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**FROM THE SAVING GLUT TO
FINANCIAL INSTABILITY: EVIDENCE
FROM THE SILICON VALLEY BANK
FAILURE**

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Abstract

I show that saving gluts spur financial instability. In the US, banks locally exposed to its root causes -- the rise in household wealth inequality and higher savings by intangible-intensive firms -- massively increased deposits since 2000, leading to an unprecedented deposit-to-GDP ratio and to a large increase in uninsured deposits. To causally identify an impact of the saving glut on financial instability, I rely on the unexpected failure of Silicon Valley Bank in March 2023: other US banks with higher local exposure to either wealth inequality or intangible-intensive firms experienced significantly larger drops in stock prices.

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From the Saving Glut to Financial Instability: Evidence from the Silicon Valley Bank Failure*

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April 8, 2023

Abstract

I show that saving gluts spur financial instability. In the US, banks locally exposed to its root causes – the rise in household wealth inequality and higher savings by intangible-intensive firms – massively increased deposits since 2000, leading to an unprecedented deposit-to-GDP ratio and to a large increase in uninsured deposits. To causally identify an impact of the saving glut on financial instability, I rely on the unexpected failure of Silicon Valley Bank in March 2023: other US banks with higher local exposure to either wealth inequality or intangible-intensive firms experienced significantly larger drops in stock prices.

*This paper has been replicated by a third party. The replication report is available on the author's website.

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1 Introduction

The saving glut is arguably one of the leading traits of present-day economies. Over the past decades, global savings by households and firms have massively increased, due to three structural shifts: the rise of emerging economies with high saving rates and limited domestic investment opportunities, but also the growing share of wealth held by the richest households, and the shift to an economy based on intangible assets. The ensuing desire for “safe” stores of value has been shown to explain a wide range of facts, including low interest rates, global imbalances, high public debt levels or the capital structure of financial intermediaries (see [Caballero et al., 2017](#), for a survey).

A recurring hypothesis is that the saving glut also spurs financial instability. [Caballero and Krishnamurthy \(2006\)](#) argue that asset shortages have the potential to fuel bubbles, while [Stein \(2012\)](#) and [Li \(2022\)](#) both show that a large demand for safe assets leads to cheap debt and to potentially excessive leveraging by financial intermediaries. Empirically, while there is abundant evidence that markets can collapse when adverse selection appears in asset markets that were otherwise perceived as “safe” ([Gorton, 2017](#); [Pérignon et al., 2018](#)), direct evidence linking financial instability to the root causes of the saving glut remains tenuous. Most comes from the observation that asset markets that were shown to cater to safety demand – notably securitization – collapsed ([Gorton and Metrick, 2012](#)).

In this paper, I make three contributions. The first one is to directly link structural changes in the financial sector to root causes of the saving glut. Early papers focused mostly on the role of emerging economies (such as China) in the rise of global savings. While major, this force leaves little room for tight identification. This is because

savings across emerging economies are likely to be invested in financial securities traded worldwide, such as US Treasuries. Even though equilibrium prices may be largely affected, it is hard to tie them to specific demand forces in the global macroeconomy. For example, a number of papers have shown that US Treasury prices incorporate a “safety premium” (Krishnamurthy and Vissing-Jorgensen, 2012; Sunderam, 2015; Nagel, 2016), but no paper, to my knowledge, has been able to causally link this safety premium to the saving rate in emerging economies or to the accumulation of foreign exchange reserves by Asian central banks.

Instead, recent research shows that a sizeable part of the saving glut also originates from domestic causes within economies such as the US, notably from (i) the rise of household wealth inequality (Mian et al., 2021; Buluz et al., 2022) and from (ii) the boom of corporate savings, primarily by intangible-intensive firms (Chen et al., 2017; Falato et al., 2022). These additional causes of the saving glut open up novel possibilities for identification. Indeed, as opposed to foreign savings, domestic savings driven either by wealth inequality or by intangible-intensive firms are less likely to be invested almost exclusively through securities markets, are more likely to be channelled through the balance sheets of financial institutions, notably banks. If so, geographical variation in the wealth share or in the prevalence of intangible-intensive firms should generate differential exposure to the saving glut in the cross-section of banks. This variation can then be used to identify how changes in the structure of financial intermediation is related to root causes of the saving glut. This is the overarching idea on which I rely: I use several data sources to construct local measures of exposure to both wealth inequality and intangibles intensity. I then exploit this variation to study within-bank variation in deposits collected (across counties and states), and across-bank variation

in capital structure and instability.

The second contribution is to show that the root causes of the saving glut can explain important facts about the structure of the US sector. Starting with the aggregate banking system, I establish three stylized facts. First, since the early 2000s, the ratio of deposits to total liabilities and equity has increased dramatically, from around 55% to around 75% – during a period in which banking assets themselves grew much faster than the economy. Second, these differential growth rates translate into a booming ratio of deposits-to-GDP. While this ratio had been mostly fluctuating between 40 and 50% for several decades, it started to increase very fast around 2000, to reach a value above 75% in 2022. While much attention has been devoted to prices in securities markets, this facet of the saving glut may not have been fully appreciated so far. Third, this growth of total deposits is associated with a growth of uninsured deposits (i.e., above FDIC coverage), which have almost doubled as a share of banks' total liabilities and equity, from below 20% in the early 2000s to above 35% in 2022.

I then relate these facts to banks' exposures to state-level wealth inequality and to county-level intangible-intensive firms. To address the concern that different banks might have endogenously decided to get more or less exposure to specific local causes of the saving glut, I use two strategies. First, I rely on lagged measures of exposure, dating 20 years back, before wealth inequality and corporate intangibles gained the importance they currently have. Second, I estimate regressions with bank fixed effects, that is, I study variation of deposit growth between 2002 and 2022 across differentially exposed counties or states, but within the same bank. I confirm that bank branches in locations with greater exposure to wealth inequality or to corporate intangibles accumulated deposits at a significantly faster rate. At the bank level, I additionally

find that these exposures translate into higher ratios of uninsured deposits and of corporate deposits in 2022. These tests thus tie the stylized facts to the saving glut.

The third contribution is to show that higher exposure to the root causes of the saving glut leads to greater fragility of deposits, thus higher instability of banks. To do so, I exploit the collapse of Silicon Valley Bank (SVB) in March 2023. This bank failure – the second largest in US history so far – is itself related to the saving glut. SVB was relying to an almost exclusive extent on uninsured deposits (with a ratio of uninsured to total deposits of 93.9%), primarily from corporations (with a ratio of corporate money market deposit accounts to total deposits of 90.6%).

I use this event as a quasi-natural experiment to study the stock price reaction of *other* US banks. A remarkable feature of the SVB failure is that it was unexpected: in the days preceding SVB's collapse, its stock returns were statistically indistinguishable from those of other US banks. I start by showing that banks with an above-median ratio of uninsured deposits to total deposits lost an extra 3.0 percentage points in market value relative to banks below the median. This corresponds to a 25.6% larger price drop for banks above relative to banks below the median ratio of uninsured deposits.

I then investigate the role that each root cause of the saving glut plays in explaining this cross-sectional heterogeneity. I repeat the difference-in-differences estimation, comparing the stock returns of banks with above- or below-median exposure to either local wealth inequality or to local corporate intangibles. The most striking result is that heterogeneous exposures to corporate intangibles explain exactly as much heterogeneity in stock returns than the heterogeneity in uninsured deposits. This is a strong result: while uninsured deposits should be an immediate predictor of financial

fragility, the relation between financial fragility and exposure to corporate intangibles is less direct. This result confirms that the corporate saving glut plays a sizable role in explaining banks' deposit fragility, as predicted by [Li \(2022\)](#). Regarding heterogeneity in household wealth, I also find significant cross-section heterogeneity: banks operating in states where wealth is more concentrated lost an extra 2.3 percentage points in market capitalization, which corresponds to more than two-third of the variation created by the exposure to uninsured deposits. Thus, in addition to the corporate saving glut, the "saving glut of the rich" also contributes to explain banks' fragility.

