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An Experiment on the Causes of Bank Run Contagions*

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Abstract

To understand the mechanisms behind bank run contagions, we conduct bank run experiments in a modified Diamond-Dybvig setup with two banks (Left and Right). The banks' liquidity levels are either linked or independent. Left Bank depositors see their bank's liquidity level before deciding. Right Bank depositors only see Left Bank withdrawals before deciding. We find that Left Bank depositors' actions significantly affect Right Bank depositors' behavior, even when liquidities are independent. Furthermore, a panic may be a one-way street: an increase in Left Bank withdrawals can cause a panic run on the Right Bank, but a decrease cannot calm markets.

Keywords: bank runs, contagion, experiment, multiple equilibria.
JEL classification numbers: C72, C92, D43

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1 Introduction

Bank runs are important economic phenomena. Over the last decade, while there was a quite visible and traditional bank run on Northern Rock, which was the first run on a UK bank in almost a century, there have been many more non-traditional runs on other financial institutions such as Bear Sterns, Lehman Brothers, as well as countries — Iceland and Greece being the most high-profile cases. The present paper seeks to understand how bank runs may spread from one economic agent to another (e.g., from Lehman Brothers to AIG; from Greece to Spain). In particular, we ask whether banking fundamentals cause contagions or whether pure panics are to blame.

Diamond and Dybvig (1983) proposed an influential analysis of bank runs.[1] In their paradigm, a bank run is one of many possible equilibria of the economic system. The driving force for a bank run is the fact that in a fractional reserve system, a bank does not hold enough liquid assets to serve all its customers, should they all decide to withdraw their deposits at one given time. Hence, if depositors believe too many people will withdraw their deposits such that in the future the bank will not have enough money to pay them, then depositors will all withdraw today. This causes a run on the bank, even if the bank is otherwise solvent. This is self-fulfilling because a bank must liquidate its investment portfolio at fire-sale prices in order to meet the unexpected demand today, which hurts its ability to pay tomorrow.

The same logic may apply to contagions. In this case, however, it is important to distinguish between cases where a run on a bank may convey information about the wider financial system; and a banking panic, which is unrelated to economic fundamentals. An example of the former case is the perceived over-exposure of banks to assets based on sub-prime mortgages. A run on an over-exposed bank could conceivably trigger a run on other banks, as it provides the market with a signal about the liquidation value of assets held by the banking sector. On the other hand, we may observe contagions that spread on the basis of pure panics. Friedman and Schwartz (1963) argue that the run on the Bank of the United States in 1930 was not based on fundamentals; yet the run on this bank nevertheless caused a panic on the US banking system, and runs on other US banks at the time.

It is difficult to distinguish information-based contagions from pure panics, since historical

[1] There are alternative models in which bank runs are caused by asymmetric information among bank depositors about banks' fundamentals. In these models, bank runs are caused by depositors' beliefs about solvency of their banks, rather than beliefs about the actions of other depositors. See for instance Chari and Jagannathan (1988); Jacklin and Bhattacharya (1988); Calomiris and Kahn (1991) and Chen (1999).

data does not afford us insight into the beliefs of investors and depositors alike. It is very difficult to ascertain what information investors are responding to, and whether or not the information is spurious. In December 11^{th} 1930, the New York Times reported that the run on the Bank of United States was based on a false rumor spread by a small merchant, a holder of stock in the bank, who claimed that the bank had refused to sell his stock (NYT, 1930). Was this information truthful? We will never know if depositors thought the rumor was true and were withdrawing because of the information; or if they thought the rumor was false, in which case they were anticipating a mass withdrawal by other depositors.

Our paper seeks to answer two questions. Firstly, can a contagion spread by panic alone? Secondly, are there differences in the way pure panic contagions form, develop and subside relative to information-based contagions? These questions are important, as policy designed to prevent and contain an information-based contagion may differ from policy designed to tackle a panic. Making public announcements about banking fundamentals may prove counter-productive, as the recent Northern Rock case highlights (Economist, 2007).[2]

We seek to answer these questions using experimental data. By abstracting away from the complex reality of financial markets, we gain an insight into how information about bank fundamentals, as well as spurious information, potentially can trigger bank run contagions in a simulated banking system. To this effect, we conduct an experiment in a modified Diamond-Dybvig setup with two banks (Left and Right). Each bank has a mix of impatient depositors, who demand their deposits immediately and patient depositors, who are willing to withdraw their deposits at a later date. The Left Bank depositors see their own bank's liquidity level and make their withdrawal decisions first. The Right Bank depositors do not know the liquidity level of either bank. They do see how many Left Bank withdrawals are made before making their own withdrawal decision.

We consider two treatments: one where both banks' liquidity levels are always the same, and another where they are independent of each other. In either treatment, it can be an equilibrium for the Right Bank depositors to imitate (or not) the decisions of the Left Bank depositors. However, we would expect information about Left Bank withdrawals to have a stronger influence on Right Bank

[2] In April 14th 1975, Credit Suisse announced it lost money in one of its branches, without clarification. In April 25th, the Swiss Central Bank announced it was prepared to lend money to Credit Suisse. This had the unintended effect of a drop in Credit Suisse's share price. For a theoretical analysis of the effect on the banking system of revealing information about fundamentals, see Kaplan (2006) and Dang et al. (2009).

depositors' decisions when both banks' liquidity levels are always the same. As such, information about past Right Bank fundamentals, as well as past actions by Right Bank depositors ought to be more relevant when liquidity levels of the two banks are independent of each other. In this sense, by studying the factors that determine a bank run contagion, we also better understand the processes that determine equilibrium selection in economic systems.

We find that the level of withdrawals by Left Bank depositors is negatively correlated with the liquidity level of their bank. That is, bank runs on the Left Bank are less likely to occur if the liquidation value of the Left Bank's assets is high. This is consistent with existing evidence on bank runs. In other words, there is a basic relationship between depositor behavior and the fundamental parameters of the banking system in the lab.

Turning to the issue of how bank runs spread and the mechanisms underlying contagions, we observe that the Right Bank depositors' expectations about their bank's liquidity level affect the likelihood of a run on the Right Bank, more so when bank liquidities are independent of each other. That is, in the absence of actual information about contemporaneous liquidity of their bank, patient Right Bank depositors look at past levels of liquidity (which in our experiment are good predictors of present liquidity) to inform their decision whether or not to withdraw early. This is particularly so in the treatment where the liquidity levels of the Left and Right Banks are independent of each other, and information about past liquidity levels is more salient.

However, actions taken by depositors in Left Bank also significantly affect Right Bank depositor behavior, especially when the two banks' liquidities are linked. This suggests that the Right Bank depositors use information about Left Bank depositors to update their beliefs about the liquidity of their bank. However, the fact that a similarly positive and significant (though weaker) relationship exists when liquidity levels of both banks are independent of each other means we cannot rule out the existence of contagion equilibria triggered by 'sunspots', or in our context, pure panic.

