Understanding bank runs: the importance of depositor-bank relationships and networks

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Publication date
2008

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

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August 2008

Abstract

We use a unique, new, database to examine micro depositor level data for a bank that faced a run. We use minute-by-minute depositor withdrawal data to understand the effectiveness of deposit insurance, the role of social networks, and the importance of bank-depositor relationships in influencing depositor propensity to run. We employ methods from the epidemiology literature which examine how diseases spread to estimate transmission probabilities of depositors running, and the significant underlying factors. We find that deposit insurance is only partially effective in preventing bank runs. Further, our results suggest that social network effects are important but are mitigated by other factors, in particular the length and depth of the bank-depositor relationship. Depositors with longer relationships and those who have availed of loans from a bank are less likely to run during a crisis, suggesting that cross-selling acts not just as a revenue generator but also as a complementary insurance mechanism for the bank. Finally, we find there are 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 Codes: G21: E58

Keywords: Bank Runs, Relationships, Loan Linkages

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We would like to thank Doug Diamond, Mark Flannery, Atif Mian, Adair Morse, George Pennacchi, Debu Purohit, David Robinson, Claire Rosenfeld, Florencio Lopez de Silanes, Phil Strahan, Per Stromberg, David Smith, Amir Sufi, Anjan Thakor, Tanju Yorulmazer, and seminar participants at the American Finance Association Meetings, New Orleans, Bank Structure and Competition conference, Fed Chicago, 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 Amsterdam, 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 Center for Financial Research for financial support.

1. Introduction

Bank runs are situations where depositors withdraw their deposits from banks for the fear of the safety of their deposits. Historically, bank runs were a prominent feature of the great depression era in the U.S, prompting the introduction of federal deposit insurance. Yet bank runs continue to be an important phenomenon, as witnessed by current trends, the dire financial condition of some banks, and recent aborted runs both in the US, and internationally [e.g., Countrywide Bank, IndyMac Bank (U.S.), Northern Rock Bank (U.K.), ICICI Bank (India)]. Even in countries which did not experience bank runs recently, the attempt to avoid them 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 crisis, understanding what factors drive depositor runs on banks is important.[1]

The theoretical literature on bank runs has helped identify potential causes for depositor runs. The literature can broadly be divided 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, 2005). 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.

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. An important question is how does such contagion effects of bank runs spread? What factors mitigate this? Are there costs of a bank run, even if the bank survives? Understanding these

[1] For the costs of banking crises, see e.g. Friedman and Schwartz, 1963; Bernanke, 1983; Ongena et al., 2003; Calomiris and Mason, 2003b; Dell'Ariccia et al., 2008. See also Lindengren, Garcia and Saal (1996) who show that in the period between 1980-96, 133 countries experienced severe banking problems.

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 pre-run 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, the role of social networks, the importance of bank-depositor relationships, and other factors in influencing depositor propensity to run.

Using micro depositor level data, we create proxies on three main dimensions across which depositors differ. These are deposit insurance; bank-depositor relationships; and social networks. First, in order to examine the effectiveness of deposit insurance, we create a measure to distinguish whether the depositor balance with the bank is above or below the insurance coverage limit. We also ask if the balance in the account, even within deposit insurance limits, affects propensity to run. Second, we identify social networks. Here we use three distinct measures. Our first measure is based on the neighborhood of residence of the depositor. Our second measure is based on the ethnic group that the depositor belongs. We sort depositors primarily into two categories Minority (Muslims) and Non-Minority (Hindus) using the last name of the depositor. Finally, 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. In general, an acquaintance that has an account with the bank provides the introduction. We use the introducer name associated with the depositors' account to capture the social network of a depositor. Third, we proxy for depositor relationships with the bank with two measures designed to capture length and depth of the relationship. One is the age of the account, which is a measure of the length of the relationship. The other is whether the depositor avails of loans from the bank, suggesting the relationship is multi-pronged or has more depth than as suggested by simply holding a deposit account.

Our investigation is at two levels. First, we examine which factors are significant in affecting depositor behavior over the period of the run. We find a number of interesting results. One, we find that deposit insurance is only partially effective in preventing bank runs. While depositors who are over the deposit insurance limit are more likely to run, even if we consider accounts below the deposit insurance limit, we find that account balance positively influences the likelihood of a withdrawal. Second, the ethnic status of the depositor also has an effect on the likelihood of a withdrawal. Depositors belonging to the minority community are more likely to run during a crisis. Third, we find both the length and the depth of the bank-depositor relationships matter. The longer the bank-depositor relationship, as proxied by the duration of the deposit account, the lower the likelihood of a withdrawal during the crisis. Further, depositors that have a deeper connection with the bank, as measured by a loan linkage, are less likely to run. We conduct robustness checks to investigate why depositors with loan linkages are less likely to withdraw, and find ex-ante differences in depositors or perceived set-offs cannot fully explain these results. Interestingly, we find that even depositors that had availed of a loan in the past (but currently have no outstanding loan) are also less likely to run. However, this result does not hold for depositors who do not have a lending relationship at the time of the crisis but forge a subsequent lending relationship suggesting that unobservable differences in characteristics of depositors with loan linkages are unlikely to be the main driver. These results suggest past loan taking and related interactions deepen the bank-depositor relationship in a way that affects depositor behavior.

Next, we examine the time variation within the period of the run. Here we are able to use the minute-to-minute depositor withdrawal data that we have access to. Our approach here is two-pronged. First, to investigate the importance of social networks, we use a Cox proportional hazard model with time varying covariates, where we measure hazard rate in one-minute spells (using the exact time of depositor withdrawal). We find that a depositors' likelihood of running is increasing in the fraction of other people in his/her network that have run. We also find that once we control for the effect of networks, minority community dummy loses significance suggesting that social networks play an important role in the behavior of minority community depositors.[2]

We further want to understand how contagion effects of bank run behavior spreads among depositors. For this purpose we explore and employ methods from the rich epidemiology literature that spends considerable effort in examining how diseases spread. There is a natural parallel from this literature to bank runs. Specifically, epidemiologists model transmission probability of a disease as the probability that a person gets infected through contact with another infected person (Geoffard and Philipson, 1995; Halloran, 1998; Hudgens et al, 2002). The parallel in bank runs can be thought of as the probability of running as result of contact with a person who has already run. Using these models we are able to estimate and quantify transmission probabilities. We estimate the average transmission probability is 3% via social groups (introducer network) and 5% via neighborhood (neighborhood based network). We also find that contagion due to social networks peaks in the second day of the crisis. We discuss implications in terms of timing of regulatory or preventive measures.

Though social networks are important, there are significant factors that mitigate depositor propensity to run. In particular, we find that the length and the depth of the relationship matter in restraining depositors from running, even accounting for social network effects. We find the longer the duration of the deposit account the lower the likelihood of a withdrawal during the run. We also find that depositors that have a loan linkage with the bank are less likely to run. These results suggest while large emphasis is placed by banks on cross-selling as a revenue generator, cross-selling also serves another important function by acting as a complementary insurance mechanism for the bank

Apart from the factors that affect depositor runs, from a policy point of view, an important question that arises is whether depositors that run return back to the bank. What are the long term effects of bank runs? If depositors that run re-deposit after the crisis, a temporary liquidity provision (lender of last resort) by the central bank would suffice to bridge the liquidity gap, with

[2] Kelly and O'Grada (2000) find that Irish depositors in New York that came from the same county in Ireland are more likely to run during the panic experienced by the Irish Immigrants bank in New York.

little long term consequence. We, however, find that the effects of the run are long lasting. Of the depositors that withdrew during the crisis, only in 10% of the cases does the account balance return to pre-crisis levels even after 6 months of the crisis. Further, we do not find that the aggregate level of deposits of the bank return to the pre-crisis 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.

In the theoretical literature on bank runs, in models such as Goldstein and Pauzner (2005), Morris and Shin (2003) depositors receive signals about fundamentals of the bank and use these signals to co-ordinate expectations whether other depositors are likely to run. One interpretation of our results is that depositors with stronger relationships with a bank receive better signals about the fundamentals of the bank (signals have a higher average) and therefore are less likely to run. Our results are also consistent with the information based theories of runs in that banks that are fundamentally solvent banks are more likely to survive the crisis despite them facing some runs.

