KEEP CALM AND BANK ON: PANIC-DRIVEN BANK RUNS AND THE ROLE OF PUBLIC COMMUNICATION

Damiano Sandri	Francesco Grigoli	Yuriy Gorodnichenko	Olivier Coibion
BIS and CEPR	Georgetown University	UC Berkeley and NBER	UT Austin and NBER

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Abstract

Using a survey with information treatments conducted in the aftermath of SVB's collapse, we study households' perspectives on bank stability, the potential for panic-driven bank runs, and the role of public communication. When informed about SVB's collapse, households become more likely to withdraw deposits, due to both a higher perceived risk of bank failure and higher expected losses on deposits in case of bank failure. Leveraging hypothetical questions and the exogenous variation in beliefs generated by the information treatments, we show that households reallocate deposit withdrawals primarily into other banks and cash, with little passthrough into spending. Information about FDIC insurance and communication about bank stability by the Federal Reserve can reassure depositors, while communication from political leaders only influences their electoral base.

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"Americans can have confidence that the banking system is safe. Your deposits will be there when you need them." President Biden (March 13, 2023).

"Our banking system is sound and resilient, with strong capital and liquidity." Fed Chair Powell (March 22, 2023).

1. Introduction

On March 9, 2023, Silicon Valley Bank (SVB) was pushed into insolvency by a bank run of extraordinary speed, involving deposit outflows of over $40 billion (Barr, 2023). Being the first major bank failure since the global financial crisis, SVB's collapse cast an ominous shadow on the U.S. banking system and raised fears that other banks could experience similar runs. The rapid dissemination of information, facilitated in part by the expanding influence of social media (Rose, 2023), further intensified these apprehensions. To reassure depositors and prevent other bank runs, U.S. authorities made public announcements expressing their confidence in the stability of the U.S. banking system. On the morning of Monday, March 13, President Biden addressed the nation to provide assurance regarding the safety of the banking sector. A few days later, Fed Chair Powell opened the FOMC press conference by declaring that the banking system was sound and resilient.

How do households perceive the stability of the U.S. banking system and what factors do they view as determining the riskiness of banks? Does information about a large bank run increase people's propensity to take deposits out of other banks? Can public statements by political and central bank authorities contain the risks of bank runs? In this paper, we address these questions by examining the results of a household survey on retail bank depositors which includes information provision experiments. We show that news about SVB's collapse makes households more likely to withdraw their bank deposits, both because they perceive their bank as riskier and because they become more pessimistic about how much of their deposits they would recover if their bank failed. We then show that households would reallocate the withdrawn deposits in other banks, additional cash holdings, and to a smaller extent purchases of other financial assets, with very little passthrough into spending decisions. News about FDIC insurance or communication from the Federal Reserve, on the other hand, tends to have offsetting effects by reassuring depositors.

To the best of our knowledge, this is the first study that uses information provision experiments to assess the potential for panic-driven bank runs and the effectiveness of public communication tools to prevent such outcomes. Our analysis is based on a new survey that collects novel information on households' banking decisions and utilizes information treatments to generate exogenous changes in beliefs. The survey begins by collecting a wide range of data on households' perceptions of deposit safety and bank risk. We find that the vast majority of survey participants are confident about the safety of their bank deposits. Furthermore, perceptions about the financial stability of banks have not deteriorated in the months preceding the survey. These results are striking given that the survey was conducted just a few weeks after the demise of SVB, at a time of heightened tensions in the U.S. banking sector. Several factors may contribute to this finding. First, we find that less than half of the survey participants knew about SVB, indicating that most people are uninformed even about major bank failures. Second, we document that people tend to have stronger confidence in their bank than in the banking sector at large and thus may discount bank failures as not being relevant to the financial prospects of their own bank. Third, people's confidence in the safety of their deposits seems underpinned by the expectation of some form of government guarantee—beyond the official FDIC insurance—since people assign a considerable risk that their bank may fail even when they consider their deposits as safe.

To gain deeper insights into the forces shaping people's confidence in bank deposits and the underlying cognitive mechanisms, we leverage the information provision experiments built into the survey. These experiments use a randomized controlled trial (RCT) design whereby survey participants are randomly assigned to either a control group or one of four treatment groups. Each treated group receives information related to the banking crisis. Specifically, one group is informed about the collapse of SVB, while the other three groups are provided with information regarding FDIC deposit insurance or public assurances by either President Biden or the Federal Reserve about the state of the U.S. banking system. The survey also collects information about people's propensity to withdraw money from banks—that we refer to as the "propensity to run"—before and after the treatments.

The econometric analysis compares changes in people's propensity to run before and after receiving the information treatments against the control group. This approach allows us to identify the causal impact of each information treatment on people's propensity to participate in a bank run. In particular, the SVB information treatment helps us to gauge the extent to which news about a large bank run may instill fear among retail depositors and assess how they respond to those fears. On the other hand, the FDIC, President Biden, and Fed information treatments offer key insights into the effectiveness of public communication campaigns in alleviating depositors' concerns.

A unique strength of our analysis is that the survey was launched within a few weeks following the collapse of SVB, specifically at the end of April 2023. This timing offers two significant advantages. First, it ensures the relevance of the information treatments and thus their potential to affect people's perceptions. If the survey had been conducted at a later date, people could have dismissed information about SVB and the authorities' public statements as outdated and thus irrelevant to the present condition of the banking system. Second, the survey was conducted at a time of heightened concerns about the U.S. banking sector. For example, the FDIC announced the closure and sale of First Republic Bank to JPMorgan Chase on May 1, 2023. Hence, the effectiveness of the information treatments is assessed against the backdrop of tensions in the U.S. banking sector, precisely when these types of public pronouncements typically occur.

Our results show that information regarding the bank run on SVB increases people's propensity to withdraw their deposits, thereby providing novel evidence in the literature that a bank run on a major institution may indeed act as a catalyst for other similar events. This effect happens through two channels. First, information about the SVB collapse leads households to perceive their own bank as riskier. Second, it makes households believe that they are likely to recover a smaller fraction of their deposits if their bank does fail. Jointly, these two effects imply that when they learn about the SVB collapse, households perceive an increase in their expected potential loss from holding bank deposits of approximately 1-1.5% of their deposits.

The analysis also provides evidence about the effects of deposit risk on households' portfolio choices. First, we examine the respondents' answers to hypothetical questions about what share of deposits they would withdraw if their bank faced a certain probability of failing as well as how they would allocate these funds across different assets. Second, we ask survey participants after the information treatments how they would allocate a given monetary windfall, making it possible to examine the sensitivity of the allocation shares to the variation in the propensity to run generated by the information treatments. We find consistent results across both approaches. Specifically, people react to heightened bank risk by withdrawing funds from their primary bank, partially relocating them to other banks, and increasing cash holdings, with a smaller fraction being used to purchase other financial assets. Using elasticities from either approach, we estimate that learning about the SVB collapse would lead households to withdraw around 2-3% of their deposits from their primary bank. Considering that only about a third of the U.S. population knew about SVB, these results are remarkably in line with actual deposit outflows from the U.S. banking sector in the days following SVB's collapse, equal to about 0.7%.

We also document systematic heterogeneity in the strength of the SVB treatment effect across individuals. For example, the effects are significantly more pronounced for those who have not been with their bank very long, consistent with the importance of banking relationships (Ilyer and Puri 2012). We also document larger effects for those who do their banking with a national bank and those who do not own any cryptocurrency. This heterogeneity implies that there are many individuals for whom news about a bank failure like SVB would lead to much larger withdrawals from their banks than our baseline estimate. To the extent that bank runs may be ignited by a few particularly sensitive depositors, our results provide guidance as to who these leading movers tend to be.

Our analysis also provides insights into whether concerns about bank deposits are likely to influence household consumption decisions. Worries regarding deposit safety could prompt people to withdraw funds and use them for durable purchases. Alternatively, they could amplify concerns about the economic outlook, leading to increased precautionary savings and discouraging consumption. The results suggest that the latter effect carries more weight, as people display a decreased propensity to buy a car when deposit risk perceptions increase. However, the quantitative magnitude of pass-through into spending is economically small.

Jointly, these results indicate that a single bank failure can lead depositors at other banks to begin withdrawing their deposits and reallocating them primarily into other banks or cash, with limited passthrough into spending decisions. Can policy communication do anything to limit the scope of this spread in deposit withdrawals? Because our survey also included three information treatments involving communication about policy or from policymakers, we can provide novel evidence on the extent to which policy communication can lean against panic-driven bank runs.

Providing information about FDIC insurance on deposits or sharing communication from the Federal Reserve about the stability of the banking system effectively counterbalances the average impact of the SVB treatment on the propensity to run. In the case of the FDIC treatment, this happens by reducing households' expected loss on deposits conditional on their bank failing. In the case of the Federal Reserve statement about a stable banking system, the effect operates instead by reducing the probability that households assign to their bank failing in the near future. Therefore, public communication by the Fed and information about deposit insurance emerge from the analysis as potentially powerful tools to contain the risk of panic-induced bank runs. In contrast, the information treatment based on President Biden's statement is found to have a more limited reach, affecting only his electoral base. This result underscores the limits of political communication in the current highly polarized political environment.

The paper is related to two main strands of research. The methodological approach builds on the insights of a recent but rapidly growing literature that uses information provision experiments in household surveys to address macroeconomic questions. Several studies examine the determinants of household inflation expectations, among which information about past and current inflation (Armantier et al., 2016; Cavallo, Cruces and Perez-Truglia, 2017), monetary policy (Coibion, Gorodnichenko and Weber, 2022; Coibion et al., forthcoming; Coibion et al., 2023b), and fiscal variables (Coibion, Gorodnichenko and Weber, 2021; Grigoli and Sandri, 2023). Other papers focus on factors influencing household consumption, such as macroeconomic forecasts (Roth and Wohlfart, 2022), news about inflation (Coibion et al., 2023a), and the role of macroeconomic uncertainty (Coibion et al., forthcoming). Our study is the first to use information provision experiments to understand households' responses to bank risk and especially to public communication geared at containing the risk of bank runs.

Naturally, our paper also contributes to the literature on bank runs. A key question in this literature is the extent to which bank runs are driven by genuine concerns about bank fundamentals rather than panic effects, possibly triggered by the failure of other financial institutions. This debate goes back to studies investigating the origins of the Great Depression. Friedman and Schwartz (1963) argued that panic was the primary driver of bank failures in the early 1930s. Subsequent studies challenged this perspective, emphasizing that bank distress was largely associated with weak fundamentals (Wicker, 1980; Eugene, 1984; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Calomiris and Mason, 2003). This debate also relates to the question of whether depositors can exercise market discipline on banks and how this depends on deposit insurance (Schumaker, 2000; Martinez Peria and Schmukler, 2001; Demirgüç-Kunt and Huizinga, 2004; Calomiris and Jaremski, 2018; Martin, Puri, and Ufier, forthcoming). By leveraging information provision experiments that alert survey participants about distress in the banking sector but do not provide any information about the financial conditions of their own bank, our analytical approach offers a clean identification of the role of panic effects in contributing to bank runs.

Our work is also related to several papers that use micro-level data to analyze depositors' reactions to bank distress (Davenport and McDill, 2006; Iyer and Puri, 2012; Iyer, Puri and Ryan, 2016; Brown, Guin and Morkoetter, 2020; Martin, Puri, and Ufier, forthcoming). These studies document considerable heterogeneity in how depositors respond to bank risk, for example highlighting the stronger responsiveness of larger depositors. Our analysis complements these results by identifying various additional demographic and socio-economic characteristics that make people more likely to engage in bank runs. Furthermore, our methodological approach provides a novel perspective on these issues by identifying possible differences in how depositors react to the same information. In contrast, the existing literature based on actual deposit data cannot ascertain whether differences across depositors arise from people having different knowledge about ongoing events or reacting differently to the same set of news. Finally, we differ from this work by relying on RCTs and hypothetical questions to attribute causality.

The paper is structured as follows. Section 2 provides details about the survey and an overview of households' perceptions of deposit and bank risk. Section 3 analyzes the impact of the information treatments. Section 4 considers the implications for portfolio choices and consumption. Section 5 concludes.

2. Survey information and descriptive evidence

The survey was conducted by YouGov, a highly reputable international data analytics company, on a sample of 6,327 individuals in the U.S.. YouGov conducts surveys online based on a registered panel of over 22 million members. Survey participants were at least 18 years old and were selected based on a host of different demographic and socioeconomic characteristics to ensure the national representativeness of the sample.

The survey was launched on April 28, 2023. Participants were invited to take the survey via email and could access the questionnaire only after entering their personal login credentials.[1] At no point in the survey were people informed about the purpose of the

[1] This is to ensure that only selected survey participants could access the survey and that they could take the survey only once. Survey respondents receive points from YouGov that can be converted into cash rewards.

analysis. Participants were randomly allocated to either a control group of about 2,000 thousand individuals or one of 4 treatment groups of about 1,000 people each.[2]

2.1 The structure of the survey

The survey questionnaire is reported in Appendix A. All participants were presented with the same set of questions, independent of whether they were assigned to the control or one of the treatment groups. This helps address possible priming effects since different questions may nudge people to provide different answers. For example, asking people whether they know about President Biden's statement on the safety of the U.S. banking sector may lead people to suspect that the banking sector is confronting challenges and thus report heightened concerns about deposit safety. Or, conversely, this question may remind people about President Biden's statement and prompt participants to express lower concerns about deposits. In either case, by presenting this question to all survey participants and comparing the treated groups against the control group, the econometric analysis can control for these priming effects.

The survey started with a screening question to keep only individuals with at least one bank account. It then included several questions to elicit people's perceptions about the risk of bank failure and the safety of bank deposits. Among these, the key question for our analysis to assess the impact of the information treatments is:

Q6: How likely are you to withdraw some of your deposits in the next 12 months because of concerns that your bank may fail?

People were asked to provide answers on a 10-point scale, ranging from "not at all likely" to "extremely likely". We interpret answers to this question as reflecting people's propensity to withdraw deposits because of concerns that the bank may fail. Hence, we will refer to this question as capturing people's "propensity to run". Participants were also asked about the probability in percentage terms that their bank would fail within 12 months. As discussed later in the analysis, we will leverage these questions to shed light on the channels behind people's propensity to run.

The survey proceeded by collecting information on people's portfolio allocation and their perceived costs to switching banks. Survey participants were then presented with hypothetical questions on how they would react if their bank faced a given probability of

[2] Appendix Table 1 confirms that the treatment group assignment is not predictable based on individual characteristics.

failure, randomly drawn on a grid between 1 and 50 percent. Participants were asked whether they would withdraw some deposits and, if so, how much; whether they would start using a different bank and, if so, which type; and how they would re-allocate their deposit withdrawals, if any.

The survey then included questions aimed at assessing participants' knowledge about the information treatments. Participants were asked if they were familiar with the acronym SVB and provided with several options to choose from, including the correct answer, "a private bank", as well as the option to select "I don't know". Participants were also asked whether they were aware that the Federal Reserve and President Biden had recently expressed a position on the safety of the U.S. banking sector. People could answer "I don't know" or choose between different options, ranging from "banks are safe" to "banks are at a critical juncture". In addition, the survey required participants to type in the FDIC insurance limit for individually owned bank accounts.

Participants were then provided with the information treatments on standalone online screens. The four treatment groups were provided with one of these statements:

A. *Considering that a few weeks ago, Silicon Valley Bank (SVB), a U.S.$200bn bank, failed after experiencing a sudden bank run,*
B. *The FDIC (Federal Deposit Insurance Corporation) is an independent agency of the United States government that protects bank depositors if a bank fails. Considering that the FDIC insures individually owned deposits up to $250,000,*
C. *Considering that a few weeks ago, President Biden declared that "Americans can have confidence that the banking system is safe,"*
D. *Considering that a few weeks ago, the Federal Reserve (Fed) declared that "the U.S. banking system is sound and resilient,"*

followed by this sentence to alert people that they would be asked again about their views on bank and deposit risk:

> *we would like to ask you again about your perceptions that your bank may fail and your propensity to take out your bank deposits.*

To keep the structure of the survey fully symmetric across the treated and control groups, people in the control group were also presented with a standalone online screen which displayed only the last sentence above.

