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. 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

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1. Introduction

Bank runs pose significant threats to the stability of the banking system. 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 classic examples of peer effects, it remains unclear what factors contribute to these effects and which types of depositors are more susceptible to influence by their peers. Understanding the role of social networks in bank runs is crucial not only for grasping the nature of these events but also for designing regulations to prevent 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 includes detailed information on depositors and their transaction records, allowing us to construct two types of social networks. The first is a money transfer network, where we identify relationships between depositors based on intra-bank transfers. The second is a neighborhood network, where we use depositors' addresses to identify neighbors within a 1-kilometer radius. Our study investigates whether depositors learn from their networks and what factors 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.

Our findings are threefold.

First, Network Structure and Characteristics: The money transfer network exhibits a relatively sparse, core-periphery structure. Depositors at the center of the network tend to be older, have larger deposits, and have access to financial instruments such as cheques, POS, and internet banking. Homophily is evident in this network—depositors with higher balances are more likely to transfer funds with others who have similarly high balances. Moreover, depositors whose peers use financial instruments are themselves more likely to use such instruments.

Second, Peer Effects in Money Transfer Networks: Depositors at the center of the network are more likely to withdraw funds following a fundamental shock. We identify significant peer effects within the money transfer network. Various factors influence the strength of these peer effects:

(1) **Strength of Social Ties:** Measured by transaction amounts and frequency, stronger ties between depositors increase the likelihood of withdrawal if their peers also withdraw.

(2) **Proximity:** Depositors are more likely to run if they live closer to their peers, especially when the social ties are weaker.

(3) **Degree Centrality:** Depositors with peers who have higher degree centrality in the network are more likely to withdraw, with this effect being particularly pronounced among uninsured depositors.

(4) **Access to Financial Instruments:** Peers who can use cheques, POS, and internet

banking have a greater influence on others' withdrawal decisions.

(5) **Bank Staff Influence:** Depositors with peers who are bank staffs are more likely to withdraw, especially if they are uninsured.

Third, Neighborhood Effects: 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. Next, 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 (2016) 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 2016; 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 2016), 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 characteristics 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 systematic banking crisis. The bank we study was a large commercial bank with over 130 branches nationwide. A substantial portion of the bank's loans were tied to the oil and gas industry. As the financial crisis unfolded, crude oil prices plummeted, severely impacting Nigeria's oil and gas sector. This situation resulted in a high level of non-performing loans for the bank. During the period of rapid expansion, the bank's management team illegally used deposits to purchase shares of their own bank. The bank's stock price fell by more than 80% in 2008. The bank had to seek financial support from the Central Bank starting in October of that year. The bank recorded a loss of ₦336 billion in 2008 and an additional loss of ₦238 billion from March to December 2009. As of June 30, 2010, the bank had total assets of $4.199 billion, total liabilities of $6.72 billion, and total equity of -$2.52 billion. However, at the time, its customers were unaware of its financial difficulties, as no negative news about the bank had been published by the media.

The Central Bank of Nigeria, the primary regulatory authority, supervises and provides liquidity to banks, while the Nigeria Deposit Insurance Corporation offers deposit insurance. 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 excessively 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 they were deemed systemically important, accounting for 39.93% of loans, 29.99% of deposits, and 31.47% of total assets as of May 31, 2009. The governor revealed that the Central Bank had decided to inject ₦400 billion into the five banks and assured the public that no bank would be allowed to fail. Additionally, the management teams of these banks were removed. The bank in focus was one of these five. It wasn't until after the press conference that the media began reporting on the bank's troubles. A few days later, the bank's president came under investigation by the Financial Crimes Commission for alleged crimes.

This announcement was a significant shock to depositors. Following the public disclosure, the total balance of savings accounts at the bank sharply declined over the next week. Figure 2.1 shows the total savings account balance during this period, with the day of the press conference marked by a vertical line. Before the press conference, savings account balances remained stable, although there had been consistent and significant outflows from current accounts since March 2009.

[Figure 2.1 inserted here]

We classify the week following the press conference as the bank run period. Following the definition by Iyer and Puri (2012), we consider a depositor to be a "runner" if he withdrew more than 75% of his deposits between August 14th and 20th, 2009. Otherwise, he is classified as a "stayer." The time when the balance first fell below 25% is defined as the withdrawal time.