Our paper is related to a number of strands of literature. First, our paper complements the empirical literature on bank runs which has largely been conducted in a macro setting to 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, 1994; Calomiris and Mason, 1997). Our analysis differs from ex-ante literature by examining bank runs on a micro level, in particular looking at minute-to-minute withdrawals of a bank that was subject to a run to empirically identify factors that affect depositor propensity to run, and to understand how contagion effects of depositor behavior spread in bank runs. Second, our paper examines the role of deposit insurance in bank runs and suggests that deposit insurance is only partially effective in preventing bank runs. Third, our paper suggests that while social networks are important, the length and depth of bank-depositor relationships reduce the propensity to run, even in the presence of social network effects. 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 protects the downside risk to a bank of runs, and effectively acts as a complementary insurance mechanism for the bank. To the best of our knowledge this role of relationships is new to the literature. Fourth, our results also contribute to the growing literature on the importance of social networks in economic choices (Bertrand, Mullainathan, and Luttmer 2000; Duflo and Saez, 2003; Munshi, 2003, Hong, Kubik and Stein, 2005). Fifth, our paper contributes 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 et al., 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 2 describes the institutional setting. Section 3 provides details of the event. Section 4 describes the data set. Section 5 presents the results. Section 6 presents the robustness checks. Section 7 concludes.

2. Institutional Details

The Indian banking system primarily constitutes of three types of banks: public sector banks, private banks and cooperative banks. 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 USD 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 takes 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.[3] In case of failure of a bank, the deposits held by a depositor cannot be adjusted against loans outstanding. The stipulated cash reserve ratio and statutory liquidity ratio to be maintained by the banks are 5.5% and 25% respectively.[4]

With regard to the co-operative banks, depositors of cooperative banks are not required to hold an equity claim in the cooperative bank. Furthermore, any depositor can avail of a loan from the bank. It is also not mandatory to open a deposit account when taking a loan. Further, shareholders of cooperative banks have limited liability.[5] 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 U.S. system the closest parallel to cooperative banks are perhaps community banks, which play an important role in the U.S. economy (see e.g., Kroszner, 2007)[6].

3. Event Description

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

[4] Statutory Liquidity Ratio (SLR) is the one which every banking company shall maintain in India in the form of cash, gold or unencumbered approved securities, an amount which 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.

[5] The bank issues shares at face value. To be a borrower the bank, the bank asks a depositor to buy shares worth 2% 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

[6] In a speech on March, 5, 2007, Federal Reserve Governor, Randall Kroszner states, "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.

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 stock brokers without appropriate collateral in contravention of the guidelines prescribed by the central bank.[7] The amount of loans given to stock brokers amounted to nearly 80% of the deposit base (Rs. 10 billion were advanced as industrial loans to stock brokers without appropriate collateral). On the 8th of March 2001, some major brokers defaulted on their pay-in obligations to the stock exchange. Rumors were floating around that the bank had over-stretched lending positions to a major stock broker who had suffered huge losses in his share dealings in a select group of stocks. This led to a run on the bank on the 9th and 12th of March 2001. As the bank failed to repay depositors on the 13th of March 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, 2007). However, there were no other banks that failed during the event window. Note that at the time of the failure the state economy was performing well thus the runs are result of an idiosyncratic shock rather than a product of weak economic fundamentals (Gorton, 1988).

After the collapse of the large bank there was a huge debate whether it should be bailed out. The revival scheme was organized in terms of a privately arranged bailout. However, the revival scheme was a non-starter.

4. 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

[7] See the report of the Joint Parliamentary Committee at www.manupatra.com/downloads/JPC/part%201.pdf

approximately Rs 300 million. This bank hardly had any interbank exposure to the failed bank. Its exposure was 0.001% of the total assets. Also, this bank did not have any correspondent banking relationship with the failed bank.

First, we obtain all the transactions for the depositors that have an account at the head quarters of the bank (the bank had 2 branches with the bulk of the deposits in the head office). The transaction data provides us 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.[8] 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, the type of loan. For the fixed 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 was liquidated. Our data set 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 if the withdrawal was made in person or through a cheque or the withdrawal was due to an internal transfer. Note that the bank did not have electronic banking or any automatic teller machines (ATMs), so the sequential service constraint is met. The only way to obtain cash is to queue up outside the bank.

To construct 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 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

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

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 the 13th of March, 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 the 1st of April 1995. We assume the opening date of these accounts to be 1st of April 1995 for computation. This provides us with the duration of each account as on the 13th of March, 2001. To obtain the total number of transactions undertaken by an account, we count the number of transactions for an account beginning the 1st of January 2000 till the 13th of March 2001. For example, if an account had 4 transactions in the period between 1st of January and 13th of March, 2001, we record the total transaction count as 4 for that account.

To determine if 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 that has 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 indicator of accounts that belong 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 the 13th of March 2001. In defining the loan linkages we exclude overdrafts or cash facilities that are taken against fixed 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 which depositors belong to are Muslims and Hindus (Gujarati). In most of the cases it is very easy to identify the ethnic profile of a depositor based on the last name. However, since we do not have an exhaustive of last names that are associated with Muslims or those who are Gujarati, we manually categorize the ethnic status of each depositor. The manual procedure also helps in correctly categorizing depositors that 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. However, from the first name 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 fraction of balance outstanding as on the 12th of March, 2001 that is deposited with the bank in the interval between the 12th and the 13th of March. 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 fraction of balance outstanding as on the 12th of March, 2001 that is withdrawn from the bank in the interval between the 12th and the 13th of March. 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 the 13th of March, 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 on the 13th of March, 2001 if the account is below the deposit insurance level and zero otherwise.

For transaction accounts we have the exact time of the day when 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 (13th of March, 2001). We evaluate failures in one minute intervals, beginning from 10:30 am on the 13th of March, 2001.[9] For example, the withdrawal by a depositor on the 13th of March, 2001 at 10:36:36 am, would have a failure time of 7.

[9] 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.

Finally, we capture the network of a depositor in 3 different ways. We first use the name of the introducer that is 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 in 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 that 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 no. 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 are 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 define two other variables to capture networks. These network measures are based on neighborhood of the depositor and his/her ethnic status. *Runners in neighborhood (t-1)* captures the fraction of other depositors in the neighborhood that are 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 sq kms). We have 71 neighborhoods in the sample. Similarly *minority runners in neighborhood (t-1)* capture the fraction of minority community depositors in the neighborhood that have run until time (t-1). 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 for taking an auto-rickshaw from the depositors' neighborhood to the bank.

5. Empirical Results

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

Table 1A (panel 1) presents the summary statistics for fixed deposit accounts. As on the 13th of March 2001, there are 4574 depositors that have fixed deposit accounts active at the head office of the bank. Out of these accounts only 6.6% of the depositors have an account balance more than the deposit insurance coverage limit (USD2500). This suggests that the majority of depositors are small depositors. For depositors that hold balances below the deposit insurance coverage limit, the average balance in fixed deposit account is Rs. 23823. We also see that 8% of depositors have/had some loan linkage with the bank. In terms of the ethnic profile of depositors, 29% of the depositors belong to the minority community. The average age of the account is 1057 days. The average time to maturity of the deposits is 384 days.

Table 1A (panel 2) presents the summary statistics for the transaction accounts (savings and current accounts). As on the 13th of March 2001, there are 10691 depositors with transaction accounts at the head office of the bank. Out of these accounts, only 1% 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. 3258. The extent of depositors with loan linkage is similar to that of fixed deposit accounts (7.4%). The average number of transactions per depositor in the period between 1st of January 2000 and 13th of

March 2001 is 14.68. In terms of the ethnic profile of the depositors, 26% of the depositors belong to the minority community. We also see that for depositors that deposited cash with the bank in the day prior to the crisis, the average deposit is 14% of the outstanding balance. On the other hand for depositors that withdrew cash in the day prior to the crisis, the average withdrawal is 0.5% of the outstanding balance. The average age of a transaction account is 2286 days.

To analyze the characteristics of depositors that withdrew during the crisis, we conduct the analysis separately for fixed deposit accounts and transaction accounts. It is necessary to separate the analysis, as there are higher costs to liquidation of fixed deposits as against withdrawals from transaction accounts. The bank charges a penalty of 2% of interest accrued if the fixed deposit account is liquidated before maturity. Furthermore, splitting the analysis also provides an additional robustness to the strength of the findings. For the fixed deposit accounts, we construct a dummy variable that takes the value of one if the depositor liquidated any part of his fixed deposit in the period between the 13th and the 15th of March, 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% of the deposit outstanding as on the 13th of March 2001. The analysis is carried out a depositor level as some of the important variables like deposit insurance coverage is at a depositor level. In all estimations we cluster standard errors by household. As robustness, we also use other thresholds like 50% and 25% and do not find any significant change in the main results.

Table 1B presents the summary statistics for the runners and stayers separately. A t-test of difference in means across the two groups shows that there are significant differences. Firstly, we find that depositors from the minority community are more likely to run. We also find that runners have shorter length of relationship with the bank. Runners are also less likely to have loan linkages with the bank. Runners have higher number of transactions with the bank and have deposits with shorter maturity. Finally, 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 fixed deposit accounts.