The survey then re-assessed people's propensity to withdraw deposits and their perceptions about the risk of bank failure. To identify the causal effect of the information treatments, the econometric analysis will examine how people in each treatment group revised answers to these questions relative to those provided earlier in the survey and compare these revisions against people in the control group.

To shed further light on the effects of the information treatments, the survey also asked respondents about their perceived recovery rate on deposits in case of bank failure, how they would invest a hypothetical financial windfall, and whether they thought it was a good time to buy durables goods, such as cars, major household items, or a house. Finally, the survey collected information about the type of bank that respondents used (e.g. national, state, credit union, etc), the reasons for using that bank, the number of years using the bank, their political affiliation, and a host of personal characteristics, among which age, income, education, and geographic location.

To ensure greater quality of the data, we impose a few restrictions throughout the analysis based on time stamps collected during the survey. Specifically, we drop respondents that spent very little time on the information treatment screens—generally less than one second—and were thus unlikely to have read the information treatments.[3] We also exclude respondents that completed the survey in less than 3 minutes or in more than an hour to remove people that rushed through the survey or were distracted by other tasks.

As described in Table 1, survey participants report using two banks on average, with those holding more than $100,000 in deposits being more likely to have multiple bank accounts. Households tend to use the same bank for nearly 14 years on average. About 35 percent of the respondents report using national banks, while 40 percent rely primarily on credit unions or local banks. Regarding deposit balances, about 50 percent of households hold less than $10,000 in their banking accounts. This is consistent with the 2019 Survey of Consumer Finances (SCF) which reports a median value of $5,300 held in checking and savings accounts of U.S. households.[4] Close to 9 percent of respondents report holding more than $100,000 in banking accounts. Regarding other asset holdings, 43 percent of the survey respondents own stocks. This proportion is again in line with the SCF, according to which 53 percent of families own stocks when also including retirement

[3] Since the information statements are of different length, we do not impose a fixed time threshold for all of them. We instead drop respondents in the lowest 5 percentile of the distribution of time spent on the screen of each information treatment. Note that to preserve full symmetry between the control and treatment groups, we implement the same procedure also for people in the control group.
[4] Income information is also consistent between our data and the SCF. In 2019, the median income of US families reported by the SCF reached $58,600. Our survey collects information about households' income in 15 brackets, with the median category being the one for people with income between $60,000 and $69,999.

accounts. The second most held asset class in our survey is bonds (29 percent of the respondents), followed by gold and commodities (21 percent) and cryptocurrencies (19 percent).

2.2 People's perceptions of deposit and bank risk

In this section, we review the answers provided by survey participants before the information treatments regarding their initial perceptions about bank risk and deposit safety. Our first finding is that respondents express a high degree of confidence in the safety of deposits. As reported in Table 2, more than 80 percent of respondents declare their bank deposits to be safe or very safe. Moreover, people's views about the safety of their bank have not deteriorated in recent months. Almost 60 percent of respondents report that their perceptions about the financial stability of their bank have remained unchanged. The rest of the respondents are roughly equally split between those that perceive an improvement in bank strength and those that perceive a worsening.

These results are striking given that the survey took place during a very turbulent time for the U.S. banking sector. Just a few weeks before the survey, the collapse of SVB and Signature Bank raised major concerns about the stability of the banking system. And while the survey was conducted, regulators took over First Republic Bank, marking the second-largest bank failure in U.S. history. Data from Google Trends (Appendix Figure 1) confirm that the survey took place when people's internet searches about bank runs and bank failures had reached historic highs, exceeding the levels during the 2008 financial crisis.

There are several potential explanations for the high degree of confidence in the safety of bank deposits observed in the survey. First, people may be uninformed about recent distress in the U.S. banking system. Or, conversely, they could be well informed (and reassured) by the U.S. authorities' public pronouncements regarding the safety of U.S. banks. The questions to assess the respondents' prior knowledge about the information treatments shed light on these issues. As reported in Table 3, only 35 percent of the respondents were aware that the acronym SVB referred to a private bank, suggesting that most of the depositors may not have known about recent events in the U.S. banking sector. The survey also reveals that only about 30 percent of respondents knew that the Fed and President Biden expressed confidence in the U.S. banking sector, although more than half of those who knew about SVB also knew about either the Fed's or Biden's statements supporting the banking system. Hence, most respondents seem to be unaware of the tensions brought about by SVB, but those who were awarewere also informed about policy responses. Both factors should act to limit concerns about deposit safety.

Second, people's perceptions about the safety of their deposits may not be materially affected by adverse events occurring in other banks. Panel A of Figure 1 presents evidence consistent with this hypothesis showing that people tend to have more confidence in their bank than in the U.S. banking sector at large. For example, the average probability of a major national bank failing in the following 12 months is 35 percent according to respondents, but they perceive a much smaller 18 percent chance on average of their own bank failing. Therefore, news regarding financial distress in other banks may have limited impact on people's opinions about the safety of their own bank. We will directly test for this hypothesis later in the analysis by assessing the impact of the SVB information treatment on the respondents' perceptions about the risk to their own bank and their propensity to withdraw deposits.

Third, even if households have concerns about the stability of their bank, they may not worry much about the safety of their deposits if they think they can easily extract their money from the bank or if they believe that their deposits are insured. Indeed, Panel B of Figure 1 provides evidence that the link between own bank stability and deposit risk is weak: while there is a positive correlation across households in terms of the perceived probability of their own bank failing and the perceived riskiness of their deposits, that correlation is limited. Moreover, many people report that they consider their deposits to be safe even though they think there is a high probability that their bank may fail.

Is this due to the fact that Americans understand FDIC insurance of bank deposits, thereby making their deposits immune to shocks hitting their bank? In fact, most people seem to have little knowledge about the FDIC. For example, as reported in Table 3, only one in four respondents knows the standard FDIC insurance limit for individually owned accounts. Alternatively, people could have a broader perception that the government is committed to protecting deposits even without knowing about FDIC insurance. Indeed, when asked about the primary factors that could lead their bank to fail, they list aggregate conditions first (financial crisis, recession, and declines in asset prices) that are more likely to induce a federal backstop than factors specific to their bank (bad investments and bad loans).

Retail depositors could also be confident in the safety of their deposits if they think that it is easy to switch their savings to other banks. Consistent with this, we find that four in five respondents report that it is either "easy" or "very easy" to switch to a different bank (Table 1). Nor would it take much for them to do so. On average they report that they would switch to a different bank if it offered them 1.7 percentage points more in interest. More generally, when respondents are asked about what factors are most important in the choice of their bank, safety is not one of their primary concerns, coming fifth after location, customer service, checking/savings account fees, and the range of banking services offered.

In the next section of the paper, we will re-examine these initial findings and their underlying drivers by estimating the causal effects of the information treatments on people's propensity to withdraw their deposits that we refer to as the "propensity to run". We note that answers to this question should be informed by people's perceptions about the risk that their bank may fail as well as by the expected recovery rate on deposits in case of bank failure. Figure 2 confirms that this holds true in our data. People's responses about their propensity to withdraw deposits are positively correlated with their perceptions about bank risk (Panel A) and negatively correlated with their expected recovery rates in case of bank failure (Panel B).[5] The analysis of the information treatment will shed light on the contribution of each of these two factors in influencing people's propensity to run.

Before we proceed, it is important to underscore that while the average banking customer is relatively confident in the safety of their deposits, there is significant cross-sectional variation in this perspective (Appendix Table 2). To explore differences across individuals, we regress the indicators of bank and deposit risk collected in the survey on a range of observable characteristics of the respondents.

The results are reported in Table 4. Several findings stand out. Respondents that have used their bank for longer tend to have more confidence in their bank, although—as intuitive—the length of the account tenure does not influence people's views about the broader banking sector. Interestingly, older people and those with higher education tend to have more confidence in their banks but less confidence in the overall banking sector. This is possibly because they believe they have developed sufficient experience or knowledge to select safer banks. Turning to economic variables, people with larger

[5] Since the survey collected people's views about bank risk before and after the information treatment, Panel A correlates the pre-treatment propensity to run with the pre-treatment bank risk perception on the full sample of survey participants. Expectations about recovery rates were instead collected only after the treatment to reduce survey fatigue. Therefore, Panel B correlates the post-treatment propensity to run with the post-treatment expected recovery rates. In this case, we only consider people in the control group to ensure that the results are not driven by the effects of the information treatments.

deposits (above $100,000) tend to be more anxious about banks while people with higher income are more at ease. These results are again intuitive given than people with larger deposits are more exposed to the consequences of bank distress while higher-income people can rely on their earnings to withstand possible deposit losses. Finally, we find some evidence that Democrats tend to be less concerned about the banking system in general, possibly reflecting stronger confidence in the government's ability to preserve financial stability under a Democratic administration.

3. Information treatment effects

In this section, we estimate the causal impact of the information treatments on people's propensity to run, that is to withdraw deposits because of concerns that their bank may fail. We first examine if information about SVB's collapse affects the willingness of households to withdraw deposits from their bank and the channels underlying this effect. We then assess if and to what extent different policy communications may push in the opposite direction by reassuring depositors. Finally, we differentiate the impact depending on people's prior knowledge of the treatments and political affiliation.

3.1 How does news about SVB's collapse affect households' propensity to run?

How does information about the collapse of a large bank affect households' willingness to hold deposits in their own bank? To answer this question, we leverage two key strengths of the survey design. First, participants were asked about their propensity to run both before and after the information treatments. This makes it possible to measure changes in the propensity to run at the individual level. Second, a control group of survey participants were presented with the same survey questionnaire but were not provided with any treatment information. This control group makes it possible to isolate changes in people's propensity to run triggered by the information treatments rather than other factors. For example, it is well known that people may change their responses during a survey because certain questions can generate cognitive associations that lead participants to reconsider their answers. The econometric analysis will control for these potential effects by comparing people in the treatment group against those in the control group, thereby allowing to obtain precise estimates for the information treatments.

Formally, we estimate the following regression

$$\Delta \mathrm{run}_i = \alpha + \sum_j \beta_j \, \mathbb{I}\left(i \in \mathrm{Treat}_j\right) + \xi X_i + \varepsilon_i \qquad (1)$$

where Δrun_i denotes the change in the propensity to run of respondent i before and after treatment. The variable $\mathbb{I}(\text{i} \in \text{Treat}_j)$ is an indicator variable that takes value one if respondent i belongs to treatment group $\text{j} = \{\text{SVB}, \text{FDIC}, \text{Fed}, \text{Biden}\}$. The vector X_i includes controls for demographic and socioeconomic characteristics—including gender, age, geographical area, employment status, number of children, educational attainment, and income level—as well as the day in which respondent i took the survey. Equation (1) is estimated using survey weights.

For now, our primary focus is on the coefficient β_{SVB}, which captures the average effect of the SVB information treatment on the propensity to run relative to the control group. The regression estimates are reported in column (1) of Table 5. The key finding is that information about the SVB's collapse increases people's propensity to run. This result speaks directly to a prominent debate in the banking literature on the extent to which banking crises can originate from panic effects rather than being driven by weak bank fundamentals. Our research design based on information provision experiments provides clear evidence that the collapse of an important bank can indeed heighten depositors' concerns about the broader banking system, thereby increasing the risk of additional bank runs.

The economic magnitude of this effect is difficult to assess. The question about willingness to withdraw funds is qualitative in nature, so the coefficients do not have a clear quantitative interpretation. Providing the SVB treatment increases people's propensity to run by 0.17 on a 10-point scale, which appears modest.[6] However, because we have more quantitative measures of households' risk perceptions, we will be able to provide subsequently a clearer interpretation of these effects.

The effect of the treatment is not homogeneous across households. In Appendix Table 3, we report estimates of equation (1) for different subsets of the population, broken down along different observable characteristics. While some of these characteristics do not appear to determine how strongly households respond (e.g. age, education, or income), others appear quite important. For example, we find that women respond strongly to the treatment whereas men do not respond much, if at all. The type of bank used by households also matters: those using national banks respond strongly to the treatment compared to those using state and local banks. Democrats and Independents respond more strongly than

[6] The average pre-treatment propensity to withdraw deposits is 4.7 and the standard deviation of the distribution across people is 3.2.

Republicans. Owners of cryptocurrency do not display any meaningful response to the SVB treatment. Finally, those who have been using their bank for less than 10 years respond far more than those who have been with their bank for a long time, consistent with relationship effects (Brown, Guin and Morkoetter 2020). This heterogeneity may be important: if some individuals are particularly willing to withdraw their deposits at the first hint of bad news, they may provide the spark to begin a bank run, thereby inducing others to also withdraw their deposits who otherwise would not have.

What makes households more likely to pull their deposits out of their bank when they find out about the SVB failure? In principle, the information treatment can operate via two distinct channels. The first is by altering people's perceptions about the risk that their bank may fail. The second is by changing their expectations of whether they will recover their deposits if their bank fails. The survey questionnaire was designed to shed light on the role of these mechanisms.

To assess the relevance of the first channel, people were asked about their perceived probability (as a percent chance) that their bank could fail within a year before and after the treatment. This makes it possible to re-estimate equation (1) by using as the dependent variable the change in the reported probability of bank failure pre- and post-treatment. We report the results of this specification in column (2) of Table 5. While the coefficient is positive, it is not statistically significant. One interpretation, emphasizing the inability to reject the null, is that learning about SVB's failure does not lead households to view their bank as riskier. Another possibility, focusing more on the large standard errors, is that the cognitive demand to answering this probabilistic question is too much for some of the participants, thereby introducing excessive noise into the variable and leading to attenuation bias. Answering this question required individuals to be familiar with the concept of probability risk within a defined time frame—an understanding that might be challenging for individuals with lower levels of education. To test if the level of education affects the estimates, we report in column (3) the same specification estimated only on those individuals with more than a high school education. Consistent with cognitive constraints being important, we now find a much larger and statistically significant coefficient. Given that splitting by education did not lead to any difference in estimates when using the qualitative measure of willingness to run (Appendix Table 3), this suggests that cognitive constraints may indeed be behind the large standard errors in column (2).

The implied magnitude of the treatment effect for high-educated individuals corresponds to an approximately 2 percentage point higher perceived risk of their own bank failing over the next 12 months. This represents about a 10 percent increase in the perceived probability of bank failure from the treatment, a considerable effect. There is again heterogeneity in the strength of treatment effects. When we split the sample along observable characteristics (Appendix Table 4), we find similar albeit noisier results as when using the qualitative measure of willingness to run (e.g., effects are larger for women, non-crypto currency owners, and those banking with a national bank).

The second channel through which households may become more willing to withdraw their deposits is if they foresee greater losses to their deposits conditional on their bank failing. To test whether the SVB information treatment also operates through this channel, the survey directly inquired about participants' views on whether they thought they would bear losses or get their deposits back if their bank failed. This question was posed after the information treatments, making it possible to assess the influence of the treatments on people's answers. To this end, we re-estimate equation (1) by using as the dependent variable the expected share of deposits lost if the respondent's bank were to fail (one minus recovery rate). Note that we did not inquire about people's expected losses conditional on bank failure before the information treatments. This was to limit cognitive strain and because we can proxy for people's pre-treatment expected losses in case of bank failure by controlling in the regression for the respondents' pre-treatment propensity to run and bank risk perceptions. Because the distribution of expected losses is somewhat bimodal (large masses at 0% and 100%), we also consider a specification in which the dependent variable is an indicator variable equal to one if the respondent expects to lose some of her deposits.

