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Social Network and Bank Run

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Abstract

We examine the effect of social network on bank runs. We construct depositors' money transfer network and neighborhood network. We find that depositors learn information from the network. The strength of social ties, distance, centrality in the network, access to financial instruments and profession all influence the impact of social network on the bank run. Depositors are affected by their nearest neighbors. ATM users are more likely to be influenced by the contagion in the neighborhood.

Keywords: bank run, social network, peer effect, word-of-mouth effect

JEL: D12, G21, O16, Z13

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1. Introduction

Banking crises have profound implications for financial stability, economic growth, and public confidence in financial institutions. The 2007-2009 financial crisis and the 2023 collapse of Silicon Valley Bank are stark reminders that bank runs are not a distant concern. While bank runs are often attributed to peer effects, the specific factors that drive these effects and the types of depositors most susceptible to them remain unclear. Understanding the role of social networks in bank runs is essential not only for grasping the dynamics of these events but also for designing regulatory measures to mitigate their spread.

In this paper, we examine the impact of social networks on bank runs using data from a commercial bank in Nigeria. The dataset contains detailed depositor information and transaction records, enabling us to construct two types of social networks: (1) a money transfer network, where depositor relationships are identified based on intra-bank transfers, and (2) a neighborhood network, where depositors' addresses are used to identify neighbors within a one-kilometer radius. We investigate whether depositors learn from their networks and explore the factors that amplify the influence of these networks.

The bank in our study was a systemic bank in Nigeria. Nigeria faced a banking crisis in 2009 triggered by the global financial crisis of 2007-2009. The bank run we analyze occurred during this crisis. The sequence of events is as follows: the bank incurred

significant losses due to bad loans, leading the central bank to conduct a stress test and hold a press conference that identified five banks as problematic, including the one we study. Despite the central bank's promise to bail out these banks and prevent their failure, a substantial run by depositors occurred immediately after the press conference.

First, we identify peer effects in the money transfer network during the bank run. To address the endogeneity of network formation, we employ an instrumental variable approach. Given that depositors' gender and balance significantly influence liquidation decisions in Africa, we use peers' gender and deposits as instrumental variables. These factors influence a peer's probability of liquidation, satisfying the relevance condition, while their effect on a depositor's liquidation decision occurs solely through peer influence, satisfying the exogeneity condition.

Second, we explore heterogeneity in peer effects. We find that peer effects are stronger among depositors with more frequent transactions, among those who live closer together. Peer effects are also amplified when the peer is centrally positioned within the network, has access to financial tools such as checks, POS, or internet banking, or is a bank employee.

Third, we examine the causal effect of word-of-mouth in a bank run. We employ a nearest-neighbor research design to estimate the impact of the nearest runners while controlling for withdrawal activities in slightly larger surrounding areas. This approach

has been used extensively in the recent empirical literature on neighborhood effects (Bayer, Ross, and Topa 2008); Linden and Rockoff 2008; Campbell, Giglio, and Pathak 2011; Currie, Greenstone, and Moretti 2011; Anenberg and Kung 2014; Currie et al. 2015; Bayer, Mangum, and Roberts 2021). Although Iyer and Puri (2012) show that depositors are more likely to run if their neighbors run on the bank, they don't distinguish between depositors run due to the common shocks or because they learn from their neighbors' actions. We identify the number of runners within 1 kilometer radius of the depositor. Then we examine whether depositors are more likely to run if their nearest neighbors run while controlling for the number of runners within 300 meters to 1000 meters. We find that depositors learn from their nearest neighbors. In addition, we examine the heterogeneity in the peer effect in the neighborhood. We find that ATM users more likely to run if their neighbors run, compared to non-ATM users. Because ATM user have to visit ATMs, they have higher chances to observe others' withdrawals. Although Internet banking users are more likely to run, they are no different from those who don't use Internet Banking in terms of the impact of peer effect in the neighborhood.

Our paper contributes to the empirical literature on bank runs. Our results provide evidence that social network provides information about bank runs. Depositors run on the bank because they know the bad fundamentals about the bank. Depositors who have a higher chance to receive the information are more likely to run. This is consistent with information-based models of runs.(See Chari and Jagannathan 1988; Jacklin and

Bhattacharya 1988; Chen 1999; Calomiris and Gorton 1991; and Diamond and Rajan 2001). The peer effect is consistent with coordination problems in bank runs. (see Bryant 1980; Diamond and Dybvig ,1983; Rochet and Vives, 2004) and Goldstein and Pauzner 2005)). Iyer, Puri, and Ryan (2016a) also find that depositors respond to bank fundamentals. This paper provides evidence that depositors can learn the bank fundamentals from their social network in the bank.

A small set of papers study the individual response to the bank run (Davenport and McDill, 2006; Iyer and Puri, 2012; Brown, Trautmann, and Vlahu, 2017; Brown, Guin, and Morkoetter, 2020; Iyer, Puri, and Ryan, 2016b; Martin, Puri, and Ufier, 2018; Artavanis et al. 2019). We provide rich data about individuals' money transfer network and neighborhood social network. In comparison to other papers (Iyer and Puri, 2012; Iyer, Puri, and Ryan, 2016b), our paper is the first to provides the analysis of depositors' money transfer network. We find that depositors learn from their money transfer network.

This paper contributes to the literature on the effect of social network on bank runs. Kelly and Gráda (2000) used depositor data from an immigrant savings bank in New York during the 1850s to verify that immigrants from the same Irish region are more likely to run together. But there are only around a hundred observations. It is uncertain whether clustering still exists in a large scale. They can't distinguish whether depositors run because they learn from their social network or simply because they live close to

each other. Iyer and Puri (2012) collected account-level data from a bank in India and identify depositors' introducers when they open the accounts. They find that social network matters in a bank run. Compared to their research, we construct new social networks, and further study what factors affect the effect of social networks on bank runs. In the neighborhood network, we employ a nearest-neighbor research design to identify the causal effect of nearest runners on depositors' probability of running. We find that ATM users are more likely to be influenced by their neighbors.

Our paper provides basis for the regulation of banks. We find that most depositors lack supervision of banks, especially those with small deposits and those who can't use financial instruments. Only a small number of depositors learn some information from social network. It is necessary for the central bank to supervise banks.

Our results have implications for bank managers to mitigate bank fragility. We find that depositors in the center of network are more likely to run and have larger impacts on others. This suggests that regulators can focus on some depositors who are prone to run. Bailouts also mean telling depositors the bank is in trouble, which may spark a run. Enhancing financial literacy education and improving information disclosure can market discipline by depositors.

The rest of paper is organized as follows. Section 2 describes the event and the data. Section 3 presents the summary statistics of money transfer network. Section 4 presents

the empirical results on the peer effect in the money transfer network. Section 5 displays the impact of neighborhood network. Section 6 concludes.

2. Event Description and Data.

2.1 Event Description

In 2009, Nigeria experienced a systemic banking crisis. The bank under study was a large commercial bank with over 130 branches nationwide. A significant portion of its loan portfolio was tied to the oil and gas industry. As the financial crisis unfolded, crude oil prices plummeted, severely impacting Nigeria's oil and gas sector and leading to a sharp rise in the bank's non-performing loans. During its period of rapid expansion, the bank's management team illegally used customer deposits to purchase shares in their own institution. In 2008, its stock price collapsed by more than 80% in 2008. It reported a loss of ₦336 billion in 2008 and an additional ₦238 billion from March to December 2009. But depositors are unaware of this information.

The Central Bank of Nigeria (CBN), the country's primary banking regulator, oversees financial institutions and provides liquidity support, while the Nigeria Deposit Insurance Corporation offers deposit protection. In 2009, the deposit insurance coverage was ₦200,000 (approximately $1,350) per depositor. On August 14, 2009, following a Special Examination, the governor of the Central Bank announced that five banks, including the one under study, had dangerously high levels of non-performing

loans and significant exposure to high-risk sectors such as capital markets and oil and gas. These banks were undercapitalized and unable to meet their obligations, yet were considered systemically important, accounting for 39.93% of total loans, 29.99% of deposits, and 31.47% of total assets as of May 31, 2009.