We next run probit estimations to understand better the factors that influence depositor runs, the results of which are reported in Table 2. We find three main results. First, deposit insurance seems only partially effective in preventing runs. Depositors with deposit balance above the deposit insurance coverage limit are more likely to liquidate their deposits. However, we also find that even for depositors with balances below the deposit insurance limit, higher account balances increase the likelihood of running. 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 neighborhood of the depositor the minority dummy is no longer significant in explaining depositor runs for fixed deposit accounts (though it continues to be significant for transaction accounts), which suggests 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 is the depositor is to run. The depth of relationship as proxied by loan linkages also matters. We find that depositors that 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 fixed deposits. Thus loan linkages do not capture the mechanical effect that could arise due to an overdraft.[10]

We further investigate the importance of loan linkages by categorizing depositors that have account balances above the insurance level based on whether there have loan linkages. In effect, we divide depositors with account balance above the insurance level into ones that have loan linkages and ones that 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 coverage level without loan linkages are more likely to run while accounts above the insurance level with loan linkages are not likely to run (column 2 and 4). 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 30% higher

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

likelihood of running.[11] To make sure that the effect of loan linkages is not limited to depositors who hold balances above the deposit insurance level, in Table 3, column 1 and 4, we estimate the probit only for accounts below the deposit insurance coverage limit. We find similar effect 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 Table 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, so depositors would not benefit from running. However, by regulation 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.[12] Second, depositors with loan linkages could be subject to a hold-up problem, as they may fear that in case they withdrew their deposits and the bank survives the run, the bank could pull back on their credit in future. Third, depositors with loan linkages could have better relationships with the bank and are therefore less likely to run. 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 that had a loan linkage in past but currently have no outstanding loan linkage differ in their behavior as 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 that had a loan linkage in the past and depositors that have a loan currently outstanding are less likely to run (column 1). As depositors with loan linkages in past are less likely to face a hold up problem by the bank and also do not have the benefit of any set-off in case of failure, the results above suggest that the explanations of set-off or hold up are unlikely to explain this result. We also check whether depositors with past loan linkages take a loan out in the future with the bank.

[11] For fixed deposit accounts, there are 61 depositors who hold balances above the insurance cover and have loan linkages. For transactions accounts the number is 6.

[12] 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 is carried out independently as separate procedures.

Only 10% of depositors fall in this category, again suggesting that hold up issues do not appear to be the rationale why past loan linkage depositors do not run.

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.[13] Results in Table 4, column 2 and 4 show that depositors who have/had loan linkages with the bank as on 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. However, a F-test rejects equality of coefficient between the depositors with outstanding loan linkage as compared to depositors with future loan linkage at 4% (column 2). Furthermore, we do not find any ex-ante differences between the depositors that availed of loan linkages after the crisis and depositors that have/had loan linkages with the bank as on the date of the crisis on a variety of additional dimensions (see table 8 and table 9). In sum, the results taken together suggest that the effect of loan linkages on deposit behavior is most likely to be a result of relationship with the bank, that is, that past loan taking and related interactions deepen the bank-depositor relationship in a way that affects depositor behavior.

5.1. Social Networks

While so far we have examined the importance of relationship with the bank in affecting 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,

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

Hirshleifer, and Welch 1992; Banerjee 1992). In the light of this, we examine the importance of social networks in depositor runs.

We create three 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 derived by crossing the neighborhood of the depositor with his/her ethnic status depositor. The idea being that, people might be more likely to interact with other people in their neighborhood who belong to their own ethnic group. Finally, we use the introducer name associated with the deposit account to create our third measure of network.

To estimate the effects of networks, we use the Cox model with time varying covariates.[14] We measure the effect of the networks by exploring whether the fraction of other depositors in a depositors' network that have run till time t-1 has an influence on the hazard rate of a depositor at time t. The Cox model we estimate is given by: $\lambda_i (t|X,\beta) = \lambda_o (t) \exp\{X'\beta\}$ where $\lambda_o (t)$ is the base line hazard function, X and β are vectors of variants and regression coefficients respectively. For estimation of the model, we use 1 minute spells, i.e., we measure withdrawals every minute.[15] Note that none of the depositors that run in the sample withdraw more than once (there are no multiple withdrawals).

As results from the estimation of the Cox model in Table 5, column 2 show, we find that higher fraction of runs by other depositors in the neighborhood increases the hazard rate. To further investigate the importance of neighborhood contacts, we cross the neighborhood of a depositor with the ethnic status of the depositor. In column 3, we find that runs by other minority community depositors in the neighborhood increases the hazard rate for a minority community

[14] We also estimated the model with a frailty term for loan linkages. All the results are robust to this.

[15] In total the bank is open for 5 ½ hrs a day (10.30-4pm). Thus we have 307 withdrawals over 3 days (990 minutes). In effect, on average we have 1 withdrawal every 3 minutes. Also in day 2 and 3 of the crisis between 11-12am, there are around 45 withdrawals. Thus on average there is a one withdrawal every 1.33 minutes. Therefore in order avoid ties in the withdrawal time, we use 1 min intervals.

depositor.[16] Interestingly, we do not find any significant of effect of runs by other majority community depositors in the neighborhood on runs by minority community depositors. We also find that minority community dummy is no longer significant. This suggests minorities run not because they are minorities per se, but only if other minorities in their neighborhood run. This results indicate that social networks play an important role in the behavior of minority community depositors.

While the results in Table 5, column 2 and 3 suggest that networks based on the neighborhood of a depositor play an important role, one could argue that these effects are driven by other omitted individual characteristics that might be correlated with neighborhoods. Thus the interpretation of network effects based on neighborhood and ethnic status of depositors could suffer from what Manski (1993) refers to as the "reflection" problem. To circumvent many of the omitted variables concerns, we look at the effect of networks based on introducer name. The advantage of using networks based on introducer name 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.

As results in column 4 shows, we again find that the behavior of other depositors in the introducer network has a significant effect. Higher fraction of runners in the social group (based on introducer network) of a depositor increases the hazard rate. However, the length and depth of the relationship, as proxied by account age and loan linkages, both go towards reducing the propensity to run. One potential concern with the results reported in column 4 could be 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. To address this concern, 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. Interestingly, we find that even within this network, the hazard rate is lower if a depositor has loan linkages with the bank and has a longer length of relationship with the bank. These results suggest that even after controlling for the

[16] To check if all minorities are concentrated in some neighbourhoods, we look at the correlation of the number majority community people in a neighbourhood and minority people in a neighbourhood. The correlation is 0.81 suggesting that there is a good mix of people from both communities in neighbourhoods'.

effect of networks, the length and depth of relationships with the bank have a significant effect on depositor behavior.

5.2 Bank-Depositor Relationships

An intriguing result is the effect of the length and depth of relationships as proxied by the age of the account and loan linkages. As we see in the Cox regressions, both age of the account and loan linkages are significant in mitigating depositor propensity to run, over and above the network effect. And even, when we restrict the estimation to those networks where at least one other depositor runs, we still find both variables – account age and loan linkages – to be significant. These results are also consistent with and lend support to the results that we obtained earlier in tables 2-4 which suggest that account age and loan linkages are significant factors in reducing the probability that depositors' run.

In the banking literature, much importance is placed on the bank-client relationship. In this literature, relationships typically give the bank information about the client. Here, however, the reverse seems to be happening. How do we relate what is happening with the theoretical literature? In the classic Diamond-Dybvig (1983) model, all depositors have the same information set, and there are sunspot equilibrium – either everyone runs or no one runs. There have been many models since then modifying the assumption in Diamond-Dybvig (1983). For instance, in Goldstein-Pauzner (2005) depositors receive noisy private signals about bank fundamentals, and use their signals to form expectations about the actions of other depositors. They obtain a unique equilibrium in which there are bank runs if fundamentals are below a certain threshold. One question that arises from such models is why would depositors who are otherwise similar, get different private signals? Our results suggest one rationale. Depositors with loan linkages get a higher signal about bank fundamentals, perhaps through repeated interaction with, and/or access to bank officers. Our results suggest that depositors also take into account the fact that others in their networks are running (as in Diamond-Dybvig (1983), see also Madies (2006)). If others in their network run, they are more likely to run, but loan linkages add to the signal and lower the probability of running. Thus, 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. Rather, here the information flow is in the opposite direction, helping the depositor get a positive signal on bank fundamentals, mitigating their propensity to run.

