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# Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks†

*By* Rajkamal Iyer and Manju Puri*

*We use unique depositor-level data for a bank that faced a run to understand the factors that affect depositor behavior. We find uninsured depositors are most likely to run. Deposit insurance helps, but is only partially effective. Bank-depositor relationships mitigate runs, suggesting that relationship with depositors help banks reduce fragility. In addition, we also find that social networks matter. Finally, we find long-term effects of a solvent bank run in that depositors who run do not return back to the bank. Our results help understand the underlying dynamics of bank runs and hold important policy implications.* (*JEL* D12, G21, O16, Z13)

Bank runs are situations where depositors withdraw their deposits from banks because of fear of the safety of their deposits. Bank runs are a prominent feature of banking systems, both historically and currently. The large number of bank runs during the Great Depression in the United States prompted the introduction of federal deposit insurance. The recent financial crisis has also been characterized by the dire financial condition of banks and prominent bank runs, both in the US and internationally (e.g., Countrywide Bank, IndyMac Bank (US), Northern Rock Bank (UK)). The attempt to avoid bank runs is at the root of deposit insurance and capital adequacy requirements, which in turn have led to a large literature on the agency problems inherent in deposit insurance or "too big to fail" policies. Given the costs associated with bank runs or crises, understanding the factors that drive depositor runs on banks is important.[1]

* Iyer: Massachusetts Institute of Technology, 50 Memorial Drive, Cambridge, MA 02142 (e-mail: riyer@mit.edu); Puri: Fuqua School of Business, Duke University, 1 Towerview Drive, Durham, NC 27708, and NBER (e-mail: mpuri@duke.edu). We would like to thank Doug Diamond, Joost Dreissen, Mark Flannery, Ines Chaieb, Atif Mian, Adair Morse, George Pennacchi, Debu Purohit, David Robinson, Claire Rosenfeld, Florencio Lopez de Silanes, Phil Strahan, Per Stromberg, David Smith, Amir Sufi, Tavneet Suri, Anjan Thakor, Haluk Unal, Tanju Yorulmazer, and seminar participants at the American Finance Association Meetings, New Orleans, Bank Structure and Competition conference, Fed Chicago, Columbia University, Duke University, European School of Management and Technology, Federal Deposit Insurance Corporation, Washington, Financial Intermediation Research Society Conference, Anchorage, Harvard Business School, Indian School of Business, NBER Corporate Finance Summer Institute, New York Fed and NYU Stern conference on Financial Intermediation, University of Michigan, Northwestern University, University of Amsterdam, University of Maryland, UBC Winter conference, Whistler, World Bank, Vanderbilt University, and CAC-FIC-SIFR conference at Wharton for helpful comments. We are grateful to Mr. Gokul Parikh, and the staff of the bank for all their help. We appreciate the excellent research assistance of Ananth Raman. We thank the FDIC for financial support.

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[1] For the costs of banking crises, see, e.g., Friedman and Schwartz (1963); Bernanke (1983); Ongena, Smith, and Michalsen (2003); Calomiris and Mason (2003); Dell'Ariccia, Detragiache, and Rajan (2008). See also Lindgren, Garcia, and Saal (1996), who show that in the period between 1980 and 1996, 133 countries experienced severe banking problems.

One of the key questions that arose in the current financial crisis is whether to extend deposit insurance broadly and widely to prevent bank runs. Because of belief in deposit insurance as an effective mechanism for preventing widespread bank runs, in the US, deposit insurance was increased from a limit of $100,000 to $250,000. Similar measures were taken around the globe, in countries such as the United Kingdom. Withdrawals by large uninsured depositors is thought to have been a key characteristic of the recent financial crisis. While deposit insurance is used worldwide as a mechanism to prevent bank runs, however, we do not have actual evidence of its effectiveness in preventing bank runs. Clearly, understanding whether deposit insurance actually prevents bank runs is of first-order importance.

Apart from empirically analyzing the role of deposit insurance, it is also important to examine whether there are other factors that affect depositors' incentives to run. How do contagion effects of bank runs spread? Are there costs of a bank run, even if the bank survives? Understanding these factors are important from multiple perspectives—from the point of view of the bank, its customers, and regulators.

In this paper, we take advantage of a unique experiment in which we examine micro-depositor–level data for a bank in India that experienced a run when a neighboring bank failed. The bank that we use for this study had no fundamental linkages with the failed bank in terms of interbank linkages or loans outstanding with the failed bank. Furthermore, our bank faced depositor withdrawals for a few days after the date of failure of the large bank, with activity returning to prerun levels in the subsequent period. We are able to obtain and use minute-by-minute depositor withdrawal data to examine the effectiveness of deposit insurance. We can analyze both the behavior of depositors who were uninsured as well as depositors who were insured. We find that depositors with balances under the insurance threshold are indeed less likely to run than those who are above the insurance limit, suggesting deposit insurance matters. We also find, however, that deposit insurance is only partially effective. Even within the insurance limit, depositors with larger balances are more likely to run.

Given that deposit insurance is only partially effective in preventing bank runs, an important question is what other factors affect depositors' propensity to run? We first examine whether bank-depositor relationships affect depositor behavior. We measure the length of the relationship by the age of the account, and depth through additional ties of taking a loan from the bank. We find that the longer the bank-depositor relationship, the lower the likelihood of a withdrawal during the crisis. Further, depositors who have a loan linkage are less likely to run. Interestingly, we find that even depositors who had availed of a loan in the past (but currently have no outstanding loan) are less likely to run. We conduct several robustness checks to address the concern that loan linkages might proxy for other omitted characteristics like wealth or the education levels of depositors. Our results suggest that the relationship with depositors can help banks reduce fragility and thus add more value than just giving the bank information about its clientele.

The second dimension that we examine is social networks. We capture social networks of a depositor using a unique feature in India: a person wishing to open an account with a bank needs an introduction from someone who already has an account with the bank. We also measure social network using the neighborhood of the depositor. We employ a variety of methods, which include simple probit models, and models that allow us to use the minute-by-minute variation in our data through Cox proportional hazard models with time-varying covariates. We also explore and employ methods from the rich epidemiology literature, which spends considerable effort in examining how diseases spread to estimate the transmission probability of an infectious disease. In all estimations we find that the same factors are important. Deposit insurance partially helps mitigate runs. Social networks matter—if other people in a depositor's network run, the depositor is more likely to run. Even in a network where other depositors are running, however, the length and depth of the bank-depositor relationship significantly mitigates the propensity of the depositor to run.

Apart from the factors that affect depositor runs, from a policy point of view, an important question that affects the decision for regulatory intervention is the long-term effect of bank runs. If the bank survives the run and stays solvent, do depositors who run return to the bank? We find that the effects of a solvent bank run are long-lasting. Of the depositors who withdrew during the crisis, only in 10 percent of the cases did the account balance return to precrisis levels even after six months of the crisis. Further, we do not find that the aggregate level of deposits of the bank return to the precrisis levels in the short run. This suggests that there are real costs to the bank that can potentially influence their asset portfolio and loans. Even if depositor runs do not lead to bank failure, the loss in deposits could lead banks to cut down on loans, which could impose high costs on borrowers in the presence of information asymmetry.

Our paper is related to a number of strands of literature. First, it relates to the large theoretical literature on bank runs.[2] As many of the theoretical models and some evidence suggest, even if the bank is fundamentally solvent, bank runs can still occur because depositors can run in anticipation of a run. Our paper helps in identifying factors influencing contagion effects of bank runs. Second, our paper complements the empirical literature on bank runs, which has largely been conducted in a macro setting[3] by looking at micro-level data to empirically identify factors that affect depositor propensity to run. In particular, our paper examines the role of deposit insurance in bank runs, which has been an important policy response in the current financial crisis. Our micro-evidence suggests that deposit insurance is useful in helping to prevent bank runs but not perfect; i.e., deposit insurance is partially effective in preventing bank runs. To the best of our knowledge, ours is the first micro-level data that provides evidence on the effectiveness of deposit insurance in preventing bank runs.

Our paper also identifies factors beyond deposit insurance that can help mitigate bank runs. We not only find that social networks are important in affecting depositor propensity to run, but interestingly, we find that the length and depth of bank-depositor relationships reduce the propensity to run. While there is an increasing literature examining the importance of cross-selling by banks related to revenue generation, our results suggest a new rationale for cross-selling; viz., cross-selling

[2] The literature can be divided broadly into two classes. In one class of models, bank runs are a result of coordination problems among depositors (Bryant 1980; Diamond and Dybvig 1983; Postlewaite and Vives 1987; Goldstein and Pauzner 2005; Rochet and Vives 2004). Runs occur due to self-fulfillment of depositors' expectations concerning the behavior of other depositors. In the other class of models, bank runs are a result of asymmetric information among depositors regarding bank fundamentals (Chari and Jagannathan 1988; Jacklin and Bhattacharya 1988; Chen 1999; Calomiris and Kahn 1991). In these models, depositor beliefs regarding the solvency of a bank play an important role in determining depositor actions.

[3] These papers helped answer questions such as whether bank distress were not merely symptoms of the Great Depression but also helped to magnify the shocks that caused the depression (Bernanke 1983; Calomiris and Mason 2003); whether solvent banks failed during the Depression by examining if banks with better fundamentals experience lower deposit withdrawals (Saunders and Wilson 1996; Calomiris and Mason 1997).

protects the downside risk to a bank of runs, and effectively acts as a complementary insurance mechanism for the bank. Thus, our results suggest that allowing banks to offer an umbrella of products (universal banking) could help strengthen bank-depositor relationships and in turn reduce fragility. To the best of our knowledge, this role of relationships is also new to the literature. This result also helps contribute to the literature that highlights the fragility of banks arising from banks funding themselves through demand deposits (e.g., Allen and Gale 2000; Diamond and Rajan 2001; Song and Thakor 2007). Not only is the coexistence of deposit-taking and lending important in reducing fragility (Kashyap, Rajan, and Stein 2002), our paper suggests it is beneficial to tie deposits and loans to the same depositor.

Finally, our paper also adds to literature that studies the real effects of bank failures on a micro-level. We find the effects of a bank run are long-lasting, even if the bank remains solvent, since depositors who run do not return to the bank. The resultant loss in deposits suggests real costs for the bank and related borrowers. These findings suggest there may be a case for early intervention even for solvent bank runs where the bank is able to survive the run.

The remainder of the paper is organized as follows. Section I describes the institutional setting. Section II provides details of the event. Section III describes the dataset. Section IV presents the results. Section V presents the robustness checks. Section VI concludes.

## I. Institutional Details

The Indian banking system constists primarily of three types of banks: public sector, private, and cooperative. The main regulatory authority of the banking system in India is the Reserve Bank of India (RBI). Cooperative banks, however, come under dual regulation; i.e., they are supervised by the RBI as well as by the local state government. The RBI is responsible for monitoring the banks' portfolios while the state government is responsible for governance issues.

The insurance cover granted under the deposit insurance scheme is Rs. 100,000 (approximately $2,500) for each depositor at a bank. The deposit insurance is based on a flat premium. Though deposit insurance is present, there are several delays in processing the claims of depositors. The central bank first suspends convertibility when a bank approaches failure and then makes a decision of whether to liquidate a bank or arrange a merger with another bank. During this period, depositors are allowed a one-time nominal withdrawal up to a maximum amount that is stipulated by the central bank.[4] In case of failure of a bank, the deposits held by a depositor cannot be adjusted against outstanding loans. The stipulated cash reserve ratio and statutory liquidity ratio to be maintained by the banks are 5.5 percent and 25 percent, respectively.[5]

Depositors of cooperative banks are not required to hold an equity claim in the bank. Furthermore, any depositor can obtain a loan from the bank. It is also not

[4] In most cases, depositors are allowed a one-time withdrawal of up to Rs. 1,000 ($25) per account.