To stabilize the financial system, the Central Bank decided to inject ₦400 billion into these five banks and assured the public that no bank would be allowed to fail. Additionally, the management teams were removed. The bank in focus was among these five and it wasn't until after the press conference that the media began reporting on its troubles. Shortly afterward, the bank's president came under investigation by the Financial Crimes Commission for alleged misconduct.

This announcement was a major shock to depositors. Following the public disclosure, the total balance of savings accounts at the bank sharply declined over the next week. Figure 1 illustrates this trend. Before the announcement, savings account balances had remained stable, although significant and continuous outflows from current accounts had been observed since March 2009. We characterize this event as a high-solvency-risk shock since the bank was insolvent even absent depositor runs.

[Figure 1 inserted here]

2.2 Data

We obtained administrative data from the bank, including balances, transactions, and

anonymized depositor information. The dataset covers transaction records from 2007 to March 2012, depositor balances as of March 5, 2012, and demographic details of account holders. To compute depositors' balances as of August 13, 2009 (prior to the press conference), we calculate the net transactions for each account from August 14, 2008, to March 5, 2012. Accounts opened after August 14, 2008, are excluded since they were not active during the bank run. Using each account's balance as of March 5, 2012, we estimate its outstanding balance before the bank run. We then aggregate balances of accounts linked to the same customer ID to determine each depositor's total balance as of August 13, 2009. If a depositor's balance exceeds ₦200,000, a portion of their funds was uninsured by deposit insurance. We create a dummy variable, "uninsured," which equals 1 if the depositor was not fully covered by deposit insurance.

The dataset also includes individual information such as age, gender, profession, account opening date, account opening branch, and address. From the transaction records, we identify whether account holders had access to various financial instruments, including ATMs, cheques, internet banking services, and POS services. We classify depositors as ATM users if they used an ATM at least once between January and June, 2009; otherwise, they are categorized as non-ATM users. Similarly, we identify cheque users, internet banking users, and POS users. Depositors with staff salary or staff savings accounts are classified as bank staff.

3. Money Transfer Network and Summary Statistics

We construct a money transfer network among depositors by matching intra-bank transactions based on amount, time, and transaction type. The dataset includes 35 million transactions from January 1, 2008, to June 30, 2009. These transactions can be categorized by channel: counter transactions (Miscellaneous Customer Credit, Miscellaneous Customer Debit, Miscellaneous Customer Debit NoCOT), ATM transactions (ATM Funds Xfer Credit Remote On Us, ATM Funds Xfer Debit Remote On Us), and online banking transactions (Internet Banking TRF CR, Internet Banking TRF DR). Table 1 provides descriptive statistics for these different transfer types.

[Insert Table 1 here]

The Customer Debit category contains 21 million transactions, most of which are fees, with an average transaction amount of ₦458,324 and a median of ₦50. The Customer Credit category includes 5.6 million transactions, with a median amount of ₦15,962. ATM and online banking transfers primarily involve intra-bank transactions, with online banking transfers generally involving larger amounts than ATM transfers.

[Insert Table 2 here]

Since we only observe intra-bank transactions, we cannot determine whether depositors are connected through other channels. The dataset contains 149,562 intra-bank transfers

among 173,724 depositors, from which we identify depositor networks. Table 2 presents descriptive statistics on these transactions. The network is characterized by a small number of highly active accounts with many transfer recipients and frequent transactions. On average, each depositor interacts with 2.96 other depositors through intra-bank transfers. The median individual transfer amount between January 2008 and June 2009 is ₦5,000, and over half of depositors made only one transfer during this period. The bilateral transfer amount, which measures total transactions between two depositors during this period, also has a median of ₦5,000. The network is sparse, with large and frequent transactions concentrated in a small number of accounts.

To visualize the money transfer network, we use the Kamada-Kawai algorithm in Pajek software. In the visualization, nodes represent depositors, and edges represent transfer relationships. The transfer network consists of multiple independent sub-networks, with the largest sub-network featuring a central-peripheral structure, where a core node is connected to 23,974 other nodes. Figure 2(a) illustrates an example of a star-shaped network. Transfer activities within this network include business transactions and personal transfers between relatives and friends. Unlike social media networks, where mutual connections are common, the money transfer network is more hierarchical, with central nodes exerting significant influence. Other structures, such as ring-shaped networks (Figure 2b), are also present.

[Insert Figures 2 here]

Table 3 provides descriptive statistics for network nodes. The balance variable represents each depositor's total account balance before the August 14, 2009 press conference, with a median of ₦3,226. The average age of depositors in the transfer network is 33 years, and women make up 33% of depositors. The average account duration is 859 days, and 7% of depositors are bank staff. Additionally, 18% have used online banking, 13% have used POS machines, and 32% have used cheques. Depositors with access to more financial tools generally demonstrate higher financial literacy, and depositors in the transfer network exhibit greater financial sophistication compared to the bank's overall customer base.

[Insert Table 3 here]

We classify the week following the press conference as the bank run period. Following the definition by Iyer and Puri (2012), a depositor is considered a "runner" if they withdrew more than 75% of their deposits between August 14 and 20, 2009. Otherwise, they are classified as a "stayer." The withdrawal time is defined as the moment when a depositor's balance first falls below 25% of its pre-run level.

[Insert Table 4 here]

Table 4 presents the percentage of runners across different depositor groups within the network. The overall runner ratio in the transfer network is 5.71%, significantly higher

than the 3% observed among all bank depositors. Runners are more likely to have higher balances; for instance, the runner ratio for depositors with balances below ₦3,000 is just 1.13%, whereas it exceeds 10% for those with balances above ₦10,000.

Age also plays a role, with middle-aged depositors (35-55 years old) exhibiting the highest likelihood of withdrawing funds. Notably, bank staff have an exceptionally high runner ratio of 17.92%, suggesting that individuals with greater knowledge of the bank's financial situation were more likely to withdraw.

Depositors who use financial tools such as cheques, online banking, and POS machines also demonstrate a higher propensity to withdraw. For instance, the runner ratio for cheque users is 9.22%, significantly higher than that of non-cheque users. Compared to the broader depositor base, those within the money transfer network are more closely connected to the bank and likely more familiar with its operations. This familiarity increases their exposure to negative information circulating within the network, making them more responsive to financial instability and more prone to withdrawing funds during a crisis.

In network analysis, centrality measures a node's importance within a network. We compute each depositor's degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality to assess their influence in the transfer network. Panel B of Table 4 shows the percentage of runners based on centrality levels. Across all centrality

measures, depositors with higher centrality are more likely to withdraw. For example, the withdrawal rate for depositors with a degree of 1 is 5.18%, whereas for those with degrees between 11 and 40, the rate rises to 12.24%.

Central depositors—those at the core of the transfer network—exhibit a stronger tendency to withdraw during a bank run. Compared to peripheral depositors, they receive negative information about the bank more rapidly, increasing their likelihood of initiating a withdrawal. However, because these depositors also rely more heavily on banking services, the cost of leaving the bank is relatively higher for them.

[Insert Table 5 here]

To assess the impact of centrality on withdrawal behavior, we estimate a logit model. Table 5 presents the marginal effects of our analysis, with Panel A showing results without control variables and Panel B incorporating them. Standard errors are clustered at the city level. A 1% increase in degree centrality raises the probability of liquidation by 0.01%. An increase of one standard deviation (0.056) in closeness centrality raises the probability by 0.59%. Panel B incorporates control variables such as age, gender, deposit balance, and account opening date. The results confirm that a 1% increase in degree centrality still corresponds to a 0.01% increase in withdrawal probability, even after accounting for these factors.

4. Peer Effect in the Money Transfer Network

4.1 Identification Strategy

Depositors are more likely to run if their peers run (Iyer and Puri 2012). But there is endogeneity problem in the peer effect. On one hand, depositors may run simultaneously upon learning the news, rather than being influenced by their peers. On the other hand, peer effect may exist because they have common characteristics. To address the endogeneity problem, we first apply instrumental variables to estimate the peer effect. We use peers' gender and deposits as instrument variables. These variables satisfy the relevant assumption: depositors' gender and balances are associated with their probability of liquidation in a bank run. Depositors with higher balances have higher likelihood of liquidation. Female depositors in Nigeria are less likely to withdraw in a bank run. Besides, these variables also satisfy exogenous assumption: peers' characteristics cannot influence egos' probability of liquidation except through peer effects.