5.3 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. Epidemiologists have a long history of modeling transmission of infectious diseases. 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 result of contact with a person who has already run. A commonly used model in epidemiology for modeling transmission probability is the following (see e.g., Geoffard and Philipson, 1995; Halloran, 1998; Hudgens et al, 2002):

$$\lambda_i (t) = C_i(t) \prod(t) P \exp \{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\} \qquad (1)$$

Interpreting the model in the context of the AIDS epidemic, $\lambda_i (t)$ is the probability that person i gets infected with AIDS in the time interval t. If we assume that the only way a person contracts AIDS is through sexual intercourse with another infected person, we can think of contact $C_i(t)$ as the number of acts of sexual intercourse by person i in the interval of time t. $\prod(t)$ is the fraction of population with AIDS in the time interval t (prevalence of the disease at time t). In turn, the transmission probability P is the average probability of getting infected though a single contact with an infected person. X_{i1} X_{i2} are other covariates like age, education etc.

In the context of bank runs, we estimate the following model:

$$\lambda_i (t) = C \prod_i(t) P (t) \exp \{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\} \qquad (2)$$

where C is the number of people in ones social network or neighborhood that one comes in contact and is assumed to be 1 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 a single contact with a person who has already run. X_{i1} X_{i2} are covariates like age of the account, loan linkage etc.

The model specified by equation (2) can be easily specified in terms of a Cox model. If we take the standard Cox model: $\lambda_i(t) = \lambda_o(t) \exp\{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\}$ (3)

and introduce a covariate log (C $\prod_i(t)$), then the model specified in equation 3 can we written as

$\lambda_i(t) = \lambda_o(t) \exp\{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz} + \beta_\prod \log(C \prod_i(t))\}$ (4)

If we constrain $\beta_\prod$ in model (4) to be equal to one, then model (4) can be specified as

$\lambda_i(t) = C \prod_i(t)\, \lambda_o(t) \exp\{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\}$ (5)

In effect, from model (2) and (5), transmission probability P(t) in model (2) can be thought of as base hazard rate of the Cox model specified in equation (5) (Geoffard and Philipson, 1995; Halloran, 1998; Hudgens et al, 2002).[17]

We fit the transmission probability model specified by equation (2) using the procedure described above and estimate the transmission probability. As results in Table 6 show, we find that the average transmission probability across time is 3% via social groups (introducer network) and 5% via neighborhoods. The maximum value that the transmission probability takes is 21% for social groups and 52% for neighborhood-based network. Interestingly, the transmission probabilities based on neighborhood networks are highest in the morning and then drops during the day. However, the transmission probability based on introducer social network peaks around lunch time the first day as opposed to when the bank opens. This is intuitive given the nature of the network. Social networks through introducer is presumably through work related or other contacts, which likely occur after working hours begin, as opposed to neighborhoods where people meet or get to know their neighbors are running first thing in the morning. Averaging across transmission probabilities in 1 hour, 10 minute intervals, we find that the average transmission probabilities are higher in day 1 and day 2 of the crisis and drop in day 3 of crisis. Understanding transmission probabilities is important if there is a case for intervention in solvent bank runs. Our results suggest that if there is intervention it should be when the transmission probabilities are highest which is early in the crisis.

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

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.

5.2. Do depositors that run return back 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 do depositors that run re-deposit 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 graph 6, we see that depositors that withdrew during the crisis do not re-deposit to the pre-crisis levels.[18] 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 pre-crisis levels after the crisis. As results in table 7, panel A, show, we find a maximum of 11% of the depositors return back to the bank. We also find that for 72% of the depositors that withdrew during the crisis, the deposit balance after 3 months remains 75% lower than the outstanding balance before the crisis (panel B, column 2). Thus, it does appear that depositors that panic do not return back 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 the 15th of March 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 the 1st of May, July and October 2001 respectively. This suggests that the effects of the runs are not reversed in a short interval of time. This could have economic real costs 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, 2007).[19]

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[18] Also, from Graph 6, one can see that the withdrawal patterns of runners was not very volatile before the crisis. Thus, further reaffirms that the runs we document are not likely to be a result of liquidity needs of depositors.

[19] For the sample of depositors we surveyed, we find that 85% would re-deposit the money that they withdrew in a public sector bank, 11% in private bank, 2% in post office and 2% at would keep the money at home. This finding is also corraborated 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 case of small borrowers.

6. 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% or more of their account balance. To make sure that our results are not sensitive to the choice of threshold, we re-estimate the model using 50% and 25% as threshold levels. As can be seen from Table 10, column 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 fixed 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 on the date of failure of the large bank (13th of March 2001). However, given that the large bank faced runs beginning the 9th of March, it is possible that a few depositors could have withdrawn their deposits in the period between the 9th and 13th of March 2001. Hence as a robustness check we rerun our regressions using the period between the 9th and the 15th of March 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 one could have 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 concern, in Table 10, column 4, we re-estimate the model where we measure 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) amount of shares in the co-operative, if any, held by depositors, we find that all our results are robust to this.

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 that withdrew during the crisis from their transaction account, along with 300 other depositors that did not withdraw and conducted a survey. The 400 depositors that we choose belong to different households. 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 the other people that own the asset.[20] For example, if 40 out of the 400 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 4 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.

In univariate tests, we did not find any significant differences between runners and stayers in terms of education, age or wealth. We also did not find any significant differences between depositors with loan linkages and other depositors along these dimensions.

In table 11, we run multivariate tests. In column 1, we introduce dummies for level of education of depositors. We find that the level of education of a depositor does not have a significant effect on the likelihood of withdrawing (not reported). We also find that even for this sub-sample that represents different households, the results are in the line with those reported before (Table 2, column 3). Note that loan linkages perfectly predict not running in this sub-sample (there are 14 depositors with loan linkages). In column 2, we introduce the age of the depositor. We do not find any significant effect of age. We also find that even after controlling for age of the depositor, account age has a significant effect on the likelihood of withdrawing. This helps address the concern that the effect of account age on withdrawing could be driven by the age of the depositor rather than the length of relationship with the bank. In column 3, we introduce the proxy for the level of wealth of a depositor. We find that the level of wealth does not have a significant effect on the likelihood of withdrawing. More importantly, we find all our results are robust to controlling for proxies of wealth, age and education.[21]

[20] In total, we were able to survey 282 depositors out of the 400.

[21] In addition, we also looked at 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.

7. 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 is only partially effective in preventing bank runs. 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. However, even within the network, the length and depth of relationships acts as a dampening factor on the depositor propensity to run. One interpretation of these results is in the light of theoretical models such as Goldstein and Pauzner (2005), and Morris and Shin (2003) where depositors with longer and deeper relationships get more positive signals about the bank fundamentals, and therefore are less likely to run despite the negative information received about other people in their network running. From the bank's point of view our results highlight the importance of relationships with a bank in influencing depositors' incentive 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 can also help protect the bank's downside by acting as complementary insurance mechanism. In terms of policy implications, our results suggest that allowing banks to provide an umbrella of products could help strengthen the relationship with the depositor, which in turn could help reduce fragility.

Our findings on the importance of bank-depositor relationships raise 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, 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, 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 long lasing effects of a bank run for the bank, even if it remains solvent? Our results suggest 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 (see e.g., Khwaja and Mian, 2007). If there are adverse long run effects of bank runs then we need to understand the appropriate timing of intervention. We address this by employing methods from the epidemiology literature, which examine how diseases spread, to estimate when the transmission probabilities of depositors running is highest which turns out to be the initial period of the run.