[5] Statutory Liquidity Ratio (SLR) is the one that every banking company shall maintain in India in the form of cash, gold, or unencumbered approved securities, an amount that shall not, at the close of business on any day, be less than such percentage of the total of its demand and time liabilities in India as on the last Friday of the second preceding fortnight.

mandatory to open a deposit account when taking a loan. Further, shareholders of cooperative banks have limited liability.[6] Thus, the cooperative structure of the banks does not lead to significant differences in characteristics of depositors as compared to banks with other ownership structures. In the US system, the closest parallel to cooperative banks is perhaps community banks, which play an important role in the US economy (see, e.g., Kroszner 2007).[7]

## II. Event Description

We now turn to the description of the event that we use in this paper. The precipitating event was a fraud in the largest cooperative bank in the state of Gujarat. The bank had granted loans to stockbrokers without appropriate collateral in contravention of the guidelines prescribed by the central bank.[8] The amount of loans given to stockbrokers amounted to nearly 80 percent of the deposit base (Rs. 10 billion were advanced as industrial loans to stock brokers without appropriate collateral). On March 8, 2001, some major brokers defaulted on their pay-in obligations to the stock exchange. Rumors were circulating that the bank had overstretched lending positions to a major stockbroker who had suffered huge losses in his share dealings in a select group of stocks (information technology, communication, and entertainment sectors).[9] This led to a run on the bank on the 9th and 12th of March 2001. As the bank failed to repay depositors on March 13, 2001, the central bank temporarily suspended convertibility and restrained the bank from making payment to depositors beyond Rs. 1,000 per account. The failure of this bank triggered runs across other cooperative banks in the state. Several other banks in the state witnessed runs immediately after the failure (Iyer and Peydro 2010). There were no other banks that failed during the event window, however. Also, it is important to note that the runs were limited to cooperative banks. In fact, in contrast to the situation at cooperative banks, public sector banks witnessed an increase in deposits in that quarter.[10] Furthermore, at the time of the failure the state economy was performing well. Put together, these facts indicate that the runs were the result of an idiosyncratic shock rather than a product of weak economic fundamentals (Gorton 1988).[11] We also

[6] The bank issues shares at face value. To be a borrower at the bank, the bank asks a depositor to buy shares worth two percent of loan amount which can be redeemed at face value at the end of the loan. In general, dividends are not paid by the bank as reserves are used to build up capital to meet capital-adequacy requirements.

[7] In a speech on March 5, 2007, Federal Reserve Governor, Randall Kroszner stated, "Community banks play an important role in the United States economy, as they have throughout our history … many community banks continue to thrive by providing traditional relationship banking services to members of their communities. Their local presence and personal interactions give community bankers an advantage in providing financial services to those customers for whom, despite technological advances, information remains difficult and costly to obtain … I believe that the most significant characteristics of community banks are: 1) their importance in small-business lending; 2) their tendency to lend to individuals and businesses in their local areas; 3) their tendency to rely on retail deposits for funding; and 4) their emphasis on personal service." Cooperative banks display the same four significant characteristics as community banks.

[8] See the report at www.manupatra.com/downloads/JPC/part%201.pdf.

[9] Note that the stocks of companies in information technology, communication, and entertainment sectors were the ones that suffered huge losses. Thus, the downturn in the stock market was most pronounced in these sectors.

[10] We find the percentage increase in deposits in public sector banks from March–June in Ahmedabad is 2.6 percent and across the state of Gujarat is 3.7 percent. The percentage increase in deposits in public sector banks from March-Sept in Ahmedabad is 8.88 percent and across the state is 8.83 percent. Thus, aggregate deposits in public sector banks rise in the same period.

[11] Gujarat's GDP growth was 9.8 percent in 2001 as compared to 0.6 percent in 2000 and −1.6 percent in 1999.

conduct a survey of the depositors that is discussed later in the paper, in which we ask depositors which banks they hold accounts with and the reasons for their withdrawals. None of the depositors of the banks we study report having deposits in the large bank that failed. Nor do we find that runners differ from depositors who stay in terms of age, education, wealth, or stock ownership. Interestingly, we find that depositors report trust in the bank as the most important factor affecting their decision to withdraw. This further suggests that the runs were not a result of aggregate liquidity shocks to depositors as a result of a downturn in the stock market, or from weak economic fundamentals, but stem from an idiosyncratic shock.

After the collapse of the large bank there was a huge debate as to whether it should be bailed out. The revival scheme was organized in terms of a privately arranged bailout. The revival scheme was a nonstarter, however.

## III. Data

We obtain data from a cooperative bank that was located in the same city as the failed bank. After the failure of the large cooperative bank, this bank faced runs in the subsequent days. There was no media report/press coverage about the bank that we use for the analysis during the event window or going forward. The press coverage was largely limited to discussions about the failed bank. Furthermore, the runs stopped on their own. There was no suspension of convertibility or intervention by the central bank. In terms of deposits, the total deposit base of this bank was approximately Rs. 300 million. This bank hardly had any interbank exposure to the failed bank. Its exposure was 0.001 percent of the total assets. Also, this bank did not have any correspondent banking relationship with the failed bank. The bank's loan portfolio was composed primarily of loans to individuals and small businesses. Unlike the cooperative bank that failed, this bank did not have any exposure to information technology, communication, or entertainment sectors, which experienced a downturn. In addition, the bank did not have any exposure to the stock market.

First, we obtain all the transactions for the depositors who have an account at the headquarters of the bank (the bank had two branches, with the bulk of the deposits in the head office). The transaction data provides us with details of every transaction undertaken by a depositor in the period between January 2000 and January 2002. For each transaction, we can identify whether it is a deposit or withdrawal, along with the time and date. We also have the opening balance of each account at the beginning of the month. This enables us to compute the total balance in each account and also the daily inflow and outflow in each account. Additionally, for each deposit account we have details of the date on which the account was opened along with information about the name of the depositor and the address of the depositor.[12] Apart from the details of deposit accounts, we also have information on the loans that have been made by the bank. For the loan accounts, also, we can identify the name of the person who has taken the loan, the address, and the type of loan. For the term deposit accounts, we have information on the name, address, the initial amount of the term deposit, the maturity amount, maturity date, and the date at which the term deposit

[12] The exact address is sometimes missing because of random inputting errors in the bank records.

was liquidated. Our dataset also allows us to identify the mode of each transaction undertaken. For instance, if on any of the days there is a withdrawal made from an account, we can identify whether the withdrawal was made in person or through a check or whether the withdrawal was due to an internal transfer. Note that the bank did not have electronic banking or any automatic teller machines (ATMs). The only way to obtain immediate cash was to queue up outside the bank.

To construct the daily balance in an account, we first use the data on daily transactions and compute the outstanding balance in an account on a daily basis. Thus, for each account we compute the balance at the close of each day. The difference in the daily balances provides us with information on whether there is a net inflow or net outflow from the account for the interval. To make sure that the algorithm we use to compute daily balances is correct, we compare the balance that we obtain at the end of the month using our algorithm with the monthly closing balance for each account provided by the bank. We do not find any difference in these two variables. We also compute the length of the days the account has been active by computing the difference between the opening date of the account and March 13, 2001. Note that as computerization of the bank data occurred only in April 1995, for some accounts the information on the opening date is not filled. These accounts had been opened before April 1, 1995. We assume the opening date of these accounts to be April 1, 1995 for computation. This provides us with the duration of each account as of March 13, 2001. To obtain the total number of transactions undertaken by an account, we count the number of transactions for an account beginning January 1, 2000 until March 13, 2001. For example, if an account had four transactions in the period between January 1 and March 13, 2001, we record the total transaction count as four for that account.

To determine whether there are loan linkages associated with an account, we first match all the accounts by the name and address associated with the account. Thus, for each account we have two separate matches. The name match indicates whether there is another account with the same name. The address match indicates whether there is another account with the same address. The name and address match algorithm that we use provides a unique number to two accounts that have the same name and, similarly, another unique number if two accounts have the same address. After the initial match using the algorithm, we manually matched the names and addresses. We then create an address match identifier that acts as an indicator of accounts belonging to the same household. As loans could be taken by any member of the household, we define an account to have a loan linkage if any member of the household has/had a loan outstanding with the bank. Thus, loan linkage is a dummy variable that takes the value of one for an account if any member of the household has/had a loan outstanding with the bank on/before March 13, 2001. In defining the loan linkages, we exclude overdrafts or cash facilities that are taken against term deposits with the bank as these may have restrictions in terms of liquidation of deposits.

To determine the ethnic status of a depositor, we first use an algorithm that sorts depositors based on their last names. The two main ethnic groups depositors belong to are Muslims and Hindus (Gujarati). In most cases, it is very easy to identify the ethnic profile of a depositor based on the last name. Since we do not have an exhaustive list of last names that are associated with Muslims or with Gujarati, however, we manually categorize the ethnic status of each depositor. The manual procedure also helps in correctly categorizing depositors who could have the same surname as a Hindu depositor but have a very distinctive Muslim first name. For example, "Patel" is a last name that is used by both Hindus and Muslims. From the first name, however, it is easy to categorize a depositor with the name "Ahmed Patel" as a Muslim as against "Vaibhav Patel." Thus, we create a minority dummy that takes the value of one if the ethnic group of the depositor is Muslim and zero otherwise.

To capture the effect of past deposits and past withdrawals, we generate two variables. The variable "change in deposits" is defined as the daily average of percentage change in deposits between January 1, 2001 and the event date. The variable change in deposits takes the value of zero if there are no deposits. Similarly, the variable "change in withdrawals" is defined as the daily average of percentage change in withdrawals between January 1, 2001 and the event date (for convenience, we use the negative of this average). The variable change in withdrawals takes the value of zero if there are no withdrawals. We also create a dummy variable called "above insurance cover" that takes the value of one if the total balance of the depositor with the bank as on March 13, 2001 is greater than the deposit insurance level. In addition, we generate a variable called "opening balance" that is the opening balance in an account as of March 13, 2001 if the account is below the deposit insurance level and zero otherwise.

For transaction accounts, we have the exact time of day when the withdrawal is made. We utilize the time of withdrawal for each depositor to create a variable called "failure time." We set the starting time as the time of failure of the large bank (March 13, 2001). We evaluate failures in one-minute intervals, beginning at 10:30 AM on March 13, 2001.[13] For example, the withdrawal by a depositor on March 13, 2001 at 10:36:36 AM would have a failure time of seven.

Finally, we capture the network of a depositor in two different ways. We first use the name of the introducer associated with a depositor's account. This information is available for the transaction accounts. In India, it is a common requirement for banks to ask a person wishing to open an account to be introduced by someone who already has an account with the bank. The main purpose of the introduction is to establish the identity of the depositor. In India, there is no social security number that can be used to easily verify the identity of a person. In general, people are introduced by an acquaintance who has an account with the bank. The introducer does not incur liability or receive any incentives from the bank. We first link all people who share the same introducer. In case we find more than one introducer within a household, we cross the networks. For example, if household number 1 has introducer A and B, we pool all depositors with introducer name A or B into a single network. We then construct a variable called *runners introducer network* $(t-1)$ at each point in time $(t)$ that captures the fraction of other depositors in the introducer network that have run until time $(t-1)$, excluding those within the household of a depositor. In case we find that the introducer is a member of the household itself or, if we find no introducer name associated with an account, we do not associate the account to any network and the variable *runners introducer network* $(t-1)$ takes the value of 0.

We also capture networks based on the neighborhood of the depositor. *Runners in neighborhood* $(t-1)$ captures the fraction of other depositors in the neighborhood

[13] The banking hours are from 10:30 AM to 4:00 PM, thus we measure time of failure in reference to the time when the bank is open for business.

who have run until time $(t-1)$, excluding those within the household of a depositor. Note that "neighborhood" is defined as the municipal ward that a depositor resides in (the average area that a ward covers is approximately 4 square kilometers). We have 71 neighborhoods in the sample. We also define a variable called *Distance* that captures the physical distance of the depositors' residence from the bank. We measure distance by measuring the travel costs incurred by taking an auto-rickshaw from the depositors' neighborhood to the bank.

## IV. Empirical Results

Before presenting the summary statistics, a look at the figures helps highlight the magnitude of the runs faced by the bank. Figure 1 presents the net amounts that are liquidated from the term deposit accounts in the period between February 1, 2001, and May 1, 2001. As can be seen from the figure, there is a sharp spike in the liquidations beginning March 13, 2001 up to March 15. This coincides with the date of failure of the large cooperative bank. Figure 2 presents the evolution of the transaction accounts for the same interval of time. Again, a similar picture unfolds. The figure shows that there is a sharp increase in withdrawals from transaction accounts immediately after the failure of the large bank. Thus, these figures highlight the extent of runs faced by the bank in the period subsequent to the failure of the large bank. To further examine the pattern of withdrawals by depositors, we plot the fraction of outstanding balance that is liquidated by depositors who withdrew during the crisis. From Figure 3, it can be seen that of the depositors who withdraw, most of them withdraw 75 percent or more of their balance, showing abnormal withdrawal activity in this period.

