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Tracing Bank Runs in Real Time

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Abstract

We use high-frequency interbank payments data to trace deposit flows in March 2023 and identify twenty-two banks that suffered a run, significantly more than the two that failed but fewer than the number with large negative stock returns. The runs were driven by a small number of large depositors and were related to weak balance-sheet characteristics. However, we find evidence for the importance of coordination because run banks were disproportionately publicly traded and many banks with similarly bad fundamentals did not suffer a run. Banks survived the run by borrowing new funds and raising deposit rates, not by selling securities.

JEL classification: E41, E58, G01, G21, G28
Key words: bank runs, payments, coordination, public signals

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1 Introduction

This paper offers novel insights on modern bank runs using confidential data on wholesale and retail payments — available intraday at the transaction level for the whole cross section of US banks — to detail the bank runs of March 2023. The use of payments data adds to the empirical literature on recent bank runs, which has either focused only on banks that ended up failing because of a run (e.g. Martin, Puri, and Ufier, 2023), has inferred runs in the cross section of publicly traded banks from the behavior of their stock prices (e.g. Cookson et al., 2023), or has relied on lower frequency historical data (e.g. Blickle, Brunnermeier, and Luck, 2024).

Depositors withdrawing funds in meaningful amounts must ultimately send that money to another bank. We therefore use confidential data on interbank transfers through the Fedwire Funds Service and the Automated Clearing House (ACH) — two key payment systems operated by the Federal Reserve — to identify banks that experience unusually large net outflows in March 2023. These data are uniquely comprehensive relative to other sources, such as stock prices (since not all banks are public) and weekly balance sheet data from the Federal Reserve's H8 collection (since only a subset of banks are in the H8 sample). Using the payments data, we find that the March 2023 runs were fast and large, mostly concentrated in two days (Friday, March 10 and Monday, March 13) with some banks' net outflows reaching 10% of assets in a single day.

We identify 22 run banks with significant net liquidity outflows on one of the days between March 9 and March 14, exceeding five standard deviations of their historical net outflows. On the one hand, this implies that the number of banks that faced a run during this period was over ten times greater than the number of banks that failed, Silicon Valley Bank (SVB) and Signature Bank. On the other hand, runs were less widespread than suggested by the decline in bank stock prices. Moreover, four of the run banks were not public, indicating that using stock prices to understand run behavior limits the focus on a subset of run banks.

We show that the runs are driven by a relatively small number of very large depositors, rather than by a large number of small depositors as the dollar payments value from run banks increases much more than the number of payments, consistent with high value transfers from large depositors. Indeed, we see almost no evidence of runs by retail depositors — looking at ACH net outflows as a proxy for retail withdrawals, the run days are not meaningfully different from other days. We cannot rule out that slower, retail-driven runs would have eventually occurred at other banks had it not been for the announcement on Sunday, March 12 of the systemic risk exception to guarantee all deposits at SVB and

Signature. But certainly the announcement did not deter larger depositors from running as we find high net outflows in Fedwire even *after* the announcement, with 19 banks run on Monday, March 13. We show evidence that these outflows were not the result of depositors pre-positioning withdrawals over the weekend, as they occur throughout the day on Monday instead of being concentrated early in the day.

Because the payments data provides the full network of liquidity flows, we can show that running depositors disproportionately flee to the largest banks with assets over $250 billion and especially do so on Friday, March 10. In turn, we find evidence that the largest banks and only the largest banks reduce their payments sent *to* run banks on Monday, March 13, while not changing their payments sent to other banks. This is consistent with precautionary behavior on the part of the largest banks, which, as the main recipients of run banks' outflows, have an informational advantage as to which banks are being run.

We then study the importance of balance-sheet characteristics such as solvency and liquidity as drivers of runs. For instance, we find that banks with lower capital ratios and higher and more concentrated uninsured deposits are more likely to be run, consistent with runs driven by both by fundamentals and by strategic complementarities (Goldstein, 2013; Chen et al., 2024). However, we show only limited predictability of runs: there are many banks in the full cross section that have worse characteristics than run banks but do not experience a run. In addition, we find that publicly traded stock is a highly significant predictor of runs, highlighting the role of public signals in coordinating runs. Indeed, on the run days — and on those days only — we find a significant relationship between banks' stock returns and liquidity outflows. The correlation is not perfect, however; of the 30 banks with cumulative stock returns worse than -20%, only nine suffered a run, which suggests that we should be cautious when using stock returns as a proxy for depositor behavior. The role of public information is also evident in the timing of the runs on Friday, March 10. Analyzing payments intraday, we find that outflows from run banks are highly concentrated after the Federal Deposit Insurance Corporation (FDIC) announced the failure of SVB, consistent with information spillovers from the announcement.

Finally, we document how banks react to deposit withdrawals in order to survive a run. Counter to the assumptions underlying liquidity regulations, which implicitly offset runnable liabilities with liquid assets including securities, we show that banks with large net outflows shore up liquidity with new borrowing instead of asset sales. Further, the new borrowing is consistent with a pecking order where banks prefer borrowing from Federal Home Loan Banks (FHLBs) over borrowing from the Federal Reserve's lender-of-last-resort facilities: we show that, while all run banks borrow from the FHLBs, only a subset borrow from the Federal Reserve's discount window and Bank Term Funding Program (BTFP) — but those that do come to the Fed borrow heavily. In fact, most run banks over-compensate for lost deposits by borrowing enough for a considerable net increase in their cash position. In contrast, we find no change in run banks' securities holdings, suggesting that banks prefer to borrow against securities at the prevailing rate rather than sell them at a loss. Over a longer horizon, run banks appear to actively seek additional deposits through adjusting deposit rates. We show that the average surviving run bank fully recovers its deposit loss compared to non-run banks by the end of June 2023, albeit at the cost of paying significantly higher interest rates.

Our use of intraday payments data adds novel insights to the empirical literature on bank runs in general and on the banking turmoil in March 2023 in particular. Several papers quantify the impact of the rapid increase in interest rates starting in 2022 on banks' fundamental value. Jiang et al. (2024) model runs arising from the combination of declining asset values through mark-to-market losses and large shares of uninsured deposits. Flannery and Sorescu (2023) estimate the potential solvency effect by comparing interest rate related losses on securities and loans to regulatory bank capital, making use of detailed call report data. Drechsler et al. (2023) and Haddad, Hartman-Glaser, and Muir (2023) similarly consider mark-to-market losses in the banking system and add a focus on the franchise value of deposits in the context of the nonlinear risks from runs by uninsured depositors. All of these papers highlight the relationship between characteristics associated with falling value and runnable liabilities that were fundamental risks of SVB.

Our paper is also related to papers exploring how other bank characteristics led to bank runs in March 2023. In contrast to our ability to use actual liquidity flows, many of these papers have to rely on bank stock returns as a proxy for deposit withdrawals or as an outcome variable. Choi, Goldsmith-Pinkham, and Yorulmazer (2023) relate bank characteristics associated with changes in fundamental value and runnable liabilities to worse stock performance, adding to evidence on the relationship between stock returns and uninsured deposits and unrealized HTM losses, but concluding that the stock market did not fully price risks related to higher interest rates. Gopalan and Granja (2023) show that bank supervisors do not respond to banks' funding risk during the monetary tightening starting early 2022 and address banks' interest rate risk only with a lag. Fischl-Lanzoni et al. (2024) study how investor attention to uninsured deposits and unrealized losses shifted in the time series and the cross-section.

Several papers highlight the importance of new technology in the 2023 bank runs, where social media exposure and digital deposits are both associated with higher probabilities of bank stress (Cookson et al., 2023, and Benmelech, Yang, and Zator, 2023, respectively). Cookson et al. (2023) look at the importance of the public signal from social media and find lower returns in March 2023 for banks with exposure to Twitter (now known as X); they further show an intraday relationship between stock market price changes and negative tweets. Benmelech, Yang, and Zator (2023) show that banks with less branch density and more IT investment that presumably attracted deposits via digital banking have lower equity returns and lose more deposits in 2023q1. However, Rose (2023) notes that the core technology allowing fast and large runs — the electronic wire transfer system that our analysis relies on — has been prominent as least since the run on Continental Illinois in 1984. Chang, Cheng, and Hong (2023) propose that banks with more uninsured deposits may be systematically different, as these banks had greater price risk, profitability, market valuations, and executive pay before their sudden stock price declines in 2023, proposing a model where banks better at risk taking attract more uninsured depositors. Consistent with this, Granja (2023) notes that riskier banks and those with more uninsured deposits had transferred more asset to HTM portfolios in 2021 and 2022.

Luck, Plosser, and Younger (2023) use confidential weekly H8 data to show that banks replace deposit outflows with FHLB funding and that deposit outflows from super-regional banks went to the largest banks. Caglio, Dlugosz, and Rezende (2023) add to this with a full set of bank characteristics as controls and show the inflows into large banks are above what would have been expected given differences in bank characteristics associated with bank failures in March 2023, including mark-to-market losses and shares of uninsured deposits.

In the earlier literature, some papers rely on detailed data from failed banks to study runs: Iyer and Puri (2012) show that uninsured depositor as well as those close to the insurance limit or with weak ties to the bank are more likely to run; Iyer, Puri, and Ryan (2016) show that uninsured depositors are particularly sensitive to bad news about a bank's solvency. Martin, Puri, and Ufier (2023) show that banks suffering outflows of uninsured deposits tend to substitute with new borrowing, including insured deposits.

A second part of the empirical literature relies on historical data to study run dynamics, including time periods or countries without deposit insurance. Kelly and Ó Gráda (2000) show the role of social networks in the panics of 1854 and 1857 (see also Ó Gráda and White, 2003). Blickle, Brunnermeier, and Luck (2024) study runs on German banks in 1931 using monthly balance sheet data and sophisticated depositors (other banks) have an informational advantage in running on banks that ultimately fail. Baron, Verner, and Xiong (2020) study close to 150 years of historical banking crises, distinguishing those with and without panics, and show that solvency shocks tend to cause panics rather than the reverse. Schumacher (2000) shows the role of solvency concerns in depositors running banks in Argentina after the Mexican devaluation in 1994; Pérignon, Thesmar, and Vuillemey (2018) find similar results for wholesale funding dry-ups faced by European banks in the years following the Great Financial Crisis of 2008. Foley-Fisher, Narajabad, and Verani (2020) show that both fundamentals and panic elements contributed to runs on life insurers in the Great Financial Crisis. Artavanis et al. (2022) find similar results for depositors running on a Greek bank in 2014. In addition, there is a developing literature studying runs in the crypto-currency space where behavior on public blockchains is observable in detail (e.g. Liu, Makarov, and Schoar, 2023).

To the best of our knowledge, the only other paper studying bank runs with payments data is Rainone (2024) who uses abnormal daily flows in the European TARGET2 payment system to identify three Italian banks with notable outflows during the paper's sample period of 2012 to 2019. Although these episodes were slower and smaller, with average losses of 3% of deposits cumulated over about four weeks, he also finds evidence of depositors fleeing to large banks and distressed banks responding with emergency borrowing.

Finally, there is an extensive theoretical literature on bank runs (see, e.g. Gorton, 2018, for a survey). Most relevant for the analysis in our paper is the distinction between fundamentals-based and panic-based runs: While the earlier literature considered bank runs as either purely a coordination failure (e.g. Diamond and Dybvig, 1983) or purely driven by fundamentals (e.g. Diamond and Rajan, 2000), the global games approach allowed for a separation between fundamentals-based runs and panic-based runs (e.g. Goldstein, 2013, Goldstein and Pauzner, 2005).

The paper proceeds as follows. Section 2 describes the data. Section 3 explains how we identify bank runs using payments data. Section 4 details the anatomy of the March 2023 run, showing the unusual payment activity and where the money goes. Section 5 contrast run banks and non-run banks. Section 6 studies the effect of stock returns and public announcements.

2 Data

We use five sources of data: (i) balance sheet information from banks' quarterly regulatory filings, (ii) confidential transaction level data on interbank payments, (iii) confidential daily data on banks' balances in their account with the Federal Reserve, including changes to the balances by settlement systems, (iv) confidential balance sheet information for a random stratified sample of banks at weekly frequency (FR 2644), and (v) stock prices of publicly traded banks at daily frequency from CRSP. In this section, we discuss each data source; detailed variable definitions and summary statistics are in Appendix A.

To form the sample of banks for our analysis, we start with all FDIC-insured banking institutions as of 2022q4 based on the FDIC's website. We consolidate banks that belong to the same parent company (e.g., a bank holding company) at the parent company level. The resulting sample includes 4,463 banks, of which 355 are bank holding companies. To get balance sheet and income statement information, we use public data from banks' quarterly regulatory report filings, starting with form FR Y-9C for banks belonging to a bank holding company and call reports (forms FFIEC 031 and FFIEC 041) for banks without holding companies. Table A1 provides the list of balance sheet variables and their definitions.

To identify run banks, in our main analysis, we use confidential data on interbank wholesale payments (wire transfers) from the Fedwire Funds Service (from now on, Fedwire). Fedwire is the main US dollar payment system operating on a real time gross settlement (RTGS) basis and allowing for the settlement of interbank payments on the books of the Federal Reserve; in 2022q4, Fedwire settled on average over 750,000 transfers per day for an average daily value of over $4 trillion.[1] Out of the 4,463 banks with regulatory filings, only 3,172 are active in Fedwire as a sender or a receiver as of 2022q4.[2] For each Fedwire transfer, we have information on the time the payment was sent, the amount sent, the sender bank, and the receiver bank. We do not have information on the customer who sent the payment. As discussed in more detail in Section 3, the majority of banks sends only very few payments per day; therefore, we focus our analysis on the banks that send at least 30 payments on average per day. This reduces the sample to 663 banks, roughly the top 20% of banks in terms of Fedwire activity.

Banks can also send payments to one another through the Automated Clearing House Network (ACH). ACH is typically used for smaller payments, such as payments by retail customers, business-to-business payments, and direct-debit payments (i.e., bills, utilities, etc). In contrast to Fedwire, ACH payments are settled on a net-basis and mostly with a lag of up to two days. The Federal Reserve operates FedACH, one of two ACH systems in the US. Since FedACH transactions settle on the books of the Federal Reserve, we have confidential data on every banks' daily ACH credit and debit; we use this information to compare wholesale and retail payments during the 2023 stress.[3] In addition, we have confidential daily data on several other settlement systems that effect changes in banks'

[1]See `https://www.frbservices.org/resources/financial-services/wires/volume-value-stats`.

