Once Bitten, Twice Shy: The S&L Crisis Experience and Depositor Reactions to Default News

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Abstract

This study investigates the impact of a banking crisis on the subsequent behavior of depositors. Using a triple difference-in-differences research design that exploits the heterogeneous exposure of U.S. counties to the Savings and Loan (S&L) crisis and within-bank, across-region variation in uninsured deposit rates, we show that depositors in counties that were exposed to the S&L crisis are more responsive to bank client defaults and more likely to withdraw deposits from the exposed branch, leading to an increase in deposit rates. Using the Edgar search data, we further document the heterogeneity in information acquisition among depositors due to their differing experiences of the S&L crisis. In cross-sectional analyses, we find that depositor responses are more pronounced when (1) their county is more exposed to the S&L crisis, (2) the default events are more salient, (3) the bankrupt client is a relationship borrower, (4) the focal bank is riskier, and (5) depositors have the financial sophistication or incentives to monitor banks. Collectively, our findings help understand depositor behavior in banking crises by showing that prior exposure to a crisis makes depositors more sensitive to bank risk.

Keywords: *Imprinting;* the *S&L Crisis*; *Deposit Market Discipline; Bank Run; Borrower Bankruptcy*

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1. Introduction

The fragility of the banking sector was once again highlighted by the U.S. Banking Crisis of 2023. A depositor run occurred recently on the Silicon Valley Bank (SVB) in March 2023, then the 15th largest bank in the United States. The failure of SVB was followed by regulators closing the Signature Bank of New York and First Republic Bank in March and May 2023, respectively. For long, economic theories have recognized that the banking system is inherently fragile because negative news about bank fundamentals can trigger depositor runs due to coordination failures (e.g., Diamond and Dybvig 1983; Chari and Jagannathan 1988; Goldstein and Pauzner 2005). While these theories characterize depositors as either patient or impatient, they do not delve into the role of depositors' personal traits and past experiences in bank runs (Tversky and Kahneman 1992). Our paper fills this void in the literature. In particular, we focus on the depositors' prior experience of banking crises to demonstrate the enduring influence of such experiences on their subsequent reactions when confronted with adverse news concerning banks. Such an investigation is critical for understanding the stability of the banking sector, given that deposits constitute over three-quarters of the sector's funding.

The rationale for the potential long-run impact of past crisis experiences on depositors is grounded in the "imprinting" literature, which argues that *"during a brief period of susceptibility, a focal entity develops characteristics that reflect prominent features of the environment and these characteristics continue to persist despite significant environmental changes in subsequent periods"* (Marquis and Tilcsik 2013). A banking crisis features a loss of trust in bank solvency, often accompanied by large-scale panic and fear. Exposure to a banking crisis can influence depositors, prompting them to engage in context-specific adaptation and develop specific preferences, attitudes, and cognitive frameworks. Specifically, individuals affected by banking crises can develop a heightened perception of financial risk, display a stronger aversion to losses, and process bankruptcy news differently than those without such experience (Malmendier, 2021; Hanlon et al., 2022).[1] Thus, we posit that prior experience with banking crises can heighten depositors' attentiveness and skepticism when encountering subsequent adverse news concerning their banks, potentially leading them to acquire more information and withdraw deposits.

To test this prediction, we exploit one of the most devastating banking crises, the savings and loan (S&L) crisis of the 1980-90s, characterized by massive bank failures (over 30% of all S&Ls). A notable feature of the S&L crisis is that there was significant geographic variation in the exposure to the crisis (see Figure 1 for illustration), which enables us to compare depositor responses in areas with significant exposure to the S&L crisis with those without meaningful exposure. This feature of the S&L crisis allows us to cleanly identify the imprinting effects of exposure to banking crises and attribute differential depositor responses to the S&L crisis imprint.[2]

Besides the experience in a *prior* crisis, we need a *concurrent* event that triggers heightened concerns about bank stability to show imprinting effects among depositors. For this purpose, we use default events of the bank's clients, i.e., borrowers, as salient informational signals to depositors about increase in bank risk (e.g., Dahiya Saunders and Srinivasan 2003; Jorion and Zhang 2009). Imprinting theory implies that a prior adverse experience in a banking crisis is expected to change depositors' skepticism about the soundness of banks. Thus, we investigate whether prior experience of the S&L crisis induces heterogeneous deposit responses to borrower defaults.

There are several challenges to test this question empirically. First, it requires granular

[1] The "experience effect" of imprinting has neuroscientific underpinnings in which nascent neuroscience research documents that human brains can be altered, through forming connections between neurons, when adapting to acute external environmental changes (LaBar and Cabeza 2006; Bear, Connors and Paradiso 2020; Malmendier 2021). In other words, modern neuroscience research discovers a growth human brain as opposed to fixed brain. In contrast to imprinting theory, traditional economic models of individual decision-making do not assume any impact of past experience on depositors beyond contemporaneous acquired information (Malmendier 2021).
[2] We also considered using the more recent Global Financial Crisis of 2007-09 (GFC) as an alternative research setting. However, unlike the S&L crisis, there was minimal geographic variation in the exposure to the GFC within the United States.

data on the behavior of depositors, especially uninsured ones, in the short window around banks' client defaults. One cannot easily attribute depositor responses to bank risk changes without such data. Second, bank client default is bank-specific and likely endogenous to time-varying bank characteristics. Thus, the difference in depositor responses can be driven by unobserved bank characteristics associated with client defaults rather than the incidence of client defaults. Third, how to identify depositors' information acquisition? We address these empirical challenges by using weekly granular bank deposit rate data for each U.S. bank branch, enabling us to account for unobserved time-varying geographic and bank characteristics. We further utilize the Edgar search data to identify information acquisitions by depositors depending on their prior S&L crisis experience.

We take advantage of the heterogeneous exposures of U.S. counties to the S&L crisis and the within-bank variations in uninsured deposit rates to implement a stacked Triple-Differences (i.e., DDD) design that exploits the following three differences: (1) difference in deposit rates of two branches of the same bank, with one branch being located in a county previously exposed to the S&L crisis and while the other was not, (2) difference in deposit rates of two branches located in the same county, with one branch belonging to a bank with a borrower default (treated bank) and the other branch belonging to another bank without any client default (control bank), and (3) difference in deposit rates before and after the bankruptcy announcement of a bank's borrower.

In a short window surrounding a borrower's bankruptcy announcement, we find an increase in uninsured deposit rates of branches in S&L crisis imprinted counties that belong to banks with borrower defaults relative to the deposit rates of other bank branches. Our research design ensures that this finding is not attributable to observed or unobserved time-varying factors at the bank or the county level. By controlling for bank-week fixed effects, the comparison is between two otherwise similar branches of the same treated bank, except that one branch is in the S&L crisis-imprinted county while the other is not. Further, by including county-week fixed effects, we net out the effect for control bank branches without any client defaults in the same county as the treated bank branches. We also alleviate the concern that bank branch-specific factors (e.g., service quality) explain our finding by including branch fixed effects. The magnitude of the effect of the S&L crisis imprinting is economically meaningful. We find that deposit rates increase by 5.5% to 10%, comparable and slightly larger than the effect documented in studies exploring the demand-side-driven deposit rate changes (e.g., Levine, Lin, Tai, and Xie, 2021). Further, the effect of S&L crisis imprinting is incremental to that of notable demographic factors, including depositors' age, financial sophistication, and education. Thus, the evidence suggests that a prior bank crisis experience has a long-run impact on depositors, making them more sensitive to bank risk changes.

We conduct several additional analyses to provide context to our main finding and increase confidence in its robustness. First, while we intend to attribute the increase in deposit rates to the demand-side effect whereby depositors withdraw their funds from treated banks, one can argue that the effect is driven by supply-side factors whereby treated banks proactively raise deposit rates. We examine deposit flows for one year following borrower bankruptcy announcements and find an outflow of deposits from the treated bank branches located in the S&L crisis imprinted counties after bank client defaults, suggesting the increase in uninsured deposit rates is attributable, at least partially if not entirely, to the withdrawals made by depositors.[3]

Second, our stacked Tripe-Differences approach and high-dimensional fixed effects largely alleviate the concern that some other county-specific characteristic (e.g., local social and economic development) can explain differential depositor responses to the same bank's client defaults. Nonetheless, to rule out alternative explanations, we show that counties that were more severely affected by the S&L crisis, and thus were more likely to have a stronger

[3] Note that we use the deposit flow analysis as supplemental evidence in that data from SOD on deposit flow is available only at branch-year level.

S&L crisis imprint, exhibit greater deposit rate increases in reaction to bank client defaults. Third, a stable local population is an assumption underlying the imprinting of the S&L crisis experience. We validate this assumption by showing that our main finding is concentrated in counties with less population migration.

Fourth, we examine depositors' information acquisition during borrower bankruptcy event windows conditional on their S&L crisis experience. This helps us to provide direct empirical evidence of the information acquisition-based bank runs modeled by prior theoretical studies (Goldstein and Pauzner, 2005; He and Manela, 2016). We use EDGAR filings' searches and the IP addresses of individuals to pinpoint the locations of those seeking information about the focal banks and the defaulting borrowing firms. We find an increase in the number of EDGAR filings searches – for both bankruptcy clients and related banks – following borrower defaults in areas exposed to the S&L crisis.

Fifth, there are no pre-trends in the deposit rates between treatment and control bank branches located in exposed and unexposed counties before the borrower bankruptcy announcements. This also suggests that bankruptcy announcements are not anticipated (e.g., Jorion and Zhang 2009). Sixth, our main inference is robust to using an alternative sample and specification.

Finally, we conduct several cross-sectional analyses to corroborate our main finding. We find that (i) local depositors imprinted by the S&L crisis experience are more responsive to bank client defaults when the defaults are more profound and salient, (ii) the reaction of the S&L crisis imprinted depositors to bank client default is more pronounced if the defaulting client is a long-run relationship borrower, (iii) the responsiveness of deposit rates to bank client defaults in counties exposed to the S&L crisis is larger for banks that are less solvent, and (iv) deposit rates of branches in exposed counties with more financially sophisticated depositors are more responsive to bank client defaults, consistent with more financially sophisticated depositors are better at monitoring the signal of bank client defaults and relate it to the focal bank’s solvency.

Our study contributes to several streams of literature. Our paper directly contributes to the literature on information-based deposit market discipline. Most prior studies used aggregate data to examine deposit responses to information signals about bank fundamentals (Martinez Peria and Schmukler 2001; Chen, Goldstein, Huang, and Vashishtha 2022; Beck, Nicoletti, and Stuber 2022). Iyer and Peydro (2011) and Beck, Nicoletti, and Stuber (2022) focus on information dissemination via different networks and document deposit withdrawal contagion across banks due to interbank linkages and shared audit firms, respectively. Our study extends this line of literature by showing that depositors behave heterogeneously around events that increase bank risk because of their prior experiences with banking crises.

Second, there is limited direct evidence of retail investors’ information acquisition in the literature (e.g., Blankespoor, Dehaan, Wertz, and Zhu 2019; Blankespoor, deHaan, and Marinovic 2020). We extend the literature by showing the effect of bank crisis imprinting on information acquisition by depositors in response to credit events that affect bank risk. Our investigation also represents a meaningful step towards validating the assumption that depositors acquire additional information when faced with noisy signals about bank health of Goldstein and Pauzner (2005) and He and Manela (2016).