The regression estimates reported in column (4) of Table 5 use the expected loss as a share of deposits as a dependent variable and confirm that this channel is operating as well. We find that when households are informed about the collapse of SVB, they expect to lose more of their deposits if their bank fails. The magnitude of this effect is similar to that found for the first channel: a 3.3 percentage point increase in the expected fraction of deposits lost compared to an average expected deposit loss rate of 45 percent, so an approximately 7 percent increase in the loss rate (or equivalently a decline in the recovery rate). As documented in column (5), we find a similar result when we use an indicator variable for expecting to lose some deposits in case of bank failure. Again, there is heterogeneity in terms of the strength of this channel, largely along the same dimensions as those found for the previous channel (Appendix Table 5 and Appendix Table 6). The treatment leads to larger effects on the expected deposit loss for those banking at a national bank, Democrats, those with smaller deposits, and those who do not own any cryptocurrency.

To get a sense of the overall economic magnitude of the SVB treatment effect, we can consider how it affects people's expected losses on deposits due to a possible failure of their bank. Since the expected loss from bank failure is $\mathrm{E[L]} = \mathrm{Pr(BF)E(L|BF)}$ where $\mathrm{Pr(BF)}$ is the probability of bank failure and $\mathrm{E(L|BF)}$ is the expected loss conditional on a bank failure, the change in this expected loss is:

$$\mathrm{dE[L]} \approx \mathrm{dPr(BF)E(L|BF)} + \mathrm{Pr(BF)dE(L|BF)}$$

The change in the probability of bank failure from the treatment is 1-2% depending on whether we rely on the estimate across all individuals or those with post-high school education. The change in the expected loss conditional on bank failure is 3%. Given that the expected deposit loss rate conditional on a bank failure is 45% on average and the average perceived probability of bank failure is 18% (Table 2), we can estimate that the information treatment increased the expected losses from possible bank failure over the next year by 1-1.5% of household deposits. Since households view it as easy to switch across banks, this suggests that the treatment likely had an economically significant effect on households' willingness to switch banks on average. Furthermore, given the wide variation in how strongly different types of individuals responded to the treatment, there are likely many individuals for whom the treatment effects are significantly larger than this. Because banks need only a fraction of their depositors to run to become illiquid, our results are consistent with runs on banks spreading potentially quickly.

3.2 The effectiveness of policy communication

Given that news about the SVB collapse can significantly change households' perceptions about the safety of their deposits, how successful are policy communications likely to be in counteracting these effects? To explore this question, we examine the effects of the other information treatments.

First, we report in column (1) of Table 5 the average effect of the policy treatments on households' propensity to run. The FDIC treatment—which involves telling people that individual deposits up to $250,000 are insured—reduces households' propensity to run. This effect is of the same order of magnitude as the SVB treatment in absolute value, suggesting that widespread knowledge of FDIC coverage could potentially undo the effects of bad news about banking stability. In addition, we find that the Fed treatment—

telling people that the Federal Reserve believes that the banking system is sound—has a similar effect, again large enough to offset the effect of the news about SVB on average. In contrast, the statement from President Biden has no discernible effect on the average willingness to run of households. This indicates that the source of the message about financial market stability is important, with the Federal Reserve having more credibility on this issue.

As with the SVB treatment, there is significant heterogeneity in terms of how different individuals respond to the policy communication treatments (Appendix Table 3). However, this heterogeneity is quite different. For example, whereas those with large deposits and small deposits had similar responses to the SVB treatment, only those with small deposits become less willing to run when receiving the FDIC and Fed treatments Households with large deposits become instead more willing to run when told about the Biden and Fed treatments. While Democrats responded particularly strongly to the information about SVB's collapse, they do not respond to messages from Biden or the Fed, nor do they respond to news about the FDIC coverage. Instead, it is Republicans who respond to FDIC news. Similarly, while those who had been with the same bank for less than 10 years became more willing to run when told about SVB, they do not respond to the policy treatments. Instead, it is those who have been staying with the same bank for more than 10 years that respond to the FDIC treatment even though news about the SVB collapse did not make them more willing to run. Jointly, these results indicate that while the Fed and FDIC treatments work on average in terms of reducing the willingness to run, they generally do not work on those specific people who become most willing to run when learning about a failing bank. This suggests that there are limits to the ability of policymakers to influence those individuals who are most likely to run on their bank in the face of bad financial news.

We also consider how the policy communication treatments affect the underlying channels driving the propensity to run. As reported in Table 5, the Fed treatment has a pronounced effect on the failure risk that households associate with their bank, especially when we focus on the higher educated. The FDIC treatment, in contrast, has no effect on the probability that households attach to their bank failing. With respect to the expected losses conditional on their bank failing, the effects are reversed. The FDIC treatment reduces the losses on deposits that households expect if their bank fails (or at least the fraction of people who expect to lose some of their deposits), whereas the Fed treatment does not. These results suggest that households largely understand the primary mechanisms through which Fed and FDIC policies operate. For example, people view deposit insurance as a tool enhancing the safety of deposits—reducing their propensity to run as shown in column (1)—but without reducing the risk of bank failure risk.[7] The Biden treatment, consistent with its lack of effect on the overall propensity to run, does not appear to have any effect on either margin.

3.3 The role of prior beliefs and political affiliation

Why would communication about bank stability from Biden have so little effect compared to equivalent statements from the Federal Reserve? One possibility is that they differ in how known they were ahead of the survey. Information that is already known by agents should have little effect on beliefs. A second possibility is that the statements are not viewed as equally credible. In this section, we focus on the potential importance of prior beliefs and political preferences in explaining differences in treatment effects.

As discussed in Haaland et al. (2022), controlling for prior beliefs is also a critical step to ensure that the results reflect genuine changes in people's perceptions triggered by the information treatments, rather than emotional reactions or survey demand effects. For example, survey participants may react to information about the SVB collapse by reporting greater concerns about deposit and bank risk because they think this is what the survey administrators expect.[8] By differentiating respondents depending on their prior knowledge of SVB, we can check whether revisions in the propensity to run are stronger among those who did not know about SVB. This would indicate that survey participants are truthfully responding to the information content of the treatment rather than mechanically altering their answers.

We also allow the effects of the Biden information treatment to differ depending on the respondents' political affiliation. To this end, we estimate the following equation:

$$\begin{aligned}\Delta \mathrm{run}_i = \alpha + \textstyle\sum_j \left(\beta_t + \gamma_j K_{i,j}\right) \times \mathbb{I}\left(i \in \mathrm{Treat}_j\right) + \sum_j \kappa_j K_{i,j} \\ + \left(\beta_B^P + \gamma_B^P K_{i,\mathrm{Biden}}\right) \times \mathbb{I}\left(i \in \mathrm{Treat}_{\mathrm{Biden}}\right) * P_i + \delta P_i + \xi X_i + \varepsilon_i\end{aligned} \quad (2)$$

The variable $K_{i,j}$ captures the degree of knowledge of respondent i about the information treatment j. Specifically, the variable $K_{i,SVB}$ is a dummy that takes value one for people

[7] People do not seem to recognize the indirect effect of deposit insurance on reducing the risk of bank failure by preventing bank runs (Diamond and Dybvig, 1983).

[8] It is worth underscoring that concerns about demand effects are much more muted in the context of online surveys, as used for our analysis, relative to in-person surveys (de Quidt et al., 2018). In the latter case, the physical presence of an interviewer places additional pressures on people to provide answers that may seem more consistent with the interviewer's expectations.

that knew that SVB was a private bank and zero otherwise. To capture the degree of knowledge about the Fed's statement, the variable $K_{i,Fed}$ is a dummy that takes value one for people that thought that the Fed said that banks were safe or that it was too early to say; and value zero for people that had no knowledge about the Fed's pronouncement or thought it said that banks were at a critical juncture. The same approach is followed to construct the dummy $K_{i,Biden}$ to assess the degree of knowledge about President Biden's statement. To measure the degree of knowledge about the FDIC, the variable $K_{i,FDIC}$ corresponds to the respondents' beliefs about the FDIC insured limit.[9] Finally, the dummy P_i captures the political affiliation of the survey respondents.

Table 6 reports the regression estimates and Figure 3 illustrates the impact of each information treatment on the propensity to run conditional on people's prior knowledge. To facilitate comparison with the average treatment effects on the general population, column (1) reports the estimates from Table 5. In column (2), we expand the regression specification by including the interactions between the treatment dummies and people's prior knowledge indicators. In this case, the coefficients on the standalone treatment dummies—denoted with β_j in equation (2)—capture the treatment effects on people with no prior knowledge of the information provided.

Focusing first on these coefficients, the estimates confirm previous findings based on the general survey population. Namely, the SVB, FDIC, and Fed treatments affect people with no prior knowledge of these treatments in the expected direction. Information about SVB increases the propensity to run while the FDIC and Fed treatments operate in the opposite direction. The point estimates also corroborate earlier findings that the FDIC and Fed treatments can quantitatively offset the impact of news about SVB. Finally, we observe that the estimated effects of the information treatment on people with no prior knowledge are about twice as large relative to the effects estimated over the entire sample reported in column (1). This implies that the treatment effects have a weaker effect on people with prior knowledge. This is consistent with Bayesian learning in which beliefs adapt to new information. For those who had prior knowledge, the treatments did not provide new information and therefore should not alter beliefs. In contrast, for those who were less informed, more weight is assigned to the new information.

[9] We winsorize the reported insurance limits at 2.5 million USD to prevent a few outliers—possibly because people accidentally typed an extra zero—from driving the results.

Indeed, the coefficient estimates on the interactions between the treatment dummies and the prior knowledge indicators—denoted with γ_j in regression (2)—reveal that the information treatments are generally ineffective on people with prior knowledge. The coefficient on the SVB interaction is negative and of similar magnitude to the treatment effect on people without prior knowledge. As shown in Panel A of Figure 3, this implies that the SVB treatment has no impact on people that knew about this event beforehand.

Panel C illustrates the same pattern for the Fed treatment. This treatment reduces the propensity to run among people who did not know the Fed had expressed confidence in the banking sector but has no effects on individuals who were already aware of this information. Shifting focus to the FDIC treatment, Panel B shows that its effectiveness is contingent upon individuals' initial perceptions of insurance limits, with a greater impact observed among those with lower expectations. Specifically, the FDIC treatment has a large impact—offsetting news about SVB—among individuals who initially perceived insurance limits to be very low or non-existent. But it has no statistically significant effect on people who already thought insurance limits were high.

These findings consistently demonstrate that the magnitude of the estimated effects is strongly influenced by individuals' prior knowledge of the information treatments. As discussed earlier, this is a crucial result that confirms the success of our survey design approach in eliciting authentic responses to the information treatments. It also implies that the estimates in Table 5 should be viewed as lower bounds on the effects of news about a banking failure on households' perceived risk of banking and their willingness to run.

The results in column (2) show that even when we differentiate people based on their prior knowledge of President Biden's statement, this information treatment continues to have statistically insignificant effects. In column (3), we thus further expand the regression to include interaction terms for the Biden treatment with a dummy capturing non-Democrat voters. As illustrated in Panel D of Figure 3, the results show that the Biden treatment tends to reduce people's propensity to run only among Democrat voters that had no prior knowledge of President Biden's statement. This treatment has no statistically significant effect on any other category. Therefore, communication by political leaders—even if holding top positions in government—emerges from the analysis as being considerably less effective in influencing public perceptions of bank risk than communication by non-political institutions, such as central banks. This finding is consistent with the literature documenting that voters with their party in power have more favorable views on the economic outlook (e.g., Bartels 2002, Kamdar and Ray 2020, Coibion, Gorodnichenko and Weber 2020).

4. Implications for portfolio allocation and consumption choices

So far, we have found that information treatments tend to alter people's perceptions about deposit safety and thus their propensity to withdraw funds. How large could these withdrawals be? And how would people re-allocate this money? To address the questions, we use two methodological approaches. We first examine the responses of survey participants to hypothetical questions asking how they would react if their bank faced a given failure risk. We then use an instrumental variable approach to capture how exogenous variation in the perceived safety of deposits triggered by the information treatments affects people's investment choices. Using the latter approach, we will also examine the impact of deposit risk on consumption choices.

4.1 Hypothetical bank failure scenario

Before receiving the information treatments, survey participants were presented with a hypothetical scenario asking how they would react if their bank faced an imminent risk of failing. More precisely, participants were asked regarding their inclination to take deposits out and the share of deposits they would withdraw if their bank faced a certain probability of failing within 3 months. Additionally, participants were asked whether they would start using a new bank and how they would allocate the funds withdrawn. The probability of failure was randomized across participants, taking values between 1, 5, 10, 15, 20, 25, and 50 percent. Hypothetical questions have been shown to be a simple way to study causal effects without resorting to RCTs while often reaching the same conclusions as those stemming from exogenous information treatments (Mei and Stantcheva, 2022; Kumar, Gorodnichenko and Coibion, forthcoming). In addition, they can allow for studying effects on outcomes that are not easily observed in RCTs.

In Table 7, we examine the effects of bank risk on deposit withdrawals. We also test for possible differences across depositors based on a rich set of observable characteristics. In columns (1) and (2), we use an OLS regression where the dependent variable is the share of deposits that people would withdraw if their bank were at risk of failing. The key regressor in this specification is the hypothetical bank failure probability

(*BFP*). This variable is also interacted with respondents' observable characteristics to explore how the sensitivity of deposit withdrawals to bank risk varies across people. Furthermore, the regression controls for the respondents' prior beliefs about the probability of bank failure as well as the interactions with individual characteristics. Columns (3) and (4) consider the case where the dependent variable is an indicator for people that withdraw deposits from the bank. In column (1), we see that a higher risk of bank failure triggers on average larger deposit withdrawals. The regression coefficient is highly statistically significant. An increase in the probability of bank failure of 10 percentage points leads to an increase in the share of deposits withdrawn of 4.7 percentage points.

There is no analogous estimate of this elasticity in prior work that we know of. Earlier papers have studied the connection between runs on banks and deposit outflows in many contexts, such as in emerging economies (Levy-Yeyati, Martinez Peria and Schmukler, 2010), in the Great Depression (Blickle, Brunnermeier and Luck, 2022), or in the Great Recession (Martin, Puri, and Ufier, forthcoming) exploiting detailed data on deposit flows. However, this line of work cannot identify the elasticity above because of lack of data on the bank failure risk perceived by households.

This elasticity provides some guidance as to the overall effect of learning about SVB on household deposits. The average effect of the SVB treatment on households' perceived probability of their own bank failing is 1-2 percentage points, depending on which estimate in Table 5 is used. Given the elasticity estimated in Table 7, this translates into a 0.5-1 percentage point change in deposits coming from the first channel that drives deposit withdrawals from the increased probability of bank failure. We also know that the second channel that drives deposit withdrawals, namely the change in expected deposit losses conditional on the bank failing, is of the same order of magnitude in terms of effects on total expected losses from holding deposits as the first channel, so the impact on deposit outflows from that channel should be similar. Hence, the SVB treatment likely leads people to withdraw approximately 2-3 percent of deposits from their bank.

The sensitivity of withdrawals to bank risk is highly heterogenous across depositors, being heavily influenced by respondents' economic conditions and education levels. Column (2) shows that deposit withdrawals are largely driven by older people and those with post high-school education. Controlling for these variables, higher income individuals tend instead to be less prone to take deposits out when bank risk increases. These results are consistent with the notion that people with higher earnings can better withstand possible losses on deposits. However, we no longer find evidence that account tenure, crypto-ownership or political affiliation influence the size of deposit withdrawals.