[2]Some banks are not active in Fedwire because they rely on correspondent banks for their Fedwire payments. Interbank payment can also be sent through CHIPS, an multilateral settlement system managed by the Clearing House, a consortium of banks; CHIPS allows banks to save on liquidity by netting payments on a multilateral basis. For each bank, the net of its CHIPS payments shows up as a Fedwire transfer and is therefore included in our analysis.

[3]FedACH processes roughly 60% of ACH payments value and a private ACH called the Electronic Payments Network (EPN) processes the remaining 40% (see details in Section 3.2). We do not have data on EPN which is operated by The Clearing House.

account balances with the Federal Reserve, including (i) payments due to interbank transfers, (ii) issuance, maturity, and principal and interest payments of Treasury and agency debt securities as well as their trades executed through the Fedwire Securities Service, and (iii) borrowing from the Federal Reserve at the discount window and at the Bank Term Funding Program (BTFP), the new 13(3) facility established in March 2023.[4]

We have weekly bank-level data on a comprehensive set of balance sheet items for a subset of banks that file form FR 2644.[5] The panel is a random stratified sample and includes 308 of the 663 banks for which we analyze payments. For these banks, we are able to gauge the extent to which banks' net liquidity flows affected their balance sheets (in particular, the levels of deposits and other borrowing).

Finally, we have stock-price data on publicly traded banks from the Center for Research in Securities Prices (CRSP) which we match to our sample using the PERMCO to RSSD ID link provided by the Federal Reserve Bank of New York.[6] The link has 345 publicly traded banks as of 2022q4, of which 245 send at least 30 payments per day on average and are therefore in the set of banks we study in this paper.

3 Identifying bank runs

In this section, we first identify banks that suffered a run in March 2023 based on abnormally large net liquidity outflows Fedwire Funds Service, the main wholesale payment system in the US. We find that 22 banks had a run, most of them on Monday, March 13. Then we check for evidence of retail depositor runs by conducting the same analysis on ACH, a key retail payment system. We find no notably different payment flows in ACH during the run days, providing the first piece of evidence that the runs were a wholesale rather than a retail phenomenon.

3.1 Identifying bank runs in Fedwire payments data

We identify run banks as banks with unusually large net payment outflows in Fedwire. A bank suffering a run will have large payment outflows but not every bank with large outflows is necessarily suffering a run because payments are volatile — especially for banks that send very few payments. In order to identify unusually large outflows, we begin by

[4]The Bank Term Funding Program was established in March 2023 to support the US economy by making funding available to banks. For a description of the program, see https://www.federalreserve.gov/financial-stability/bank-term-funding-program.htm.

[5]The data are collected as of Wednesday and used to produce the H.8 release. See https://www.federalreserve.gov/releases/h8/about.htm

[6]See https://www.newyorkfed.org/research/banking_research/crsp-frb.

normalizing daily net liquidity flows at the bank level. For each bank i in Fedwire on every day t starting January 1, 2023, we look for outsize flows using the daily z-score of net payments received n_{it} as $z_{it} = (n_{it} - \mu_i)/\sigma_i$ where we calculate the mean μ_i and standard deviation σ_i of bank i's net payments n_{it} on one year of data pre-March 2023 (from March 1, 2022 to February 28, 2023).

Defining a run in terms of z-score — as opposed to dollar net outflows — deals with two issues. First, some banks have persistent positive or negative net flows in Fedwire with persistent offsetting net flows in another payment system, such as ACH; demeaning the net payments takes care of this issue. Second, some banks have much more volatile net payments than others. These banks could be flagged as experiencing a run only because a large net outflow happens to occur during the March turmoil, though such an outflow is not unusual for the bank; normalizing by the standard deviation takes care of this issue.

While there are over 3,000 FDIC-insured banks active in Fedwire in this pre-March sample, the median bank sends only 5.4 Fedwire payments per day on average. To ensure a reliable z-score calculation, we exclude any bank with less than 30 payments per day on average in the pre-March sample; this filter reduces the size of our sample to 663 banks, roughly the top 20% in terms of Fedwire activity. Throughout our analysis, we exclude SVB and Signature Bank starting with the dates of their failures (March 10 and 12, respectively) so that any unusual payment patterns once they went under FDIC control do not affect our results. We also exclude Silvergate Bank from the sample altogether; as a bank catering to crypto-currency clients, Silvergate had lost over 50% of its deposits and 80% of its market capitalization in 2022q4 and announced a plan to voluntarily liquidate on March 8.[7]

Finally, banks experiencing a run — and therefore a reduction in their available liquidity — may react to the payment outflows by borrowing from FHLBs which, along with the discount window, act as lenders of last resort (see, e.g. Ashcraft, Bech, and Frame, 2010); since such borrowing from FHLBs shows up as an incoming payment in Fedwire, it would bias the z-score upward, possibly masking the run itself; in order to correct for that, we exclude from the computation of the z-score net payments to FHLBs.[8]

Figure 1 illustrates the tails of the cross-sectional distribution of daily Fedwire payment z-scores from January through April 2023 by plotting the 1st, 5th, 95th and 99th percentiles of the z-scores. In January and February 2023, the tails of the distribution of net payment flows show no notable movements. During the run, however, the acceleration of payment

[7]See `https://dfpi.ca.gov/2023/03/08/dfpi-statement-silvergate-bank-to-begin-voluntary-liquidation/`.

[8]Banks could also react to liquidity outflows by borrowing at the discount windows or, starting March 13 the newly established BTFP; such borrowing activity, however, does not settle on Fedwire, and therefore we do not need to correct for it.

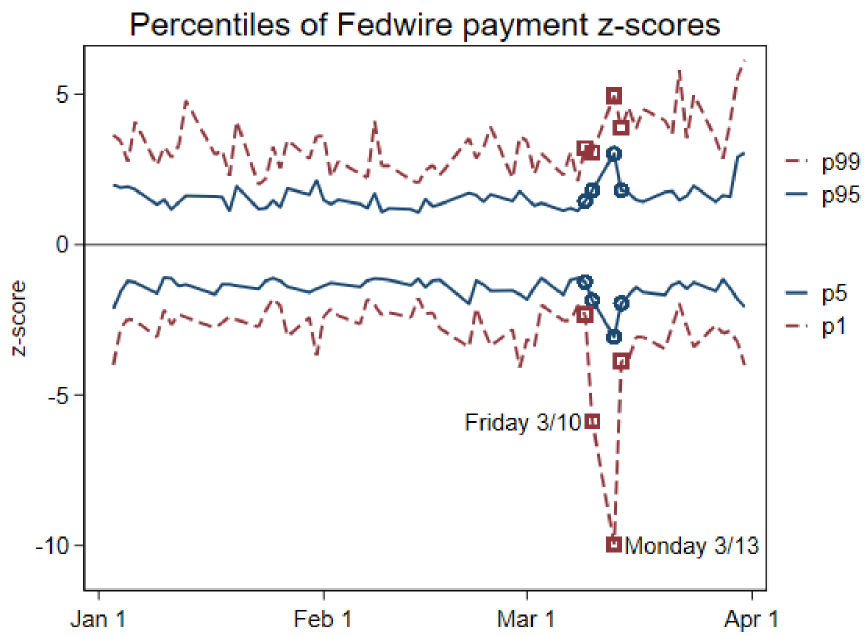

Figure 1: Percentiles of daily Fedwire payment z-scores. The figure shows the daily percentiles of banks' net payment z-scores (excluding payments vis-à-vis FHLBs). Circles indicate the candidate run days (March 9–14,2023). The sample includes all banks we calculate z-scores for. The number of banks per day ranges from 632 to 638. Any failed banks are excluded starting with their failure date.

outflows from some banks is sharp and sudden. On Friday, March 10, the 1st percentile of z-scores drops to -5.9 and on Monday, March 13 it plummets to -10.0, considerably below its average of -2.9 between January 1 and April 1; similarly, the 5th percentile drops to -3.1 on Monday, March 13 compared to its average of -1.4. Given that the sample includes over 630 banks each day, this implies that at least 6 banks had extreme outflows on Monday, March 13 and up to thirty banks had highly unusual outflows. These changes in payment distribution are even more remarkable since, as we mention above, SVB is no longer included in the data starting Friday, March 10, Signature Bank starting Monday, March 13, and Silvergate altogether.

Note that in the right tail of the distribution both the 95th and the 99th percentile moved upward concurrently, albeit much less so than the downward shift in the left tail. This indicates that the money flowing out of the banks suffering runs moved disproportionately to some individual institutions rather than being spread evenly across all other banks. We discuss this further in Section 4.

Because the tails of the distribution only moved on March 10 and March 13, we focus on a narrow window around these days, specifically the days between March 9 and March 14. We consider banks that suffered unusual outflows — as measured by the z-score — on one of these four days as being run. In particular, since the 1st percentile of the z-score distribution dropped below -5 on March 10, we use -5 as the z-score cutoff below which we consider a bank having suffered a run; in the twelve month pre-sample through March 8, less than 0.2% of bank-day observations had a z-score below -5. To reduce the possibility of false positives, we exclude from the run classification any bank that ever had a z-score below -5 during the pre-sample, as well as any bank that had a z-score above $+5$ on the day before the z-score below -5. After applying these filters there are 22 unique banks with a run on at least one of the days March 9 to March 14. On Friday, March 10, five banks had a run while on Monday, March 13, 19 banks had a run (several of the banks have a run on more than one day).

3.2 Runs in other payment systems?

Fedwire is used by banks mainly for large, wholesale payments. Banks can also transfer funds via ACH, which in contrast is mainly used for smaller transfers, such as payroll and retail transfers. If retail depositors use online banking to move money between their accounts at different banks, these payments are most likely to occur through ACH.

We therefore repeat the analysis above now using daily total ACH credits and debits for each bank from confidential data on banks' daily total activity with FedACH, the ACH

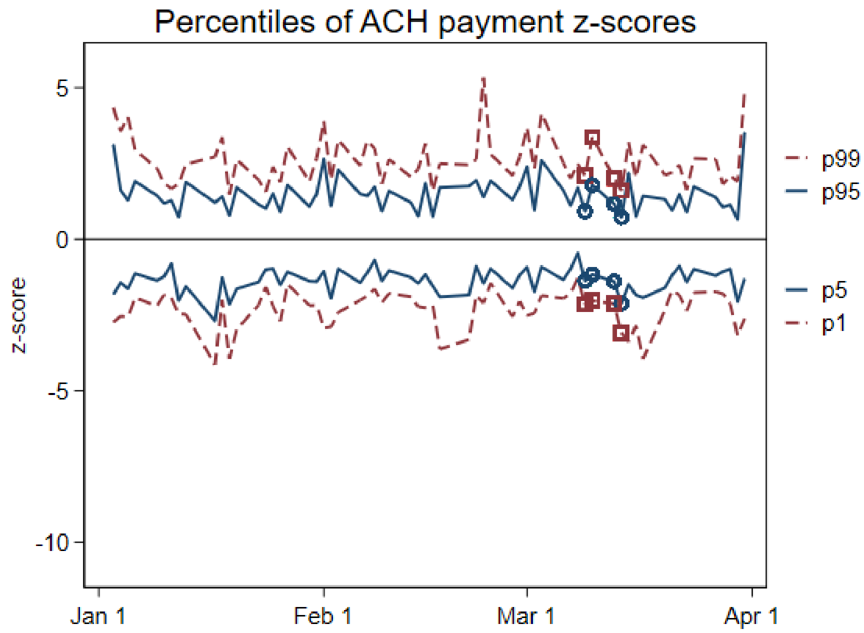

Figure 2: Percentiles of daily ACH payment z-scores. The figure shows the daily percentiles of banks' net payment z-scores. Circles indicate the candidate run days (March 9–14, 2023). The sample includes all banks we calculate Fedwire z-scores for that are active in ACH. The number of banks included per day ranges from 501 to 507. Any failed banks are excluded starting with their failure date.

operated by the Federal Reserve, which processes roughly 60% of ACH payments.[9] A bank run by retail depositors would therefore show up in the data as a large negative z-score of daily net ACH payments.

Analogous to Figure 1, Figure 2 shows the 1st, 5th, 95th and 99th percentile of daily ACH payment z-scores in early 2023 on the same sample of banks. In contrast to the Fedwire percentiles, there is no comparable movement in the ACH percentiles in mid-March with only the first percentile declining moderately in the week of March 13. Given that ACH transfers settle with a lag of up to two days, this decline could could indicate some retail depositor withdrawals initiated on the candidate run days (which are indicated by circles). This implies that retail depositors who are more likely to have used ACH to transfer their money, did not meaningfully contribute to runs during this period.

[9]Total ACH payments in 2022 were $76.7 trillion (see `https://www.nacha.org/content/ach-network-volume-and-value-statistics`) and FedACH accounted for $46.6 trillion (see `https://www.federalreserve.gov/paymentsystems/fedach_data.htm`). The remaining $30.1 trillion were processed by EPN, a private ACH operated by The Clearing House.

4 Anatomy of the 2023 runs

In this section, we describe in detail the anatomy of the March 2023 runs. We first analyze the unusual payment activity characterizing the run. We find that the dollar value of payments sent by run banks on the days they are run is three times larger than normal, whereas the number of payments sent is only about 20% larger; this adds to the evidence that the runs were a wholesale rather than a retail phenomenon.

We then make use of the full network structure of payments to trace where the running depositors flee to and how other banks respond to the runs. We find that the unusual payments from run banks predominantly flow to the largest banks, consistent with flight-to-safety. In turn, we show that only the largest banks reduce the payments they send to banks, consistent with precautionary behavior.

Finally, we study how run banks respond to the loss of deposits in order to survive the run. In the short term, we show that run banks substitute for lost deposits with new borrowing, rather than, e.g. sales of securities. Over a longer horizon, run banks are able to recover their lost deposits with new deposits but at the cost of paying significantly higher interest rates.