When analyzing the dynamics of bank run contagions, we find evidence which suggests a banking panic may be a one-way street: an increase in Left Bank withdrawals can cause a panic run on the Right Bank, but a decrease cannot calm markets as effectively. A fall in Right Bank liquidity levels between periods $t-2$ and $t-1$ leads to a rise in withdrawal levels by patient Right Bank depositors in period t in both treatments. However, the opposite effect is only statistically significant when liquidities are linked. In other words, changes in banking fundamentals can be effective in either triggering or quelling bank runs, particularly in the treatment where liquidity levels are independent. This is likely due to the fact that past liquidity levels are particularly salient information for depositors when the behavior of the other bank's depositors is not informative. Finally, we find some gender differences in behavior.

Our paper contributes to both the literature on bank runs, as well as the experimental literature on coordination games. In the former case, the empirical evidence on bank runs and possible contagion effects is scarce, since bank failures are infrequent, as governments and financial authorities are keen to prevent them from occurring. The strand of empirical literature focusing on the determinants of bank runs finds that the likelihood of a run on a bank during a crisis is positively correlated with the fundamentals of that bank (Calomiris and Mason, 1997; Schumacher, 2000; Martinez Peria and Schmukler, 2001). The failure of a large cooperative bank in India in 2001 has generated an interesting case study on the study of bank runs and contagion. Iyer and Puri (2012) study depositor behaviour on a bank that had been affected by that failure, and study the institutional determinants of a run on a bank. They find depositor insurance, as well as long-standing bank-depositor relationships can effectively mitigate the extent of a run. Iyer and Peydro (2011) study the impact that same failure had on the likelihood of a run on other local banks that had exposure as institutional depositors. They find that banks with high exposure to the failed bank had a higher likelihood of incurring large deposit withdrawals. Banks with weaker fundamentals are also more likely to suffer a run.

The experimental literature on bank runs is both small and very recent (see Dufwenberg, 2012 for a recent survey). We are only aware of three experimental studies on bank runs, all of which study cases with only one bank. Madies (2006) analyses the possibility and persistence of self-fulfilling bank runs. Schotter and Yorulmazer (2009) find when there is uncertainty about the rate of return on deposits, the presence of insiders (depositors who know the true rate of return) is welfare enhancing. Garratt and Keister (2008) find that uncertainty regarding the number of impatient depositors increases the likelihood of a bank run; increasing the number of withdrawal opportunities also results in a higher number of bank runs.

Our paper also contributes to the literature of coordination games with Pareto-ranked equilibria (see Camerer, 2003 and Devetag and Ortmann, 2006 for surveys of the evidence). Perhaps paradoxically, by employing a more complex setup, we are able to shed some light on how beliefs about a particular equilibrium being played are shaped, and how they depend on contextual information, as well as strategically relevant information.

The remainder of the paper is organized as follows. Section 2 outlines the experimental design and the theoretical predictions. Section 3 presents the empirical results. Section 4 considers implications of our results.

2 Theory and Experimental Design

In this section, we present a simplified version of the Diamond-Dybvig model, which forms the basis of our experimental design and hypothesis. We conclude the section by outlining the experimental procedures.

2.1 A Version of the Diamond-Dybvig Model

The Diamond-Dybvig (1983) model (DD) is the basis of our experimental design. In our version of this three-period model, depositors place their money in a bank in period 0 (yesterday) before learning whether they are impatient or patient.[3] In the former case, depositors need to withdraw their money in period 1 (today), as they get relatively very little utility for the money tomorrow. In the latter case, depositors can wait until period 2 (tomorrow) to withdraw; however, can always withdraw the money today and hold on to it until tomorrow. There is an equal proportion of patient and impatient depositors.

The bank has short-term and long-term investment opportunities for the money. The short-term investment (reserves) returns the exact amount invested. The long-term investment returns an amount $R > 1$ tomorrow. However, it is illiquid and returns only $L < 1$ today.

The depositors that invested X yesterday have a contract with the bank. They can withdraw their money today and receive X or wait until tomorrow and receive $R \cdot X$.[4] The bank needs to offer a contract contingent upon withdrawal time, since it does not know which depositors are patient and which are impatient, just the overall fraction. To fulfil this contract, the bank places half its deposits in the short-term investment and half its deposits in the long-term investment.

If all the depositors withdraw the money according to their respective types, then the bank will be able to meet both the demand for cash today and tomorrow. In this case, each depositor has the incentive to indeed withdraw according to his true type. An impatient depositor prefers X today to $R \cdot X$ tomorrow. A patient depositor prefers $R \cdot X$ tomorrow to X today. Hence, all

[3] Another way to interpret types is to assume an idiosyncratic shock to individual's liquidity needs.

[4] The original Diamond and Dybvig model also considers an insurance aspect to the bank, in the sense that a sufficiently risk averse depositor is insured against being impatient and receives more than X today and less $R \cdot X$ tomorrow. This is not the focus of our experiment.

impatient depositors withdrawing today and all patient depositors withdrawing tomorrow is a Nash equilibrium.

While the contract is fulfilled in this Nash equilibrium, in other cases the bank cannot always remain solvent, leading to another Nash equilibrium. If too many depositors try to withdraw today, the bank would not be able to meet the contract tomorrow. For instance, if a fraction $q > 1/2$ of depositors withdraw today, then the bank will have sell part of its long-term asset at the liquidation price. If $\frac{1}{2}L \leq q - \frac{1}{2}$, then even if the bank liquidates all of its assets, there will not be enough cash to pay current demand. Waiting until tomorrow will return nothing so even the patient depositors would prefer to withdraw today and receive something rather than wait until tomorrow and receive nothing. This is a bank run equilibrium where everyone withdraws today.[5]

2.2 Experimental Design

Our design expands the DD model by adding another bank, such that we have a Left Bank and a Right Bank. Each bank has ten depositors, five of whom are patient and the other five are impatient. A participant took the role of a depositor and stays with his assigned bank throughout the experiment. In each of the 30 rounds in the experiment, subjects had to make a single decision: to withdraw today or to withdraw tomorrow. In every round, the computer randomly assigned subjects to one of two types: patient (who are able to wait to withdraw tomorrow) and impatient (who strictly prefer to withdraw in today). While patient depositors had a less important role to play in the experiment, their existence created additional strategic uncertainty regarding impatient depositors' decisions.

A bank with strictly more than five depositors withdrawing today would face an excess demand for liquidity and had to sell its long-term investments and receive a rate of return of $L < 1$, while waiting until tomorrow yielded a rate of return $R > 1$ on assets.

We also extended the original model by allowing each bank to have two possible levels of L. That is, a bank could have high liquidity (i.e. $L = 0.8$), or it could have low liquidity (i.e. $L = 0.2$). Each bank's type was determined by a Markov process, where the transition probability was 1/3. This means there was a two-thirds probability that a bank would maintain its liquidity level in consecutive periods.