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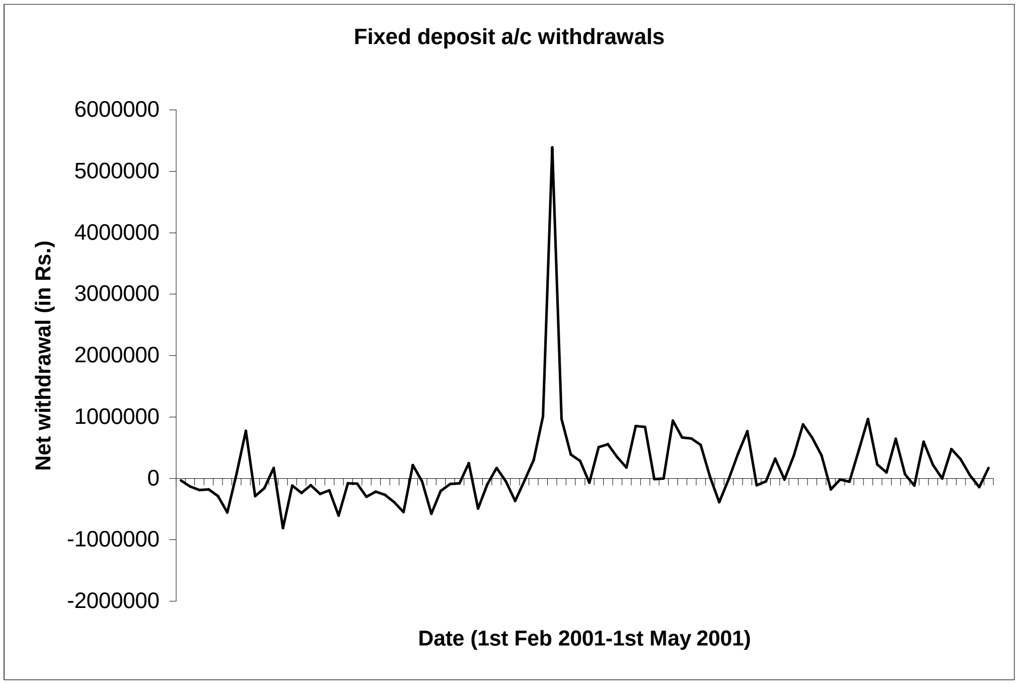
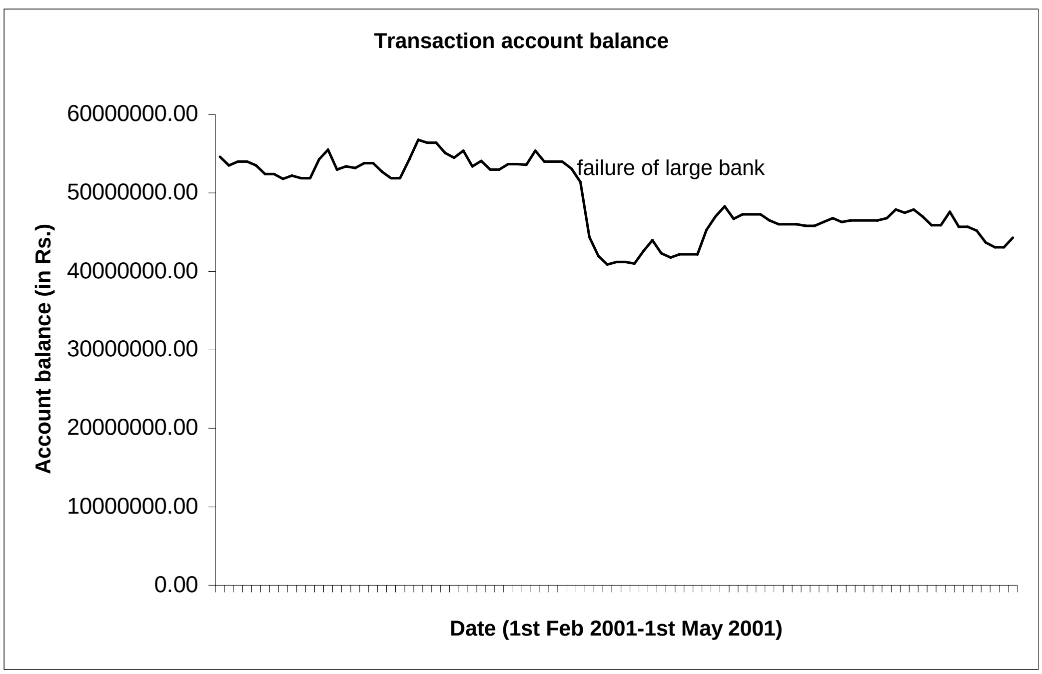
Graph 1: Withdrawals from Fixed deposit accounts from Feb-May 2001 (13th of March is the date of failure of the large bank)



Graph 2: Deposit Balance in transaction accounts for the period between February-May 2001



Graph 3: Percentage of outstanding account balance (transaction a/c) withdrawn by a depositor that withdrew during the crisis

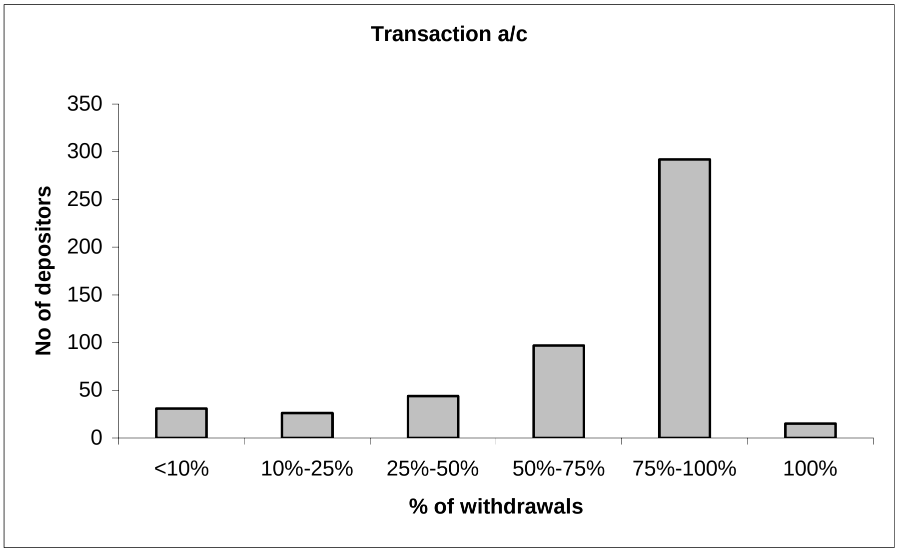


Table 1A: Summary statistics

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 is a dummy variable that takes the value of 1 for a depositor if his/her balance in the bank as on the event date is above the deposit insurance coverage limit. Change in deposits is the percentage change in deposits between the 12th of March, 2001 and event date if there is an inflow and is zero otherwise. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. Opening balance is the deposit balance (amount in Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. Age of account is the length of time (days), for which the account has been open as on the event date. No. of transactions is the total number of transactions (deposits, withdrawals, transfers) associated with an account between the 1st of January 2000 and event date. Loan linkage is 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 on event date. Days to maturity are the number of days left for maturity for the fixed deposit account.

Fixed Deposit a/c (panel 1)	Observation	Mean	Median	Std. Dev	Min	Max
Minority community	4574	0.293	0	0.455	0	1
Above Insurance Cover	4574	0.066	0	0.248	0	1
Opening balance	4271	23823	16813	21365	402	99906
Age of account	4574	1057	1105	562	1	7585
Loan linkage	4574	0.080	0	0.272	0	1
No of Days to maturity	4574	384	262	378	0	2248
Transaction a/c (panel 2)						
Minority community	10691	0.267	0	0.442	0	1
Above Insurance cover	10691	0.010	0	0.103	0	1
Opening balance	10575	3258	683	9131	0.39	99780
Change in deposits	10691	0.141	0	5.711	0	428.08
Change in withdrawals	10691	0.005	0	0.062	0	0.994
Age of account	10691	2286	2173	1307	8	16640
No. of transactions	10691	14.68	4	50.26	0	1421
Loan linkage	10691	0.074	0	0.262	0	1

Table 1B

For fixed 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, stayer otherwise. For transaction account runner is defined as a depositor who withdraws more than 75% of the opening balance as on the event date in the period between the 13th and the 15th of March, stayer otherwise. In the row with opening balance, we only report statistics for depositors with accounts below the deposit insurance cover.

	Runners			Stayers			
Fixed deposit a/c	obs	Mean	Std.Dev	Obs	Mean	Std.Dev	Diff (t-stat)
Minority community	249	0.369	0.483	4325	0.289	0.453	2.704***
Above Insurance cover	249	0.080	0.272	4325	0.065	0.247	0.918
Opening balance	229	27177	19900	4042	23633	21432	2.443**
Age of account	249	873	591	4325	1067	559	-5.310***
Loan linkage	249	0.024	0.153	4325	0.083	0.276	-3.365***
No. of Days to maturity	249	261	423	4325	391	374	-5.273***
Transaction a/c							
Minority community	307	0.335	0.472	10384	0.265	0.441	2.71***
Above Insurance cover	307	0.133	0.340	10384	0.007	0.084	21.50***
Opening balance	266	22903	23247	10309	2752	7718	37.87***
Age of account	307	1872	69.33	10384	2298	12.83	-5.63***
No. of transactions	307	49.23	118.2	10384	13.66	46.40	12.30***
Loan linkage	307	0.022	0.149	10384	0.076	0.265	-3.50***

Table 2
Which Depositors Run?

