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 depositors.

Keywords: bank runs, contagion, experiments, multiple equilibria.

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1 Introduction

Bank runs are important economic phenomena. Over the last decade, we have witnessed visible and traditional bank runs on banks such as Northern Rock, which was the first run on a UK bank in 140 years and Countrywide Financial in the USA. 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 institution to another (e.g., from Lehman Brothers to AIG; from Greece to Spain). In particular, we ask whether changes in banking fundamentals cause contagions or are pure panics are to blame.

Diamond and Dybvig (1983) proposed an influential analysis of bank runs. 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 all depositors will 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.[1]

[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).

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 was the perceived over-exposure of banks to assets based on sub-prime mortgages during the 2007-09 financial crisis. 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.[2] 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, leading to runs on other US banks at the time.

It is difficult to distinguish information-based contagions from pure panics, since historical 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, but nonetheless they were anticipating a mass withdrawal by other depositors.

[2] Goldstein and Pauzner (2005) analyze this type of contagion effects through a 2-bank model where investors get noisy signals about fundamentals about country 2 after observing aggregate outcomes pertaining to country 1.

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.[3]

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 key fundamental parameter we manipulate is the liquidation value of the both banks' long-term investment (liquidity). 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; however, they do see how many Left Bank withdrawals are made before making their own withdrawal decision.

[3]As the *Economist* reported at the time: "Only when the Bank of England said that it would stand by the stricken Northern Rock did depositors start to run for the exit. Attempts by Alistair Darling, the chancellor of the exchequer, to reassure savers served only to lengthen the queues of people outside branches demanding their money. The run did not stop until Mr Darling gave a taxpayer-backed guarantee on September 17th that, for the time being, all the existing deposits at Northern Rock were safe." (The Economist, 20/09/2007). For a theoretical analysis of the effect on the banking system of revealing information about fundamentals, see Kaplan (2006) and Dang et al. (2009).

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 depositors' decisions when both banks' liquidity levels are always the same, as this would be an indication of the liquidity level of the Right Bank. In contrast, information about past Right Bank liquidity, as well as past withdrawals on the Right Bank ought to be more relevant to Right Bank depositors when liquidity levels of the two banks are independent of each other. All the above are plausible mechanisms that drive banking contagion. By studying these factors, we also better understand the processes that determine equilibrium selection in economic systems.

We find that actions taken by depositors in the Left Bank 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: when both banks' liquidity levels are independent of each other, an increase in Left Bank withdrawals can cause a panic run on the Right Bank, but a decrease in Left Bank withdrawals cannot calm depositors as effectively.

Changes in the Right Bank's liquidity over time also regulate the likelihood of a run on that bank. Increases in the Right Bank's liquidity level between rounds $t-2$ and $t-1$ lead to increases in withdrawal levels by patient Right Bank depositors in round t and vice-versa, but only significantly in the case where liquidities are independent. 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.

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 run contagions is scarce, because historically banking contagions are themselves infrequent. 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 generated an interesting case study on the study of bank runs and contagion. Iyer and Puri (2012) study depositor behavior 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 were 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). This literature has focused on designs 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. Kiss et al. (2012a; 2012b) look at the effect of observability of actions on the likelihood of bank runs to emerge. Arifovic et al. (2013) study the likelihood of the emergence of runs as a function of the fraction of the set of depositors who are required to wait in order for the bank to remain solvent. They find that for very low fractions, runs are very frequent, and for high fractions runs are rare. They identify a parameter region for which runs depend on the history of play. Arifovic and Jiang (2013) study the effect of sunspot bank runs by studying the effect of announcements forecasting the number of early withdrawals on the likelihood of runs occurring. They find subjects react to sunspot announcements in the intermediate region identified by Arifovic et al. (2013) but not in regions where one of the equilibria is stable.[4]

Our paper is related to Brown et al. (2012), who have independently investigated

[4]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.

in the lab the determinants of contagion. Like our paper, Brown et al. (2012) conduct experiments with two banks, in which the depositors of one bank make their decisions first, and the depositors of a second bank make their decisions after observing the actions of the first bank depositors. Like our paper, Brown et al. (2012) implement a treatment where there are economic linkages between the two banks, and a treatment where there are no linkages. The two papers differ in three important aspects of the experimental design: the number of depositors in each bank, strategic uncertainty regarding types, and the economic variable which links the two banks.