4.1 Daily liquidity flows

Interbank payments exhibit significant volatility at the daily frequency, including sharp spikes on month, quarter, and year ends. The top-left panel of Figure 3 shows the daily median and interquartile range of payments activity (as a percentage of 2022q4 assets) across the over 600 banks in our sample, for the first three months of 2023; dashed lines indicate the run period from March 8 to March 14. Though there is a small increase in the bottom quartile of net payments received, we find little evidence for a dramatic increase in either payment outflows or inflows. That is, for most banks the pattern of payments did not change during the run.

In the top-right panel of Figure 3, we repeat the analysis of the top-left panel for the 22 banks identified in Section 3 as run banks. In contrast to what we observe for all banks, among run banks there is a sharp increase in payments sent and a corresponding sharp decrease in net payments received. On Monday, March 13, the median run bank sent payments of over 4% of its assets and the 75th percentile over 6%, compared to only 1.0% and 1.7%, respectively, on average before March 9. The unusual outflows come in the form of large value transfers: if we look at the distribution of the number of payments in the bottom-right panel of Figure 3, the median run bank is not notably different on the run days. In fact, only the right tail of the distribution of the number of payments sent shifts

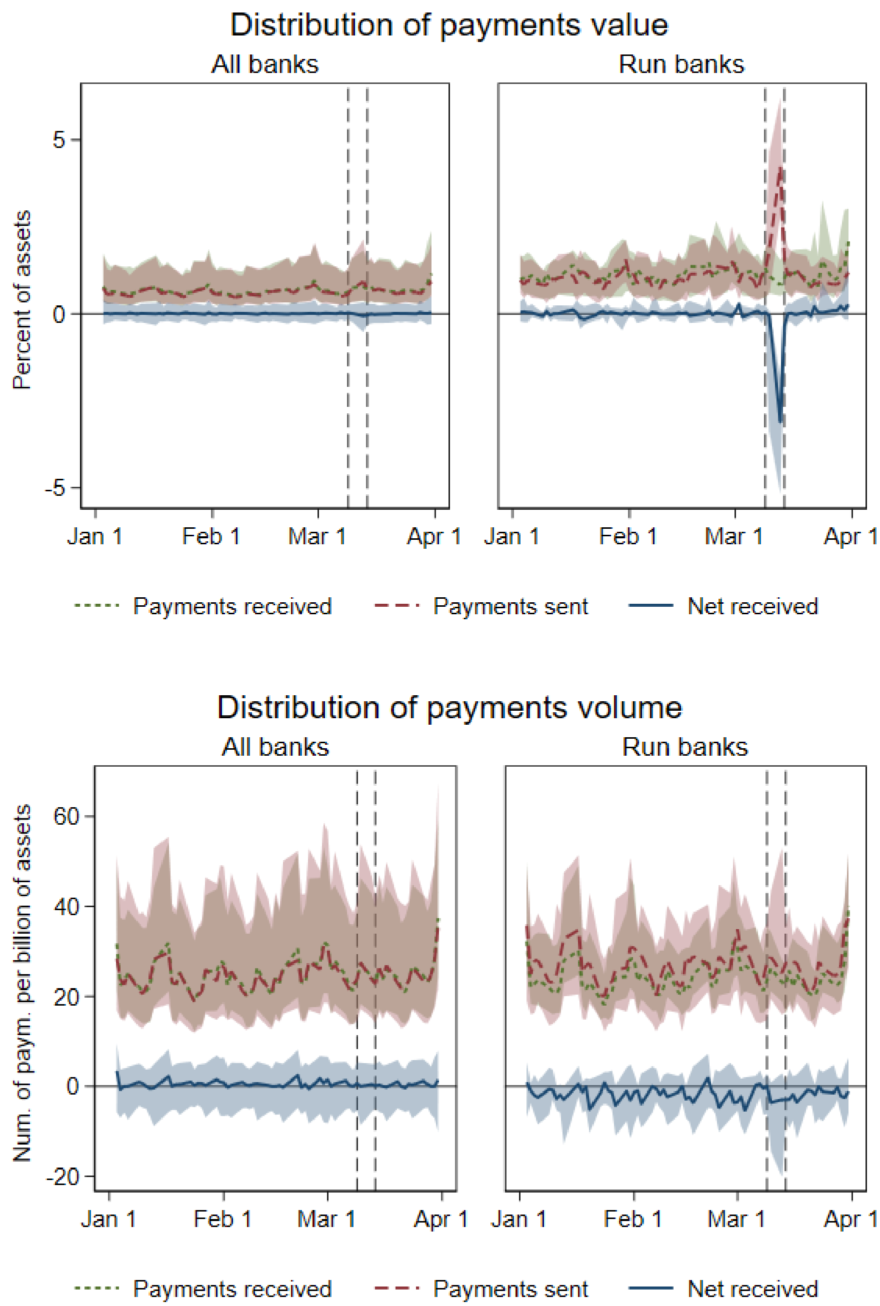

Figure 3: Distributions of Fedwire payments activity. The figure shows the daily median and interquartile range of payments sent, received, and net received. The top panel shows dollar value of payments as a percentage of 2022q4 assets and the bottom panel number of payments per billion dollars in 2022q4 assets. Dashed lines indicate March 9, 2023 and March 14, 2023. The sample includes all banks we calculate z-scores for. Any failed banks are excluded starting with their failure date.

Table 1: Payments activity on run days. The table shows linear regressions of a bank's daily log total payments value and volume, and daily log average payment size, sent and received (excluding payments to/from FHLBs), as indicated at in the column header, on the interaction of dummies for individual days with dummies for banks run on the respective days, as well as date and bank fixed effects. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 1/1 to 3/14. Any failed banks are excluded starting with their failure date. Appendix A provides variable definitions and summary statistics.

	Log paym. value		Log paym. volume		Log avg. paym. size	
	Sent	Rcvd.	Sent	Rcvd.	Sent	Rcvd.
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Mar10}_t \times \text{RunMar10}_i$	1.540***	-0.006	0.229**	-0.064	1.311***	0.057
	(0.152)	(0.063)	(0.103)	(0.048)	(0.193)	(0.087)
$\text{Mar13}_t \times \text{RunMar13}_i$	1.316***	-0.228**	0.181**	-0.043*	1.135***	-0.185**
	(0.141)	(0.098)	(0.076)	(0.024)	(0.137)	(0.092)
Date & bank FEs	Y	Y	Y	Y	Y	Y
Observations	31,144	31,145	31,144	31,145	31,144	31,145
Adjusted R^2	0.937	0.934	0.979	0.986	0.774	0.771

up, with the 75th percentile increasing to 53 payments per billion in assets compared to only 38 before March 9.

To better understand the liquidity flows during run days, in Table 1, we show the results of panel regressions of payments activity for bank i on date t on the interactions of date dummies for the main run days March 10 and March 13 with bank dummies for the banks run on March 10 and March 13, respectively, as well as bank and date fixed effects:

$$y_{i,t} = \sum_{\tau \in \{\text{Mar10,Mar13}\}} \Big(\beta_\tau \times \mathbb{I}[t = \tau] \times \mathbb{I}[i \text{ is run on date } \tau] \Big) + \phi_i + \varphi_t + \varepsilon_{i,t} \qquad (1)$$

The dependent variable $y_{i,t}$ is the log of the total dollar value of payments sent or received by bank i on day t in columns 1 and 2; the log of the total number of payments in columns 3 and 4; and the log average payment size in columns 5 and 6. $\mathbb{I}[\cdot]$ are a set of indicator variables for the run days (March 10 and 13) and for whether bank i is run on one of the run days; ϕ_i and φ_t are bank and date fixed effects. Standard errors are clustered at the bank level.

Run banks send significantly more payments on the days they are run, a roughly threefold increase in the amount sent (see the coefficients in column 1, indicating a log change of roughly 1.4) and an increase of roughly 20% in the number sent (column 3). As also suggested by Figure 3, the value of payments sent by run banks increases much more

Table 2: Payments value vis-à-vis different bank size categories on run days. The table shows linear regressions of a bank's daily log total payments value sent to and received from different bank categories, as indicated at the top, on the interaction of dummies for individual days with dummies for banks run on the respective days, as well as date and bank fixed effects. Bank sizes: "largest" is over \$250b in total assets; "large" is \$250b to \$100b; "small" is under \$100b. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 1/1 to 3/14 and includes as receivers/senders all institutions active in Fedwire. Any failed banks are excluded starting with their failure date. Appendix A provides variable definitions and summary statistics.

	Log payments value					
	Sent to			Received from		
	Largest (1)	Large (2)	Small (3)	Largest (4)	Large (5)	Small (6)
$\text{Mar10}_t \times \text{RunMar10}_i$	2.031***	1.670***	0.633**	0.001	-0.320	-0.049
	(0.172)	(0.298)	(0.254)	(0.152)	(0.209)	(0.121)
$\text{Mar13}_t \times \text{RunMar13}_i$	0.975***	1.336***	0.810***	-0.312***	-0.050	-0.190
	(0.187)	(0.431)	(0.213)	(0.105)	(0.180)	(0.161)
Date & bank FEs	Y	Y	Y	Y	Y	Y
Observations	31,156	31,156	31,156	31,156	31,156	31,156
Adjusted R^2	0.916	0.653	0.825	0.895	0.668	0.825

than the number of payments, resulting in the average payment size more than doubling (column 5). Therefore, the depositors running the banks generated relatively few, large payments rather than many, small payments. This pattern indicates that the runs were driven by large institutional depositors rather than small retail ones; it is also consistent with the fact that Signature suffered 1,600 withdrawals totaling \$18.6 billion, i.e. the average depositor withdrew \$11.6 million.[10]

Note that when looking at the payments received by run banks on run days (columns 2, 4 and 6 of Table 1) there is not much change on Friday, March 10 with respect to non-run days. On Monday, March 13, however, run banks receive approximately 20% less in payments value and the average size of their payments received decreases correspondingly, suggesting that other banks reduced their payments to run banks, especially large payments. Overall, the decrease in payments received on March 13 is consistent with other banks or depositors at other banks being hesitant to send money to banks that appear stressed.

In Table 2, we re-estimate equation (1) but splitting total daily payments sent (re-

[10]See page 32 of the New York State Department of Financial Services Internal Review of the Supervision and Closure of Signature Bank, available at https://www.dfs.ny.gov/system/files/documents/2023/04/nydfs_internal_review_rpt_signature_bank_20230428.pdf.

ceived) by the size of the receiving (sending) bank: the largest banks with assets over \$250 billion, large banks between \$250 billion and \$100 billion, and small banks below \$100 billion.[11] On Friday, March 10, payments sent by run banks went predominantly to the very largest banks with payments sent to the largest banks increasing more than six-fold, payments sent to other large banks increasing more than four-fold and payments sent to smaller banks increasing by "only" 90% (log changes of 2.0, 1.7 and 0.63, respectively, in columns 1 to 3). In comparison, the increase in payments sent by run banks on Monday, March 13 is more evenly spread across receiving banks of different sizes.

This overall pattern of a flight-to-safety towards large, potentially too-big-to-fail banks is consistent with the results of Caglio, Dlugosz, and Rezende (2023) and Luck, Plosser, and Younger (2023) who document increases in deposits at the largest banks during the 2023 run, using the weekly balance sheet data for the subset of banks that file form FR 2644. Using daily data, we show that this effect was much stronger on Friday than on Monday. Note that a depositor running a bank by wire transfer needs an account at another bank to wire the money into. If opening a new account takes some time, then the result is consistent with the Friday runs being dominated by larger, institutional depositors who already have an account with one of the largest banks.

Turning to the source of run banks incoming payments in columns 4 to 6 of Table 2, we see no notable change except for a decrease of about 30% in the payments value coming from the largest banks on Monday, March 13.[12] How do we interpret this result? The largest banks were the main recipients of running depositors' money on Friday and, by observing which banks the money was coming from, they had an informational advantage about which banks were facing runs. It is therefore plausible that the largest banks became hesitant to send payments to banks they perceived at risk of failing.

4.2 What do banks do as net outflows accelerate?

We identify 22 banks that suffered a run between March 9 and March 14, 2023 but only two banks failed during this period.[13] For all banks that suffered a run but survived, we can therefore study how they responded to the liquidity outflows. Banks can respond to the loss of deposits during a run in three ways: (i) they can allow their cash balance do drop; (ii) they can sell less liquid assets such as securities or loans; (iii) they can borrow

[11] Appendix Table B6 shows the same regressions for payments volume.

[12] Note that the largest banks did not hoard liquidity by reducing their payments to all banks as suggested, e.g. by Acharya and Rajan (2024); in fact, the largest banks' payment value sent increased by 11% on average on Monday, March 13 (see Appendix Table B7).

[13] Remember that Silvergate Bank announced a plan to voluntarily liquidate on March 8 and is excluded from our sample.

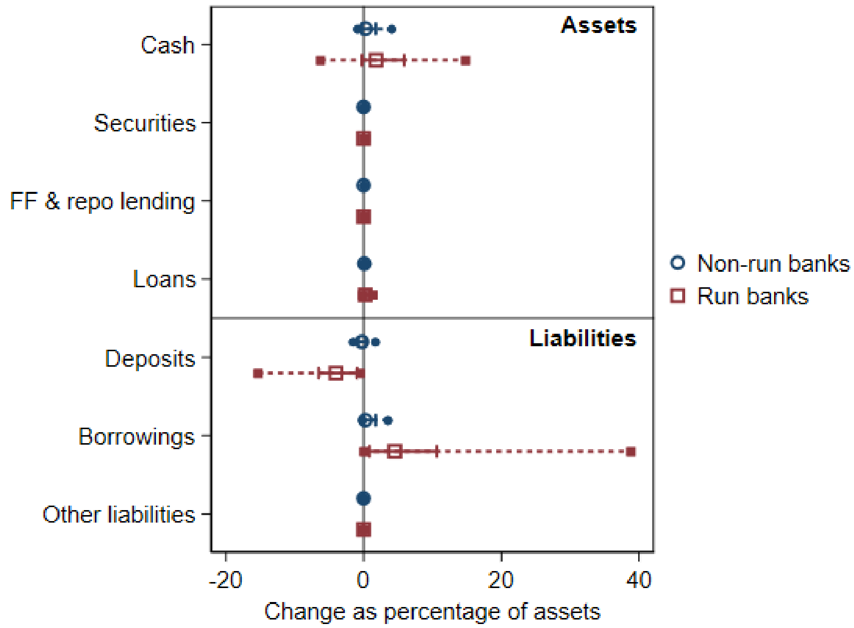

Figure 4: Change in balance sheet items pre/post run. The figure shows changes between 3/8 and 3/15 as a percentage of assets for an exhaustive list of balance sheet items. The figure shows median, p25/p75 range (solid) and p10/p90 range (dashed). Sample includes all banks we calculate z-scores for that are in the FR 2644 data. Any failed banks are excluded starting with their failure date.

from other sources, including FHLBs or the discount window.