Table 1A (panel A) presents the summary statistics for term deposit accounts. As on March 13, 2001, there are 4,574 depositors who have term deposit accounts active at the head office of the bank. Of these accounts, only 6.6 percent of the depositors have an account balance more than the deposit insurance coverage limit (\$2,500). This suggests that the majority of depositors are small depositors. For depositors who hold balances below the deposit insurance coverage limit, the average balance in term deposit account is Rs. 23,823. We also see that 8 percent of depositors have/had some loan linkage with the bank. In terms of the ethnic profile of depositors, 29 percent of the depositors belong to the minority community. The average age of the account is 1,057 days. The average time to maturity of the deposits is 384 days.

Table 1A, panel B presents the summary statistics for the transaction accounts (savings and current accounts). As of March 13, 2001, there are 10,691 depositors with transaction accounts at the head office of the bank. Out of these accounts, only 1 percent of the depositors have an account balance that is more than the deposit insurance level. For depositors with balances within the deposit insurance coverage limit, the average account balance is Rs. 3,259. The extent of depositors with loan linkage is similar to that of term deposit accounts (7.5 percent). The average number of transactions per depositor in the period between January 1, 2000, and March 13, 2001 is 14.69. In terms of the ethnic profile of the depositors, 26 percent of the depositors belong to the minority community. We also see that the daily average change in deposit is 9 percent. On the other hand, the daily average change in withdrawal is 0.4 percent. The average age of a transaction account is 2,286 days.

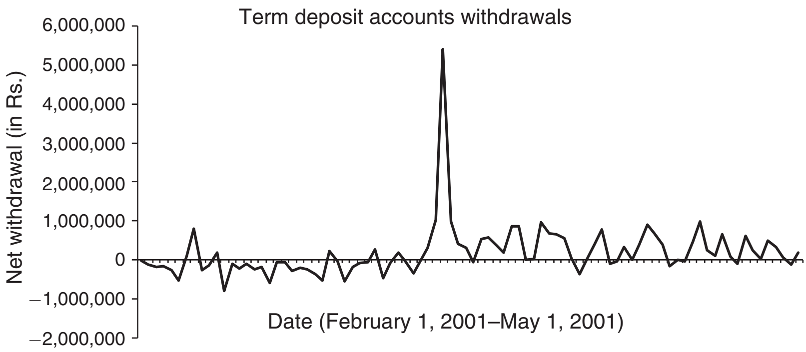


FIGURE 1. WITHDRAWALS FROM TERM DEPOSIT ACCOUNTS FROM FEBRUARY TO MAY 2001

*Note:* March 13th is the date of failure of the large bank.

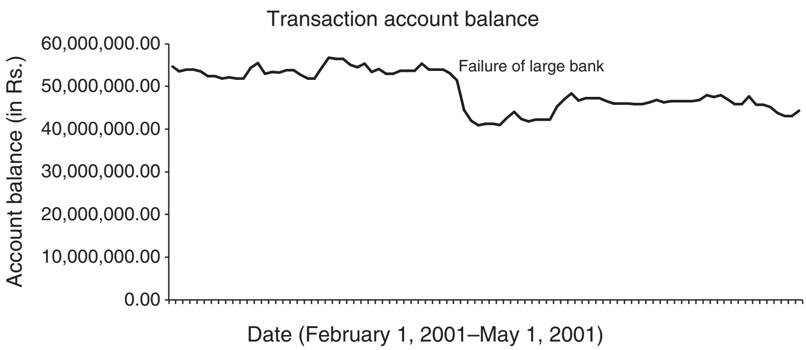


FIGURE 2. DEPOSIT BALANCE IN TRANSACTION ACCOUNTS FOR THE PERIOD BETWEEN FEBRUARY AND MAY 2001

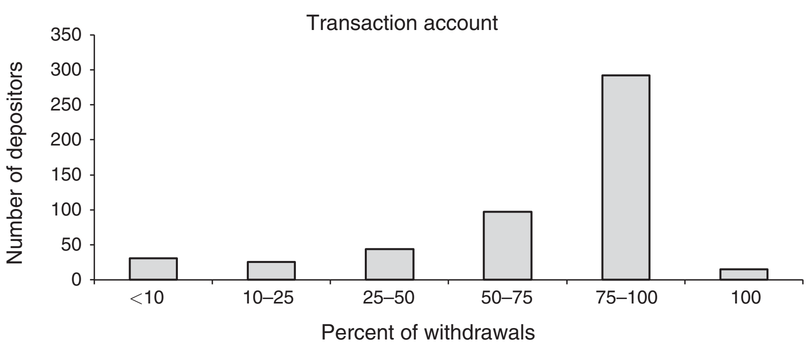


FIGURE 3. PERCENT OF OUTSTANDING ACCOUNT BALANCE WITHDRAWN BY A DEPOSITOR WHO WITHDREW DURING THE CRISIS

To analyze the characteristics of depositors who withdrew during the crisis, we conduct the analysis for term deposit accounts and for transaction accounts separately. It is necessary to separate the analysis, as there are higher costs to liquidation of term deposits as against withdrawals from transaction accounts. If a term deposit

Table 1A—Summary Statistics

| | Observations | Mean | Median | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| *Panel A. Term deposit accounts* | | | | | | |
| Minority community | 4,574 | 0.294 | 0 | 0.455 | 0 | 1 |
| Above insurance cover | 4,574 | 0.066 | 0 | 0.248 | 0 | 1 |
| Opening balance | 4,271 | 23,823 | 16,813 | 21,365 | 402 | 99,906 |
| Age of account | 4,574 | 1,057 | 1,105 | 563 | 1 | 7,585 |
| Loan linkage | 4,574 | 0.080 | 0 | 0.272 | 0 | 1 |
| Number of days to maturity | 4,574 | 384 | 262 | 379 | 0 | 2,248 |
| *Panel B. Transaction accounts* | | | | | | |
| Minority community | 10,691 | 0.268 | 0 | 0.442 | 0 | 1 |
| Above insurance cover | 10,691 | 0.011 | 0 | 0.103 | 0 | 1 |
| Opening balance | 10,575 | 3,259 | 683 | 9,131 | 0.39 | 99,780 |
| Change in deposits | 10,691 | 0.094 | 0.0003 | 1.268 | 0 | 93.19 |
| Change in withdrawals | 10,691 | 0.004 | 0 | 0.015 | 0 | 0.469 |
| Age of account | 10,691 | 2,286 | 2,173 | 1,307 | 8 | 16,640 |
| Number of transactions | 10,691 | 14.69 | 4 | 50.26 | 0 | 1,421 |
| Loan linkage | 10,691 | 0.075 | 0 | 0.262 | 0 | 1 |

*Notes:* Age of account is the length of time (days), for which the account has been open as on the event date. Days to maturity are the number of days left for maturity for the term deposit account. Definition of other variables can be found in Appendix 1.

account is liquidated before maturity, the bank calculates the total interest payments due on the principal amount based on the current prevailing rates for a term deposit with a maturity period similar to the time for which the initial deposit was held at the bank (at the point of liquidation), minus 2 percent as penalty. Furthermore, splitting the analysis also provides an additional robustness to the strength of the findings. For the term deposit accounts, we construct a dummy variable that takes the value of one if the depositor liquidated any part of his term deposit in the period between March 13 and March 15, 2001. For the transaction accounts, classification of a depositor as a runner is more difficult as transaction accounts are also used to meet daily liquidity needs. We therefore categorize a depositor as a runner if he/she withdraws more than 75 percent of the deposit outstanding as of March 13, 2001. The analysis is carried out at a depositor level as some of the important variables, like deposit insurance coverage, are at a depositor level. In the estimations we also cluster standard errors by household. As robustness, we also use other thresholds like 50 percent and 25 percent and do not find any significant change in the main results.

Table 1B presents the summary statistics for the runners and stayers separately. About 5.7 percent of the term deposit accounts and 3 percent of the transaction accounts depositors run. These numbers are in line with the fact that even a small number of depositors can cause a bank run with severe consequences. These numbers are comparable to those known from other bank runs. Kelly and O Grada (2000) document that in the bank run on Emigrants Industrial Savings Bank that occurred between December 11 and December 30, 1854, 234 account holders (7 percent of account holders) closed their accounts. Similarly, the number of depositors who ran in the recent IndyMac case was less than 5 percent.[14]

[14] As of March 31, IndyMac had total deposits of $19.06 billion from some 275,000 deposit accounts. Of those, some 10,000 depositors had funds in excess of the insured limit, for a total of $1 billion in potentially uninsured funds, according to the FDIC. On average, the balance per deposit account is $69,090. Senator Schumer questioned

Table 1B

| | Runners | | | Stayers | | | |
|---|---|---|---|---|---|---|---|
| | Observations | Mean | SD | Observations | Mean | SD | Diff (*t*-stat) |
| *Panel A. Term deposit accounts* | | | | | | | |
| Minority community | 249 | 0.369 | 0.483 | 4,325 | 0.289 | 0.453 | 2.704*** |
| Above insurance cover | 249 | 0.080 | 0.272 | 4,325 | 0.065 | 0.247 | 0.918 |
| Opening balance | 229 | 27,178 | 19,900 | 4,042 | 23,633 | 21,432 | 2.443** |
| Age of account | 249 | 873 | 591 | 4,325 | 1,067 | 559 | −5.310*** |
| Loan linkage | 249 | 0.024 | 0.153 | 4,325 | 0.084 | 0.276 | −3.365*** |
| Number of days to maturity | 249 | 261 | 423 | 4,325 | 391 | 374 | −5.273*** |
| *Panel B. Transaction accounts* | | | | | | | |
| Minority community | 307 | 0.336 | 0.472 | 10,384 | 0.265 | 0.441 | 2.71*** |
| Above insurance cover | 307 | 0.134 | 0.340 | 10,384 | 0.007 | 0.084 | 21.50*** |
| Opening balance | 266 | 22,904 | 23,247 | 10,309 | 2,752 | 7,718 | 37.87*** |
| Age of account | 307 | 1,872 | 69.33 | 10,384 | 2,298 | 12.83 | −5.63*** |
| Number of transactions | 307 | 49.23 | 118.2 | 10,384 | 13.66 | 46.40 | 12.30*** |
| Loan linkage | 307 | 0.023 | 0.149 | 10,384 | 0.076 | 0.265 | −3.50*** |

*Notes:* For term deposit accounts, "runner" is defined as a depositor who liquidates any part of his/her account in the period between the 13th and the 15th of March; he/she is termed a "stayer" otherwise. For transaction account, runner is defined as a depositor who withdraws more than 75 percent of the opening balance as of the event date in the period between March 13 and March 15; he/she is a stayer otherwise.

A *t*-test of difference in means across the two groups shows that there are significant differences. We find that depositors from the minority community are more likely to run. We also find that runners have a shorter length of relationship with the bank. Runners are also less likely to have loan linkages with the bank. Runners have a higher number of transactions with the bank and have deposits with shorter maturity. We also see that while for transaction accounts runners are more likely to have deposits above the insurance cover, we do not find any significant difference for term deposit accounts. Finally, we also find that runners are more likely to have larger account balances.

We next run probit estimations to better understand the factors that influence depositor runs, the results of which are reported in Table 2. We find three main results. Depositors with deposit balances above the deposit insurance coverage limit are more likely to liquidate their deposits. This suggests that the presence of deposit insurance helps reduce depositor panic. Our results also suggest, however, that deposit insurance seems only partially effective in preventing runs. We find that for depositors with balances below the deposit insurance limit, higher account balances increase the likelihood of running. This is intuitive. Even with deposit insurance, the presence of any transaction costs would induce this kind of behavior. Second, we find that depositors belonging to the minority community (Muslims) are more likely to run as compared to other depositors. Interestingly, however, when we control for the neighborhood of the depositor, the minority dummy is no longer significant in explaining depositor runs for term deposit accounts (though it continues to be significant for

IndyMac's ability to survive the housing crisis in late June, and over the next 11 business days, depositors withdrew more than \$1.3 billion, according to the Office of Thrift Supervision (OTS). Assuming that the average balance is \$69,090, the withdrawal of \$1.3 billion corresponds to withdrawals by approximately 14,500 depositors. This is 5 percent of the total number of depositors. This is an upper bound, however. If we assume that the bulk of the withdrawals were from uninsured depositors (10,000 depositors), this corresponds to around 3.5 percent of the total number of depositors.