Next, we incorporate the timing of runs into the analysis. We estimate the increase of the likelihood of liquidation after peers have run. Identifying the timing of withdrawals helps us identify the direction of the peer effect. We construct an unbalanced panel data: if depositor *i* in branch *b* ran on day *t*, run_{ibt} is 1, and the observation does not appear in the panel data for subsequent dates, otherwise, run_{ibt} is 0. If depositor *i*'s peer *j* ran on day *t* or before day *t*, $peer\ run_{ij1:t}$ is 1, otherwise, $peer\ run_{ij1:t}$ is 0. We conduct a multidimensional fixed-effects model to estimate the peer effect in the bank run:

$$run_{ibt} = \beta_1 peer\ run_{ij1:t} + \sigma_{ij} + u_b + \epsilon_{ijt}. \quad (1)$$

β_1 estimates depositor *i's* increase in the likelihood of running due to the withdrawal of his peer j. To explore the factors that determine the size of the peer effect, we run the following regression:

$$run_{ibt} = \beta_1 peer\ run_{ij1:t} + \beta_2 peer\ run_{ij1:t} \times X_{ij} + \sigma_{ij} + u_b + \epsilon_{ijt}. \quad (2)$$

where X_{ij} include $high\ amount_{ij}$, $high\ frequency_{ij}$, $\log of\ distance_{ij}$, $\log of\ degree_{ij}$, $peer\ cheque_{ij}$, $peer\ pos_{ij}$, $and\ peer\ internet_{ij}$. We use *high amount* and *high frequency to* measure transaction relationship. $high\ amount_{ij}$ is a dummy variable that equals 1 if the total amount of transfers between depositor *i* and *j* exceed ₦5,000 from January 2008 to June 2009, and 0 otherwise. $high\ frequency_{ij}$ is a dummy variable that equals 1 if the total frequency of transfers between depositor *i* and *j* exceed 1 from January 2008 to June 2009, and 0 otherwise. $\log of\ distance_{ij}$ is the log of distance between depositor *i* and *j*. $\log of\ degree_{ij}$ is the degree centrality of peer *j*. $peer\ cheque_{ij}$ is a dummy variable that equals 1 if peer *j* is a cheque user. $peer\ pos_{ij}$ is a dummy variable that equals 1 if peer *j* is a pos user. $peer\ internet_{ij}$ is a dummy variable that equals 1 if peer *j* uses internet banking service. β_2 measures the heterogeneity effect of peer effect in a bank run.

4.2 Empirical Results

Table 6 presents two-stage least squares estimates of peer effect in a bank run. We report the coefficients of the first and second stage regression. The result shows that the probability of liquidation increases by 17% when the peer run. Column 2 add branch

fixed effect and the peer effect is still robust.

[insert table 6 here]

Table 7 presents the estimates of regression (1). After controlling for regional and individual fixed effects, we find that a peer's withdrawal significantly increases the probability of the ego (the focal depositor) running by 1.7% in the following days. Given that the average daily probability of running is 1.2%, the peer effect within the transfer network raises the ego's likelihood of withdrawal by 1.4 times. We further divide depositors into four groups based on their degree centrality. Columns 2 to 5 present the estimates of peer effects for egos with varying levels of degree centrality. From column 2 to column 4, we observe that as the ego's degree centrality increases, the peer effect becomes more pronounced. However, when the ego's degree centrality exceeds 60, the peer effect drops to 0.89%, about half of the average level. A plausible explanation for this decrease is that depositors with very high centrality rely heavily on their central network accounts for transactions, making the cost of leaving the bank high and thus reducing their susceptibility to peer influence.

[insert table 7 here]

4.2.1 Strength of Social Ties

The strength of social ties significantly influences the magnitude of peer effects. Stronger social ties between depositors and their peers lead to greater information exchange, thereby amplifying the peer effect. To measure the strength of these ties, we use the amount and frequency of transfers between egos and their peers as proxies.

Higher amounts and frequencies of transfers indicate closer connections. Table 8 presents the regression estimates, with coefficients multiplied by 100. When the transfer amount between depositors and their transaction counterparts is high, the depositor's likelihood of withdrawal increases by 2.1% due to the counterpart's withdrawal. This effect is nearly twice as strong as the effect observed among counterparts with lower transfer amounts. In Column 2, the result remains robust after adding branch fixed effects. The third column compares the peer effects among depositors with different transfer frequencies. Among depositors with high transfer frequencies, the peer effect is 18.6% stronger than among those with lower transfer frequencies.

[Insert Table 8 here]

4.2.2 Distance

Table 9 shows the impact of distance on peer effects, with coefficients multiplied by 100. In column 1, a 1% increase in the distance between peers reduces the peer effect by 0.16%. Distance constrains the spread of information, which is particularly important in areas where the internet is not yet widely available. We further examine how distance affects peer effects among depositors with different transfer amounts. In Column 2, which includes only depositors with transfer amounts exceeding 5,000 Naira, a 1% increase in distance results in a 0.108% decrease in the ego's withdrawal likelihood. In Column 3, which includes only depositors with transfer amounts below 5,000 Naira, the same increase in distance leads to a 0.187% decrease. This suggests that distance has a greater impact on depositors with lower transfer amounts. For

depositors with weaker social ties, geographical distance influences their interactions, whereas those with stronger ties can overcome geographical constraints. This pattern holds even when analyzing depositors with different transfer frequencies. The heterogeneity in peer effects concerning distance further confirms that depositors are indeed influenced by their peers in a bank run.

[Insert Table 9 here]

4.2.3 Degree Centrality

Table 10 shows the differences in peer effects when peers' degree centrality varies, with coefficients multiplied by 100. Peers with higher degree centrality have a significantly larger peer effect compared to those with lower degrees, which suggests that depositors with higher degrees have greater influence on others. In a bank run, these depositors are the source of panic. Deposit insurance protects depositors from financial losses. Depositors with balances exceeding the insured limit are more eager to ensure the bank's financial stability. As a result, they pay closer attention to their peers' behavior, especially when those peers are central within the network. Column 2 includes only depositors whose balances fall within the insured limit, while Column 3 includes those whose balances exceed the coverage limit. The impact of network centrality is significantly stronger among uninsured depositors.

[Insert Table 10 here]

4.2.4 Use of Financial Tools

In Nigeria, a significant portion of the population lacks bank accounts, let alone familiarity with financial tools such as checks, online banking, and POS machines. Depositors who use these tools tend to have higher financial literacy and better socioeconomic status. They also have broader access to banking services and are more attuned to banking information, making them more likely to run when a bank is in trouble. Their actions are often perceived as more informed and, as a result, are more likely to be imitated by others.

Table 11 presents the heterogeneous effect among peers who have different access to financial tools. The variable "peer internet" is a dummy variable that equals 1 if the peer uses online banking and 0 otherwise. "Peer pos" indicates whether the peer uses a POS machine for transactions, while "peer cheque" represents check usage. Column 1 estimates the effect of online banking usage on peer effects. When a peer uses online banking, the ego's probability of running increases by 2.04% due to the peer's withdrawal, compared to 1.18% when the peer does not use online banking. Column 2 shows that egos are more influenced by peers with access to POS machines. Column 3 estimates the effect of check usage, finding that depositors with access to checks also exhibit greater peer effects. Among these, the effect of online banking is the strongest, likely because online banking allows for quicker and more effective communication, thereby amplifying the peer effect.