Finally, I conclude by discussing theoretical and policy implications of these results. A key question is whether deposit insurance should be extended in the context of a saving glut. While the short-term financial stability benefits of an extension are clear, its distributive effects are less well understood. Wouldn't an extension of government-backed safety for wealthy household or corporate depositors come with large distributive effects, borne primarily by agents deprived of large-scale deposits? Another open question is whether insured deposits can credibly coexist with large uninsured deposits in the capital structure of the same intermediaries, or whether uninsured deposits create an ex post hold-up problem forcing governments to intervene and provide extra safety to formally uninsured agents.

Related literature

This paper contributes to two strands of the literature. First, to the growing body of work on the saving glut and the associated demand for safe assets, as surveyed by [Caballero et al. \(2017\)](#) and [Gorton \(2017\)](#). Inspired by [Bernanke \(2005\)](#), research

initially focused on the contribution of emerging economies to the saving glut, and on the resulting global imbalances (Caballero, 2006; Caballero et al., 2008). Recent papers also highlight domestic factors contributing to the saving glut. Mian et al. (2021) provide evidence of a “saving glut of the rich”, arising from the increasing concentration of household wealth. Chen et al. (2017) document a global boom in corporate saving since the 1990s. As shown by Falato et al. (2022), this trend is explained by the rise of intangible-intensive firms. I add to this literature by showing that the rise in both wealth inequality and intangibles contributes to the fast growth of deposits, including uninsured deposits, in the economy.

Second, there is a literature showing how the demand for safe stores of value explains key features of banks and of other financial intermediaries. Prominent theoretical contributions on deposits as safe (information-insensitive) assets include Gorton and Pennacchi (1990), Dang et al. (2017) and Diamond (2020). These models consider the fragility of privately-created safe assets, which are subject to informational panics, thus providing a rationale for deposit insurance. Recently, a number of papers study the issuance of private safe assets beyond deposits (Kacperczyk et al., 2021) and by non-banks (Sunderam, 2015). Stein (2012) discusses the fragility of these assets and the optimal policy response. A key paper connecting the literature on financial instability to research on the saving glut is by Li (2022). In his model, intangible-intensive firms hold large savings, which provide cheap leverage to banks and cause a build-up of financial risk. Relative to these papers, I causally relate the fragility of banks’ capital structure to the root causes of the saving glut.

2 Testable hypotheses and data

I start by discussing testable hypotheses and the data used in the analysis.

2.1 Predictions from theory

Agents need stores of value for a variety of purposes, including saving for retirement or corporate investment. However, “all stores of value are not created equal” (Caballero et al., 2017). Some of them are immune to adverse selection and can thus confidently be bought without information production. These “safe” assets are more liquid, money-like, and specifically appealing to uninformed savers, who may be willing to pay a “safety premium” to buy them (Gorton, 2017). These safe assets can be issued both by governments and by private institutions, notably banks.

Safe assets, however, cannot be created in unlimited quantities: when some cash flows are made safe, others become more risky, and some agents must be induced to bear this risk. Safe government debt repayments come at the cost of greater risk for taxpayers (Jiang et al., 2022), while safe deposits come at the cost of greater risk for bank equity holders (Gorton and Pennacchi, 1990). Because safe assets cannot be supplied with perfect elasticity, an exogenous rise in demand raises the safety premium. The leverage of agents issuing safe assets becomes cheaper and incentivizes them, whether governments (Blanchard, 2019) or financial intermediaries (Li, 2022), to increase supply. Theoretically, there should thus be a direct relation between aggregate safety demand (i.e., the saving glut) and the capital structure of safe asset issuers (Diamond, 2020).

Cross-sectionally, which safe asset issuers benefit relatively more from an exoge-

nous rise of safety demand depends on the identity of the agents from which this demand emanates. If safe asset demand increases relatively more among agents prone to investment in securities markets – such as foreign investors or foreign central banks –, then a higher saving glut will fuel the issuance of tradable securities, in the form of either government bonds or privately-issued debt securities (such as securitization). Instead, if the saving glut emanates from agents prone to save via bank deposits, then this asset class should grow relatively faster than others. Ultimately, which class of agents drives variation in safety demand depends on deep economic factors, such as the structure of wealth inequality or of the productive sector.

Hypothesis 1 relates local variation in these structural factors to cross-sectional variation in the capital structure of banks.

Hypothesis 1. *Banks locally more exposed to the root causes of the saving glut accumulate relatively more deposits.*

This hypothesis should hold true only for structural factors affecting agents likely to save through banks. Among the structural factors that have been shown to empirically contribute to the saving glut, two meet this criterion. First, the rise in household wealth inequality (Piketty and Zucman, 2014; Mian et al., 2021), in a context where a sizable fraction of household financial assets are held via banks. Second, the shift to an economy based on intangibles (Crouzet et al., 2022). Theoretically, a fundamental property of intangibles is that they cannot be pledged as collateral in debt contracts, and thus require to be financed with cash. To the extent corporate savings are used to make payments or for recurring investment needs, at least part of them should be held in banks. Practically, Hypothesis 1 states that banks relatively more exposed either to

wealth inequality or to corporate intangibles should accumulate more deposits. This prediction should hold true for both insured and uninsured deposits. Indeed, even if they are episodically subject to runs or panics, uninsured deposits can be understood as the outcome of a security design mechanism catering to safety-seeking savers ([Gorton and Metrick, 2012](#); [Dang et al., 2017](#)). Obviously, any form of government guarantees, including deposit insurance schemes, further increase the desirability of deposits for agents seeking safety.

The fact that safe assets cannot be created in unlimited quantity helps formulating a second hypothesis. Because increases in safety for some securities come at the cost of lower safety for others, there is always a risk that safety production is unsustainable beyond some point. Increases in public debt may raise concerns about a government's future fiscal capacity and credit risk. Similarly, concerns about the quality of assets backing deposits or other privately-issued safe assets may resurface when shocks hit.

While such “tipping points” are hard to predict, their existence is theoretically clear. In the context of the corporate saving glut, a model of the relation between safety demand and financial instability is by [Li \(2022\)](#). In his model, an exogenous rise in the need to invest in intangibles makes firms more eager to save and lowers the equilibrium interest rate, fueling cheap leverage for intermediaries (as also predicted by Hypothesis 1). Greater intermediary leverage is then associated with more severe crises when negative shocks hit. I follow this logic to formulate Hypothesis 2.

Hypothesis 2. *Deposits in banks locally more exposed to the root causes of the saving glut are relatively more fragile.*

Hypothesis 2 is especially likely to hold for uninsured deposits. Such deposits are more

likely to exist if wealth inequality is large. Indeed, with more concentrated wealth, a greater fraction of aggregate deposits exceed deposit insurance thresholds. Uninsured deposits are also more likely to be large if corporate deposits are high, which is more likely to be the case for banks exposed to intangible-intensive firms.

2.2 Banking data

To test Hypotheses 1 and 2, I rely on several data sources, further described in Appendix A. To produce stylized facts, I rely on balance sheet data from call reports, covering all banks in the US over the period from 2001 to 2022. For the quasi-natural experiment, I restrict attention to publicly listed banks, and obtain daily stock prices from CRSP.¹ As of end-2022, the full sample of banks, described in Panels A and B of Table 1, comprises 4,756 banks. The sample of listed banks, observed from January 3rd to March 24th, 2023, is composed of 110 institutions. Furthermore, from the Summary of Deposits (provided by the FDIC), I obtain data on the location and on the amount of deposits in each branch for the years 2002 and 2022. I aggregate these deposits at the bank-county-year or bank-state-year levels and denote respectively $D_{b,c,t}$ and $D_{b,s,t}$ the total amount of deposits held by bank b in year t , respectively in county c or in state s .

3 The saving glut and rising (uninsured) deposits

In this section, I describe stylized facts on the growth of deposits over the past two decades, and relate them to the root causes of the saving glut (Hypothesis 1).

¹Listed financial institutions are almost always bank holding companies (BHCs), not individual banks. Individual banks are matched to the bank holding company that is their higher holder. When doing so, bank-level balance sheet data are aggregated at the BHC level.

3.1 Stylized facts

A stylized fact, whose importance may not have been fully appreciated, is the considerable growth of deposits in the US since the early 2000s, as illustrated in Figure 1.

The top-left panel plots the ratio of aggregate deposits to aggregate liabilities and equity of all US banks filing call reports. This ratio increased from around 55% in the mid-2000s to around 75% in 2022, indicating a sizable change in financing structure for the US banking system: deposits have grown much faster than banking assets.