2.2 Data

We obtained administrative data on balances, transactions, and anonymized depositor information from the bank. The transaction accounts mainly consist of current and savings accounts. The dataset includes transaction records from 2007 to March 2012, the balances of depositors as of March 5, 2012, and demographic information of the depositors. The transaction data provides details on whether the transaction was a deposit or withdrawal, the transaction amount, the exact time of the transaction (down to the second), the transaction branch, and the transaction channel. The transaction channels allow us to distinguish between cash deposits at the counter, cash withdrawals at the counter, ATM cash withdrawals, cheque deposits, cheque withdrawals, internet banking transactions, POS purchases, and more.

To compute the 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 the balance of each account as of March 5, 2012, we determine each account's outstanding balance before the bank run. We then aggregate the balances of accounts associated with the same customer ID to obtain each depositor's outstanding balance as of the close of August 13, 2009. If a depositor's balance exceeds ₦200,000, part of her funds is uninsured by the deposit insurance. We create a dummy variable, "uninsured," which equals 1 if the depositor is not fully protected by deposit insurance.

The individual information includes age, gender, profession, account opening date,

account opening branch, and address. From the transaction records, we can identify whether account holders have access to various financial instruments, such as ATMs, cheques, internet banking services, and POS services. We categorize depositors as ATM users if they used an ATM at least once between January 1, 2008, and June 30, 2009. If they did not, we assume they do not have ATM access and classify them as non-ATM users. Similarly, we identify cheque users, internet banking users, and POS users. If depositors hold accounts such as staff salary accounts or staff savings accounts, we classify them as bank staff.

We obtain administrative data on balances, transactions and anonymous depositor information from the bank. Transaction accounts are mainly current or savings accounts. The transaction data covers transaction records from 2007 to 2012 March, depositors' balance on March 5, 2012, and depositors' demographic information. From these records, we can know whether it is a deposit or withdrawal, amount of the transaction, time of the transaction, transaction branch, and the transaction channel. Transaction time is accurate to the second. From transaction channel, we can identify whether it's a cash deposit at the counter, a cash withdrawal at the counter, an ATM cash withdrawal, a cheque deposit, a cheque withdrawal, an internet banking transaction, a POS consumption, etc.

To compute depositors' balances on August 13, before the press conference, we calculate the net transactions of each account between August 14, 2008 and March 5, 2012. Accounts with an opening date after August 14 are deleted because these accounts didn't appear in the bank run. According to each account's balance on March 5, 2012, we get each account's outstanding balance before the bank run. Then we aggregate the accounts

balances belonging to the same customer ID and obtain each depositor's outstanding balance at the close of August 13, 2009. If the depositor's balance is above ₦200,000, part of her money is uninsured by the deposit insurance. We generate a dummy variable "uninsured" equal to 1 if the depositor is not fully protected by deposit insurance.

Individual information includes: age, gender, profession, account opening date, account opening branch, and address. From transaction records, we can identify whether account holders have access to some financial instruments, such as: ATM, cheque, internet banking service, POS service, etc. We regard depositors as ATM users if they used ATM at least once from January 1, 2008 to June 30, 2009. Otherwise, we assume that they can't use ATM and regard them as non-ATM users. Analogously, we identify cheque users, internet banking user, and POS users respectively. If depositors have accounts such as staff salary accounts or staff savings accounts, we regard these depositors as bank staff.

3. Money Transfer Network

3.1 summary statistics

We construct a money transfer network between depositors at the bank by matching intra-bank transactions based on the amount, time, and transaction type. The money transfer data includes 35 million transactions from January 1, 2008, to June 30, 2009. Based on transaction types, these records can be classified as transactions through counters (Miscellaneous Customer Credit, Miscellaneous Customer Debit, Miscellaneous Customer Debit NoCOT), through ATMs (ATM Funds Xfer Credit Remote On Us, ATM Funds Xfer Debit Remote On Us), and through online banking (Internet Banking TRF

CR, Internet Banking TRF DR). Table 3.1 provides descriptive statistics of these different types of transfer amounts. There are 21 million observations in the Customer Debit category, most of which are fees. The average debit amount is 458,324 Naira, with a median of 50 Naira. There are 5.6 million observations in the Customer Credit category, with a median of 15,962 Naira. ATM and online banking transfers are mostly intra-bank transactions, with online banking transfers generally involving larger amounts than ATM transfers.

[Insert Table 3.1 here]

Since we can only document intra-bank transactions, we do not know whether depositors know each other through other channels. There are 149,562 intra-bank transfer transaction records between 173,724 depositors. We identify depositors' peers from this network. Table 3.2 presents the descriptive statistics of the transfer data between different depositors within the bank. In the transfer network, a few active accounts have many transfer recipients and frequent transfer records. On average, a depositor makes intra-bank transfers with 2.96 other depositors. The median individual transfer amount between January 2008 and June 2009 is 5,000 Naira, and more than half of individuals made only one transfer during this period. The bilateral transfer amount, which refers to the total amount transferred between two people from January 2008 to June 2009, also has a median of 5,000 Naira. The network is characterized by a sparse structure, with large and frequent transactions occurring on a small number of accounts.