For respondents that declared they would take at least some deposits out if their bank faced an imminent risk of failure, the survey included a follow-up question asking which type of alternative bank—credit union, local, state, national, online—they would choose to possibly redeposit a portion of the withdrawn funds. As illustrated in Panel A of Figure 4, half of the respondents would choose the same type of bank that they currently use. We also see a tendency for people to move from larger banks to credit unions. The share of respondents that would start using credit unions increases from 18 to 28 percent. In contrast, the share of people using state or national banks declines from 49 to 37 percent. These results are consistent with data gathered earlier in the survey showing that credit unions are generally considered safer banks, being associated with a lower propensity by depositors to take money out because of concerns about bank risk as shown in Panel B of Figure 4.

Besides estimating the extent of deposit withdrawals in response to heightened bank risk, we can also shed light on how households would *reallocate* these funds across different financial instruments and asset classes. To this end, the survey questionnaire gathered information about the different ways in which withdrawn deposits could be held. These options included deposits into other banks, cash, stocks, bonds, gold, cryptocurrencies, real estate, and debt repayments. Based on these answers, we can assess the impact of bank risk on people's desired portfolio allocations. To do so, we construct the hypothetical portfolio share in asset class a, $\mathrm{port}_{\mathrm{i,a}}^{\mathrm{hyp}}$, that respondent i would hold if her bank were exposed to the hypothetical bank failure probability BFP_{i} indicated in the survey question. We then examine how the portfolio shares vary with the level of bank risk by estimating the following regression:

$$\mathrm{port}_{\mathrm{i,a}}^{\mathrm{hyp}} = \alpha_{\mathrm{a}} + \beta_{\mathrm{a}}\, BFP_{\mathrm{i}} + \gamma_{\mathrm{a}}\, \mathrm{port}_{\mathrm{i,a}}^{\mathrm{pre}} + \delta BFP_{i}^{pre} + \xi_{\mathrm{a}} \mathrm{X}_{\mathrm{i}} + \varepsilon_{\mathrm{i,a}} \tag{3}$$

where X_{i} denotes the set of individual controls used in previous regression specifications and BFP_{i}^{pre} is the individual's prior belief of the risk their bank could fail over the next 12 months. In the initial sections of the questionnaire, participants were also asked about the allocation of their savings across various financial assets. Hence, when considering financial assets, the regression also controls for people's initial portfolio shares, $\mathrm{port}_{\mathrm{i,a}}^{\mathrm{pre}}$.

Table 8 reports the estimates of β_{a} for each type of asset. An increase in bank risk triggers deposit outflows that are mostly transferred into other banks or held in cash.

Specifically, column (2) shows that a hypothetical increase of 10 percentage points in the probability of bank failure leads to a 4.7 percentage reduction in deposits, consistent with Table 7. However, one-third of the deposits withdrawn from the primary bank would be reallocated to different banks. Of the remaining two-thirds of the withdrawn deposits, about 65% would be held in the form of cash. The remaining 35% would be split between paying off debt and purchasing other assets such as stocks, gold, and real estate. We find no evidence that people would respond to heightened bank risk by increasing holdings of cryptocurrencies, confirming the insights from Table 7 that cryptocurrencies are not seen as a viable alternative to deposits in case of bank distress. This interpretation is consistent with surveys (e.g., Weber et al. 2023) documenting that households perceive cryptocurrency as highly risky.

These results provide novel evidence on how own-bank failure risk affects the portfolio decisions of households, allowing us to quantify not just the extent to which households would like to withdraw deposits from their primary bank, but also how they would tend to reallocate those withdrawals across different assets, including depositing funds into other banks. However, as shown in section 3, a higher risk of their own bank failing is not the only channel through which news about other banks failing may induce withdrawals by households. We therefore turn to a broader analysis of how the willingness to run might affect the portfolio and spending decisions of households.

4.2 Instrumental variable approach

In this section, we revisit the results on the implications of deposit risk for portfolio allocation by exploiting the exogenous variation in the propensity to withdraw deposits generated by the information treatments. After being presented with the information treatments, survey participants were asked how they would allocate a $10,000 windfall across deposits, cash, bonds, stock, gold, and crypto assets. We focus on a potential windfall because actual portfolios tend to adjust only gradually to new information (Giglio et al. 2021). To understand whether concerns about deposit safety influence portfolios, we regress the windfall share, $\mathrm{port}_{i,a}^{win}$, allocated to asset class a by survey respondent i on her post-treatment propensity to run, run_i^{post}:

$$\mathrm{port}_{i,a}^{win} = \alpha_a + \beta_a \, \mathrm{run}_i^{post} + \gamma_a \, \mathrm{run}_i^{pre} + \delta_a \, \mathrm{port}_{i,a}^{pre} + \xi_a X_i + \varepsilon_{i,a} \tag{4}$$

The regression also controls for the pre-treatment propensity to run, run_i^{pre}, the initial pre-treatment portfolio allocation, $\mathrm{port}_{i,a}^{pre}$, and our usual set of individual controls X_i.

To identify the causal effects of deposit risk on portfolio allocation, we instrument the post-treatment propensity to run with the information treatments by estimating this first-stage regression specification:

$$\mathrm{run}_i^{\mathrm{post}} = \alpha_a + \sum_j \beta_{j,a} \mathbb{I}\left(i \in \mathrm{Treat}_j\right) + \gamma_a \mathrm{run}_i^{\mathrm{pre}} + \delta_a \mathrm{port}_{i,a}^{\mathrm{pre}} + \xi_a X_i + \varepsilon_{i,a} \tag{5}$$

By doing so, we exploit the exogenous variation in the propensity to run triggered by the information treatment. This is a critical step of the analysis because the relationship between the respondents' propensity to run and their preferred portfolio allocation could otherwise be driven by omitted factors.

Table 9 reports the regression estimates for equation (4). The *F*-statistics of the first-stage regressions indicate that the instruments are weak. Therefore, we estimate the equation with the continuously updated (CUE) GMM estimator and provide confidence intervals (in square brackets) and *p*-values (in the last row of the table) that are robust to weak instruments (Stock, Wright and Yogo 2002). The results are consistent with the earlier findings based on respondents' answers to the hypothetical risk of their bank failing. Namely, heightened concerns about deposits prompt people to reduce their portfolio share invested in bank deposits (column 1) and increase cash holdings (column 2).[10] We still find no evidence that people would tilt their portfolio towards cryptocurrencies in response to heightened concerns about deposits.

Regarding the magnitudes of the deposit outflows, our estimates imply that the collapse of SVB—which generates an increase in uninformed people's propensity to run by 0.32 points (Table 6)—would trigger a drop in the marginal willingness to hold deposits of about 2.5 percentage points. The latter applies to total deposits across all banks, so deposits in the main bank could fall by significantly more if households reallocate some of those deposits to other banks, as found in Table 7. Our estimates are remarkably close to actual deposit outflows from the U.S. banking sector observed in the immediate aftermath of the SVB collapse. Considering that only about a third of our survey participants knew about SVB (Table 3), our results imply deposit outflows equal to about 0.8 percent. In comparison, weekly data on U.S. commercial banks' deposits recorded a decline of 0.7 percent in the days following SVB's collapse.[11]

[10] Note that the survey questionnaire asked people how they would allocate a $10,000 windfall across financial asset classes, without providing the options to invest these funds in real estate or repay debt as was done instead in the hypothetical scenario about the risk of bank failure. Hence, compared to Table 8, the results in Table 9 suggest that if people are not provided with real estate investment and debt repayment options, they tend to further increase cash holdings, broadly offsetting the reduction in deposits.
[11] Deposits declined from 17,563 billion on March 8 to 17,440 billion on March 15, 2023.

4.3 Effects on durable goods purchases

Portfolio rebalancing effects need not be the only channel through which bank risk affects household decision-making. The fact that overall deposit drawdowns are broadly matched by an increase in cash holdings, for example, suggests that deposit risk generates strong precautionary motives. To further explore this aspect, we examine the implications of deposit risk for purchases of durable goods. In principle, deposit risk has ambiguous effects on the purchase of durable goods. Households may react to concerns about the safety of their deposits by opting to invest their savings in durable items, such as real estate or a new car. Alternatively, they may associate deposit risk with a deterioration of the economic outlook, calling for restraining consumer spending.

To shed light on these competing hypotheses, the survey questionnaire asked participants whether it was a good time to buy a car, major household items, or a house. These questions were asked after the information treatments, so we can examine whether the exogenous variation in the respondents' propensity to run triggered by the treatments influences their consumption plans, which help predict actual consumer spending (e.g., Carroll, Fuhrer, and Wilcox 1994). To this end, for each good category g, we construct a binary variable, $\mathrm{buy}_{i,g}^{post}$, taking value 1 for respondents that declare it is a good time to buy and value 0 for those who are not sure or think it is not a good time to buy. We then regress this variable over the pre- and post-treatment propensity to run:

$$\mathrm{buy}_{i,g}^{post} = \alpha_g + \beta_g\, \mathrm{run}_{i,g}^{post} + \gamma_g\, \mathrm{run}_i^{pre} + \xi_g X_i + \varepsilon_{i,g} \tag{6}$$

We instrument the post-treatment propensity to run using the information treatments. The first-stage regression is given by:

$$\mathrm{run}_{i,g}^{post} = \alpha_g + \textstyle\sum_j \beta_{j,g} * \mathbb{I}\left(i \in \mathrm{Treat}_j\right) + \gamma_g\, \mathrm{run}_i^{pre} + \xi_g X_i + \varepsilon_{i,g} \tag{7}$$

Table 10 reports the regression estimates for equation (6) using the continuously updated GMM estimator and providing confidence intervals (in square brackets) and *p*-values (in the last row of the table) that are robust to weak instruments. The negative coefficient on the post-treatment propensity to run in column 1 shows that heightened concerns about deposit risk make households less inclined to buy new cars. The point estimates remain negative also in the case of major household items and house purchases, although they do not reach statistical significance. These results thus suggest that deposit risk tends to strengthen precautionary motives and deter spending on durables.

Quantitatively, however, this channel appears to be quite small. News about SVB may reduce people's propensity to buy cars by only 0.03 points on a 2-point scale, which suggests that even if bank risk leads to significant deposit withdrawals by households, the associated uncertainty and portfolio rebalancing by itself is unlikely to translate into large effects on spending.

5. Conclusion

In this paper, we have used information provision experiments in a household survey to study whether depositors increase their propensity to withdraw deposits when they learn about the collapse of an important financial institution. We find strong evidence that news about SVB's collapse makes households more willing to withdraw deposits from their bank, because they both see more risk of their bank failing and expect to receive less of their deposits back if their bank does fail. Through a combination of hypothetical questions and exogenous variation created by the information treatments, we show that the heightened banking risk associated with learning about the SVB failure leads households to primarily reallocate their deposits across new banks and increase cash holdings. We find no evidence that bank risk increases households' propensity to hold cryptocurrencies and very modest effects on durable goods spending..

These results speak to an important literature on bank runs and provide novel evidence on the potential size of deposit outflows and the degree of heterogeneity across individuals. Unlike prior work, our approach allows us to estimate directly how much deposits are likely to respond to changes in perceived bank risk, which can help discipline models of bank runs and guide banking supervision questions at a time in which bank runs have returned to the limelight. We also document extensive heterogeneity in these elasticities with some individuals being much more sensitive to bank risk in terms of withdrawing deposits than others. Because bank runs may take on a life of their own once they are started, more work should be done in understanding the extent to which a small group of highly sensitive depositors may, through their actions, spur less sensitive depositors to also begin withdrawing their deposits.

One potential limitation of our approach is that we are restricted to retail depositors with relatively small deposits, whereas recent bank runs have been driven more by corporate accounts and other large uninsured deposits. However, while we do uncover a lot of heterogeneous behavior across depositors, we generally do not find that large depositors behave differently than other individuals. Second, there is little evidence that corporate depositors behave all that differently from retail ones. Boyle et al. (2022), for example, find that the crisis-response of finance professionals in terms of deposits does not differ substantively from non-finance professionals. Thus, our results could apply quite generally to many types of deposits held in banks.

Importantly, our information treatments speak to the role of policy communication in response to bank runs. We find, for example, that because knowledge about FDIC insurance remains limited, providing more information about this insurance system can considerably reduce households' desire to withdraw deposits, by lowering the expected losses on deposits in case of bank failure. Communication from the Federal Reserve is also powerful when heard, reducing the propensity to withdraw deposits by making households less worried about the risk of their bank failing. These results suggest that communication about FDIC insurance and by respected policymakers that successfully reaches retail depositors could potentially offset many of the pressures on deposits that may arise during times of crisis. But reaching these retail depositors may be a challenge in era where they are already bombarded with information of all kinds.

Other challenges to successful policy responses can be seen in our results. One is the limited effect of communication from political leaders, whose message seems to resonate only with their electoral base. In a time of crisis, communication on a bipartisan basis may become increasingly important to ensure not just that all individuals hear the message of financial stability but they also believe in it. A second is the disconnect between those who are likely to engage in bank runs and those who are responsive to policy communication. Even though we find that policy communication on average offsets the increase in the propensity to run triggered by the SVB crisis, it appears to be different individuals who become more willing to run in a time of crisis and those who are appeased by policy communication. This is likely to significantly constrain the ability of policymakers to stop a bank run through the type of communication used so far, calling for further research on how to reassure those individuals that are more sensitive to bank risk.

References

Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert Van der Klaauw, and Basit Zafar. 2016. “The price is right: Updating inflation expectations in a randomized price information experiment.” *Review of Economics and Statistics*, 98(3): 503–523.

Barr, Michael S. (2023). “Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank,” Board of Governors of the Federal Reserve System. Available online.

Bartels, Larry, 2002. “Beyond the Running Tally: Partisan Bias in Political Perceptions,” *Political Behavior* 24: 117-150.

Blickle, Kristian S., Markus Brunnermeier and Stephan Luck, 2022. “Who Can Tell Which Banks Will Fail?” Federal Reserve Bank of New York Staff Report 1005-2022.

Brown, Martin, Benjamin Guin, and Stefan Morkoetter. 2020. “Deposit Withdrawals from Distressed Banks: Client Relationships Matter,” *Journal of Financial Stability*, 46: 100707.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia. 2017. “Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments.” *American Economic Journal: Macroeconomics*, 9(3): 1–35.

Calomiris, Charles W. and Matthew Jaremski. 2018. “Stealing Deposits: Deposit Insurance, Risk-Taking, and the Removal of Market Discipline in Early 20th-Century Bank,” *Journal of Finance*, 74(2); 711–754.

Calomiris, Charles W. and Joseph R. Mason. 1997. “Contagion and bank failures during the Great Depression: The June 1932 Chicago banking panic,” *American Economic Review*, 87 (5), 863–883.

Calomiris, Charles W. and Joseph R. Mason. 2003. “Fundamentals, Panics, and Bank Distress During the Depression,” *American Economic Review*, 93(5): 1615–1647.

Carroll, Christopher D., Jeffrey C. Fuhrer, and David W. Wilcox. 1994. “Does Consumer Sentiment Affect Household Spending? If So, Why?” *American Economic Review* 84(5): 1397-1408.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020. "Political Polarization and Expected Economic Outcomes," NBER Working Paper 28044.

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, Geoff Kenny, and Michael Weber. Forthcoming. “The Effect of Macroeconomic Uncertainty on Household Spending.” *American Economic Review*.

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Maarten van Rooij. 2023a. “How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial.” *American Economic Journal: Macroeconomics*, 15(3): 109–52.

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Michael Weber. Forthcoming. “Forward Guidance and Household Expectations.” *Journal of the European Economic Association*.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2021. "Fiscal Policy and Households' Inflation Expectations: Evidence from a Randomized Control Trial." NBER Working Paper 28485.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2022. "Monetary policy communications and their effects on household inflation expectations." *Journal of Political Economy*, 130(6): 1427–1716.

Coibion, Olivier, Yuriy Gorodnichenko, Edward S Knotek II, and Raphael Schoenle. 2023b. "Average inflation targeting and household expectations." *Journal of Political Economy Macroeconomics*, 1(2): 403–446.

de Quidt, Jonathan, Johannes Haushofer, and Christopher Roth. 2018. "Measuring and Bounding Experimenter Demand," *American Economic Review*, 108 (11), 3266–3302.