This large increase in deposits is significant for the economy as a whole, as it took place over a period during which banking assets grew themselves much faster than GDP – at an average rate of 6% per year. The historical anomaly resulting from this joint dynamics can be seen in the top-right panel of Figure 1, which plots the ratio of aggregate deposits (from the FDIC Historical Bank Data) over US GDP starting in 1947. While the deposit-to-GDP ratio had been mostly fluctuating in a range between 40 and 50% over a period of more than 60 years, it started to increase very fast around 2000, to reach a value above 75% in 2022. This deposit-to-GDP ratio is most likely unprecedented in history.

The two bottom panels of Figure 1 further show that these trends are paralleled by an increase in the share of uninsured deposits, both as a fraction of total deposits, and as a share of total liabilities and equity. For example, the latter share almost doubled over the past 20 years, from below 20% to above 35%.² This increase means that deposits above the FDIC coverage threshold have become far more common, even though this threshold has increased over the sample period (from 100,000 USD before

²The dotted parts in the bottom panels of Figure 1 correspond to jumps created by changes in deposit insurance coverage following the global financial crisis of 2008.

2008 to 250,000 USD afterwards).

These rising uninsured deposits are not driven only by a subset of large institutions, but affect the entire banking system. To see this, Figure 2 plots the kernel density of uninsured deposits over total deposits in the cross-section of US banks, in both 2002 and 2022. An economically meaningful right shift in the distribution is observed over time. Over 20 years, the mode of the distribution shifts from about 17% to about 32%. These observations are confirmed when comparing mean and median values of uninsured deposits in Panels A and B of Table 1.

3.2 Measurement of exposures to the saving glut

Next, I investigate whether these stylized facts are related to the root causes of the saving glut, as suggested in Hypothesis 1. So far, the literature has largely neglected the impact of the saving glut on banks, to focus on pricing in securities markets. This is because the dominant source of the saving glut was thought to be savings and central bank reserves from emerging economies, such as China, which are held almost exclusively in the form of US-issued securities (or similar securities from other countries), as opposed to deposits in US banks. Instead, recent empirical studies show that domestic factors, within countries such as the US, explain at least as much of the saving glut as do foreign savings. These domestic factors are household wealth inequality (Mian et al., 2021) and corporate savings (Chen et al., 2017; Falato et al., 2022). As opposed to foreign savings, domestic savings are more likely to be (at least partially) held in the form of bank deposits. If so, the stylized facts from Section 3.1 could be a new facet of the saving glut.

Bank-channelled savings offer a key advantage for identification: banks' balance

sheets allow drawing an explicit link between aggregate facts and the root causes of the saving glut. Empirically, at the local level, banks and bank branches that are most exposed to either wealth inequality or to corporate intangibles should contribute relatively more to the aggregate rise of both total deposits and uninsured deposits. To test this hypothesis, I construct measures of exposure to the saving glut at the local (state or county) level, and aggregate them at the bank-level. These measure are then used to study variation in exposure to the saving glut both within and across banks.

First, to measure the local exposure to wealth inequality, I use data on the share of total wealth held by the top-10% of the distribution in each state from [Mian et al. \(2021\)](#), who estimate this share from the Distributional national accounts (DINA) microfiles provided by [Piketty et al. \(2018\)](#). I denote $Ineq_{s,t}$ the top-10% wealth share for state s in year t .³ I use this variable to compute the exposure of any bank b to household wealth inequality as the deposit-weighted average of top-10% wealth share across all states in which bank b operates, that is

$$ExpIneq_{b,t} = \sum_s \frac{D_{b,s,t}}{D_{b,t}} \cdot Ineq_{s,t}, \quad (1)$$

where $D_{b,t}$ is the total amounts of deposits held by bank b at date t across all states.

Second, I build a measure of banks' exposure to intangible-intensive firms at the county level. To do so, I rely on the County Business Patterns data (provided by the US census) to obtain the share $\omega_{c,ind,t}^{emp}$ of total employment in county c and year t that is in industry ind . For each of these industries, measured at the 3-digit NAICS level, I estimate the reliance on intangibles using the method proposed by [Dell'Ariccia et al.](#)

³This share can only be computed until 2008, after which state-level information no longer appears in the DINA microfiles. Whenever I use the most recent value of $Ineq$, this refers to year 2008.

(2021). From the Fixed Assets Accounts Tables provided by the Bureau of Economic Analysis, I measure the reliance of each industry on intangibles as the ratio between intangibles (“intellectual property products”) and tangibles (the sum of “equipment” and “structures”), denoted respectively IP_{ind} , E_{ind} and S_{ind} . The exposure of county c to intangibles at date t is therefore

$$Int_{c,t} = \sum_{ind} \omega_{c,ind,t}^{emp} \cdot \frac{IP_{ind}}{E_{ind} + S_{ind}}. \quad (2)$$

I then compute the exposure of any bank b to intangible-intensive industries as the deposit-weighted average of $Int_{c,t}$, across all counties in which bank b operates, that is

$$ExpInt_{b,t} = \sum_c \frac{D_{b,c,t}}{D_{b,t}} \cdot Int_{c,t}. \quad (3)$$

The distribution of both exposure measures, $ExpIneq$ and $ExpInt$, is reported in Panel C of Table 1. In both cases, there is significant variation in the cross-section of banks. In the sample of listed banks, there is a 20 percentage points difference in the exposure to the top-10% wealth share between institutions at the 10th and the 90th percentiles (43.6% versus 63.0%). Regarding the exposure to intangibles, it doubles in magnitude when moving from the 10th to the 90th percentile of the distribution of listed banks (12.5% versus 23.3%).

3.3 Explaining total deposits with the saving glut

I now empirically assess Hypothesis 1, that is, I evaluate whether the stylized facts on the growth of deposits are related to the root causes of the saving glut, either wealth inequality or corporate intangibles, as measured by $ExpIneq$ and $ExpInt$.

To do so, the main identification concern arises from the fact that banks' exposures may be partially endogenous: banks actively decide whether to open or close branches in specific locations in which wealth inequality or intangible-intensive firms are more or less prevalent – for example to exploit differences in business models or competitive advantages. Therefore, an OLS estimate of a bank's deposit growth on contemporaneous measures of exposure to wealth inequality or intangibles intensity could not be interpreted as causal.

I address this concern using two strategies. First, I use lagged values of exposures to the saving glut. Specifically, I regress the growth rate of deposits over the 2002-2022 period for a bank b in location l (either a county c or a state s), denoted $\Delta Dep_{b,l}^{2022-2002}$, on either state or county-level measures of exposure to the saving glut as of 2002. The rationale is that, back in 2002, the geographical location of bank branches is less likely to have been determined by either local wealth inequality or the presence of intangible-intensive firms, since these two phenomena amplified only after the early 2000s. One can thus consider bank locations in 2002 as partly exogenous with respect to the root causes of the saving glut: some banks got “treated,” over the 2002-2022 period, because they happened to be, in the early 2000s, in geographical areas either where wealth accumulation by the richest households would amplify or where intangible-intensive firms would grow.

The second element of my identification strategy uses bank fixed effects. For banks operating in multiple states or counties, the estimation with bank fixed effects eliminates many potential conflicting stories – such as ones based on the selection of banks in specific areas. The idea is to exploit the fact that, within the same bank, some branches get relatively more “treated” by the saving glut. I test whether branches that

were more exposed, back in 2002, to the factors that would later be associated with the saving glut, are indeed the ones in which deposits grew relatively faster in the 2002-2022 period.

To summarize, the estimated equations are respectively, for the relation between wealth inequality and deposit growth at the bank-state level,

$$\Delta Dep_{b,s}^{2022-2002} = \beta \cdot Ineq_{s,2002} + \phi_b + \epsilon_{b,s}, \quad (4)$$

and for the relation between corporate intangibles and deposit growth at the bank-county level,

$$\Delta Dep_{b,c}^{2022-2002} = \beta \cdot Int_{c,2002} + \phi_b + \nu_s + \epsilon_{b,c}, \quad (5)$$

where the latter equation also allows for state fixed effects (ν_s) in addition to bank fixed effects (ϕ_b). In both equations (4) and (5), $\Delta Dep_{b,l}^{2022-2002}$ is computed using data from the Summary of Deposits.