[Insert Table 3.2 here]

We use the Kamada-Kawai algorithm in Pajek software to visualize the money transfer network, where nodes represent account holders, and the lines between nodes represent transfer relationships between individuals. The transfer network consists of many independent sub-networks, with the largest sub-network featuring a core center node connected to 23,974 other nodes. This sub-network exhibits a central-peripheral structure. Figure 3.1(a) illustrates an example of a star-shaped network. Transfer activities in this network include business transactions and transfers between relatives and friends. The money transfer network's sparse structure differs from social media networks, where individuals with mutual friends are more likely to know each other. In this central-peripheral structure, individuals at the central nodes have significant influence over others. Other network structures, such as the ring-shaped network shown in Figure 3.1 (b), also exist within the transfer network.

[Insert Figures 3.1 here]

Table 3.3 provides descriptive statistics for the network nodes. The "balance" variable represents the total balance of each depositor's accounts before August 14, 2009, the date of the press conference, with the median of 3,226 Naira. The average age of depositors in the transfer network is 33 years, with women comprising 33% of the depositors. The average account opening duration is 859 days. Bank staff represent 7% of the network. 18% of depositors have used online banking, 13% have used POS machines, and 32% have used cheques. Depositors with access to more financial tools generally exhibit higher financial literacy. Compared to the bank's average, depositors in the transfer

network display higher financial literacy.

[Insert Table 3.3 here]

In the network structure, centrality measures how central a node is within the network. Common centrality indicators include degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. Degree centrality measures the number of connections a node has, representing how many other nodes it is directly connected to. Betweenness centrality measures how often a node lies on the shortest path between other nodes, indicating its role as a "bridge." Closeness centrality measures a node's proximity to all other nodes, calculated by the sum of the shortest paths to other nodes. Eigenvector centrality is similar to degree centrality but assigns weights to the connected nodes based on their centrality. Table 3.4 describes the centrality features of the nodes. The average node degree is 3.2, meaning that, on average, each person has transactional connections with 3.2 other depositors. The median degree centrality is 1, indicating that over half of the depositors are only connected to one other depositor, confirming the central-peripheral structure of the transfer network. Due to the network's sparse structure, the average and median values for betweenness and eigenvector centrality are close to 0.

[Insert Table 3.4 here]

Table 3.5 describes the degrees of depositors with different characteristics. While a small number of accounts engage in transactions with many others, most accounts interact with just one other account. More than half of the depositors have only one transfer connection,

and 90% have fewer than three. This indicates the transfer network's sparse structure. Accounts with higher balances tend to have higher degrees. Bank staff have an average degree of 14.8, compared to 2.22 for others, indicating greater involvement in the network. Depositors with access to certain financial instruments also have higher degrees, as do those over 55 years old.

[Insert Table 3.5 here]

The transfer network exhibits homophily, where depositors tend to interact with others who share similar characteristics. Table 3.6 describes the proportions of adjacent accounts among different types of depositors. In terms of age, balance, profession, and gender, depositors are more similar to their peers. For example, depositors with high balances are more likely to be connected to other high-balance depositors. Although bank staff make up only 7% of all depositors, they represent 38.9% of all peers, indicating extensive contacts within the network. Figures 3.2, 3.3, and 3.4 show that depositors who use the same financial tools are also more likely to establish transfer connections. Among internet banking users, 70% of their peers use internet banking, compared to 25% for non-internet users.

[table 3.6 inserted here]

[figure 3.2. 3.3, 3.4 inserted here]

3.2 Centrality and Bank Run

Compared to all bank depositors, those within the money transfer network have closer ties to the bank, likely due to their greater familiarity with banking operations. This

familiarity makes them more attuned to the bank's condition and more likely to hear negative information from their peers through the transfer network. Consequently, when a bank run occurs, depositors within this network are more prone to withdraw their funds.

Table 3.7 shows the runner ratio across different groups in the transfer network. Overall, the runner ratio for depositors in the transfer network is 5.71%, significantly higher than the overall runner ratio of 3%.

Depositors with higher balances are more likely to run. For instance, the runner ratio for those with balances below 3,000 Naira is 1.13%, while it exceeds 10% for those with balances above 10,000 Naira. Among various age groups, middle-aged depositors (ages 35-55) show the highest likelihood of running. Notably, the runner ratio among bank staff surges to a striking 17.92%. In this bank run, individuals with more information about the bank are more inclined to withdraw their deposits. Additionally, users of financial tools such as checks, online banking, and POS machines are also more likely to run compared to non-users. For example, the runner ratio for check users is 9.22%, significantly higher than that of non-check users.

