in the next 4 weeks because of the coronavirus pandemic?” (Q10)	Census Household Pulse Survey
Spending changes due to concerns about the economy/layoff	An indicator that equals one if a respondent or his household changed spending due to concerns about being laid off or having hours reduced and/or concerns about the economy (Q19)	Census Household Pulse Survey
Individual characteristics		
Female	An indicator that equals one if the respondent is female (Q2)	Census Household Pulse Survey
Hispanic	An indicator that equals one if the respondent is Hispanic (Q3)	
White	An indicator that equals one if the respondent is white (Q4)	
Education	Education level (Q5)	
#HHMember	The number of household members (Q7)	
#Kids	The number of children (age below 18) in the household (Q8)	
Employed	An indicator that equals one if the respondent is employed (Q11)	
HH job loss	An indicator that equals one if any household member experienced a loss of employment income since March 13, 2020 (Q9)	
Income	Income level by category (Q50)	
Health	Health status by category (Q31)	

References

Acharya, V. V., and N. Mora. 2015. A crisis of banks as liquidity providers. *Journal of Finance* 70:1–43.

Acharya, V. V., and S. Steffen. 2020a. 'Stress tests' for banks as liquidity insurers in a time of COVID. VoxEU.org.

———. 2020b. The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *Review of Corporate Finance Studies* 9:430–71.

Agarwal, S., and W. Qian. 2014. Consumption and debt response to unanticipated income shocks: evidence from a natural experiment in Singapore. *American Economic Review* 104:4205–30.

Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott. 2020. Aggregate and firm-level stock returns during pandemics, in real time. Working Paper, Harvard University.

Baker, S. R., N. Bloom, S. J. Davis, K. Kost, M. Sammon, and T. Viratyosin. 2020. The unprecedented stock market reaction to COVID-19. *Review of Asset Pricing Studies* 10:742–58.

Ben-David, I., A. Palvia, and C. Spatt. 2017. Banks' internal capital markets and deposit rates. *Journal of Financial and Quantitative Analysis* 52:1797–826.

Berger, A. N., and T. H. Hannan. 1989. The price-concentration relationship in banking. *Review of Economics and Statistics* 71:291–9.

———. 1991. The rigidity of prices: Evidence from the banking industry. *American Economic Review* 81: 938–45.

Ryssdal, K., and K. Wiles. 2020. Interview with Ben Bernanke. *Marketplace*, March 23. https://www.marketplace.org/2020/03/23/former-fed-chair-bernanke-covid19-downturn/.

Browning, M., and A. Lusardi. 1996. Household saving: micro theories and micro facts. *Journal of Economic Literature* 34:1797–855.

Carroll, C. D., and A. A. Samwick. 1998. How important Is precautionary saving? *Review of Economics and Statistics* 80:410–9.

Chen, Q., I. Goldstein, Z. Huang, and R. Vashishtha. 2020. Bank transparency and deposit flows. Working Paper, Duke University.

Chetty, R., J. Friedman, N. Hendren, M. Stepner, and t. O. I. Team. 2020. The economic impacts of COVID-19: Evidence from a new public database built from private sector data. Working Paper, Stanford.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser. 2020. Bank liquidity provision across the firm size distribution. Working Paper, Harvard University.

Cornett, M. M., J. J. McNutt, P. E. Strahan, and H. Tehranian. 2011. Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics* 101:297–312.

D'Acunto, F., T. Rauter, C. Scheuch, and M. Weber. 2020. Perceived precautionary savings motives: Evidence from digital banking. Working Paper, Boston College.

Engen, E. M., and J. Gruber. 2001. Unemployment insurance and precautionary saving. *Journal of Monetary Economics* 47:45–79.

Eren, E., A. Schrimpf, and V. Sushko. 2020. US dollar funding markets during the Covid-19 crisis-the money market fund turmoil. Report, Bank for International Settlements Bulletin.

Falato, A., I. Goldstein, and A. Hortaçsu. 2020. Financial fragility in the COVID-19 crisis: the case of investment funds in corporate bond markets. Working Paper, Federal Reserve Board.

Gatev, E., and P. E. Strahan. 2006. Banks' advantage in hedging liquidity risk: theory and evidence from the commercial paper market. *Journal of Finance* 61:867–92.

Gormsen, N. J., and R. S. J. Koijen. 2020. Coronavirus: impact on stock prices and growth expectations. *Review of Asset Pricing Studies* 10:574–97.

Greenwald, D. L., J. Krainer, and P. Paul. 2020. The credit line channel. Working Paper, Federal Reserve Bank of San Francisco.

Haddad, V., A. Moreira, and T. Muir. 2021. When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the Fed's response. *Review of Financial Studies* 34:5309–51.

Ivashina, V., and D. Scharfstein. 2010. Bank lending during the financial crisis of 2008. *Journal of Financial Economics* 97:319–38.

Kargar, M., B. Lester, D. Lindsay, S. Liu, P.-O. Weill, and D. Zúñiga. 2021. Corporate bond liquidity during the COVID-19 crisis. *Review of Financial Studies* 34:5352–401.

Kashyap, A. K., R. Rajan, and J. C. Stein. 2002. Banks as liquidity providers: an explanation for the coexistence of lending and deposit-taking. *Journal of Finance* 57:33–73.

Li, L., Y. Li, M. Macchiavelli, and X. Zhou. 2021. Liquidity restrictions, runs, and central bank interventions: Evidence from money market funds. *Review of Financial Studies* 34:5402–437.

Li, L., P. E. Strahan, and S. Zhang. 2020. Banks as lenders of first resort: Evidence from the COVID-19 crisis. *Review of Corporate Finance Studies* 9:472–500.

Lin, L. 2019. Bank deposits and the stock market. *Review of Financial Studies* 33:2622–58.

Martin, C., M. Puri, and A. Ufier. 2018. Deposit inflows and outflows in failing banks: The role of deposit insurance. Working Paper, Duke University.

O'Hara, M., and X. A. Zhou. Forthcoming. Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics*.

Pástor, L., and M. B. Vorsatz. 2020. Mutual fund performance and flows during the COVID-19 crisis. *Review of Asset Pricing Studies* 10:791–833.

Reinhart, C. M., 2020. This time truly is different. *Project Syndicate*, March 23. https://www.project-syndicate.org/commentary/covid19-crisis-has-no-economic-precedent-by-carmen-reinhart-2020-03.