Davenport, Andrew M., and Kathleen M. McDill. 2006. "The depositor behind the discipline: A micro-level case study of Hamilton Bank," *Journal of Financial Services Research*, 30, 93–109.

Demirgüç-Kunt, Asli and Harry Huizinga. 2004. "Market discipline and deposit insurance," *Journal of Monetary Economics*, 51(2): 375–399.

Diamond, Douglas W. and P. Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 91(6): 401–419.

Friedman, Milton and Anna J Schwartz. 1963. "A monetary history of the United States, 1867–1960," Princeton, NJ: Princeton University Press.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021. "Five Facts about Beliefs and Portfolios," *American Economic Review* 111(5): 1481-1522.

Grigoli, Francesco and Damiano Sandri. 2023. "Public Debt and Household Inflation Expectations," *CEPR Discussion Paper 18010*.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart. 2023. "Designing information provision experiments," *Journal of Economic Literature*, 61(1): 3–40.

Iyer, Rajkamal, and Manju Puri. 2012. "Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks." *American Economic Review*, 102(4): 1414–45.

Iyer, Rajkamal, Manju Puri, and Nicholas Ryan. 2016. "A Tale of Two Runs: Depositor Responses to Bank Solvency Risk." *Journal of Finance*, 71(6): 2687–2726.

Kamdar, Rupal, and Walker Ray, 2020. Polarized Expectations, manuscript.

Kumar, Saten, Yuriy Gorodnichenko and Olivier Coibion. Forthcoming. "The Effect of Macroeconomic Uncertainty on Firm Decisions," *Econometrica*.

Levy-Yeyati, Eduardo, Maria Soledad Martinez Peria and Sergio L. Schmukler, 2010. "Depositor Behavior under Macroeconomic Risk: Evidence from Bank Runs in Emerging Economies," *Journal of Money, Credit and Banking* 42(4): 585-614.

Martin, Christopher, Manju Puri and Alexander Ufier. Forthcoming. "Deposit Inflows and Outflows in Failing Banks: The Role of Deposit Insurance, *Journal of Finance*.

Martinez Peria, Maria Soledad, and Sergio L. Schmukler, 2001, Do depositors punish banks for bad behavior? Market discipline, deposit insurance, and banking crises, *Journal of Finance*, 56 (3), 1029–1051.

Mei, Pierfrancesco and Stefanie Stantcheva, 2022. "Heterogeneous Spending and Saving Behavior: What can we learn from survey experiments?" Manuscript.

Rose, Jonathan (2023). "Understanding the Speed and Size of Bank Runs in Historical Comparison," *Economic Synopses*, No. 12, https://doi.org/10.20955/es.2023.12

Roth, Christopher, and Johannes Wohlfart, 2020. "How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?" *Review of Economics and Statistics*, 102(4): 731–48.

Saunders, Anthony, and Berry Wilson. 1996. "Contagious Bank Runs: Evidence from the 1929-1933 Period," *Journal of Financial Intermediation*, 5(4): 409–423.

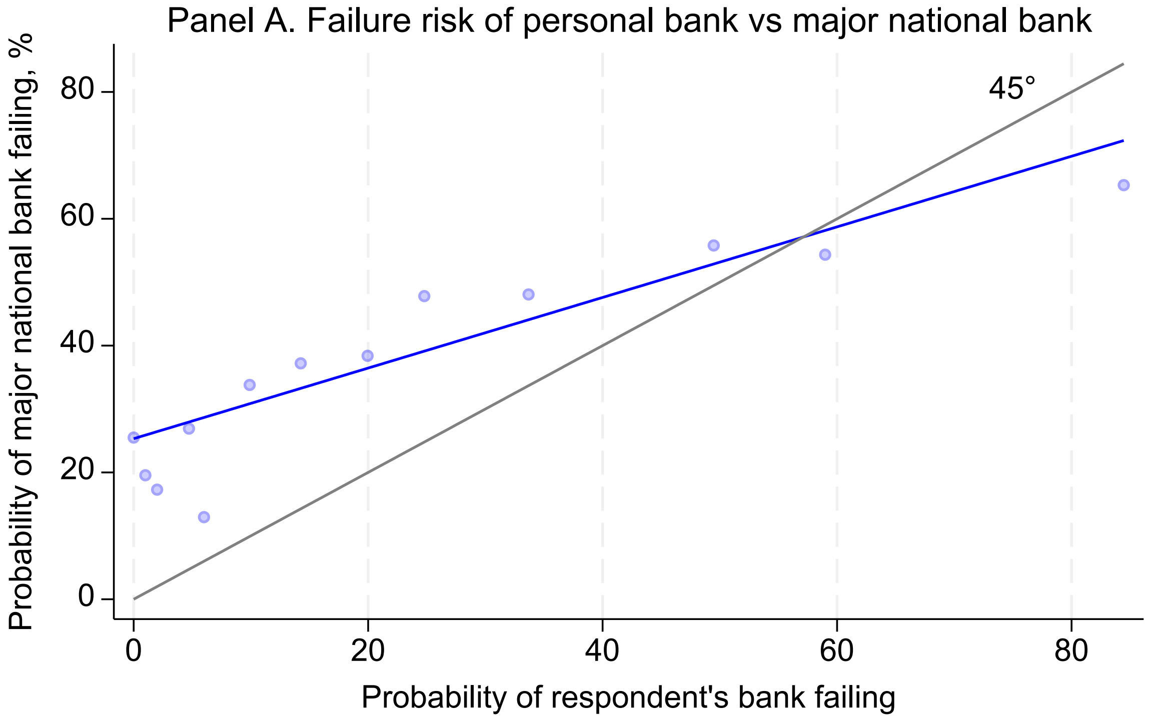
Stock, James, Jonathan Wright, Motohiro Yogo, 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business & Economic Statistics* 20(4): 518-529.

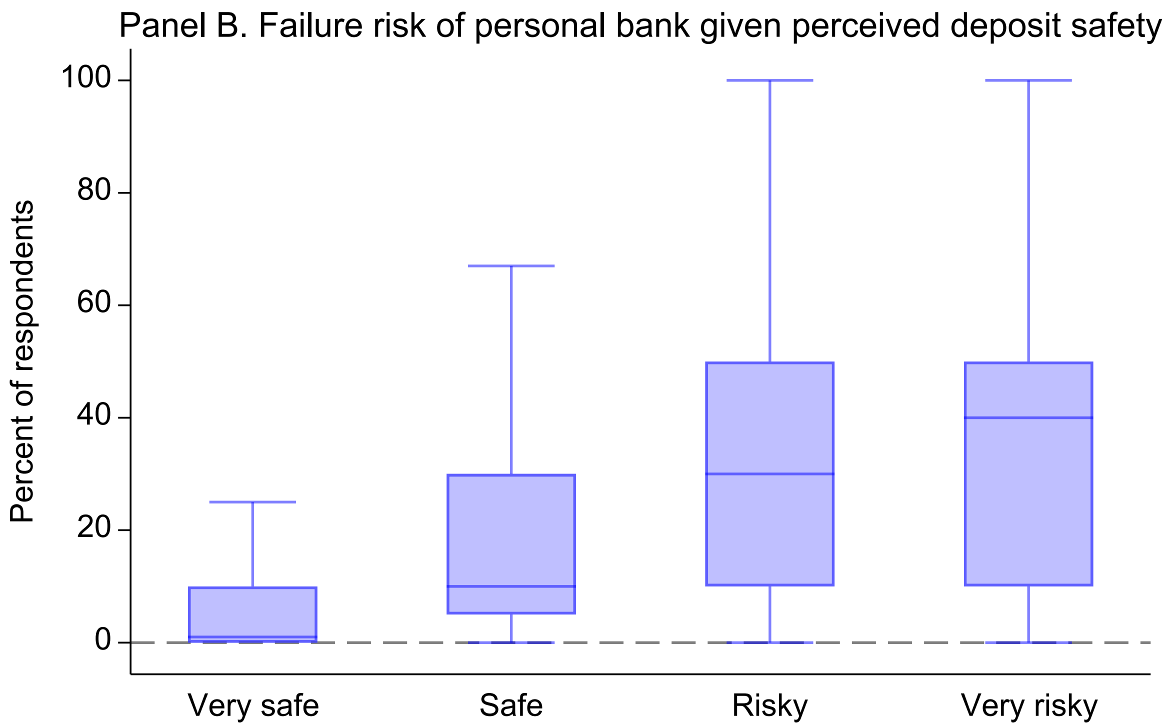
Weber, Michael, Bernando Candia, Olivier Coibion and Yuriy Gorodnichenko. 2023. "Do You Even Crypto, Bro? Cryptocurrencies in Household Finance," NBER Working Paper 31284.

White, Eugene N. 1984. "A Reinterpretation of the Banking Crisis of 1930," *Journal of Economic History*, 44(1): 119–38.

Wicker, Elmus. 1980. "A Reconsideration of the Causes of the Banking Panic of 1930," *Journal of Economic History*, 40(3): 571–83.

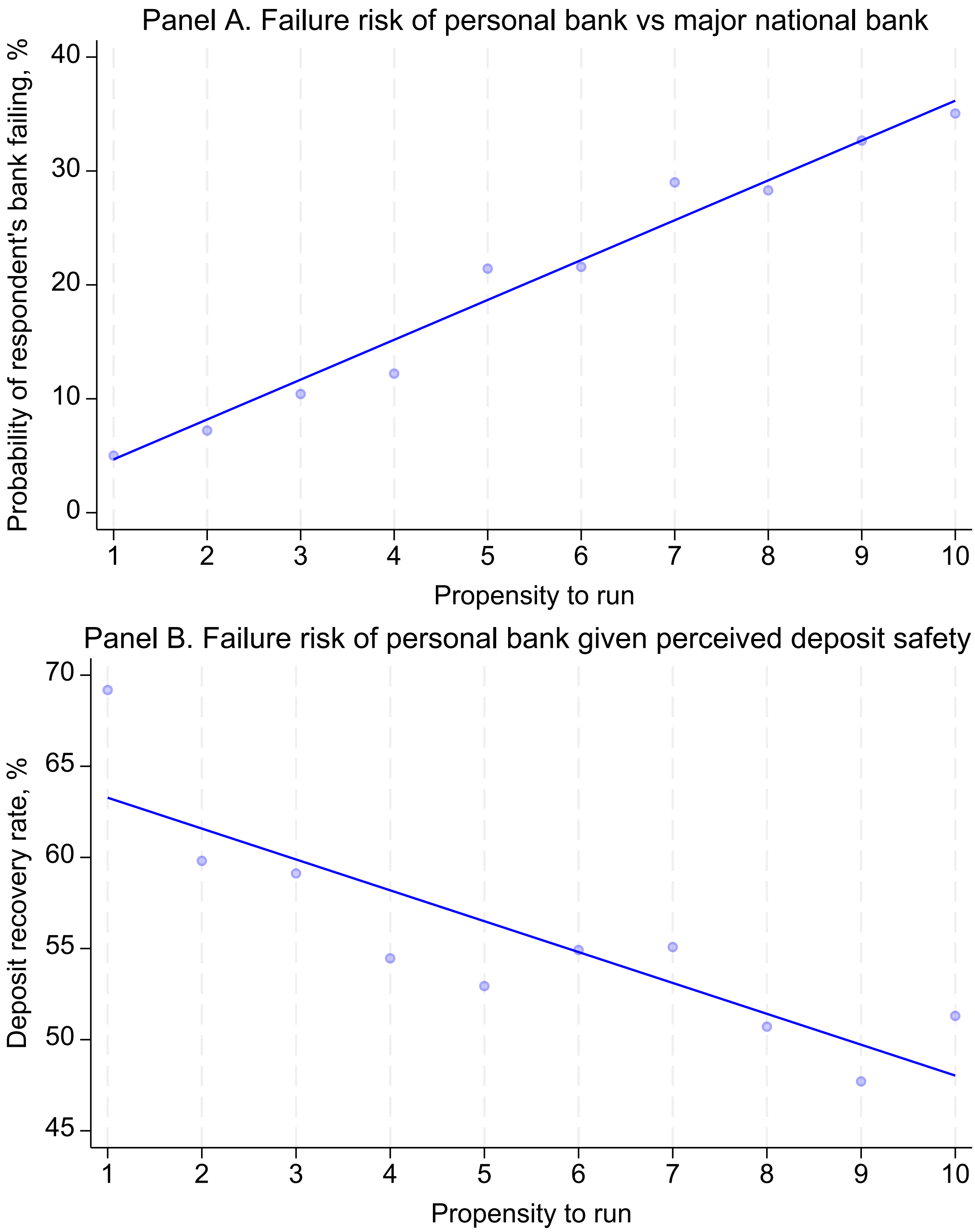
Figure 1. Perceived risk of bank failure





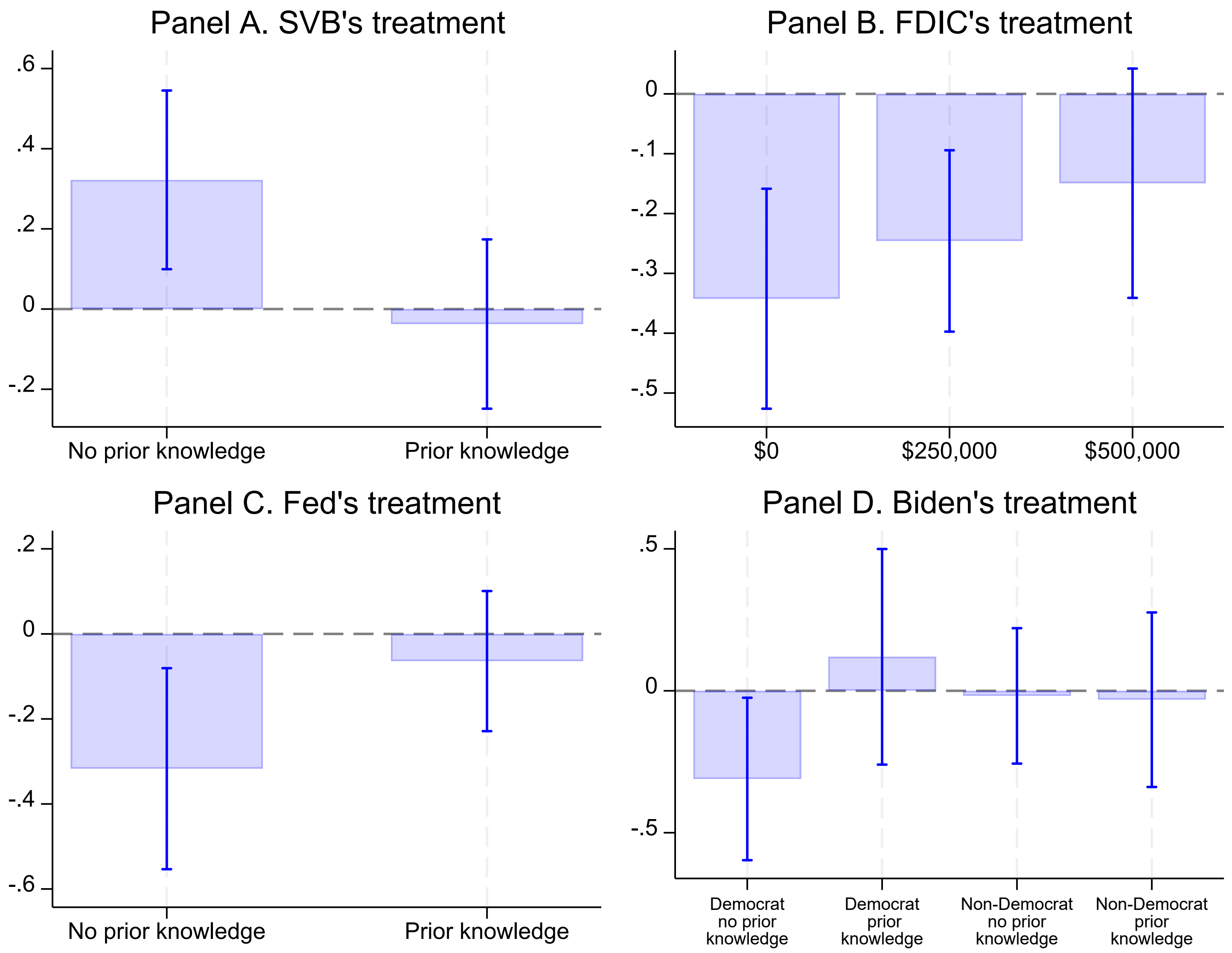
Notes: Panel A presents a binscatter for questions eliciting information about the safety of the banking system vs the respondent's bank. Panel B shows the distribution of subjective probabilities of personal bank failure across qualitative responses about the safety of the personal bank.