[table 3.7 inserted here]

Depositors at the center of the transfer network exhibit a higher propensity to withdraw funds during a bank run. Central depositors have more peers who are also attuned to bank-related information. Compared to those on the network periphery, these central depositors are likely to receive negative information about the bank more rapidly, prompting them

to initiate a run. Additionally, central depositors rely more heavily on banking operations, making the cost of leaving the bank higher for them.

Table 3.8 displays the percentage of runners among depositors with varying levels of centrality. Across different measures of centrality, those with higher centrality are more inclined to withdraw. The withdrawal rate for depositors with a degree of 1 is 5.18%, whereas the rate for those with a degree between 11 and 40 is 12.24%.

[Insert Table 3.8 here]

To quantify the effects of centrality on withdrawal propensity, we employ a logit model. Table 3.9 presents the marginal effects from our estimates. Panel A shows the results without control variables, while Panel B includes them. Standard errors are clustered at the city level, as indicated in parentheses. The dependent variable is a binary indicator, set to 1 if the depositor is a runner (she withdrew more than 75% of her funds from August 14 to August 20). Panel A indicates that higher centrality correlates with a greater likelihood of withdrawing funds. A 1% increase in degree centrality raises the liquidation probability by 0.01%. An increase of one standard deviation (0.056) in closeness centrality increases the probability by 0.59%, while a similar increase in eigenvector centrality (0.002) raises the probability by 0.05%. For betweenness centrality, an increase of one standard deviation (0.001) results in a 0.02% increase in the likelihood of a withdrawal.

Panel B incorporates control variables such as age, gender, deposit balance, and account

opening date, with city-level clustering of standard errors. Given the non-linear impact of age on withdrawal propensity, we also include the square of age in the regression. The results show that a 1% increase in degree centrality continues to correspond to a 0.01% increase in withdrawal probability.

[Insert Table 3.9 here]

Depositors with higher centrality are connected to more peers. This raises the question: Are they more likely to withdraw because they learn from their peers within the network? In the next section, we explore whether depositors are influenced by their peers in the money transfer network and what factors shape this peer effect.

4. Peer Effect in the Money Transfer Network

4.1 Identification Strategy

The exogenous impact of information release helps alleviate the endogeneity problem of transfer networks. However, depositors may run simultaneously upon learning the news, rather than being influenced by their peers. We incorporate the timing of runs into the analysis. If egos run because their peer ran, then the ego's probability of running (hazard rate) will significantly increase after the peer runs.

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:

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

β_1 estimates depositor *i's* increase in the likelihood of running due to the withdrawal of his peer j. What determines the size of the peer effect? We run the following regression:

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

4.2 Empirical Results

Table 4.1 estimates the peer effect in the money transfer network in the bank run. 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 of Table 4.1 present the 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.

[table 4.1 inserted 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. Using transfer records from January 2008 to June 2009, we calculated the total amount and frequency of transfers between depositors. Peers were then categorized into two groups based on whether the total transfer amount exceeded 5,000 Naira. Table 4.2 presents the regression estimates, with coefficients multiplied by 100. As shown in Column 1, if the peer runs and the transfer amount is less than 5,000 Naira, the ego's likelihood of running increases by 1.18%. However, if the transfer amount exceeds 5,000 Naira, the likelihood of running increases by 2.11%. This suggests that peer effects are twice as strong in cases of strong social ties compared to weaker ones. In Column 2, the result remains robust after adding branch fixed effects. We also categorize peers based on transfer frequency, with a threshold of one transaction. Column 3 indicates that the probability of running due to the withdrawal of peers with high transaction frequency is 0.31% higher than that associated with low-frequency peers. The result is consistent in Column 4 after controlling for branch fixed effects. Thus, peer effects are indeed stronger when social ties are stronger.

[Insert Table 4.2 here]

4.2.2 Distance

Distance plays a crucial role in the spread of information, with peer effects diminishing

as the physical distance between peers increases. We calculated the distance between peers based on their addresses. Table 4.3 presents estimates of the impact of distance on peer effects, with coefficients multiplied by 100. Column 1 shows that a 1% increase in the distance between peers reduces the peer effect by 0.16%. As the distance grows, egos are less likely to withdraw following the withdrawal of their peers.