We study banks' response to the runs in March 2023 by using confidential balance sheet data from form FR 2644 collected weekly as of Wednesday by the Federal Reserve for a subset of banks, which includes 308 of the banks in our sample, i.e., about half. We compare the post-run balance sheet of Wednesday, March 15 to the pre-run balance sheet of Wednesday, March 8. Results are shown in Figure 4; Appendix Table B8 provides actual statistics.

On the liability side, run banks show (as expected) a decrease in deposits, which drop by 4.0% of assets at the median run bank and by 15.4% of assets at the 10th percentile. The vast majority of run banks reacted to the outflows by increasing borrowing from other sources. Overall, the increase in borrowings is larger than the decrease in deposits, especially in the tails, with the median run bank increasing borrowings by 4.5% and the 90th percentile run bank by 38.8%, more than twice the corresponding deposit loss by the 10th percentile run bank. This suggests that that several run banks more than offset their deposit losses with borrowing from other sources.

As a result, 75% of run banks show an increase in their cash holdings on the asset side with the 75th percentile run bank increasing cash by 5.9% of assets and the 90th percentile run bank by 14.8%. Even many non-run banks increased their cash holdings in response to the turmoil, indicating an increased demand for liquidity across all banks. However, for run banks and in contrast to non-run banks, demand for liquidity increased considerably more, so that they chose to borrow above their deposit losses to shore up their cash position. Importantly, run banks did not change their holdings of other asset categories during the run. In particular, we do not see any material changes in their holdings of securities, suggesting that, because of run banks' ability to borrow to cover for the outflows, they did not have to sell securities in the middle of the run. This could have been because the BTFP allowed banks to borrow against their securities at par; however, as of Wednesday 3/15, the vast majority (93%) of emergency borrowing from the Federal Reserve was from the discount window which does not value securities at par.[14] Overall, our results using the FR 2644 data are consistent with similar analysis by Caglio, Dlugosz, and Rezende (2023) and Luck, Plosser, and Younger (2023); differently from their work, we are able to identify which banks were run based on the actual pattern of outflows instead of relying on balance sheet characteristics. As we show in Section 5 such characteristics are not reliable proxies for bank runs, given the considerable overlap in their distribution across run and non run banks.

While the FR 2644 data provides a comprehensive view of a bank's balance sheet — including both assets and liabilities — it does not cover the full sample of banks and does not break down total borrowings into different sources, such as FHLBs and the discount window. To understand better the emergency borrowing of run banks, we therefore turn to data on each bank's Federal Reserve account balance which is nearly identical to the bank's cash holdings reported on form FR 2644.[15] The data includes information on all settlement systems that effect changes in the balances, including Fedwire and ACH but also the discount window.

Figure 5 shows the change in banks' Fed account balances between March 8 and March 15, as a percentage of 2022q4 assets, for the FR 2644 sample (left panel) and for the full sample (right panel); Appendix Table B9 provides the actual statistics. The lower part of the figure shows all the possible sources of changes in reserve balance: net ACH payments received, net Fedwire payments received (excluding payments to/from FHLBs), net pay-

[14]The Fed's H.4.1 released on March 16 shows that discount window loans (primary credit) on March 15 totaled $153 billion while BTFP loans totaled only only totaled $12 billion. See `https://www.federalreserve.gov/releases/h41/20230316/`.

[15]Small differences can arise because FR 2644 cash includes a bank's balance with other banks and physical cash while the Federal Reserve account balance includes cash held on behalf of other banks. In our sample, the correlation between FR 2644 cash and Federal Reserve account balance on March 15, 2023 is 99.8% for non-run banks and 95.9% for run banks.

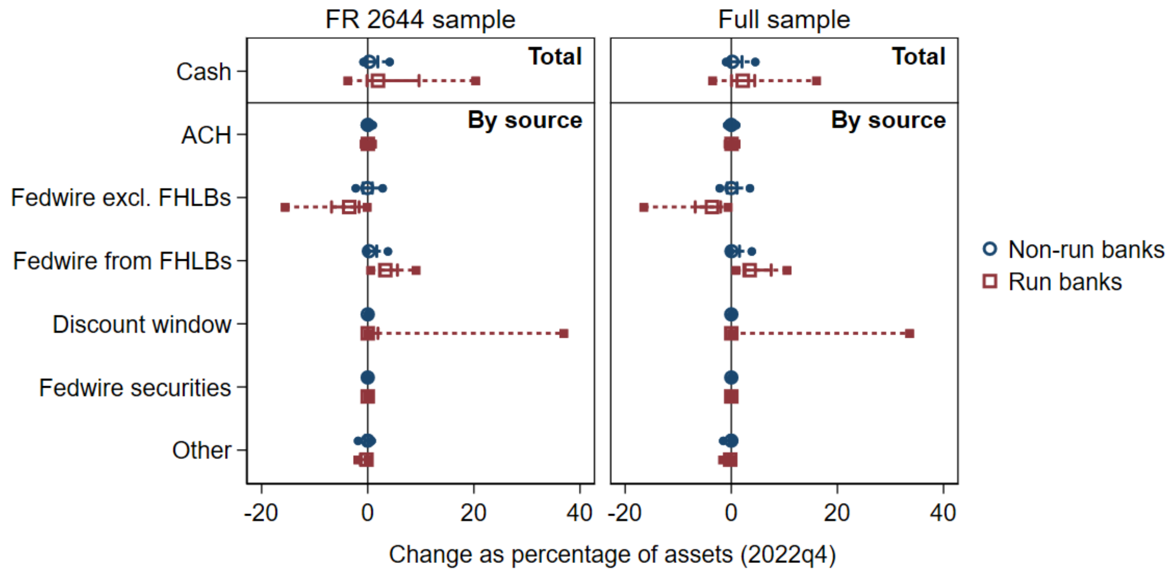

Figure 5: Change in banks' Fed account balances by source pre/post run. The figure shows changes between 3/8 and 3/15 in banks' Federal Reserve account balance as a percentage of 2022q4 assets for an exhaustive list of sources. The figure shows median, p25/p75 range (solid) and p10/p90 range (dashed). Sample includes all banks we calculate z-scores for. Any failed banks are excluded starting with their failure date.

ments received from FHLBs, net change in discount window borrowing, and net payments received for transfers of Treasuries and agency debt securities in Fedwire Securities,[16] and other sources. There is no notable difference between the FR 2644 sample and the full sample, the change in the overall balance is consistent with the change in cash in Figure 4 as is the absence of notable securities settlement.

First, Figure 5 illustrates that the runs were entirely a wholesale phenomenon: liquidity outflows were only due to Fedwire Funds payments with no role for retail payments through ACH. Second, the figure allows us to break out from the total increase in run banks' borrowings the proportion that comes from FHLBs and that comes from the discount window. In particular, almost all run banks borrowed from FHLBs, with the median run bank borrowing 3.5% of assets and the 90th percentile run bank 10.5%; by doing so, they mitigated and even reversed the impact of the run on their cash balances. In addition, some but not all run banks borrowed from the discount window.[17] Note that the median run bank borrowed from FHLBs but not from the discount window; even at the

[16]Trading in most securities would affect banks' cash balances as Fedwire Funds inflows or outflows. Only trading in securities that settles through Fedwire Securities on the balance sheet of the Federal Reserve — mainly Treasuries and agency debt — affects banks' account balance outside of Fedwire Funds.

[17]As we mentioned above, borrowing from the BTFP in the first week of the run was very small.

Table 3: Deposit share and deposit rate. The table shows linear regressions of a bank's quarterly deposit share (deposits/assets) and deposit rate (deposit interest expense/deposits) in percent, as indicated at the top, on dummies for individual quarters and for run banks, and their interactions, as well as date and bank fixed effects, as indicated at the bottom. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 2022q1–2023q2 and includes all banks with z-scores on the run days. Appendix A provides variable definitions and summary statistics.

	Deposit share (%)		Deposit rate (%)	
	(1)	(2)	(3)	(4)
2023q1$_t$	-2.263***		0.667***	
	(0.152)		(0.018)	
2023q2$_t$	-2.659***		0.973***	
	(0.166)		(0.024)	
RunBank$_i$	-0.060		0.214***	
	(1.327)		(0.071)	
2023q1$_t$ × RunBank$_i$	-5.295***	-4.840**	0.344***	0.357***
	(1.981)	(1.985)	(0.104)	(0.097)
2023q2$_t$ × RunBank$_i$	-0.934	-0.700	0.432***	0.428***
	(0.902)	(0.997)	(0.109)	(0.099)
Date & bank FEs	N	Y	N	Y
Observations	3,783	3,783	3,714	3,714
Adjusted R^2	0.011	0.932	0.366	0.775

75th percentile, run banks borrowed funds amounting to 7.5% of assets from FHLBs but only 1.0% from the discount window. In contrast, at the 90th percentile, run banks borrowed much more heavily from the discount window than from FHLBs, borrowing 33.6% of assets from the discount window compared to only 10.5% from FHLBs. This evidence is consistent with FHLBs acting as a "lender of next-to-last resort" (Ashcraft, Bech, and Frame, 2010), where banks in urgent need of liquidity follow a pecking order, preferring to first borrow from FHLBs and only when this has become impossible they tap the discount window.[18]

4.3 Impact of runs on deposit rates

Finally, we study the impact of a run on bank deposits and interest expenses. To that purpose, we run the following panel regression, with quarterly data, from 2022q1 to 2023q2

[18]See Drechsler et al. (2016) for a related analysis of European banks lender of last resort borrowing.

(results are in Table 3):

$$y_{i,t} = \sum_{\tau \in \{2023q1, 2023q2\}} \Big(\beta_\tau \times \mathbb{I}[t = \tau] \times \mathbb{I}[i \text{ is run}] \Big) + \phi_i + \varphi_t + \varepsilon_{i,t}$$

The dependent variable $y_{i,t}$ is the deposit share (deposits/assets) of bank i in quarter t in the first panel regression (columns 1 and 2) and the deposit rate (deposit interest expense/deposits) in the second panel regression (column 3 and 4);[19] $\mathbb{I}[\cdot]$ are a set of indicator variables for 2023q1 and 2023q2 and for whether bank i is a run bank; ϕ_i and φ_t are bank and date fixed effects.

Column 1 shows that banks' deposit as a share of assets are 2.3pp lower in 2023q1 than the average share in 2022, and 2.7pp lower in 2023q2, consistent with an overall reduction in deposits in an environment of rising interest rates. However, run banks' deposit share is significantly lower at the end of 2023q1 — immediately after the run — by an additional 5.3pp. The difference disappears by the end of 2023q2, suggesting that run banks were able to restore their deposit shares over the three months following the run. Column 2 confirms the effect of the interactions in the regression saturated with date and bank fixed effects.

Turning to the interest rates banks pay on their deposits, column 3 shows that banks pay 67bp higher interest rates on their deposits in 2023q1 than in 2022, and 97bp in 2023q2, consistent with the rising interest rate environment, and that run banks already pay 21bp higher deposit rates in 2022. However, run banks have to pay significantly higher higher deposit rates after the run, by 34 basis points in 2023q1 and by 43 basis points in 2023q2. Column 4 again confirms the effect of the interactions in the regression saturated with date and bank fixed effects.[20] In sum, although run banks had made up for the loss of deposits by the end of 2023q2, they did so at the cost of notably higher interest expenses relative to non-run banks.

5 Are run banks different from non-run banks?

In this section, we study first what observable characteristics are associated with banks that suffered a run in March 2023. Consistent with other work on the 2023 banking turmoil such as Jiang et al. (2024) and Choi, Goldsmith-Pinkham, and Yorulmazer (2023)), we find

[19] Deposit interest expense is the total expense paid throughout a quarter so, for the numerator of the deposit rate, we use the average of the current and the previous quarter's end-of-quarter level of deposits.

[20] The average deposit share and deposit rate are 81.5% and 0.6%, respectively, for 2022q1–2023q2, and 79.7% and 1.3% for 2023q2.

Table 4: Balance sheet characteristics of run banks. The table shows means and standard deviations of characteristics as of 12/31/2022 for run banks and non-run banks as well as the difference in means and the statistic for a two-group mean comparison t-test for unpaired data with unequal variances. Significance: * 0.1, ** 0.05, *** 0.01, $^{\circ}$ 0.005, $^{\circ\circ}$ 0.0025, $^{\circ\circ\circ}$ 0.0005. Sample includes all banks with z-scores on the run days (3/9–3/14). Appendix A provides variable definitions and summary statistics.

	Run banks		Non-run banks		Difference	
	Mean	Std.	Mean	Std.	Diff.	p-val.
Total assets ($b)	52.026	60.020	41.487	251.501	10.539	0.523
Assets over $250b	0.000	0.000	0.023	0.151	-0.023$^{\circ\circ\circ}$	0.000
Assets $250b to $100b	0.136	0.351	0.028	0.166	0.108	0.165
Assets under $100b	0.864	0.351	0.949	0.221	-0.085	0.273
Cash/assets	0.037	0.025	0.066	0.079	-0.029$^{\circ\circ\circ}$	0.000
Securities/assets	0.195	0.112	0.194	0.125	0.000	0.991
Loans/assets	0.708	0.108	0.672	0.158	0.036	0.146
CRE/total loans	0.443	0.174	0.483	0.192	-0.040	0.308
RRE/total loans	0.213	0.167	0.215	0.165	-0.002	0.965
Deposits/assets	0.806	0.064	0.817	0.101	-0.011	0.441
FHLB borr./assets	0.116	0.094	0.068	0.089	0.048**	0.027
Tier-1 cap./assets	0.089	0.012	0.100	0.027	-0.011$^{\circ\circ}$	0.001
Unins./total deposits	0.490	0.198	0.394	0.168	0.097**	0.034
Num. unins./tot. dep. ($m)	0.439	0.156	0.544	0.170	-0.105***	0.005
Corp./total deposits	0.504	0.191	0.412	0.186	0.091**	0.038
HTM loss/tier-1 cap.	0.099	0.192	0.053	0.108	0.046	0.277
Deposit growth (yoy)	0.098	0.237	0.062	0.200	0.036	0.493
Asset growth (yoy)	0.138	0.246	0.081	0.181	0.057	0.297
Publicly traded	0.818	0.395	0.365	0.482	0.453$^{\circ\circ\circ}$	0.000
Observations	22		602		624	

that run banks were more vulnerable along several dimensions, including both solvency (lower capital ratios) and liquidity (lower cash holdings), as well as higher and more concentrated uninsured deposits. However, many other banks are similar along one or multiple of these dimensions and do not suffer a run, suggesting a considerable degree of indeterminacy in terms of which bank does or does not suffer a run. In addition, run banks are over twice as likely to be publicly traded than non-run banks, even after accounting for all other characteristics; this suggests a role for public signals in coordinating runs which we study in more detail in Section 6.