Third, our study fits into the broad literature on the long-run impact of prior experience on subsequent behaviors, defined as “imprinting” in Marquis and Tilcsik (2013) and “experience effect” in Malmendier (2021). Prior research has documented that past experience leaves an imprint on a variety of professionals in their subsequent decision-making, including corporate managers, auditors, investment bankers, and financial advisors (Oyer 2008; Malmendier, Tate, and Yan 2011; Bernile, Bhagwat, and Rau 2017; Law and Zuo 2021). Capital market participants' past experiences influence their investment decisions (Chiang, Hirshleifer, Qian, and Sherman 2011). However, little is known about how the behavior of bank depositors is influenced by their prior experiences. Our study provides some of the first empirical evidence of previous experience in a banking crisis triggering differential depositor reactions to events affecting bank solvency.

Finally, our paper is also related to studies on the transmission of borrower defaults to banks' stakeholders, which document an adverse stock market reaction to bank client defaults (Dahiya, Saunders, and Srinivasan 2003; Jorion and Zhang 2009). We extend this literature by documenting the reactions of another key bank stakeholder – the depositors. Importantly, we show that prior experience of banking crises results in differential reactions of local depositors to bank client defaults.

2. Related Literature and Conceptual Framework

Our empirical predictions are based on the following two arguments: (1) prior experience in the S&L crisis has a long-term impact on depositors' judgment and decision-making, a process known as "imprinting," and (2) depositors discipline banks in response to client defaults.

(1) The S&L Crisis imprint on depositors

The traditional economic models of individual decision-making consider contemporaneous available information (i.e., information-based decision making) and do not account for the effect of past experiences on the beliefs of individuals (Malmendier 2021). An emerging stream of the literature shows that early-life experiences (e.g., living through a financial crisis) affect individuals' career choices, risk taking and other behaviors (see Malmendier (2021) and Hanlon, Yeung, and Zuo (2022) for a review). For example, Malmendier, Tate, and Yan (2011) find that mangers who grew up in the Great Depression rely much less on external financing. Schoar and Zuo (2017) show that managers who start their careers in recessions adopt a more conservative corporate strategy, including lower investments and debt levels. Bernile, Bhagwat, and Rau (2017) document that experiencing an early-life disaster impacts managers' risk-taking. Ru, Yang, and Zou (2022) find that people in countries exposed to the 2003 SARS pandemic were more attentive and responded more proactively to the COVID-19 pandemic in early 2020.

Marquis and Tilcsik (2013) formalize the persistent effect of historical experience on subsequent personal beliefs and decision-making as “imprinting.” The imprinting argument embeds two features: (1) in a prior period, susceptible individuals are exposed to prominent environmental conditions, and (2) the effect of the exposure on subsequent behaviors is persistent despite environmental changes. Modern neuroscience research argues that personal experience can proactively shape the human brain to adapt to new experiences throughout life, resembling exercises for muscles (Malmendier 2021). Every new experience forms a connection (synapse) between two neurons, which enables neuron communication about the reaction to the experience. The pre-synaptic and post-synaptic neurons interact by receiving and sending neurochemical messages, and are reinforced by emotional arousal (LaBar and Cabeza 2006; Bear, Connors, and Paradiso 2020). In other words, modern neuroscience research establishes that rather than being fixed, brain structure can be altered to adapt to new environmental changes. This provides a rational for why past experiences have a long-lasting impact on individual beliefs, judgment, and subsequent economic decisions, which can’t be solely explained by acquired information in reaction to new environmental changes.

Building on the above literature, we extend the imprinting argument to bank depositor behavior and explore how depositors’ prior experience in the S&L crisis of the 1980s and 1990s affects their subsequent decisions in allocating deposits. Featured by large-scale bank failures (more than 30% failed incidences in federally insured savings and loan institutions), the S&L crisis is considered one of the most devastating banking crises. To this end, the S&L crisis was a prominent environmental condition that exposed depositors to panic, fear, and loss of confidence in banks. An experience of the S&L crisis is thus likely to impact depositors’ perception and judgment of later economic events related to their banks.[4]

In sum, while the traditional decision-making model suggests that depositors react only to acquired information, the imprinting theory implies that differential historical exposure to the S&L crisis can trigger heterogeneous responses among depositors even in the existence of the same information set. Depositors imprinted by previous crisis experiences are thus expected to be more responsive to adverse informational events about their banks.

(2) Depositor discipline in response to bank client default

Depositor market discipline refers to depositors responding to information about, or perceiving, an increase in bank risk by withdrawing their funds (Martinez Peria and Schmukler 2001; Egan, Hortaçsu, and Matvos 2017). Two classes of theories explain bank run/deposit withdrawals: an information-based theory which demonstrates that depositors withdraw their funds when they receive information signals of weaker bank fundamentals (Chari and Jagannathan 1988; Gorton 1988; Allen and Gale 1998); a panic-based theory which introduces depositor beliefs about bank insolvency as an important determinant of depositors' actions and shows that a bank run can occur when depositors anticipate a bank failure even if the bank is fundamentally solvent (Diamond and Dybvig 1983). More recently, Goldstein and Pauzner (2005) and Egan, Hortaçsu, and Matvos (2017) combine information-based and panic-based theories and show that shocks to bank fundamentals can be amplified by coordination failures among depositors. Several studies provide empirical evidence in support of these theories. (e.g., Martinez Peria and Schmukler 2001; Iyer and Puri 2012; Iyer, Puri, and Ryan 2016).

Building upon this literature, we exploit bank client defaults as trigger events that depositors perceive as informational signals about banks' risk spikes and potential insolvency. Our rationale is twofold. First, stakeholders consider borrower defaults as material adverse

[4] We discuss the S&L crisis in detail in Section 3.2.

events whose announcement results in heightened concern about bank health, loss of reputation, and increased regulatory scrutiny. As a consequence, banks that experience borrower bankruptcies lose market value and struggle to attract other lenders in syndicated loans (e.g., Dahiya, Saunders, and Srinivasan 2003; Jorion and Zhang 2009; Gopalan, Nanda and Yerramilli 2011). In extreme cases, client default can push a bank towards default, a phenomenon identified as counterparty risk (e.g., Jorion and Zhang 2009). Thus, depositors can react to bank client defaults by withdrawing deposits insofar as they interpret these bankruptcy events as indications of deterioration in bank health. Note that research on coordination failure and strategic complementarity suggests that depositors may respond by mass withdrawals even if these bankruptcy events are not severe enough to cause bank failure, as long as some depositors anticipate other depositors withdrawing, likely driven by panic or fear (e.g., Goldstein and Pauzner 2005; He and Manela 2016).

Another reason to choose bank client default as a triggering event is that the imprinting theory requires domain-specific concurrent events regarding the S&L crisis. The lingering impact of prior experiences on subsequent decision-making does not alter the risk perception of general issues but is concentrated on a domain that shares some similarities with past experience (Malmendier 2021). This "domain specificity" feature of imprinting theory is well grounded in the neuroscience literature, which finds that different cognitive domains are processed in specific brain regions and separate brain modules are specialized in particular kinds of stimuli (Karmiloff-Smith 2018). In this regard, borrower bankruptcies are domain-specific events comparable to client defaults and bank failures during the S&L crisis, extreme, rare, and salient events posing a profoundly negative impact on stakeholders. In other words, prior experience in bank failures can shape depositors' risk perception of bankruptcy incidences and render them more attentive to subsequent events as bank client defaults.

Collectively, building on (1) the imprinting theory that the S&L crisis experience leaves an imprint on depositors, rendering them more susceptible to subsequent bankruptcy events and (2) depositors impose market discipline on banks experiencing client defaults by withdrawing deposits, we hypothesize:

H1: Depositors imprinted by the S&L crisis are more responsive to bank client defaults and more likely to withdraw deposits, leading to an increase in bank deposit rates of the affected branches relative to other depositors without such crisis experience.

3. Data, Key Variable Measurement and Descriptive Statistics

3.1 Data

Large time deposits are more likely to be uninsured than smaller deposits. Thus, we utilize the deposit rate of the likely uninsured deposit products, those with minimum account amounts exceeding the FDIC deposit insurance limit threshold of $250,000 since 2008. This deposit product was not popular until 2010. Thus, our initial sample consists of all banks in the RateWatch database between 2010 and 2020, which collects bank branch-level data on different deposit products weekly. [5] Both banks and regulators have widely used the RateWatch database.

We obtain branch-level deposit balances from the Summary of Deposits (SOD) database maintained by the Federal Deposit Insurance Corporation (FDIC). Unlike the RateWatch data, the SOD data are available for each bank branch at an *annual* frequency. We match the RateWatch deposit rate data with the SOD deposit flow data using the FDIC branch identifier.

Data on county-level historical exposure to the S&L crisis during 1980-1994 are obtained from the FDIC. Data on Chapter 11 bankruptcies are retrieved from the New Generation Research's BankruptcyData.com, which is the largest bankruptcy dataset and has been used extensively in prior bankruptcy research (e.g., Jorion and Zhang 2007; Jiang, Li and Wang 2012; Eckbo, Thorburn, and Wang 2016; Ma, Tong, and Wang 2022).[6] We use the DealScan database,

[5] The deposit insurance limit threshold had been $100,000 prior to 2008.

[6] The number of bankruptcy cases included in BankruptcyData.com is much larger compared with an alternative database, the UCLA-LoPucki Bankruptcy Research Database, which covers Chapter 11 filings by large U.S. public firms with assets of $100 million and above (Ma, Tong, and Wang, 2022). To ensure that we have a

which provides information about bank-client relationships in the U.S. primary loan market, to identify whether a given bankrupt firm is a client of the sample banks. We obtain bank financial data from the quarterly Consolidated Report of Condition and Income (i.e., the Call Reports) for publicly listed and privately held banks in the U.S. Stock price information for publicly traded banks is obtained from the CRSP database.

Commonly used county-level demographic data, like information about education and income levels etc., are obtained from the U.S. Census Bureau in 2000 and the Bureau of Economic Analysis in 2004. County-level social capital data are from Chetty et al. (2022a, 2022b).[7] These data capture the extent to which people with low vs. high socioeconomic status are friends with each other in a given county. Data on state-level government unemployment insurance are from the Department of Labor. State-level financial literacy index data are retrieved from the National Financial Capability Study (NFCS), which has been widely used in earlier research (Lusardi and Mitchell 2014; Cheng, Severino, and Townsend 2021; Hayes, Jiang, and Pan 2021).

We obtain the number of searches for firm filings on the EDGAR platform using the following steps. First, we retrieve all the available EDGAR Log File data between January 2010 and June 2017.[8] Each data record contains the IP version 4 address of the requesting user, the date and time of the request, and the identifier (i.e., CIK) of the filing firm. The first three octets of the IP address are publicly available. In the second step, following Cao, Du, Yang, and Zhang (2021) and Chen (2023), we match the first three octets of IP addresses in the log file to the location lookup tables via IP-API to obtain the country, state, county, and postal code information for each request/search from EDGAR users. In the last step, we aggregate

relatively complete list of bankruptcy cases, we mainly rely on BankruptcyData.com to identify Chapter 11 filings but cross check the data with Bankruptcy Research Database for completeness

[7] We thank Chetty et al. (2022a, 2022b) for providing the data, which can be found at https://socialcapital.org/?dimension=EconomicConnectednessIndividual&dim1=EconomicConnectednessIndividual&dim2=CohesivenessClustering&dim3=CivicEngagementVolunteeringRates&geoLevel=county&selectedId=06037

[8] The EDGAR Log File data are not available for the period after June 2017.

the search data at the CIK-county-week level and merge them with the list of banks and borrowing firms in our sample using the identifier CIK.