In our experiment, each bank has 10 depositors, as opposed to two in Brown et al. (2012). This arguably makes for a more difficult coordination problem for participants to tackle. Furthermore, in our design subjects are randomly allocated types from round to round, which closely follows the Diamond-Dybvig model and adds strategic uncertainty to the experiment, while this feature is absent from Brown et al.'s design. Finally, as mentioned above, the variable which we allow to vary in our experiment is the liquidation value of the long term asset of the bank, while Brown et al. allow the rate of return to the long term asset to vary. Unlike our paper, Brown et al. (2012) only find evidence of contagion when there are explicit economic linkages between the two banks, which indicates that the mechanisms behind panic-based contagions may be due to fears about short-term liquidity in the banking system, rather than the returns on long-term assets, thus vindicating Friedman and Schwartz's view.

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.[5] When impatient, depositors need to withdraw their money in period 1 (today), as they get relatively very little utility for the money tomorrow (impatient depositors have utility $u(x_1 + \alpha \cdot x_2)$ where x_1 is money today, x_2 is money tomorrow, and $0 \leq \alpha < 1$). When patient, depositors can wait until period 2 (tomorrow) to withdraw; however, can always withdraw the money today and hold on to it until tomorrow (patient depositors have utility $u(x_1 + x_2)$). 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 (but strictly less than $1/\alpha$). 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 $R \cdot X$ (that is,

[5] Types are equivalent to an idiosyncratic shock to individuals' liquidity needs.

they can choose between $(x_1, x_2) = (X, 0)$ and $(x_1, x_2) = (0, R \cdot X)$).[6] 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 fulfill 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 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. In this alternative equilibrium, too many depositors try to withdraw today and the bank is not able to meet the contract tomorrow. For instance, if a fraction $q > 1/2$ of depositors withdraw today, then the bank will have to 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.

[6]The original DD model also considers an insurance aspect to a 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. Hence, we use a parameterization with a contract devoid of this insurance aspect. This is only the optimal contract when depositors have log utility.

This is a bank run equilibrium where everyone withdraws today.[7]

2.2 Experimental Design

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

A bank with strictly more than five depositors withdrawing today faced 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 modified the original model by allowing each bank to have two possible levels of L. A bank could have high liquidity, $L = 0.8$, or it could have low liquidity, $L = 0.2$. 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 rounds. The rate of return was constant throughout at $R = 1.25$.

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

[7]There is also a symmetric mixed-strategy Nash equilibrium in which patient depositors withdraw early with some positive probability. This equilibrium is, however, dynamically unstable.

two banks' liquidity levels followed independent Markov processes. In the second treatment, Linked, the two banks' liquidity levels were always the same. Table 4 displays payoffs in a manner similar to that presented to the participants.[8]

In both treatments, Left Bank depositors knew their bank's liquidity level 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 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.

From a strategic point of view, the addition of the Right Bank does not affect the set of equilibria of the Left Bank. This is because the actions of depositors in the second bank carry no payoff consequences to the first bank. In both banks and in either treatment, the bank run and the no-run equilibria are possible. Solution concepts such as sequential equilibrium do not reduce the set of equilibria relative to Nash equilibrium. For example, in either Linked or Independent, Right Bank depositors imitating the actions of Left Bank depositors is a Nash (and sequential) equilibrium. Also, Right Bank depositors ignoring the actions of Left Bank depositors is also a Nash (and sequential) equilibrium.

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

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

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 subsection, there are multiple equilibria. 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 the Left Bank's liquidity levels are low.*

We turn to the main hypotheses of the paper, which concern the way in which a contagion may spread. 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 which 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. We describe them in turn.

The first mechanism relates to the relationship between beliefs about liquidity and the likelihood of withdrawing early. 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 fraction of early withdrawals by patient Right Bank depositors will be correlated with the total number of early withdrawals on the Left Bank. This correlation will be higher in* Linked *than in* Independent.

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 Left Bank depositor behavior conveys information to Right Bank depositors by comparing the aforementioned correlation in Linked to that in Independent. If indeed the correlation between withdrawals by Left Bank depositors and withdrawals by 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. The second mechanism postulates that the level of L in the previous round can be informative about the level of L in the current round, 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 liquidity in the previous round.*

Alternatively, in a third potential mechanism, a patient Right Bank depositor may believe that other patient Right Bank depositors will withdraw early if there was a run on the Right Bank in the previous round, irrespective of the Right Bank's liquidity in the previous round.