5.1 Balance sheet characteristics of run banks

Table 4 shows balance sheet characteristics of run banks and non-run banks as of 2022q4, the last regulatory filing before the run.[21] Although the average run bank is not significantly larger than the average non run-bank, none of the largest banks (above $250bn) is among the run bank group. The size bracket with the highest probability of being run is banks between $250 billion and $100 billion, with a probability of 15% compared to only 3.2% for small banks (below $100 billion).

Run banks' balance sheets differ from non-run banks' along several dimensions, highlighting that bank runs have both fundamental and panic elements (Goldstein, 2013; Chen et al., 2024). Run banks have significantly lower capital ratios, consistent with idea that depositors run on a bank that is at risk of insolvency; run banks also have greater liquidity mismatch with less liquid assets (lower cash holdings) and more liquid liabilities (higher uninsured and corporate deposits), consistent with the idea that greater liquidity transformation increases fragility; further, their uninsured deposits are more concentrated (smaller number of uninsured accounts relative to total deposits), consistent with a panic element driven by stronger strategic complementarities with "large players" (Corsetti et al., 2004). Run banks also have higher unrealized losses on HTM securities, although the difference to non-run banks is not statistically significant at conventional levels. Strikingly, whereas less than 40% of non-run bank are publicly traded, over 80% of run banks are publicly traded (18 of the 22). Publicly traded banks have a run probability of 7.5% compared to only 1.0% for private banks, an effect that remains after controlling for covariates, as we show next.

To control for all determinants of bank runs simultaneously, we show in Table 5 results of the following cross-sectional regression

$$y_i = \alpha + \beta X_i + \varepsilon_i,$$

where y_i is either a dummy variable equal to 1 if bank i had a run (columns 1 to 3) or bank i's lowest payment z-score during the run days March 9 through March 14 (columns 4 to 6), and X_i is a vector of bank balance sheet characteristics as of 2022Q4. The columns in Table 5 report the results of regressions with an increasing set of bank characteristics, starting with uninsured deposits, unrealized HTM losses and their interaction, which have been show as important, e.g. by Cookson et al. (2023) and Choi, Goldsmith-Pinkham,

[21] The table lists 19 comparisons so a Bonferroni correction to account for the multiple comparisons problem would require multiplying the p-values by about 20. We therefore indicate higher significance levels with circles up to a level of $p < 0.0005$ (three circles) which corresponds to a corrected level of $p < 0.01$.

Table 5: Predicting run banks. The table shows linear regressions of an indicator for a run bank or a bank's lowest payment z-score on the run days 3/9 to 3/14, as indicated at the top, on the listed controls as of 12/31/2022. All continuous variables standardized to mean zero and standard deviation one (before interacting). Robust standard errors in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample includes all banks with z-scores on the run days (3/9–3/14). Appendix A provides variable definitions and summary statistics.

	Run bank dummy			Lowest z-score 3/9–3/14		
	(1)	(2)	(3)	(4)	(5)	(6)
Unins./total deposits	0.017**	0.020**	0.019**	-0.306**	-0.324**	-0.309**
	(0.008)	(0.008)	(0.008)	(0.150)	(0.133)	(0.141)
HTM loss/tier-1 cap.	0.003	0.007	0.007	-0.100	-0.163	-0.148
	(0.008)	(0.008)	(0.008)	(0.119)	(0.130)	(0.124)
Unins. dep. × HTM loss	0.011	0.010	0.009	-0.253*	-0.218**	-0.187*
	(0.010)	(0.008)	(0.008)	(0.140)	(0.106)	(0.104)
Publicly traded	0.061***	0.058***	0.051***	-0.810***	-0.694***	-0.628***
	(0.018)	(0.018)	(0.017)	(0.229)	(0.194)	(0.197)
Assets \$250b to \$100b		0.152**	0.165**		-3.796**	-3.938**
		(0.068)	(0.066)		(1.886)	(1.833)
Assets under \$100b		0.074***	0.099***		-1.109**	-1.233**
		(0.025)	(0.034)		(0.492)	(0.578)
Cash/assets		-0.007	-0.004		0.106	0.071
		(0.005)	(0.005)		(0.078)	(0.088)
Loans/assets		0.010	0.010		-0.171	-0.149
		(0.006)	(0.008)		(0.140)	(0.129)
FHLB borr./assets			0.014			-0.210
			(0.009)			(0.140)
Tier-1 cap./assets			-0.007			0.049
			(0.005)			(0.080)
Deposits/assets			0.002			-0.153
			(0.008)			(0.172)
Num. unins./tot. dep.			-0.017*			0.236**
			(0.009)			(0.120)
Corp./total deposits			0.009			-0.170*
			(0.007)			(0.094)
Observations	624	624	624	624	624	624
Adjusted R^2	0.044	0.054	0.065	0.072	0.112	0.127
Area under ROC curve	0.766	0.783	0.833	n/a	n/a	n/a

and Yorulmazer (2023), as well as a dummy for publicly traded banks, and then adding increasingly granular balance sheet characteristics; continuous variables are standardized to mean zero and standard deviation one (before interacting).

Under all specifications, the share of uninsured deposits correlates with the run: a one standard deviation increase in the share of uninsured deposits increases the probability of a run by 1.7 to 2.1pp, an increase that is significant both statistically and economically, given the unconditional run probability of 3.5%. Being publicly traded also significantly increases run risk under all specifications, by 5 to 6pp. Note that the fraction of run banks among private banks is 1.0% (4 out of 386), and climbs to 7.6% among public banks (18 out of 238); conditioning on all other characteristics therefore barely changes the impact of being public. Further, the concentration of uninsured depositors is a significant predictor of being run, even after controlling for the reliance on uninsured deposits overall. It is important to note that HTM losses are not a significant predictor of run risk. Indeed, across all banks, as noted by Jiang et al. (2024), SVB was at the 1st percentile in terms of uninsured deposits but only the 10th percentile for mark-to-market losses. Consistent with perceived too-big-to-fail status and with the stringent regulatory regime, being very large (above $250 billion) is negatively associated with runs: banks smaller than $250 billion are 7 to 15pp more likely to be run.

In columns 4 to 6 of Table 5 we find similar results when using a bank's lowest net payment z-scores during the run period as the dependent variable instead of the run dummy; however, the interaction of uninsured deposits and HTM losses is now significant with the expected sign. In addition, the reliance on corporate deposits is now also significant with the expected sign even though the regression controls for reliance on uninsured deposits which tend to be corporate (Chang, Cheng, and Hong, 2023).

Overall, we find that run banks were on average more vulnerable along several dimensions, notably lower cash holdings, lower capital ratios, higher and more concentrated uninsured deposits (Table 4); some of these variables continue to have predictive power in a multivariate setting (Table 5). That said, notable variation in run behavior is left unexplained. For the regressions predicting the binary run bank dummy (columns 1 to 3), the area under the receiver operating characteristic (ROC) curve is about 0.8; this implies an intermediate level of predictability as our model assigns a higher run probability to a run bank than to a non-run bank 80% of the time. For the regressions predicting the continuous liquidity outflows variable (columns 4 to 6), the R^2 is below 13%; this implies that the there is substantial variability in the magnitude of outflows that's left unexplained. Finally, the average predicted probability of a run is 10.9% for run banks and 3.3% for non-run banks (using the regression in column 3); in other words, many banks with weak fundamentals

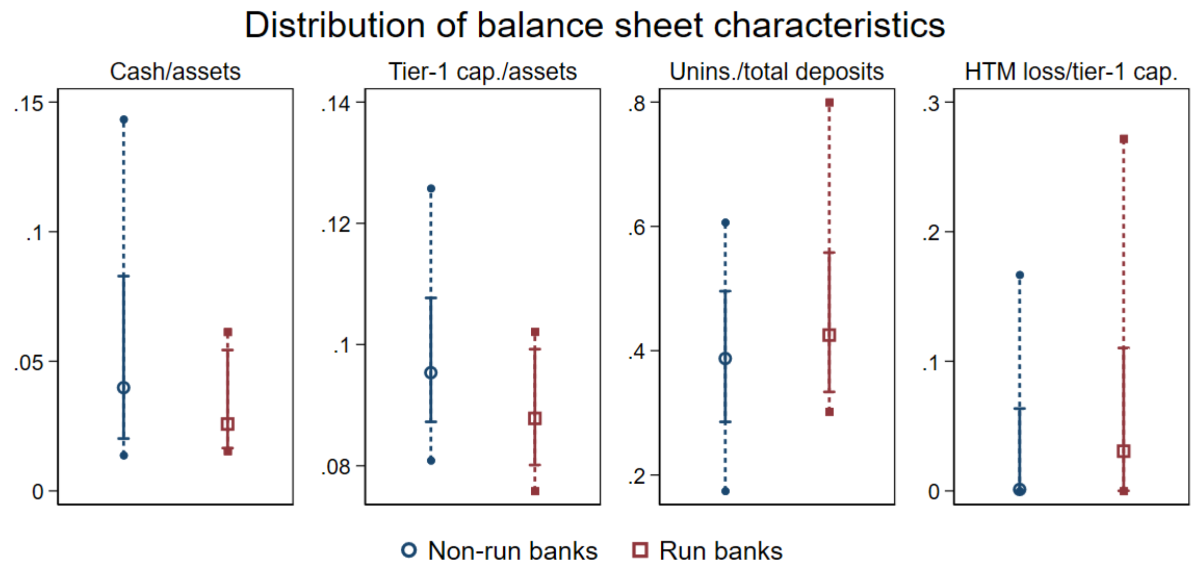

Figure 6: Distribution of balance sheet characteristics. The figure shows the distribution of different balance sheet characteristics as of 12/31/2022 distinguishing non-run banks and run banks. The figure shows median, p25/p75 range (solid) and p10/p90 range (dashed). Sample includes all banks with z-scores on the run days (3/9–3/14).

were not run.

5.2 Many banks with similar balance sheet characteristics were not run

Figure 6 shows the distributions of cash holdings, capital ratios, uninsured deposits, and HTM losses, separately for non-run banks and run banks.[22] Whereas the median run bank looks worse than the median non-run bank along each of these four dimensions, the distributions overlap considerably; indeed, along each dimension, the weakest 25% non-run banks have balance sheet characteristics similar to or worse than the median run bank. In terms of the tails of the distributions across all banks, 9 of the 22 run banks are not in the worst decile of any of the four measures and 10 are each in only one of the worst deciles. In contrast, 148 of the 602 non-run banks are in the worst decile for one measure and 37 are in the worst decile for two or more measures.

To investigate why some banks are *not* run, we focus on the weakest non-run banks, i.e. banks that have balance-sheet characteristics that we find significant for run behavior but that were not run; we study whether these differ along some other dimension from non-

[22]We carry out this analysis for the key variables that we found significant in Table 4 in addition to HTM losses, which are found as an important run predictor in Choi, Goldsmith-Pinkham, and Yorulmazer (2023) and Cookson et al. (2023).

run banks with similar run risk; in other words, we study whether characteristics that were not associated with run risk in the overall sample, significantly predict run behavior if we restrict to banks with bad balance sheet characteristics. This could happen, for instance, because of some non-linearity in the relationship between banks' characteristics and run behavior.

In Table 6, we repeat the mean comparison tests of Table 4, comparing run banks to subgroups of non-run banks with bad balance sheet characteristics. In columns 3 to 6, we compare run banks to the worst decile of non-run banks in terms of cash holdings, capital ratio, uninsured deposits, and HTM losses. In light of the evidence of Choi, Goldsmith-Pinkham, and Yorulmazer (2023) and Cookson et al. (2023) on the interaction of uninsured deposits and unrealized losses, in column 7 we also compare run banks to non-run banks with both uninsured deposits *and* unrealized HTM losses above the 70th percentile. Finally, in column 8, we run the same exercise matching each run bank with three non-run banks using a propensity score methodology on the four balance-sheet characteristics listed above; and Table 7 repeats the regressions of Table 5 on the propensity-score matched sample.[23]

As Tables 6 and 7 show, no additional variable becomes significant when we compare run and weak non run banks, with the possible exception of loans/assets, consistent with more illiquid assets making a bank more vulnerable. Allowing for non-linearities between our explanatory variables and run outcomes, therefore, does not uncover any additional determinants of run behavior. In other words, in as much as there is unexplained variation in run behavior, this is largely a sun spot outcome.

Finally, Figure 7 shows the net payment z-scores of the six groups of weak non-run banks we identified above. Not only were these weak banks not run, but there are no notable liquidity outflows from them at all. If depositors were at all concerned about these banks, we would expect at least to see the median or 25th percentile drifting down; instead, we see no evidence of increased outflows from these banks.

6 Effects of public information

In Section 5, we show that being publicly traded is a risk factor for bank runs. The finding is consistent with the idea that public information may be a catalyst for run behavior, either because it makes bank liabilities informationally sensitive or because it acts as a coordinating device. In Section 6.1, we focus on bank-specific signals and study the relation

[23] We chose the 70th percentile for column 7 and three closest matches for column 8 to have comparison samples of similar size to the ones using worst deciles in columns 3 to 6.