Table 2—Which Depositors Run?

| | Term deposit accounts | | Transaction accounts | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Minority community | 0.007 | 0.004 | 0.006** | 0.008** |
| | (0.005) | (0.010) | (0.002) | (0.003) |
| Above insurance cover | 0.021* | 0.024 | 0.329** | 0.356*** |
| | (0.014) | (0.023) | (0.044) | (0.049) |
| Opening balance | 0.003*** | 0.004*** | 0.013*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Loan linkage | −0.033** | −0.039*** | −0.013*** | −0.014*** |
| | (0.005) | (0.007) | (0.002) | (0.002) |
| Account age | −0.016** | −0.013*** | −0.006*** | −0.006*** |
| | (0.002) | (0.003) | (0.001) | (0.001) |
| Days to maturity | −0.020*** | −0.023*** | | |
| | (0.001) | (0.002) | | |
| Number of transactions | | | 0.002 | 0.001 |
| | | | (0.001) | (0.001) |
| Change in withdrawals | | | 0.114** | 0.123** |
| | | | (0.057) | (0.056) |
| Change in deposits | | | −0.001 | −0.001 |
| | | | (0.001) | (0.001) |
| Distance | | −0.007 | | −0.000 |
| | | (0.005) | | (0.001) |
| Neighborhood control | No | Yes | No | Yes |
| Observations | 4,574 | 3,182 | 10,691 | 8,708 |
| Pseudo/Adj. $R^2$ | 0.140 | 0.164 | 0.237 | 0.260 |

*Notes:* This table presents results of probit models (coefficients reported are marginal effects). For term deposit accounts, the dependent variable is an indicator variable that takes the value of one if the depositor liquidates any part of his/her account in the period between March 13 and March 15. For transaction account, the dependent variable takes the value of one if the depositor withdraws more than 75 percent of the opening balance as of the event date in the period between March 13 and March 15, 2001. The analysis is conducted separately for term deposit accounts and transaction accounts. The definition of other variables can be found in Appendix 1. White heteroscedasticity-consistent standard errors are reported in parentheses. In columns 2 and 4 the standard errors are clustered at the household level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

transaction accounts), which suggests that this result warrants further investigation, which we undertake later in the paper. Third, we find that the length and depth of the depositor-bank relationship matters. The longer the depositor has had an account with the bank, the less likely the depositor is to run. The depth of relationship as proxied by loan linkages also matters. We find that depositors who have/had a loan linkage with the bank are less likely to run during a crisis. We are careful in measuring loan linkages to not include overdrafts taken against term deposits. Thus, loan linkages do not capture the mechanical effect that could arise due to an overdraft.[15]

We further investigate the importance of loan linkages by categorizing depositors who have account balances above the insurance level based on whether they have loan linkages. In effect, we divide depositors with account balance above the insurance level into those who have loan linkages and those who do not have any linkage. As results in Table 3 show, there is a striking difference in the behavior of depositors with loan linkages. We find that depositors with accounts above the insurance

[15] Depositors who have taken an overdraft against a term deposit cannot liquidate their deposit. Thus, including overdrafts in the definition of loan linkages could lead mechanically to a negative coefficient.

TABLE 3—HOW IMPORTANT ARE LOAN LINKAGES?

| | Term deposit accounts | | | Transaction accounts | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Minority community | 0.006 | 0.008 | 0.006 | 0.006** | 0.006** | 0.007** |
| | (0.006) | (0.006) | (0.010) | (0.002) | (0.002) | (0.003) |
| Above insurance with loan linkage | | †† | †† | | †† | †† |
| Above insurance with no loan linkage | | 0.028** | 0.034 | | 0.342*** | 0.373*** |
| | | (0.016) | (0.027) | | (0.046) | (0.051) |
| Opening balance | 0.003*** | 0.003*** | 0.004** | 0.013*** | 0.013*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Loan linkage | −0.028*** | −0.028*** | −0.035*** | −0.012*** | −0.013*** | −0.012*** |
| | (0.006) | (0.007) | (0.008) | (0.002) | (0.002) | (0.002) |
| Account age | −0.016*** | −0.016*** | −0.014*** | −0.006*** | −0.006*** | −0.006*** |
| | (0.002) | (0.002) | (0.003) | (0.001) | (0.001) | (0.001) |
| Days to maturity | −0.020*** | −0.021*** | −0.024*** | | | |
| | (0.001) | (0.001) | (0.002) | | | |
| Number of transactions | | | | −0.0007 | 0.002 | 0.001 |
| | | | | (0.001) | (0.001) | (0.001) |
| Change in withdrawals | | | | 0.161** | 0.115** | 0.124** |
| | | | | (0.063) | (0.057) | (0.056) |
| Change in deposits | | | | −0.001 | −0.0009 | −0.0008 |
| | | | | (0.001) | (0.001) | (0.0009) |
| Distance | | | −0.007 | | | −0.000 |
| | | | (0.005) | | | (0.001) |
| Neighborhood control | No | No | Yes | No | No | Yes |
| Observations | 4,271 | 4,513 | 3,133 | 10,575 | 10,685 | 8,702 |
| Pseudo/Adj. $R^2$ | 0.137 | 0.139 | 0.163 | 0.203 | 0.238 | 0.261 |

*Notes:* This table presents results of probit models (coefficients reported are marginal effects). Columns 1 and 4 report the results excluding depositors above the insurance coverage limit. For term deposit accounts, the dependent variable is an indicator variable that takes the value of one if the depositor liquidates any part of his/her account in the period between March 13 and March 15. For transaction account, the dependent variable takes the value of 1 if the depositor withdraws more than 75 percent of the opening balance as of the event date in the period between March 13 and March 15, 2001. The analysis is conducted separately for term deposit accounts and transaction accounts. Above insurance with loan linkage is a dummy variable that takes the value of 1 if a depositor is over the deposit insurance limit and has a loan linkage with the bank. Above insurance with no loan linkage is a dummy variable that takes the value of 1 if the depositor is over the deposit insurance limit and the depositor has no loan linkage with the bank. The definition of other variables can be found in Appendix 1. White heteroscedasticity-consistent standard errors are reported in parentheses. The standard errors are clustered at the household level in columns 3 and 6.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
†† Indicates perfect prediction of failure (not running).

coverage level without loan linkages are more likely to run while accounts above the insurance level with loan linkages are not likely to run (columns 2, 3, 5, and 6). Though the number of observations of depositors above insurance cover with loan linkages is small, these results help highlight the importance of loan linkages, given the findings in Table 2, that depositors with accounts that have deposits above the insurance level have over a 30 percent higher likelihood of running.[16] To make sure that the effect of loan linkages is not limited to depositors who hold balances above

[16] For term deposit accounts, there are 61 depositors who hold balances above the insurance cover and have loan linkages. For transactions accounts, the number is six.

the deposit insurance level, in Table 3, columns 1 and 4, we estimate the probit only for accounts below the deposit insurance coverage limit. We find similar effects of loan linkages as reported in Table 2. Thus, we find that even for depositors who hold balances below the deposit insurance level, loan linkages are important.

The findings in Tables 2 and 3 suggest that loan linkages significantly reduce the likelihood of running. This raises the question: why are depositors with loan linkages less likely to run? There are several potential explanations. First, in the event of bank failure, deposits might be offset against outstanding loans. By regulation, however, banks are not allowed to set off deposits outstanding with the bank against loans outstanding in the event of failure. Nonetheless, depositors with loan linkages might perceive a set-off/offset and therefore might be less likely to run.[17] Second, depositors with loan linkages could have better relationships with the bank and are therefore less likely to run. The channels by which relationships could reduce the likelihood of running are the following: depositors with loan linkages might fear that they could jeopardize their relationship with the bank, in case they withdraw their deposits and the bank survives the run; i.e., the bank could pull back/limit access to credit in the future (hold-up problem). Alternatively, a better relationship with the bank might enable depositors to have better information about the fundamentals of the bank. Finally, depositors with loan linkages might differ from other depositors in terms of education, wealth, etc., that might make them less likely to run.

We conduct a number of tests to distinguish between these explanations. We first look at whether depositors who had a loan linkage in the past but currently have no outstanding loan linkage differ in their behavior compared to other depositors. Interestingly, we find that depositors with loan linkages in the past are also less likely to run (Table 4). We find that both depositors who had a loan linkage in the past and depositors who have a currently outstanding loan are less likely to run (columns 1 and 4). As depositors with loan linkages in the past do not have the benefit of any set-off in case of failure, the results above suggest that the explanation of set-off is unlikely to be the only explanation of this result.

We conduct additional robustness checks to see if there are differences in depositors with loan linkages in other, unobservable dimensions that we do not capture that might explain our results. We examine depositors who started a loan relationship with the bank after the crisis but have a deposit account with the bank at the time of the crisis. These depositors have a deposit account with the bank at the time of the crisis, but do not have any loan linkage with the bank in the past or any loan that is currently outstanding. In addition, these depositors availed of a loan from the bank for the first time after the crisis.[18] Results in Table 4, columns 2, 3, 5, and 6 show that depositors who have/had loan linkages with the bank as of the date of the crisis are less likely to run, but not depositors who obtain a loan only in the future. Assuming time consistency, future loan takers should be similar in characteristics to current and past loan takers. An $F$-test rejects equality of coefficient between the depositors with outstanding loan linkage as compared to depositors with future loan linkage at

[17] Only under exceptional circumstances, with the permission of the central bank, set-offs could be allowed. Even in those cases, the recovery of assets and the payment to depositors are carried out independently as separate procedures.

[18] We measure future loan linkages until January 2006.

TABLE 4—IS THERE A DIFFERENCE IN THE BEHAVIOR OF DEPOSITORS WHO HAD AVAILED OF A LOAN IN THE PAST VERSUS DEPOSITORS WHO AVAIL OF A LOAN IN THE FUTURE?

| | Term deposit accounts | | | Transaction accounts | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Minority community | 0.008 | 0.008 | 0.006 | 0.006** | 0.006** | 0.007** |
| | (0.005) | (0.005) | (0.010) | (0.002) | (0.002) | (0.003) |
| Account age | −0.016*** | −0.016*** | −0.013*** | −0.006*** | −0.006*** | −0.006*** |
| | (0.002) | (0.002) | (0.003) | (0.001) | (0.001) | (0.001) |
| Above insurance cover | 0.019 | 0.020 | 0.024 | 0.329*** | 0.333*** | 0.363*** |
| | (0.014) | (0.014) | (0.023) | (0.044) | (0.045) | (0.050) |
| Opening balance | 0.003*** | 0.003*** | 0.004*** | 0.014*** | 0.013*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Outstanding loan linkage | −0.035*** | −0.035*** | −0.040*** | −0.013** | −0.013** | −0.013** |
| | (0.005) | (0.005) | (0.006) | (0.003) | (0.003) | (0.003) |
| Past loan linkage | −0.028* | −0.028* | −0.033** | −0.013** | −0.013** | −0.013* |
| | (0.008) | (0.008) | (0.009) | (0.002) | (0.002) | (0.002) |
| Future loan linkage | | −0.007 | −0.009 | | −0.008 | −0.010 |
| | | (0.018) | (0.026) | | (0.007) | (0.006) |
| Days to maturity | −0.020*** | −0.020*** | −0.023*** | | | |
| | (0.001) | (0.001) | (0.002) | | | |
| Change in deposits | | | | −0.002 | −0.001 | −0.001 |
| | | | | (0.001) | (0.001) | (0.001) |
| Change in withdrawals | | | | 0.114** | 0.117** | 0.126** |
| | | | | (0.057) | (0.057) | (0.056) |
| Number of transactions | | | | 0.001 | 0.001 | 0.001 |
| | | | | (0.001) | (0.001) | (0.001) |
| Distance | | | −0.007 | | | 0.000 |
| | | | (0.005) | | | (0.001) |
| Neighborhood controls | No | No | Yes | No | No | Yes |
| Observations | 4,574 | 4,574 | 3,182 | 10,691 | 10,691 | 8,708 |
| Pseudo $R^2$ | 0.140 | 0.139 | 0.164 | 0.237 | 0.238 | 0.260 |