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 round.*

Hypotheses 3 and 4 distinguish between two different inter-temporal mechanisms of propagation of runs. Hypothesis 3 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 round indicates a two-thirds chance of the same occurring. Hypothesis 4 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 round. 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: *Changes in the number of early withdrawals in the Left Bank will be positively correlated with withdrawals by patient Right Bank depositors.*

Hypothesis 5 complements Hypothesis 2 by looking at how groups reach an equilibrium. Note that it is possible to observe a correlation between Left Bank withdrawals and Right Bank withdrawals in level terms without observing any effect in terms of changes. All one would require for this to be the case is for different sessions (which proxy markets) to have different initial conditions and remain at their respective states. For instance, in one market we could observe a run in the Left Bank which triggers a run on the Right Bank, and this equilibrium could remain throughout the experiment. In another market we could observe no run on the Left Bank, and that behavior is followed by Right Bank depositors. Although there is a correlation between behavior across banks, that correlation is driven by variation across markets, rather than an adjustment process within a market.

2.4 Experimental Procedures

We provided written instruction sets (see Appendix A), which informed participants of all the features of the market. We generated six independent sessions for each treatment (In-

DEPENDENT 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 depositor of that bank for the whole experiment. In each round, each participant was randomly assigned a depositor 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 round (which is L in our model), as well as how many withdrawals were made either today or tomorrow at their bank.

The participants' payment was the sum of their payoffs from three rounds, which were 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 one had participated in similar experiments before. The sessions took place in March and October 2011. The average payment was £13.15 ($20.66).[9]

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

	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.

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.[10] 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).[11] Note that these depositors knew their bank's liquidity levels before deciding. This is our first result.

[10]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 impatient Right Bank depositors was 96% for both liquidity levels.

[11]Whenever performing tests using non-parametric statistics, we use session-level averages, as is common practice; p denotes p-values on hypotheses.

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 cannot observe their own bank's liquidity level suggests that they may be relying on the behavior of the 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 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 probit regressions using the withdrawal decision by patient Right Bank depositor i in period t as

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 rounds.

the dependent variable.[12] The specification used was

$$\text{withdraw}_{it} = I\{\beta_0 + \beta_1 TWRB_{t-1} + \beta_2 RBL_{t-1} + \beta_3 TWLB_t + \varepsilon_{it} > 0\}, \tag{1}$$

where $I\{\cdot\}$ is an indicator function which is equal to one if the left-hand side of the inequality is positive and takes a value of zero otherwise. The regressors are: $TWRB_{t-1}$, the total number of withdrawals on the Right Bank in the previous round; RBL_{t-1}, the liquidity level of the Right Bank in the previous round; and $TWLB_t$, the total number of withdrawals on the Left Bank in the current period. 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 B for details).

[12] We do not estimate a random effects probit, because, although we have multiple observations per subjects, we do not have a proper panel. This is because in each period subjects are randomly assigned a type by the computer, which means that when we restrict our analysis to patient depositors, there are multiple missing observations per subject. As such we estimate a standard probit with clustered standard errors at market level.

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 $TWLB_t$ in both treatments. The larger coefficient is, as expected, in the LINKED treatment, and it is significantly larger than in the INDEPENDENT treatment.[13] 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 Hypothesis 2, in that Left Bank depositor behavior influences 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 pure panics as potential causes of bank run contagions. This relationship in INDEPENDENT can be compared to the sunspot equilibrium found in Arifovic and Jiang (2013). However, in our paper, the sunspots are created endogenously and rather than the message being there is a high number of depositors expected to withdraw from your bank, the message perceived by the Right-Bank depositors is that there is a run on the Left Bank and this indicates there would be a high number withdrawing from your bank.

We now turn to the effect of past liquidity levels in the Right Bank on current depositor behavior. In INDEPENDENT, though not in LINKED we see a negative and significant effect of the Right Bank's liquidity level in the previous round on the level of withdrawals in the current round. The coefficient is larger in absolute value in the INDEPENDENT re-

[13] Appendix B, Table 7: LINKED $\times$ TWLB$_t = 0.044, p = 0.090$.

gression, and that difference is statistically significant.[14] In other words, patient Right Bank depositors are influenced by past liquidity conditions in their own bank in INDEPENDENT but not in LINKED.