We implemented two distinct treatments. In the first treatment, Independent, the two

[5] There is also a symmetric mixed-strategy Nash equilibrium in which patient depositors withdraw early with some positive probability, p.

Payoffs to impatient depositors										
Low L	Total # of other customers withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	86	75	67	60
Withdraw Tomorrow	50	50	50	50	50	50	0	0	0	0
High L	Total # of other customers withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	100	100	100	90
Withdraw Tomorrow	50	50	50	50	50	50	47	42	31	0
Payoffs to patient depositors										
Low L	Total # of other depositors withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	86	75	67	60
Withdraw Tomorrow	125	125	125	125	125	125	0	0	0	0
High L	Total # of other depositors withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	100	100	100	90
Withdraw Tomorrow	125	125	125	125	125	125	117	104	78	0

Table 1: Payoffs

banks' liquidity levels followed independent Markov processes. In the second treatment, LINKED, the two banks' liquidity levels were always the same. In our design, we set $L = 0.2$ or $L = 0.8$ and $R = 1.25$. Table 4 displays payoffs in a manner similar to that presented to the subjects.[6]

In both treatments, Left Bank depositors knew their bank's liquidity level (L_{Left}) before making their withdrawal decision. Right Bank depositors could only observe the total number of withdrawals on the Left Bank in that round before deciding. They did not know what their bank's liquidity level (L_{Right}) was in that round. They did however, know what their bank liquidity level was in the previous round, except in the first round of the experiment.

[6]Our payoffs in case of excess demand in period 1 equal the expected payoffs rather than being based on a sequential service constraint. This was done to facilitate participants' understanding of the task; it also imposes risk neutrality. Note that the terms 'patient' and 'impatient' were replaced with 'type-A' and 'type-B'. Likewise, 'L' was called 'Reserves'. See Appendix for a copy of the instructions.

2.3 Hypotheses

We start by looking at the Left Bank depositors, who are playing a game similar to the DD model. As discussed in the previous sub-section, it is possible for multiple equilibria to exist. In some equilibria, patient depositors withdraw tomorrow, and a run on the bank does not occur; in other equilibria, patient depositors withdraw early, and a run on the bank takes place. The Nash equilibrium concept does not rule out any relationship between the liquidity level, L, and the likelihood of a run. Using an evolutionary dynamic process to study the DD model, Temzelides (1997) states that as banks become more illiquid, the likelihood of a run increases. As such, we should observe more runs when L is low, as opposed to when L is high, which forms our first hypothesis.

Hypothesis 1: *The frequency of early withdrawals by patient Left Bank depositors will be higher when its liquidity levels are low.*

We turn to the main hypotheses of the paper, which concern the way in which a contagion may spread. Again, standard theory is unable to guide our understanding of why one equilibrium is played over another. There are three potential mechanisms for the spread of contagion, each of whom relies on different assumptions about how individuals form beliefs about the liquidity of their own bank (we fix all other relevant parameters of the model, hence only L matters in determining the likelihood of a run), and individuals' beliefs about their counterparts' actions.

Firstly, a patient Right Bank depositor may believe other patient Right Bank depositors will withdraw early if they believe the Right Bank has low liquidity. Therefore, a run on the Right Bank may be triggered by depositors believing their bank has a low L. This belief could be formed by observing Left Bank depositors running on their bank.

Hypothesis 2: *The likelihood of an early withdrawal by patient Right Bank depositors will be correlated with the number of early withdrawals on the Left Bank, particularly in* LINKED.

Hypothesis 2 is tested by examining the correlation between behavior of patient Right Bank depositors with total number of withdrawals in Left Bank in both treatments. We test whether Right Bank depositor conveys information to Left Bank depositors by comparing the aforementioned correlation in the LINKED and INDEPENDENT treatments. If indeed the correlation between Left Bank depositors and patient Right Bank depositors is solely driven by information-based revision of beliefs, then we should observe a positive correlation in LINKED but not in INDEPENDENT. If we find a positive correlation in the latter case, this would be evidence supporting pure panic-based contagions.

The previous two hypotheses concerned how a bank run can spread from one bank to another contemporaneously. We can also look at how a run on a bank propagates over time? In our experiment, the level of liquidity of a given bank follows a Markov process, where the transition probability is 1/3. Furthermore, Right Bank depositors are told at the end of each round their bank's liquidity, L, in that round. As such, past levels of L can be informative about the current level of L, and therefore may affect the likelihood of a run in the current round. This leads to our next set of hypotheses.

Hypothesis 3: *The likelihood of an early withdrawal by patient Right Bank depositors will be correlated with the Right Bank's L in the previous period.*

Alternatively, a patient Right Bank depositor may believe other patient Right Bank depositors will withdraw early if there was a run on the Right Bank in the previous period, irrespective of the Right Bank's liquidity in the previous period (which is unknown in the present).

Hypothesis 4: *The likelihood of an early withdrawal by patient Right Bank depositors will be correlated with the total number of early withdrawals on the Right Bank in the previous period.*

Hypotheses 3 and 4 distinguish between two different inter-temporal mechanisms of propagation of runs. The former is based on fundamentals of the bank, namely its liquidity level. If indeed a bank run equilibrium is more likely when liquidity is low, then observing low liquidity in the previous period indicates a 2/3 chance of the same occurring. The latter concerns a panic mechanism of propagation: a run now triggers a run in the future, even though the fundamentals of the bank may since have changed. To understand which of the two is at work, we need to estimate the likelihood of an early withdrawal as a function of the level of past liquidity of the bank, as well as the number of past withdrawals on the same bank in the previous period. If only the former is a significant predictor of behavior, then only fundamentals drive the persistence of a bank run; if the latter is also a significant predictor of current depositor behavior, then we have evidence for the existence of panic propagation mechanisms.

We conclude our analysis by looking at how banking contagions can spread over time. In particular, we wish to understand how changes the number of withdrawals in one bank (i.e. the start or the end of a run in that bank) affect the change in the likelihood of a run in another bank. In other words, we wish to understand how dynamics of banking contagions operate.

Hypothesis 5: *An increase in the number of withdrawals in the Left Bank will have a stronger positive effect on the likelihood of early withdrawals by patient Right Bank depositors than the negative effect on that likelihood from a decrease in the number of withdrawals in the Left Bank.*

Hypothesis 5 asks if it is easier to trigger a bank run contagion than it is to end it. In other words, are bank run contagions subject to asymmetric hysteresis effects? It also seeks to distinguish the source of this potential asymmetry. If depositor behavior is solely driven by beliefs about liquidity, then we should not observe any asymmetry: contagions should be as easy to start as to stop, since changes in depositor behavior in the Left Bank should be mirrored by patient depositors in the Right Bank. However, if beliefs which are unrelated to banking fundamentals are driving the spread of runs over time, then one would expect the spread of a panic to be stronger than its quelling.