Figure 2. Propensity to run



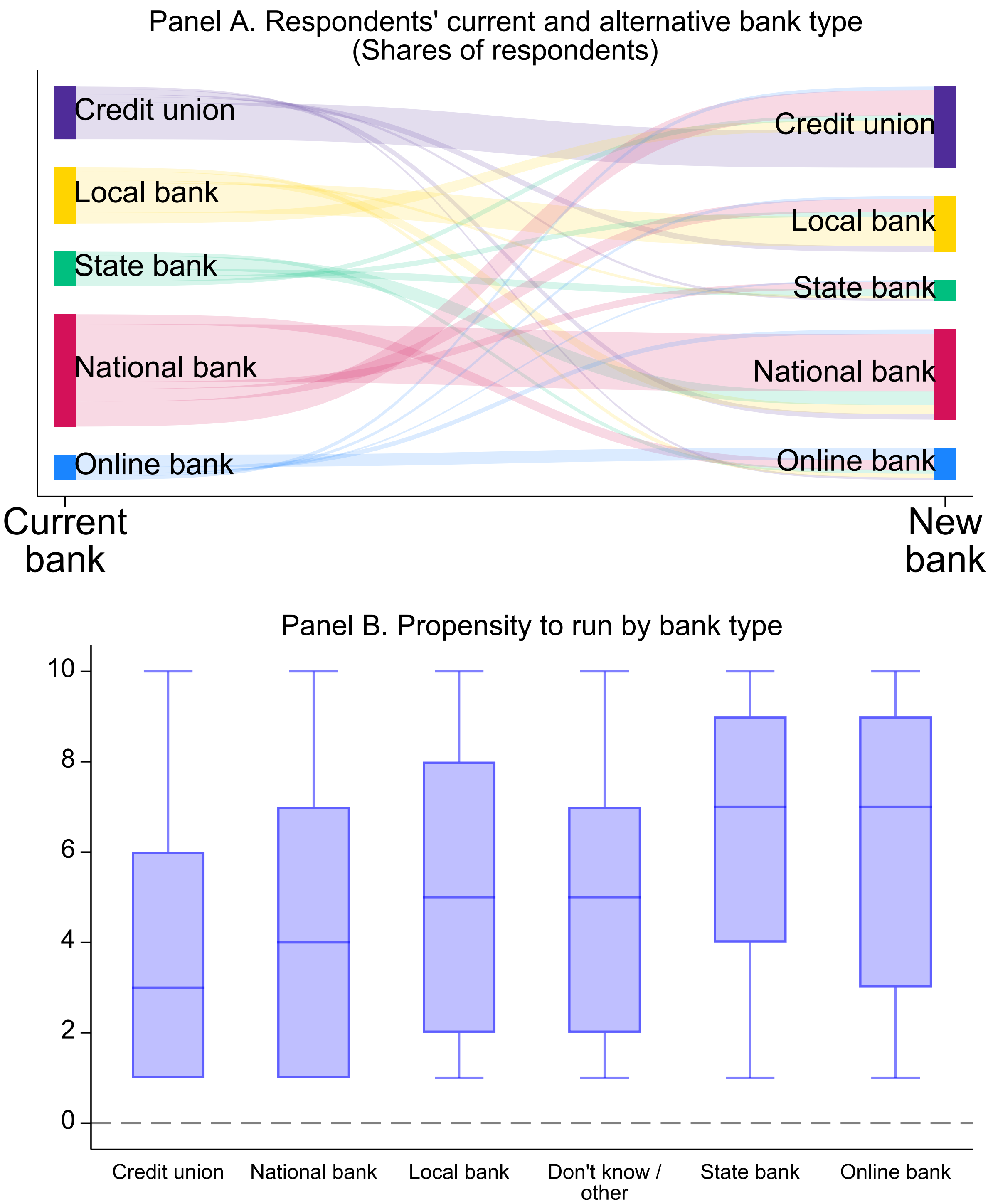
Notes: Panel A presents a binscatter for questions about the subjective estimate of propensity to run (1 [not at all likely] to 10 [extremely likely] scale) and the subjective probability of failure for the respondent's personal bank. Panel B presents a binscatter for questions about the subjective estimate of propensity to run (1 [not at all likely] to 10 [extremely likely] scale) and the subjective estimate of how much money (deposit) is going be recovered if the respondent's personal bank fails.

Figure 3. Treatment effects given prior knowledge and political orientation



Notes: The figure visualizes the treatment effects reported in Table 6. The bars show the point estimates. The whiskers show the 90 percent confidence intervals.

Figure 4. Bank types and depositors' risk perceptions



Notes: Panel A shows how respondents would reallocate their banking in response to a hypothetical change in the probability of their personal bank's failure. Panel B shows the distribution of propensity to tun (1 [not at all likely] to 10 [extremely likely] scale) by bank type.

Table 1. Respondents' financial information

	Percentage of respondents (or average values where indicated)				
	Full sample	Up to high school education	Post high school education	Deposits < $100k	Deposits > $100k
Bank deposits					
Number of banks with deposit accounts (average)	1.9	2.1	1.9	1.9	2.4
Number of years using current primary bank (average)	13.9	11.7	15.6	13.9	13.7
Typical deposit amount in primary bank					
< $10,000	50.4	52.3	49.0	55.2	-
$10,000 - $40,000	29.5	31.2	28.3	32.4	-
$40,000 - $100,000	11.3	10.4	12.0	12.4	-
$100,000 - $250,000	5.4	3.6	6.6	-	61.1
> 250,000	3.4	2.4	4.1	-	38.9
Primary bank type					
Credit Union	19.6	17.1	21.4	19.9	16.4
Local bank	20.8	24.7	17.9	21.3	16.3
State bank	10.0	12.8	7.9	9.8	12.5
National bank	35.6	28.4	40.9	35.2	38.0
Online bank	8.7	9.8	7.9	8.4	12.0
Other or don't know	5.3	7.2	4.0	5.4	4.7
Reason to use bank					
Convenient location	47.7	44.9	49.7	48.8	37.7
Customer service	36.2	33.3	38.3	36.5	34.5
Low account fees	37.1	30.2	42.1	37.8	31.5
Multiple banking services	31.3	30.0	32.3	30.9	37.2
Safer than other banks	25.2	24.5	25.7	25.1	24.3
Fraud and identity theft protection	22.0	22.1	21.9	21.3	26.5
Low ATM fees	22.9	20.4	24.7	22.8	24.5
Better interest rates	19.0	20.6	17.9	17.9	31.5
Wealth management services	8.6	9.3	8.1	7.2	23.1
Work well for my business	11.8	13.2	10.7	10.8	21.6
Other	7.9	5.8	9.4	8.4	3.2
Bank switching costs					
How easy to change bank?					
Easy or very easy	77.8	80.0	76.2	77.1	84.4
Difficult or very difficult	22.2	20.0	23.8	22.9	15.6
Interest rate differential to switch bank (average)	1.7	1.3	2.0	2.2	2.2
Portfolio allocation					
Respondents with investments in					
Stocks	42.6	32.2	50.2	40.0	70.8
Bonds	28.6	25.3	30.9	26.4	51.3
Gold/commodities	20.9	22.4	19.8	18.6	45.0
Cryptocurrencies	19.1	21.0	17.7	16.9	42.0
Portfolio shares (average)					
Bank deposits	65.0	72.3	59.8	67.1	43.2
Cash	8.8	8.7	8.9	8.3	14.4
Stocks	14.3	7.7	19.1	13.9	18.1
Bonds	5.2	4.1	6.0	4.9	8.8
Gold/commodities	3.2	3.3	3.1	2.8	6.8
Cryptocurrencies	3.4	3.9	3.1	2.9	8.7

Notes: Survey participants could select multiple reasons to use their bank. Hence, the sum of the percentages across answer categories exceeds 100. Since the question about the reasons to use banks was posed at the end of the survey, hence after the information treatments, the results are based considering only the control group to ensure that the results are not affected by the information treatments. Standard deviations for non-indicator variables are reported in Appendix Table 2.

Table 2. Pre-treatment risk perceptions

	Percentage of respondents (or average values where indicated)				
	Full sample	Up to high school education	Post high school education	Deposits < $100k	Deposits > $100k
Risk perceptions about personal bank					
Perceived safety of personal deposits					
Very safe or safe	84.7	80.5	87.7	84.7	84.4
Risky or very risky	15.3	19.5	12.3	15.3	15.6
Change in bank risk perceptions in recent months					
No change	59.4	52.6	64.4	61.4	37.2
Safer than before	19.1	26.1	13.9	17.7	34.5
Less safe than before	21.5	21.3	21.7	20.9	28.3
Probability of personal bank failing within a year (average)	17.6	20.9	15.2	17.0	24.6
Propensity to withdraw deposits because of bank risk (average)	4.7	5.4	4.1	4.6	6.0
Expected recovery share on deposits if bank fails (average)	55.0	53.6	56.3	55.1	54.1
Risk perceptions about the U.S. banking sector					
Perceived safety of deposits in U.S. banks					
Very safe or safe	77.6	76.4	78.4	77.5	77.6
Risky or very risky	22.4	23.6	21.6	22.5	22.4
Probability of major national bank failing within a year (average)	35.1	32.8	36.8	35.1	35.1
Sources of bank risk					
General financial crisis	36.4	33.8	38.2	36.8	31.3
Recession	36.7	37.1	36.4	37.6	27.3
Bad investments	32.8	28.7	35.7	33.0	29.2
Sudden decline in the value of bank assets	31.3	27.0	34.3	31.1	32.6
Too many customers asking for their money back	28.4	26.6	29.7	28.2	30.6
Bad loans	25.9	25.3	26.4	25.7	27.7
Fed raising interest rates	23.3	23.0	23.6	23.7	19.9
Lack of credit from the Fed	15.3	16.6	14.4	14.9	20.3
Lack of credit from other financial institutions	10.8	13.6	8.7	10.3	16.2

Notes: Survey participants could select up to 3 sources of bank risk. Hence, the sum of the percentages across answer categories exceeds 100. Standard deviations for non-indicator variables are reported in Appendix Table 2.

Table 3. Prior knowledge of the information treatments

	Percentage of respondents		Percentage of respondents
SVB's acronym		**FDIC standard deposit insurance**	
A private bank	35.2	< $250,000	25.2
Other options	18.4	$250,000	23.3
I don't know	46.4	>$250,000	2.0
		I don't know	49.5
Fed's assessment of U.S. banks		**President Biden's assessment of U.S. banks**	
Banks are sound	22.1	Banks are safe	29.3
Too early to say	11.3	Too early to say	8.2
Banks are at a critical juncture	13.4	Banks are at a critical juncture	13.2
I don't know	53.2	I don't know	49.3

Table 4. Bank and deposit risk perceptions across individuals

	Personal bank				Banking system	
	Propensity to run	Deposit risk	Bank risk	Expected loss	Deposit risk	Bank risk
	(1)	(2)	(3)	(4)	(5)	(6)
Years with account	-0.83***	-0.08***	-4.42***	-0.51	-0.02	1.69
	(0.11)	(0.03)	(0.79)	(2.42)	(0.03)	(1.12)
Female	-0.13	0.01	0.15	2.28	0.05*	-0.83
	(0.09)	(0.03)	(0.72)	(2.13)	(0.03)	(0.94)
Age	-0.06***	-0.01***	-0.26***	-0.53***	-0.00	0.08**
	(0.00)	(0.00)	(0.03)	(0.09)	(0.00)	(0.04)
Post high-school education	-0.60***	-0.04	-2.43***	-2.66	0.06*	3.25***
	(0.11)	(0.03)	(0.85)	(2.48)	(0.03)	(1.13)
Income above 80k	-0.19**	-0.07***	-1.02	-2.71	-0.13***	-0.94
	(0.09)	(0.03)	(0.72)	(2.12)	(0.03)	(1.01)
Deposits above 100k	1.25***	0.02	7.68***	4.72	-0.02	3.06**
	(0.15)	(0.04)	(1.27)	(3.42)	(0.05)	(1.53)
Democrat	0.09	-0.09***	1.80**	0.52	-0.19***	-4.86***
	(0.10)	(0.03)	(0.83)	(2.50)	(0.03)	(1.09)
Republican	0.33***	-0.02	2.07**	3.31	-0.00	1.06
	(0.11)	(0.03)	(0.87)	(2.65)	(0.03)	(1.22)
Observations	5,078	5,080	5,071	1,676	5,077	5,068
R^2	0.24	0.07	0.10	0.10	0.04	0.03

Notes: All regressions use sampling weights and include controls for employment status, geographical area, day fixed effects, and a constant. The regressions in columns (4) uses only survey participants in the control group since it is based on a question that was asked after the provision of the information treatments. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 5. Average treatment effects

	Change in propensity to run	Change in perceived bank risk		Expected loss (percent) if the bank fails	1= Expected loss if the bank fails
	Full sample	Full sample	Post high school education	Full sample	Full sample
	(1)	(2)	(3)	(4)	(5)
T = SVB	0.17**	0.82	2.29***	3.33*	0.04**
	(0.08)	(0.81)	(0.88)	(1.70)	(0.02)
T = FDIC	-0.15*	0.07	0.07	-2.12	-0.04**
	(0.08)	(0.84)	(0.90)	(1.65)	(0.02)
T = Fed	-0.17**	-1.49*	-2.36***	2.22	0.01
	(0.08)	(0.87)	(0.91)	(1.68)	(0.02)
T = Biden	0.09	-0.08	-0.33	-0.55	0.01
	(0.08)	(0.81)	(0.91)	(1.63)	(0.02)
Estimation	OLS	OLS	OLS	OLS	Probit
Observations	5,617	5,601	3,791	5,615	5,609
R^2	0.01	0.02	0.02	0.10	

Notes: All regressions use sampling weights and include controls for age, age squared, gender, education, income, employment status, political affiliation, geographical area, and day fixed effects. Column (5) reports the marginal effects of a probit model where the dependent variable is a dummy that takes value of 1 to denote respondents that expect to suffer losses on their deposits if their bank fails. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 6. Treatment effects given prior knowledge and political affiliation

	Change in propensity to run		
	(1)	(2)	(3)
T = SVB	0.17**	0.32**	0.32**
	(0.08)	(0.14)	(0.14)
T = FDIC	-0.15*	-0.34***	-0.34***
	(0.08)	(0.11)	(0.11)
T = Fed	-0.17**	-0.31**	-0.32**
	(0.08)	(0.14)	(0.14)
T = Biden	0.09	-0.13	-0.31*
	(0.08)	(0.12)	(0.17)
T = SVB × prior knowledge SVB		-0.35**	-0.36**
		(0.18)	(0.18)
T = FDIC × prior beliefs FDIC insurance limits		0.04	0.04
		(0.03)	(0.03)
T = Fed × prior knowledge Fed		0.25	0.25
		(0.17)	(0.17)
T = Biden × prior knowledge Biden		0.15	0.43
		(0.18)	(0.29)
T = Biden × non-democrat			0.29
			(0.22)
T = Biden × prior knowledge Biden × non-democrat			-0.44
			(0.37)
Observations	5,617	2,931	2,931
R-squared	0.01	0.03	0.03