Result 3: *In* INDEPENDENT*, Patient Right Bank depositors are more likely to withdraw early if the liquidity level of their bank in the previous round was low.*

We finalize this analysis by looking at the 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 round 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.[15]

Result 4: *There is evidence that patient Right Bank depositors are more likely to withdraw the higher the total number of withdrawals on their bank was in the previous round.*

We now focus on how patient Right Bank depositors react to changes in market conditions. In particular, we analyze how changes in early withdrawals by patient Right Bank depositors are affected by changes in the number of early withdrawals from the previous round to the current round in the Left Bank, as well as changes in the liquidity of the Right Bank from two round ago to the previous round. To do so, we report a series of random effects least squares regressions. The dependent variable is the change in the proportion of early withdrawals by patient Right Bank depositors. We used aggregated data as opposed

[14] Appendix B, Table 7: $\text{RBL}_{t-1} = -0.261, p < 0.001$; LINKED $\times$ $\text{RBL}_{t-1} = 0.201, p <= 0.001$.

[15] Appendix B, Table 7: LINKED $\times$ $\text{TWRB}_{t-1} = -0.013, p = 0.663$.

	Linked		Independent	
	(1)	(2)	(3)	(4)
$TWLB_t$	0.079***	0.059***	0.034**	0.059**
	(0.022)	(0.020)	(0.015)	(0.026)
RBL_{t-1}	-0.061	-0.048	-0.260***	-0.248***
	(0.045)	(0.074)	(0.026)	(0.053)
$TWRB_{t-1}$	0.036	0.057***	0.048*	0.031
	(0.018)	(0.017)	(0.025)	(0.020)
Second Half $\times$ $TWLB_t$		0.032***		0.036
		(0.010)		(0.028)
Second Half $\times$ RBL_{t-1}		-0.028		-0.014
		(0.071)		(0.053)
Second Half $\times$ $TWRB_{t-1}$		-0.034		0.036
		(0.022)		(0.032)
Second Half		0.061		0.141
		(0.173)		(0.133)
Round	0.002		0.007	
	(0.002)		(0.004)	
Groups; N	870	870	870	870

Clustered standard errors at market level in parentheses.

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

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

to individual-level data because participants were randomly assigned a role (patient or impatient) in every round. As such, on average, half of the time participants who were patient depositors in one round were impatient depositors in the following round.

We consider two econometric specifications, which we describe in turn. The first specification is

$$\Delta WRB_{it} = \beta_0 + \beta_1 \Delta TWLB + \beta_2(\Delta L = 0(\mathit{high})) + \beta_3(\Delta L > 0) + \beta_4(\Delta L < 0) + \beta_5 \mathit{Round} + \alpha_i + \varepsilon_{it}, \tag{2}$$

and has as regressors $\Delta TWLB$, 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 round, $(\Delta L > 0)$, $(\Delta L < 0)$, 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.[16] The coefficient on $(\Delta TWLB)$ is positive and highly significant for both Independent and Linked. An increase in the number of early withdrawals in the Left Bank leads to an increase in early withdrawals in the Right Bank, although the effect is significantly higher in Linked than Independent.[17] 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 withdrawals by patient Right Bank depositors; there is no difference in effect size between treatments.[18] On the other hand, the coefficient on $(\Delta L < 0)$ is positive in

[16]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 B.

[17]Appendix B, Table 8, Regression (Agg1): $(\Delta TWLB) \times$ Linked $= 0.438, p < 0.01$.

[18]Appendix B, Table 8, Regression (Agg1): $(\Delta L > 0) \times$ Linked $= 0.069, p = 0.433$.

	(Lnk 1)	(Ind 1)	(Lnk 2)	(Ind 2)
$\Delta TWLB$	1.029***	0.592***		
	(0.121)	(0.109)		
$\Delta TWLB > 0$			0.189***	0.154***
			(0.055)	(0.055)
$\Delta TWLB < 0$			-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, N	6, 168	6, 168	6, 168	6, 168
R^2	0.36	0.34	0.24	0.29

Clustered standard errors at group level in parentheses.