The interaction between distance and the strength of social ties may affect the peer effect in different ways. One hypothesis is that distance and strong social ties may complement each other in spreading panic. Strong social ties typically encourage communication, but greater distances may pose communication barriers, leading to a more significant decrease in peer effects for peers with strong ties than for those with weak ties. Another hypothesis suggests that distance and social ties may have a substitute effect on peer influence. Peers with strong ties will communicate regardless of distance, whereas peers with weak ties are less likely to communicate over long distances, as they may not make deliberate efforts to overcome these barriers. In this scenario, distance may have a greater impact on peers with weaker social ties.

To test these hypotheses, we divided peers into strong and weak social tie groups based on transfer amounts and frequencies. Columns 2 and 4 focus on peers with strong ties, while Columns 3 and 5 examine peers with weak ties. When using transfer amounts to differentiate tie strength, Column 2 shows that for the strong tie group, a 1% increase in distance results in a 0.108% decrease in the ego's withdrawal likelihood due to the withdrawal of peers. In the weak tie group (Column 3), the same distance increase leads to a 0.187% decrease. The effect is even more pronounced when using transfer frequency

to proxy tie strength. For peers with strong ties, distance has no significant effect, whereas for peers with weak ties, a 1% increase in distance leads to a 0.203% reduction in peer effects. This suggests that distance and the strength of social ties have a substitute effect on peer influence during a bank run.

[Insert Table 4.3 here]

4.2.3 Degree Centrality

Peers with higher degree centrality exert a greater influence on peer effects. Table 4.4 highlights the differences in peer effects based on peers' degree centrality, with coefficients multiplied by 100. Column 1 shows that peers with higher degree centrality have a significantly larger peer effect compared to those with lower degrees. The impact of peers' degree on peer effects also varies across egos. Depositors with higher degrees are more engaged with the bank and may have more information about its condition. Uninsured depositors, who are more concerned about the safety of their deposits, are particularly sensitive to the behavior of peers with high degrees. To explore this further, we divided egos into insured and uninsured groups. Column 2 examines the peer effect on insured depositors, while Column 3 focuses on uninsured depositors. The results indicate that the influence of peers' degree centrality is more pronounced among uninsured egos. Uninsured depositors are more likely to be influenced by the actions of peers with high degrees than their insured counterparts.

[Insert Table 4.4 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 4.5 presents the regression results, with all coefficient values multiplied by 100. 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 4.5 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 4.6 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 4.6 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 5.1 inserted here]

Based on the coordinates, we identified each depositor's neighbors within a 1 km radius. Table 5.1 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 5-1 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 5.1 inserted here]

Table 5.2 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 5.2 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:

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

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 5.3 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 5.3 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

$$run_i = \beta_1 runner\ No.(0-300m)_i + \beta_2 runner\ No.(300m-700m)_i + \beta_3 runner\ No.(700m-1000m)_i + \beta X_i + \epsilon_i.$$

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 5.4 presents the result.

[table 5.4 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.

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

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 5.5 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 5.4, 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 5.5 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 5.6 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 5.6 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

In this paper, we use depositors' information and transaction data to examine the effect of social network on bank runs. We construct depositors' money transfer network and neighbor network. We find that depositors learn information from their network. Depositors in the center of network or who use financial instruments are more likely to run on the bank after a fundamental shock. Depositors are more likely to run if their peers in the money transfer network run. The strength of social ties influences the magnitude of peer effects. Depositors are more likely to be influenced by peers with whom they have strong social ties. Depositors are less likely to be affected by their peers if their peers live far away. The effect of distance is stronger among peers with weak social ties. Depositors are more likely to be affected by their peers if their peers are in the center of network, or their peers can use financial instruments, or their peers are bank staff. Uninsured depositors are more likely to be affected by peer effects.

Generally, depositors lack information about banks, especially in developing countries. Therefore, they rely on their social network to obtain information. Improving information disclosure can help depositors discipline banks. Depositors in center of network, or who can use more financial instruments, or who are bank staffs have huge impact on others when a bank run happens. Focusing on certain class of depositors may help reduce the scope of runs.