2.4 Experimental Procedures

We provided written instruction sets (see Appendix), which informed subjects of all the features of the market. We generated six independent sessions for each treatment (Independent and Linked). Each session had 20 participants, who interacted with each other for the duration of the experiment. There were 30 rounds in the experiment. At the beginning of the experiment, each participant was assigned to a bank (Left or Right), and remained a customer of that bank for the whole experiment. In each round, each participant was randomly assigned a customer type, A or B (corresponding to patient or impatient depositor), for his bank.

Participants sat at a booth which did not allow visual or verbal communication and interacted via a computer terminal. At the end of each round, participants were reminded about their own decision, and were told what the level of reserves their bank had that period (which is L in our model), as well as how many withdrawals were made either today or tomorrow at their bank.

The participant's payment was a the sum of their payoffs from three rounds randomly picked by the computer. This was done to avoid income effects. At the end of the experiment, participants filled in a socio-demographic questionnaire before being paid and leaving the lab. Each session lasted on average 90 minutes. A total of 240 undergraduate students from a variety of backgrounds participated in our experiments. No one participated in more than one session and no

	LINKED		INDEPENDENT	
	Left Bank	Right Bank	Left Bank	Right Bank
$L = 0.2$	0.71	0.62	0.73	0.55
$L = 0.8$	0.12	0.26	0.17	0.45

Table 2: Fraction of early withdrawals by Patient Depositors.

one had participated in similar experiments before. The sessions took place in March and October 2011. The average payment was £13.15 ($20.66).[7]

3 Experimental Results

We begin by analyzing the effect of bank liquidity on the fraction of depositors who withdraw early. Impatient depositors, as predicted, almost always withdrew early, regardless of the level of liquidity of their bank.[8] Patient depositors were much more responsive to liquidity levels. Table 2 reports the fraction of early withdrawals conditional on the liquidity level of their banks. The first observation is that there are significantly many more early withdrawals by Left Bank depositors when $L = 0.2$ than when $L = 0.8$, regardless of the treatment condition (LINKED: $p = 0.03$; INDEPENDENT: $p = 0.03$, both comparisons with Wilcoxon signed-rank test (WSR) for paired samples). In fact, we find no difference in the withdrawal behavior of Left Bank depositors in either treatment ($L = 0.2$: $p = 0.69$; $L = 0.8$: $p = 0.38$, Mann-Whitney test (MW) for independent samples). Note that these depositors knew their bank's liquidity levels before deciding. This is our first result.

Result 1: *Patient Left Bank depositors run more often when their bank's liquidity levels are low.*

We find the same pattern in patient Right Bank depositors, although to a lesser extent. The difference in fraction of early withdrawals is only significantly different from zero in the LINKED treatment (LINKED: $p = 0.03$; INDEPENDENT: $p = 0.21$, WSR). The fact that we observe a similar, though weaker pattern of behavior by the Right Bank depositors, when those depositors could not observe their own bank's liquidity level suggests that they may be relying on the behavior of the

[7]The software was programmed in Z-Tree (Fischbacher, 2007) and we used the recruitment software ORSEE (Greiner, 2004).

[8]The frequency of early withdrawals for impatient Left Bank depositors was 99% when liquidity levels were low and 98% when liquidity levels were high. The frequencies of early withdrawals by Right Bank impatient depositors was 96% for both liquidity levels.

Total Left Bank withdrawals	0 - 3	4	5	6	7	8	9	10
LINKED	-	0.27	0.23	0.31	0.45	0.61	0.65	0.68
N	-	3	50	27	21	27	35	17
INDEPENDENT	-	0.20	0.34	0.45	0.57	0.56	0.45	0.71
N	-	1	36	33	29	27	26	28

Table 3: Fraction of withdrawals by Patient Right Bank depositors as a function of total Left Bank withdrawals – all periods.

Left Bank depositors to inform their own choices. As one would expect, this is stronger in the LINKED treatment rather than the INDEPENDENT treatment.

Given that Right Bank depositors know the total number of early withdrawals on the Left Bank before they make their decision, it is pertinent to calculate the fraction of early withdrawals by Patient Right Bank depositors conditional on the total number of early withdrawals by Left Bank depositors. Table 3 summarizes this information. There is a positive (almost monotonic) relationship in both treatments between total withdrawals by Left Bank depositors and the fraction of Patient Right Bank depositors who decide to withdraw early. In the LINKED treatment, the Spearman's rho is 0.64 ($p < 0.01$), while in the INDEPENDENT treatment, the Spearman's rho is 0.43 ($p < 0.01$).

We have now established that the past level of liquidity of the Right Bank, as well as information about the behavior of the Left Bank's depositors are correlated with the Right Bank depositors' decisions. It is therefore important to understand each relationship, while statistically controlling for the effect of the other. Table 4 reports results of random effects probit regressions using the withdrawing decision by Patient Right Bank depositors as the dependent variable. The regressors are the total number of withdrawals on the Right Bank in the previous period, the liquidity level of the Right Bank in the previous period, and the total withdrawals on the Left Bank. The regressions in Table 4 report on data from each treatment individually. We conducted a separate regression, which pooled all the data and used treatment interaction dummies to test for treatment differences (see Table 7 in Appendix C for details).

We start by looking at the effect of withdrawals by Left Bank depositors on patient Right Bank depositor behavior. We find a positive and significant coefficient on *Total Withdrawals Left Bank*$_t$ in both treatments. The larger coefficient is, as expected, in the LINKED treatment, and it is significantly larger than in the INDEPENDENT treatment.[9] This is our second result.

Result 2: *Patient Right Bank depositors are more likely to withdraw early, the higher the total number of early withdrawals by Left Bank depositors. This result is stronger in the* LINKED *treatment.*

This lends support to both hypothesis 2 and 2′, in that left bank depositor behavior influences the Right Bank depositors, particularly when it conveys information which can be used to update beliefs about fundamentals. However, the fact that this relationship is significant in the INDEPENDENT treatment means we cannot rule out 'sunspots' as potential causes of bank run contagions.

We now turn to the effect of past liquidity levels in the Right Bank on current depositor behavior. In both LINKED and INDEPENDENT treatments, we see a negative and significant effect of the Right Bank's liquidity level in the previous period on the level of withdrawals in the current period. The coefficient is larger in absolute value in the INDEPENDENT treatment, and that difference is statistically significant.[10] In other words, patient Right Bank depositors are more influenced by past liquidity conditions in their own bank in INDEPENDENT than in LINKED.

Result 3: *Patient Right Bank depositors are more likely to withdraw early if the liquidity level of their own bank in the previous period was low. This effect is significantly stronger in the* INDEPENDENT *treatment.*

We finalize this analysis by looking at the effect of persistence of bank runs. Will patient Right bank depositors be more likely to withdraw early if total early withdrawals on the Right Bank in the previous period were high? We find no correlation between past withdrawal levels and current withdrawal decision in the LINKED treatment, but a positive weakly significant correlation in the INDEPENDENT treatment. The difference between correlations across treatments is not significant.[11]

Result 4: *Patient Right Bank depositors in the* INDEPENDENT *treatment are more likely to withdraw, the higher the total number of withdrawals on their bank was in the previous period. This is not the case in the* LINKED *treatment.*

[9] Appendix C, Table 7: Total Withdrawals Left Bank$_t$ × LINKED $= 0.12, p < 0.001$.