The results are presented in Panel A of Table 2. In columns (1) and (2), I find that deposit growth over a 20-year period are significantly explained, at the 1% level, by lagged exposure to wealth inequality. This holds true both in regressions without and with bank fixed effects. Furthermore, the economic magnitude is significant: in the within-bank specification, a one standard-deviation increase in top-10% wealth share is associated with an increase in state-level deposits by an amount equal to one-third of the standard deviation of $\Delta Dep_{b,s}^{2022-2002}$ (equal to 1.646).

Turning to columns (3) to (6), I find that lagged intangible shares also significantly explain the growth rate of deposits. For this variable, regressions are at the bank-county level, and thus allow for state fixed effects in addition to bank fixed effects.

Isolating variation within banks and across differentially exposed counties of the same state provides tight identification. With this specification, I again estimate statistically significant coefficients (at the 1% level) and with sizable magnitudes: a one-standard deviation increase in exposure to intangibles is associated with an increase in county-level deposits by an amount equal to 13% of the standard deviation of $\Delta Dep_{b,c}^{2022-2002}$ (equal to 2.290). These findings confirm that root causes of the saving glut explain a sizable fraction of the aggregate deposit growth.

3.4 Explaining uninsured deposits with the saving glut

All regressions so far use the growth rate of total deposits as dependent variable. A natural question is whether these findings carry through to uninsured deposits. Unfortunately, this question cannot be dealt with using the same within-bank variation, because the only available measure of deposits at the level of bank branches in the Summary of Deposits is total deposits. Instead, uninsured deposits can only be observed at the bank level (from the call reports). The only source of variation that can be used is thus cross-sectional, which is what I exploit by estimating

$$\frac{Uninsured_{b,2022}}{Deposits_{b,2022}} = \beta \cdot Exp_{b,2002} + \epsilon_{b,2022}, \quad (6)$$

where $Exp_{b,2002}$ is a bank-level exposure measure as of 2002, either $ExpIneq_{b,t}$ (defined in Equation 1) or $ExpInt_{b,t}$ (defined in Equation 3). In sum, I assess whether lagged exposure to the saving glut predicts the ratio of uninsured deposits to total deposits 20 years later.

The findings are reported in Panel B of Table 2. In columns (1) and (2), I confirm

that banks that were more exposed to wealth inequality or to intangibles in 2002 were more likely to have higher levels of uninsured deposits in 2022, an effect which is statistically significant at the 1% level. Economically, both regressions yield sizable magnitudes: a one standard-deviation increase in exposure to wealth inequality and to corporate intangibles in 2002 is associated with an increase in the share of uninsured deposits in 2022 that amounts to respectively 23.1% and 21.0% of the cross-sectional standard deviation. Column (3) further shows that reliance on corporate deposits (measured as corporate money market deposit accounts over total deposits) is also predicted by lagged exposure to corporate intangibles.

Overall, the results in this section confirm that fundamental drivers of the saving glut did significantly affect the dynamics of deposits, and can explain a sizable part of the unprecedented increase in the deposit-to-GDP ratio over the past two decades.

4 The saving glut and financial instability: The SVB experiment

I now use the failure of Silicon Valley Bank to test Hypothesis 2 and provide causal evidence that the saving glut also spurs financial instability.

4.1 The Silicon Valley Bank failure

To test Hypothesis 2, I use the unexpected failure of Silicon Valley Bank (SVB) on March 9th, 2023, as a quasi-natural experiment. This event has several appealing characteristics for this purpose. First, it is a large-scale event that affected the entire banking system. In terms of total assets, SVB is the second-largest bank failure in US

history (after Washington Mutual in 2008). It was a major shock to the US banking system as a whole.

Second, it was unexpected until the day of the collapse. This can be seen in Figure 3, which plots the stock price of SVB (normalized to 1 on February 28th, 2023) as well as the equally-weighted stock price of all other listed US banks, around March 9th, 2023. Until that day (after which trading was suspended), the stock price of SVB was indistinguishable from that of other banks. Another indication of the unexpected character of the failure is that the credit rating of SVB was downgraded by Moody's only once the collapse had occurred, on March 10th (and from a investment-grade rating).

Third, the failure of SVB exemplifies the forces highlighted in Section 3, at least with respect to the role played by intangible-intensive firms in the rise of aggregate savings: SVB was catering to intangible-intensive corporations from the Silicon Valley, and had a ratio of uninsured deposits over total deposits of 93.9% in December 2022. Its ratio of corporate money market deposit accounts to total deposits was 90.6%. A comparison with other banks, in Panel B of Table 1, shows that these numbers were far above the US average. Ultimately, the collapse of SVB was a run by uninsured corporate depositors, which forced the bank to liquidate assets and recognize losses.

The collapse of SVB on March 9th triggered a series of public interventions ([Metrick and Schmelzing, 2023](#)) to protect insured depositors and contain the contagion of the run to other institutions. On March 10th, SVB was closed and placed into receivership by the FDIC, while existing deposits were transferred to a newly created vehicle. On March 12th, the Federal Reserve announced the creation of an emergency lending facility called "Bank Term Funding Program" (BTFP). On March 13th, the FDIC

further announced that most of SVB’s deposits beyond the coverage limit of 250,000 USD would be guaranteed ([Federal Deposit Insurance Corporation, 2023](#)).

To a large extent, the collapse of SVB constitutes anecdotal evidence in favor of Hypothesis 2: some of the root causes of the saving glut had made SVB overly dependent on uninsured deposits, thus exposing it to a run. However, this event does not provide causal evidence. For identification, the main idea behind my tests is to exploit this quasi-exogenous failure to study the market valuation of other listed US banks, in a sample that excludes SVB. Given the size of SVB, the market capitalization of the entire US banking sector dropped, as seen in Figure 3). This aggregate drop nonetheless hides significant cross-sectional variation in bank stock returns following March 9th. Understanding the sources of this variation is informative about the fundamental causes of banking fragility.

To visualize the extent of valuation heterogeneity across banks after the run on SVB, a natural starting point is to isolate banks with high or low reliance on uninsured (and thus “runnable”) deposits. Specifically, I use data from the call reports to compute the share of uninsured deposits to total deposits for every listed bank as of December 2022. I then estimate the following difference-in-differences equation

$$Y_{b,t} = \beta \cdot Post_t \cdot Treated_b + \phi_b + \nu_t + \epsilon_{b,t}, \quad (7)$$

where $Post_t$ is a dummy variable equal to one after March 9th, 2023, and $Treated_b$ is a dummy variable equal to one for banks with an above-median ratio of uninsured to total deposits. The dependent variable $Y_{b,t}$ is the stock price of bank b at the end of trading day t , which I normalize to one for all banks on the last trading day of

February. Additionally, ϕ_b and ν_t are respectively bank and day fixed effects. Equation (7) is estimated with standard errors clustered at the bank level, in a sample that runs from 10 days prior to 10 days after the event date.

The estimates are displayed in Table 3. Across specifications without of with fixed effects, I consistently find that banks with an above-median ratio of uninsured deposits perform worse. This result is statistically significant at the 5% level, and is economically meaningful: the post-event decline in stock prices for banks with a below-median ratio of uninsured deposits was 11.7%; for banks with an above-median ratio, the valuation drop was 3.0 percentage points larger. This corresponds to a drop in market capitalization that is 25.6% larger for “treated” banks relative to “control” banks.

To further assess the robustness of this finding, I re-estimate Equation (7) after interacting the $Treated_b$ dummy with day fixed effects. The estimated coefficients, together with 90% confidence intervals, are plotted in Figure 4. Two lessons are drawn from this figure. First, there is evidence in favor of the parallel trends assumption: before March 9th, there was no differential valuation of banks with below- or above median ratios of uninsured deposits. Second, the valuation drop for banks that are highly reliant on uninsured deposits persists throughout the sample period, and does not seem to be significantly affected by the policy interventions from the FDIC and the Fed.

4.2 Exposure to the saving glut and bank stock returns

I then test Hypothesis 2 by assessing whether the root causes of the saving glut can explain the heterogeneity in banks’ stock market returns following the SVB failure.