This table presents results of probit models (co-efficients reported are marginal effects). For fixed 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 the 13th and the 15th of March. For savings and current account the dependent variable takes the value of one if the depositor withdraws more than 75% of the opening balance as on the event date in the period between the 13th and the 15th of March, 2001. The analysis is conducted separately for fixed deposit accounts and transaction accounts (savings and current a/c). 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 is a dummy variable that takes the value of 1 for a depositor if his/her balance in the bank as on the event date is above the deposit insurance coverage limit. Opening balance is the balance (amount in ten thousands of Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. Loan linkage is dummy variable that takes the value of 1 for a depositor if the household (associated with the depositor) has/had a loan account with the bank as on event date. Account age is the log of the length of time, for which the account has been open as on the event date. Days to maturity are the log of the number of days left for maturity for the fixed deposit account plus one. No. of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between the 1st of January 2000 and event date. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. Change in deposits is the percentage change in deposits between the 12th of March 2001 and event date if there is an inflow and is zero otherwise. All dummy variables are 0 otherwise. Distance is the physical distance of the depositors residence from the bank and is measured as the traveling cost to the bank in tens of Rs. Neighborhood controls represents the municipal ward where the depositor resides. White heteroscedasticity consistent standard errors are reported in parentheses. In column 2 and 4 the standard errors are clustered at the household level. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively.

	Fixed deposit a/c		Transaction a/c	
	(1)	(2)	(3)	(4)
Minority community	0.007	0.004	0.006**	0.007**
	(0.005)	(0.010)	(0.002)	(0.003)
Above Insurance cover	0.020*	0.024	0.307***	0.331***
	(0.014)	(0.023)	(0.053)	(0.049)
Opening balance	0.003***	0.004***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Loan linkage	-0.032***	-0.038***	-0.014***	-0.013***
	(0.005)	(0.007)	(0.002)	(0.002)
Account age	-0.015***	-0.013***	-0.005***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.001)
Days to Maturity	-0.020***	-0.022***		
	(0.001)	(0.002)		
No. of transactions			0.003***	0.002*
			(0.001)	(0.001)
Change in withdrawals			0.025*	0.031**
			(0.013)	(0.013)
Change in deposits			0.002*	0.002*
			(0.001)	(0.001)
Distance		-0.006		-0.000
		(0.005)		(0.001)
Neighborhood control	no	yes	no	yes
N	4574	3182	10691	8708
Pseudo/Adj R2	0.140	0.163	0.248	0.272

Table 3

How important are loan linkages?

This table presents results of probit models (co-efficients reported are marginal effects). Column 1 and 4 report the results excluding depositors above the insurance coverage limit. For fixed 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 the 13th and the 15th of March. For savings and current account the dependent variable takes the value of one if the depositor withdraws more than 75% of the opening balance as on the event date in the period between the 13th and the 15th of March, 2001. The analysis is conducted separately for fixed deposit accounts and transaction accounts (savings and current a/c). 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 is a dummy variable that takes the value of 1 for a depositor if the depositors' balance as on the event date is above the deposit insurance coverage limit. 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. Opening balance is the deposit balance (amount in ten thousands of Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. Loan linkage is dummy variable that takes the value of 1 for a depositor if the household (associated with the depositor) has/had a loan account with the bank as on event date. Account age is the log of the length of time, for which the account has been open as on the event date. Days to maturity are the log of the number of days left for maturity for the fixed deposit account plus one. No. of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between the 1st of January 2000 and event date. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. Change in deposits is the percentage change in deposits between the 12th of March, 2001 and event date if there is an inflow and is zero otherwise. Distance is the physical distance of the depositors residence from the bank and is measured as the traveling cost to the bank in tens of Rs. Neighborhood controls represents the municipal ward where the depositor resides. White heteroscedasticity consistent standard errors are reported in parentheses. The standard errors are clustered at the household level in column 2 and 4. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively. The symbol &&& indicates perfect prediction of failure (not running).

	Fixed deposit a/c		Transaction a/c	
	(1)	(2)	(3)	(4)
Minority community	0.005	0.005	0.005**	0.007**
	(0.006)	(0.010)	(0.002)	(0.003)
Above Insurance with loan linkage		&&&		&&&
Above Insurance with no loan linkage		0.033		0.349***
		(0.027)		(0.051)
Opening balance	0.003***	0.004**	0.012***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Loan linkage	-0.027***	-0.035***	-0.012***	-0.012***
	(0.006)	(0.008)	(0.002)	(0.002)
Account age	-0.016***	-0.013***	-0.005***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.001)
Days to Maturity	-0.019***	-0.023***		
	(0.001)	(0.002)		
No. of transactions			0.000	0.002*
			(0.001)	(0.001)
Change in withdrawals			0.030***	0.032**
			(0.011)	(0.013)
Change in deposits			0.002*	0.002*
			(0.001)	(0.001)
Distance		-0.007		-0.000
		(0.005)		(0.001)
Neighborhood control	no	yes	no	yes
N	4271	3133	10575	8702
Pseudo/Adj R2	0.137	0.162	0.212	0.273

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?

This table presents results of probit models (co-efficients reported are marginal effects). For fixed 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 the 13th and the 15th of March. For transactions account the dependent variable takes the value of one if the depositor withdraws more than 75% of the opening balance as on the event date in the period between the 13th and the 15th of March, 2001. The analysis is conducted separately for fixed deposit accounts and transaction accounts. Minority community is a dummy variable that takes the value of 1 if the account belongs to a depositor from the minority community. Account age is the log of the length of time, for which the account has been open as on the event date. Above Insurance cover is a dummy variable that takes the value of 1 for a depositor if the depositors' balance as on the event date is above the deposit insurance coverage limit. Opening balance is the deposit balance (amount in ten thousands of Rs.) in an account as on the event date if the depositors balance is below the deposit insurance coverage limit. 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. Days to maturity are the log of the number of days left for maturity for the fixed deposit account plus one. Change in deposits is the percentage change in deposits between the 12th of March, 2001 and event date if there is an inflow and is zero otherwise. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. No. of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between the 1st of January 2000 and event date. Distance is the physical distance of the depositors residence from the bank and is measured as the traveling cost to the bank in tens of Rs. Neighborhood controls represents the municipal ward where the depositor resides. White heteroskedasticity consistent standard errors are reported in parentheses. In column 2 and 4 the standard errors are clustered at the household level. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively.

	Fixed Deposit a/c		Transaction a/c	
	(1)	(2)	(3)	(4)
Minority community	0.007	0.005	0.006**	0.007**
	(0.005)	(0.010)	(0.002)	(0.003)
Account age	-0.015***	-0.012***	-0.005***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.001)
Above Insurance cover	0.019	0.024	0.307***	0.338***
	(0.014)	(0.023)	(0.044)	(0.050)
Opening balance	0.003***	0.004**	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Outstanding loan linkage	-0.034***	-0.040***	-0.013**	-0.013**
	(0.005)	(0.006)	(0.001)	(0.003)
Past loan linkage	-0.028*	-0.033**	-0.013**	-0.012**
	(0.008)	(0.009)	(0.000)	(0.002)
Future loan linkage		-0.008		-0.012
		(0.026)		(0.004)
Days to maturity	-0.020***	-0.022***		
	(0.001)	(0.002)		
Change in deposits			0.002*	0.002*
			(0.001)	(0.001)
Change in withdrawals			0.025*	0.031**
			(0.013)	(0.013)
Number of transactions			0.003***	0.002*
			(0.001)	(0.001)
Distance		-0.007		0.000
		(0.005)		(0.001)
Neighborhood controls	no	yes	no	yes
N	4574	3182	10691	8708
Pseudo R2	0.139	0.164	0.248	0.273

Table 5
Cox proportional hazard model with time varying covariates to analyze networks effects

This table presents coefficients from the estimation of the cox model with time varying covariates. The failure time is the time in minutes until withdrawal by a depositor with starting time of 10:30 am on the 13th of March 2001 (date of failure of the large bank). Each interval of time represents one minute. *Runners in neighborhood (t-1)* is the fraction of other depositors in the neighborhood of the depositor that have run until time t-1 (excluding runs associated with the depositor household). *Minority runners in neighborhood (t-1)* is the fraction of minority community depositors in the neighborhood of the depositor that have run until time t-1 (excluding runs associated with the depositor household). *Majority runners in neighborhood (t-1)* is the fraction of majority community depositors in the neighborhood of the depositor that have run until time t-1 (excluding runs associated with the depositor household). We also construct the social network of the depositor using the introducer name associated with the deposit account. *Runners introducer network (t-1)* is the fraction of other depositors in the social network of the depositor that have run until time t-1 (excluding runs associated with the depositor household). Column 5 report 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*. 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. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively.