Notes: All regressions use sampling weights and include controls for age, age squared, gender, education, income, employment status, political affiliation, geographical area, day fixed effects, and a constant. The regressions in columns (2) and (3) also control for each treatment's knowledge indicators. Column (3) also includes a non-Democrat dummy. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 7. Deposit withdrawals given hypothetical bank failure risk

	Share of deposits withdrawn		1 = people withdrawing deposits	
	(1)	(2)	(3)	(4)
Bank failure probability (BFP)	0.47***	0.09	0.47***	0.18
	(0.04)	(0.15)	(0.05)	(0.18)
BFP × years with account		0.08		0.04
		(0.09)		(0.12)
BFP × female		-0.01		-0.21**
		(0.08)		(0.10)
BFP × (age/100)		0.48*		0.47
		(0.27)		(0.34)
BFP × post high-school education		0.33***		0.46***
		(0.09)		(0.10)
BFP × income above 80k		-0.20**		-0.32***
		(0.08)		(0.10)
BFP × deposits above 100k		0.17		0.17
		(0.12)		(0.17)
BFP × democrat		-0.10		-0.00
		(0.08)		(0.10)
BFP × crypto investors		0.08		0.05
		(0.10)		(0.13)
Observations	5,061	5,061	5,061	5,061
R-squared	0.05	0.07		
Estimation	OLS	OLS	Probit	Probit

Notes: The regressions in columns (1) and (2) are estimated with OLS where the dependent variable is the share of deposits (in percent) a respondent would withdraw in response to a provided hypothetical probability of bank failure. The regressions in columns (3) and (4) are estimated with a probit model where the dependent variable takes value one if the respondent declares that she would withdraw some or all her deposits and zero if she would not withdraw any funds;the reported coefficients are the marginal effects multiplied by 100. All regressions use sampling weights and include controls for age, age squared, gender, education, income, employment status, political affiliation, geographical area, day fixed effects, and a constant. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 8. Portfolio re-allocation given hypothetical bank failure risk

VARIABLES	Deposits			Other assets						
	Total deposits	Primary bank	Other bank	Cash	Bonds	Stocks	Gold	Crypto	Real estate	Debt repaym.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bank failure probability (BFP)	-0.31***	-0.47***	0.15***	0.20***	0.01*	0.02**	0.01*	0.01	0.03***	0.05***
	(0.04)	(0.04)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control for actual portfolio share	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	No
Observations	5,053	5,061	5,061	5,053	5,053	5,053	5,053	5,053	5,061	5,061
R-squared	0.05	0.05	0.04	0.09	0.11	0.09	0.09	0.14	0.05	0.02

Notes: All regressions use sampling weights and include controls for years with bank account, age, gender, education, income, employment status, political affiliation, geographical area, and day fixed effects, and a constant. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 9. Portfolio reallocation triggered by deposit risk

	Deposits	Cash	Bonds	Stocks	Gold	Crypto
	(1)	(2)	(3)	(4)	(5)	(6)
Post-T propensity to run	-7.82**	7.75**	2.41*	0.30	-2.39	-1.74
	(3.83)	(3.79)	(1.38)	(1.91)	(1.96)	(1.18)
	[-16.33,-0.98]	[1.27,15.95]	[0.02, 5.52]	[-4.01, 4.84]	[-6.54, 0.92]	[-4.37, 0.30]
Observations	5,565	5,565	5,565	5,565	5,565	5,565
1st stage F-stat	6.352	6.383	6.388	6.653	6.139	6.431
p-value (weak IV robust)	0.061	0.050	0.098	0.903	0.234	0.160

Notes: The regressions are estimated using CUE GMM. The post-treatment propensity to run is instrumented with the information treatments. The 90 percent confidence interval robust to weak IV is reported in square brackets. p-value (weak IV robust) is the p-value for the coefficient on the endogenous variable robust to weak IV. Inference robust to weak IV is based on conditional likelihood estimation. All regressions use sampling weights and include controls for age, age squared, gender, education, income, employment status, political affiliation, geographical area, and day fixed effects, and a constant. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Table 10. Changes in durable purchases triggered by deposit risk

	Car	Major household appliance	House
	(1)	(2)	(3)
Post-T propensity to run	-0.096*	-0.059	-0.064
	(0.051)	(0.053)	(0.048)
	[-0.208, -0.015]	[-0.172, 0.035]	[-0.168, 0.017]
Observations	5,599	5,597	5,598
1st stage F-stat	6.632	6.566	6.591
p-value (weak IV robust)	0.050	0.299	0.197

Notes: The regressions are estimated using CUE GMM. The dependent variable takes value 1 if respondents declare that this is a good time to buy and zero otherwise. Post-treatment propensity to run is instrumented with the information treatments. All regressions use sampling weights and include controls for age, age squared, gender, education, income, employment status, political affiliation, geographical area, and day fixed effects. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Appendix A. Survey questionnaire

Question to ensure that survey participants have at least one bank account

1. How many banks do you have checking or savings accounts in? Please type in a number
   - _____

Perceptions of bank risk and propensity to withdraw deposits

2. How safe do you think it is to deposit money into your bank?
   - *4-point scale from "Very risky" to "Very safe"*

3. How safe do you think it is to deposit money into American banks in general?
   - *4-point scale from "Very risky" to "Very safe"*

4. If you had to put a probability on the possibility of **your bank** failing in the next 12 months, what would that probability be?
   - _____ *%*

5. If you had to put a probability on the possibility **of at least one of the major national U.S. banks** failing in the next 12 months, what would that probability be?
   - _____ *%*

6. How likely are you to withdraw some of your deposits in the next 12 months because of concerns that your bank may fail?
   - *10-point scale from "Not at all Likely" to "Extremely likely"*

7. Has your perception of the financial stability of your bank changed in recent months?
   - *No*
   - *Yes, I think my bank is safer than before*
   - *Yes, I think my bank is less safe than before*

8. What do you think are the main sources of risk that could cause your bank to fail in the next few months? Please choose a maximum of 3. [Answer categories are randomized]
   - *Too many customers asking for their money back*
   - *Giving out too many bad loans*
   - *Lack of available credit from the Federal Reserve*
   - *Lack of available credit from other financial institutions*
   - *Sudden declines in the value of assets held by the bank*
   - *Bad investments by the bank*
   - *General financial crisis*
   - *Federal Reserve raising interest rates*
   - *Recession*

Financial position and portfolio allocation

9. When thinking about the combined amount that you keep in your checking and savings account in your primary bank in a typical month, is the amount:
    - *Usually less than $10,000*
    - *Usually between $10,000 and $20,000*
    - *Usually between $20,000 and $40,000*
    - *Usually between $40,000 and $100,000*
    - *Usually between $100,000 and $250,000*
    - *Usually between $250,000 and $500,000*
    - *Usually above $500,000*

10. Do you have financial investments beyond your checking and savings account?
    - *Yes*
    - *No*

11. [If Q10 is Yes] Please describe how your investment portfolio is broadly allocated across:
    - *Cash:* ______%
    - *Checking/savings:* ______%
    - *Stocks:* ______%
    - *Bonds:* ______%
    - *Gold/commodities* ______%
    - *Cryptocurrency* ______%

    Please type in numbers that add to 100

Bank switching costs

12. How easy do you think would it be for you to change banks?
    - *4-point scale from "Very difficult" to "Very easy"*

13. What interest rate do you currently earn on your bank deposits?
    - ______ *%*
    - *Not sure*

14. What interest rate should another bank pay for you to move your deposits there?
    - ______ *%*
    - *Not sure*

Hypothetical scenario – risk of bank failure

15. If you thought that there was a [randomize 1%, 5%, 10%, 15%, 20%, 25%, 50%] probability that your bank might fail in the next 3 months, how would you likely react?
    a. *I would not change anything in my banking decisions.*
    b. *I would take some of my money out of the bank but keep using my bank for regular banking activities.*

c. *I would take some of my money out of the bank and start using another bank for regular banking activities.*
d. *I would move all of my money to a new bank.*
e. *I would take all of my money out of the banking system.*

16. [If Q15 is b or c] What fraction of your money do you think you would take out of your current bank?
    - _____ *%*

17. [If Q15 is b-d] If you were to move your money to a new bank, what would your new bank most likely be? [Answer categories are randomized]
    - *A local bank*
    - *A statewide bank*
    - *A national bank*
    - *A credit union*
    - *An online bank*
    - *Other*

18. [If Q15 is b-e] How would you allocate the money you take out of your bank across the following categories:
    - *cash:* _____*%*
    - *other banks:* _____*%*
    - *real estate:* _____*%*
    - *stocks:* _____*%*
    - *bonds:* _____*%*
    - *gold:* _____*%*
    - *cryptocurrency:* _____*%*
    - *paying off debt:* _____*%*

    Please type in numbers that add to 100

Prior beliefs about the information treatments[12]

19. What dollar amount of individually owned bank deposits at a bank do you think is insured, if any, by the Federal government?
    - _____
    - *Not sure*

20. In recent weeks, there has been talk in the media about developments at SVB. Do you know what is SVB? [Answer categories are randomized]
    - *A government agency*
    - *A private bank*
    - *An investment platform for Bitcoins*

[12] The order of these questions varies slightly across treatment groups to ensure that people are asked about their knowledge of the information treatment they are presented with right before the information is provided. For example, the question assessing people's knowledge about SVB is move last people in this section for people that are treated with information about SVB.

- *A hedge fund*
- *A pension fund*
- *I don't know.*

21. Do you know if President Biden has expressed a position on the safety of the U.S. banking sector in recent weeks?
    - *No, I don't know.*
    - *Yes, he said that the banking sector is at a critical juncture.*
    - *Yes, he said that it is too early to assess the soundness of the banking sector.*
    - *Yes, he said that the banking sector is safe.*

22. Do you know if the Federal Reserve (Fed) has expressed a position on the safety of the U.S. banking sector in recent weeks?
    - *No, I don't know.*
    - *Yes, the Fed said that the banking sector is at a critical juncture.*
    - *Yes, the Fed said that it is too early to assess the soundness of the banking sector.*
    - *Yes, the Fed said that the banking sector is sound.*

Information treatments

A. Considering that a few weeks ago, Silicon Valley Bank (SVB), a U.S.$200bn bank, failed after experiencing a sudden bank run, …
B. The FDIC (Federal Deposit Insurance Corporation) is an independent agency of the United States government that protects bank depositors if a bank fails. Considering that the FDIC insures individually owned deposits up to $250,000, …
C. Considering that a few weeks ago, President Biden declared that "Americans can have confidence that the banking system is safe," …
D. Considering that a few weeks ago, the Federal Reserve (Fed) declared that "the U.S. banking system is sound and resilient," …

… We would like to ask you again about your perceptions that your bank may fail and your propensity to take out your bank deposits.

Post-treatment risk perceptions and propensity to withdraw deposits

23. If you had to put a probability on the possibility of your bank failing by the end of the year, what would that probability be?
    - _____ *%*

24. How likely are you to withdraw some of your bank deposits by the end of the year because of concerns that your bank may fail?
    - *10-point scale from "Not likely at all" to "Extremely Likely"*

Perceptions about deposit recovery rates if bank fails

25. If your bank were to fail, what do you think would happen to the money you keep in your checking and/or savings account?

a. I would lose all the money
b. I would get some of the money back
c. I would get all the money back

26. [if Q25 is b] Approximately what fraction of your money would you expect to recover if your bank failed?
    - _____ *%*

Hypothetical scenario – lottery win

27. If you unexpectedly received $10,000, how would you allocate it across the following forms:
    - _____ *Cash*
    - _____ *Checking/saving*
    - _____ *Stocks*
    - _____ *Bonds*
    - _____ *Gold*
    - _____ *Cryptocurrency*

    Please type in numbers that add to 100

Background banking information

28. Is your primary bank a: [Answer categories are randomized]
    - *Local bank*
    - *State bank*
    - *National bank*
    - *Credit union*
    - *Online bank*
    - *Other*
    - *Don't know*

29. Why do you choose to use your primary bank rather than other banks? Please select all that apply or rank [Answer categories are randomized]
    - *Low fees on checking or savings accounts*
    - *Low ATM fees*
    - *Convenient location*
    - *Better interest rates on savings account*
    - *They offer multiple banking services that I use*
    - *Wealth management services*
    - *It's safer than other banks*
    - *Customer service*
    - *Fraud and identity theft protection*
    - *They work well for my business*
    - *Other, please specify:* _____

30. How long have you used your primary bank? Please type in the number of years

- ______

Propensity to purchase durable goods

31. Do you think now is a good or bad time to buy a new vehicle (car, pickup, van or SUV)?
    - *Good*
    - *Bad*
    - *I don't know*

32. Do you think now is a good or bad time to buy major household items (furniture, appliances)?
    - *Good*
    - *Bad*
    - *I don't know*

33. Do you think now is a good or bad time to buy a house?
    - *Good*
    - *Bad*
    - *I don't know*

Political affiliation

34. Generally speaking, do you think of yourself as a…?
    - *Democrat*
    - *Republican*
    - *Independent*
    - *Other, please specify:* ______
    - *Not sure*

Appendix B. Additional figures and tables

Appendix Table 1. Predictability of assignment to treatment groups

	F-statistic	p-value
	(1)	(2)
SVB	0.487	0.996
FDIC	0.754	0.859
Fed	0.921	0.607
Biden	0.875	0.685

Notes: The table reports the F-statistic and associated p-value for the joint statistical significance of the regression coefficients in $\mathbb{I}(i \in Treat_j) = \alpha + \xi\, \boldsymbol{X}_i + \varepsilon_i$, where i and j denotes the survey respondent and treatment assignment, and $\boldsymbol{X}_i$ is a vector of individual characteristics including age, age squared, education, income, employment status, political affiliation, geographical area, and day fixed effects. All regressions use sampling weights.

Appendix Table 2. Respondents' financial information and pre-treatment risk perceptions, standard deviation

	Standard deviation				
	Full sample	Up to high school education	Post high school education	Deposits < $100k	Deposits > $100k
Bank deposits					
Number of banks with deposit accounts	2.7	3.6	1.9	2.8	1.8
Number of years using current primary bank	12.1	11.7	12.2	12.1	12.1
Bank switching costs					
Interest rate differential to switch bank	11.3	12.0	10.8	10.3	10.3
Portfolio allocation					
Portfolio shares					
Bank deposits	39.4	37.8	39.6	39.0	36.3
Cash	16.4	17.4	15.7	16.3	16.8
Stocks	23.8	15.9	27.2	24.0	21.5
Bonds	11.1	9.1	12.4	10.9	12.6
Gold/commodities	7.9	7.4	8.3	7.6	9.9
Cryptocurrencies	9.2	9.3	9.1	8.3	14.2
Risk perceptions about personal bank					
Probability of personal bank failing within a year	23.2	24.9	21.5	22.8	26.6
Propensity to withdraw deposits because of bank risk	3.2	3.2	3.1	3.2	3.4
Expected recovery share on deposits if bank fails	29.3	30.0	28.4	29.3	29.1
Risk perceptions about the U.S. banking sector					
Probability of major national bank failing within a year	30.6	29.1	31.6	30.6	30.6

Notes: The table reports standard deviations for non-indictor variables listed in Table 1.