*Notes:* This table presents results of probit models (coefficients reported are marginal effects). For term deposit accounts, the dependent variable is an indicator variable that takes the value of one if the depositor liquidates any part of his/her account in the period between March 13 and March 15. For transaction accounts, the dependent variable takes the value of one if the depositor withdraws more than 75 percent of the opening balance as of the event date in the period between March 13 and March 15, 2001. The analysis is conducted separately for term deposit accounts and transaction accounts. Outstanding loan linkage is a dummy variable that takes the value of 1 for a deposit account if the household (associated with the account) has a loan account with the bank as on event date. Past loan linkage is a dummy variable that takes the value of 1 if any member of the household (associated with the account) had a loan account with the bank before event date and there is no outstanding loan linkage. Future loan linkage is a dummy variable that takes the value of 1 for a deposit account if the household (associated with the account) had no loan account with the bank before/on the event date but availed of a loan from the bank in the future. Definition of other variables can be found in Appendix 1. White heteroskedasticity-consistent standard errors are reported in parentheses. In columns 3 and 6 the standard errors are clustered at the household level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

8 percent (columns 2, and 3), however. Furthermore, we do not find any significant ex ante differences between the depositors who availed of loan linkages after the crisis and depositors who have/had loan linkages with the bank as of the date of the crisis on a variety of additional dimensions (see Tables 8 and 9).[19] In addition to

[19] Note that in Table 8, account age is higher for depositors with loan linkages as compared to depositors with future loan linkages (though the difference is not statistically significant), suggesting that depositors might need to have a longer history of transacting with the bank before availing of a loan.

these tests, using data from a survey of a random sample of depositors (see Table 12), we find that loan linkages significantly reduce the likelihood of running even after controlling for the wealth and education levels of depositors. Thus, it seems unlikely that the results on loan linkages are driven by other unobservable characteristics of depositors. In sum, the results taken together suggest that the effect of loan linkages on depositor behavior is most likely to be a result of relationship with the bank; that is, past loan-taking and related interactions deepen the bank-depositor relationship in a way that affects depositor behavior.[20]

In the banking literature, much importance is placed on the bank-client relationship. In this literature, bank-depositor relationships typically give the bank information about the client. Our results suggest that there are additional channels by which depositor relationships could help banks in reducing fragility. For instance, in Goldstein and Pauzner (2005), depositors receive noisy private signals about bank fundamentals, and use their signals to form expectations about the actions of other depositors. Depositors with loan linkages might get a higher signal about bank fundamentals, perhaps through repeated interaction with, and/or access to, bank officers in turn, mitigating their propensity to run. Perhaps these depositors have greater trust in the bank because of their repeat interactions over time.[21] Alternatively, depositors with loan linkages might fear loss of future relationships with the bank in case they withdraw their deposits and therefore might have lower incentive to run. Thus, our evidence suggests that depositor relationships can help banks in more dimensions than traditionally envisaged.

## V. Social Networks

While so far we have examined the importance of relationship with the bank in affecting a depositor's propensity to run, one can imagine depositors talking to other depositors who have run and in turn deciding to withdraw their own deposits. In effect, information obtained from the actions of other depositors may be an important factor in deciding whether to run (Bikhchandani, Hirshleifer, and Welch 1992; Banerjee 1992; Kelly and O Grada 2000). A visual representation of the data of depositors who run suggests that the patterns are not random (see Figure 4, where the runners are depicted on Google maps). In some apartment buildings, multiple households run, and in others none do.[22] Social networks could potentially explain this pattern. Accordingly, we examine more formally the importance of social networks in depositor runs.[23]

We create two different measures of depositor networks. Our first measure is based on the neighborhood of residence of a depositor. We examine the effect of the actions of other depositors in the neighborhood on the behavior of a depositor. Our second measure of network is based on the introducer name associated with

[20] While we find that only 10 percent of the depositors with past loan linkage take a loan out in the future with the bank, our results on the importance of relationships are consistent both with the hold-up and better information explanation.

[21] A growing literature examines the effect of trust on financial decisions; see, e.g., Carlin, Dorobantu, and Viswanathan (2009); Guiso, Sapienza, and Zingales (2008).

[22] For the Google Earth files, see: http://faculty.fuqua.duke.edu/~mpuri/research.htm.

[23] See also Madies (2006), Duflo and Saez (2003), and Hong, Kubik, and Stein (2005).

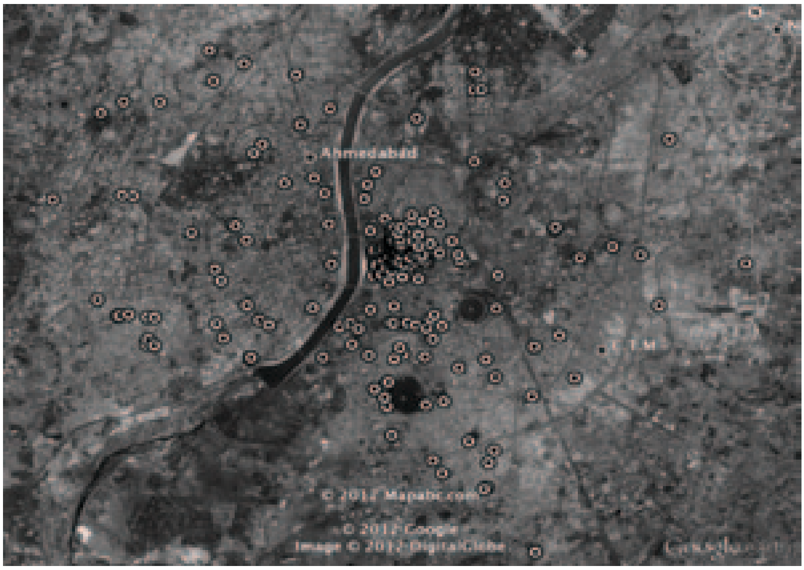


FIGURE 4. GOOGLE EARTH PLOT OF HOUSEHOLDS THAT RUN

the deposit account. The advantage of using networks based on introducer names is that they are based on actual contacts. This helps us overcome a major hurdle that has plagued the empirical literature on social networks, as datasets rarely contain information on the actual contacts of people.

To estimate the effects of networks, we first use simple probit models and examine how the fraction of depositors who are running in a depositors network is associated with the likelihood of a depositor running. As results from the estimation in Table 5, column 1, show, we find that the likelihood of a depositor running is increasing in the fraction of runners in a depositors' introducer network. In column 2, we find similar effects based on the fraction of runners in a depositors' neighborhood. While the results above suggest that depositor networks play an important role, one could be concerned that the results are primarily driven by the socioeconomic backgrounds of depositors that are being captured by our measure of networks (Manski 1993). For example, depositors who are poorer or less educated may be more likely to run as they trust the bank less and they are also more likely to know each other and to live in the same neighborhood. In column 3, we include introducer-based networks and networks based on neighborhood in the same estimation and find that the results are still significant. In addition, we also estimate the effects of networks controlling for wealth and education levels for a subsample of depositors (see Table 12). We find that introducer networks continue to be highly significant in explaining depositor incentive to run. The effect of networks based on neighborhoods also remains positive but is not significant at conventional levels (significant at 11 percent).

While the probit models help examine the effects of networks on a first-order basis, these estimations ignore the timing of depositor withdrawals. For example, in the probit estimations, if in a depositor's network there are two other depositors running, then we would treat them in the same way, irrespective of whether they withdrew before or after the depositor. Ideally, one would like to measure the effect of

Table 5—Do Social Networks Matter?

| | Transaction accounts | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Minority community | 0.005* | 0.006** | 0.005* | 0.264** | 0.270 |
| | (0.002) | (0.002) | (0.002) | (0.133) | (0.270) |
| Account age | −0.003** | −0.005*** | −0.002** | −0.274*** | −0.362*** |
| | (0.001) | (0.001) | (0.001) | (0.060) | (0.097) |
| Above insurance cover | 0.266*** | 0.320*** | 0.259*** | 3.140*** | 2.865*** |
| | (0.043) | (0.044) | (0.044) | (0.189) | (0.356) |
| Opening balance | 0.011*** | 0.012*** | 0.010*** | 0.005*** | 0.005*** |
| | (0.000) | (0.001) | (0.001) | (0.0002) | (0.0004) |
| Loan linkage | −0.011*** | −0.012*** | −0.009*** | −1.288*** | −1.276*** |
| | (0.002) | (0.002) | (0.002) | (0.406) | (0.497) |
| Runners in neighborhood | | 0.535*** | 0.438*** | 17.136*** | 31.558*** |
| | | (0.072) | (0.066) | (4.414) | (6.514) |
| Runners introducer network | 0.139*** | | 0.122*** | 5.090*** | 3.809*** |
| | (0.012) | | (0.012) | (0.700) | (0.792) |
| Change in deposits | −0.008 | −0.009 | −0.007 | −0.035 | −0.006 |
| | (0.007) | (0.010) | (0.006) | (0.040) | (0.017) |
| Change in withdrawals | 0.119** | 0.122** | 0.119*** | 2.604 | 7.865 |
| | (0.051) | (0.052) | (0.046) | (2.689) | (5.075) |
| Number of transactions | −0.001 | 0.0009 | −0.001 | 0.001 | −0.0002 |
| | (0.001) | (0.001) | (0.001) | (0.0007) | (0.001) |
| Number of subjects | 10,691 | 10,383 | 10,383 | 10,383 | 1,504 |
| Observations | 10,691 | 10,383 | 10,383 | 2,342,915 | 305,589 |
| | | | | $\chi^2(10) = 867.82$ | $\chi^2(10) = 259.72$ |
| Prob > $\chi^2$/psuedo $R^2$ | 0.331 | 0.258 | 0.354 | 0.0000 | 0.0000 |

*Notes:* This table presents coefficients from the estimation of the probit model (columns 1, 2, and 3) and Cox model with time-varying covariates (columns 4 and 5). For the probit, the dependent variable takes the value of one if the depositor withdraws more than 75 percent of the opening balance as on the event date in the period between March 13 and March 15, 2001. For the Cox model, failure time is the time in minutes until withdrawal by a depositor with starting time of 10:30 am on March 13, 2001 (date of failure of the large bank). Each interval of time represents one minute. Column 5 reports results of the estimation where at a point in time, only depositors in whose network there is at least one other depositor running (*runners network* $(t-1) > 0$) are included in the estimation. Definition of other variables can be found in Appendix 1. The Breslow method is used to adjust for ties in the Cox regression (ties represent two subjects with same failure time). The Cox model estimated in column 1 does not have any time-varying covariates.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

the networks by exploring whether the fraction of other depositors in a depositors' network that have run until time $t-1$ has an influence on a depositor's likelihood of running at time $t$. Thus, to incorporate the information contained in the timing of withdrawals, we use the Cox model with time-varying covariates. For estimation of the model, we use one-minute spells, i.e., we measure withdrawals every minute, which allows us to take advantage of the minute-by-minute nature of our data.[24]

As results from the estimations of the Cox model in Table 5, column 4 show, we find that the hazard rate is increasing in the fraction of runners in the social group

[24] In total, the bank is open for 5½ hours a day (10:30 am–4 pm). Thus, we have 307 withdrawals over 3 days (990 minutes). In effect, on average we have one withdrawal every three minutes. Also, in days 2 and 3 of the crisis between 11 am and 12 pm, there are around 45 withdrawals. Thus, on average there is a one withdrawal every 1.33 minutes. Therefore in order to avoid ties in the withdrawal time, we use one-minute intervals. Also, note that none of the depositors who run in the sample withdraw more than once (i.e., there are no multiple withdrawals).