3.2 Key Variable Measurement

3.2.1. The S&L crisis experience

The S&L crisis in the 1980s and 1990s was one of the most devastating banking crises, featuring over 1,043 federally insured savings and loan institutions (or over 30% of all 3,234 institutions) with assets over $500 billion being shut down between 1986 and 1995 (Curry and Shibut 2000). The S&L crisis was triggered by (1) high and volatile interest rates during the late 1970s, which exposed S&Ls to interest rate risk and asset-liability maturity mismatch, and (2) the deregulation of the S&L industry and reduced regulatory capital requirements without an accompanying increase in examination resources. Regardless, the S&L crisis provides an ideal setting to examine the S&L crisis imprint on depositors' response as it disproportionately affected S&Ls in certain areas like Texas, Louisiana, Arkansas, Colorado, and New Mexico, which relied more on the agricultural sector. This is illustrated in Figure 1, which plots a heatmap of the geographic distribution of bank failures during the S&L crisis.

The substantial geographic variation in local exposure to the S&L crisis is crucial to our identification as it allows us to compare deposit responses of two otherwise identical branches of the same bank, except one branch is located in a county that was exposed to the S&L crisis while the other is in an unexposed county (See Figure 2). Thus, we define a county-level indicator variable, *S&LCounty*, that takes the value of one for a county with direct exposure to the S&L crisis, i.e., experiencing more than one bank failure during the 1980s and 1990s and zero otherwise.

3.2.2. Bank solvency risk and bank client default

The imprinting theory suggests that local depositors imprinted by the S&L crisis are more likely to respond to (the perception of) an increase in their bank's insolvency risk. Accordingly, our Triple-Differences design exploits the default of a bank's borrower as a salient event indicative of a change in a bank's solvency risk. Banks with client/borrower defaults are considered to be riskier compared with counterparts without any client bankruptcy. The intuition is that borrower defaults represent the deterioration of banks' financial health and can affect banks' reputations (Jorion and Zhang 2009). Consistent with this idea, borrower bankruptcy or default announcements have been found to lead to negative abnormal returns for the borrower's bank (Dahiya, Saunders, and Srinivasan 2003). Thus, building on existing literature, we posit a transmission of asset-side client bankruptcy to liability-side deposit reactions.

We define a bank-level indicator variable, *TreatedBank*, that takes the value of one for a bank that experiences a default incidence of its clients/borrowers during the sample period and zero otherwise (See Figure 2). Conversely, banks that do *not* experience any client default throughout the sample period are classified as control banks, *ControlBank*.

3.2.3. The depositor response

As our primary dependent variable, we use bank-branch specific weekly deposit rates (*Deposit Rate*) of a commonly used deposit product that is likely uninsured: the 12-month certificates of deposit with a minimum account size of $250,000 (CD250K). Relative to small amount time deposit products, large time deposits are more likely to be uninsured (e.g., Egan, Hortaçsu, and Matvos 2017).

We acknowledge that a shift in either the supply or demand curve of local deposits can drive the change in deposit rates. For instance, instead of depositors withdrawing their funds from banks with client defaults, affected banks (i.e., treated banks) may raise their deposit rates to retain depositors. Thus, our analysis of deposit response also explores deposit flows. It is worth pointing out that, unlike deposit rate data that are granular at weekly frequency, SOD deposit balance data at the bank branch level are available at an annual frequency. We define the annual deposit flow for each bank branch, *Deposit Flow*, as the log change in branch deposits in two consecutive years. We thus use the deposit flow for supplemental tests.

3.3 Descriptive Statistics

As illustrated in Figure 3, the incidence of bank client defaults varies significantly over time. Not surprisingly, default events rarely occur. Table 1 presents the summary statistics for branch-level weekly deposit rates (Panel A) and annual deposit flows (Panel B), bank quarterly financial characteristics (Panel C), county-level characteristics (Panel D), as well as state-level characteristics (Panel E) and Edgar searches (Panel F). Table A1 of the Appendix provides the detailed variable definitions. In our sample, the mean (median) weekly deposit rate for 12-month CDs with $250,000 or more is 0.31 (0.20)%. Also, the average bank has total assets of $705 million, a ratio of equity to assets of 11.3%, a return on assets of 0.5%, a ratio of non-performing loans of 1.3%, and a Z-score of 3.029. These bank characteristics are quantitatively comparable to those in the literature (e.g., Lin 2020; Levine, Lin, Tai, and Xie 2021). Also, there is significant variation in county- and state-level characteristics.

4. Main Results

4.1 S&L Crisis Imprint on Deposit Response to Bank Client Default

The incidence of borrower bankruptcy is staggered in nature over time. A staggered Triple-Differences (or DDD) estimation is susceptible to bias, driven by heterogeneous treatment effects, when using already treated units as controls for later treated units (Baker, Larcker, and Wang, 2022; Goodman-Bacon, 2021). To address this issue, we adopt a stacked DDD approach by using never-treated banks (i.e., without client defaults) as the clean control banks and stacking the bankruptcy-wave datasets in relative time to obtain an average treatment effect across all bankruptcy events (Cengiz, Dube, Lindner, and Zipperer 2019; Dey, Heese, and Pérez-Cavazos 2021). In particular, we examine the role of the S&L crisis imprint on depositor response to bank client defaults by estimating the following stacked DDD regression:

$$Deposit\ Rate_{br,c,t} = \beta\ S\&LCounty_{c} \times TreatedBank_{b} \times Post_{b,t} + d_{br} + l_{b,t} + \varphi_{c,t} + \varepsilon_{br,c,t}, \quad (1)$$

where *Deposit Rate* is the weekly branch deposit rate on 12-month CDs. *b, br, s, c,* and *t* denote bank, branch, state, county, and week, respectively. We focus on a short event window ([-4 weeks, +4 weeks]) surrounding each borrower default event. For each event window, we define an indicator variable, *Post*, that equals one for the period after the filing for borrower bankruptcy and zero otherwise. *S&LCounty* and *TreatedBank* are indicator variables defined in the previous section.

There are two identification challenges in documenting the imprint of the S&L crisis experience on depositors in their reaction to bank borrower defaults. First, bank solvency risk indicated by borrower defaults is endogenous to depositors' response. Thus, the difference in deposit rates between a bank with a client default (treated bank) and a bank without (control bank) may be driven by unobserved yet time-varying bank characteristics or the actions of the two banks. Second, county-level characteristics, rather than local experience in the S&L crisis, may explain the differential depositor responses between the exposed and unexposed counties.

To address the first challenge, we include bank-week fixed effects, $l_{b,t}$, to allow for a clean comparison between two otherwise similar branches of the same treated bank, except that one branch is located in an S&L crisis-exposed county. In contrast, the other branch is located in an unexposed county.[9] The set of bank-week fixed effects absorbs the effect of all time-varying bank characteristics that can affect the deposit rates, such as bank profitability, size, leverage, and capital adequacy ratio, which are considered important determinants of deposit rates. To address the second identification threat, in Equation (1), we include county-week fixed effects, $\varphi_{c,t}$, to account for observed or unobserved time-varying factors at the county level, such as local economic development, local deposit demand, and local lending

[9] This within-bank estimation (by controlling for bank-time fixed effects) implicitly assumes that lending decisions are made primarily at the bank level instead of branch level, which is well supported in existing research that documents the fact that banks reallocate funds using internal branch networks (Drechsler, Savov, and Schnabl 2017; Ben-David, Palvia, and Spatt 2017). Note that deposit rates can be different for different branches of the same bank, which is crucial to our identification strategy.

opportunities. Note that the high-dimensional county-week fixed effects also subsume any time-varying policy change related to deposits at the state level as well as any macroeconomic economic fluctuations, including changes in the federal funds rate and other benchmark interest rates, all of which are relevant for deposit pricing. In addition, our DDD research design enables us to net out the counterfactual of what the difference in deposit rates (of control banks) between *S&L county* and *non-S&L county* would be had there been no bankruptcy occurrence. Figure 2 illustrates the key ideas of our identification strategy.

Including branch fixed effects, d_{br}, ensures that time-invariant branch-level factors like the market power of branches do not confound our estimates. Note that all the lower order interaction terms, $S\&LCounty_c \times Post_{b,t}$, $TreatedBank_b \times Post_{b,t}$, and $S\&LCounty_c \times TreatedBank_b$, are subsumed by the high-dimensional county-week, bank-week and branch fixed effects. The coefficient β on the triple interaction term $S\&LCounty_c \times TreatedBank_b \times Post_{b,t}$ in Equation (1) captures the effect of the S&L crisis imprint on deposit rate response to bank client defaults among treated banks after netting out the effect for banks without any client default.

Panel A of Table 2 reports the main results of estimating Equation (1), with (Column (1) and (3)) or without (Column (2)) branch fixed effects. The coefficients on the variable of interest, *S&LCounty×TreatedBank×Post*, in all columns are significantly positive, suggesting an increase in deposit rates of treated bank branches imprinted by the S&L crisis following the focal bank's client default. In terms of economic magnitude, the coefficients on the triple interaction term show that after a borrowing firm's bankruptcy, the deposit rates of bank branches located in counties with the S&L crisis imprint increased by 5.5% (= 0.0171/0.312) to 10% (= 0.031/0.312) of the sample average compared with branches of the same treated bank located in counties without the S&L crisis imprint, relative to control bank branches. The magnitude of the deposit rate increase is larger compared to that of Levine, Lin, Tai, and Xie (2021), who document a demand-side-driven deposit rate change of between 4% and 7% of the sample average in deposit rates in response to COVID-19 for one standard deviation increase in the log of infection cases. We also investigate whether the effect of the S&L crisis imprint is incremental to other salient demographic features that influence deposit rates, including *Financial Literacy*, *Social Connectedness Index, Age, and Education*. Results in Appendix Table A2 show that none of the above demographics subsume the impact of the S&L crisis imprint on deposit rate changes.

A shift in either the demand or supply curve of local deposits can drive the change in deposit rates. In other words, an alternative supply-side argument may explain the documented increase in deposit rates of branches imprinted by the S&L crisis following bank client defaults that treated banks raise their deposit rates to retain existing depositors. Deposit outflow (inflow) and an increase in deposit rates in response to bank client defaults support demand-side (supply-side) explanations. To distinguish the demand-side from supply-side effects, in Panel B of Table 2, we replace *Deposit Rate* in Equation (1) with *Deposit Flow*, which is the log change in the total branch deposit amount. Due to data limitation from the SOD on deposit flows, the unit of analysis for the deposit flows is branch-year, and thus, we consider it supplemental evidence. The significantly negative coefficients on *S&LCounty*×*TreatedBank*×*Post* in both columns of Panel B of Table 2 suggest there were deposit outflows from treatment bank branches located in the S&L-crisis-imprinted counties after bank client defaults, corroborating the findings in Panel A.