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

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

both treatments, but significantly different than zero only in INDEPENDENT. Furthermore the difference in coefficients between the two conditions is significant.[19] In other words, the effect of a drop in Right Bank liquidity on Right Bank withdrawals is only significant in INDEPENDENT. 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. This specification permits us to infer whether or not increases in Left Bank withdrawals have a different qualitative effect than decreases in Left Bank withdrawals. The new specification is

$$\Delta WRB_{it} = \beta_0 + \beta_1(\Delta TWLB > 0) + \beta_1(\Delta TWLB < 0) + \beta_2(\Delta L = 0(high)) + \beta_3(\Delta L > 0) + \\ + \beta_4(\Delta L < 0) + \beta_5 Round + \alpha_i + \varepsilon_{it}, \quad (3)$$

which includes $(\Delta TWLB > 0)$ and $(\Delta TWLB < 0)$, 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 on $(\Delta TWLB > 0)$ in both treatments, with no statistical difference between the two.[20] We find negative coefficients in $(\Delta TWLB < 0)$ in both treatments, though only significant in LINKED. An increase in L leads to a decrease in withdrawals by patient Right Bank depositors, though only significantly so in INDEPENDENT. Likewise a decrease in L leads to an increase in withdrawals by patient Right Bank depositors, though again only significantly so in INDEPENDENT. 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*

[19]Appendix B, Table 8, Regression (Agg1): $(\Delta L < 0) \times$ LINKED $= -0.177, p = 0.041$.

[20]Appendix B, Table 8, Regression (Agg2): $(\Delta TWLB > 0) \times$ LINKED $= 0.036, p = 0.649$.

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 rounds* $t-2$ *and* $t-1$ *leads to a fall (rise) in withdrawal levels by patient Right Bank depositors in rounds* t*, particularly in* INDEPENDENT.

We conclude the data analysis by exploring the explanatory power of individual-level heterogeneity in our participant 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 or less 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*). The new specification is

$$\text{withdraw}_{it} = I\{\beta_0+\beta_1 TWRB_{t-1}+\beta_2 RBL_{t-1}+\beta_3 TWLB_t+\beta_4 Male+\beta_5 Business+\alpha_i+\varepsilon_{it} > 0\}, \tag{4}$$

Table 9 presents the results of the new estimations. We find some gender differences, depending on the treatment. In LINKED, men are significantly more responsive to withdrawal levels in the Left Bank. They are marginally less responsive than women to past liquidity levels in their own bank in INDEPENDENT, 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 round.

Additional Observation: *Men are more responsive to total withdrawals made in the Left Bank than women in* LINKED. *Men are significantly less sensitive than women to the Right Bank's previous liquidity level in* INDEPENDENT.

4 Discussion

The theoretical literature on bank runs distinguishes two main causes of 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.

	Linked		Independent	
$TWLB_t$	0.045*	(0.024)	0.043**	(0.017)
RBL_{t-1}	-0.039	(0.044)	-0.286***	(0.043)
$TWRB_{t-1}$	0.016	(0.017)	0.039	(0.039)
Male	-0.389	(0.286)	-0.134	(0.108)
Business	-0.337	(0.394)	-0.091	(0.185)
Male $\times TWLB_t$	0.070***	(0.023)	-0.023	(0.020)
Male $\times RBL_{t-1}$	-0.041	(0.067)	0.123*	(0.064)
Male $\times TWRB_{t-1}$	0.0004	(0.016)	0.008	(0.029)
Business $\times TWLB_t$	0.007	(0.046)	0.012	(0.020)
Business $\times RBL_{t-1}$	-0.032	(0.074)	-0.079	(0.099)
Business $\times TWRB_{t-1}$	0.048*	(0.027)	0.024	(0.016)
Round	0.003	(0.002)	0.006	(0.004)
N	870		870	

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

Clustered standard errors at group level in parentheses

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

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 impossible to gauge depositors' beliefs about banking fundamentals, as well as beliefs about other depositors' actions. 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. When the bank's liquidity is low, if one patient depositor withdraws early, all depositors who withdraw later will receive a payoff of zero. When the bank's liquidity is high, it is possible for some patient depositors to withdraw early and for there to be enough funds to serve depositors who 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. In our experiment, the fact that banks' liquidity levels follow a Markov process means that when current liquidity is unknown, participants can partially infer it from the level of liquidity in the previous round. 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 run 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. By manipulating 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 contagion 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, runs on the latter bank are as easy to start as to stop. However, panic-based contagions are harder 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 contagions may be more persistent than information-based ones.