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Table 3.1 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 3.2 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 3.3 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

Table 3.4 Summary Statistics on Centrality

Variables	observations	mean	median	Standard deviation	min	max
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 3.5 Centrality and Other Characteristics

	Observations	degree			
		mean	10^{th} percentile	median	90^{th} percentile
Total	173,723	3.18	1	1	3
Balance					
0~3,000	74,726	2.33	1	1	3
3,000~10,000	29,232	2.59	1	1	3
10,000~100,000	38,856	3.28	1	1	4
100,000~200,000	7,226	3.42	1	1	5
200,000+	13,288	6.80	1	1	6
Gender					
Female	57,152	3.37	1	1	4
Male	116,571	3.08	1	1	4
Age					
18~34	102,293	2.89	1	1	3
35~55	44,364	2.78	1	1	3
55+	27,066	4.91	1	1	4
Profession					
Bank staff	10,690	14.80	1	5	43
Others	135,164	2.22	1	1	3
Financial instruments					
Internet banking user	25,983	7.41	1	2	22
Non-Internet banking user	119,871	2.21	1	1	3
POS user	19,252	6.20	1	2	16
Non-POS user	126,602	2.67	1	1	3
Cheque user	46,291	4.77	1	1	9
Non-cheque user	99,563	2.38	1	1	3

Table 3.6 Homophily in Money Transfer Network

Panel A.

	Age (%)			Balance (%)				
	18-34	35-55	55+	0-3000	3000-10000	10000-100000	100000-200000	200000+
Total	45.2	19.0	35.8	23.2	10.5	22.0	3.8	24.4
Age								
18-34	50.0	17.1	32.9	25.7	11.3	23.0	3.8	24.3
35-55	38.4	21.9	39.7	19.8	9.2	20	3.4	24.2
55+	38.5	21.4	40.1	19.0	9.8	21.5	4.4	25.2
Balance								
0-3,000	47.8	18.1	34.1	26.4	10.9	21.6	3.5	23
3,000-10,000	46.5	19.3	34.3	23.1	11.3	23.9	4.1	24.6
10,000-100,000	44.1	19.2	36.7	21.3	10.4	23.3	4.1	25.7
100,000-200,000	42.1	19.3	38.6	19.5	9.9	22.2	4.0	27.9
200,000+	39.9	21.2	38.8	17.3	9.1	20.9	4.2	31.3
Gender								
Female	44.0	19.0	37.0	20.8	10.4	23.1	4.1	24.1
Male	45.8	19.0	35.2	24.3	10.6	21.5	3.7	24.1
Profession								
Bank staff	57.8	20.7	21.5	26.9	14.5	27.9	5.6	16.5
Others	44.4	19.0	36.6	22.4	10.2	21.6	3.7	24.4

Panel B.

	Gender (%)		Profession (%)	
	Female	Male	Bank staff	Others
Total	42.7	57.3	38.9	61.1
Age				
18-34	41.1	58.9	40.8	59.2
35-55	45.4	54.6	33.5	66.5
55+	44.2	55.8	40.8	59.2
Balance				
0-3000	41.2	58.8	38.7	61.3
3000-10000	41.3	58.7	43.8	56.2
10000-100000	44.2	55.8	40.2	59.8
100000-200000	44.6	55.4	38.5	61.5
200000+	45.7	54.3	34.6	65.4
Gender				
Female	44.7	55.3	43.6	56.4
Male	41.7	58.3	36.6	63.4
Profession				
Bank staff	29	71	62.8	37.2
Others	43.5	56.5	36.1	63.9

Table 3.7 Runners with Different Characteristics

	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

Table 3.8 Centrality and the Proportion of Runners

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

Table 3.9 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 4.1 Peer Effect and Centrality

	(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 4.2 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 4.3 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 4.4 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 4.5 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 4.6 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 5.1 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 5.2 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 5.3 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 5.4 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 5.5 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 5.6 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 * $p<0.1$