Taken together, the evidence in Table 2 indicates that prior adverse experience in banking crises drives depositors to react differently to changes in subsequent bank solvency risks associated with client defaults relative to depositors without such crises imprint.

4.2 Dynamic Effects and Robustness Tests

4.2.1. Parallel-trend assumption and dynamic effects

The identification assumption in our Triple-Differences design in Equation (1) is that, in the absence of bank client defaults, changes in deposit rates of branches exposed to the S&L crisis, relative to those without such exposure, would follow parallel trends. To validate the parallel trends assumption and provide insight into the dynamic effects, we follow Bertrand and Mullainathan (2003) and estimate the specification below:

$$Deposit\ Rate_{br,c,t} = \Sigma\, \beta_{(\tau)}\ S\&LCounty_c \times TreatedBank_b \times Post_{b,t}\ (\tau) + d_c + l_{b,t} + \varphi_{s,t} + \varepsilon_{br,c,t}\,, \qquad (2)$$

in which τ denotes week τ relative to the bankruptcy event week (τ=0). *S&LCounty×TreatedBank×Post(τ)* denotes a series of dummy variables indicating each of the four weeks before the event week and the subsequent weeks in and after the client default. The week before the bankruptcy week serves as the benchmark and is thus omitted.

Table 3 presents the results of estimating Equation (2). Supporting the parallel pre-trend assumption, the coefficients on *S&LCounty×TreatedBank×Post(τ)* are statistically indistinguishable from zero in the pre-treatment weeks. This also implies that bankruptcy announcements are not anticipated, which is consistent with Jorion and Zhang (2009). In contrast, deposit rates of branches with the S&L crisis imprint increase after a client default, evidenced by the significantly positive coefficients for treated banks relative to control banks.

4.2.2. Falsification test

We acknowledge that borrower default does not occur randomly. It can be an identification threat if borrower default is correlated with bank characteristics that affect depositor response. A bank with certain characteristics correlated with borrower defaults is matched with borrowers more responsive to changes in banks' solvency risks. Our within-bank estimation enables us to compare two branches of the same bank exposed to borrower defaults, rendering it less of a concern whether a bankruptcy event is endogenous or exogenous. Nevertheless, to strengthen the causal inference, we conduct a falsification test in which we randomly assign client bankruptcy treatments to our sample banks. Repeating the random assignments 1,000 times, we obtain 1,000 DDD estimators (coefficients on *S&LCounty×TreatedBank×Post*). We then plot the distribution of the coefficients and present the result in Figure 4. The figure shows that the distribution is centered at zero rather than around the actual coefficient, represented by the solid line. The significant deviation in the distribution of the randomized coefficients implies that our finding is unlikely to be driven by other unobserved factors, such as correlated omitted bank characteristics.

4.2.3. Alternative samples

The sample period in our baseline specification covers the COVID-19 pandemic in 2020. Although our empirical strategy of using high-dimensional fixed effects, including bank-week and county-week fixed effects, accounts for macroeconomic and social fluctuations, we repeat our baseline analysis in Table 2 by excluding the COVID-19 period (i.e., 2020) to provide additional comfort. Panel A of Table 4 reports the results based on a sample that excludes observations from the COVID-19 period. The results in all columns of Panel A of Table 4 show a significant increase in deposit rates of treated bank branches located in S&L-crisis-imprinted counties following a client default of the treated bank.

4.2.4. Alternative specification

As a robustness test, we use an alternative specification to compare the changes in deposit rates of bank branches located in exposed counties imprinted by the S&L crisis after bank client defaults relative to branches in unexposed counties. We restrict the sample to include only banks with client defaults to implement this test. We regress *Deposit Rate* (*Deposit Flow*) on *S&LCounty×Post* and report the results in Columns (1) and (2) (Columns (3) and (4)) of Panel B, Table 4. Again, the joint results of a significant increase in deposit rates and a decrease in deposit inflow for branches in counties imprinted by the S&L crisis after bank client defaults provide evidence consistent with prior adverse experiences in banking crises leads depositors to be more sensitive to defaults of bank clients. We prefer the Triple-Differences design in Equation (1) because the difference in deposit rates of the different branches of control banks (i.e., banks without any client default) serves as the counterfactual for treated banks. By netting out this counterfactual, which indicates the difference in deposit rates for branches with or without the S&L crisis imprint absent any bank client defaults, we can estimate the impact of the S&L crisis imprint on changes in bank risk more cleanly.

4.2.5. The effect of population change

An implicit assumption underlying the finding of a long-run impact of the S&L crisis is that the local population is relatively stable. In other words, the effect of the S&L crisis imprint on depositor actions to subsequent default events is expected to be observed if there are relatively minimal population changes in counties. To shed light on this, we conduct a validation test considering the population stability of U.S. counties. In particular, we split the sample into terciles based on the non-mover population of counties over 1995-2020. The non-mover population is the average population (over every five years) that has not moved in or out of a county (i.e., fewer migrants). A large non-mover population reflects more stability in the composition of a county's population. Panel C of Table 4 presents the results, confirming that our primary finding is mainly concentrated among counties with a more stable local population, i.e., less population flow into and out of a county.

4.3 Evidence about the Imprint of the S&L Crisis

4.3.1. Intensity of the S&L crisis imprint

To further attribute differential deposit response to the imprint of local depositors' S&L crisis experience, we examine whether deposit response to bank client defaults varies with the intensity of the imprint. We take advantage of the heterogeneity in the counties' exposure to the S&L crisis because of the varying number of bank failures within counties (see Figure 1), which indicates cross-sectional variation across counties in the intensity of the S&L crisis imprint. We thus expect to see a stronger deposit reaction to bank client defaults in counties where the S&L crisis left a stronger imprint on depositors' memory. To test this prediction, we replace *S&LCounty* with a continuous variable to capture the intensity of imprinting, *S&LIntensity*, defined as the log of one plus the number of failed banks in a county during the S&L crisis period. This measure equals zero for counties without any bank failures during the S&L crisis. A larger value of *S&LIntensity* indicates a more significant crisis imprint. The results of these analyses are presented in Panel A of Table 5. Consistent with our conjecture, we find a positive and significant coefficient on the variable of interest, *S&LIntensity×TreatedBank×Post*.

4.3.2. Evidence from EDGAR searches

Imprinting theory suggests that prior experience in the S&L crisis makes local depositors more attentive to increases in bank insolvency risk, and thus, they react to subsequent adverse bank events. In this section, we provide direct evidence of the existence of the S&L crisis imprint. In particular, we examine whether there is heightened attention and information acquisition for bankrupt clients and related banks from areas exposed to the S&L crisis in the aftermath of bank client defaults.

We utilize the granular data about EDGAR filings searches to measure local depositors' attention and information acquisition. A notable feature of the EDGAR filings search data is the geographic variation in the number of searches for EDGAR filings of a firm at a point in time. Thus, we can establish the locations (postal code, county, and state) of EDGAR users, as well as their number of searches via the platform. This feature enables us to explore the geographic dispersion of searches for bankrupt clients and their banks as measures of local depositors' attention and information acquisition. We expect a higher search frequency for bankrupt clients and related banks from areas with the S&L crisis imprint in the aftermath of bank client defaults.

Panel B of Table 5 presents the results of estimating the likelihood and intensity of EDGAR searches for bankrupt borrowing firms after their default from depositors imprinted by the S&L crisis. We focus on a short eight-week [-4 weeks, +4 weeks] window surrounding the bankruptcy events to remain consistent with our main regression in Equation (1).[10] *Search_Client* is the number of EDGAR searches for the bankrupt borrowing firm from local depositors in a county in a week. *Search_Client_Dummy* is a dummy variable indicating at least

[10] Note that instead of looking at EDGAR searches for the universe of firms, we restrict the sample of firms to the borrowing firms in our baseline analysis in Table 2.

one search for the bankrupt firm from local depositors. For counties without any relevant searches in the event window, *Search_Client* and *Search_Client_Dummy* are coded as zero. We control for borrowing firm fixed effects and county-week fixed effects to account for time-invariant factors of firms and time-varying (and time-invariant) characteristics of counties.

In Column (1), the coefficient on *S&LCounty×Post* is 2.053 and significant, translating into a nearly 56% increase from the sample average of EDGAR searches for bankrupt firms. Column (2) also reports a positive coefficient on the interaction term when the dependent variable is *Search_Client_Dummy*. Next, we study whether deposits' information acquisition varies with the intensity of the imprint. We take advantage of the heterogeneity in the counties' exposure to the S&L crisis because of the varying number of bank failures within counties (see Figure 1), which indicates cross-sectional variation across counties in the intensity of the S&L crisis imprint. We replace *S&LCounty* in columns (1) and (2) with a continuous variable to capture the intensity of imprinting, *S&LIntensity*, in columns (3) and (4). Results in Column (3) and (4) of Panel A, Table 5, show that depositors are more attentive to bank client bankruptcies when they are more heavily imprinted by prior banking crisis experiences.

Next, we examine EDGAR searches by depositors for the focal banks following client defaults. Panel C of Table 5 presents the results, in which we repeat the baseline Triple-Differences analysis in Equation (1) by replacing the dependent variable with *Search_Bank* or *Search_Bank_Dummy*. *Search_Bank* and *Search_Bank_Dummy* are defined similarly as *Search_Client* or *Search_Client_Dummy*, respectively, except that the search targets are the focal banks, i.e., banks with at least one of their clients defaulting.[11] In all columns of Panel B, the coefficients on *S&LCounty×TreatedBank×Post* are significantly positive, indicating that local depositors become more attentive to and thus acquire more information about the related bank when one of its clients defaults. Regarding economic magnitude, there is a 47% increase

[11] These analyses are restricted to banks registered with the SEC because filings for other banks are not available on EDGAR.

from the sample average of EDGAR searches for the affected banks (Column (1)). The heightened depositors' attention and information acquisition for banks that experience borrower default supports the transmission of an increase in bank asset-side risk to liability-side deposit response.

Overall, the evidence in Table 5 suggests that the differential response of depositors in counties exposed to the S&L crisis to bank client defaults can be attributed to the imprinting of their bank crisis experience.

5. Cross-Sectional Analyses

Our Triple-Differences research design enables us to compare (1) within a treated bank, the difference in deposit rates between branches located in counties with or without prior exposure to the S&L crisis so that we can attribute the depositors' response to the imprint of the S&L crisis experience, and (2) within a county, the deposit rate gaps between treated and control banks before and after the client defaults of treated banks. In this section, to further strengthen the inference that prior adverse bank crisis experience has a long-term effect on the local deposit market, we identify circumstances under which the documented effect is magnified or attenuated. In particular, we conduct several tests conditional on the salience of default events, the existence and strength of banking relationships, bank solvency risk, local depositors' ability to understand default events, and their willingness to take any action.

5.1 Salience of Default Events

The degree to which depositors are aware and thus act on the default of bank clients hinges on the premise that those events are salient and catch the depositors' attention. Thus, we expect the impact of the S&L crisis imprinting on deposit rate responses to bank client defaults to be more pronounced when the default event is more salient to depositors.