(based on introducer network) and the fraction of runners in the neighborhood of a depositor.[25] Note that we also examine the timing of withdrawals when depositors from the same introducer group run. We first restrict ourselves to introducer groups where at least two depositors are running and then examine their withdrawal timings. We code two depositors as coming together if their withdrawals are sequentially one after the other (i.e., they stood in the line together). Interestingly, we find that when depositors of a same introducer group run, in approximately 35 percent of the cases they also show up to the bank at the same time (this excludes depositors in the same household).[26] The finding that a large fraction of depositors from the same introducer group also have similar withdrawal timings further suggests that the effects of networks are not driven purely by the socioeconomic background of depositors. In Table 5, column 5, we estimate the model by limiting the sample to introducer networks where at least one other depositor in the network is running.[27] We again find that the behavior of other depositors in the network has a significant effect. Interestingly, we also find that even within these networks where some depositors are running, the hazard rate is lower if a depositor has loan linkages with the bank and has a longer relationship with the bank. These results suggest that even after controlling for the effect of networks, the length and depth of relationships with the bank have a significant effect on depositor behavior.

## A. *Transmission Probabilities*

On a big-picture level, one of the things that we want to understand is the magnitude of contagion in bank runs. In order to model this, we draw on a long, time-honored literature on contagion of infectious diseases in the epidemiology literature. They model transmission probability as the probability that a person gets infected through contact with another infected person. The parallel in bank runs is the probability of running as a result of contact with a person who has already run. Drawing on the models in epidemiology (see, e.g., Geoffard and Philipson 1995; Halloran 1998; Hudgens et al. 2002), in the context of bank runs, we estimate the following model:

$$\lambda i(t) = C \textstyle\prod_i(t) P(t) \exp\{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\}, \tag{1}$$

where $C$ is the number of people in one's social network or neighborhood whom one comes in contact and is assumed to be one per time interval; $\prod_i(t)$ is *runners introducer network* $(t-1)$ or *runners in neighborhood* $(t-1)$; $P(t)$ is the transmission probability, which is the probability for running due to a single contact with a person who has already run; $X_{i1}$ $X_{i2}$ are covariates like age of the account, loan linkage, etc.[28]

[25] To further investigate the importance of neighborhood contacts, we cross the neighborhood of a depositor with the ethnic status of the depositor. We find that only the behavior of depositors in the neighborhood who belong to the ethnic group of the depositor has a significant effect (not reported).

[26] Conditional on running, if depositors' arrival time is random and independent, a rough back-of-the-envelope calculation yields an estimated probability of 6 percent that two depositors of a same network line up one after the other.

[27] This also helps further address the concern that introducer networks where some of the depositors are running could be different in unobservable dimensions from those networks that do not have depositors running.

[28] In the model above, the hazard rate of running is zero if $\prod_i(t)$ is equal to zero.

Table 6—Estimation of Transmission Probability

| Transmission probability | Mean | Standard error | Lower CI (95%) | Upper CI (95%) |
|---|---|---|---|---|
| Via social network | 0.036 | 0.005 | 0.024 | 0.047 |
| Via neighborhood | 0.061 | 0.006 | 0.049 | 0.074 |

*Notes:* This table presents results of estimation of transmission probability using the model. The transmission probability is estimated using the model specified in the text. The Breslow method is used to adjust for ties (ties represent two subjects with same failure time). Each interval of time represents one minute. The mean transmission probability is the average of transmission probabilities $(P(t))$ across time. The confidence bands are derived from the estimated transmission probabilities.

As results in Table 6 show, we find that the average transmission probability across time is 3.6 percent via social groups (introducer network) and 6 percent via neighborhoods.[29] Understanding transmission probabilities is important if there is a case for intervention in solvent bank runs. To get a sense of the magnitude, we compare the transmission probability to the unconditional probability of a depositor running when there are no other runners in his/her network. The unconditional observed probability of a depositor running in our sample is 2.8 percent. Comparing it to the probability of running if a depositor comes in contact with some other depositor in his/her network who has run, we find that there is a jump in the probability of running from 2.8 percent to 6 percent; i.e., an increase of more than 100 percent. Thus, our results suggest that if there is intervention it should be early in the crisis, to effectively limit the loss in deposits and prevent further propagation of the shock through social networks.

From a policy point of view, does it make sense to intervene if the bank remains solvent? The answer to this question depends on whether there are long-term costs to a bank run. We now turn our attention to this question.

### B. *Do Depositors Who Run Return to the Bank?*

While so far our analysis focuses on factors that affect depositor runs, an interesting question that arises is whether there are long-term effects of a bank run. In particular, a question of interest is whether depositors who run redeposit their money in the bank after an interval of time? To the best of our knowledge, previous literature has not been able to answer this question because of data constraints. From Figure 5, we see that depositors who withdrew during the crisis do not redeposit to the precrisis levels.[30] To further examine this question, we first take all the transaction accounts that withdrew during the crisis. For these accounts, we compute the fraction of depositors for which the deposit balance returns to the precrisis levels after the crisis. As results in Table 7, panel A, show, we find a maximum of 11 percent of the depositors return back to the bank. We also find that for 73 percent of the depositors who withdrew during the crisis, the deposit balance after 3 months remains 75 percent lower than the outstanding balance before the crisis (panel B, column 2).

[29] These are statistically different from zero.

[30] Also, from Figure 5, one can see that the withdrawal patterns of runners was not very volatile before the crisis. This further reaffirms that the runs we document are not likely to be a result of the liquidity needs of depositors.

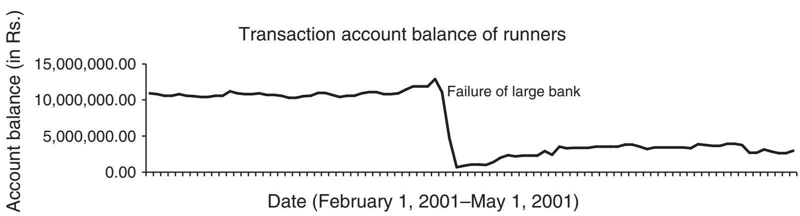


Figure 5. Do Depositors Who Withdraw during the Crisis Return?

*Note:* Figure 5 presents the deposit balance in transaction account from February 1, 2001 to May 1, 2001 for depositors that withdrew during the crisis.

Table 7

| | Transaction accounts | | |
|---|---|---|---|
| | After 1 month | After 3 months | After 6 months |
| *Panel A* | | | |
| Fraction of depositors with balance higher than precrisis level | 0.058 | 0.110 | 0.065 |
| Fraction of depositors with balance 25 percent higher than precrisis level | 0.035 | 0.068 | 0.048 |
| Fraction of depositors with balance 50 percent higher than precrisis level | 0.032 | 0.068 | 0.042 |
| Fraction of depositors with balance 75 percent higher than precrisis level | 0.022 | 0.045 | 0.029 |
| *Panel B* | | | |
| Fraction of depositors with balance 75 percent lower than precrisis level | 0.824 | 0.729 | 0.762 |
| Fraction of depositors with balance 50 percent lower than precrisis level | 0.872 | 0.791 | 0.843 |
| Fraction of depositors with balance 25 percent lower than precrisis level | 0.902 | 0.843 | 0.889 |

*Notes:* This table reports the fraction of depositors who withdrew during the crisis and returned to the bank after the crisis. After one month (May 1, 2001), after three months (July 1, 2001), and after six months (Oct. 1, 2001) are the dates in the future where the deposit balance is examined.

Thus, it does appear that depositors who panic do not return to the bank. We also find that in terms of aggregate deposits, the bank does not receive fresh deposits from other depositors to compensate for the loss in deposits. As compared to the aggregate transaction account balance of Rs. 41.9 million on March 15, 2001 (immediately after the crisis), the aggregate transaction balance stood at Rs. 42.3 million, Rs. 41.8 million, and Rs. 42.2 million on May 1, July 1, and October 1, 2001, respectively. This suggests that the effects of the runs are not reversed in a short interval of time. Note that from the survey of depositors we also find that depositors are likely to redeposit funds with government banks. The loss of the deposits due to the run could still have economic real costs, however, as it could affect credit available to borrowers of the bank who might find it difficult to raise funds from other sources due to information asymmetry problems (Khwaja and Mian 2008).[31]

[31] For the sample of depositors we surveyed, we find that 85 percent would redeposit the money that they withdrew in a public sector bank, 11 percent in a private bank, 2 percent in the post office, and 2 percent would keep the money at home. This finding is also corroborated by the aggregate data that shows an increase in deposits at public sector banks in the subsequent quarter. Note that even if deposits do not move out of the banking system due to information asymmetry, it is still likely that borrowers find it difficult to substitute credit, especially in the case of small borrowers.

Table 8—Ex Ante Differences in Characteristics of Depositors

| | Accounts without loan linkages | | | Accounts with loan linkages | | | |
|---|---|---|---|---|---|---|---|
| Transaction accounts | Observations | Mean | SD | Observations | Mean | SD | Diff (*t*-stat) |
| Account balance | 9,893 | 4,873 | 21,639 | 798 | 6,094 | 58,418 | −1.265 |
| Account age | 9,893 | 7.558 | 0.710 | 798 | 7.579 | 0.706 | −0.847 |
| | Accounts without loan linkages below insurance coverage limit | | | Accounts with loan linkages below insurance coverage limit | | | |
| Account balance | 9,783 | 3,260 | 9,173 | 792 | 3,247 | 8,604 | 0.037 |
| Account age | 9,783 | 7.559 | 0.706 | 792 | 7.587 | 0.695 | −1.058 |
| | Accounts with loan linkages | | | Accounts with future loan linkages | | | |
| Account balance | 798 | 6,094 | 58,418 | 84 | 12,735 | 49,137 | −0.912 |
| Account age | 798 | 7.578 | 1.050 | 84 | 7.445 | 0.705 | −1.567 |
| Term deposit accounts | Accounts without loan linkages | | | Accounts with loan linkages | | | |
| Account balance | 4,206 | 36,149 | 89,373 | 368 | 78,716 | 224,890 | −7.332*** |
| Account age | 4,206 | 6.703 | 0.962 | 368 | 6.653 | 1.040 | 0.948 |
| | Accounts without loan linkages below insurance coverage limit | | | Accounts with loan linkages below insurance coverage limit | | | |
| Account balance | 3,964 | 23,705 | 21,381 | 307 | 25,345 | 21,136 | −1.296 |
| Account age | 3,964 | 6.700 | 0.970 | 307 | 6.640 | 1.078 | 1.033 |
| | Accounts with loan linkages | | | Accounts with future loan linkages | | | |
| Account balance | 368 | 78,717 | 224,890 | 59 | 44,031 | 42,838 | 1.180 |
| Account age | 368 | 6.653 | 1.040 | 59 | 6.771 | 0.800 | −0.832 |

*Notes:* This table presents the comparison of means for accounts with loan linkages versus accounts without loan linkages and accounts with loan linkages in the future. Account balance is the opening balance (amount in Rs.) in an account as of the event date. The definition of other variables can be found in Appendix 1.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 9—Distribution of Depositors with Loan Linkages

| | Term deposit accounts | Transaction accounts |
|---|---|---|
| Percent of depositors with loan linkages with account balance | | |
| Lower than 1,000 | 0.032 | 0.066 |
| Between 1,000 and 25,000 | 0.069 | 0.089 |
| Between 25,000 and 50,000 | 0.082 | 0.062 |
| Between 50,000 and 75,000 | 0.068 | 0.088 |
| Between 75,000 and 100,000 | 0.082 | 0.029 |
| Higher than 100,000 | 0.208 | 0.054 |

*Note:* This table reports the percentage of depositors with loan linkages based on different account balances.