It is informative to compare our results to those of Brown et al. (2012). This paper uses a similar setup as our paper, in that they look at a Diamond-Dybvig game with two banks. Instead of linkages in the redemption value of the long-term investment, L, they consider the effect of linkages in the return to the long-term asset, R. They find contagions only take place when the two banks have linkages. Our results combined with the findings from Brown et al. suggest that pure panic contagions may be triggered by fears about liquidity, rather than solvency-related issues.

This suggests there is value not only in reinforcing banking inter-linkages for their value in diversifying risk (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 subsections. We presented a separate sheet of paper with the payoff tables, which is included in the instruction text.

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.

To clarify ideas, consider the following examples.

Example 1:

- Your bank has low reserves.

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

- 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.

Linked – 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.

Linked – 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: Auxiliar Regressions

	(1)		(2)	
$TWLB_t$	0.034**	(0.014)	0.059**	(0.025)
RBL_{t-1}	-0.261***	(0.026)	-0.250***	(0.052)
$TWRB_{t-1}$	0.048**	(0.024)	0.031	(0.020)
Round	0.007	(0.004)		
Linked	-0.478***	(0.170)	-0.440	(0.286)
Linked × $TWLB_t$	0.044*	(0.026)	-0.0001	(0.032)
Linked × RBL_{t-1}	0.201***	(0.051)	0.202**	(0.089)
Linked × $TWRB_{t-1}$	-0.013	(0.029)	0.025	(0.025)
Linked × *Round*	-0.005	(0.005)		
Second Half × $TWLB_t$			-0.036	(0.027)
Second Half × RBL_{t-1}			-0.014	(0.051)
Second Half × $TWRB_{t-1}$			0.036	(0.031)
Second Half			0.141	(0.127)
Second Half × Linked			-0.080	(0.207)
Second Half × $TWLB_t$ × Linked			0.068**	(0.029)
Second Half × RBL_{t-1} × Linked			-0.013	(0.084)
Second Half × $TWRB_{t-1}$ × Linked			-0.069*	(0.037)
N	1740		1740	

Clustered standard errors at market level in parentheses.

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

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

	(Agg 1)		(Agg 2)	
$\Delta TWLB$	0.592***	(0.109)		
$\Delta TWLB > 0$			0.154***	(0.056)
$\Delta TWLB < 0$			-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)
$\Delta TWLB$ × Linked	0.438***	(0.163)		
$\Delta TWLB > 0$ × Linked			0.036	(0.078)
$\Delta TWLB < 0$ × Linked			-0.119	(0.080)
$\Delta L = 0$ (high) × Linked	0.066	(0.078)	0.150*	(0.082)
$\Delta L > 0$ × Linked	0.069	(0.089)	0.165*	(0.092)
$\Delta L < 0$ × Linked	-0.177**	(0.087)	-0.171*	(0.093)
Linked	-0.052	(0.082)	-0.070	(0.100)
Round	-0.002	(0.003)	-0.001	(0.003)
Round × 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	

Clustered standard errors at group level in parentheses.

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

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

	(1)	
$TWLB_t$	0.043***	(0.016)
RBL_{t-1}	-0.287***	(0.040)
$TWRB_{t-1}$	0.039	(0.037)
Male	-0.134	(0.103)
Business	-0.091	(0.176)
Male × $TWLB_t$	-0.023	(0.019)
Male × RBL_{t-1}	0.123**	(0.061)
Male × $TWRB_{t-1}$	0.008	(0.028)
Business × $TWLB_t$	0.012	(0.019)
Business × RBL_{t-1}	-0.079	(0.095)
Business × $TWRB_{t-1}$	0.024	(0.015)
Round	0.006	(0.004)
$TWLB_t$ × Linked	0.002	(0.028)
RBL_{t-1} × Linked	0.247***	(0.060)
$TWRB_{t-1}$ × Linked	-0.024	(0.040)
Male × Linked	-0.255	(0.292)
Business × Linked	-0.246	(0.414)
Male × $TWLB_t$ × Linked	0.093***	(0.029)
Male × RBL_{t-1} × Linked	-0.164*	(0.089)
Male × $TWRB_{t-1}$ × Linked	-0.008	(0.032)
Business × $TWLB_t$ × Linked	-0.005	(0.048)
Business × RBL_{t-1} × Linked	0.047	(0.118)
Business × $TWRB_{t-1}$ × Linked	0.024	(0.030)
Round × Linked	-0.003	(0.005)
Linked	-0.224	(0.182)
Groups; Observations	1740	

Clustered standard errors at group level in parentheses.

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

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