To test this conjecture, we partition the sample into terciles based on two proxies for the salience of bank client defaults and re-estimate Equation (1). The first proxy is the geographic distance between a bank branch and the headquarters of the bankrupt firm. Presumably, the news of the bankruptcy of firms located nearby, relative to more distant areas, is more likely to attract the attention of depositors imprinted by prior banking crises and induce deposit withdrawals. Panel A of Table 6 reports the subsample analysis, corresponding to the bank branch-bankrupt client distance being short (Column (1)), medium (Column (2)), or long (Column (3)). The coefficient on *S&LCounty*×*TreatedBank*×*Post* is significantly positive in the subsample where the distance between a bank branch and a bankrupt client is relatively short. In contrast, the coefficients are statistically insignificant for the other two subsamples.

Our second proxy for the salience of client defaults is the stock market reaction of a treated bank to the default announcement of the bank's client filing for Chapter 11 bankruptcy. Prior studies document a transmission effect through the bank-borrower lending relationship: a borrower's financial distress negatively affects the lender bank's stock market valuation (Dahiya, Saunders, and Srinivasan 2003; Jorion and Zhang 2009). Thus, we use a bank's stock market reaction to capture the degree of public awareness of the bank's borrower default, defined as the five-day cumulative standardized abnormal returns (SCAR) following Campbell, Lo, and MacKinlay (1997). We report the descriptive statistics of SCAR in the lower panel of Panel B, Table 6, and the subsample results conditional on the upper, medium, or bottom tercile of SCAR in the upper panel of Panel B, Table 6. The significant positive coefficient on *S&LCounty*×*TreatedBank*×*Post* in Column (1) of Panel B, coupled with insignificant coefficients in Column (2) and (3), suggests that the S&L crisis imprint on the local depositor reactions to bank client default is mainly concentrated around events that trigger more adverse equity market reactions.

5.2 Strength of the Relationship with the Defaulting Client

Relationship banking involves collecting private information from borrowers and is considered a credible commitment to monitor borrower behavior (Bharath, Dahiya, Saunders, and Srinivasan 2011; Boot and Ratnovski 2016). A relationship borrower default may be considered a monitoring failure and cause a more significant reputation loss for the focal bank than the default by a non-relationship borrower. Therefore, we expect the depositor response in S&L crisis imprinted counties to bank client default to be greater when the bankrupt client was a relationship borrower.

We follow Bharath, Dahiya, Saunders, and Srinivasan (2011) to classify a loan as a relationship loan (i.e., whether a relationship bank extends the loan). We first identify the lead lender for each loan facility based on three criteria: whether the lead arranger credit is marked as "Yes"; whether the lender role is explicitly described as one of the following: "Mandated Lead arranger," "Lead bank," "Arranger," "Admin agent," "Lead arranger," and "Mandated arranger"; whether the lender has the largest share in a loan facility for loans with available lender allocation amount information. Then, we identify whether the lead lender is a relationship lender for each given loan facility. We look back at the prior five-year borrowing history of the firm and identify all the lead lenders in each one of its loans. We consider the lead lender extending the most loans to the borrower over the prior five years as the relationship lender/bank. Finally, a loan extended by a relationship lender is classified as a relationship loan.

In Panel A of Table 7, we partition the sample based on whether the lender to a bankrupt borrower is a relationship bank. The results show that depositors imprinted by the S&L crisis are more responsive to a borrower default when the focal bank is a relationship lender, evidenced by the positive and significant coefficient on *S&LCounty*×*TreatedBank*×*Post* in Column (1) of Panel A. In Column (2), the coefficient on *S&LCounty*×*TreatedBank*×*Post* is also positive and significant, but its magnitude (and statistical significance) is smaller (lower) compared to that of the coefficient in Column (1).

In addition to the existence of relationship banking, we also consider the strength of the relationship by exploiting the number and amount of prior loans extended by a relationship bank. In particular, we sort the sample into terciles based on whether the number (amount) of relationship loans as a proportion of a borrower's total number (amount) of loans is in the top, middle, or bottom terciles. We report the results of these analyses in panels B and C of Table 7. Corroborating the finding in Panel A, the increase in deposit rates for branches located in exposed counties following borrower defaults is more pronounced in subsamples with the strongest relationship lending ties, as represented by the number and amount of loans from a relationship bank.

5.3 The Effect of Bank Solvency Risk

Consistent with imprinting theory, the finding of deposit outflow and subsequent deposit rate increase in response to borrower defaults for bank branches exposed to the S&L crisis, as opposed to unexposed branches, indicates that depositors with adverse bank crises experience are more sensitive to subsequent bankruptcies of borrowers, and are more likely to relate bank client defaults to increases in bank insolvency risk. This suggests that the sensitivity of deposit rates to bank client defaults for depositors imprinted by the S&L crisis depends on the focal bank's ex ante financial soundness.

We measure bank solvency using two proxies:(1) Tier one capital (*Tier1Cap*), and (2) bank Z-score (*Z-score*). *Tier1Cap* is defined as banks' Tier 1 capital divided by risk-weighted assets. *Bank Z-score* is the log of the return on assets plus capital-to-asset ratio divided by the standard deviation of asset returns over the past twelve quarters (Laeven and Levine 2009). Bank Z-score is inversely related to the probability of bank default (Roy 1952).

We divide our sample into terciles based on proxies of bank solvency and re-estimate Equation (1). Table 8 reports the results of these analyses. We find that the effect of the S&L crisis imprint on depositors' response to banks' client defaults is concentrated in the subsample of banks that are the riskiest. That is, the coefficient on *S&LCounty*×*TreatedBank*×*Post* is positive and significant only in the subsample of banks belonging to the lowest tercile of the tier 1 ratio and Z-score.

5.4 Effect of Depositor's Financial Sophistication and the Local Safety Net

The extent to which depositors imprinted by prior banking crises play a disciplinary role after a similar bankruptcy event occurring to a bank's client depends on the local depositors' overall ability (i.e., financial sophistication) and willingness (i.e., safety net) to take action. This implies that exposed counties with more financially sophisticated depositors are hypothetically more sensitive to bank client defaults (Drechsler, Savov, and Schnabl 2017). Those depositors are more likely to withdraw their funds from banks with borrower defaults.

To test this conjecture, we first exploit the geographic variation in demographic characteristics related to local depositors' financial sophistication, including state-level financial literacy index, county-level personal income, and education. An individual is considered to be financially literate if she is more financially adept in understanding bank financial information, earns a higher level of income, or is better educated (Cole, Paulson, and Shastry 2014; Drechsler, Savov, and Schnabl 2017; Noh, So, and Zhu 2022). Our proxies for depositors' financial sophistication include the financial literacy index, personal income (natural log of personal income in a county), and education (proportion of county population aged 25 years and above with a college degree or higher in the county). The financial literacy index is calculated as the proportion of accurate answers to five basic questions related to compound interest, inflation rate, interest rate, bond price, mortgage, and investment diversification in different states (Lusardi and Mitchell 2014; Cheng, Severino, and Townsend 2021; Hayes, Jiang, and Pan 2021).[12]

We partition our sample into terciles based on these three different proxies for financial sophistication and re-estimate Equation (1). The results of these analyses are reported in Table

[12] These five representative questions are included in the National Financial Capability Study (see https://finrafoundation.org/knowledge-we-gain-share/nfcs).

9. In Panel A (Panel B) [Panel C], we measure depositors' financial sophistication using the financial literacy index (personal income) [education]. We find that our main effect is mainly concentrated among depositors that are highly financially literate, wealthier, and better educated, as evidenced by the significant positive coefficients on *S&LCounty×TreatedBank×Post* in the high-financial-sophistication group (Column (3) of all three panels).

Next, we leverage the geographic variation in local depositors' social safety net and study whether the impact of the S&L crisis imprint on depositors' response to the bankruptcy of borrowing firms is more pronounced when their deposits are less likely to be protected by a social safety net. We capture the extent of the safety net arising from state-level unemployment insurance as well as the bank-level proportion of uninsured/insured deposits, the idea being that depositors are relatively less willing to monitor and discipline banks for their client defaults when they have an implicit government or social guarantee, or when their loss on deposits are more likely to be recovered in the extreme case of bank defaults. Thus, exposed counties with a lower (higher) level of state unemployment insurance are considered to have a lower (higher) government implicit guarantee, rendering depositors more (less) vulnerable to adverse informational events related to the focal banks. We find evidence consistent with this conjecture in Panel A of Table 10, which shows that our main finding is concentrated among states with a low level of unemployment insurance.

Next, we exploit the variation in the proportion of uninsured deposits among banks to test whether local depositors imprinted by prior banking crises react more intensively when the affected bank has a higher proportion of uninsured deposits. The intuition is that depositors have incentives to withdraw their funds in reaction to a public signal of weakening of bank fundamentals since they expect other depositors will do so, referred to as within-bank strategic complementarity by Goldstein, Kopytov, Shen, and Xiang (2020). Panel B of Table 10 reports the subsample analysis conditional on banks' ex ante percentage of uninsured deposits to total deposits. Consistent with our prediction, the deposit response in counties exposed to the S&L crisis is more pronounced for the subsample of banks with a higher proportion of uninsured deposits.

6. Conclusion

By providing 75% of bank funding, depositors play an indispensable role in the banking sector's stability. While the role of depositors amid a banking crisis is well established, we know much less about whether a banking crisis has any long-run effect on depositors in their subsequent decision making. Our study sheds light on this question by examining the extent to which a prior experience of banking crises induces heterogeneous responses among local depositors to an increase in bank insolvency risk.

For identification, we exploit the S&L crisis and within-bank and cross-region variation in deposit rates. In this way, we can attribute deposit rate differences to the S&L crisis experience by comparing two branches of the same bank, one in a crisis-imprinted county and the other in an unexposed county. In addition, we can account for any socioeconomic confounding at the county level by including county-time fixed effects and comparing banks with client defaults to those without client defaults within the same county. The deposit rate data at a weekly frequency also enables us to capture immediate deposit responses surrounding bankruptcy announcements.

Using a stacked Triple-Differences approach with high-dimensional fixed effects, we find that depositors in counties with prior experience in the S&L crisis are more likely to withdraw likely uninsured deposits in response to bank clients' bankruptcies from the affected bank branches, leading to an increase in deposit rates. Such an effect is larger when the intensity of the exposure to the S&L crisis is greater. This finding is consistent with the imprinting theory, which implies that a prior experience in a banking crisis can shape depositors' risk perception of borrower bankruptcy incidences and make depositors more attentive to subsequent events that increase bank insolvency risk. Relying on the within-client, within-bank, and across-region variation in EDGAR filings searches, we find that depositors imprinted by the S&L crisis are more likely to request and search for information about the bankrupt borrowing firms and the related banks after borrowers' bankruptcy announcements.

Furthermore, we document a stronger sensitivity of depositor responses to bank client defaults among the S&L crisis-imprinted depositors when the default events are more salient, when the defaulting borrower is a relationship banking client, when the focal bank is less solvent, and when local depositors are more financially sophisticated or highly motivated.

Our findings that heterogeneity in depositor responses to changes in banks' insolvency risk arises from prior experiences of banking crises should interest regulators, policymakers, and banking professionals. An implication of our evidence is that banks need to be extra attentive to depositors with prior experience of banking crises to limit deposit withdrawals in response to increases in bank risk.