Appendix Table 3. Average treatment effects for the change in the propensity to run by subsamples

	Treatment				Obs.	R^2
	SVB	FDIC	Fed	Biden		
	(1)	(2)	(3)	(4)	(5)	(6)
Women	0.25**	-0.17	-0.17	0.05	2964	0.02
	(0.12)	(0.13)	(0.12)	(0.12)		
Men	0.07	-0.14	-0.16	0.13	2653	0.02
	(0.11)	(0.10)	(0.11)	(0.10)		
47 years old or less	0.14	0.01	-0.13	0.17	2851	0.02
	(0.11)	(0.10)	(0.11)	(0.11)		
48 years old or more	0.18	-0.33**	-0.20	0.01	2766	0.02
	(0.12)	(0.13)	(0.12)	(0.12)		
High school or less	0.24	-0.20	-0.16	0.09	1820	0.02
	(0.15)	(0.14)	(0.16)	(0.15)		
More than high school	0.15*	-0.13	-0.16*	0.07	3797	0.02
	(0.09)	(0.09)	(0.09)	(0.09)		
Income less than $80K	0.19*	-0.14	-0.13	0.20*	3206	0.02
	(0.11)	(0.11)	(0.11)	(0.11)		
Income of $80K or more	0.15	-0.15	-0.22*	-0.06	1879	0.03
	(0.12)	(0.12)	(0.12)	(0.14)		
Deposits less than $100K	0.17**	-0.18**	-0.22**	0.07	5050	0.01
	(0.08)	(0.09)	(0.09)	(0.09)		
Deposits of $100K or more	0.13	0.29	0.43*	0.36**	542	0.12
	(0.28)	(0.24)	(0.23)	(0.17)		
National bank	0.48**	0.07	0.21	0.11	1084	0.03
	(0.19)	(0.18)	(0.21)	(0.19)		
Credit union	0.24*	-0.22	-0.33***	0.01	2086	0.03
	(0.13)	(0.15)	(0.12)	(0.14)		
Bank account for 10 years or less	0.28***	-0.02	-0.16	0.10	3150	0.02
	(0.10)	(0.10)	(0.10)	(0.10)		
Bank account for 11 years or more	0.03	-0.31**	-0.17	0.07	2467	0.02
	(0.12)	(0.13)	(0.13)	(0.12)		
Democrat	0.38***	-0.19	-0.23	0.09	2082	0.03
	(0.13)	(0.13)	(0.15)	(0.12)		
Republican	-0.18	-0.38***	-0.11	-0.05	1561	0.03
	(0.15)	(0.14)	(0.14)	(0.15)		
Independent	0.22*	0.02	-0.17	0.26*	1974	0.02
	(0.13)	(0.15)	(0.13)	(0.15)		
Own crypto currency	0.06	0.13	-0.09	-0.07	1123	0.06
	(0.15)	(0.17)	(0.14)	(0.14)		
No crypto currency	0.20**	-0.22**	-0.19**	0.13	4494	0.01
	(0.09)	(0.09)	(0.10)	(0.09)		

Notes: OLS estimates that correspond to column (1) in Table 5. Robust standard errors are in parentheses.
***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Appendix Table 4. Average treatment effects for the change in the perceived bank risk by subsamples

	Treatment				Obs.	R^2
	SVB	FDIC	Fed	Biden		
	(1)	(2)	(3)	(4)	(5)	(6)
Women	1.61	0.57	0.55	0.04	2958	0.02
	(1.21)	(1.18)	(1.16)	(1.20)		
Men	0.28	-0.34	-3.52***	-0.09	2643	0.03
	(1.08)	(1.17)	(1.31)	(1.07)		
47 years old or less	1.07	0.92	-0.35	0.26	2840	0.03
	(1.25)	(1.21)	(1.32)	(1.17)		
48 years old or more	0.67	-0.98	-2.62**	-0.59	2761	0.01
	(1.04)	(1.15)	(1.13)	(1.12)		
High school or less	-1.07	-0.11	-0.33	0.29	1810	0.03
	(1.47)	(1.55)	(1.66)	(1.46)		
More than high school	2.29**	0.07	-2.36**	-0.33	3791	0.02
	(0.88)	(0.90)	(0.91)	(0.91)		
Income less than $80K	0.30	-0.05	-1.78	-0.92	3197	0.02
	(1.11)	(1.18)	(1.26)	(1.05)		
Income of $80K or more	1.17	0.03	-1.82	-0.12	1876	0.04
	(1.36)	(1.31)	(1.35)	(1.37)		
Deposits less than $100K	1.02	0.08	-1.55*	-0.15	5039	0.02
	(0.84)	(0.88)	(0.92)	(0.85)		
Deposits of $100K or more	-1.42	-0.66	0.28	1.01	540	0.07
	(3.16)	(2.73)	(2.84)	(2.62)		
National bank	3.79*	1.85	-0.53	-0.82	1082	0.06
	(1.94)	(2.27)	(1.90)	(1.61)		
Credit union	2.21*	-0.17	-2.67*	0.14	2081	0.03
	(1.13)	(1.22)	(1.39)	(1.17)		
Bank account for 10 years or less	0.07	0.90	-1.95	-0.43	3145	0.02
	(1.14)	(1.08)	(1.26)	(1.12)		
Bank account for 11 years or more	1.67	-1.21	-1.15	-0.21	2456	0.03
	(1.13)	(1.29)	(1.15)	(1.15)		
Democrat	0.65	1.19	-2.74*	1.43	2079	0.03
	(1.27)	(1.46)	(1.65)	(1.39)		
Republican	-0.63	-1.59	-2.97*	-2.59*	1553	0.03
	(1.67)	(1.58)	(1.64)	(1.48)		
Independent	2.31*	0.36	0.86	-0.10	1969	0.03
	(1.30)	(1.32)	(1.14)	(1.30)		
Own crypto currency	-3.24	-0.28	-4.43**	-2.75	1123	0.05
	(2.19)	(2.35)	(1.98)	(2.13)		
No crypto currency	1.73**	0.17	-0.87	0.49	4478	0.02
	(0.87)	(0.88)	(0.99)	(0.86)		

Notes: OLS estimates that correspond to column (2) in Table 5. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Appendix Table 5. Average treatment effects for the expected loss (1 if a respondent expects to lose all money) if a bank fails by subsamples

	Treatment				Obs.
	SVB	FDIC	Fed	Biden	
	(1)	(2)	(3)	(4)	(5)
Women	0.07**	-0.05*	-0.01	-0.01	2960
	(0.03)	(0.03)	(0.03)	(0.03)	
Men	0.00	-0.03	0.02	0.02	2649
	(0.03)	(0.03)	(0.03)	(0.03)	
47 years old or less	0.02	-0.04	-0.00	0.03	2846
	(0.03)	(0.03)	(0.03)	(0.03)	
48 years old or more	0.04	-0.04	0.02	-0.01	2763
	(0.03)	(0.03)	(0.03)	(0.03)	
High school or less	0.08**	-0.03	-0.02	-0.02	1816
	(0.03)	(0.03)	(0.03)	(0.03)	
More than high school	0.02	-0.05**	0.02	0.03	3793
	(0.02)	(0.02)	(0.02)	(0.02)	
Income less than $80K	0.04*	-0.07**	-0.00	0.01	3199
	(0.03)	(0.03)	(0.03)	(0.03)	
Income of $80K or more	0.04	-0.00	0.01	0.02	1879
	(0.03)	(0.03)	(0.03)	(0.03)	
Deposits less than $100K	0.04**	-0.04**	0.01	0.01	5045
	(0.02)	(0.02)	(0.02)	(0.02)	
Deposits of $100K or more	-0.04	-0.05	-0.03	0.00	540
	(0.06)	(0.06)	(0.06)	(0.06)	
National bank	0.10**	0.04	0.02	-0.03	1082
	(0.04)	(0.04)	(0.04)	(0.04)	
Credit union	0.04	-0.05*	0.02	0.05*	2084
	(0.03)	(0.03)	(0.03)	(0.03)	
Bank account for 10 years or less	0.05*	-0.05**	-0.02	-0.00	3150
	(0.03)	(0.02)	(0.03)	(0.03)	
Bank account for 11 years or more	0.02	-0.03	0.03	0.02	2459
	(0.03)	(0.03)	(0.03)	(0.03)	
Democrat	0.06*	-0.03	0.03	0.03	2080
	(0.03)	(0.03)	(0.03)	(0.03)	
Republican	-0.02	-0.10***	-0.01	-0.01	1559
	(0.04)	(0.04)	(0.04)	(0.04)	
Independent	0.06*	-0.01	-0.02	-0.02	1970
	(0.03)	(0.03)	(0.03)	(0.03)	
Own crypto currency	0.00	-0.07*	-0.02	-0.00	1120
	(0.04)	(0.04)	(0.04)	(0.04)	
No crypto currency	0.05**	-0.03	0.01	0.01	4486
	(0.02)	(0.02)	(0.02)	(0.02)	

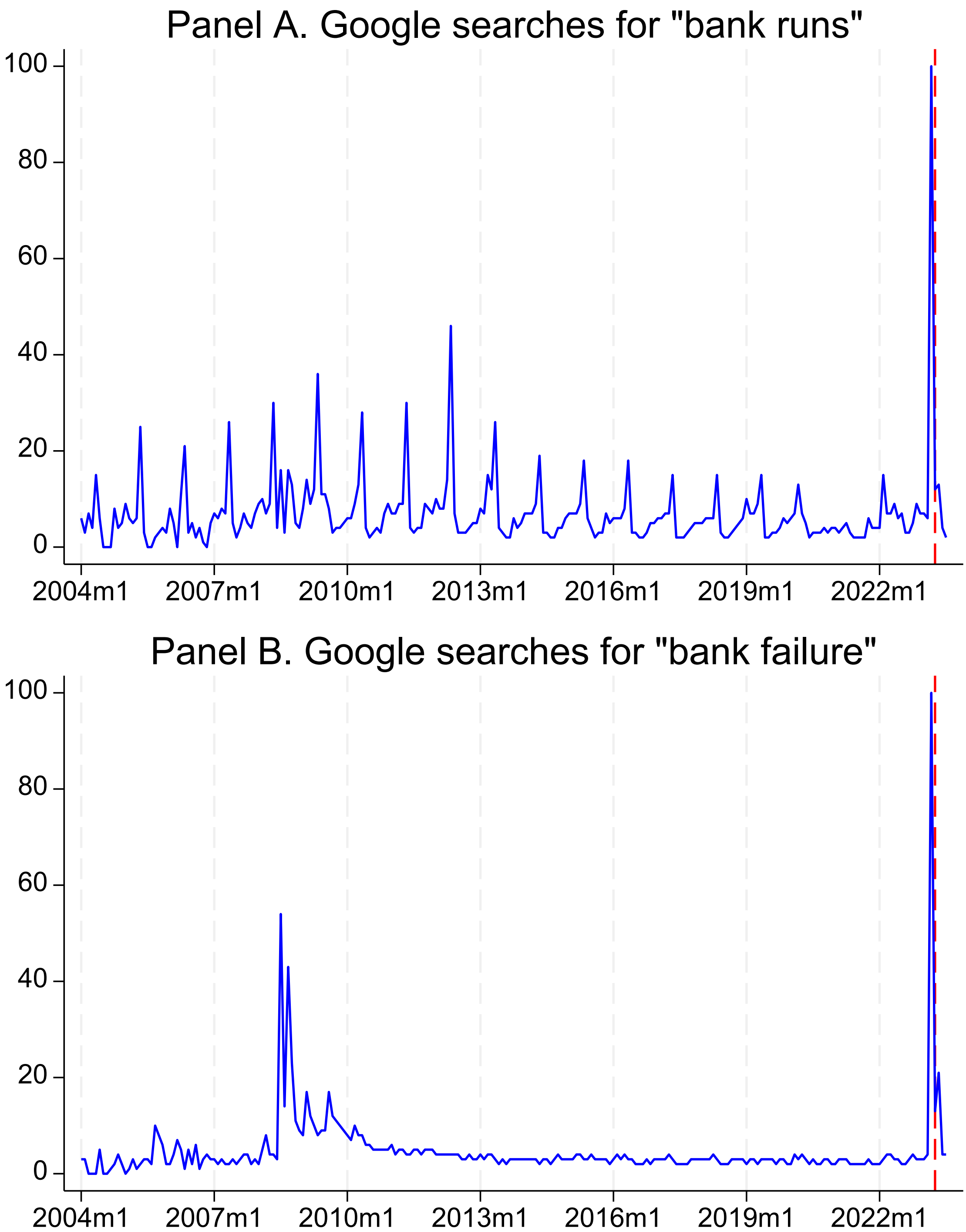
Notes: Marginal effects from probit estimates as in column (5) of Table 5. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Appendix Table 6. Average treatment effects for the expected loss (percent) if a bank fails by subsamples.

	Treatment				Obs.	R^2
	SVB	FDIC	Fed	Biden		
	(1)	(2)	(3)	(4)	(5)	(6)
Full sample	3.33*	-2.12	2.22	-0.55	5615	0.10
	(1.70)	(1.65)	(1.68)	(1.63)		
Women	3.81	-2.95	1.83	-2.11	2965	0.10
	(2.43)	(2.40)	(2.37)	(2.30)		
Men	1.88	-1.44	2.21	0.62	2650	0.13
	(2.36)	(2.21)	(2.35)	(2.28)		
47 years old or less	1.30	-2.76	3.80	-0.73	2850	0.05
	(2.51)	(2.42)	(2.42)	(2.43)		
48 years old or more	4.53**	-1.61	1.10	0.08	2765	0.08
	(2.27)	(2.20)	(2.25)	(2.12)		
High school or less	6.82**	-0.64	1.49	-1.78	1817	0.09
	(3.11)	(2.98)	(3.00)	(2.91)		
More than high school	0.79	-2.98	2.42	0.44	3798	0.10
	(1.86)	(1.84)	(1.91)	(1.85)		
Income less than $80K	4.81**	-3.93*	4.07*	2.05	3208	0.10
	(2.35)	(2.18)	(2.34)	(2.25)		
Income of $80K or more	1.10	1.17	0.47	-6.84***	1876	0.16
	(2.55)	(2.66)	(2.53)	(2.32)		
Deposits less than $100K	3.83**	-2.04	2.43	-0.02	5048	0.10
	(1.80)	(1.75)	(1.78)	(1.72)		
Deposits of $100K or more	-1.53	-2.78	-1.91	-7.88	543	0.19
	(5.39)	(4.67)	(4.78)	(4.88)		
National bank	10.78***	4.68	6.66*	1.80	1084	0.14
	(3.82)	(3.79)	(3.72)	(3.50)		
Credit union	3.03	-1.66	3.14	0.85	2085	0.11
	(2.56)	(2.65)	(2.64)	(2.50)		
Bank account for 10 years or less	4.10*	-1.75	3.01	0.73	3147	0.08
	(2.38)	(2.26)	(2.27)	(2.29)		
Bank account for 11 years or more	1.51	-3.27	0.35	-2.30	2468	0.10
	(2.38)	(2.37)	(2.45)	(2.29)		
Democrat	4.85*	-3.84	2.21	-1.26	2081	0.14
	(2.74)	(2.59)	(2.71)	(2.59)		
Republican	1.20	-4.54	3.62	0.08	1559	0.13
	(3.07)	(2.99)	(3.19)	(3.11)		
Independent	2.46	0.62	0.50	-1.20	1975	0.09
	(2.95)	(2.86)	(2.85)	(2.74)		
Own crypto currency	-0.96	-3.20	1.68	-1.11	1123	0.11
	(3.70)	(3.73)	(3.53)	(3.60)		
No crypto currency	4.42**	-1.68	1.64	-0.27	4492	0.09
	(1.90)	(1.81)	(1.87)	(1.79)		

Notes: OLS estimates that correspond to column (4) in Table 5. Robust standard errors are in parentheses. ***, **,* denote statistical significance at 1, 5, and 10 percent levels.

Appendix Figure 1. Public attention to banking sector's problems



Notes: The figures show time series for Google searches for specific word combinations. Numbers represent searches relative to the highest point on the chart, normalized to 100. The vertical red line denotes the time when the survey was conducted.