Table 6: Characteristics of run banks and differences for subgroups of non-run banks. The table shows the mean of characteristics as of 12/31/2022 for run banks and the difference in means between run banks and different subgroups of non-run banks. "lo cash" is bottom decile cash/assets; "lo t1 cap." is bottom decile tier-1 capital/assets; "hi unin. dep." is top decile uninsured/total deposits; "hi HTM loss" is top decile HTM losses/tier-1 capital; "hi unin. & loss" is over 70th percentile for both uninsured/total deposits and HTM losses/tier-1 capital; "PS match" is sample of three closest matches using propensity scores based on cash/assets, tier-1 capital/assets, uninsured/total deposits, and HTM losses/tier-1 capital. Significance: * 0.1, ** 0.05, *** 0.01, $^{\circ}$ 0.005, $^{\circ\circ}$ 0.0025, $^{\circ\circ\circ}$ 0.0005. (Based on two-group mean comparison t-test for unpaired data with unequal variances.) Sample includes all banks with z-scores on the run days (3/9–3/14). Appendix A provides variable definitions and summary statistics.

	Mean	Difference to non-run banks						
	Run banks (1)	All (2)	lo cash (3)	lo t1 cap. (4)	hi unin. dep. (5)	hi HTM loss (6)	hi unin. & loss (7)	PS match (8)
Total assets ($b)	52.026	10.539	45.094$^{\circ\circ}$	-221.550**	-16.249	-83.340	-99.211	-19.837
Assets over $250b	0.000	-0.023$^{\circ\circ\circ}$	0.000	-0.175$^{\circ\circ}$	-0.053*	-0.117***	-0.093**	-0.034
Assets $250b to $100b	0.136	0.108	0.136*	0.084	0.084	0.103	0.099	0.136*
Assets under $100b	0.864	-0.085	-0.136*	0.092	-0.031	0.014	-0.007	-0.102
Cash/assets	0.037	-0.029$^{\circ\circ\circ}$		-0.066$^{\circ\circ\circ}$	-0.092$^{\circ\circ\circ}$	-0.023**	-0.052$^{\circ\circ}$	0.001
Securities/assets	0.195	0.000	-0.050*	-0.063*	-0.005	-0.141$^{\circ\circ\circ}$	-0.077**	-0.040
Loans/assets	0.708	0.036	0.028	0.186$^{\circ\circ\circ}$	0.131$^{\circ\circ}$	0.176$^{\circ\circ\circ}$	0.139$^{\circ\circ\circ}$	0.045
CRE/total loans	0.443	-0.040	-0.071	0.090*	-0.045	0.000	-0.037	-0.065
RRE/total loans	0.213	-0.002	-0.082*	-0.027	0.069*	-0.025	0.009	0.005
Deposits/assets	0.806	-0.011	-0.003	0.020	0.024	-0.021	-0.017	-0.016
FHLB borr./assets	0.116	0.048**	0.002	0.051**	0.062**	0.063***	0.062***	0.027
Tier-1 cap./assets	0.089	-0.011$^{\circ\circ}$	-0.005		-0.006	0.004	-0.001	-0.001
Unins./total deposits	0.490	0.097**	0.128**	0.058		0.027		0.002
Num. unins./tot. dep. ($m)	0.439	-0.105***	-0.123$^{\circ\circ}$	-0.001	-0.044	-0.087**	-0.092**	-0.116°
Corp./total deposits	0.504	0.091**	0.119**	0.026	-0.007	0.071	0.007	0.068
HTM loss/tier-1 cap.	0.099	0.046	-0.003	-0.025	0.011			0.006
Deposit growth (yoy)	0.098	0.036	0.067	-0.008	0.085	0.089	0.109*	0.020
Asset growth (yoy)	0.138	0.057	0.064	0.027	0.098	0.106*	0.113**	0.036
Publicly traded	0.818	0.453$^{\circ\circ\circ}$	0.326°	0.397$^{\circ\circ}$	0.573$^{\circ\circ\circ}$	0.318°	0.355$^{\circ\circ}$	0.404$^{\circ\circ\circ}$
Observations	22	624	83	79	79	82	76	80

Table 7: Predicting run banks on propensity-score matched sample. The table shows linear regressions of an indicator for a run bank or a bank's lowest payment z-score on the run days 3/9 to 3/14, as indicated at the top, on the listed controls as of 12/31/2022. All continuous variables standardized to mean zero and standard deviation one (before interacting). Robust standard errors in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample includes run banks as well as three non-run banks matched to each run bank using a propensity score methodology on cash/assets, tier-1 capital/assets, uninsured deposits/assets and HTM losses/assets. Appendix A provides variable definitions and summary statistics.

	Run bank dummy			Lowest z-score 3/9–3/14		
	(1)	(2)	(3)	(4)	(5)	(6)
Unins./total deposits	0.028	-0.038	-0.117	-1.528*	0.190	0.912*
	(0.051)	(0.060)	(0.071)	(0.801)	(0.473)	(0.527)
HTM loss/tier-1 cap.	-0.117	-0.050	0.005	1.117	0.072	-0.286
	(0.071)	(0.079)	(0.079)	(0.763)	(0.663)	(0.656)
Unins. dep. × HTM loss	0.073**	0.017	-0.018	-1.116***	0.657	0.933**
	(0.034)	(0.040)	(0.042)	(0.302)	(0.400)	(0.404)
Publicly traded	0.373***	0.334***	0.237*	-4.290***	-2.725***	-1.610
	(0.114)	(0.114)	(0.123)	(1.360)	(0.974)	(0.966)
Assets \$250b to \$100b		0.991***	1.184***		-28.500***	-30.572***
		(0.312)	(0.336)		(3.937)	(4.001)
Assets under \$100b		0.283	0.523**		-3.399*	-5.363***
		(0.222)	(0.242)		(1.760)	(1.846)
Cash/assets		0.046	0.087		-0.177	-0.359
		(0.053)	(0.054)		(0.475)	(0.485)
Loans/assets		0.075*	0.079		-1.078***	-1.286**
		(0.040)	(0.067)		(0.340)	(0.586)
FHLB borr./assets			0.041			0.113
			(0.048)			(0.436)
Tier-1 cap./assets			0.016			0.214
			(0.072)			(0.652)
Deposits/assets			0.004			-0.011
			(0.056)			(0.472)
Num. unins./tot. dep.			-0.137***			1.162***
			(0.047)			(0.391)
Corp./total deposits			0.071			-0.847
			(0.062)			(0.587)
Observations	80	80	80	80	80	80
Adjusted R^2	0.137	0.191	0.244	0.183	0.645	0.671
Area under ROC curve	0.767	0.792	0.881	n/a	n/a	n/a

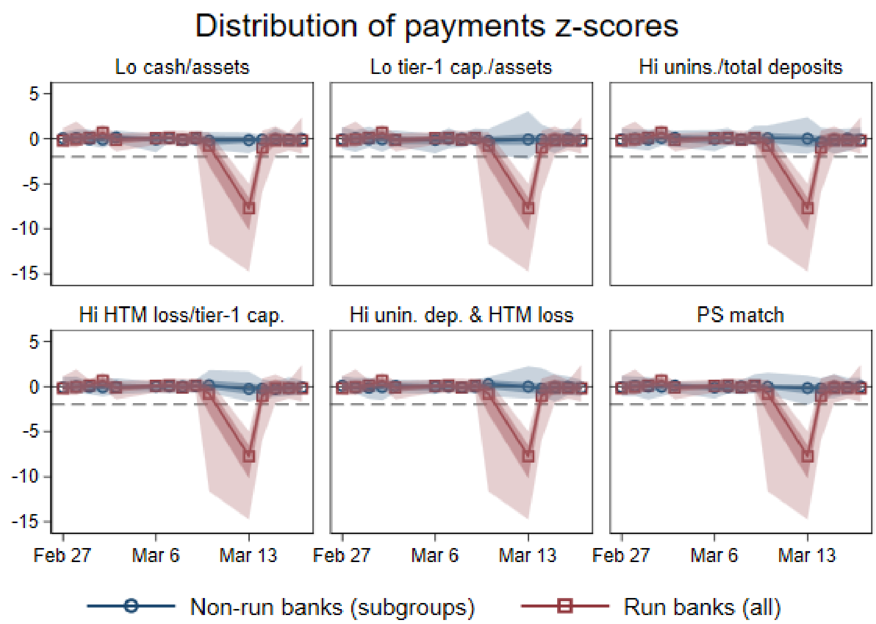

Figure 7: Distributions of payments z-scores for run banks and subgroups of non-run banks. The figure shows daily median, p25/p75 range (dark shade) and p10/p90 range (light shade) of payment z-scores for run banks and different sub-groups of non-run banks from Monday 2/27 through Friday 3/17. Dashed lines indicates a z-score of -2 (two standard deviations below the mean). The sample includes all banks we calculate z-scores for. Any failed banks are excluded starting with their failure date. .

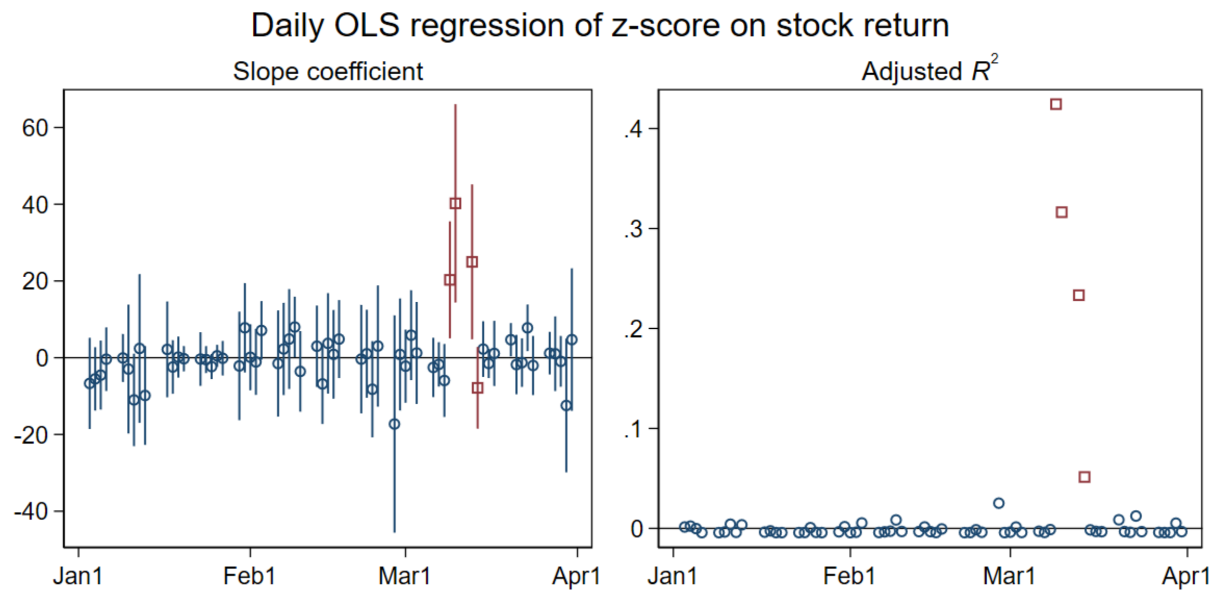

Figure 8: Daily regression of z-score on stock return. The figure shows the slope coefficient and R^2 for a set of daily OLS regressions of banks' z-scores on their stock returns. Whiskers indicate 95% confidence intervals based on robust standard errors. Red squares and whiskers indicate the run days 3/9 through 3/14. The sample includes all banks we calculate z-scores for that are publicly traded; we exclude First Republic Bank on 3/16, New York Community Bank on 3/20 and First Citizens Bank on 3/27; the number of banks ranges from 235 to 240 per day. Any failed banks are excluded starting with their failure date.

between individual banks' stock returns and liquidity outflows. In Section 6.2, we focus on market-wide signals and study how public announcements on Friday, March 10 and Sunday, March 12 affected the runs.

6.1 Banks' stock returns

The cross-section of stock returns of publicly traded banks during the March 2023 runs have received considerable attention in the literature (Choi, Goldsmith-Pinkham, and Yorulmazer, 2023 and Cookson et al., 2023). Whereas SVB and Signature both had large negative stock returns on the day of their run, it is unclear to what extent negative stock returns correlate with deposit outflows across all banks.

To understand this better, we study the relation between banks' stock returns and their liquidity flows. Figure 8 shows the slope coefficient β_t and R_t^2 for a set of daily cross-sectional regressions of banks' payment z-scores on their stock return, run separately on each day t between January 1 and April 1, 2023:

$$r_{it} = \alpha_t + \beta_t z_{it} + \varepsilon_{it}$$

To reduce the possibility of picking up effects due to unusual public announcements, we exclude the following data points from the regression sample in Figure 8: First Republic Bank on the day the FDIC announced their receipt of $30 billion in deposits from a consortium of 11 large banks (March 16);[24] New York Community Bank on the day the FDIC announced their purchase of Signature Bank's assets (Monday, March 20 after the announcement on Sunday, March 19);[25]; First Citizens Bank on the day the FDIC announced their purchase of Silicon Valley Bank's assets (Monday, March 27 after the announcement on Sunday March 26).[26]

There is no relation between stock returns and payment flows in normal times: the confidence interval always contains zero and the R^2 is close to zero. In contrast, during the first three days of the run period, the regression slope turns positive and significant, showing a positive relation between stock returns and payment flows: the slope hovers between 20 and 40 and the R^2 between 23% and 42%. For example, on Monday, March 13 the regression slope is 25, indicating that a 20% drop in a bank's stock price is associated with a z-score of -5 , reflecting exceptionally large net outflows. Cumulating returns and payment z-scores through the four run days yields consistent results with a coefficient of 43.2 ($p < 0.01$) and an R^2 of 38%; on days where banks have runs, we therefore find a significant relation with banks that have negative stock return, on average, suffering liquidity outflows.

Note that even during run days, the relationship between stock prices and outflows only explains less than half of the variation in liquidity flows. There are banks that had very negative stock returns but did not suffer large outflows and banks that suffered large outflows but did not have very negative stock returns. As a result, of the 30 banks with cumulative stock returns worse than -20% from Thursday through Tuesday, only 9 suffered a run; moreover, 9 banks suffered a run without their stock return dropping by more than 20%. Also importantly, the relationship between stock returns and outflows broke down on March 14, as stock prices recovered but net outflows from banks persisted, suggesting a stronger momentum in the deposit outflows.