[Insert Table 11 here]

4.2.5 Bank Staff

Unlike regular depositors, bank staff possess higher financial literacy and are more aware of the bank's condition. Given the bank's dire financial situation, the proportion of bank staff who participate in a run is notably higher. We test whether the ego is more likely to run if a peer is a bank staff member. The variable "peer staff" is a dummy that equals 1 if the peer is bank staff and 0 otherwise. Table 12 estimates the difference in peer effects between peers who are bank staff and those who are not. Column 1 includes all depositors in the transfer network and shows that if the peer is a bank staff member, their withdrawal increases the ego's probability of running by 1.9%. If the peer is not a bank staff member, the increase is only 1.3%. This effect is particularly pronounced among depositors who are not fully covered by deposit insurance, as they are more concerned about the bank's condition and pay closer attention to the behavior of bank staff. Column 2 examines depositors fully covered by deposit insurance, while Column 3 focuses on those not covered. The results indicate that the peer effect of bank staff is more substantial among uninsured depositors.

[Insert Table 12 here]

5. Social Network in Neighborhood

5.1 Measuring social network in the neighborhood

The bank account information includes both the branch address where the account was opened and the depositor's personal address, which is accurate down to the street level.

Using the Google Maps API and the Here Maps API, we geocoded 2.98 million individual addresses. Figure 5.1 shows the geographic distribution of these bank depositors, who are spread across 158 cities nationwide.

[Figure 3 inserted here]

Based on the coordinates, we identified each depositor's neighbors within a 1 km radius. Table 13 provides summary statistics on the number of neighbors within this distance. During the geocoding process, depositors in close proximity may have been assigned the same coordinates, which could lead to an overestimation of the number of nearby accounts. The maximum number of neighbors within 0-300 m is 34,273, with a mean of 9,718 and a median of 1,168. For the 300-700 m range, the maximum number of neighbors is 4,338, with a mean of 1,721 and a median of 574. Within the 700-1,000 m range, the maximum number of neighbors is 4,206, with a mean of 1,723 and a median of 797. Table 13 also describes the distribution of runners within 1 km of each depositor. The definition of runners remains consistent with earlier sections. Approximately half of the depositors have at least 34 runners within 300 meters. The average number of runners within 300-700 meters is 53, while the median is 18. For the 700-1,000 meter range, the average number of runners is 51, with a median of 20. Notably, the number of runners varies significantly across different depositors. Among runners, the proportion of runners is higher in closer proximity. Conversely, for depositors who did not participate in the run, the withdrawal tendency does not increase with proximity.

[Table 13 inserted here]

Table 14 shows the average proportion of runners within a specified range around a runner compared to that around a stayer, with standard errors in parentheses. Within 300 meters of a runner, the probability of a depositor running on the bank is 4.04%, while within 300 meters of a stayer, it is 2.97%. In the 300-700 meter and 700-1,000 meter ranges, the probability of running in the runner's neighborhood is not significantly different from that in a stayer's neighborhood. The proportion of runners decreases with distance from a runner: it is 4% within 300 meters but drops to 2.96% in the 700-1,000 meter range. Within 0-300 meters, the proportion of runners around a runner is 1.07% higher than that around a stayer. This difference diminishes rapidly at greater distances, illustrating the clustering effect of a bank run within neighborhoods.

[Table 14 inserted here]

Areas with a higher concentration of bank accounts are typically economically developed and densely populated urban centers. Are people more likely to run if they have more neighbors in the same bank? We conducted the following regression to estimate the effect of the number of nearby depositors on a depositor's probability of running on the bank:

$$run_i = \beta_1 * \log(1km\ depositor\ number) + \beta_2 X + u_i. \quad (3)$$

Here, run_i is a binary variable that equals 1 if depositor *i* is a runner, and 0 otherwise. Control variables include the depositor's age, age squared, gender, deposit amount, and account opening time. If depositors in areas with a higher concentration of bank

accounts are more likely to withdraw, the coefficient β_1 will be significantly positive. Table 15 presents the results. Columns 1 and 2 show the OLS estimation, while Columns 3 and 4 use logistic regression, with marginal effects presented at the mean level. Control variables are included in Columns 2 and 4. The results indicate no significant correlation between the number of nearby accounts and the depositor's likelihood of withdrawal. One possible explanation is that bank account holdings are private, so depositors may not know how many other depositors from the same bank are nearby and thus are not influenced solely by the concentration of depositors. Additionally, depositors need information to decide whether to run or not. A higher number of depositors nearby does not necessarily mean more information is available. Therefore, the number of bank accounts in a depositor's vicinity appears unrelated to their own withdrawal behavior.

[table 15 inserted here]

5.2 The Causal Effect of Social Network on Bank Run

A key concern is that depositors in the same neighborhood may withdraw funds due to exposure to a common information shock. To mitigate this issue, we employ a nearest-neighbor research design. This approach allows us to estimate the impact of hyper-local withdrawal behavior on a depositor's likelihood to withdraw, while controlling for the withdrawal behavior in a slightly larger surrounding area. This research design has been widely adopted in recent empirical studies on neighborhood effects to identify various spatial spillovers. We run the following regression

$$run_i = \beta_1 runner\ No.(0-300m)_i + \beta_2 runner\ No.(300m-700m)_i +$$

$\beta_3 runner\ No.(700m-1000m)_i + \beta X_i + \epsilon_i.$ (4)

Here, $runner\ No.(0-300m)_i$ represents the number of runners within 300 meters of depositor i. $runner\ No.(300m-700m)_i$ represents the number of runners within 300 to 700 meters of depositor i. $runner\ No.(700m-1000m)_i$ represents the number of runners within 700 to 1000 meters of the depositor. We control for the number of runners in more distant areas (300m-700m and 700m-1000m) to test whether depositors learn from their immediate neighbors. After including control variables, approximately 2 million depositors are incorporated in the regression. The control variables include the depositor's age, gender, deposit amount, and account opening time. The coefficient β_1 measures the impact of nearest runners on the depositor while controlling for liquidation behaviors in the larger surrounding area. Table 16 presents the result.

[table 16 inserted here]

The model is a linear probability model. After incorporating control variables, the regression analysis includes approximately 2 million depositors. The control variables include the depositor's age, gender, deposit amount, and account opening time. A one standard deviation increase (693) in the number of runners within a 300-meter range raises the depositor's probability of running by 0.2%. Given the depositor's average probability of running, which is 3%, this results in a 6.7% relative increase in their likelihood of running, demonstrating economic significance. Columns 2 and 3 add the number of runners at greater distances to control for localized information shocks. The

influence of nearby runners remains significant, while the impact of runners in more distant areas is not.

5.3 Heterogeneity in the Peer Effect

Which depositors are more likely to be influenced by peer effects? We compare ATM users with non-ATM users. Since ATM users need to physically visit the ATM, they are more likely to observe others withdrawing funds. As a result, ATM users are more susceptible to the panic spreading in their neighborhood compared to non-ATM users. To test this, we run a regression to examine the difference in peer effects between ATM users and non-ATM users.

$$run_i = \beta_1 runner\ No.(0-300m)_i + \beta_2 ATM_i + \beta_3 runner\ No.(0-300m)_i * ATM_i + \beta_4 runner\ No.(300m-700m)_i + \beta_5 runner\ No.(300m-700m)_i * ATM_i + \beta_6 runner\ No.(700m-1000m)_i + \beta_7 runner\ No.(700m-1000m)_i * ATM_i + \beta X + \epsilon_i. \quad (5)$$

Here, ATM_i is a dummy variable equal to 1 if the depositor is an ATM user. The coefficient β_3 measures the difference in the impact of nearby runners on the likelihood of withdrawal between ATM users and non-ATM users. Table 17 presents the results. The data show that ATM users are more likely to withdraw funds during a bank run, and they are significantly more influenced by nearby withdrawers compared to non-ATM users. Column 1 indicates that an increase of one standard deviation (693) in the number of runners within 300 meters raises the withdrawal probability for ATM users by 0.57% relative to non-ATM users. According to Table 16, this same increase

raises the withdrawal probability for all depositors by 0.2%. This highlights a significant difference in peer effects between ATM users and non-ATM users. Column 2 accounts for the number of runners within 300-700 meters and 700-1000 meters, revealing no significant difference in the influence of distant runners on the withdrawal tendencies of ATM versus non-ATM users. Column 3 includes depositor characteristics as control variables, and the results remain consistent. The findings suggest that ATM users, who are more likely to observe withdrawal actions in their neighborhood, are also more likely to be influenced by nearby runners.