[10] Appendix C, Table 7: Right Bank $L_{t-1} = -0.681, p < 0.001$; Right Bank L_{t-1} × LINKED $= 0.380, p = 0.009$.

[11] Appendix C, Table 7: Total Withdrawals Right Bank$_{t-1}$ × LINKED $= -0.053, p = 0.334$.

DV: Patient Right Bank Withdrawal$_t$	Linked	Independent
Total Withdrawals Left Bank$_t$	0.275***	0.120***
	(0.029)	(0.028)
Right Bank L$_{t-1}$	-0.302***	-0.681***
	(0.112)	(0.094)
Total Withdrawals Right Bank$_{t-1}$	0.007	0.062*
	(0.042)	(0.037)
Round	0.009	0.027***
	(0.006)	(0.006)
Groups; Observations	6; 870	6; 870

***,** ,*: significance at 1%, 5%, 10% level, respectively.

Table 4: Marginal effects from random effects probit regression on the determinants of patient Right Bank depositors' withdrawals.

We now focus on how Right Bank depositors react to changes in market conditions, In particular, we now analyze how changes in early withdrawals by patient Right Bank depositors are affected by changes in the number of early withdrawals from the previous period to the current period in the Left Bank, as well as changes in the liquidity of the Right Bank from two periods ago to the previous period. To do so, we report a series of random effects least square regressions. The dependent variable is the change in the proportion of early withdrawals by patient Right Bank Depositors. We used aggregated data as opposed to individual-level data because subjects were randomly assigned a role (patient or impatient) in every period. As such, half of the time subjects who were patient depositors in one period were impatient depositors in the following period.

We consider two econometric specifications, which we describe in turn. The first has as regressors the change in total withdrawals by Left Bank depositors, in addition to dummies for positive and negative changes in the Right Bank's liquidity in the previous period ($\Delta L > 0$, $\Delta L < 0$), a dummy for no change in L when L was already high ($\Delta L = 0$ (high)), as well as a time trend (*Round*). We conduct a separate regression for each treatment, whose results are presented in Table 5.[12] The coefficient on (Δ Total Withd Left) is positive and highly significant for both Independent and Linked. An increase in the number of early withdrawals in the Left Bank

[12]To estimate treatment effects, we conduct an additional regression on pooled data with a treatment dummy plus interaction dummies with each variable. See Table 8 in Appendix C.

Dep var: Δ Patient Withd Right	(Cor 1)	(Ind 1)	(Cor 2)	(Ind 2)
Δ Total Withd Left	1.029***	0.592***		
	(0.121)	(0.109)		
Δ Total Withd Left > 0			0.189***	0.154***
			(0.055)	(0.055)
Δ Total Withd Left < 0			-0.169***	-0.051
			(0.058)	(0.055)
$\Delta L = 0$ (high)	0.014	-0.052	0.091	-0.058
	(0.056)	(0.054)	(0.059)	(0.056)
$\Delta L > 0$	-0.168***	-0.238***	-0.065	-0.229***
	(0.065)	(0.060)	(0.069)	(0.062)
$\Delta L < 0$	0.069	0.246***	0.077	0.248***
	(0.063)	(0.060)	(0.069)	(0.062)
Round	0.001	-0.002	0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.0003	0.052	-0.058	0.012
	(0.059)	(0.057)	(0.071)	(0.070)
Groups, Observations	6, 168	6, 168	6, 168	6, 168
R^2	0.36	0.34	0.24	0.29

***,**,*: significance at 1%, 5%, 10% level, respectively.

Table 5: Random effects least squares estimation of changes in early withdrawals.

leads to an increase in early withdrawals in the Right Bank, although the effect is significantly higher in LINKED than INDEPENDENT.[13] The coefficient on $\Delta L = 0$ (high) is non-significant in both treatments, suggesting no difference relative to the default category ($\Delta L = 0$ (low)). The coefficient on $\Delta L > 0$ is negative and highly significant, which means an increase in liquidity levels is correlated with a decrease in the number of patient Right Bank withdrawals; there is no difference in effect size between treatments.[14] On the other hand, the coefficient on $\Delta L < 0$ is positive in both treatments, but significantly different than zero only for the INDEPENDENT treatment. Furthermore the difference in coefficients between the two conditions is significant.[15] In other words, the effect of a drop in Right Bank liquidity on Right Bank withdrawals is only significant in the INDEPENDENT treatment. Finally, we do not observe any time trend effect on either treatment.

The second econometric specification considers the sign of changes in the number of withdrawals in the Left Bank, rather than the size of the effect. The new specification includes Δ Total Withd Left > 0 and Δ Total Withd Left < 0, which are dummy variables for increases and decreases in total withdrawals in the Left Bank, respectively. The omitted category is no change in withdrawals. We find positive and significant coefficients in Δ Total Withd Left > 0 in both treatments, with no statistical difference between the two.[16] We find negative coefficients in Δ Total Withd Left < 0 in both treatments, though only significant in the LINKED treatment. An increase in L leads to a decrease in withdrawals by patient Right Bank depositors, though only significantly so in the INDEPENDENT treatment. Likewise a decrease in L leads to an increase in withdrawals by patient Right Bank depositors, though again only significantly so in the INDEPENDENT treatment. We do not observe any time trend effect. We summarize the findings from this analysis below.

Result 5a: *A rise in total Left Bank withdrawals leads to an increase in withdrawals by patient Right Bank depositors. However, there is no significant change when there is a drop in total Left Bank withdrawals in* INDEPENDENT.

Result 5b: *A rise (fall) in Right Bank liquidity levels between periods $t-2$ and $t-1$ leads to a fall (rise) in withdrawal levels by patient Right Bank depositors in period t, particularly in the* INDEPENDENT *treatment. We find weak evidence of the first effect in the* LINKED *treatment.*

[13] Appendix C, Table 8, Regression (Agg1): Δ Total Withd Left $\times$ LINKED $= 0.45, p = 0.005$.
[14] Appendix C, Table 8, Regression (Agg1): $\Delta L > 0 \times$ LINKED $= 0.069, p = 0.433$.
[15] Appendix C, Table 8, Regression (Agg1): $\Delta L < 0 \times$ LINKED $= -0.177, p = 0.041$.
[16] Appendix C, Table 8, Regression (Agg2): Δ Total Withd Left $> 0 \times$ LINKED $= 0.036, p = 0.649$.