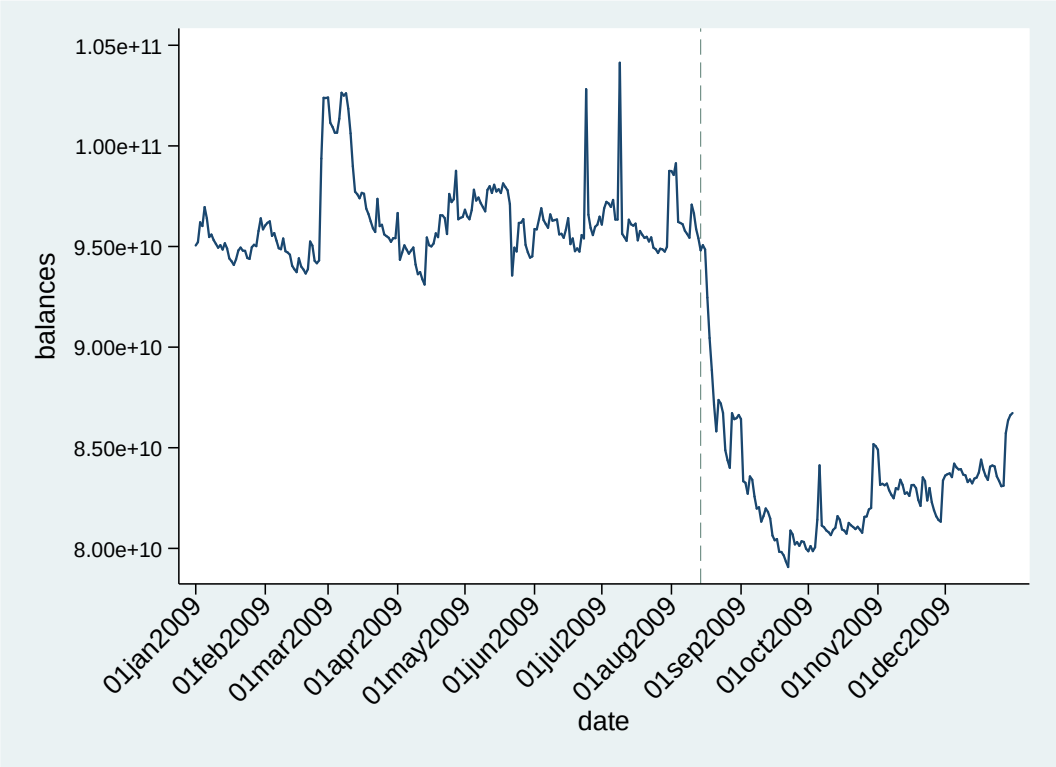
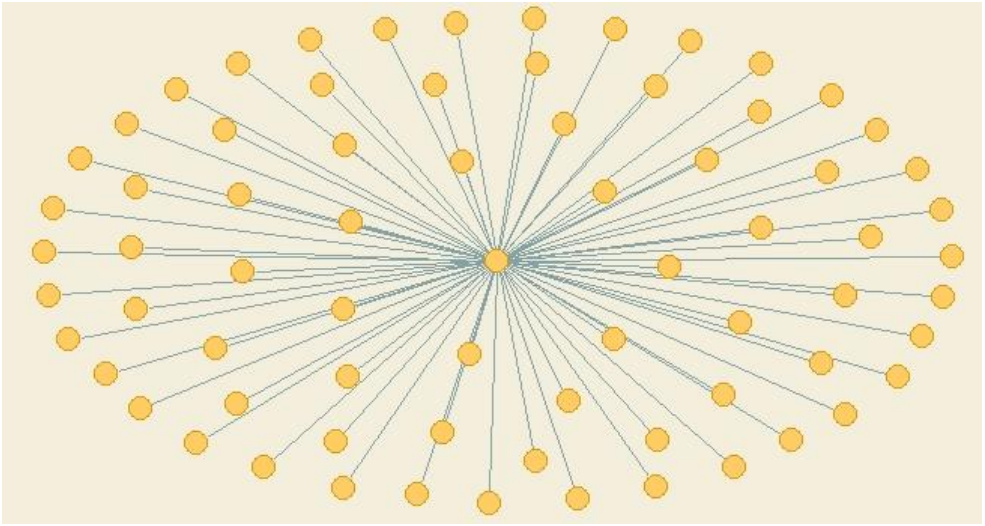
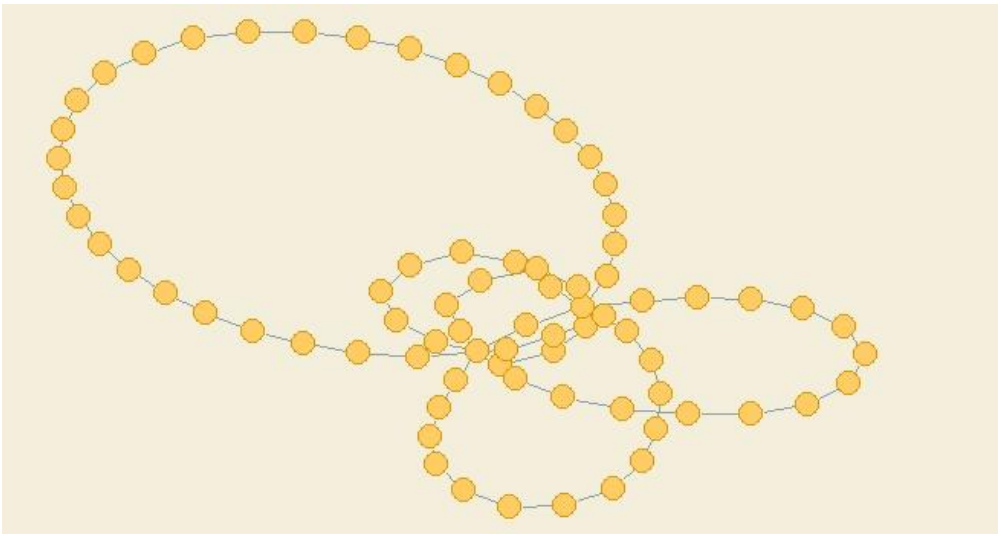


Figure 2.1 balances of savings account.