[table 17 inserted here]

In contrast, internet banking users do not need to visit bank branches and are therefore less likely to observe other depositors withdrawing funds in their neighborhood. We test the difference in peer effects between internet banking users and non-internet banking users. Table 18 presents the results. Although internet banking users have a higher overall likelihood of withdrawing funds, the word-of-mouth effect does not significantly differ between internet banking users and non-internet banking users. Column 1 shows that an increase in the number of runners within 300 meters does not have a significantly different impact on the withdrawal tendencies of internet banking users versus non-internet banking users. Column 2 includes the number of runners within 300-700 meters and 700-1000 meters, with the results remaining unchanged. The influence of distant runners on the probability of a run is not significantly different between online and non-online banking users. Column 3, which includes individual

control variables, also shows consistent results. Since online banking users do not increase their visits to bank branches, they do not have a significant advantage in observing neighborhood withdrawals. Consequently, there is no significant difference in the word-of-mouth effect between internet banking users and non-internet banking users.

[table 18 inserted here]

This heterogeneity in the word-of-mouth effect further supports its existence. If depositors were withdrawing funds solely due to exposure to the same shock, we would not observe why ATM users are more influenced by their neighbors while internet banking users are not.

6. Conclusion

Our study provides empirical evidence that social networks play a critical role in bank runs. By analyzing transaction records and depositor data from a systemic bank in Nigeria during the 2009 banking crisis, we demonstrate that depositors are significantly influenced by their peers when making withdrawal decisions. Both money transfer networks and neighborhood networks serve as channels for information diffusion, amplifying the likelihood of coordinated withdrawals.

We find that peer effects are stronger among depositors with frequent transactions,

those who live closer to each other, and those with access to financial instruments such as checks, POS systems, and internet banking. Additionally, depositors at the center of social networks exert a disproportionate influence on others. The nearest-neighbor research design further confirms that word-of-mouth effects drive withdrawal behavior, particularly among ATM users who are more likely to observe peer actions.

Our findings contribute to the broader literature on bank runs by highlighting the mechanisms through which social networks facilitate depositor coordination. While prior research has identified the presence of peer effects, our study advances this understanding by identifying key factors that amplify these effects.

From a policy perspective, our results emphasize the need for central banks and regulators to consider the role of social networks in financial stability. Enhancing financial literacy, improving information disclosure, and closely monitoring influential depositors could mitigate the risks of contagion during periods of financial distress. Moreover, our findings suggest that while bailouts may provide temporary relief, they also signal distress to depositors, potentially accelerating runs.

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Table 1. Descriptive Statistics of Transfer Amounts

variables	observations	mean	10^{th} percentile	median	90^{th} percentile
Credit	5,617,435	2,235,367	500	15,962	132,061
Debit	2.12e+07	458,324	10	50	1000
Debit(NoCOT)	2,922,187	1,412,307	10	40	8433
ATM Xfer Credit	2,636,558	34,045	5	200	18,900
ATM Xfer Debit	2,636,495	34,047	5	200	18,900
Internet Banking Credit	386,358	36,255	2,000	12,000	100,000
Internet Banking Debit	386,358	36,269	2,000	12,000	100,000

Note：period is from 2008.01.01 to 2009.06.30

Table 2. Summary Statistics of Transactions within the Bank

Variables	observations	mean	min	median	max
Number of peers	173,725	2.96	1	1	23,974
Individual transfer amount	173,725	1.4e+07	0.01	5,000	1.44e+11
Individual transfer frequency	173,725	17	1	1	300,000
Edge transfer amount	514,135	4,747,115	0.01	5,000	2.85e+10
Edge transfer frequency	514,135	5.8	1	1	173,341

Table 3. Summary Statistics on Nodes

Variables	observation	mean	median	Standard deviation	min	max
Age	152,747	33	30	11	0.0770	100
Female	173,723	0.330	0	0.470	0	1
Account holding days	173,723	859	770	499	157	6,668
balances	173,723	870,525	3226	1.100e+08	-1.300e+10	2.900e+10
Internet Banking	145,854	0.18	0	0.38	0	1
Pos	145,854	0.13	0	0.34	0	1
Cheque	145,854	0.32	0	0.47	0	1
Bank staff	145,854	0.07	0	0.26	0	1
Uninsured	173,723	0.08	0	0.27	0	1
Degree	173723	3.200	1	72	1	23985
closeness	173723	0.200	0.210	0.0560	1.20e-05	0.360
betweenness	173723	1.90e-05	0	0.00110	0	0.390
eigenvector	173723	0.000700	2.80e-05	0.00230	0	0.690

Table 4. Runners with Different Characteristics

Panel A.

	Observation	Number of runners	Proportion of runners (%)
Full sample	173,723	9,972	5.74
balance			
0~3,000	74,726	844	1.13
3,000~10,000	29,232	1,950	6.67
10,000~100,000	38,856	4,907	12.63
100,000~200,000	7,226	869	12.03
200,000+	13,288	1,399	10.53
Gender			
Female	57,152	2,898	5.07
Male	116,571	7,064	6.06
Age			
18~34	102,293	5,258	5.14
35~55	44,364	3,123	7.04
55+	27,066	1,583	5.85
Bank staff			
staff	10,690	1,916	17.92
Non-staff	135,164	8,015	5.93
Financial instrument			
Internet user	25,983	2,276	8.76
Non-internet user	119,871	7,648	6.38
Pos user	19,252	1,715	8.91
Non-Pos user	126,602	8,216	6.49
Cheque user	46,291	4,268	9.22
Non-cheque user	99,563	5,665	5.69

Panel B.

	Observation	Number of runners	Proportion of runners (%)
degree			
1	116,050	6,017	5.18
2	33,003	1,704	5.16
3	7,954	513	6.45
4	3,490	302	8.65
5-10	6,363	565	8.88
11-40	5,139	629	12.24
41+	1,724	235	13.63
Betweenness			
High	50,557	3,572	7.07
Low	123,166	6,393	5.19
eigenvector			
High	83,906	5,358	6.39
low	89,817	4,607	5.13
Closeness			
Lowest	8,686	420	4.84
Lower	79,185	4,064	5.13
Higher	61,407	4,089	6.66
highest	24,445	1,392	5.69

Table 5. Cross-Sectional Analysis of Centrality and the Propensity to Run

Panel A.

VARIABLES	(1)	(2)	(3)	(4)
Log of degree	0.0151***			
	(0.00167)			
closeness		0.106***		
		(0.0277)		
eigenvector			0.210**	
			(0.102)	
betweenness				0.144
				(0.114)
Observations	173,723	173,723	173,723	173,723

Panel B.

	(1)	(2)	(3)	(4)
Log of degree	0.0116***			
	(0.000964)			
eigenvector		-0.191		
		(0.369)		
closeness			0.0787***	
			(0.0224)	
betweenness				-0.408
				(0.721)
age	0.00407***	0.00438***	0.00430***	0.00438***
	(0.000499)	(0.000582)	(0.000554)	(0.000582)
age2	-5.06e-05***	-5.57e-05***	-5.46e-05***	-5.56e-05***
	(5.84e-06)	(7.09e-06)	(6.76e-06)	(7.10e-06)
female	-0.0111***	-0.0124***	-0.0126***	-0.0124***
	(0.00168)	(0.00188)	(0.00184)	(0.00188)
Log of balance	0.0160***	0.0164***	0.0164***	0.0164***
	(0.000702)	(0.000533)	(0.000525)	(0.000535)
Account hold days	-5.22e-06***	-4.39e-06**	-4.14e-06**	-4.35e-06**
	(1.65e-06)	(1.83e-06)	(1.76e-06)	(1.83e-06)
Observations	144,772	144,772	144,772	144,772

The table shows the marginal estimates from a logit model. The dependent variable is a dummy

variable indicating whether a depositor is a runner. A depositor is considered a runner if she withdrew more than 75% of her deposits between August 14th and August 20th. City-level clustered robust SEs are in parentheses with *** p<0.01, ** p<0.05, and * p<0.1.