Figure 9 shows cumulative stock returns starting from March 1, distinguishing between all banks and run banks. Consistent with the regression results in Figure 8, run banks have worse stock returns during the run period but there is considerable overlap in the cross-sectional distributions with the median non-run bank's stock return very close to the 75th percentile run bank's stock return. Interestingly, the surviving run banks' stock

[24]See https://www.fdic.gov/news/press-releases/2023/pr23020.html.
[25]See https://www.fdic.gov/news/press-releases/2023/pr23021.html.
[26]See https://www.fdic.gov/news/press-releases/2023/pr23023.html.

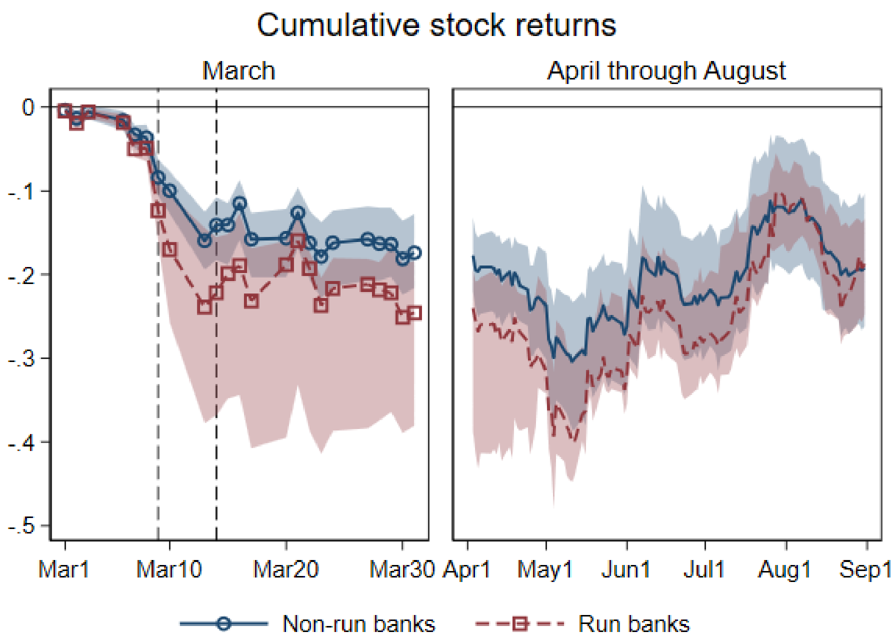

Figure 9: Cumulative stock returns. The figure shows daily median and interquartile range of banks' cumulative stock returns, distinguishing between non-run banks and run banks. Dashed lines indicate 3/9/2023 and 3/14/23. The sample includes all banks we calculate z-scores for that are publicly traded (231 to 238 banks per day). Any failed banks are excluded starting with their failure date.

prices appear to make up lost ground in the medium term with the distributions becoming indistinguishable by the beginning of August. That is, although run banks had overall worse characteristics as highlighted by our regression results in Section 5, following the run, the cumulative 6-month stock performance of the surviving banks was similar to that of non-run banks, potentially because the official sector policy interventions helped the weaker institutions.

6.2 Public announcements

Two important public announcements occurred during our run period: on Friday, March 10 just before 12PM Eastern Time, the FDIC announced the closure of SVB and on Sunday, March 12 at 6:15PM Eastern Time, the Treasury Department, the Federal Reserve and the FDIC jointly announced that deposit insurance would be extended to *all* depositors of SVB and Signature, including those over the insurance limit.[27] In this section, we study whether these announcements had any effect on the runs. Specifically, we study (i) whether the SVB closure announcement was a trigger of the runs on Friday and (ii) whether the insurance extension announcement on Sunday impacted the runs on Monday.

To study the impact of two announcements, we look at the intraday timing of payments on Friday, March 10 and Monday, March 13 by splitting each bank's total payments sent into the share sent before and after 12PM Eastern Time. For Friday, this captures the time of the SVB closure announcement and for Monday, this serves as a natural cutoff for payments pre-positioned over the weekend. In Table 8, we show the estimates of the regression model (1), using as dependent variables the afternoon percentage of payments value sent and received (columns 1 and 2), and of payments volume sent and received (columns 3 and 4). Looking at the banks that were run on Friday, March 10, the afternoon share of payments value sent on Friday is 28pp higher than on other days (column 1), increasing the afternoon share to roughly 90% on a day when these banks' overall value sent more than tripled (column 1 of Table 1).[28] In other words, the Friday runs were concentrated in

[27]SVB was closed by the California Department of Financial Protection and Innovation, which appointed the Federal Deposit Insurance Corporation (FDIC) as receiver; see `https://www.fdic.gov/news/press-releases/2023/pr23016.html`. News of the announcement appeared in Bloomberg at 11:39AM and Dow Jones reported it at 11:58AM. For the joint statement on Sunday, see `https://www.federalreserve.gov/newsevents/pressreleases/monetary20230312b.htm`. In a concurrent statement, the Fed announced the provision of additional funding through the Bank Term Funding Program (BTFP); see `https://www.federalreserve.gov/newsevents/pressreleases/monetary20230312a.htm`.

[28]On an average day, banks send 66% of their payments value after 12PM Eastern Time (see the summary statistics in Table A5). This is consistent with time zone effects, where banks operating under Central, Mountain and Pacific Time send payments later in the day. Table 8 also shows that run banks' afternoon share of payments value received on Friday increased by 11.1pp (column 2). However, this effect is economically much less significant since run banks' overall value received on Friday was not different than on other days

Table 8: Share of afternoon payments activity on run days. The table shows linear regressions of a bank's percentage of daily total payments value or volume sent or received after 12PM EST (excluding payments to/from FHLBs), as indicated at the top, on the interaction of dummies for individual days with dummies for banks run on the respective days, as well as date and bank fixed effects. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 1/1 to 3/14. Any failed banks are excluded starting with their failure date. Appendix A provides variable definitions and summary statistics.

	PM % of value		PM % of volume	
	Sent	Rcvd.	Sent	Rcvd.
	(1)	(2)	(3)	(4)
$\text{Mar10}_t \times \text{RunMar10}_i$	28.21***	11.07***	4.77	1.16
	(2.61)	(3.27)	(3.95)	(0.96)
$\text{Mar13}_t \times \text{RunMar13}_i$	4.67	1.85	-1.98	0.31
	(3.62)	(4.26)	(1.60)	(0.93)
Date & bank FEs	Y	Y	Y	Y
Observations	31,146	31,147	31,146	31,147
Adjusted R^2	0.472	0.430	0.658	0.556

the afternoon, consistent with an information spillover from the announcement of SVB's closure. This matches the FDIC's observation that "On March 10, 2023, [Signature] began to experience deposit withdrawals, with deposit outflows accelerating significantly after the announced closure of SVB."[29] Notably, our result holds whether or not we include Signature Bank in the sample and is therefore representative of *all* banks run on Friday.

In contrast, we see no intraday concentration of payments on Monday, March 13: as Table 8 shows, there is no significant difference in the afternoon share of payments for banks run on Monday with the coefficients on the interactions for March 13 economically small and statistically insignificant. We therefore find no evidence that the runs on Monday were due to depositors who requested their withdrawals before the announcement of the deposit insurance extension on Sunday night, whose transfers would have been executed early in the morning. Instead, the pattern of intraday payments on Monday was similar to that of non-run days, suggesting that the deposit insurance extension had little impact on the intraday pattern of run behavior.

or for other banks (column 2 of Table 1).

[29]See page 15 of the FDIC's review of the supervision of Signature, available at `https://www.fdic.gov/news/press-releases/2023/pr23033a.pdf`.

7 Conclusion

While we have had hundreds of years of bank runs, understanding the causes remains elusive. The novel perspective of intraday payments data sheds new light on these old questions by exploring the patterns of bank runs and banks' responses to being run in March of 2023. The evidence shows that bank runs have both fundamental and panic elements, with a notable "sunspot residual" that cannot be explained with observables. In 2023, we saw evidence of the importance of shared public signals in terms of stock prices, as well as banks with weak balance sheet characteristics that nevertheless saw few net payments outflows. Institutional depositors clearly act the most quickly, and even official sector intervention may not fully stem their withdrawals.

The speed of the 2023 runs and the large discount window borrowing from a small set of run banks highlights the importance for banks to be operationally ready to borrow at the discount window, with enough collateral prepositioned. Indeed, a recent proposal from the G30 Working Group on the 2023 Banking Crisis would require banks to post enough collateral at the discount window to cover all their runnable liabilities[30] Given the important role of discount window borrowing for a subset of run banks, efforts to reduce discount window stigma could meaningfully ameliorate the financial stability implications of a run (see Armantier, Cipriani, and Sarkar, 2024, for an analysis of stigma after the Great Financial Crisis). Finally, the fact that the March 2023 runs continued for a full day after all deposits in the two failed banks were guaranteed suggests that some depositors may run even if they expect to be fully insured — potentially because they do not want to continue to bank with a failing institution — a finding important for regulators as they assess a bank's optimal liquidity level.

The implications of these results for future deposit runs leave space for additional research. What makes publicly traded banks more vulnerable to runs — is it the common signal in the stock price movements, associated news coverage or the read(ier) availability of SEC filings relative to bank regulatory data? These results are not consistent with informed retail depositor monitoring of bank fundamentals. Is there any scale of shock that would induce widespread retail depositor runs? We leave these questions for future work.

[30]See https://group30.org/publications/detail/5264.

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Appendix

A Variable definitions and summary statistics

Table A1: Variable definitions. The table provides definitions of the balance sheet variables used in the analysis. Codes starting with "B" such as "BHCK2170" refer to form FR Y-9C and codes starting with "R" such as "RCFD2170" and "RCON2170" refer to call reports (forms FFIEC 031 and FFIEC 041, respectively).

Variable	Definition
Log assets ($m)	Log of total assets in millions (BHCK2170; RCFD2170).
Assets over $250b	An indicator for assets greater than $250 billion (nominal).
Assets $250b to $100b	An indicator for assets between $100 billion and $250 billion (nominal).
Assets under $100b	An indicator for assets less than $100 billion (nominal).
Publicly traded	An indicator for publicly traded banks (source: CRSP).
Cash/assets	Ratio of cash and balances due from depository institutions (BHCK0081, BHCK0395, BHCK0397; RCFD0010) to total asset.
Securities/assets	Ratio of total securities to total assets. Our FR Y-9C definition of total securities is held-to-maturity (HTM) securities (BHCKJJ34) plus available-for-sale (AFS) securities (BHCK1773) plus equity securities with readily determinable fair values not held for trading (BHCKJA22). Our call report definition of total securities is total book value of investment securities (RCFD1754, RCFD1773) plus total equity securities (RCFDJA22) minus changes in allowances for credit losses on HTM debt securities (balance end of current period) (RIADJH93).
Loans/assets	Ratio of total loans to total assets. Total loans is defined as loans and leases held for sale (BHCK5369; RCFD5369) plus total loans and leases, net of unearned income (BHCKB528; RCFDB528).
CRE/total loans	Ratio of total commercial real estate loans (BHCKF158, BHCKF159, BHDM1460, BHCKF160, BHCKF161; RCONF158, RCONF159, RCON1460, RCONF160, RCONF161) to total loans.
RRE/total loans	Ratio of 1–4 family residential domestic real estate loans (BHDM5367, BHDM5368, BHDM1797; RCON1797, RCON5367, RCON5368) to total loans.
Deposits/assets	Ratio of total deposits (BHDM6631, BHDM6636, BHFN6631, BHFN6636; RCON6631, RCON6636, RCFN6631, RCFN6636) to total assets.
FHLB borr./assets	Ratio of total FHLB borrowing (RCFDF055, RCFDF056, RCFDF057, RCFDF058, RCFD2651, RCFDB565, RCFDB566) to assets.
Tier-1 cap./assets	Ratio of tier-1 capital (BHCA8274; RCFA8274) to total assets.

Continued on next page.

Table A1: Variable definitions. *Continued from previous page.*

Variable	Definition
Unins./total deposits	Ratio of uninsured deposits to total deposits, which is calculated as one minus the ratio of insured deposits to toal deposits. Insured deposits and total deposits are retreived from the FDIC.
Num. unins./tot. dep. ($m)	Ratio of the number of uninsured deposit accounts (RCONF052, RCONF048) to total deposits (in millions).
Corp./total deposits	Ratio of corporate deposits (RCONP757, RCONP759, RCONB549 net of RCONP753 & RCONP754) to total deposits.
HTM loss/tier-1 cap.	Ratio of HTM losses to tier-1 capital.
Deposit growth (yoy)	Year-over-year total deposit growth.
Asset growth (yoy)	Year-over-year total asset growth.
Deposit rate	Ratio of interest expense on deposits (current quarter's total; RIAD4508, RIAD0093, RIADHK03, RIADHK04; BHCKHK03, BHCKHK04, BHCK6761) to total deposits (average of current and previous quarter's end-of-quarter level).

Table A2: Summary statistics for bank characteristics. The table shows summary statistics for the variables used in regressions with balance sheet characteristics in Tables 5 and 7. Sample includes all banks with z-scores on the run days (3/9–3/14). Any failed banks are excluded starting with their failure date.

	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Run bank	0.04	0.18	0.00	0.00	0.00	0.00	0.00	624
Lowest z-score 3/9 to 3/14	-1.44	2.55	-2.72	-1.60	-0.85	-0.38	-0.15	624
Unins./total deposits	0.40	0.17	0.18	0.29	0.39	0.50	0.61	624
Num. unins./tot. dep. ($m)	0.54	0.17	0.36	0.45	0.55	0.64	0.72	624
Corp./total deposits	0.42	0.19	0.16	0.31	0.41	0.53	0.66	624
HTM loss/tier-1 cap.	0.05	0.11	0.00	0.00	0.00	0.07	0.17	624
Assets $250b to $100b	0.03	0.18	0.00	0.00	0.00	0.00	0.00	624
Assets under $100b	0.95	0.23	1.00	1.00	1.00	1.00	1.00	624
Publicly traded	0.38	0.49	0.00	0.00	0.00	1.00	1.00	624
Cash/assets	0.07	0.08	0.01	0.02	0.04	0.08	0.14	624
Loans/assets	0.67	0.16	0.48	0.59	0.71	0.79	0.83	624
CRE/total loans	0.48	0.19	0.20	0.39	0.50	0.60	0.73	624
RRE/total loans	0.21	0.17	0.04	0.10	0.19	0.28	0.39	624
FHLB borr./assets	0.07	0.09	0.00	0.00	0.04	0.11	0.18	624
Tier-1 cap./assets	0.10	0.03	0.08	0.09	0.09	0.11	0.12	624
Deposits/assets	0.82	0.10	0.73	0.79	0.84	0.87	0.90	624

Table A3: Summary statistics for daily payments activity. The table shows summary statistics for the variables used in regressions of daily Fedwire payments activity in Table 1. Sample is 1/1 to 3/14. Any failed banks are excluded starting with their failure date.