	Transaction accounts				
	(1)	(2)	(3)	(4)	(5)
Minority community	0.301**	0.301**	0.005	0.274**	0.298
	(0.122)	(0.124)	(0.199)	(0.122)	(0.239)
Account age	-0.284***	-0.291***	-0.306***	-0.260***	-0.323***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.093)
Above Insurance cover	3.039***	3.062***	3.120***	3.028***	2.913***
	(0.183)	(0.186)	(0.187)	(0.183)	(0.338)
Opening balance	0.475***	0.485***	0.485***	0.475***	0.453***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.037)
loan linkage	-1.328***	-1.276***	-1.390***	-1.346***	-1.408***
	(0.387)	(0.387)	(0.417)	(0.386)	(0.526)
Runners in neighborhood (t-1)		17.438***			
		(5.906)			
Majority runners in neighborhood (t-1)			15.981**		
			(6.586)		
Majority runners Neighbor (t-1) x Minority community			7.800		
			(10.723)		
Minority runners in neighborhood (t-1)			1.562		
			(5.088)		
Min runners Neighbor (t-1) x Minority community			12.707*		
			(6.517)		
Runners introducer network (t-1)				5.157***	4.131***
				(0.622)	(0.795)
Change in deposits	0.012**	0.012**	0.011***	0.012***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)
Change in withdrawals	0.539	0.713	0.341	0.580	2.094***
	(0.649)	(0.650)	(0.723)	(0.639)	(0.676)
Number of transactions	0.206***	0.186***	0.194***	0.202***	0.069
	(0.046)	(0.050)	(0.050)	(0.047)	(0.144)
No of subjects	10691	10383	9927	10691	1509
No of obs	10691	2342915	2239864	2411757	306398
	$\chi2(8)$=609.1	$\chi2(9)$=605.3	$\chi2(12)$=607.4	$\chi2(9)$=646.4	$\chi2(9)$=205.8
Prob>$\chi2$	0.0000	0.0000	0.0000	0.0000	0.0000

Table 6

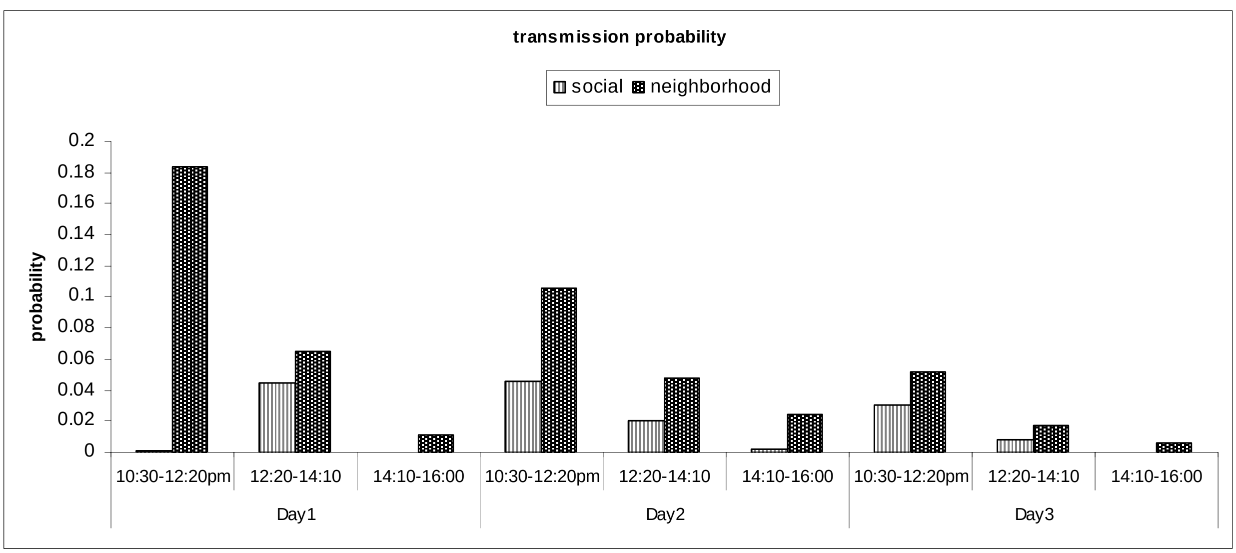
Estimation of transmission probability

Transmission probability is the probability of running (getting infected) as result of single contact with a person who has already run (infected person).

This table presents results of estimation of transmission probability using the model: $\lambda_i(t) = C \prod_i P(t) \exp\{\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_z x_{iz}\}$ where $\prod_i$ is *runners network(t-1) or neighborhood runners (t-1)* . *C* is the number of people in ones social network or neighborhood that one comes in contact and is assumed to be 1 per time interval. *P (t)* is the transmission probability, that is the probability for running due contact with a person who has already run. This model can be thought of as the cox model with the base hazard rate equal to P(t) and log-transformed $\prod$ that is $x_{\prod} = \log(\prod)$, is a covariate having a coefficient equal to one. The transmission probability via social networks is estimated using the model described above with the covariates specified in table 7 column 1 along with *runners network(t-1)* whose coefficient is constrained to be one. Note that in the estimation at any 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*. *Similarly the* transmission probability via neighborhood is estimated with the coefficient of *neighborhood runners (t-1)* constrained to be one. Also the estimation at any point in time, only includes depositors in whose network there is at least one other depositor running (*neighborhood runners (t-1)>0).* 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 P(t) across time.

Transmission Probability	Mean	Std. Dev	Min	Max
via social network	0.030	0.040	0.0004	0.213
via neighborhood	0.052	0.076	0.0007	0.520

The graph 5, below represents the average transmission probability via social networks and neighborhood at different points in time (1 hr 10 minute intervals). The average transmission probability for an interval is obtained by computing the average of estimated transmission probabilities across failure times within an interval.



Do depositors that withdraw during the crisis return?

Graph 6, below presents the deposit balance in transaction account from 1st February 2001 through to 1st May 2001 for depositors that withdrew during the crisis

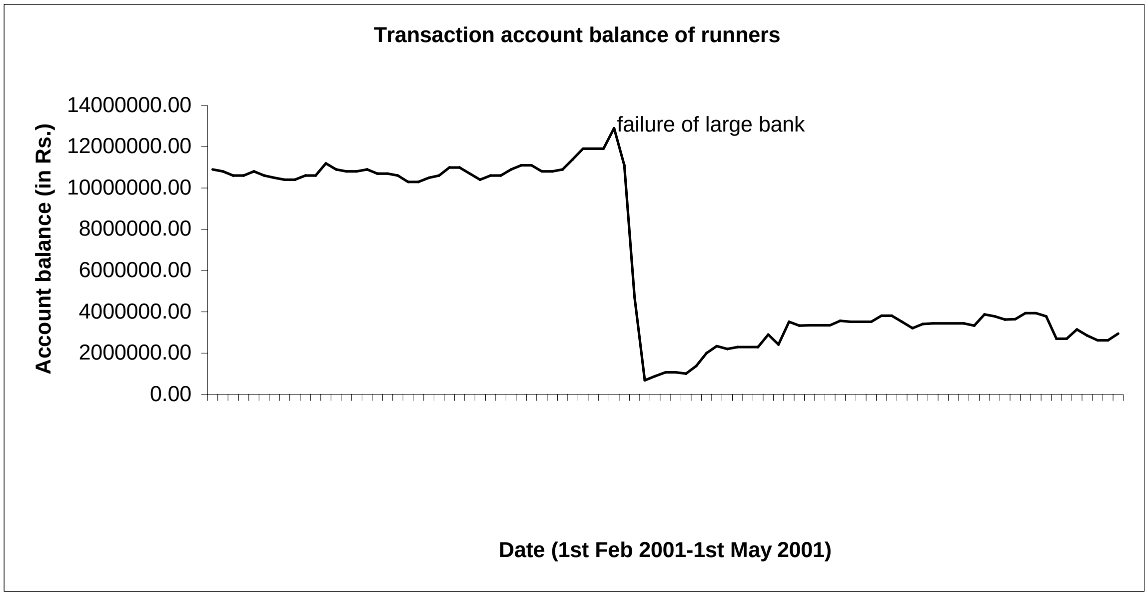


Table 7

This table reports the fraction of depositors who withdrew during the crisis and retuned to the bank after the crisis. After 1 month (May 1st, 2001), After 3 months (July 1st 2001), After 6 months (Oct 1st, 2001) are the dates in the future where the deposit balance is examined.