## VI. Robustness

We conduct a number of robustness checks. First, we have carried out the analysis for transaction accounts defining a depositor as running if they withdraw 75 percent or more of their account balance. To make sure that our results are not sensitive to the choice of threshold, we reestimate the model using 50 percent and 25 percent as

Table 10

| | Transaction accounts | | | | |
|---|---|---|---|---|---|
| | 50% threshold | 25% threshold | 9th–15th March | Account age | Cluster network |
| Minority community | 0.006 | 0.006 | 0.006* | 0.007** | 0.007** |
| | (0.003) | (0.004) | (0.003) | (0.003) | (0.003) |
| Account age | −0.008*** | −0.008*** | −0.006*** | −0.004*** | −0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Above insurance cover | 0.354*** | 0.390** | 0.381*** | 0.363*** | 0.353*** |
| | (0.048) | (0.049) | (0.047) | (0.048) | (0.046) |
| Opening balance | 0.018*** | 0.020*** | 0.014*** | 0.013*** | 0.012*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Loan linkage | −0.014*** | −0.011*** | −0.011*** | −0.012*** | −0.013*** |
| | (0.003) | (0.004) | (0.002) | (0.002) | (0.002) |
| Change in deposits | −0.001 | −0.0009 | −0.0009 | −0.0003 | −0.001 |
| | (0.001) | (0.0008) | (0.001) | (0.0004) | (0.0009) |
| Change in withdrawals | 0.283*** | 0.381*** | 0.166*** | 0.145*** | 0.128*** |
| | (0.099) | (0.124) | (0.060) | (0.055) | (0.057) |
| Number of transactions | 0.005** | 0.008** | 0.002* | 0.000 | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |
| Neighborhood controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 9,910 | 9,910 | 10,047 | 9,910 | 9,910 |
| Pseudo $R^2$ | 0.231 | 0.234 | 0.261 | 0.254 | 0.257 |

*Notes:* This table presents results of probit models (coefficients reported are marginal effects). In column 1, the dependent variable takes the value of 1 if the depositor withdraws more than 50 percent of the opening balance as of the event date in the period between March 13 and March 15, 2001. Similarly, in column 2 the threshold is set at 25 percent. In column 3, the dependent variable takes the value of 1 if the depositor withdraws more than 75 percent of the opening balance with the event window defined as withdrawals between March 9 and March 15, 2001. Column 4 presents the results with the standard event window (withdrawal between March 13 and March 15, using the 75 percent threshold), where account age is defined as the maximum time that an account has been open in the household of the depositor. Column 5 reports the results of the estimation where standard errors are clustered at the introducer network level. The definition of other variables can be found in Appendix 1. White heteroscedasticity-consistent standard errors are reported in parentheses.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

threshold levels. As can be seen from Table 10, columns 1 and 2, we do not find significant differences in the results if we change the threshold level. Furthermore, that we find similar results when we analyze term deposit accounts adds further validity to the robustness of the results.

Second, we expand the time period being analyzed. In our analysis so far, we begin measuring depositor withdrawals as of the date of the failure of the large bank (March 13, 2001). Given that the large bank faced runs beginning March 9, however, it is possible that a few depositors could have withdrawn their deposits in the period between March 9 and March 13, 2001. Hence as a robustness check we rerun our regressions using the period between March 9 and March 15, 2001 as the event window. As can be seen in Table 10, column 3, we do not find any significant difference in the results.

Third, we use a different measure of account age. One potential concern is that our measure of account age does not correctly reflect the length of the relationship with the bank. One could argue that the true length of the relationship is the earliest date of opening an account by any member of the household. To address this

Table 11—Summary Statistics (*Survey*)

| | Observations | Mean | Median | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| Education | 279 | 2.234 | 2.000 | 0.634 | 1 | 3 |
| Wealth | 270 | 0.014 | 0.015 | 0.006 | 0.004 | 0.026 |
| Age | 265 | 3.860 | 4.000 | 0.398 | 3 | 5 |
| Stock | 276 | 0.120 | 0 | 0.325 | 0 | 1 |

*Notes:* Education level takes the value of 1 if the depositor holds a postgraduate degree (master's degree), 2 for a graduate degree (bachelor's), and 3 for primary school. Wealth is a proxy for the total level of wealth of a depositor (refer to the text for the details of the construction). Age takes the value of 3 if the depositor is between 15–35 years, 4 if between 35–59 years, and 5 if higher than 59 years. Stock is a dummy that takes the value of 1 if the depositor invests in the stock market.

concern, in Table 10, column 4, we reestimate the model, measuring account age as the maximum length of the account associated with the household of a depositor. As the results show, we still find that the length of the relationship with the bank reduced the likelihood of withdrawing. We also included in the regressions (not reported) the amount of shares in the cooperative, if any, held by depositors. We find that all our results are robust to this. Finally, to address the concern that a majority of the runners may share a common introducer network, in column 5 we cluster the standard errors based on the introducer network of the depositors. We find that there are 217 distinct introducer networks associated with depositors who run. This alleviates the concern that the bulk of the runners have a common linkage. Further, as reported in column 5, we find similar results even after clustering standard errors at the introducer network level.

Finally, to further investigate the robustness of the results, for a sample of depositors we collected information on age, education, and proxies for wealth using a survey. We randomly selected 100 depositors who withdrew during the crisis from their transaction account, along with 300 other depositors who did not withdraw, and conducted a survey. The 400 depositors we chose belong to different households. In total, we were able to visit 282 depositors out of the 400 initially sampled. Note that the main reason for not being able to survey the remaining 118 depositors was due to them not being at their residences when the surveyor visited. Thus, the attrition is not due to depositors' refusal to participate in the survey.

To construct a measure of depositor wealth, we asked whether the household of the depositor owns a car, bike, land, and apartment. The survey questions are listed in the Appendix. We use these responses to create a measure of depositor wealth by weighting the asset ownership based on the fraction of other people who own the asset. For example, if 40 depositors own a car, the weight each depositor with a car will receive is 0.025 (1/40). Our proxy for wealth for an individual depositor is derived by summing up the weights for the four questions of asset ownership. Apart from the questions on asset ownership, we also surveyed depositors for their age and level of education. We conduct additional tests with this sample.

Table 11 reports the summary statistics of the variables collected using the survey. The median depositor in the sample has a college degree (row 1). We also create a measure of depositor wealth using the procedure described above. We find that 98 depositors own a car, 255 possess a bike, 250 own an apartment, and 131 depositors own some land. Thus, ownership of bike and apartment is prevalent among most of the depositors, while ownership of car and land is less widespread. The average wealth level for a depositor is 0.014 (row 2). We also find that the average age of the depositor is between 36 and 59 years (row 3). Finally, we do not find a high level of participation in the stock market among the depositors in the sample (row 4). In univariate tests, we did not find any significant differences between runners and stayers in terms of education, age, wealth, or stock ownership. We also did not find any significant differences between depositors with loan linkages and other depositors along these dimensions (not reported).

In Table 12, we run multivariate tests. In column 1, we introduce dummies for depositors' level of education. We find that the level of education of a depositor does not have a significant effect on the likelihood of withdrawing. We also find that even for this subsample that represents different households, the results are in line with those reported before (Table 2, column 3).[32] Note that loan linkages perfectly predict not running in this subsample (there are 14 depositors with loan linkages).[33] In column 2, we introduce the age of the depositor, the level of wealth of a depositor, and the dummy variable that indicates whether a depositor has investments in the stock market. We do not find any significant effect of age. We also find that the level of wealth does not have a significant effect on the likelihood of withdrawing. In addition, depositors with investments in the stock market do not have a significantly higher likelihood of running, suggesting that the runs were not primarily driven by liquidity shocks experienced by depositors due to a drop in the value of their stocks. Note that 87 percent of the depositors report using banks as their main savings mechanism. Only 11 percent of the depositors report any form of investment in the stock market. Also, as stated earlier, there is no significant difference in this fraction between runners and stayers. More importantly, we find all our results are robust to controlling for proxies of wealth, age, education, and stock holdings.[34] Note that we also asked depositors what was the main reason for withdrawing/not withdrawing their deposits from the bank. All the depositors listed trust in the bank as an important factor affecting their decisions. Also, none of the depositors surveyed reported having a deposit account with the large bank that failed. This further corroborates that the runs were not primarily driven by the liquidity needs of depositors.

While in Table 5 we find evidence that suggests that social networks influence the likelihood of running, one could still be concerned that these effects are primarily driven by omitted characteristics of people within a network. In columns 3 and 4, we estimate the effects of social networks through neighborhood and introducers after controlling for age, wealth, and education. We find that introducer- (significant at 1 percent) and neighborhood- (significant at 11 percent) based networks are important in explaining the likelihood of a depositor running. These results further suggest that social networks have an influence on depositor behavior, and omitted variables are unlikely to be a main explanation of this result.

[32] Account age is negative but no longer statistically significant.

[33] The results are robust to inclusion of neighborhood fixed effects. Also, the results are robust to including age, wealth, and stock dummy separately (not reported).

[34] In addition, we looked at the effect of literacy and wealth level (proxied by the density of slums) in the neighborhood of the depositor based on census data. We did not find any significant effect of these variables on the likelihood of withdrawing.

Table 12—Robustness

| | Transaction accounts | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Minority community | 0.080 | 0.042 | 0.007 | –0.006 |
| | (0.057) | (0.089) | (0.099) | (0.097) |
| Account age | –0.062 | –0.071 | 0.024 | 0.035 |
| | (0.046) | (0.059) | (0.104) | (0.097) |
| Above insurance cover | 0.634*** | 0.629*** | 0.604*** | 0.604*** |
| | (0.113) | (0.107) | (0.119) | (0.120) |
| Opening balance | 0.164*** | 0.314*** | 0.334*** | 0.340*** |
| | (0.053) | (0.061) | (0.063) | (0.065) |
| Loan linkage | &&& | &&& | &&& | &&& |
| Change in deposits | 0.082 | 0.120 | 0.148 | 0.166 |
| | (0.088) | (0.099) | (0.153) | (0.148) |
| Change in withdrawals | 3.952 | –9.027 | –12.06 | –11.93 |
| | (5.250) | (6.985) | (8.885) | (8.941) |
| Number of transactions | 0.002 | 0.021*** | 0.020*** | 0.019*** |
| | (0.004) | (0.007) | (0.007) | (0.007) |
| Age | | 0.030 | 0.047 | 0.048 |
| | | (0.103) | (0.118) | (0.119) |
| Wealth | | 0.245 | 1.317 | 3.285 |
| | | (6.664) | (7.492) | (7.585) |
| Stock | | –0.105 | –0.068 | –0.066 |
| | | (0.124) | (0.144) | (0.149) |
| Graduate | –0.021 | –0.038 | –0.062 | –0.059 |
| | (0.079) | (0.117) | (0.125) | (0.127) |
| School | 0.040 | 0.119 | 0.115 | 0.107 |
| | (0.088) | (0.121) | (0.136) | (0.141) |
| Runners introducer network | | | 1.767*** | 1.804*** |
| | | | (0.544) | (0.569) |
| Runners in neighborhood | | | | 6.326 |
| | | | | (3.855) |
| Neighborhood controls | No | No | No | No |
| Observations | 265 | 240 | 240 | 240 |
| Pseudo $R^2$ | 0.380 | 0.548 | 0.618 | 0.625 |

*Notes:* This table presents results of probit models (coefficients reported are marginal effects). For transaction account, the dependent variable takes the value of 1 if the depositor withdraws more than 75 percent of the opening balance as on the event date in the period between March 13 and March 15, 2001. Age is the age of the depositor. Wealth represents the wealth of a depositor. Education levels are dummies for the level of education attained by a depositor (omitted category is postgraduate degree holders). Definition of other variables can be found in Appendix 1. White heteroscedasticity-consistent standard errors are reported in parentheses.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
&&& indicates perfect prediction of failure (not running).

## VII. Conclusion

This paper uses a new, unique dataset from a bank that faced a run. We are able to access minute-to-minute depositor withdrawal data to understand the role of deposit insurance, networks, and bank-depositor relationships.

Our analysis suggests that deposit insurance helps in mitigating depositor panic. Uninsured depositors are more likely to run. While deposit insurance helps, we also find that it is only partially effective in preventing bank runs. Within the deposit insurance limit, depositors with larger balances are more likely to run. An intriguing finding is that the length and depth of bank-depositor relationships (as measured by account age and loan linkages) are important factors in mitigating the propensity to run. We also find that social networks are important. The more people in the depositors' network that run, the more likely is the depositor to run. Even within the network, however, the length and depth of relationships acts as a dampening factor on depositors' propensity to run.

Our results suggest that bank-depositor relationships are important but not the way traditionally envisaged by the banking literature, where these relationships give the bank information about its clientele. Our results suggest that there are additional channels by which depositor relationships could help banks in reducing fragility. Depositors with a better relationship with the bank might be less likely to run as that might jeopardize the value of the bank relationship in the future. Alternatively, the depositors with better relationship might receive positive signals about bank fundamentals (Morris and Shin 2003; Goldstein and Pauzner 2005), or have higher trust in the bank, which in turn reduces their likelihood of running. Thus, our evidence suggests that depositor relationships can help banks in multiple dimensions beyond the ways traditionally envisaged.