3.1 Individual-level Effects

We finalize the data analysis by exploring the explanatory power of individual-level heterogeneity in our subject pool. While there is little variation in income and age in our sample, there are two characteristics which are worthy of attention: gender and academic background. There is a large and growing literature examining the differences in preferences between men and women (see Croson and Gneezy, 2009 for a review). This literature finds that women are more risk-averse than men, and women's preferences are more sensitive than men's to contextual cues. It is therefore interesting to understand how gender differences play out in the context of bank runs and banking contagions. We also wish to explore how different academic backgrounds can affect individual decisions. Some experimental evidence has sought to explore differences in preferences between economics students and non-economics students (Marwell and Ames, 1981; Carter and Irons, 1991). Are economists (or business majors) more prone to panics than non-business-oriented students?

We extend the analysis of Table 4, by adding a dummy for men (*Male*), as well as a dummy for Business School students, majoring in Economics, Accounting, Finance or Management (*Business*). Table 9 presents the results of the new estimations. We find systematic gender differences, depending on the treatment. In the LINKED treatment, men are significantly more responsive to withdrawal levels in the Left Bank, while marginally significantly less responsive than women to Left bank withdrawals in the INDEPENDENT treatment. They are marginally less responsive than women to past liquidity levels in their own bank in the INDEPENDENT treatment, though no different than women in LINKED. We find no gender differences with respect to the effect of past Right Bank withdrawals. When we compared the behavior of business school students to that of other undergraduates, we found almost no differences, except Total Withdrawals in the Right Bank in previous period. We summarize our finding as follows.

Result 6: *Men are more responsive to total withdrawals made in the Left Bank than women in the* LINKED *treatment; and less responsive to the same information in the* INDEPENDENT *treatment. Men are also significantly less sensitive than women to the Right Bank's previous liquidity level, but only so in the* INDEPENDENT *treatment.*

DV: Patient Right Bank Withdrawal$_t$	Linked		Independent	
Total Withdrawals Left Bank$_t$	0.183***	(0.043)	0.155***	(0.042)
Right Bank L$_{t-1}$	-0.237	(0.167)	-0.777***	(0.139)
Total Withdrawals Right Bank$_{t-1}$	-0.065	(0.062)	0.022	(0.052)
Male	-1.338	(0.852)	-0.414	(0.681)
Business	-1.033	(0.842)	-0.388	(0.742)
Male × Total Withdrawals Left Bank$_t$	0.213***	(0.056)	-0.101*	(0.055)
Male × Right Bank L$_{t-1}$	-0.161	(0.227)	0.344*	(0.189)
Male × Total Withdrawals Right Bank$_{t-1}$	0.020	(0.079)	0.060	(0.066)
Business × Total Withdrawals Left Bank$_t$	0.007	(0.057)	0.058	(0.061)
Business × Right Bank L$_{t-1}$	-0.048	(0.228)	-0.190	(0.209)
Business × Total Withdrawals Right Bank$_{t-1}$	0.160**	(0.076)	0.055	(0.070)
Period	0.011*	(0.006)	0.026	(0.006)
Groups; Observations	6; 870		6; 870	

***,**,*: significance at 1%, 5%, 10% level, respectively.

Table 6: Marginal effects from random effects probit regression on the determinants of patient Right Bank depositors' withdrawals – individual effects.

4 Discussion

The theoretical literature on bank runs distinguishes two main causes for bank runs, and banking contagions. They can be caused by one or more institutions being insolvent, or due to insufficient short-term liquidity. From an empirical point of view, the former is easier to detect, as evidence will be present in the balance sheets of the financial institutions that suffered the run. The latter is more difficult to detect, as it is driven by beliefs about the bank's short-term liquidity, as well as beliefs about the behavior of other depositors.

Experiments are useful methods to research the causes of bank runs and banking contagions. Experimental evidence complements empirical data on bank runs on several dimensions. Real bank runs are rare, and even when they do occur, it is not possible to gauge depositors' beliefs about banking fundamentals. We tackle this question by simplifying the problem faced by real depositors to its core: a coordination problem among depositors. In this environment, the role of depositor beliefs (both about fundamentals and about what other depositors will do) is crucial in determining which action depositors take, and in turn which equilibrium is selected.

We find evidence that banking fundamentals, in our case short-term liquidity, are strongly correlated not only with the likelihood of a run on a bank, but also with the likelihood of contagion spreading to a separate bank. We identify three mechanisms through which short-term liquidity affects runs.

The first is the contemporaneous effect of liquidity under perfect information. When liquidity levels are known, there is a clear relationship between liquidity and the likelihood of a run. While the no-run equilibrium is Pareto-superior to the run-equilibrium, irrespective of liquidity levels, its riskiness increases when the bank's liquidity is low. In the former case, if one patient depositor withdraws early, all depositors who withdraw later will receive zero payoff. When the bank's liquidity level is high, it is possible for some patient depositors to withdraw early and for there to be enough funds to serve depositors to withdraw late. This indicates the importance of off-equilibrium payoffs in determining the likelihood of players picking a particular equilibrium. Higher liquidity levels mean higher payoffs for players selecting an out-of-equilibrium action (e.g. withdrawing late when the best-response should be withdrawing early).

The second and third mechanisms concern the formation of beliefs about liquidity when that information is not known. The second mechanism is the bank's previous level of liquidity. The fact that banks' liquidity levels follow a Markov process means that when current liquidity is unknown, one can infer it from the immediate past level of liquidity. This indicates a way in which bank runs can persist over time in a given bank. If depositors anchor their beliefs about current liquidity on past liquidity, a bank could potentially persist over time even when fundamentals no longer support the existence of such an equilibrium, as per the first mechanism.

The third mechanism concerns the updating of beliefs about one's bank based on the behavior of depositors in another bank. We manipulate the information structure of depositors in one bank, we can understand the extent to which a run on a bank can provide useful information to depositors in another bank. If depositors believe that under perfect information bank runs are more likely when liquidity levels are low, a run by informed depositors in one bank may trigger a run by uninformed depositors in another bank, as long as it is common knowledge that both banks have the same liquidity. This is an information-based contagion: a run on one bank is a signal which leads depositors in other banks to revise their beliefs about fundamentals in their own institution thus causing a run on another bank.

We also find evidence that banking contagions can be caused by panic. This is demonstrated by observing the effect a run on one bank has on the likelihood of depositors of another bank running when both banks' liquidities are independent of each other. In this case, the behavior of depositors in the first bank is a meaningless signal and should be ignored. However, we find evidence suggesting contagions may be triggered in this manner. This is a panic-based contagion: depositors in the second bank erroneously taking into account spurious information and trigger a run on their institution.

Distinguishing between these two types of contagions matters because they display different dynamics. When bank liquidities are linked, the level of withdrawals in the Left Bank acts as a coordination device for Right Bank depositors. As such, bank runs on the latter bank are as easy to start as to stop. However, panic based runs are less difficult to stop when started. In the absence of a reliable signal, depositors may not be able to coordinate on the no-run equilibrium and as such panic-based runs may be more persistent than information-based ones.