		Transaction a/c	
Panel A	After 1 month	After 3 months	After 6 months
fraction of depositors with balance higher than pre-crisis level	0.058	0.110	0.065
fraction of depositors with balance 25% higher than pre-crisis level	0.035	0.068	0.048
fraction of depositors with balance 50 % higher than pre-crisis level	0.032	0.068	0.042
fraction of depositors with balance 75 % higher than pre-crisis level	0.022	0.045	0.029
Panel B			
fraction of depositors with balance 75% lower than pre-crisis level	0.824	0.729	0.762
fraction of depositors with balance 50 % lower than pre-crisis level	0.872	0.791	0.843
fraction of depositors with balance 25 % lower than pre-crisis level	0.902	0.843	0.889

Table 8 A

Ex-ante differences in characteristics of depositors with loan linkages as compared to depositors without loan linkages

Table 8A and 8B presents the comparison of means for accounts with loan linkages versus accounts without loan linkages. Table 8C reports the percentage of depositors with loan linkages based on different account balances. The analysis is conducted separately for fixed deposit accounts and transaction accounts (savings and current a/c). Accounts with loan linkages is a dummy variable that takes the value of 1 for a depositor if the household (associated with the depositor) has/had a loan account with the bank as on event date. Account Balance is the opening balance (amount in Rs.) in an account as on the event date. Account age is the log of the length of time, for which the account has been open as on the event date. ***, **, * indicates significantly different than zero at the 1%, 5%, and 10% level, respectively, in a two-sided t-test of the mean of accounts without linkages versus accounts with loan linkages.

	Fixed deposit a/c		Transaction a/c	
	Account Balance	Account age	Account Balance	Account age
Accounts without loan linkages				
Mean	36149	6.703	3280	7.556
Standard Error	(1378)	(0.014)	(93.47)	(0.007)
N	4206	4206	9893	9893
Accounts with Loan Linkages				
Mean	78716	6.653	3226	7.578
Standard Error	(11723)	(0.054)	(303.57)	(0.024)
N	368	368	798	798
Diff between means (t-stats)	-7.331***	0.948	0.158	-0.847

Table 8 B: Excluding depositors above insurance cover

	Fixed deposit a/c		Transaction a/c	
	Account Balance	Account age	Account Balance	Account age
Accounts without loan linkages				
Mean	23705	6.700	3259	7.559
Standard Error	(339)	(0.015)	(92.74)	(0.007)
N	3964	3970	9783	9783
Accounts with Loan Linkages				
Mean	25345	6.640	3246	7.587
Standard Error	(1206)	(0.061)	(305.7)	(0.024)
N	307	307	792	792
Diff between means (t-stats)	-1.295	1.033	0.03	-1.058

Table 8 C: distribution of depositors with loan linkages

	Fixed deposit a/c	Transaction a/c
% of depositors with loan linkages with account balance		
lower than 1000	0.032	0.066
between 1000 and 25000	0.069	0.089
between 25000 and 50000	0.082	0.062
between 50000 and 75000	0.068	0.088
between 75000 and 100000	0.082	0.029
Higher than 100000	0.208	0.054

Table 9

Ex-ante differences in characteristics of depositors with loan linkages as compared to depositors who obtained a loan in the future

This presents the comparison of means for accounts with loan linkages versus accounts with loan linkages in the future. The analysis is conducted separately for fixed deposit accounts and transaction accounts. Accounts with loan linkages 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 on event date. Accounts with 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 Balance is the opening balance (amount in Rs.) in an account as on the event date. Account age is the log of the length of time, for which the account has been open as on the event date. ***, **, * indicates significantly different than zero at the 1%, 5%, and 10% level, respectively, in a two-sided t-test of the mean of accounts with linkages versus accounts with future loan linkages.

	Fixed deposit a/c		Transaction a/c	
	Account Balance	Account age	Account Balance	Account age
Depositors with Loan Linkage				
Mean	78716	6.653	3226	7.578
Standard Error	11723	0.054	303.5	0.024
N	368	368	798	798
Depositors with future loan linkage				
Mean	44030	6.771	4153	7.444
Standard Error	5577	0.104	1218.2	0.114
N	59	59	84	84
Diff between means (t-stats)	1.180	-0.832	-0.912	-1.567

Table 10 (Robustness)

This table presents results of probit models (co-efficient reported are marginal effects). In column 1, the dependent variable takes the value of one if the depositor withdraws more than 50% of the opening balance as on the event date in the period between the 13th and the 15th of March, 2001. Similarly in column 2 the threshold is set at 25%. In column 3, the dependent variable takes the value of one if the depositor withdraws more than 75% of the opening balance with the event window defined as withdrawals between the 9th and the 15th of March, 2001. Column 4 presents the results with the standard event window (withdrawal between 13^{th} and 15^{th} March, using the 75% threshold) where account age is defined as the maximum time that an account has been open in the household of the depositor. 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 is a dummy variable that takes the value of 1 for a depositor if his/her balance in the bank as on the event date is above the deposit insurance coverage limit. Opening balance is the balance (amount in ten thousands of Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. Loan linkage is dummy variable that takes the value of 1 for a depositor if the household (associated with the depositor) has/had a loan account with the bank as on event date. No. of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between the 1st of January 2000 and event date. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. Change in deposits is the percentage change in deposits between the 12th of March 2001 and event date if there is an inflow and is zero otherwise. All dummy variables are 0 otherwise. Neighborhood controls represents the municipal ward where the depositor resides. White heteroscedasticity consistent standard errors are reported in parentheses. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively.

	Transaction a/c			
	50% threshold	25% threshold	Event window 9^{th}-15^{th} March	
Minority community	0.005 (0.003)	0.006 (0.004)	0.006** (0.002)	0.006** (0.003)
Account age	-0.008*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.004*** (0.001)
Above Insurance cover	0.325*** (0.047)	0.360*** (0.049)	0.423*** (0.057)	0.337*** (0.047)
Opening balance	0.018*** (0.001)	0.020*** (0.001)	0.013*** (0.001)	0.012*** (0.001)
loan linkage	-0.015*** (0.003)	-0.012** (0.004)	-0.013*** (0.002)	-0.012*** (0.002)
Change in deposits	0.003* (0.002)	0.003* (0.002)	0.006*** (0.002)	0.002** (0.001)
Change in withdrawals	0.059*** (0.015)	0.074*** (0.016)	-0.030 (0.020)	0.031** (0.012)
Number of transactions	0.008*** (0.001)	0.012*** (0.002)	0.005*** (0.001)	0.002* (0.001)
Neighborhood controls	yes	yes	yes	yes
N	9910	9910	9993	9910
Pseudo R2	0.240	0.242	0.290	0.265

Table 11 (Robustness)

This table presents results of probit models (co-efficient reported are marginal effects). For transaction account the dependent variable takes the value of one if the depositor withdraws more than 75% of the opening balance as on the event date in the period between the 13th and the 15th of March, 2001. 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 is a dummy variable that takes the value of 1 for a depositor if his/her balance in the bank as on the event date is above the deposit insurance coverage limit. Opening balance is the balance (amount in ten thousands of Rs.) in an account as on the event date if the depositor is below the deposit insurance coverage limit. Loan linkage is dummy variable that takes the value of 1 for a depositor if the household (associated with the depositor) has/had a loan account with the bank as on event date. Account age is the log of the length of time, 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 fixed deposit account. No of transactions is the total number of transactions (deposits, withdrawals, and transfers) in hundreds associated with an account between the 1st of January 2000 and event date. Change in withdrawals is the percentage change in deposits between the 12th of March, 2001 and event date if there is an outflow and is zero otherwise. Change in deposits is the percentage change in deposits between the 12th of March 2001 and event date if there is an inflow and is zero otherwise. All dummy variables are 0 otherwise. 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. Neighborhood controls represents the municipal ward where the depositor resides. White heteroscedasticity consistent standard errors are reported in parentheses. The symbols ***, **, * indicate significance levels of 1%, 5%, and 10% respectively. The symbol &&& indicates perfect prediction of failure (not running). The symbol $$$ indicates perfect prediction of success (running).

	Transaction a/c			
Minority community	0.113**	0.104*	0.098*	0.132
	(0.056)	(0.056)	(0.056)	(0.094)
Account age	-0.082**	-0.081**	-0.082**	-0.142***
	(0.035)	(0.036)	(0.036)	(0.055)
Above Insurance cover	0.541***	0.535***	0.475**	0.507**
	(0.162)	(0.163)	(0.191)	(0.194)
Opening balance	0.149***	0.143***	0.142***	0.166***
	(0.047)	(0.047)	(0.045)	(0.049)
loan linkage	&&&	&&&	&&&	&&&
Change in deposits	$$$	$$$	$$$	$$$
Change in withdrawals	0.171	0.208	0.038	-0.292
	(0.396)	(0.393)	(0.420)	(0.619)
Number of transactions	0.316	0.297	0.361	0.347
	(0.262)	(0.257)	(0.318)	(0.289)
Age		0.002	0.022	0.085
		(0.063)	(0.066)	(0.099)
Wealth			3.328	4.887
			(4.635)	(5.587)
Education level dummies	yes	yes	yes	yes
Neighborhood controls	no	no	no	yes
N	261	246	238	195
Pseudo R2	0.364	0.357	0.357	0.388