Specifically, I re-estimate Equation (7) with alternative definitions of the treatment group. To study the role of heterogeneous exposures to local wealth inequality, I define banks to be treated if their value of $ExpIneq_{b,t}$, defined in Equation (1), is above the sample median. Similarly, in a different set of regressions, I assess the role of exposures to corporate intangibles by defining banks to be treated if their value of $ExpInt_{b,t}$, defined in Equation (3), is above the sample median. All difference-in-differences regressions are again estimated with standard errors clustered at the bank level.

The regression estimates are in Tables 4 and 5, respectively for definitions of the treatment based on exposures to wealth inequality and to corporate intangibles. Two main findings emerge from these tables. Most importantly, the heterogeneity in market valuations created by banks' exposures to intangibles (in Table 5) is exactly of the same magnitude as the heterogeneity due to exposures to uninsured deposits. Banks above the median in terms of exposure to corporate intangibles face a stock price drop which is 3.1 percentage points larger than for banks below the median. Economically, this corresponds to a drop in market capitalization which is 26.3% larger for highly exposed banks. This finding is consistent with the hypothesis that exposure to the saving glut creates financial instability, because it raises banks' exposure to uninsured deposits.

Moreover, Table 4 shows that exposure to wealth inequality also plays a role. While the statistical significance is smaller (at the 10% level), the magnitude remains large: banks above the median exposure face stock price drops which are larger by 2.3 percentage points on average, which corresponds to a 18.9% larger fall in market capitalization. Economically, this corresponds to 76.7% of the total variation created by the exposure to uninsured deposits. This confirms that exposure to the root causes

of the saving glut are a source of fragility for banks.

In such difference-in-differences settings, the key identifying assumption is the parallel trends assumption. To provide support in favor of this assumption, I re-estimate the previous equations after interacting the $Treated_b$ dummy with day fixed effects. The resulting estimates are plotted in Figure 5, respectively for definitions of the treatment based on exposures to wealth inequality (Panel A) and to corporate intangibles (Panel B), together with 90% confidence intervals. Before the collapse of SVB on March 9th, there is no significant difference between treated and control banks, regardless of the definition of the treatment. This evidence provides support in favor of the parallel trends assumption. After the collapse, estimated coefficients drop and remain low until the end of the sample period, 10 days after the shock. Thus, the valuation differential persists long after the FDIC and the Fed have taken action to stabilize the US banking sector.

5 Conclusion and implications

This paper empirically shows that US banks that are more exposed to the root causes of the saving glut – either to the rise in the wealth share of the richest households or to the growing savings of firms using intangibles – are also more fragile. Over the years, US banks have increased their reliance on deposits, including uninsured deposits. Economy-wide, the ratio of deposits-to-GDP is at its highest level since World War II (and probably at an all-time high), while the share of uninsured deposits over total bank liabilities has been doubling over the past 20 years. To causally identify the impact of this “deposit glut” on financial stability, I use the unexpected failure of SVB

in March 2023 as a quasi-natural experiment. Following the sudden collapse of SVB, other US banks that were more exposed either to a high local wealth inequality or to intangible-intensive firms experienced significantly larger drops in stock prices.

These findings raise theoretical and policy questions. In a context of rising wealth inequality and growing corporate savings, an increasing share of bank deposits is uninsured and held by sophisticated agents. This implies that these deposits are increasingly fragile, and that deposit insurance schemes – a key institution allowing banks to issue safe assets to the private sector – are slowly losing bite on the banking system. A legitimate question is whether deposit insurance coverage could be further expanded. While the short-term benefits of such measures are clear, its costs are less well-known. For example, wouldn't a general extension of the FDIC's coverage beyond 250,000 USD per depositor act as a subsidy to the wealthiest households and to cash-rich firms, who could then obtain greater safety for their financial holdings at the expense of other agents in the economy? Unfortunately, the distributive effects of deposit insurance are still poorly understood, both theoretically and empirically.

Alternatively, if the distributive effects associated with expanded deposit insurance are too large, a legitimate question is whether savings above the deposit insurance coverage threshold should be held as uninsured deposits within the same banks, or should be channelled through other investment vehicles (such as money market funds, bond funds, etc.). Indeed, combining government-insured deposits with large amounts of uninsured deposits within the same balance sheets may create a hold-up problem: in order to protect insured deposits, deposit insurance schemes may be forced to stabilize all deposits ex post, thus offering some safety to formally uninsured deposits. This concern may call for new savings vehicles, outside banks, catering specifically to agents

at the heart of the saving glut, be them wealthy households or corporations.

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Table 1: Descriptive statistics

This table provides descriptive statistics on US banks' deposits and their breakdown in 2002 (Panel A) and 2022 (Panel B), as well as on other variables used in the analysis to study the exposure of banks to deposits (Panel C). In Panels A and B, "MMDA" stands for "money market deposit accounts." See Appendix A for additional details on the data sources and on the construction of the variables.

Panel A: Deposits in December 2002

	10th	25th	Mean	Median	75th	90th	St. dev.	Obs.
Deposits / Liabilities + Equity	0.716	0.796	0.813	0.847	0.884	0.906	0.140	8468
Uninsured deposits / Deposits	0.056	0.104	0.200	0.171	0.260	0.372	0.143	8378
Uninsured deposits / Liabilities + Equity	0.042	0.083	0.158	0.139	0.211	0.294	0.106	8468
Nontransaction deposits / Deposits	0.588	0.663	0.733	0.739	0.812	0.888	0.127	8378
Interest-bearing deposits / Deposits	0.752	0.815	0.847	0.863	0.901	0.932	0.100	8378
MMDA / Nontransaction deposits	0.026	0.078	0.198	0.161	0.274	0.417	0.167	8357

Panel B: Deposits in December 2022

	10th	25th	Mean	Median	75th	90th	St. dev.	Obs.
Deposits / Liabilities + Equity	0.762	0.825	0.843	0.871	0.904	0.927	0.133	4756
Uninsured deposits / Deposits	0.127	0.225	0.347	0.334	0.459	0.564	0.177	922
Uninsured deposits / Liabilities + Equity	0.096	0.188	0.287	0.275	0.376	0.472	0.145	922
Nontransaction deposits / Deposits	0.388	0.463	0.584	0.558	0.688	0.872	0.180	4704
Interest-bearing deposits / Deposits	0.588	0.666	0.735	0.741	0.809	0.892	0.129	4704
MMDA / Nontransaction deposits	0.039	0.143	0.319	0.287	0.456	0.641	0.225	4690
Household MMDA / MMDA	0.101	0.278	0.439	0.436	0.600	0.748	0.245	817
Corporate MMDA / MMDA	0.136	0.282	0.456	0.426	0.613	0.810	0.249	818

Panel C: Other variables

	10th	25th	Mean	Median	75th	90th	St. dev.	Obs.
Top 10 wealth share in bank locations	0.432	0.481	0.513	0.520	0.586	0.630	0.117	110
Intangibles share in bank locations	0.124	0.150	0.176	0.175	0.204	0.233	0.050	110

Table 2: Explaining deposit growth with lagged local characteristics

This table regresses several measures of deposits growth between 2002 and 2022 or of deposits in 2022 on lagged measures of local exposure to the saving glut as of 2002. In panel A, the dependent variable is the growth rate of total deposits at the bank-state level (columns 1 to 2) or the bank-county level (columns 3 to 6) between 2002 and 2022. The independent variables are the lagged top 10% wealth share at the state level (*Ineq*) or the lagged employment-weighted ratio of intangibles to tangibles at the county-level (*Int*, defined in Equation 2), as of 2002. Some specifications include bank and/or state fixed effects. In panel B, the dependent variable is either the ratio of uninsured deposits to total deposits or of corporate money market deposit accounts to total deposits at the bank level, as of 2022. The independent variables are the deposit-weighted top 10% wealth share at the bank level (*ExpIneq*) or the lagged employment-weighted ratio of intangibles to tangibles at the bank level (*ExpInt*), as of 2002. Robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels. See Appendix A for additional details on the data sources and on the construction of the variables.