This suggests there is value not only in reinforcing banking inter-linkages for their value in spreading risk and mitigating contagion (Allen and Gale, 2000), but also in making those linkages common knowledge. This is because avoiding the spread of contagion can then be achieved by focusing on its origin, as opposed to panic-based contagions, which may require action throughout the financial system in order to be quelled.

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Appendix A: Instructions

Note: The instructions presented to Left and Right Bank depositors in both treatments had a common section, which explained the game, and a role and treatment-specific section. To economize on space, we will divide the common and specific sections in separate sub-sections.

Common Part

Experimental Instructions

Welcome to the experiment. Please read these instructions carefully. Through your decisions and the decisions of others, you may stand to gain a significant amount of money.

In this experiment, your decisions will earn you payoffs. These payoffs are denominated in Experimental Currency Units (ECU). 100 ECU are worth £5.00. At the end of the experiment, we will calculate your payoff in ECU and convert it into pounds and pay it in cash.

In this experiment, there are two banks: Left Bank and Right Bank. Each bank serves 10 customers. In the experiment you will be a customer of one of the banks. You will be told in the following sheet what is your bank. You will always be a customer of the same bank throughout the experiment.

You have a savings account with your bank worth 100 ECU. You may decide to withdraw your money today or you may decide to wait until tomorrow. The bank may or may not have enough money to be able to pay you, depending on how many of the other customers decide to withdraw their money today.

Some customers will prefer to withdraw today; those customers are type-A customers. Other customers will prefer to withdraw tomorrow; those customers are type-B customers.

Your type will be allocated to you at random and will change from round to round. You will see your type on screen before you make your choice.

Regardless of what type of customer you are, your bank will always serve 5 type-A and 5 type-B customers.

Provided it has enough money, the bank will pay you according to the following table.

		Withdrawal date	
		Today	Tomorrow
Customer Type	Type-A	100	50
	Type-B	100	125

While the bank anticipates that five customers will prefer to withdraw today, it will only have enough cash for a limited number of early withdrawals.

If the number of customers wishing to withdraw their cash today is greater than five, then payoffs will depend upon the banks reserves. Bank reserves can be high or low.

The following tables display the payoffs to type-A and type-B customers depending on their banks reserves, whether they withdraw today or tomorrow, and what other customers do.

Payoffs to Type-A Customer										
Low Reserves	Total # of other customers withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	86	75	67	60
Withdraw Tomorrow	50	50	50	50	50	50	0	0	0	0
High Reserves	Total # of other customers withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	100	100	100	90
Withdraw Tomorrow	50	50	50	50	50	50	47	42	31	0

Payoffs to Type-B Customer										
Low Reserves	Total # of other depositors withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	86	75	67	60
Withdraw Tomorrow	125	125	125	125	125	125	0	0	0	0
High Reserves	Total # of other depositors withdrawing today									
	0	1	2	3	4	5	6	7	8	9
Withdraw Today	100	100	100	100	100	100	100	100	100	90
Withdraw Tomorrow	125	125	125	125	125	125	117	104	78	0

To clarify ideas, consider the following examples.

Example 1:

- Your bank has low reserves.
- You are a type-A customer and you decide to withdraw today;
- 4 other customers wish to withdraw today and the remaining 5 wish to withdraw tomorrow.

- Your payoff is 100 ECU.
- Had you withdrawn tomorrow, your payoff would have been 50 ECU.

Example 2:

- Your bank has high reserves.
- You are a type-B customer and you decide to withdraw tomorrow
- 6 other customers wish to withdraw today and 3 others wish to withdraw tomorrow.
- Your payoff is 117 ECU.
- Had you withdrawn today, your payoff would have been 100 ECU.

Example 3:

- Your bank has low reserves.
- You are a type-B customer and you decide to withdraw tomorrow; 8 other customers wish to withdraw today and the 1 other customer withdraws tomorrow.
- Your payoff is 0 ECU.
- Had you withdrawn today, your payoff would have been 67 ECU.

Example 4:

- Your bank has high reserves.
- You are a type-A customer and you decide to withdraw tomorrow
- All other customers wish to withdraw today.
- Your payoff is 0 ECU.
- Had you withdrawn today, your payoff would have been 90 ECU.

Contagion – Left Bank

Each bank will have a different set of ten customers (5 type-A and 5 type-B), but the same level of reserves.

You are a customer of the Left Bank. In every period, the computer will randomly determine whether you are a type-A or a type-B customer. It will also determine the level of reserves of both banks (high or low).

The probability of the banks having high or low reserves will depend on what type of reserves the banks had in the previous period. The banks will maintain the same level of reserves as last period with probability of 2/3 and switch reserve levels with probability 1/3.

For example, if in period 1 the banks had high reserves, then there is a 2-in-3 chance that it will have also high reserves in period 2 (and a 1-in-3 chance that it will change to low reserves in period 2).

You will know what reserve levels your bank has before you make your withdrawal decision.

Customers of the Left Bank will make their withdrawal decisions before customers of the Right Bank. Before making their decisions, customers of the Right Bank observe how many Left Bank customers chose to withdraw today and how many chose to withdraw tomorrow. However, they will not know the level of reserves of Left Bank, nor the payoffs to Left Bank customers.

Once all Left Bank and Right Bank customers make their decisions, the payoffs for the period will be displayed on your screen.

There will be 30 periods in this experiment. Your payoff will be the sum of 3 randomly determined periods.

Contagion – Right Bank

Each bank will have a different set of ten customers (5 type-A and 5 type-B), but the same level of reserves.

You are a customer of the Right Bank. In every period, the computer will randomly determine whether you are a type-A or a type-B customer. It will also determine the level of reserves of both banks (high or low).

The probability of the banks having high or low reserves will depend on what type of reserves the banks had in the previous period. The banks will maintain the same level of reserves as last period with probability of 2/3 and switch reserve levels with probability 1/3.

For example, if in period 1 the banks had high reserves, then there is a 2-in-3 chance that it will have also high reserves in period 2 (and a 1-in-3 chance that it will change to low reserves in period 2).

You will know what reserve levels your bank has only after you make your withdrawal decision.

However, customers of the Left Bank will make their withdrawal decisions before customers of the Right Bank.

Also, Left Bank customers know the level of reserves of the Left Bank before making their withdrawal decisions.

Before making their decisions, customers of the Right Bank observe how many Left Bank customers chose to withdraw today and how many chose to withdraw tomorrow. However, they will not know the level of reserves of Left Bank, nor the payoffs to Left Bank customers.

Once all Left Bank and Right Bank customers make their decisions, the payoffs for the period will be displayed on your screen.

There will be 30 periods in this experiment. Your payoff will be the sum of 3 periods, which will be randomly determined.

Independent – Left Bank

Each bank will have a different set of ten customers (5 type-A and 5 type-B), as well as its own independent level of reserves.