Table 6. Peer effect -- Instrumental Variable

variable	(1)	(2)
Peer run	0.170***	0.139***
	(0.0185)	(0.0202)
Age	0.000228***	0.000125*
	(6.58e-05)	(6.64e-05)
Female	-0.0168***	-0.0149***
	(0.00145)	(0.00145)
Log of balance	0.0177***	0.0175***
	(0.000310)	(0.000312)
Account holding days	-7.26e-06***	-1.00e-05***
	(1.45e-06)	(1.63e-06)
constant	-0.106***	-0.0320***
	(0.00357)	(0.00607)
R-squared		0.016
F-statistic	79.23	45.60
First stage	Peer run	Peer run
age	0.000190***	0.000101
	(6.91e-05)	(6.98e-05)
female	0.0108***	0.0106***
	(0.00151)	(0.00151)
Log of balance	-0.00116***	-0.00146***
	(0.000326)	(0.000327)
Account holding days	1.04e-05***	6.96e-06***
	(1.50e-06)	(1.70e-06)
Peer gender	-0.0830***	-0.0760***
	(0.00167)	(0.00170)
Peer log of balance	0.00159***	0.000723***
	(0.000219)	(0.000224)
constant	0.0876***	0.145***
	(0.00390)	(0.00615)
Branch control	No	Yes
Observations	121,345	121,345

Table 7. Peer Effect

	(1)	(2)	(3)	(4)	(5)
		degree			
Variables	all	1-2	3-15	16-60	61+
Peer run	1.709***	1.094***	2.114***	2.814***	0.888***
	(0.0802)	(0.0861)	(0.144)	(0.184)	(0.139)
intercept	0.761***	0.550***	0.894***	1.311***	0.386***
	(0.00394)	(0.00372)	(0.00772)	(0.0103)	(0.00660)
Peer FE	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y
Observations	3,423,751	1,130,461	608,972	849,382	834,936
R-squared	0.225	0.226	0.223	0.218	0.240

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. Columns 2-5 categorize depositors into four groups based on their own degree centrality. The values in parentheses are branch-level robust clustered standard errors with *** p<0.01, ** p<0.05, and * p<0.1.

Table 8. Peer Effect and Social Ties

	(1)	(2)	(3)	(4)
Peer run	1.176***	1.176***	1.602***	1.602***
	(0.0869)	(0.0869)	(0.0820)	(0.0820)
Peer run × high amount	0.940***	0.940***		
	(0.0968)	(0.0968)		
Peer run × high frequency			0.313*	0.313*
			(0.176)	(0.176)
Constant	0.760***	0.760***	0.760***	0.760***
	(0.00410)	(0.00410)	(0.00408)	(0.00408)
Peer FE	Y	Y	Y	Y
Branch FE	N	Y	N	Y
Observations	3,423,751	3,423,751	3,423,751	3,423,751
R-squared	0.225	0.225	0.225	0.225

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. "High amount" is a dummy variable that takes the value of 1 if the total transfer amount between two individuals from January 2008 to June 2009 exceeds 5,000 Naira; otherwise, it is 0. "High frequency" is a dummy variable that takes the value of 1 if the total number of transfers between two individuals from January 2008 to June 2009 exceeds one; otherwise, it is 0. The values in parentheses are branch-level robust clustered standard errors with *** p<0.01, ** p<0.05, and * p<0.1.

Table 9. Peer Effect and Distance

VARIABLES	(1) all	(2) High amount	(3) Low amount	(4) High frequency	(5) Low frequency
Peer run	2.763***	2.799***	2.547***	2.689***	2.769***
	(0.247)	(0.287)	(0.387)	(0.379)	(0.290)
Peer run×log distance	-0.160***	-0.108*	-0.187**	-0.0479	-0.203***
	(0.0520)	(0.0584)	(0.0785)	(0.0958)	(0.0576)
Constant	1.006***	1.109***	0.888***	1.082***	0.971***
	(0.0103)	(0.0121)	(0.0102)	(0.0188)	(0.00872)
Peer FE	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y
Observations	1,085,804	580,848	504,956	341,426	744,378
R-squared	0.219	0.216	0.224	0.217	0.221

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. In Column (2) (high amount), the total transfer amount between transaction partners from January 2008 to June 2009 exceeds 5,000 Naira, while in column (3), the total transfer amount between transaction partners during the same period is less than 5,000 Naira. In column (4), the total number of transfers between transaction partners from January 2008 to June 2009 exceeds one, while in column (5), the total number of transfers between transaction partners during this period is one. Log distance refers to the natural logarithm of the distance (in km) between transaction partners. The values in parentheses are branch-level robust clustered standard errors with *** $p<0.01$, ** $p<0.05$, and * $p<0.1$

Table 10. Peer Effect and the Centrality of Peers

VARIABLES	(1) All	(2) insured	(3) uninsured
Peer run	1.375***	1.620***	0.547***
	(0.0905)	(0.110)	(0.140)
Peer run×log degree	0.133***	0.0613*	0.396***
	(0.0320)	(0.0368)	(0.0712)
Constant	0.759***	0.793***	0.601***
	(0.00270)	(0.00305)	(0.00562)
Peer FE	Y	Y	Y
Branch FE	Y	Y	Y
Observations	3,423,751	2,824,164	599,587
R-squared	0.225	0.229	0.200

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. Log degree is the natural logarithm of the degree centrality of transaction partners. In Column 2, the deposit amounts for all depositors are below 200,000 Naira. In Column 3, the deposit amounts for all depositors are above 200,000 Naira. The values in parentheses are robust clustered standard errors at the edge level formed between the depositors and their transaction partners with *** $p<0.01$, ** $p<0.05$, and * $p<0.1$

Table 11. Peer Effect and Financial Instrument

	(1)	(2)	(3)
Peer run	1.178***	1.613***	1.474***
	(0.157)	(0.0991)	(0.149)
Peer run×Peer internet	0.860***		
	(0.222)		
Peer run×Peer pos		0.240*	
		(0.130)	
Peer run×Peer cheque			0.339*
			(0.175)
Constant	0.763***	0.766***	0.765***
	(0.00458)	(0.00474)	(0.00472)
Peer FE	Y	Y	Y
Branch FE	Y	Y	Y
Observations	2,834,974	2,834,974	2,834,974
R-squared	0.225	0.225	0.225

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. Peer internet is a dummy variable that takes the value of 1 if the peer uses internet banking, otherwise 0. Peer POS is a dummy variable that takes the value of 1 if the peer uses POS (Point of Sale), otherwise 0. Peer cheque is a dummy variable that takes the value of 1 if the peer uses cheques, otherwise 0. The values in parentheses are robust clustered standard errors at the branch level with *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 12. Peer Effect and Profession

	(1)	(2)	(3)
	all	insured	uninsured
Peer run	1.303***	1.878***	0.769***
	(0.177)	(0.223)	(0.286)
Peer run×peer staff	0.650***	0.276*	1.119***
	(0.248)	(0.141)	(0.282)
Constant	0.763***	0.933***	0.588***
	(0.00466)	(0.0130)	(0.0157)
Peer FE	Y	Y	Y
Branch FE	Y	Y	Y
Observations	2,834,974	1,997,883	508,798
R-squared	0.225	0.228	0.200

This table shows estimates of linear probability model for the probability of running on the bank. The dependent variable is a dummy variable, which takes the value of 1 if the depositor runs on day t and 0 otherwise. A depositor is considered to run on the bank if she withdrew more than 75% of their deposits between August 14th and August 20th. The run date is defined as the day t when the depositor withdrew 75% or more of her funds. This is an unbalanced panel. If depositor i run on day t, she did not appear in the panel data for subsequent days. The estimated coefficients are multiplied by 100. Peer staff is a dummy variable that takes the value of 1 if the peer is a bank staff, otherwise 0. In Column 2, the depositors' amounts are less than 200,000 Naira, meaning they are fully covered by deposit insurance. In Column 3, the depositors' amounts are greater than 200,000 Naira. The values in parentheses are robust clustered standard errors at the branch level with *** p<0.01, ** p<0.05, and * p<0.1.