Panel A: Within-bank variation

	Δ Dep.	Δ Dep.	Δ Dep.	Δ Dep.	Δ Dep.	Δ Dep.
Top-10 wealth in 2002 (by state)	3.009*** (0.520)	5.575*** (2.119)				
Intangibles share in 2002 (by county)			5.504*** (0.338)	4.895*** (0.368)	6.076*** (0.542)	5.831*** (0.538)
Bank FE	No	Yes	No	No	Yes	Yes
State FE	No	No	No	Yes	No	Yes
Robust st. err.	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.007	0.255	0.042	0.076	0.213	0.229
Obs.	4643	431	10457	10457	7814	7814

Panel B: Across-bank variation

	Uninsured	Uninsured	Corp. dep.
Top-10 wealth in 2002 (bank-level)	0.283*** (0.090)		
Intangibles share in 2002 (bank-level)		0.591*** (0.092)	0.259*** (0.073)
Robust st. err.	Yes	Yes	Yes
Adj. R2	0.019	0.068	0.022
Obs.	822	819	742

Table 3: Difference-in-differences analysis around SVB failure – Exposure to uninsured deposits

This table provides estimates of the difference-in-differences regression in Equation (7). The event of interest corresponds to the collapse of Silicon Valley Bank on March 9th, 2023. The dependent variable is a bank’s high holder stock price, normalized to 1 on February 28th, 2023. Treated banks are those in the top 50% of uninsured deposits to total deposits. The event window runs from 10 days prior to the event to 10 days after the event. Standard errors, clustered at the bank level, are in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels. See Appendix A for additional details on the data sources and on the construction of the variables.

	Stock price	Stock price	Stock price
Post * Treated	-0.030** (0.012)	-0.030** (0.012)	-0.030** (0.012)
Post	-0.117*** (0.006)	-0.117*** (0.006)	
Treated	-0.001 (0.002)		
Bank FE	No	Yes	Yes
Day FE	No	No	Yes
Adj. R2	0.565	0.730	0.803
Obs.	2314	2314	2314

Table 4: Difference-in-differences analysis around SVB failure – Exposure to wealth inequality

This table provides estimates of the difference-in-differences regression in Equation (7). The event of interest corresponds to the collapse of Silicon Valley Bank on March 9th, 2023. The dependent variable is a bank’s high holder stock price, normalized to 1 on February 28th, 2023. Treated banks are those in the top 50% of deposit-weighted wealth inequality at the state-level. Wealth inequality is measured as the share of wealth held by the top 10% of the distribution. The event window runs from 10 days prior to the event to 10 days after the event. Standard errors, clustered at the bank level, are in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels. See Appendix A for additional details on the data sources and on the construction of the variables.

	Stock price	Stock price	Stock price
Post * Treated	-0.023* (0.012)	-0.023* (0.012)	-0.023* (0.012)
Post	-0.122*** (0.009)	-0.122*** (0.009)	
Treated	-0.004* (0.002)		
Bank FE	No	Yes	Yes
Day FE	No	No	Yes
Adj. R2	0.561	0.727	0.800
Obs.	2293	2293	2293

Table 5: Difference-in-differences analysis around SVB failure – Exposure to corporate intangibles

This table provides estimates of the difference-in-differences regression in Equation (7). The event of interest corresponds to the collapse of Silicon Valley Bank on March 9th, 2023. The dependent variable is a bank’s high holder stock price, normalized to 1 on February 28th, 2023. Treated banks are those in the top 50% of deposit-weighted intangibles share at the county level. This measure captures the employment-weighted ratio of intangibles to tangibles at the county level. The event window runs from 10 days prior to the event to 10 days after the event. Standard errors, clustered at the bank level, are in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels. See Appendix A for additional details on the data sources and on the construction of the variables.

	Stock price	Stock price	Stock price
Post * Treated	-0.032** (0.012)	-0.031** (0.012)	-0.031** (0.012)
Post	-0.118*** (0.008)	-0.118*** (0.008)	
Treated	-0.004 (0.002)		
Bank FE	No	Yes	Yes
Day FE	No	No	Yes
Adj. R2	0.569	0.731	0.804
Obs.	2293	2293	2293

Figure 1: Stylized facts on US deposits

This figure presents stylized facts about deposits in the US banking system. The top left panel plots the aggregate amount of deposits over the aggregate amount of all liabilities and equity in US banks over the period from 2001 to 2022. The top right panel plots the aggregate amount of deposits in US banks over the US GDP over the period from 1947 to 2022. The bottom left and right panels plot respectively the aggregate amount of uninsured deposits over either aggregate deposits of the aggregate amount of all liabilities and equity in US banks over the period from 2002 to 2022. See Appendix A for additional details on the data sources and on the construction of the variables.

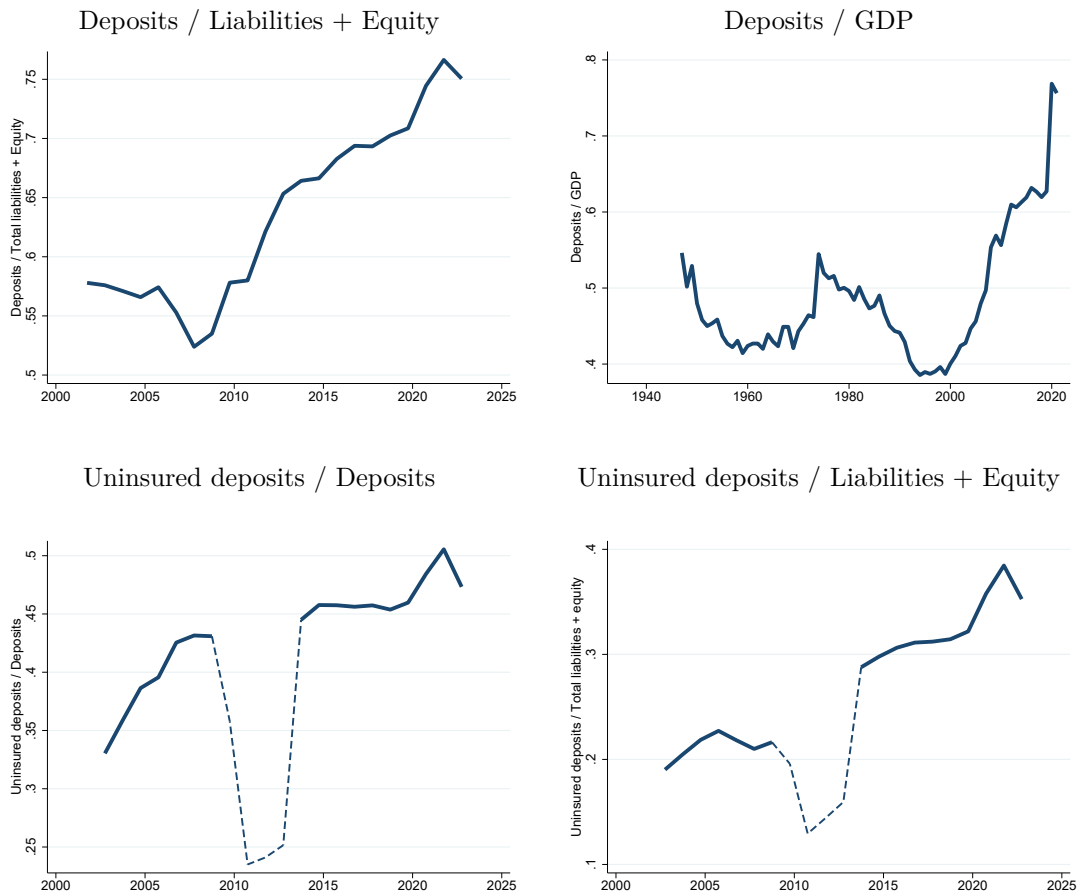


Figure 2: Uninsured deposits in the cross-section of US banks

This figure plots the cross-sectional distribution (approximated with a kernel density) of the ratio of uninsured deposits over total deposits in US banks. The light blue line is for the year 2002 and the dark blue line for the year 2022. See Appendix A for additional details on the data sources and on the construction of the variables.