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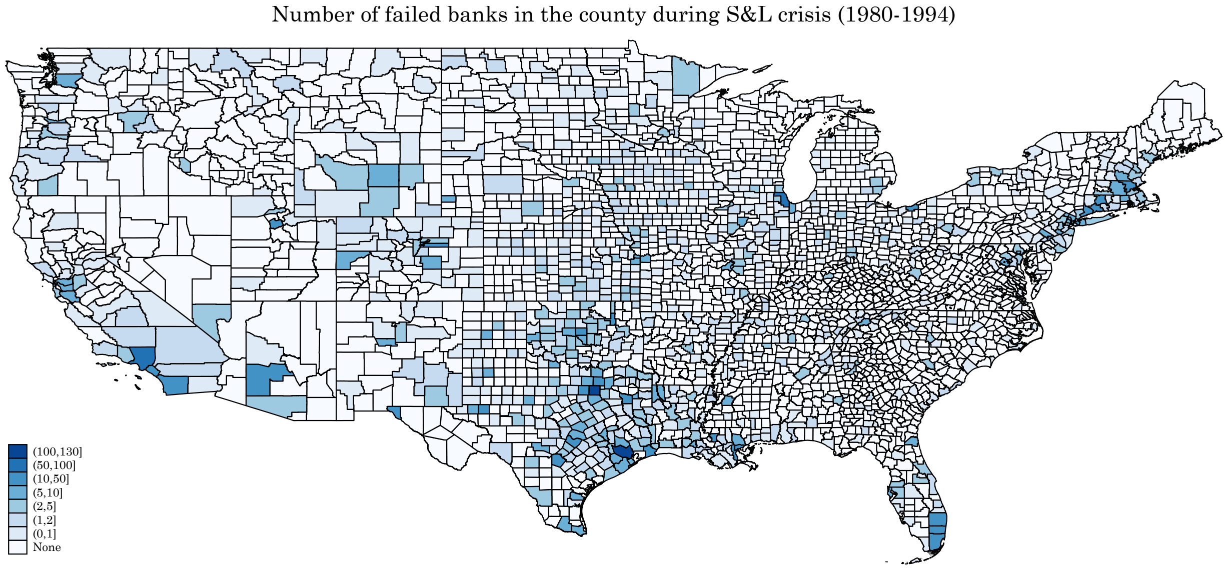
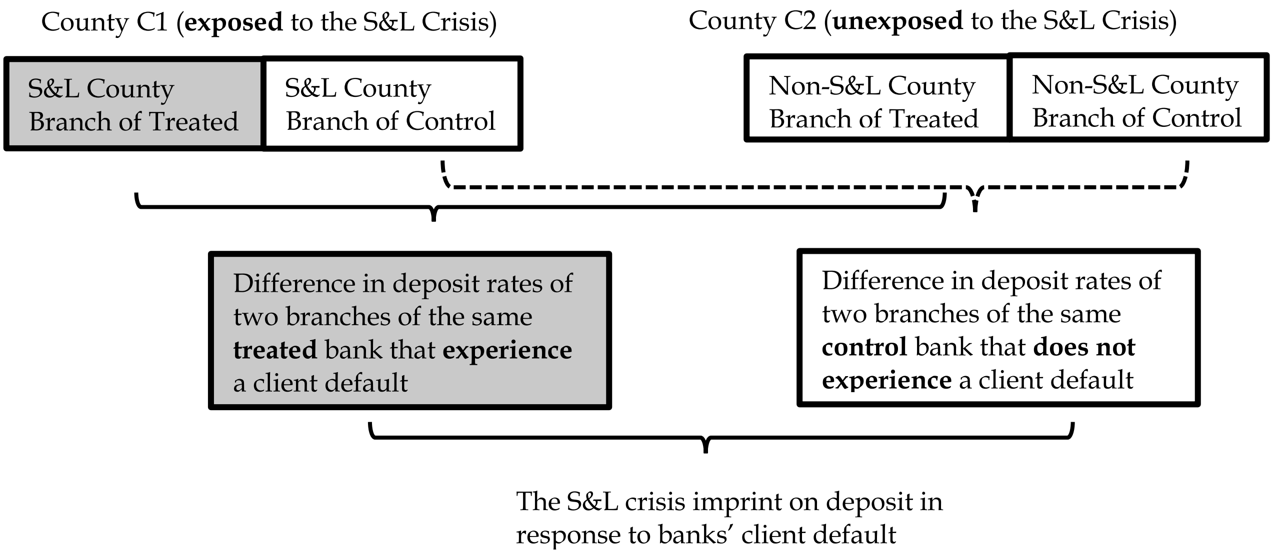


Figure 1. Heatmap of Bank Failures during the S&L Crisis

This figure displays the heatmap of bank failures during the S&L Crisis across U.S. counties. The color scale on the bottom left refers to the number of bankrupt banks during the crisis.



$$Deposit\ Rate_{br,c,t} = \beta\ S\&LCounty_c \times TreatedBank_b \times Post_{b,t} + d_{br} + l_{b,t} + \varphi_{c,t} + \varepsilon_{br,c,t}, \qquad \text{(Eq. (1))}$$

Figure 2. Identification Strategy

This figure illustrates our identification strategy. Suppose Bank A (treated bank) experienced a borrower default at time *t*. Bank B (control bank) has not experienced any client default. County *C1* (exposed county) has bank branches of Bank A (S&L County Branch) and Bank B (S&L county Branch), while County *C2* (unexposed county) also has bank branches of Bank A (Non-S&L County Branch) and Bank B (Non-S&L County Branch). We predict that depositors of banks that experience borrower defaults (treated banks) located in counties with higher exposure to the S&L crisis (exposed counties) are more responsive to the default incidences compared with borrowers located in unexposed counties, controlling for the actions of depositors of banks that do not experience client defaults (control bank).

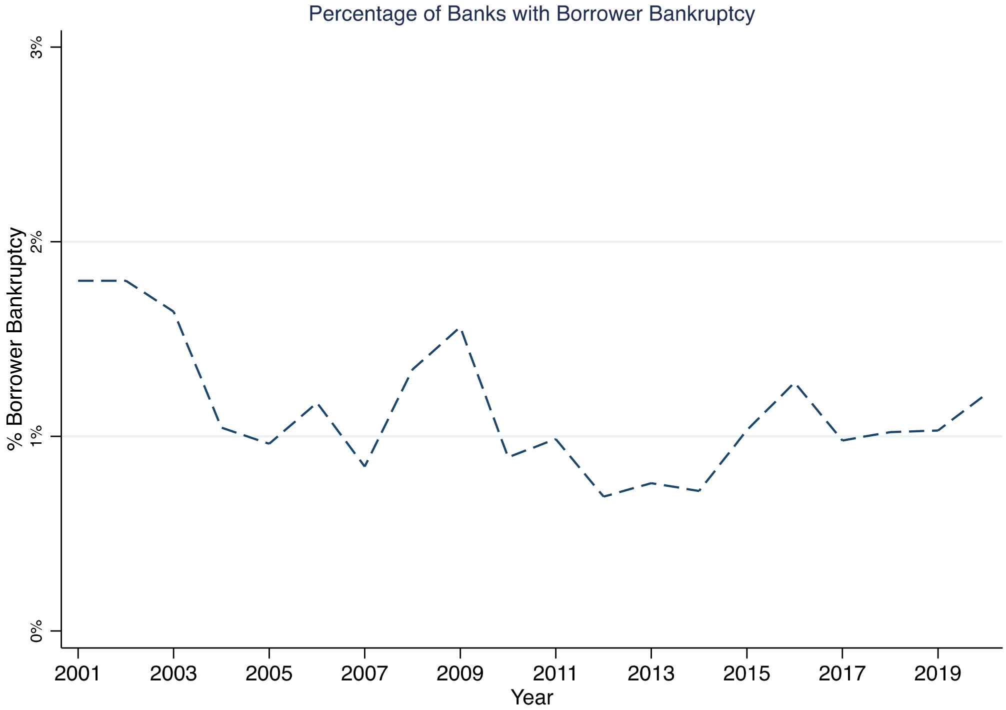


Figure 3. Proportion of Banks Exposed to Client Defaults

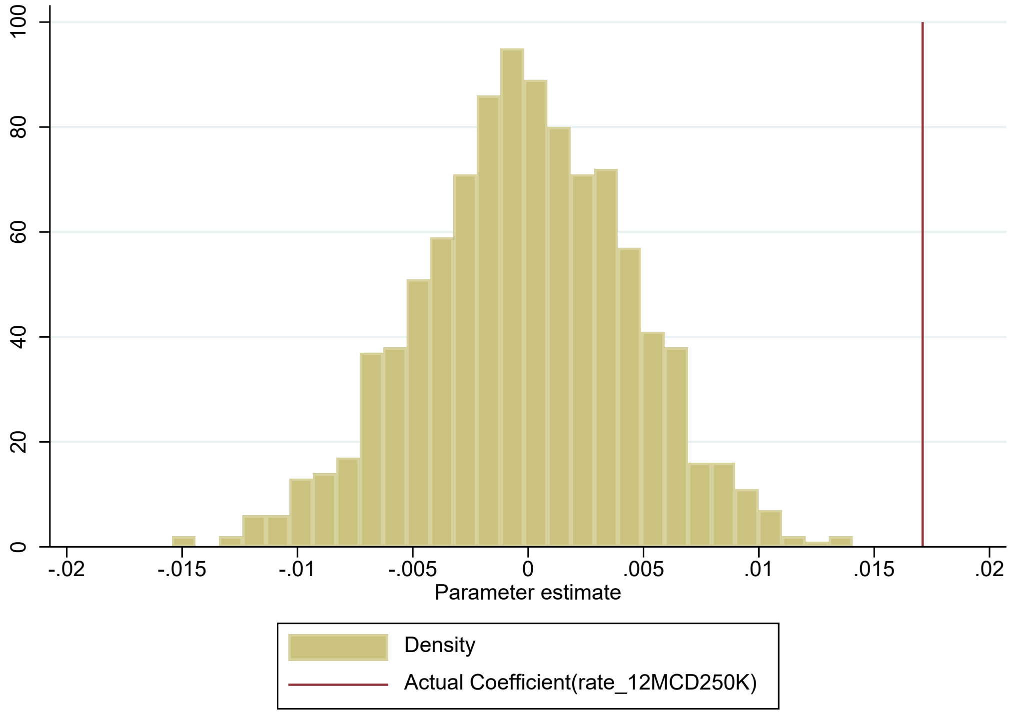


Figure 4: Distribution of the Results Estimated from Placebo Tests

The figure above compares the actual treatment effect with placebo effects. We keep the treatment period unchanged and randomly assign "placebo treatments" to our sample banks. Based on this pseudo-treatment-control sample, we estimate the coefficient on *S&LCounty*×*TreatedBank*×*Post*. We repeat this practice 1000 times and plot the distribution of these coefficients. The red line represents the actual coefficient on *S&LCounty*×*TreatedBank*×*Post* estimated from Equation (1).

Table 1. Descriptive Statistics

This table presents descriptive statistics for variables for weekly branch deposit rates (Panel A), annual branch deposit flows (Panel B), bank quarterly financial characteristics (Panel C), county characteristics (Panel D), state characteristics (Panel E), and other variable characteristics (Panel F). Appendix Table A1 presents variable definitions.