From the bank's point of view, our results highlight the importance of relationships with a bank in influencing depositors' incentives to run. Our results also suggest that one rationale to encourage cross-selling of deposits and loans to depositors is not simply to enhance revenues, as is often thought, but also to help protect the bank's downside by acting as a complementary insurance mechanism. In terms of policy implications, our results suggest that allowing banks to provide an umbrella of products, not just loans but other investment products and services, could help strengthen the relationship with the depositor, which in turn could help reduce fragility. Thus, our results hold importance for the debate concerning narrow banking.

Our findings on the importance of bank-depositor relationships present food for thought on a number of dimensions, particularly in the context of the broader banking literature. The banking literature suggests that small banks generally supply more credit to small borrowers and give better terms. The interpretation of this result has been that small banks are better at processing soft information. Our results suggest that, even absent soft information, small banks should lend to their small borrowers to help reduce their vulnerability to runs. Similarly, another result in the banking literature is that banks tend to give better terms to depositors who borrow from them. The rationale provided for this has been informational economies of scope. Again, our results suggest that, even absent informational economies of scope, it makes sense for banks to lend to their depositors, even at slightly better terms, as this acts as a complementary insurance mechanism.

An important question that has not been addressed in prior literature is whether there are long-lasting effects of a bank run for the bank, even if it remains solvent. Our results suggest that the effects of a bank run are indeed long-lasting since few depositors who run return to the bank. The effect of long-term erosion of the depositor base can affect bank lending, and affect credit to borrowers, particularly as research has shown that liquidity crunches in banks typically affect smaller and information-intensive firms. Thus, from a policy perspective, early intervention may be necessary to mitigate the real effects that arise due to erosion of deposits even for solvent bank runs.

# Appendix 1: Definition of Variables

| Variable name | Definition |
|---|---|
| Minority community | Minority community is a dummy variable that takes the value of 1 if the account belongs to a depositor from the minority community. |
| Above insurance cover | Above insurance cover is a dummy variable that takes the value of 1 for a depositor if his/her balance in the bank as of the event date is above the deposit insurance coverage limit. |
| Change in deposits | Change in deposits is the daily average of percentage change in deposits between January 1, 2001 and the event date if there are inflows, and is zero otherwise. |
| Change in withdrawals | Change in withdrawals is the daily average of percentage change in withdrawals between January 1, 2001 and the event date if there are outflows, and is zero otherwise. We use the negative of the calculated average in the tables. |
| Opening balance | Opening balance is the deposit balance (amount in hundreds of Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. |
| Number of transactions | Number of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between January 1, 2000 and the event date. |
| Loan linkage | Loan linkage is a dummy variable that takes the value of 1 for a deposit account if the household (associated with the account) has/had a loan account with the bank as of the event date. |
| Outstanding loan linkage | Outstanding loan linkage is a dummy variable that takes the value of 1 for a deposit account if the household (associated with the account) has a loan account with the bank as of the event date. |
| Past loan linkage | Past loan linkage is a dummy variable that takes the value of 1 if any member of the household (associated with the account) had a loan account with the bank before the event date and there is no outstanding loan linkage. |
| Future loan linkage | Future loan linkage is a dummy variable that takes the value of 1 for a deposit account if the household (associated with the account) had no loan account with the bank before/on the event date but availed of a loan from the bank in the future. |
| Account age | Account age is the log of the length of time for which the account has been open as of the event date. |
| Days to maturity | Days to maturity is the log of the number of days left for maturity for the term deposit account plus one. |
| Distance | Distance is the physical distance of the depositor's residence from the bank and is measured as the traveling cost to the bank in tens of Rs. |
| Neighborhood controls | Neighborhood controls represents the municipal ward where the depositor resides. |
| Runners in neighborhood $(t-1)$ | Runners in neighborhood $(t-1)$ is the fraction of other depositors in the neighborhood of the depositor who have run until time $t-1$ (excluding runs associated with the depositor household). |
| Runners introducer network $(t-1)$ | Runners introducer network $(t-1)$ is the fraction of other depositors in the social network of the depositor who have run until time $t-1$ (excluding runs associated with the depositor household). |

## Appendix 2: Survey Questionnaire

1) What is your full name?

2) What is your age?

3) What is your level of education?
   a) School
   b) Bachelor's degree
   c) Master's degree

4) Does your family have a car? Yes/No

5) Does your family have a bike? Yes/No

6) Does your family own a house? Yes/No

7) Does your family own other land? Yes/No

8) Primarily where do you put most of your savings?
   a) Banks—savings and term deposit
   b) Mutual funds
   c) Stocks
   d) Post office deposits

9) Do you remember the failure of MMCB bank? Yes/No

10) Did you have an account with MMCB? Yes/No

11) After the failure of MMCB, what affected your decision to withdraw/not withdraw your deposits?
    a) Trust in the bank
    b) How well the bank is doing/performing
    c) Others (specify)

12) If you withdrew money from your bank, where would you put it?
    a) Public sector bank
    b) Private bank
    c) Post office
    d) At home
    e) Other, specify

## REFERENCES


**Allen, Franklin, and Douglas Gale.** 2000. *Comparing Financial Systems*. Cambridge, MA: MIT Press.

**Banerjee, Abhijit V.** 1992. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics* 107 (3): 797–817.

**Bernanke, Ben S.** 1983. "Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression." *American Economic Review* 73 (3): 257–76.

**Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch.** 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change in Informational Cascades." *Journal of Political Economy* 100 (5): 992–1026.

**Bryant, John.** 1980. "A Model of Reserves, Bank Runs, and Deposit Insurance." *Journal of Banking and Finance* 4 (4): 335–44.

**Calomiris, Charles W., and Charles M. Kahn.** 1991. "The Role of Demandable Debt in Structuring Optimal Banking Arrangements." *American Economic Review* 81 (3): 497–513.

**Calomiris, Charles W., and Joseph R. Mason.** 1997. "Contagion and Bank Failures during the Great Depression: The June 1932 Chicago Banking Panic." *American Economic Review* 87 (5): 863–83.

**Calomiris, Charles W., and Joseph R. Mason.** 2003. "Consequences of Bank Distress during the Great Depression." *American Economic Review* 93 (3): 937–47.

**Carlin, Bruce Ian, Florin Dorobantu, and S. Viswanathan.** 2009. "Public Trust, the Law, and Financial Investment." *Journal of Financial Economics* 92 (3): 321–41.

**Chari, V. V., and Ravi Jagannathan.** 1988. "Banking Panics, Information, and Rational Expectations Equilibrium." *Journal of Finance* 43 (3): 749–61.

**Chen, Yehning.** 1999. "Banking Panics: The Role of the First-Come, First-Served Rule and Information Externalities." *Journal of Political Economy* 107 (5): 946–68.

**Dell'Ariccia, Giovanni, Enrica Detragiache, and Raghuram Rajan.** 2008. "The Real Effect of Banking Crises." *Journal of Financial Intermediation* 17 (1): 89–112.

**Diamond, Douglas W., and Philip H. Dybvig.** 1983. "Bank Runs, Deposit Insurance, and Liquidity." *Journal of Political Economy* 91 (3): 401–19.

**Diamond, Douglas W., and Raghuram G. Rajan.** 2001. "Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking." *Journal of Political Economy* 109 (2): 287–327.

**Duflo, Esther, and Emmanuel Saez.** 2003. "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment." *Quarterly Journal of Economics* 118 (3): 815–42.

**Friedman, Milton, and Anna Jacobson Schwartz.** 1963. *A Monetary History of the United States, 1867–1960*. Princeton: Princeton University Press.

**Geoffard, Pierre-Yves, and Tomas Philipson.** 1995. "The Empirical Content of Canonical Models of Infectious Diseases: The Proportional Hazard Specification." *Biometrika* 82 (1): 101–11.

**Goldstein, Itay, and Ady Pauzner.** 2005. "Demand-Deposit Contracts and the Probability of Bank Runs." *Journal of Finance* 60 (3): 1293–327.

**Gorton, Gary.** 1988. "Banking Panics and Business Cycles." *Oxford Economic Papers, N. S.* 40 (4): 751–81.

**Guiso, Luigi, Paola Sapienza, and Luigi Zingales.** 2008. "Trusting the Stock Market." *Journal of Finance* 63 (6): 2557–600.

**Halloran, M. Elizabeth.** 1998. "Concepts of Infectious Disease Epidemiology." In *Modern Epidemiology*, 2nd ed. Edited by Kenneth J. Rothman and Sander Greenland, 529–54. Philadelphia: Lippincott Williams and Wilkins.

**Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein.** 2005. "Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers." *Journal of Finance* 60 (6): 2801–24.

**Hudgens, Michael G., Ira M. Longini, Jr., Suphak Vanichseni, Dale J. Hu, Dwip Kitayaporn, Philip A. Mock, M. Elizabeth Halloran, Glen A. Satten, Kachit Choopanya, and Timothy D. Mastro.** 2002. "Subtype-Specific Transmission Probabilities for Human Immunodeficiency Virus Type 1 Among Injecting Drug Users in Bangkok, Thailand." *American Journal of Epidemiology* 155 (2): 159–68.

**Iyer, Rajkamal, and Jose-Luis Peydro.** 2011. "Interbank Contagion at Work: Evidence from a Natural Experiment." *Review of Financial Studies* 24 (4): 1337–77.

**Iyer, Rajkamal, and Manju Puri.** 2012. "Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks: Dataset." *American Economic Review*. http://dx.doi.org/10.1257/aer.102.4.1414.

**Jacklin, Charles J., and Sudipto Bhattacharya.** 1988. "Distinguishing Panics and Information-Based Bank Runs: Welfare and Policy Implications." *Journal of Political Economy* 96 (3): 568–92.

**Kashyap, Anil K., Raghuram Rajan, and Jeremy C. Stein.** 2002. "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking." *Journal of Finance* 57 (1): 33–73.

**Kelly, Morgan, and Cormac Ó Gráda.** 2000. "Market Contagion: Evidence from the Panics of 1854 and 1857." *American Economic Review* 90 (5): 1110–24.

**Khwaja, Asim Ijaz, and Atif Mian.** 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review* 98 (4): 1413–42.

**Kroszner, Randall S.** 2007. "Community Banks: The Continuing Importance of Relationship Finance." Speech at America's Community Bankers Government Affairs Conference, Washington, DC, March 5.

**Lindgren, Carl-Johan, Gillian Garcia, and Matthew I. Saal.** 1996. *Bank Soundness and Macroeconomic Policy*. Washington, DC: International Monetary Fund.

**Madies, Philippe.** 2006. "An Experimental Exploration of Self-Fulfilling Banking Panics: Their Occurrence, Persistence, and Prevention." *Journal of Business* 79 (4): 1831–66.

**Manski, Charles F.** 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies* 60 (3): 531–42.

**Morris, Stephen, and Hyun Song Shin.** 2003. "Global Games: Theory and Applications." In *Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress*, edited by M. Dewatripont, L. Hansen and S. Turnovsky, 56–114. New York: Cambridge University Press.

**Ongena, Steven, David C. Smith, and Dag Michalsen.** 2003. "Firms and Their Distressed Banks: Lessons from the Norwegian Banking Crisis." *Journal of Financial Economics* 67 (1): 81–112.

**Postlewaite, Andrew, and Xavier Vives.** 1987. "Bank Runs as an Equilibrium Phenomenon." *Journal of Political Economy* 95 (3): 485–91.

**Rochet, Jean-Charles, and Xavier Vives.** 2004. "Coordination Failures and the Lender of Last Resort: Was Bagehot Right after All?" *Journal of the European Economic Association* 2 (6): 1116–47.

**Saunders, Anthony, and Berry Wilson.** 1996. "Contagious Bank Runs: Evidence from the 1929–1933 Period." *Journal of Financial Intermediation* 5 (4): 409–23.

**Song, Fenghua, and Anjan V. Thakor.** 2007. "Relationship Banking, Fragility, and the Asset-Liability Matching Problem." *Review of Financial Studies* 20 (6): 2129–77.

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