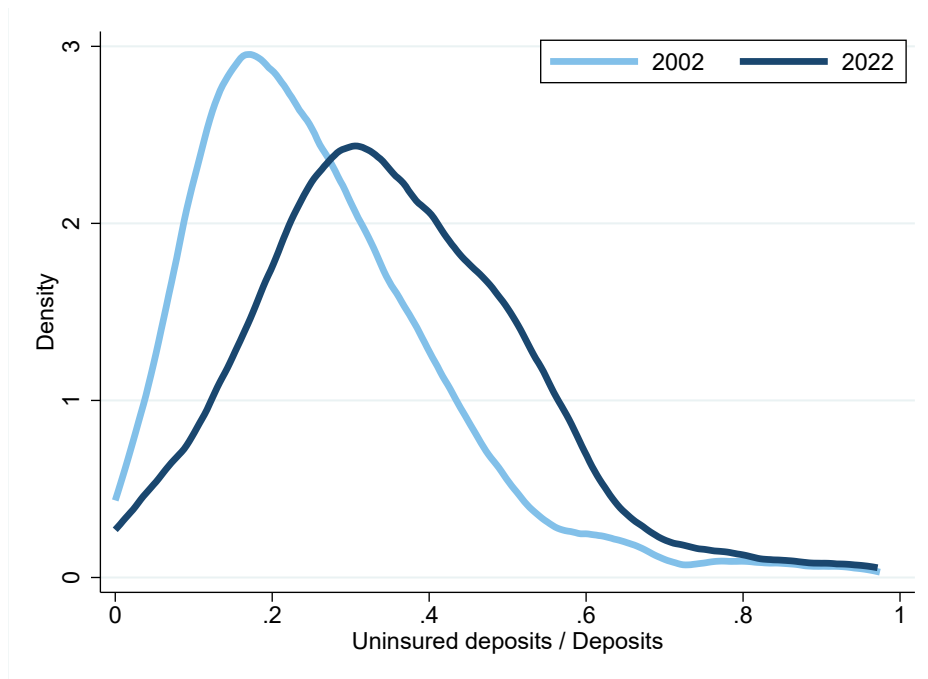


Figure 3: Stock prices around the SVB failure

This figure plots the stock price of SVB Financial Group, the high holder of Silicon Valley Bank, in a period of time surrounding its collapse on March 9th, 2023 (dark blue). The average stock prices of all other listed banks in the US is also plotted (light blue). All prices are normalized to 1 on February 28th, 2023. The vertical line indicates corresponds to the day of SVB's collapse. See Appendix A for additional details on the data sources and on the construction of the variables.

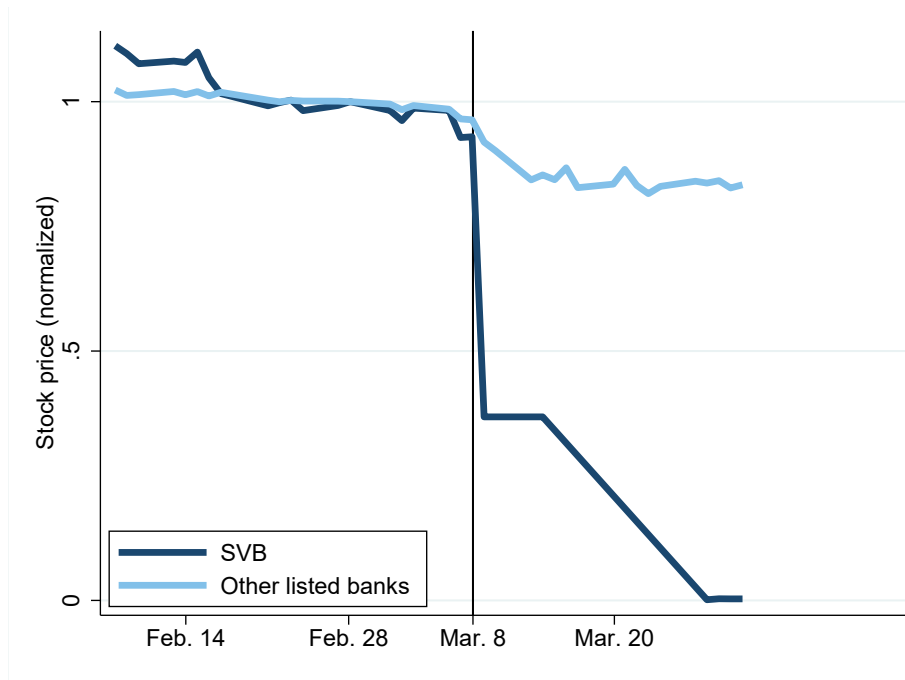


Figure 4: Bank stock returns around the SVB failure – Exposure to uninsured deposits

This figure plots the point estimates and the 90% confidence intervals of the difference-in-differences regression in Equation (7). The event of interest (date t) corresponds to the collapse of Silicon Valley Bank on March 9th, 2023. The dependent variable is a bank's high holder stock price, normalized to 1 on February 28th, 2023. Treated banks are those in the top 50% of uninsured deposits over total deposits. The plotted coefficient is the one corresponding to the $Post * Treated$ interaction, in a specification including both bank and day fixed effects. The event window runs from 10 days prior to the event to 10 days after the event. See Appendix A for additional details on the data sources and on the construction of the variables.

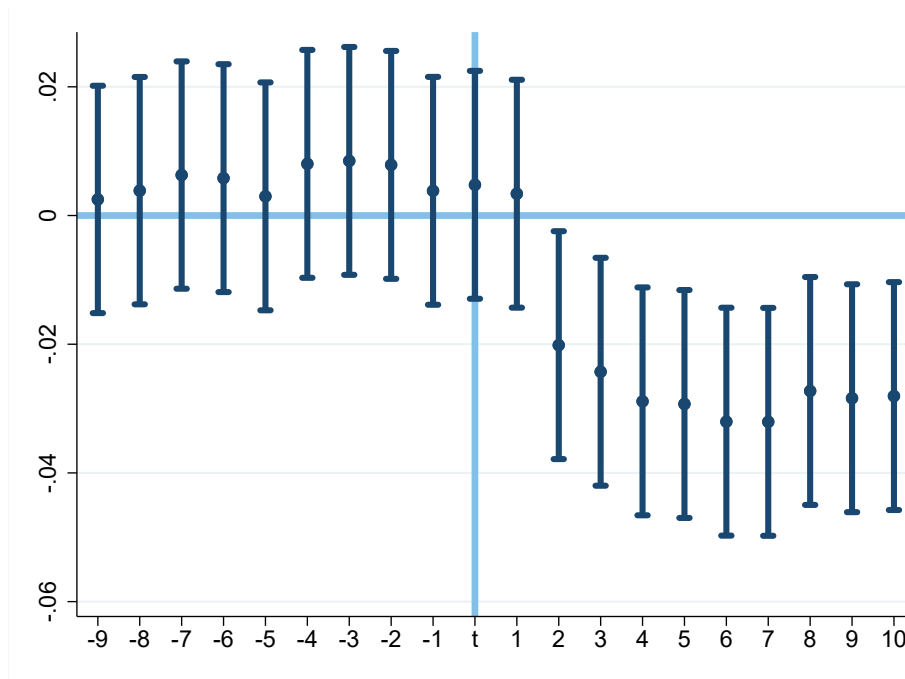
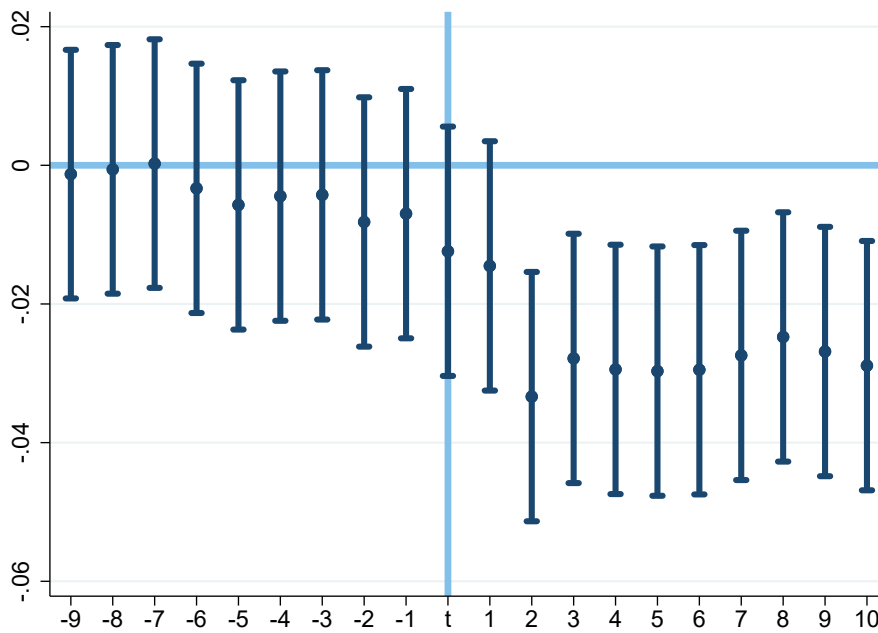