(a)



(b)

Figure 3.2 subnetworks of money transfer network



Figure 3.2 Shares of Cheque Users in Peers

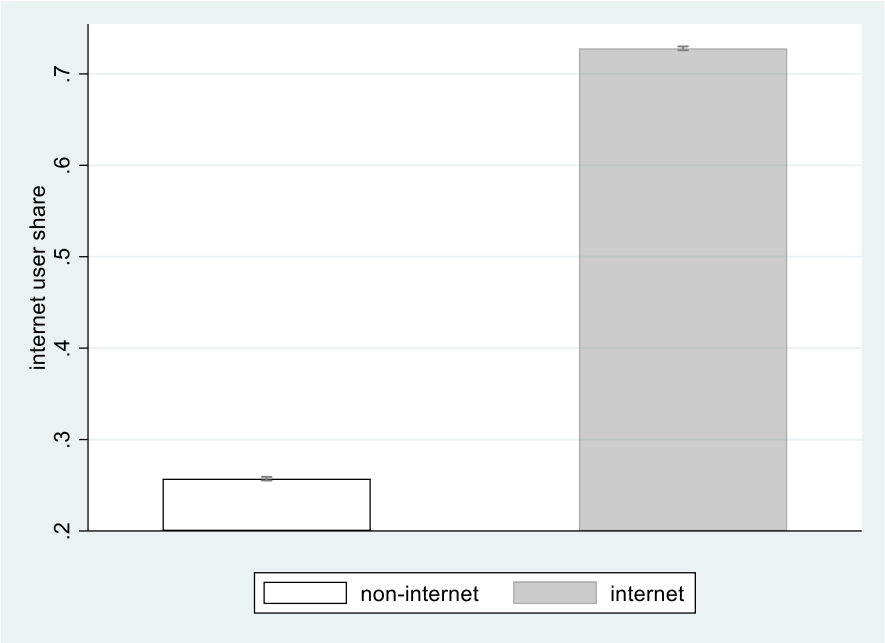


Figure 3.3 Shares of Internet Banking Users in Peers



Figure 3.4 Shares of POS Users in Peers

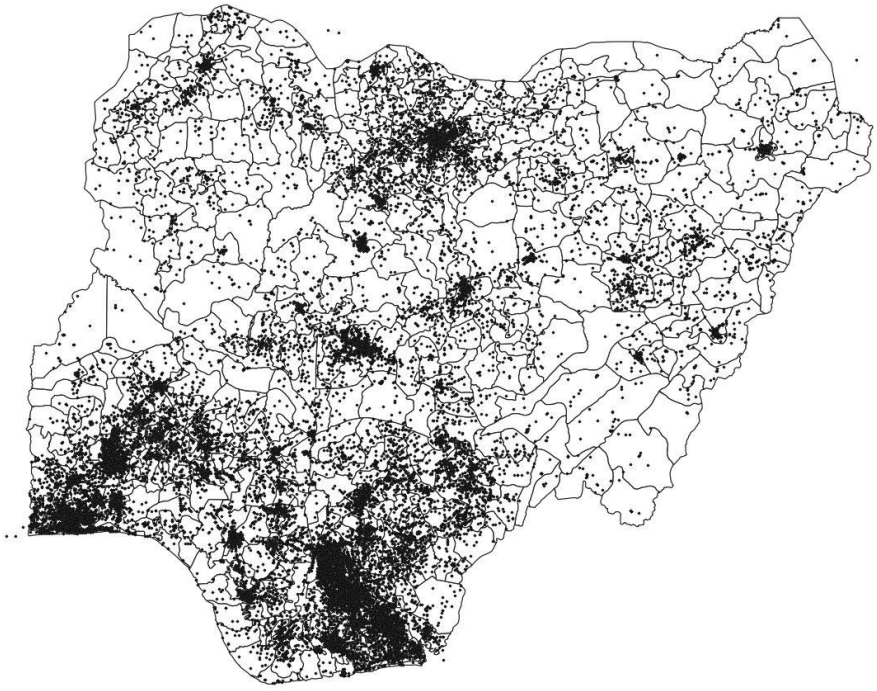


Figure 5.3 Depositors locations