Table 13. Neighbors and Runners

	mean	Standard deviation	10th percentile	median	90th percentile
Number of neighbors nearby					
0-300m	9,718	19,845	95	1168	34,273
300m-700m	1,721	3,746	11	574	4,338
700m-1,000m	1,703	3,721	7	797	4,206
Number of runners nearby					
0-300m	315	693	2	34	1,079
300m-700m	53	123	0	18	131
700m-1,000m	51	125	0	20	130

Table 14. Proportions of Runners in the Neighborhood（%）

	runners	stayers	diff	P-value
0-300m	4.04	2.97	1.07	170
	(0.02)	(0.00)		
300m-700m	3.42	3.41	0.01	0.13
	(0.02)	(0.00)		
700m-1,000m	2.96	2.93	0.03	2.83
	(0.01)	(0.00)		

Table 15. The Number of Depositors Nearby and the Probability of Running

Variables	(1)	(2)	(3)	(4)
Log(the number of depositors nearby)	5.91e-05	0.000135	5.92e-05	-2.39e-05
	(0.000161)	(0.000335)	(0.000162)	(0.000307)
Age		0.00292***		0.00248***
		(0.000225)		(0.000242)
Age2		-3.41e-05***		-3.16e-05***
		(2.55e-06)		(2.85e-06)
Female		-0.00737***		-0.00587***
		(0.000598)		(0.000609)
Log(balances)		0.0142***		0.0133***
		(0.000302)		(0.000242)
Account holding days		5.76e-06***		5.01e-06***
		(6.16e-07)		(5.61e-07)
intercept	0.0306***	-0.240***		
	(0.00151)	(0.0145)		
model	ols	ols	logit	logit
Observations	2,380,394	1,930,499	2,380,394	1,930,499
R-squared	0.000	0.029		

This table presents a cross-sectional regression analysis on the relationship between the number of nearby accounts and the propensity to run on the bank. The dependent variable is a dummy variable that equals 1 if the depositor is a runner. A runner is defined as a depositor who withdrew more than 75% of their deposits between August 14th and August 20th. Log(the number of depositors nearby) measures the natural logarithm of the total number of accounts within 1 km of the depositor. The values in parentheses are robust standard errors clustered at the city level with *** p<0.01, ** p<0.05, and * p<0.1.

Table 16. The Number of Runners in the Neighborhood and the Probability of Running

	(1)	(2)	(3)
The number of runners (0-300m)	3.01e-06***	2.99e-06***	2.96e-06***
	(7.27e-07)	(7.36e-07)	(7.55e-07)
The number of runners (300-700m)		-3.02e-06	-2.56e-06
		(3.51e-06)	(3.15e-06)
The number of runners (700-1000m)			-2.33e-06
			(1.59e-06)
Age	0.00291***	0.00290***	0.00290***
	(0.000203)	(0.000204)	(0.000202)
Age2	-3.39e-05***	-3.39e-05***	-3.38e-05***
	(2.30e-06)	(2.30e-06)	(2.29e-06)
Female	-0.00732***	-0.00730***	-0.00734***
	(0.000597)	(0.000597)	(0.000595)
Log(balances)	0.0142***	0.0142***	0.0142***
	(0.000300)	(0.000299)	(0.000297)
Account holding days	6.14e-06***	6.09e-06***	6.04e-06***
	(6.66e-07)	(6.43e-07)	(6.23e-07)
Intercept	-0.246***	-0.245***	-0.244***
	(0.0142)	(0.0138)	(0.0133)
Observations	1,999,097	1,961,520	1,930,499
R-squared	0.029	0.029	0.029

This table presents the estimates of the linear probability model. The dependent variable is a dummy variable that equals 1 if the depositor is a runner, and 0 otherwise. A runner is defined as a depositor who withdrew more than 75% of her deposits between August 14th and 20th. The values in parentheses are robust standard errors clustered at the city level with *** p<0.01, ** p<0.05, and * p<0.1.

Table 17. The Effect of Runners in the Neighborhood on ATM Users

	(1)	(2)	(3)
The number of runners (0-300m)	-1.57e-06***	-1.58e-06***	6.92e-07
	(2.10e-07)	(2.01e-07)	(4.41e-07)
ATM	0.0211***	0.0206***	0.0200***
	(0.00107)	(0.00106)	(0.000934)
ATM×The number of runners (0-300m)	8.27e-06***	8.31e-06***	3.71e-06***
	(1.40e-06)	(1.37e-06)	(8.75e-07)
The number of runners (300-700m)		-7.85e-07	-4.88e-06
		(1.90e-06)	(3.22e-06)
ATM×The number of runners (300-700m)		6.62e-06**	3.56e-06
		(2.64e-06)	(2.43e-06)
The number of runners (700-1000m)		-1.03e-07	-2.72e-06
		(1.04e-06)	(2.04e-06)
ATM×The number of runners (700-1000m)		2.19e-06	-1.79e-06
		(2.75e-06)	(2.16e-06)
Age			0.00308***
			(0.000196)
Age2			-3.42e-05***
			(2.14e-06)
Female			-0.00619***
			(0.000558)
Log(balances)			0.0140***
			(0.000294)
Account holding days			5.43e-06***
			(6.12e-07)
Intercept	0.0231***	0.0232***	-0.246***
	(0.000498)	(0.000533)	(0.0130)
Observations	2,461,432	2,380,394	1,930,499

R-squared	0.005	0.005	0.033

This table presents the estimates of the linear probability model. The dependent variable is a dummy variable that equals 1 if the depositor is a runner, and 0 otherwise. A runner is defined as a depositor who withdrew more than 75% of her deposits between August 14th and 20th. ATM is a dummy variable that equals 1 if the depositor is an ATM user, and 0 otherwise. ATM user is defined as a depositor who has used an ATM to withdraw money at least once between 2008 and June 2009.The values in parentheses are robust standard errors clustered at the city level with *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 18. The Effect of Runners in the Neighborhood on Internet-Banking Users

	(1)	(2)	(3)
The number of runners (0-300m)	7.94e-07***	7.85e-07***	2.95e-06***
	(2.85e-07)	(2.81e-07)	(7.87e-07)
Internet banking	0.0511***	0.0482***	0.0429***
	(0.00745)	(0.00664)	(0.00564)
Internet banking×The number of runners (0-300m)	2.61e-06	3.00e-06	-8.02e-07
	(1.83e-06)	(2.10e-06)	(2.58e-06)
The number of runners (300-700m)		6.74e-07	-3.59e-06
		(1.68e-06)	(3.00e-06)
Internet banking×The number of runners (300-700m)		3.90e-05*	3.98e-05
		(2.28e-05)	(2.44e-05)
The number of runners (700-1000m)		2.87e-07	-2.64e-06
		(1.04e-06)	(1.60e-06)
Internet banking×The number of runners (700-1000m)		1.59e-06	-3.61e-06
		(1.03e-05)	(1.18e-05)
Age			0.00288***
			(0.000197)
Age2			-3.36e-05***
			(2.21e-06)
Female			-0.00750***
			(0.000600)
Log(balances)			0.0141***
			(0.000303)
Account holding days			6.28e-06***
			(6.25e-07)
Intercept	0.0301***	0.0301***	-0.248***
	(0.000598)	(0.000646)	(0.0134)
	接下		
	接上		
Observations	2,461,432	2,380,394	1,930,499

R-squared	0.001	0.001	0.030

This table presents the estimates of the linear probability model. The dependent variable is a dummy variable that equals 1 if the depositor is a runner, and 0 otherwise. A runner is defined as a depositor who withdrew more than 75% of her deposits between August 14th and 20th. Internet Banking is a dummy variable, which equals 1 if the depositor is an internet banking user and 0 otherwise. Internet Banking users are defined as depositors who have used internet banking at least once between 2008 and June 2009.The values in parentheses are robust standard errors clustered at the city level with *** $p<0.01$, ** $p<0.05$, and * $p<0.1$