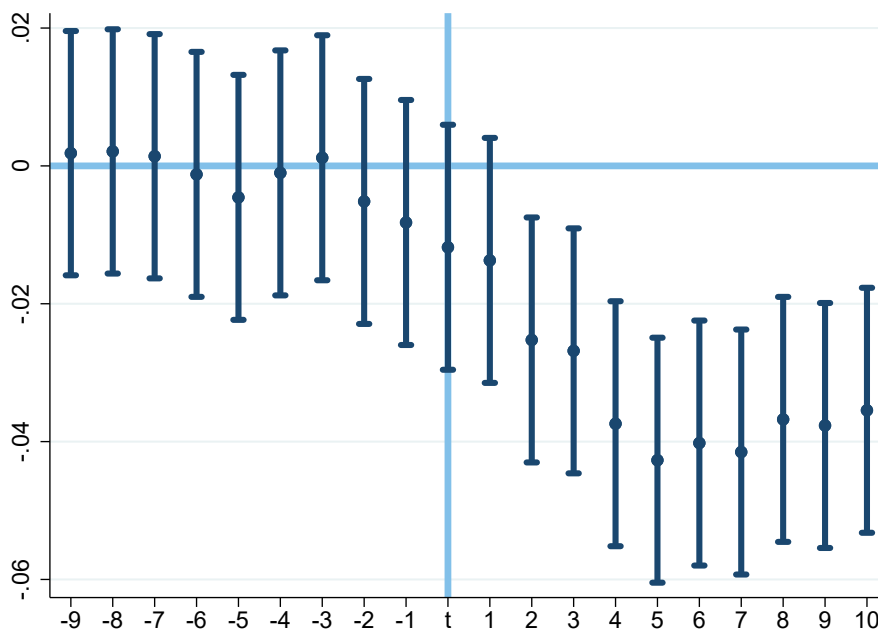
Figure 5: Bank stock returns around the SVB failure

This figure plots the point estimates and the 90% confidence intervals of the difference-in-differences regression in Equation (7), for two definitions of the treatment. The event of interest (date t) corresponds to the collapse of Silicon Valley Bank on March 9th, 2023. The dependent variable is a bank's high holder stock price, normalized to 1 on February 28th, 2023. In panel A, treated banks are those in the top 50% of deposit-weighted wealth inequality at the state level, defined as the share of wealth held by the top 10% of the distribution. In panel B, treated banks are those in the top 50% of deposit-weighted intangibles at the county level, defined as the employment-weighted ratio of intangibles to tangibles. The plotted coefficient is the one corresponding to the $Post * Treated$ interaction, in a specification including both bank and day fixed effects. The event window runs from 10 days prior to the event to 10 days after the event. See Appendix A for additional details on the data sources and on the construction of the variables.

Panel A: Exposure to wealth inequality



Panel B: Exposure to corporate intangibles



A Data sources and definition of the variables

This appendix provides additional information on the datasets used in the analysis and on the construction of the variables.

A.1 Call reports

From the website of the Federal Financial Institutions Examination Council (FFIEC), I download call reports for all US banks as of December 31st of each year, from 2001 to 2022. The data are structured in a number of thematic schedules. I extract variables from the schedules entitled ENT, RC, RCC-I, RCE, RCO and RI. From these schedules, I extract and/or construct the following variables:⁴

- **Total deposits:** Sum of total transaction accounts (variable *RCON2215*) and total nontransaction accounts, including MMDAs (variable *RCON2385*).
- **Total liabilities + Equity:** Total liabilities, limited-life preferred stock, and equity capital (variable *RCON3300*).
- **Uninsured deposits:** Estimated amount of uninsured assessable deposits in domestic offices on the bank iand in insured branches in Puerto Rico and U.S. territories and possessions, including related interest accrued and unpaid (variable *RCON5597*).
- **Interest- and noninterest-bearing deposits:** Total interest-bearing deposits in foreign and domestic offices (variable *RCON6636*) and noninterest bearing deposits (variable *RCON6631*).
- **Money market deposit accounts (MMDA):** Total amount of money market deposit accounts (variable *RCON6810*). MMDAs held by households are respectively identified with the variables entitles “Total deposits in those MMDA deposit products intended primarily for individuals for personal, household, or family use” and “deposits in all other MMDAs of individuals, partnerships and corporations” (variables *RCONP756* and *RCONP757*).

⁴Variables are here indicated with the prefix *RCON*. When relevant – for institutions with foreign activities – I use the same variables with the prefix *RCFD*.

A.2 CRSP data

From CRSP (accessed via WRDS), I obtain daily stock prices for all bank holding companies (BHCs) in the US from January 3rd, 2023, to March 24th.⁵ All BHCs are identified by a PERMCO number. For each PERMCO-day, the variable I use is the daily close price (variable *PRCCD*).

To match bank-level data to CRSP data, I proceed in two steps. First, for each bank identified with a unique RSSD number (variable *RSSDID*) in the Call reports, I obtain the RSSD identifier of its high holder (variable *RSSD9364*). Second, to match the RSSD of high holders to PERMCO identifiers in CRSP, I rely on the PERMCO-RSSD links (or CRSP-FRB links) publicly provided on the website of the Federal Reserve Bank of New York’s website, and updated as of September 30th, 2022.

A.3 Summary of deposits data

From the website of the FDIC, I download yearly data from the Summary of Deposits (SOD), for the years 2002 and 2022. These data contain information on all US bank branches as of June 30th of each year, including the amount of deposits in each branch (variable *DEPSUMBR*) and their location, including their state (variable *STNUMBR*) and county (variable *STCNTYBR*). Banks are characterized with the same identifier as in the call reports (variable *RSSDID*). When computing the change in total deposits ΔDep in Equations (4) and (5), the changes are winsorized at the 1st and at the 90th percentiles.

A.4 FDIC data

From the FDIC’s Historical Bank Data, I obtain data on the aggregate amount of deposits (variable *DEP*) of FDIC-insured banks over the period from 1934 to 2021.

A.5 County business patterns data

From the US census, I retrieve County Business Patterns (CBP) data for the years 2002 and 2020 (the latest year available). It contains data on employment and on the size distribution of establishments for each county and NAICS codes (at various levels of granularity).

To compute a county-level measure of intangibles, I keep only data at 3-digit NAICS. These data are then matched to BEA data on the intensity of intangibles,

⁵In the US, banks are generally not listed on their own. Instead, the BHCs that own them are the listed entities.

also at 3-digit NAICS. Each industry-level measure of the reliance on intangibles is then weighted by the employment share in these 3-digit NAICS within each county.

A.6 BEA data

Data from the U.S. Bureau of Economic Analysis (BEA) is used to compute the reliance of each industry, at the 3-digit NAICS level, on intangibles. I use Fixed Assets Accounts Tables, and more specifically data from Tables 3.1E (“Current-Cost Net Stock of Private Equipment by Industry”), 3.1I (“Current-Cost Net Stock of Intellectual Property Products by Industry”) and 3.1S (“Current-Cost net Stock of Private Structures by Industry”). The reliance on intangibles is then measured as the ratio of intangibles to tangibles, measured as *Intellectual Property Products* / (*Equipment* + *Structures*). This approach is similar to the one by [Dell’Ariccia et al. \(2021\)](#).

A.7 Wealth inequality data

I obtain data on state-level household wealth inequality from the replication kit of the paper by [Mian et al. \(2021\)](#). The variable I use is called *hweal* in the file called *SYdinawealth.dta*. I compute the top-10% wealth share as the sum of household wealth for the top-5% and the top-10 excluding the top-5%, divided by total wealth. These variables are computed by [Mian et al. \(2021\)](#) from the Distributional national account (DINA) microfiles publicly provided by [Piketty et al. \(2018\)](#). State-level wealth shares are only available until 2008, after which no state identifiers are recorded in the DINA microfiles.

A.8 Macroeconomic data

From the FRED database (provided by the Federal Reserve Bank of St-Louis), I obtain data on the nominal seasonally-adjusted US GDP (variable *GDP*) at a yearly frequency from 1947 to 2022.