	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Log total paym. amount sent	17.35	2.20	15.15	15.88	16.85	18.36	20.20	31,144
Log total paym. amount rcvd.	17.38	2.22	15.13	15.88	16.91	18.41	20.25	31,145
Log total num. of paym. sent	4.83	1.50	3.37	3.74	4.45	5.54	6.74	31,144
Log total num. of paym. rcvd.	4.84	1.53	3.33	3.76	4.48	5.58	6.82	31,145
Log average paym. size sent	12.52	1.12	11.37	11.82	12.35	13.04	13.84	31,144
Log average paym. size rcvd.	12.53	1.15	11.32	11.80	12.37	13.10	13.91	31,145
Mar10_t (in percent)	2.03	14.11	0.00	0.00	0.00	0.00	0.00	31,156
Mar13_t (in percent)	2.03	14.10	0.00	0.00	0.00	0.00	0.00	31,156
RunMar10_i (in percent)	0.78	8.80	0.00	0.00	0.00	0.00	0.00	31,156
RunMar13_i (in percent)	2.99	17.03	0.00	0.00	0.00	0.00	0.00	31,156

Table A4: Summary statistics for payments activity vis-à-vis different bank categories. The table shows summary statistics for the variables used in regressions of payments sent to/received from different bank categories in Tables 2 and B6. Sample is 1/1 to 3/14. Any failed banks are excluded starting with their failure date.

	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Pct. of value sent to banks $\geq$ \$250b	46.71	26.15	11.44	25.05	45.98	67.29	83.36	31,155
Pct. of value sent to \$250b to \$100b	10.13	12.93	0.37	1.83	5.74	12.82	25.67	31,155
Pct. of value sent to banks $<$ \$100b	31.50	25.13	3.91	10.55	25.01	47.95	71.17	31,155
Pct. of value rcvd. from banks $\geq$ \$250b	44.02	27.05	8.98	21.14	41.54	65.28	83.64	31,156
Pct. of value rcvd. from \$250b to \$100b	9.96	13.45	0.32	1.70	5.34	12.30	25.20	31,156
Pct. of value rcvd. from banks $<$ \$100b	32.11	26.02	3.61	9.75	25.55	49.91	72.91	31,156
Pct. of vol. sent to banks $\geq$ \$250b	51.66	12.90	34.91	43.10	51.89	60.53	68.00	31,155
Pct. of vol. sent to \$250b to \$100b	10.89	5.75	4.26	7.04	10.29	14.00	18.18	31,155
Pct. of vol. sent to banks $<$ \$100b	31.52	12.65	16.98	22.33	29.91	39.42	48.28	31,155
Pct. of vol. rcvd. from banks $\geq$ \$250b	49.75	12.96	32.95	41.15	50.10	58.56	65.67	31,156
Pct. of vol. rcvd. from \$250b to \$100b	11.84	6.29	4.62	7.69	11.26	15.21	19.23	31,156
Pct. of vol. rcvd. from banks $<$ \$100b	31.17	13.42	15.56	21.22	29.53	39.62	49.38	31,156
Log value sent to banks $\geq$ \$250b	16.44	2.53	13.93	14.82	16.06	17.64	19.46	31,156
Log value sent to \$250b to \$100b	14.03	3.52	10.79	12.72	14.22	15.73	17.55	31,156
Log value sent to banks $<$ \$100b	15.81	2.15	13.58	14.45	15.50	16.91	18.74	31,156
Log value rcvd. from banks $\geq$ \$250b	16.36	2.63	13.67	14.64	16.00	17.70	19.49	31,156
Log value rcvd. from \$250b to \$100b	14.02	3.55	10.81	12.70	14.16	15.75	17.58	31,156
Log value rcvd. from banks $<$ \$100b	15.83	2.12	13.56	14.50	15.58	16.94	18.72	31,156
Log vol. sent to banks $\geq$ \$250b	4.12	1.52	2.56	3.00	3.78	4.89	6.12	31,156
Log vol. sent to \$250b to \$100b	2.59	1.53	1.10	1.61	2.30	3.30	4.48	31,156
Log vol. sent to banks $<$ \$100b	3.60	1.40	2.20	2.64	3.26	4.19	5.53	31,156
Log vol. rcvd. from banks $\geq$ \$250b	4.09	1.55	2.48	3.00	3.78	4.87	6.13	31,156
Log vol. rcvd. from \$250b to \$100b	2.68	1.55	1.10	1.61	2.40	3.40	4.58	31,156
Log vol. rcvd. from banks $<$ \$100b	3.58	1.40	2.20	2.64	3.26	4.22	5.47	31,156
Mar10_t (in percent)	2.03	14.11	0.00	0.00	0.00	0.00	0.00	31,156
Mar13_t (in percent)	2.03	14.10	0.00	0.00	0.00	0.00	0.00	31,156
RunMar10_i (in percent)	0.78	8.80	0.00	0.00	0.00	0.00	0.00	31,156
RunMar13_i (in percent)	2.99	17.03	0.00	0.00	0.00	0.00	0.00	31,156

Table A5: Summary statistics for share of afternoon payments activity. The table shows summary statistics for the variables used in regressions of percentage of total daily payments activity after 12PM EST in Table 8. Sample is 1/1 to 3/14. Any failed banks are excluded starting with their failure date.

	Mean	Std.	p10	p25	p50	p75	p90	Obs.
PM pctg. of paym. amount sent	66.02	24.95	28.22	49.57	70.16	86.58	95.99	31,146
PM pctg. of paym. amount rcvd.	60.85	24.02	25.06	44.73	63.67	80.12	91.07	31,147
PM pctg. of num. of paym. sent	66.94	15.66	48.00	57.14	66.67	76.81	87.50	31,146
PM pctg. of num. of paym. rcvd.	57.79	10.67	45.41	51.69	57.81	64.29	70.77	31,147
Mar10_t (in percent)	2.03	14.10	0.00	0.00	0.00	0.00	0.00	31,147
Mar13_t (in percent)	2.03	14.09	0.00	0.00	0.00	0.00	0.00	31,147
RunMar10_i (in percent)	0.78	8.80	0.00	0.00	0.00	0.00	0.00	31,147
RunMar13_i (in percent)	2.99	17.03	0.00	0.00	0.00	0.00	0.00	31,147

B Additional tables and figures

Table B6: Payments volume vis-à-vis different bank size categories on run days. The table shows linear regressions of a bank's daily log total payments volume sent to and received from different bank categories, as indicated at the top, on the interaction of dummies for individual days with dummies for banks run the respective days, as well as date and bank fixed effects. Bank sizes: "largest" is over \$250b; "large" is \$250b to \$100b; "small" is under \$100b. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 1/1 to 3/14 and includes as receivers/senders all institutions active in Fedwire. Any failed banks are excluded starting with their failure date.

	Log payments volume					
	Sent to			Received from		
	Largest (1)	Large (2)	Small (3)	Largest (4)	Large (5)	Small (6)
$\text{Mar10}_t \times \text{RunMar10}_i$	0.215*	0.260***	0.153***	-0.065***	-0.045	0.037
	(0.114)	(0.073)	(0.049)	(0.023)	(0.116)	(0.030)
$\text{Mar13}_t \times \text{RunMar13}_i$	0.138*	0.161*	0.208***	-0.047*	-0.146*	-0.070*
	(0.079)	(0.086)	(0.078)	(0.025)	(0.084)	(0.037)
Date & bank FEs	Y	Y	Y	Y	Y	Y
Observations	31,156	31,156	31,156	31,156	31,156	31,156
Adjusted R^2	0.973	0.937	0.959	0.980	0.942	0.965

Table B7: Payments value of different bank size categories on run days. The table shows linear regressions of a bank's daily log total payments volume sent and received, by bank categories as indicated at the top, on dummies for individual days, as well as day-of-week and bank fixed effects. Bank sizes: "largest" is over \$250b; "large" is \$250b to \$100b; "small" is under \$100b. Standard errors clustered at the bank level in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is 1/1 to 3/14 and includes as receivers/senders all institutions active in Fedwire. Any failed banks are excluded starting with their failure date.

	Log payments value					
	Sent by			Received by		
	Largest (1)	Large (2)	Small (3)	Largest (4)	Large (5)	Small (6)
$Mar10_t$	-0.066	0.116	0.116***	0.221*	0.107	0.170***
	(0.084)	(0.182)	(0.025)	(0.109)	(0.096)	(0.027)
$Mar13_t$	0.107***	0.224*	0.347***	0.385***	0.440**	0.498***
	(0.030)	(0.126)	(0.029)	(0.110)	(0.163)	(0.038)
Day-of-week & bank FEs	Y	Y	Y	Y	Y	Y
Observations	686	995	29,474	686	995	29,475
Adjusted R^2	0.981	0.923	0.873	0.975	0.914	0.870

Table B8: Change in balance sheet items pre/post run. The table summarizes changes between 3/8 and 3/15 as a percentage of assets for an exhaustive list of balance sheet items. Sample includes all banks we calculate z-scores forthat are in the H8 data. Any failed banks are excluded starting with their failure date.

	Non-run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Cash	1.22	3.77	-0.95	-0.26	0.31	1.77	4.02	293
Securities	-0.05	0.52	-0.12	-0.02	-0.00	0.00	0.14	293
FF & repo lending	-0.07	0.88	-0.01	0.00	0.00	0.00	0.01	293
Loans	0.15	0.51	-0.13	-0.00	0.11	0.24	0.47	293
Deposits	0.00	2.54	-1.57	-0.74	-0.24	0.31	1.66	293
Borrowings	1.11	2.21	-0.24	0.00	0.27	1.75	3.49	293
Other liabilities	0.13	2.75	-0.24	-0.07	0.00	0.03	0.09	293
	Run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Cash	3.07	7.34	-6.32	-0.24	1.82	5.88	14.76	15
Securities	0.05	0.27	-0.05	-0.02	-0.01	0.00	0.24	15
FF & repo lending	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15
Loans	0.39	0.57	-0.20	0.07	0.25	0.69	1.33	15
Deposits	-6.21	9.58	-15.40	-6.51	-4.03	-0.93	-0.58	15
Borrowings	10.03	15.59	0.00	0.85	4.52	10.64	38.75	15
Other liabilities	-0.02	0.20	-0.33	-0.13	0.00	0.04	0.23	15

Table B9: Change in banks' Fed account balances by source pre/post run. The table summarizes changes between 3/8 and 3/15 in banks' Federal Reserve account balance as a percentage of 2022q4 assets for an exhaustive list of sources. Sample includes all banks we calculate z-scores for. Any failed banks are excluded starting with their failure date.

(a) FR 2644 sample.

	Non-run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Total	1.08	3.01	-0.85	-0.22	0.28	1.90	4.08	293
ACH	0.07	3.00	-0.61	-0.15	0.00	0.34	0.90	293
Fedwire excl. FHLBs	1.54	15.21	-2.32	-0.91	-0.08	0.86	2.76	293
Fedwire from FHLBs	1.21	3.22	-0.24	0.00	0.23	1.69	3.75	293
Discount window	0.05	0.43	0.00	0.00	0.00	0.00	0.00	293
Fedwire securities	-0.41	4.14	-0.17	0.00	0.00	0.00	0.00	293
Other	-1.39	13.97	-1.87	-0.49	-0.01	0.04	0.70	293
	Run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Total	4.29	8.20	-3.79	-0.14	1.94	9.67	20.30	15
ACH	0.04	0.58	-0.73	-0.48	0.02	0.60	0.82	15
Fedwire excl. FHLBs	-6.94	9.55	-15.62	-6.82	-3.49	-1.63	-0.17	15
Fedwire from FHLBs	4.20	3.01	0.52	2.34	3.31	5.59	9.04	15
Discount window	7.80	16.19	-0.00	0.00	0.00	1.93	36.90	15
Fedwire securities	-0.11	0.42	0.00	0.00	0.00	0.00	0.00	15
Other	-0.70	1.04	-1.92	-1.35	-0.25	-0.07	0.00	15

(b) Full sample.

	Non-run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Total	1.57	8.91	-1.02	-0.25	0.20	2.02	4.48	612
ACH	0.01	8.29	-0.83	-0.22	0.00	0.22	0.88	612
Fedwire excl. FHLBs	13.92	293.92	-2.23	-0.80	0.00	1.09	3.47	612
Fedwire from FHLBs	1.02	6.46	-0.25	0.00	0.05	1.55	3.82	612
Discount window	0.09	0.66	0.00	0.00	0.00	0.00	0.00	612
Fedwire securities	-0.22	2.90	0.00	0.00	0.00	0.00	0.00	612
Other	-13.25	286.06	-1.56	-0.41	-0.00	0.03	0.46	612
	Run banks							
	Mean	Std.	p10	p25	p50	p75	p90	Obs.
Total	3.77	7.17	-3.58	0.04	2.16	4.42	16.02	20
ACH	0.09	0.54	-0.66	-0.19	0.05	0.42	0.85	20
Fedwire excl. FHLBs	-6.82	8.73	-16.53	-6.80	-3.63	-2.02	-0.65	20
Fedwire from FHLBs	4.76	3.41	0.84	2.59	3.46	7.52	10.46	20
Discount window	6.34	14.28	-0.00	0.00	0.00	0.96	33.57	20
Fedwire securities	-0.07	0.37	0.00	0.00	0.00	0.00	0.00	20
Other	-0.54	0.94	-1.66	-0.62	-0.21	-0.00	0.02	20