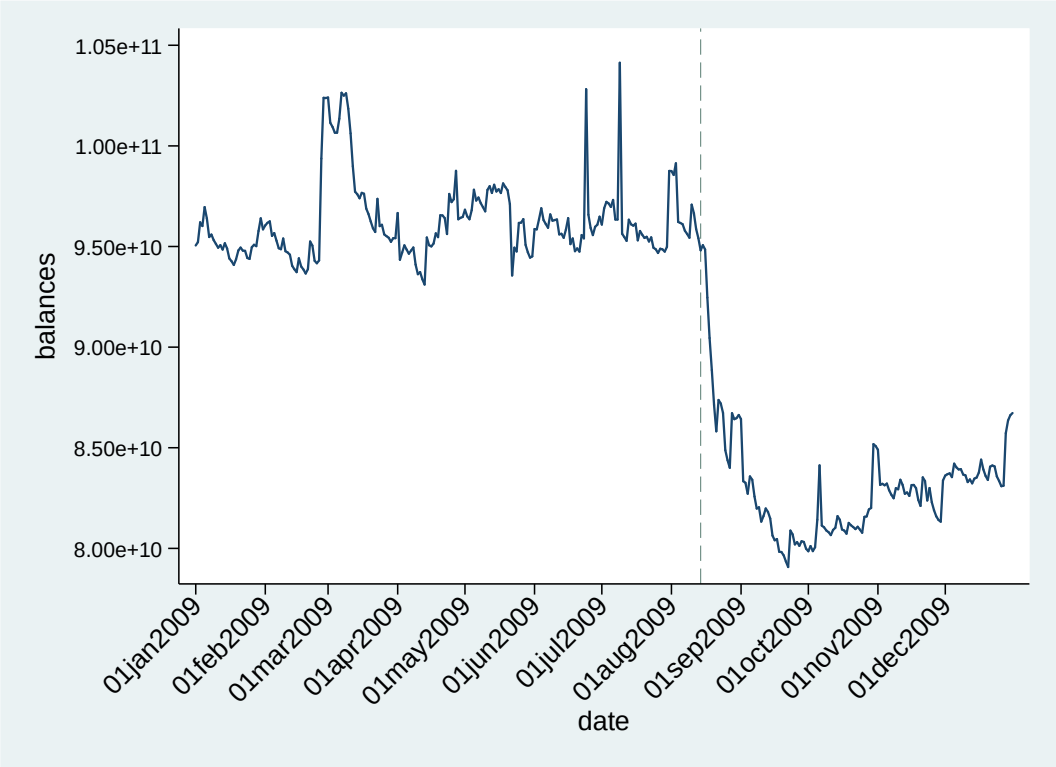
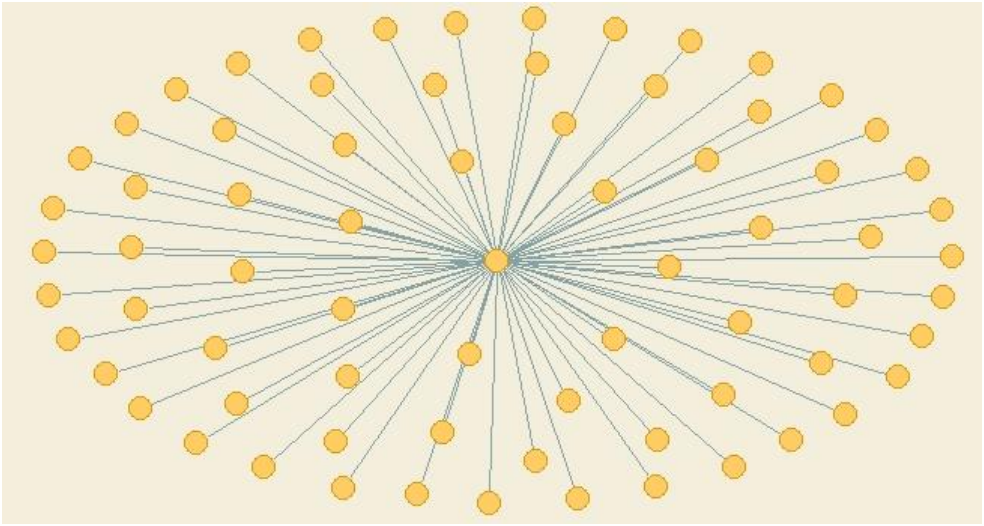
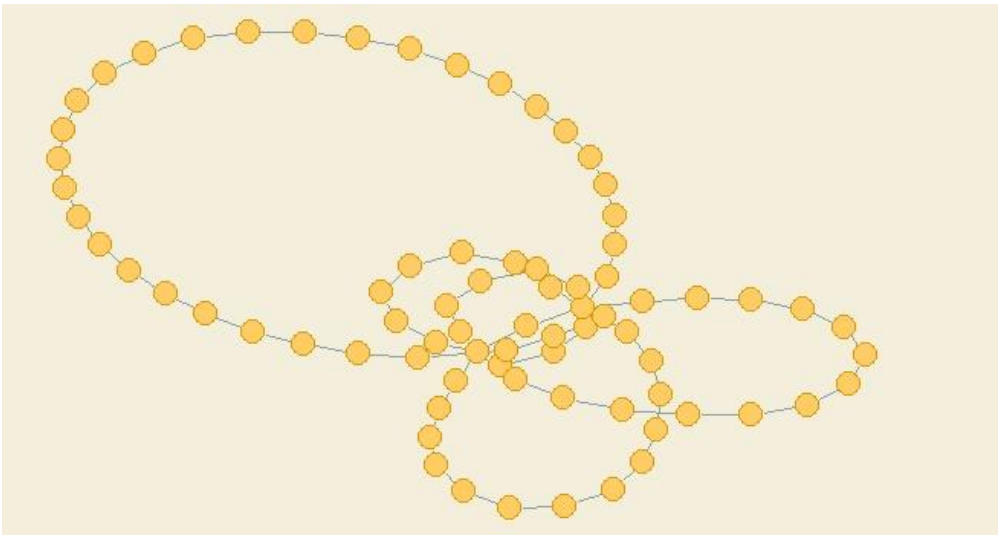


Figure 1. balances of savings account.



(a)



(b)

Figure 1. subnetworks of money transfer network

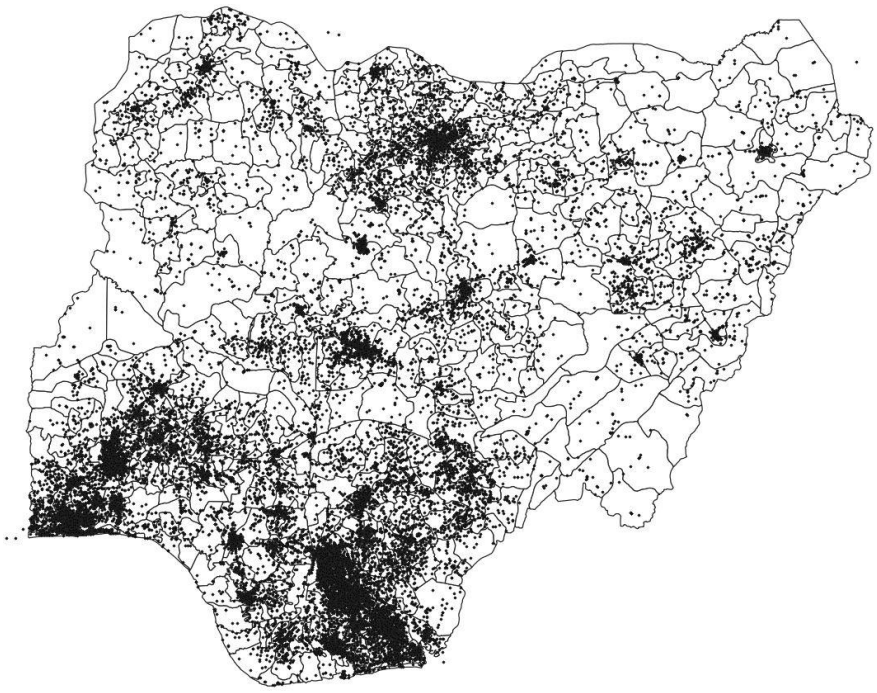


Figure 2. Depositor locations