	N	Mean	SD	P25	Median	P75
Panel A. Weekly branch deposit rates						
Deposit Rate	126360	0.312	0.414	0.100	0.200	0.350
Panel B. Annual branch deposit flow						
Deposit Flow	251262	0.066	0.338	-0.039	0.033	0.126
Panel C. Bank quarterly financial characteristics						
Customer Bankruptcy	557663	0.006	0.074	0.000	0.000	0.000
Size	557663	12.030	1.354	11.127	11.879	12.736
Total_Asset ('000)	557663	705265	2879428	67963	144150	339642
Equity_Ratio	557663	0.113	0.051	0.088	0.102	0.124
ROA	557663	0.005	0.007	0.002	0.005	0.009
NPL	557663	0.013	0.019	0.002	0.007	0.017
Z-score	557663	3.029	0.320	2.843	3.000	3.183
Uninsured deposit%	557663	0.325	0.207	0.215	0.303	0.413
Tier1Cap	543944	0.171	0.111	0.116	0.142	0.187
Panel D. County characteristics						
Personal Income	3139	25120	6235	21255	24119	27359
Education	3136	0.165	0.078	0.113	0.145	0.193
Panel E. State characteristics						
Financial Literacy	51	0.744	0.028	0.723	0.743	0.767
Unemployment Insurance	51	232.228	39.334	202.662	227.253	257.578
Panel F. Other variable characteristics						
Search_Bank	153748	6.953	141.481	0.000	0.000	0.000
Search_Client	11145078	0.268	23.334	0.000	0.000	0.000
Number of Relationship Loans	4507	0.046	0.092	0.000	0.000	0.061
Relationship Loan Amount	4507	0.047	0.095	0.000	0.000	0.061
Relationship Bank	4507	0.490	0.500	0.000	0.000	1.000
Num_FailedBank	974	2.992	7.281	1.000	1.000	2.000

Table 2. Main Results of S&L Crisis Imprinting on Deposits: A Triple-Differences Analysis

This table presents our main results of the S&L crisis imprint on *Deposit Rate* (Panel A) and *Deposit Flow* (Panel B) in response to banks' client defaults. Branch deposit rate (flow) data are available at weekly (annual) frequency. Panel A (Panel B) reports estimates from the following stacked Triple-Differences regression at bank branch-county-week (bank branch-county-year) level: $Deposit\ Rate_{br,c,t}$ ($Deposit\ Flow_{br,c,t}$)= $\beta\ SL_c \times TB_b \times P_{b,t} + d_{br} + l_{b,t} + \varphi_{c,t} + \varepsilon_{br,c,t}$. The key independent variable is the triple term *SL×TB×P*. *SL* is an indicator variable equal to one for exposed counties with at least one bank failure during the S&L crisis between 1980 and 1994 and zero otherwise. *TB* is an indicator variable equal to one for banks with more than one borrower default incidence and zero otherwise. *P* is an indicator equal to one for the week of a borrower default and all subsequent weeks in the event window and zero otherwise. Appendix Table A1 presents variable definitions. Standard errors are clustered by county and week in Panel A (year in Panel B). ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Panel A: Deposit rate

VARIABLES	(1) *Deposit Rate*	(2) *Deposit Rate*	(3) *Deposit Rate*
TreatedBank×Post	-0.0097		
	(0.007)		
S&LCounty×TreatedBank		0.0020	
		(0.031)	
S&LCounty×TreatedBank×Post	0.0249***	0.0310***	0.0171**
	(0.009)	(0.011)	(0.007)
	-0.0478		
Size	(0.058)		
	-1.1706*		
ROA	(0.677)		
	-0.8709*		
Equity_ratio	(0.455)		
	0.6469		
NPL_ratio	(1.008)		
Observations	126,360	126,360	126,360
Adjusted R-squared	0.986	0.976	0.996
Branch FE	Yes	No	Yes
Bank FE	Yes	No	No
Bank-week FE	No	Yes	Yes
County-week FE	Yes	Yes	Yes

Panel B: Deposit flow

VARIABLES	(1) *Deposit Flow*	(2) *Deposit Flow*	(3) *Deposit Flow*
TreatedBank×Post	-0.0272		
	(0.018)		
S&LCounty×TreatedBank		-0.0509	
		(0.028)	
S&LCounty×TreatedBank×Post	-0.1098***	-0.0641*	-0.0660**
	(0.022)	(0.035)	(0.027)
Size	-0.1458		
	(0.090)		
ROA	-2.4217*		
	(1.265)		
Equity_ratio	0.8313**		
	(0.394)		
NPL_ratio	-1.9230		
	(1.285)		
Observations	251,262	251,262	251,262
Adjusted R-squared	0.487	0.442	0.523
Branch FE	Yes	No	Yes
Bank FE	Yes	No	No
Bank-year FE	No	Yes	Yes
County-year FE	Yes	Yes	Yes

Table 3. Dynamic Effects of S&L Crisis Imprinting on Deposit

This table presents the dynamic effects of the S&L crisis imprint on *Deposit Rate* in response to banks' client defaults by estimating the following specification: $Deposit\ Rate_{br,c,t} = \Sigma\ \beta_{(\tau)}\ S\&LCounty \times TreatedBank \times Post(\tau)_{c,t} + d_c + l_{b,t} + \varphi_{s,t} + \varepsilon_{br,c,t}$. Appendix Table A1 presents variable definitions. ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) *Deposit Rate*
S&LCounty×*TreatedBank*×*Post (-4)*	-0.0123
	(0.011)
S&LCounty×*TreatedBank*×*Post (-3)*	-0.0092
	(0.009)
S&LCounty×*TreatedBank*×*Post (-2)*	-0.0007
	(0.005)
S&LCounty×*TreatedBank*×*Post (0)*	0.0080*
	(0.004)
S&LCounty×*TreatedBank*×*Post (1)*	0.0083*
	(0.005)
S&LCounty×*TreatedBank*×*Post (2)*	0.0132**
	(0.007)
S&LCounty×*TreatedBank*×*Post (3)*	0.0160**
	(0.008)
S&LCounty×*TreatedBank*×*Post (4)*	0.0124*
	(0.007)
Observations	126,360
Adjusted R-squared	0.996
Branch FE	Yes
Bank-week FE	Yes
County-week FE	Yes

Table 4. Robustness Tests

This table reports the results of a series of robustness tests on the effect of the S&L crisis imprint on depositors' response to banks' client defaults using different samples (Panel A), implementing an alternative research design (Panel B), and partitioning the sample based on counties' population stability (Panel C). Appendix Table A1 presents variable definitions. Standard errors are clustered by county and week. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Panel A: Excluding the COVID-19 period

	(1) **Exclude COVID-19** *Deposit Rate*
S&LCounty×TreatedBank×Post	0.0144*
	(0.008)
Observations	117,263
Adjusted R-squared	0.996
Branch FE	Yes
Bank-week FE	Yes
County-week FE	Yes

Panel B: Alternative specification

VARIABLES	(1) *Deposit Rate*	(2) *Deposit Rate*	(3) *Deposit Flow*	(4) *Deposit Flow*
S&LCounty×Post	0.0011*	0.0019***	-0.0102**	-0.0083*
	(0.001)	(0.000)	(0.005)	(0.004)
Size		0.0383		0.2273***
		(0.082)		(0.077)
ROA		10.5787		1.2630
		(7.166)		(2.156)
Equity_ratio		2.3871**		-0.4227
		(1.056)		(0.380)
NPL_ratio		6.8851***		-1.0245
		(1.984)		(1.070)
Observations	84,711	84,711	212,012	212,012
Adjusted R-squared	0.971	0.901	0.290	0.239
Branch FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
Bank-week/Bank-year FE	Yes	No	Yes	No
County-week/County-year FE	Yes	Yes	Yes	Yes

Panel C: Population stability

	Deposit Rate		
	Small (1)	Medium (2)	Large (3)
S&LCounty×TreatedBank×Post	-0.0015	0.0098*	0.0453**
	(0.001)	(0.005)	(0.018)
Observations	42,107	42,132	42,121
Adjusted R-squared	0.998	0.996	0.997
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Table 5. Evidence on the S&L Crisis Imprint

This table presents evidence of the existence of the S&L crisis imprint. In Panel A, we replace *S&LCounty* with a continuous variable, *S&LIntensity*, defined as the log of one plus the number of failed banks in a county during the S&L crisis period. We examine the EDGAR search frequency in response to the bankruptcy events of the focal borrowers (Panel B) and the related banks (Panel C). We aggregate EDGAR searches on a weekly frequency. In Panel B, *Search_Client* is the number of EDGAR searches from depositors in a county in a week for the bankrupt borrowing firms. *Search_Client_Dummy* is an indicator variable equal to one if there is at least one search for the bankrupt borrowing firms that comes from local depositors in a county in a week. In Panel C, *Search_Bank* is the number of EDGAR searches from depositors in a county in a week for the banks whose borrowers defaulted. *Search_Bank_Dummy* is a dummy variable, indicating that at least one depositor in a county searched during the week for a bank whose borrowers defaulted. Appendix Table A1 presents variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Panel A: Intensity of the S&L crisis imprint

	Deposit Rate
S&LIntensity ×TreatedBank×Post	0.0089**
	(0.004)
Observations	126,360
Adjusted R-squared	0.996
Branch FE	Yes
Bank-week FE	Yes
County-week FE	Yes

Panel B: EDGAR search for bankruptcy borrowers

	(1) *Search_Client*	(2) *Search_Client_ Dummy*	(3) *Search_Client*	(4) *Search_Client_ Dummy*
S&LCounty×Post	2.0527***	0.0124***		
	(0.665)	(0.002)		
S&LIntensity×Post			0.9043**	0.0071***
			(0.449)	(0.001)
Observations	930,762	930,762	930,762	930,762
R-squared	0.515	0.697	0.515	0.697
Firm-week FE	Yes	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes	Yes

Panel C: EDGAR search for related banks

	(1) *Search_Bank*	(2) *Search_Bank_ Dummy*	(3) *Search_Bank*	(4) *Search_Bank_ Dummy*
S&LCounty×TreatedBank×Post	17.7313*	0.0357**		
	(10.720)	(0.018)		
S&LIntensity×TreatedBank×Post			11.7515*	0.0278**
			(6.067)	(0.013)
Observations	74,697	74,697	74,697	74,697
Adjusted R-squared	0.846	0.881	0.846	0.881
Branch FE	Yes	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes	Yes