You are a customer of the Left Bank. In every period, the computer will randomly determine whether you are a type-A or a type-B customer. It will also determine the level of reserves of your bank (high or low).

The probability of a bank having high or low reserves will depend on what type of reserves the bank had in the previous period. The bank will maintain the same level of reserves as last period with probability of 2/3 and switch reserve levels with probability 1/3.

For example, if in period 1 the bank had high reserves, then there is a 2-in-3 chance that it will have also high reserves in period 2 (and a 1-in-3 chance that it will change to low reserves in period 2).

You will know what reserve levels your bank has before you make your withdrawal decision.

Customers of the Left Bank will make their withdrawal decisions before customers of the Right Bank. Before making their decisions, customers of the Right Bank observe how many Left Bank customers chose to withdraw today and how many chose to withdraw tomorrow. However, they will not know the level of reserves of Left Bank, nor the payoffs to Left Bank customers.

Likewise, Right Bank customers will not know the level of reserves of Right Bank, nor the payoffs to Right Bank customers.

Once all Left Bank and Right Bank customers make their decisions, the payoffs for the period will be displayed on your screen.

There will be 30 periods in this experiment. Your payoff will be the sum of 3 randomly determined periods.

Independent – Right Bank

Each bank will have a different set of ten customers (5 type-A and 5 type-B), as well as its own independent level of reserves.

You are a customer of the Right Bank. In every period, the computer will randomly determine whether you are a type-A or a type-B customer. It will also determine the level of reserves of your bank (high or low).

The probability of a bank having high or low reserves will depend on what type of reserves the bank had in the previous period. The bank will maintain the same level of reserves as last period with probability of 2/3 and switch reserve levels with probability 1/3.

For example, if in period 1 the bank had high reserves, then there is a 2-in-3 chance that it will have also high reserves in period 2 (and a 1-in-3 chance that it will change to low reserves in period 2).

You will know what reserve levels your bank has only after you make your withdrawal decision.

However, customers of the Left Bank will make their withdrawal decisions before customers of the Right Bank.

Also, Left Bank customers know the level of reserves of the Left Bank before making their withdrawal decisions.

Before making their decisions, customers of the Right Bank observe how many Left Bank customers chose to withdraw today and how many chose to withdraw tomorrow. However, they will not know the level of reserves of Left Bank, nor the payoffs to Left Bank customers.

Once all Left Bank and Right Bank customers make their decisions, the payoffs for the period will be displayed on your screen.

There will be 30 periods in this experiment. Your payoff will be the sum of 3 periods, which will be randomly determined.

Appendix B: Theory

Appendix C: Auxiliar Regressions

Dep Var: Patient Right Bank Withd (t)	Agg	
Total Withd Left Bank (t)	0.121 ***	(0.028)
Right Bank L (t-1)	-0.681***	(0.094)
Total Withd Right Bank (t-1)	0.061**	(0.037)
Total Withd Left Bank (t) × Linked	0.153***	(0.040)
Right Bank L (t-1) × Linked	0.380***	(0.146)
Total Withd Right Bank (t-1) × Linked	-0.053	(0.055)
Linked	-1.113*	(0.559)
Period	0.027***	(0.006)
Period × Linked	-0.018**	(0.009)
Groups; Observations	12; 1740	

***,** ,*significance at 1%, 5%, 10% level, respectively.

Table 7: Marginal effects from random effects probit regression on the determinants of withdrawal level by patient Right Bank depositors – treatment comparisons

Dep var: Δ Patient Withd Right	(Agg 1)		(Agg 2)	
Δ Total Withd Left	0.592***	(0.109)		
Δ Total Withd Left> 0			0.154***	(0.056)
Δ Total Withd Left< 0			-0.051	(0.056)
$\Delta L = 0$ (high)	-0.052	(0.054)	-0.058	(0.057)
$\Delta L > 0$	-0.238***	(0.059)	-0.229***	(0.063)
$\Delta L < 0$	0.246***	(0.059)	0.248***	(0.063)
Δ Total Withd Left $\times$ LINKED	0.438***	(0.163)		
Δ Total Withd Left$> 0 \times$ LINKED			0.036	(0.078)
Δ Total Withd Left$< 0 \times$ LINKED			-0.119	(0.080)
$\Delta L = 0$ (high) $\times$ LINKED	0.066	(0.078)	0.150*	(0.082)
$\Delta L > 0 \times$ LINKED	0.069	(0.089)	0.165*	(0.092)
$\Delta L < 0 \times$ LINKED	-0.177**	(0.087)	-0.171*	(0.093)
LINKED	-0.052	(0.082)	-0.070	(0.100)
Period	-0.002	(0.003)	-0.001	(0.003)
Period $\times$ LINKED	0.003	(0.004)	0.003	(0.004)
Constant	0.052	(0.057)	0.012	(0.071)
Groups, Observations	12, 28		12, 28	
R^2	0.35		0.26	

***,** ,*: significance at 1%, 5%, 10% level, respectively.

Table 8: Random effects least squares estimation of changes in early withdrawals – treatment comparisons.

DV: Patient Right Bank Withdrawal (t)		
Total Withdrawals Left Bank (t)	0.162***	(0.039)
Right Bank L (t-1)	-0.759***	(0.133)
Total Withdrawals Right Bank (t-1)	0.031	(0.048)
Male	-0.305	(0.638)
BS	-0.302	(0.719)
Male × Total Withdrawals Left Bank (t)	-0.106**	(0.054)
Male × Right Bank L (t-1)	0.329*	(0.186)
Male × Total Withdrawals Right Bank (t-1)	0.053	(0.064)
BS × Total Withdrawals Left Bank (t)	0.054	(0.060)
BS × Right Bank L (t-1)	-0.202	(0.208)
BS × Total Withdrawals Right Bank (t-1)	0.050	(0.069)
Period	0.026***	(0.006)
Total Withdrawals Left Bank (t) × LINKED	0.015	(0.051)
Right Bank L (t-1) × LINKED	0.479***	(0.171)
Total Withdrawals Right Bank (t-1) × LINKED	-0.112*	(0.059)
Male × LINKED	-1.193	(0.917)
BS × LINKED	-0.888	(0.998)
Male × Total Withdrawals Left Bank (t) × LINKED	0.325***	(0.074)
Male × Right Bank L (t-1) × LINKED	-0.460*	(0.278)
Male × Total Withdrawals Right Bank (t-1) × LINKED	-0.022	(0.095)
BS × Total Withdrawals Left Bank (t) × LINKED	-0.042	(0.081)
BS × Right Bank L (t-1) × LINKED	0.186	(0.295)
BS × Total Withdrawals Right Bank (t-1) × LINKED	0.122	(0.097)
Period × LINKED	-0.015*	(0.009)
Groups; Observations	6; 870	

***,** ,*: significance at 1%, 5%, 10% level, respectively.

Table 9: Marginal effects from random effects probit regression on the determinants of patient Right Bank depositors' withdrawals – individual effects.