Table 6. Effect of the Salience of Default Events

This table reports the subsample analyses for the effect of the S&L crisis imprint on depositors' response to banks' client defaults, conditional on the salience of client default events. We partition the sample into terciles based on measures of the salience of client defaults. Default event salience is measured by the distance between a bank branch and a bankrupt borrower's headquarters (Panel A) and the five-day standardized cumulative abnormal return (SCAR) of banks, which is the cumulative abnormal returns divided by the standard deviation of returns, in a [-5 days, +5 days] window around a borrower's default (Panel B). Appendix Table A1 presents variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	Deposit Rate		
	Small	Medium	Large
	(1)	(2)	(3)
Panel A: Subsample by distance between bank branches and bankrupt borrower headquarters			
S&LCounty×TreatedBank×Post	0.0105***	0.0041	-0.0017
	(0.004)	(0.004)	(0.010)
Observations	30,540	30,540	30,540
Adjusted R-squared	0.995	0.997	0.999
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel B: Subsample by bank SCAR			
S&LCounty×TreatedBank×Post	0.0036***	-0.0000	-0.0116
	(0.001)	(0.000)	(0.007)
Observations	24,132	24,132	24,131
Adjusted R-squared	0.998	0.987	0.994
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Terciles of SCAR	N	Mean	SD
Small	24131	-1.174	0.706
Median	24132	0.0279	0.240
Large	24132	1.164	0.593
Total	72395	0.006	1.102

Table 7. Strength of the Banking Relationship with the Defaulting Client

This table reports the analyses for the effect of the S&L crisis imprint on depositors' response to banks' client defaults, conditional on the defaulting client's relationship with their bank. In Panel A, we partition the sample based on whether the loan to the defaulting borrower was a relationship loan. Following Bharath, Dahiya, Saunders, and Srinivasan (2011), we first identify the lead lender for each loan facility based on three criteria: whether the lead arranger credit is marked as "Yes"; whether the lender role is explicitly described as one of the following: "Mandated Lead arranger," "Lead bank," "Arranger," "Admin agent," "Lead arranger," and "Mandated arranger"; whether the lender has the largest share in a loan facility for loans with available lender allocation amount information. Then, we identify whether the lead lender is a relationship lender for each given loan facility. We look back at the prior 5-year borrowing history of the firm and identify all the lead lenders in each of its loans. We define the lead lender extending the largest number of loans to the borrower as the relationship lender/bank. In Panel B and Panel C, we partition the sample into terciles based on the strength of the lending relationship. The strength of the lending relationship in Panel B (Panel C) is measured by the number (amount) of relationship loans extended by a relationship bank divided by the total number (amount) of loans obtained by the borrower in the past five years. Appendix Table A1 presents variable definitions. ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10%, respectively.

	Deposit Rate	
	Dummy=1	Dummy=0
	(1)	(2)
Panel A: Subsample by relationship bank		
S&LCounty×TreatedBank×Post	0.0180***	0.0090*
	(0.007)	(0.005)
Observations	66,670	42,424
Adjusted R-squared	0.994	0.999
Branch FE	Yes	Yes
Bank-week FE	Yes	Yes
State-week FE	Yes	Yes

	Deposit Rate		
	Small	Medium	Large
	(1)	(2)	(3)
Panel B: Subsample by number of relationship loans			
S&LCounty×TreatedBank×Post	-0.0020	0.0108	0.0118**
	(0.007)	(0.007)	(0.006)
Observations	35,894	36,917	36,283
Adjusted R-squared	0.976	0.996	0.995
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel C: Subsample by relationship loan amount			
S&LCounty×TreatedBank×Post	0.0017	0.0042	0.0101**
	(0.005)	(0.007)	(0.005)
Observations	36,575	36,154	36,365
Adjusted R-squared	0.999	0.977	0.999
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Table 8. Effect of Bank Solvency

This table shows the results of analyses examining the effect of the S&L crisis imprint on depositors' response to banks' client defaults, conditional on bank solvency. We partition the sample terciles based on two measures of bank solvency. First, bank solvency is measured by *Tier1Cap*, which is banks' Tier 1 capital divided by risk-weighted assets (Panel A). Second, we measure bank solvency using the *bank Z-score*, which captures the banks' distance to default and is estimated as the log of the return on assets plus capital-to-asset ratio divided by the standard deviation of asset returns over the past 12 quarters (Panel B). Appendix Table A1 presents variable definitions. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10%, respectively.

	Deposit Rate		
	Small	Medium	Large
	(1)	(2)	(3)
Panel A: Subsample by Tier1Cap			
S&LCounty×TreatedBank×Post	0.0219***	0.0092	-0.0000
	(0.006)	(0.008)	(0.000)
Observations	34,268	34,268	34,268
Adjusted R-squared	0.989	0.998	0.997
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel B: Subsample by bank Z-score			
S&LCounty×TreatedBank×Post	0.0195**	0.0093	-0.0046
	(0.009)	(0.011)	(0.003)
Observations	41,946	42,010	41,980
Adjusted R-squared	0.999	0.999	0.996
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Table 9. Effect of Depositor Financial Sophistication

This table reports the results of analyses examining the effect of the S&L crisis imprint on depositors' response to banks' client defaults, conditional on depositor financial sophistication. We partition the sample into terciles based on depositors' financial sophistication. We measure depositor financial sophistication using three proxies: (1) *financial literacy,* which is a state-level financial literacy index developed by NFCS (Panel A); (2) *personal income*, which is the natural log of county-level personal income (Panel B); and (3) *education*, which is the proportion of county population aged 25 years old and above with a bachelor's degree or higher (Panel C). Appendix Table A1 presents variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	Deposit Rate		
	Low	Medium	High
	(1)	(2)	(3)
Panel A: Subsample by financial literacy			
S&LCounty×TreatedBank×Post	0.0003	0.0142	0.0162***
	(0.003)	(0.011)	(0.005)
Observations	42,010	41,946	41,980
Adjusted R-squared	0.982	0.998	0.996
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel B: Subsample by personal income			
S&LCounty×TreatedBank×Post	0.0040	0.0049*	0.0409**
	(0.004)	(0.003)	(0.021)
Observations	41,978	41,979	41,979
Adjusted R-squared	0.981	0.999	0.982
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel C: Subsample by education			
S&LCounty×TreatedBank×Post	0.0030	0.0018	0.0714**
	(0.002)	(0.003)	(0.029)
Observations	41,966	41,990	41,980
Adjusted R-squared	0.990	0.999	0.989
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Table 10. Effect of the Social Safety Net

This table reports the results of analyses examining the effect of the S&L crisis imprint on depositors' response to banks' client defaults, conditional on depositors' social safety net. We partition the sample into terciles based on local social safety net measures. The local social safety net is measured by (1) *state unemployment insurance*, which is the amount of unemployment insurance payment scaled by population in a state (Panel A), and (2) *%uninsured deposit*, which is the percentage of uninsured deposits as a proportion of the total amount of deposits at bank level (Panel B). Appendix Table A1 presents variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	Deposit Rate		
	Low	Medium	High
	(1)	(2)	(3)
Panel A: Subsample by state unemployment insurance			
S&LCounty×TreatedBank×Post	0.0047**	0.0022	-0.0088
	(0.002)	(0.003)	(0.015)
Observations	41,975	41,979	41,982
Adjusted R-squared	0.999	0.988	0.998
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes
Panel B: Subsample by %uninsured deposits			
S&LCounty×TreatedBank×Post	0.0064	0.0216	0.0316**
	(0.017)	(0.015)	(0.015)
Observations	42,086	42,150	42,124
Adjusted R-squared	0.996	0.998	0.999
Branch FE	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes

Appendix Table A1. Variable Definition

Variable	Definition	Source
Deposit Rate	Weekly deposit rates (in %) at the branch level for 12-month certificate of deposits (CDs) with an account size of $250,000	RateWatch
Deposit Flow	The log change in annual deposits held at a branch	Summary of Deposits
S&LCounty×TreatedBank×Post	Interaction of *S&LCounty, TreatedBank* and *Post*	
S&LCounty	An indicator variable equal to one if the county has more than one failed bank during 1980-1994 S&L crisis	FDIC
S&LIntensity	The log of one plus the number of failed banks in a county during 1980-1994 S&L crisis (*Num_FailedBank*), which measure the intensity of the crisis	FDIC
TreatedBank	An indicator variable that equals one if the bank has ever had any customer bankruptcy	BankruptcyData.com and Call report
Post	An indicator of the [-4, +4] window before/after a customer bankruptcy for a bank	
Size	The natural logarithm of bank total assets (in thousands)	Call report
ROA	Net income divided by total bank assets	Call report
NPL	Nonperforming loans (loans past-due by over 90 days) divided by total loans	Call report
Equity_Ratio	Book value of total equity divided by book value of total assets	Call report
Z-score	The natural logarithm of return on assets plus the capital-asset ratio divided by the standard deviation of asset returns estimated over the past 12quarters	Call report
Tier1Cap	Tier 1 capital divided by risk-weighted assets	Call report
Uninsured deposit%	For each bank in a quarter, the amount of uninsured deposits as a proportion of the total amount of deposits	Call report
Personal Income	Natural log of personal income in a county	Bureau of Economic Analysis
Education	Proportion of county population aged 25 years old and above with a bachelor's degree or higher	Census survey
Financial Literacy	Financial literacy index developed by NFCS. The index reflects the accuracy rates of answers to five basic questions related to compound interest, inflation rate, interest rate, bond price, mortgage and investment diversification	National Financial Capability Study
Unemployment Insurance	Total amount of state unemployment insurance payment scaled by local population	US Department of Labor
Distance to Bankrupt Borrower's Headquarter	The distance between the branch and headquarter of the defaulted customer	
SCAR	5-day standardized cumulative abnormal returns surrounding events	Eventus
Search_Client	The number of EDGAR searches from depositors in a county in a week for the bankrupt borrowing firms	EDGAR

Search_Bank	The number of EDGAR searches from depositors a county in a week for the banks whose borrowers defaulted	EDGAR
Relationship Bank	An indicator variable equal to one if the bank is a relationship bank for the defaulted customer	Dealscan
Number of Relationship Loans	The relationship loan between the defaulted customer and its relationship bank	Dealscan
Relationship Loan Amount	The natural logarithm of loan amount between the bank and the defaulted customer	Dealscan

Appendix Table A2. A Horse Race

This table reports the analyses from a horse race for the effect of the S&L crisis imprint on depositors' response to banks' client defaults. In the horse race, we include the following demographic variables: *Financial Literacy, Social Connectedness Index, Education, State Fiscal Condition, and Age. Social Connected Index* captures the extent to which low-social-status individuals are friends to high-social-status individuals within a county (Chetty et al., 2022a; 2022b). Appendix Table A1 presents variable definitions. ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) *Deposit Rate*	(2) *Deposit Rate*	(3) *Deposit Rate*	(4) *Deposit Rate*
S&LCounty	0.0148**	0.0148**	0.0126**	0.0124**
×*TreatedBank*×*Post*	(0.006)	(0.007)	(0.006)	(0.005)
Financial Literacy	0.0294***	0.0244**	0.0308***	0.0301***
×*TreatedBank*×*Post*	(0.011)	(0.010)	(0.011)	(0.011)
Social Connected Index		-0.0164**	-0.0122	-0.0143*
×*TreatedBank*×*Post*		(0.008)	(0.008)	(0.008)
State_fiscal			-0.0246*	-0.0216**
×*TreatedBank*×*Post*			(0.014)	(0.011)
Age				0.0309*
×*TreatedBank*×*Post*				(0.018)
Education				0.0309*
×*TreatedBank*×*Post*				(0.018)
Observations	125,874	125,874	125,874	125,874
Adjusted R-squared	0.996	0.996	0.996	0.996
Branch FE	Yes	Yes	Yes	Yes
Bank-week FE	Yes	Yes	Yes	Yes
County-week FE	Yes	Yes	Yes	Yes